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Developing integrated maintenance strategies for renewable energy sources based on analytical methods and artificial intelligence (AI) : comparisons and case study

Aisha Sa'ad

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Ph.D

in

Automatique, Traitement du Signal et des Images, Génie Informatique

By

Aisha SA'AD

Developing integrated maintenance strategies for renewable energy sources based on analytical methods and artificial intelligence (AI): comparisons and case study.

Defended on 08/06/2023, before a jury composed of:

Rapporteurs

Abdellatif BENABDELHAFID Professor emeritus, Université le Havre Normandie, France
Bertrand ROSE Professor, Université de Strasbourg, France.

Examiners

Ali SIADAT Professor, Ecole Nationale Supérieure des Arts et Métiers, Metz, France. Jury President
Hamid ALLAOUI Professor, Université d'Artois, Arras, France.
Akilu Y. KALTUNGO Dr, University of Manchester, Manchester, UK.
Linda ZHANG Dr (HDR), IESEG School of Management, Paris, France

Invited guest

S.U. MUHAMMED Assoc. Prof. Nigerian Defence Academy, Kaduna, Nigeria

Thesis Director

Zied HAJEJ Assoc. Prof. (HDR), Université de Lorraine, Metz, France

Co-Director

Aimé C. NYOUNGUE Dr, Université de Lorraine, Metz, France

DEDICATION

This thesis is dedicated to almighty Allah, my family and friends whose everlasting support kept me going, without which this cannot be achieved.

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ABSTRACT (ENGLISH VERSION)

The development of renewable energy especially solar and wind energy over the recent years has gained global attention as an alternative method of generating energy experiencing exceptional growth in its production. In the Global Energy report, global solar energy is expected to have reached a cumulative capacity of 1TW while the wind energy is expected to have multiplied up to 3 to 4 times from mega production in the year 2020. This increase in the solar and wind power implies very significant financial investments. However, with this huge investment potential and significant increase in generation capacity, there is an additional, often overlooked responsibility: managing the power plants to ensure the lowest total life cycle cost (Life Cycle Cost). Like any standard production system, renewable energy (solar and wind energy in our case) generation components are subject to random failure which interrupts production and supply of demand.

Maintenance is identified as a major cause of accidents, lack of technical know-how of an equipment and the absence of a good maintenance routine plan. As part of the efforts to improve the efficiency and performance of renewable energy power plants, we propose models to optimize the power production and maintenance of our selected case studies (Sokoto solar plant and Katsina wind farm). In this regard, we developed new integrated maintenance strategies integrated with production of the energy production from solar and wind energy systems. The preventive maintenance strategy adopted in this thesis is perfect maintenance strategy on the selected components for maintenance and an imperfect selective maintenance on the system (solar PV and wind turbine). Battery shortage in case of under-production and maintenance losses are challenges considered in this study. The methodology we developed entails solving the problem of energy production and maintenance optimization by using the analytical method as well as machine learning method (ANN and SVR) in order to satisfy a random demand of energy during a finite horizon. We also studied the influence of environmental and operational condition of the systems and then validated the models by numerical examples and sensitivity studies proving the robustness of the developed models

Keywords: production, maintenance, renewable energy, artificial neural network (ANN), support vector regression (SVR), energy production, integrated maintenance.

RESUME (VERSION FRANCAISE)

Au cours de ces récentes années, le développement des énergies renouvelables, en particulier l'énergie solaire et l'énergie éolienne, a attiré comme méthode alternative de production d'énergie, l'attention du monde entier avec une croissance exceptionnelle de sa production. Selon le rapport de Global Energy, l'énergie solaire mondiale devrait avoir atteint une capacité cumulée de 1 TW, tandis que l'énergie éolienne devrait avoir été multipliée par 3 ou 4 mégas par rapport à la production en 2020. Cette augmentation des énergies solaire et éolienne implique des investissements financiers très importants. Cependant, avec cet énorme potentiel d'investissement et l'augmentation significative de la capacité de production, il y a une responsabilité supplémentaire, souvent négligée : la gestion des centrales électriques pour assurer le coût total du cycle de vie le plus bas (Life Cycle Cost). Comme tout système de production standard, les composants de production d'énergie renouvelable (solaire et éolienne dans notre cas) sont sujets à des défaillances aléatoires qui interrompent la production et l'approvisionnement de la demande.

La maintenance est identifiée comme une cause majeure d'accidents, on peut noter le manque de savoir-faire technique dans l'exploitation d'un équipement ou l'absence d'un bon plan de routine de maintenance. Dans le cadre des efforts visant à améliorer l'efficacité et la performance des centrales électriques à énergie renouvelable, nous proposons des modèles pour optimiser la production d'énergie et la maintenance dans nos études de cas sélectionnées (centrale solaire de Sokoto et parc éolien de Katsina au Nigéria). À cet égard, nous avons développé de nouvelles politiques de maintenance intégrées à la production d'énergie des systèmes d'énergie solaire et éolienne. La stratégie de maintenance préventive adoptée dans cette thèse est une stratégie de maintenance parfaite sur les composants sélectionnés pour la maintenance et une maintenance sélective imparfaite sur le système (solaire PV et éolienne). Le manque de batterie en cas de sous-production et les pertes de maintenance sont des défis considérés dans cette étude. La méthodologie que nous avons développée consiste à résoudre le problème d'optimisation de la production d'énergie et de la maintenance en utilisant la méthode théorique ainsi que la méthode d'apprentissage automatique (ANN et SVR) afin de satisfaire une demande aléatoire d'énergie pendant un horizon fini. Nous avons également étudié l'influence des conditions environnementales et opérationnelles des systèmes, puis validé les modèles par des exemples numériques et des études de sensibilité prouvant la robustesse des modèles développés.

Mots-clés : production, maintenance, énergies renouvelables, artificial neural network (ANN), support vector regression (SVR), production d'énergie, maintenance intégrée.

Introduction Générale

La population mondiale compte 940 millions de personnes, dont environ 13 % n'ont pas accès à l'électricité. La plupart d'entre elles se trouvent dans les pays en voie de développement de l'Afrique subsaharienne. Rien qu'au Nigeria, environ 44,6 % de la population n'a pas accès à l'électricité, principalement dans les zones rurales et reculées. De plus, le secteur de l'énergie au Nigeria est confronté à d'énormes défis et faiblesses tels que le manque d'installations modernes pouvant générer et distribuer de l'énergie de manière fiable, le faible accès à l'énergie moderne pour cuisiner, l'augmentation de la population entraînant une augmentation de la demande d'énergie, le coût élevé de l'énergie, le coût élevé de l'électrification rurale du réseau, les fréquentes coupures de courant et la forte dépendance aux produits pétroliers. Dans le cadre des efforts déployés pour atténuer les crises énergétiques et soulager la forte dépendance à l'égard du réseau électrique au Nigeria, l'agence d'électrification rurale (REA) du Nigeria a proposé des moyens de décentraliser l'énergie du réseau. Ces solutions, pour générer quelques watts ou kW d'électricité, sont par exemple la production de l'énergie solaire sur les toits des habitations, pour alimenter les maisons et pomper l'eau dans les zones rurales. Il existe d'autres mégaprojets d'une capacité de plusieurs MW sur la base d'énergies renouvelables. L'on a des grands projets tels que la centrale solaire de Sokoto et le parc éolien de Katsina, capables d'alimenter les habitations des villes et des zones géographiques environnantes.

À cet égard, nous avons développé de nouvelles politiques de maintenance intégrées à la production d'énergie à partir de systèmes d'énergie solaire et éolienne. Ces politiques ont pour objectif de minimiser le coût total de production, de stockage, de la pénurie et de la maintenance ainsi que de maximiser la disponibilité des systèmes éoliens et photovoltaïques. La stratégie de maintenance préventive adoptée dans ce contexte est une stratégie périodique de maintenance parfaite/Imparfaite sur les composants sélectionnés. Si tous les composants sont sélectionnés, nous considérons une maintenance parfaite sur l'ensemble du système (solaire PV et éolienne). Sinon, une maintenance sélective imparfaite est réalisée lorsque seulement quelques composants ont été sélectionnés. La méthodologie que nous avons développée commence par la résolution du problème d'optimisation de la production d'énergie, en utilisant la méthode théorique ainsi que la méthode d'apprentissage automatique (ANN et SVM), afin de satisfaire une demande aléatoire d'énergie pendant un horizon fini. Les résultats obtenus sont considérés comme une entrée ou bien une contrainte dans le développement de la stratégie de maintenance, en considérant l'impact de la variation de la production d'énergie sur le niveau de dégradation de l'éolienne et du panneau solaire PV. Cet impact est caractérisé par une nouvelle relation analytique et paramétrique du taux de défaillance en fonction du temps et du taux de production. Nous avons également étudié l'influence des conditions environnementales et opérationnelles des systèmes, puis validé les modèles par des exemples numériques et des études de sensibilité prouvant la robustesse des modèles développés.

En résumé, dans la première partie de ce chapitre, nous avons présenté une étude bibliographique détaillée des différents types et stratégies de maintenance dans le domaine

industriel ainsi que les différentes politiques d'optimisation de la maintenance ; cette étude s'intéresse également aux différents travaux faisant le couplage de la production et de la maintenance sous différentes contraintes telles que les contraintes environnementales et le taux de service. Dans un deuxième chapitre, nous développons un modèle d'optimisation du plan de production d'énergie afin de déterminer le nombre optimal de panneaux solaires, d'éoliennes et de batteries de stockage nécessaires pour satisfaire la demande de charge pour chaque période de production. Après la planification de la production, un modèle de maintenance a été développé pour déterminer le plan optimal de maintenance parfaite, en minimisant le coût total des actions de maintenances préventive et corrective. Dans le chapitre trois, nous considérons une stratégie de maintenance sélective prioritaire afin d'obtenir une disponibilité maximale du système de production d'énergie. La stratégie adoptée consiste à sélectionner les composants à entretenir au moment de la maintenance préventive en fonction de leur fiabilité, de sorte qu'un seuil de fiabilité est imposé. Dans le chapitre quatre, en se basant sur le constat que les durées importantes des actions de maintenances préventives et correctives peuvent impacter la production et la non satisfaction des demandes et génèrent des coûts de perte de production, nous avons développé un modèle intégré de production et de maintenance qui minimise le coût total du cycle de vie des systèmes renouvelables (de production, de stockage, de pénurie et perte de production). L'algorithme développé vise à déterminer simultanément le plan économique de production et le plan optimal de maintenance tout en respectant la contrainte de continuité de fiabilité et du taux de service du client.

CHAPITRE 1 : Stratégies de production et de maintenance dans le secteur des énergies renouvelables (Photovoltaïque, éolien) : État de l'art

De nos jours, dans le domaine des énergies renouvelables, la maintenance intégrée est considérée comme l'une des fonctions techniques les plus sensibles. Compte tenu du risque qu'elle peut faire courir, de l'importance dans la stabilité de la production d'énergie et l'amélioration de la rentabilité des systèmes d'énergie renouvelable, notamment pour les installations solaires et éoliennes. Par conséquent, l'optimisation et la planification adéquate de cette maintenance sont devenues une nécessité dans la prise de décision. Dans ce chapitre, nous avons effectué une revue de la littérature relative à notre sujet. Tout d'abord, nous avons discuté des types de maintenance, et des actions de maintenance effectuées pour chaque opération. Nous avons également examiné les différents types de politiques d'optimisation de la maintenance appliquées dans l'industrie en général. Ensuite, nous avons introduit l'intelligence artificielle pour la planification de la maintenance, en nous concentrant sur l'aspect apprentissage automatique. Dans cette partie, nous avons examiné les différents types d'outils d'apprentissage automatique et le processus d'optimisation qu'elles impliquent. Après cela, nous avons ensuite mené une étude sur l'industrie des énergies renouvelables, son importance, les différentes optimisations de la production dans ce secteur et les revers rencontrés. Nous nous sommes également concentrés sur les secteurs de l'énergie du solaire et des éoliennes ; son importance, les différentes optimisations de la production et les problèmes que l'on y rencontre. Cela nous aide à cadrer notre recherche en identifiant certaines boucles dans les politiques de maintenance des énergies renouvelables.

Nous avons pu comprendre que la plupart des travaux de la littérature analysés traitait la production séparément de la maintenance. D'après nos recherches, très peu d'ouvrages se sont penchés sur les politiques intégrées de production et de maintenance des systèmes énergétiques. Nous avons donc décidé d'utiliser la technique de l'apprentissage automatique : le réseau artificiel de neurones (ANN) et le support vecteur régression (SVR) pour prévoir/estimer la production d'énergie des centrales électriques. Nous avons également observé que l'influence du taux de la variation de la production, des conditions environnementales et opérationnelles du système de production d'électricité sur le taux de défaillance du système. Cet aspect n'était pas généralement discuté et prise en compte lors de la planification de la maintenance. De plus, au meilleur de notre connaissance, il existe très peu de travaux discutant des stratégies de maintenance intégrées avec une étude approfondie de la fiabilité des systèmes d'énergie photovoltaïque et éolienne sous des contraintes économiques, environnementales et de sécurité. Par conséquent, dans cette étude, nous avons réussi à identifier les lacunes dans le domaine de l'intégration de la production et de la maintenance et avons souligné les principaux objectifs du travail ainsi qu'une brève méthodologie générale prévue pour le travail.

CHAPITRE 2 : Développer et optimiser une stratégie de production et de maintenance des énergies renouvelables

Dans ce second chapitre, nous avons développé des méthodologies de maintenances intégrées qui optimisent conjointement une centrale solaire et un parc éolien. Le concept de système de production d'énergie a été défini pour les systèmes d'énergie solaire et éolienne en se basant sur l'apprentissage automatique et les méthodes théoriques. Comme mentionné dans le chapitre 1, notre travail se concentre sur le réseau neuronal artificiel (ANN), la régression par vecteur de support (SVR) et la technique théorique traditionnelle. L'objectif principal est de développer un plan optimal de production d'énergie et de l'intégrer à la politique de maintenance afin de minimiser les coûts de production et de maintenance. La démarche suivie est l'utilisation d'une méthode séquentielle qui consiste à déterminer d'abord le plan économique de production en déterminant le nombre optimal de panneaux solaires, d'éoliennes et de batteries nécessaires pour satisfaire la demande aléatoire et le coût total correspondant. La batterie n'est pas une unité de production mais un système de stockage d'énergie qui alimente la charge en cas de manque d'électricité et stocke le surplus lorsque l'énergie produite dépasse la charge. Dans certains cas, lorsqu'il y a pénurie d'énergie pour satisfaire la demande, l'externalisation est envisagée, par conséquent, notre conception a pris en compte le coût de la pénurie dans l'optimisation du système.

Il existe plusieurs façons de calculer les coûts de ce type de système (Bernal-Agustín et al., 2006 ; Dufo-López et al., 2007). Dans notre travail, nous faisons l'hypothèse que le coût du cycle de vie du système, composé du coût du capital initial et des coûts opérationnels. De cette façon, nous avons développé le modèle mathématique du coût total de production à optimiser afin d'obtenir le plan optimal de production qui minimise le coût total, en déterminant le nombre correct et optimal de composants (panneaux solaires, éoliennes et batteries) contraint par l'énergie disponible dans les batteries, la gamme de nombre de panneaux/éoliennes à utiliser ainsi que la demande de charge.

Nous avons utilisé, comme cas d'études, les données issues de deux installations d'énergie renouvelable du Nigeria : la centrale solaire de Sokoto et le parc éolien de Katsina. Nous avons obtenu des données antérieures sur les centrales dans le site Web de la NASA pour les conditions climatiques et la production d'énergie de la centrale. Ces données nous ont servi à initialiser notre modèle de production. Nous avons utilisé ces données pour former et tester les modèles développés, basés sur l'ANN et le SVR. Les modélisations de l'énergie solaire et de l'énergie éolienne ont été considérées comme des variables aléatoires. Nous avons donc utilisé la fonction bêta pour modéliser l'énergie solaire en considérant l'irradiation, et la température du site sélectionné comme la principale variable d'entrée. Pour l'énergie éolienne, nous avons effectué une modélisation basée sur la fonction de Weibull où la vitesse du vent était prise comme la variable d'entrée. En utilisant les techniques d'apprentissage automatique, nous avons été en mesure de prévoir la production d'électricité attendue pour 1 an, ce qui était notre horizon sélectionné, et nous avons fait de même pour les méthodes théoriques adoptées.

Les résultats obtenus à partir du plan de production ont ensuite été intégrés dans la modélisation du problème de maintenance, ainsi, l'influence de la production d'énergie a été prise en compte lors de l'estimation du taux de défaillance.

Rappelons que l'objectif principal de notre étude est d'optimiser conjointement la production et la maintenance en adoptant une méthode de résolution séquentielle. En utilisant une relation paramétrique entre les facteurs de risque de fonctionnement et de défaillance, le taux de défaillance des éoliennes/panneaux solaires augmente au cours de chaque période de production en fonction à la fois du temps et de la variation du taux de production (facteur de fonctionnement).

Afin de considérer l'impact du taux de production sur la dégradation du système, nous établissons une relation paramétrique entre le taux de défaillance nominal ($\lambda_n(t)$), modélisé en utilisant la fonction de Weibull qui dépend du temps) et la fonction de production d'énergie ($f(P_k) = P_k/P_{max}$) pour chaque période de production k ($k : 1 \dots H$) [Hajej et al 2021]).

L'objectif principal de la planification de la maintenance est de déterminer le nombre optimal des actions de maintenances préventives (N^*) à effectuer sur l'horizon de production (H), en tenant compte du plan de production optimal ainsi que des coûts associés aux maintenances préventives et correctives. Dans notre travail, la stratégie de maintenance adoptée est une stratégie périodique de maintenance préventive parfaite avec réparation minimale. Une maintenance parfaite est appliquée à chaque action préventive, qui restaure le système à son état neuf (AGAN : as good as new). Tandis qu'une maintenance corrective avec réparation minimale (ABAO : as bad as old) s'applique à chaque défaillance survenue entre deux actions successives de maintenance préventive en n'impactant pas l'allure du taux de défaillance. Dans ce cas, le nombre moyen de pannes pendant l'intervalle de maintenance préventive T déterminé par le calcul de l'intégrale de la fonction taux de panne qui doit être une fonction monotone croissante.

Pour chacune des études de cas sélectionnées (centrale solaire de Sokoto et parc éolien de Katsina, Nigeria), nous avons estimé le coût de la maintenance ainsi que le nombre optimal de maintenances (N^*) à effectuer. Dans l'étude sur l'énergie solaire, l'ANN a été la meilleure approche

pour la planification de la production car elle a permis d'obtenir un coût de production minimum nécessitant un nombre de panneaux moins élevé, suivi par le SVR et ensuite la technique théorique.

De même, dans le cas de l'analyse de l'énergie éolienne, le résultat de la production optimale obtenus avec l'ANN donne le meilleur plan optimal pour le plan de production, suivi par le SVR et ensuite la technique théorique. Dans l'analyse de l'énergie éolienne, l'estimation du nombre de turbines à partir de la technique théorique est deux fois plus élevée que celle obtenues par l'ANN, ce qui signifie un coût plus élevé dans la planification de la production dans l'approche théorique. Ceci peut être expliqué par l'influence des variables aléatoires dans les paramètres de Weibull.

Pour obtenir le coût optimal de production d'énergie, l'ANN s'est avéré être le plus efficace dans l'analyse de la production d'énergie solaire et éolienne. De cette analyse, nous pouvons déduire que l'approche d'apprentissage automatique donne les meilleurs résultats.

En ce qui concerne la stratégie de maintenance, la méthode théorique présente les coûts minimaux en considérant le coût de maintenance total ou global, tandis que la méthode ANN a été considérée comme optimale en termes de minimisation des coûts. Après avoir étudié la planification de la production et de la maintenance des systèmes d'énergie solaire et éolienne dans ce second chapitre, nous pouvons conclure que l'approche ANN est la meilleure forme pour l'estimation de la puissance et la maintenance pour l'énergie éolienne. Cela peut s'expliquer par la capacité de l'ANN à apprendre des caractéristiques pertinentes à partir des données et à bien s'adapter aux données après l'entraînement. Cependant, le SVR a un problème de dimensionnalité qui a une mauvaise propriété de généralisation.

A la fin, nous avons effectué une analyse de sensibilité afin de comprendre les impacts de certains paramètres variables sur la production du système ainsi que sur les coûts de maintenance. Et aussi, pour comprendre leur influence sur le nombre optimal de maintenances à effectuer pour chaque système.

CHAPITRE 3 : Développer et optimiser une stratégie de maintenance intégrée maximisant la disponibilité, sous contraintes opérationnelles et environnementales.

Dans ce chapitre, nous avons développé des modèles de planification de la maintenance pour une centrale solaire et un parc éolien qui maximisent la disponibilité de chacun des systèmes de notre étude de cas mentionnée ci-dessus. L'objectif ici était de développer une stratégie de maintenance qui minimise les temps d'arrêt (les durées des actions de maintenances préventives et correctives non négligeables) en sélectionnant les composants prioritaires sur lesquels la maintenance serait effectuée lors de la période de maintenance préventive (PM). Dans ce cadre, nous déterminerons également le nombre optimal d'actions de maintenance préventive (N^*) qui permettrait d'obtenir la disponibilité maximale sur un horizon fini choisi sans discontinuité. Pour ce faire, nous avons développé un modèle de maintenance sélective prioritaire. Ce modèle choisit les composants à remplacer pendant chaque période de maintenance de manière à garantir la fiabilité des équipements et leurs disponibilités maximales.

Notre démarche combine les stratégies de maintenance préventive et sélective pour décider de la meilleure combinaison qui fournit le nombre optimal d'actions de maintenance préventive. A chaque période de maintenance préventive $k = 1, 2, \dots, N^*$, l'objectif de la maintenance sélective prioritaire est de sélectionner les bons composants $i = 1, 2, \dots, N_c$ (N_c = nombre de composants) à maintenir, de manière à garantir un niveau de fiabilité requis jusqu'au prochain arrêt. La sélection est basée sur des critères de fiabilité tel que le seuil minimal de fiabilité est défini. Chaque fin de période de production, la fiabilité du composant par rapport au seuil est évalué. Lorsque la fiabilité du composant est inférieure au seuil de fiabilité fixé (R^*), il est automatiquement sélectionné pour la maintenance. Avec cette technique, la durée de la maintenance est minimisée puisque tous les composants ne sont pas sélectionnés à chaque période de maintenance préventive.

Par conséquent, lorsque tous les composants sont sélectionnés pour la maintenance, une maintenance préventive parfaite est menée. Cela implique que tous les composants seront remplacés et que le système sera restauré dans un état "comme neuf (AGAN)" avec un taux de défaillance proche de zéro. À l'inverse, lorsqu'un, deux ou trois composants sont sélectionnés, une maintenance imparfaite est effectuée. Cela réduit le taux de défaillance du système mais ne le rend pas aussi bon que neuf. Dans notre travail, nous avons également pris en considération et utilisé comme contraintes dans notre modélisation de la maintenance l'influence des conditions climatiques et opérationnelles affectant les systèmes d'énergie PV/éolienne. L'influence du taux de production a été prise en compte car elle affecte largement le système d'énergie éolienne en raison du fonctionnement de l'éolienne. À cet égard, la modélisation de la production obtenue en utilisant les techniques d'apprentissage automatique est intégrée dans la technique de planification de la maintenance afin d'obtenir une disponibilité maximale. L'estimation de la fiabilité du système photovoltaïque a été réalisée en tenant compte des composants critiques qui sont les plus touchés pendant la production d'énergie. Ainsi que des composants qui aident à fournir et à transformer l'énergie générée (courant continu par courant alternatif). Pour l'éolienne, cependant, l'énergie générée par l'éolienne est déjà sous sa forme consommable (CA), par conséquent, nous avons considéré uniquement les composants critiques qui sont sujets à des défaillances fréquentes dans l'éolienne. Dans ce contexte, l'arbre principal, le roulement principal, le générateur et la boîte de vitesse ont été les composants sélectionnés sur lesquels la fiabilité de l'éolienne a été modélisée. La modélisation du taux de défaillance pour chaque système était basée sur les différentiels de fiabilité des systèmes (PV et éolien) par rapport au temps pour chaque période de production.

La nouveauté de ce travail est que la fiabilité des énergies solaire et éolienne a été modélisée en fonction des conditions environnementales et opérationnelles. Dans l'étude solaire, les principales conditions environnementales affectant chacun des composants considérés ont été définies et la maintenance a été planifiée en tenant compte de l'influence de ces conditions climatiques sur l'ensemble du système. Nous avons d'abord déterminé le plan de maintenance optimal dans des conditions nominales (idéales), puis nous avons fait de même en tenant compte de l'influence de l'environnement sur les composants. D'après les résultats obtenus, le plan de maintenance optimal pour les deux conditions s'est avéré être le même. Cependant, une disponibilité maximale plus élevée a été obtenue dans des conditions idéales, ce qui est

compréhensible. Alors que, une valeur de disponibilité légèrement inférieure a été obtenue lorsque l'impact environnemental a été pris en compte.

Dans l'analyse de l'étude de l'énergie éolienne, l'influence des conditions opérationnelles et l'impact du taux de production ont été pris en compte en plus des conditions climatiques. En effet, une éolienne est composée de pièces rotatives : les arbres et les engrenages. De ce fait, l'usure et les autres propriétés mécaniques des composants détériorer de l'éolienne peuvent réduire le rendement de l'éolienne. Nous avons modélisé la stratégie de maintenance de telle sorte que l'impact sur la production soit intégré simultanément dans le plan de maintenance. Le plan de maintenance optimal obtenu est de deux (2) maintenances préventives avec le SVR et trois (3) maintenances préventives pour l'ANN. Cependant, si l'on analyse la disponibilité maximale, l'ANN présente le système avec une disponibilité maximale de 99,92% alors que la disponibilité avec le plan de production défini par SVR était de 99,87%. On peut en déduire que le taux de production a une influence sur le plan de maintenance. Le SVR a un pourcentage de disponibilité plus faible malgré le fait qu'il ait un nombre optimal de maintenances à effectuer plus faible. Comme nous l'avons mentionné dans le chapitre 2, l'ANN a une meilleure capacité à s'adapter aux données en raison de sa capacité à apprendre et à ajuster facilement son taux d'apprentissage sans problème de dimensionnalité, qui est souvent rencontré avec le SVR.

Nous avons également effectué une analyse de sensibilité sur chacun des systèmes en faisant varier la différence entre les temps de maintenance corrective et de maintenance préventive afin de comprendre son effet sur la maintenance. Nous variés les conditions climatiques ainsi que le seuil de fiabilité des systèmes afin d'analyser leur impact sur le nombre de maintenances préventives. Nous pouvons conclure que, pour l'analyse du système solaire, le temps de maintenance corrective influence le nombre de maintenance préventive (N^*), mais pas tellement d'effet sur la disponibilité. Nous pouvons également dire que le seuil de fiabilité influence à la fois le N^* et la disponibilité. Si l'on considère l'impact environnemental, celui-ci entraîne une diminution de la disponibilité. Avec la production d'énergie par éolienne, lorsque la différence de temps entre PM et CM est importante, l'augmentation du temps de CM entraine celle de N^* , et ceci pour les deux techniques. Cependant, lorsque la différence est faible l'augmentation du temps de CM réduit le N^* aussi bien pour l'ANN que pour le SVR. En ce qui concerne la sélection du seuil de fiabilité, l'augmentation du seuil entraine celle de N^* mais n'a pas beaucoup d'influence sur la disponibilité de l'installation.

CHAPITRE 4 : Développement et optimisation d'une stratégie intégrée de production et de maintenance d'énergie, minimisant les Pertes Economiques sous contraintes de fiabilité

Dans ce 4^{ème} chapitre, nous avons développé une stratégie de maintenance intégrée à la planification de la production des systèmes d'énergie photovoltaïque et éolienne. Cette stratégie tient compte de l'implication des coûts de pénurie et de perte de production. Dans ce cas, la production d'énergie et le stockage dans les batteries ne sont pas en mesure de répondre à la demande de la charge à causes de la perte de production toute au long des durées importantes et non négligeables des actions de maintenances préventives et correctives. L'objectif de ce chapitre est d'optimiser simultanément la production et la maintenance afin de minimiser le coût total de

production, de stockage, de la pénurie et de la perte de production en tenant compte de l'implication du temps de maintenance préventive et corrective.

La stratégie de maintenance préventive adoptée, est la maintenance parfaite/sélective avec réparation minimale. Ceci nous a permis de déterminer le nombre optimal de maintenance préventive (N^*) à coût minimal sur un horizon fini choisi. Il s'agit d'un problème d'optimisation contraint par le seuil de fiabilité, le taux de service et la production d'énergie du système, de sorte que la fiabilité et le taux de service ne tombent pas en dessous d'un seuil minimum fixé. Dans ce cas, la stratégie que nous utiliserons ici est une stratégie de sélection prioritaire pour choisir les composants les plus critiques à maintenir pendant la maintenance préventive. Ainsi, l'on prendra soins que leur fiabilité ne tombe pas en dessous du seuil de fiabilité (R^*). Ce seuil de fiabilité (R^*) maximise en même temps la fiabilité et le coût total de production du cycle de vie du système.

Ce chapitre présente une intégration des méthodologies utilisés dans les chapitres précédents (chapitres 2 et 3). Cette intégration des méthodologies est réalisée simultanément pour atteindre un coût minimal. L'objectif ici est de déterminer simultanément le plan optimal de production d'énergie et le plan optimal de maintenance caractérisé par la quantité d'énergie stockée et les pertes encourues, lorsque la demande en énergie n'est pas satisfaite. Notre Stratégie a pour but de, minimiser le coût total attendu du cycle de vie du système de production d'énergie (production, stockage, pénurie et de perte), dépend du plan de maintenance sur un horizon fini. Dans ce chapitre, nous avons également considérés le taux de service. La modélisation du taux de défaillance dans ce chapitre a été faite sur la base des différentiels de fiabilité comme dans la stratégie de modélisation du taux de défaillance dans le chapitre 3. Ici, la stratégie de maintenance suivie est une stratégie de production et de maintenance sont intégrée. La maintenance sélective prioritaire sélectionne les composants à entretenir en fonction de leur fiabilité pendant une période de maintenance préventive programmée. Le but est de minimiser le temps de la maintenance par un processus de sélection qui maximise la fiabilité du système et minimise le cycle de vie total du système.

Les résultats obtenus ont prouvé que les données de la vie réelle fonctionnent mieux avec la méthode ANN de la technique de production d'énergie, suivie par le SVR et la technique théorique traditionnelle respectivement. Ceci peut être expliqué par la capacité des techniques d'apprentissage automatique à apprendre et à s'adapter aux données complexes du système. Les résultats obtenus montrent que l'ANN présente les meilleurs résultats avec un coût total minimal pour le système PV et pour les systèmes éoliens, suivi par le SVR et les techniques théoriques. Nous avons également observé que même le temps d'exécution pris par l'approche d'apprentissage automatique est inférieur à celui pris par l'approche théorique. L'ANN présente également un temps inférieur par rapport au SVR. D'une manière générale, nous pouvons dire que l'application de données réelles présente un résultat plus raisonnable que l'approche théorique ; puisque l'approche théorique est réalisée par un calcul de probabilité utilisant la fonction de distribution Gamma/Weibull.

Conclusion Générale

La principale contribution de ce travail de recherche est la mise en œuvre de politiques de production d'énergie et de stratégies de maintenance pour un système d'énergie renouvelable (solaire PV et éolien) soumis à certaines contraintes. Dans cette thèse, nous nous sommes concentrés sur le développement de nouvelles stratégies de maintenance intégrées dans le système de production d'énergie (Solaire et éolienne), en prenant en considération l'influence des conditions environnementales et opérationnelles sur la dégradation du système. Le modèle que nous avons développé était soumis à des contraintes de fiabilité tout en assurant la disponibilité des équipements, et la satisfaction de la demande des consommateurs.

Dans le premier chapitre, nous avons réalisé une étude bibliographique sur les travaux de recherche portant essentiellement sur la production et la maintenance de la production d'énergie solaire et éolienne. Nous avons également étudié les stratégies de maintenance intégrée en relation avec les systèmes de production. A partir de cette étude bibliographique, nous avons repéré l'existence de lacunes dans la littérature. D'après la littérature, nous comprenons que très peu de travaux ont rapporté la planification de la production d'énergie renouvelable en considérant la pénurie d'approvisionnement et la possibilité d'externalisation. De plus, l'influence du taux de production variable, des conditions environnementales et opérationnelles du système de production d'électricité sur le taux de défaillance du système n'était pas communément discutée et prise en compte lors de la planification de la maintenance. De plus, à notre connaissance, il existe très peu de stratégies de maintenance intégrées avec une étude approfondie de la fiabilité des systèmes d'énergie solaire photovoltaïque et éolienne sous des contraintes économiques, environnementales et de sécurité. Par conséquent, dans cette étude, nous avons réussi à identifier les lacunes dans le domaine de l'intégration de la production et de la maintenance et avons souligné les principaux objectifs du travail.

Dans le deuxième chapitre, nous avons défini notre système de production d'énergie pour les systèmes d'énergie solaire et éolienne. En tenant compte de notre étude de cas, nous avons développé un modèle d'optimisation basé sur l'apprentissage automatique (ANN et SVR) et des techniques analytiques, afin d'optimiser le système de production et de déterminer le nombre optimal de composants requis ; panneaux solaires, éoliennes et nombre de batteries de stockage pour chaque système avec toutes les techniques. L'objectif de la planification de la production était de déterminer le coût optimal de la production en déterminant la puissance optimale produite ainsi que le nombre optimal de composants qui satisfont la demande par période. La nouveauté de ce travail est qu'il considère le coût de la pénurie lors de la planification de la production de sorte que les pertes économiques associées au système de production soient minimisées. Nous avons ensuite développé un modèle de maintenance pour une (1) éolienne et un (1) panneau solaire en intégrant le résultat de la planification de la production dans le modèle de maintenance pour déterminer le coût de la maintenance.

Dans le troisième chapitre, nous avons développé avec succès un modèle de maintenance intégré qui maximise la disponibilité des systèmes d'énergie solaire et éolienne sous des contraintes environnementales et opérationnelles. Dans les deux systèmes, les composants qui sont les plus

affectés par les conditions environnementales. Afin d'atteindre notre objectif, nous avons développé notre stratégie sur le processus de maintenance sélective, de sorte que différents composants sont sélectionnés pour la maintenance pendant la période de maintenance préventive. Cela nous permet de minimiser les temps d'arrêt pour la maintenance. Le processus a également été construit sur la base d'une contrainte de seuil de fiabilité telle que la fiabilité d'un composant ne dépasse pas le seuil. Nous avons également déterminé le nombre optimal de maintenances à effectuer afin d'atteindre l'objectif de disponibilité maximale.

Dans le dernier chapitre, nous avons intégré le coût de la perte de production d'énergie due aux durées non négligeables des actions de maintenance. Nous avons développé un modèle intégré de production/maintenance qui vise à minimiser le coût total de production, de stockage et de la perte du système pour les systèmes d'énergie solaire et éolienne. Dans ce chapitre, nous avons développé un modèle d'optimisation simultanée de la planification de la production et de la maintenance sous contraintes du taux de service et de la fiabilité du système. Par conséquent, ce chapitre est une extension intégrée des modèles développés dans les deux (2) chapitres précédents.

Les résultats prometteurs obtenus dans cette thèse peuvent conduire à des perspectives intéressantes. Au-delà de cette étude, ces contributions peuvent être appliquées à d'autres modèles. Notre système de production d'énergie peut être étendu à un système hybride composé de systèmes éoliens et solaires, ainsi qu'à d'autres sources d'énergie renouvelables telles que l'hydraulique et la biomasse. Suite à cette étude, et en guise de perspective, nous pouvons proposer des stratégies de maintenance en intégrant la gestion des pièces détachées et l'externalisation éventuelle du personnel de maintenance auprès de sociétés de maintenance.

THESIS OVERVIEW

With the advent of increase in energy demand, the pressure on the present and conventional energy generating sources is vast. Coupled with the expected depletion of the oil reserves, this gives birth to the need for energy resource diversification especially in renewable energy sector. Over the years, harnessing wind and solar energy sources receives more attention due to their abundant availability. According to Global Wind Energy Council Report, (2019), global solar energy has a cumulative installed capacity of about 633.7 GW by the end of 2019 and expected to reach 1TW by 2023, which increases the solar penetration capacity by 23%. The development of wind energy is also visible through the increase in wind power installed annually and in global wind production. The year 2020 was the best year in history for the global wind industry with 93 GW of new installed capacity - a 52% increase from 2019 (GWEC, 2021). This increase in the solar and wind power implies very significant financial investments. However, with this huge investment, potential and significant increase in generation capacity, there is an additional, yet often overlooked responsibility: managing power plants to ensure lowest total life Cycle Cost (LCC). Increase in integration of renewable energy aids in mitigating the ailing environment from climate change and global warming. These challenges are caused by the increase in carbon foot print as a result of greenhouse gas (GHG) emission into the atmosphere.

The world population is about 7.8 billion people with about 13% lacking access to electricity out of which most of them are in the developing nations from sub-Saharan Africa. In Nigeria alone, about 44.6% of its population (200 million people) lack electricity mostly in the remote and rural areas. However, the energy sector in Nigeria is faced with so many challenges and weaknesses, such as Lack of modern facilities that can generate and distribute energy, low access to modern energy for cooking, increase in population leading to increase in energy demand, high cost of energy, high cost of rural electrification from the grid, frequent power outage and high dependence on petroleum products. In order to mitigate the energy crises and relief from high grid-dependence in Nigeria, the rural electrification agency (REA) of Nigeria proposed ways of decentralizing energy from the grid. The essence is to generate few watts or kW, such as rooftop solar to power homes and pump water in the rural areas. Other mega projects in mega Watts (MW) capacity, such as Sokoto power plant and Katsina wind farm were established. These mega projects are capable of supplying some locals around the plant location in the geographical zones.

Like any standard production system, renewable energy (solar and wind energy in our case) generation components are subject to random failure, thereby disrupting production and supply of demand. Some random phenomena, such as aging, maintenance time, production shortage and failure are observed to cause delays in timely satisfaction of the customer demand. In this study, to improve the efficiency and performance of renewable energy power plants, we propose models to optimize power production and maintenance in the selected case studies (Sokoto solar plant and Katsina wind farm). Kamenopoulos & Tsoutsos, (2015) identified some factors and risks associated with maintenance, which constitute a major part of accidents (causing fear in the maintenance personnel), lack of technical know-how of an equipment as well as the absence of a good maintenance routine plan. In this case therefore, we proposed an integrated maintenance strategy

to optimize Sokoto solar power plant and Katsina wind farm in Nigeria, to minimize the total lifecycle cost of the system by reducing losses especially economic and time loss.

Within few years, "maintenance" function has become one of the strategic functions for any risky production system, particularly energy production systems. Undeniably, it has changed from the "traditional maintenance function" considered as a financial burden to a "necessary" activity considered for generating profit. Thus, making it possible to minimize maintenance costs and maximize the availability of production systems (Learney et al., 1999). Maintenance and production are two main functions for any type of production system. In practice, these two functions are often managed separately despite the fact that they are in fact closely linked. These functions have often been treated separately in the literature. But in recent years, particular attention has been paid to maintenance strategies integrated into production. This trend is motivated by the fact that integration strategies can improve productivity and significantly reduce losses.

In this regard, we developed new integrated maintenance strategies integrated with production of energy from solar and wind energy systems. The preventive maintenance strategy adopted in this work is Perfect maintenance strategy with minimal repair and a combined Imperfect/Selective maintenance strategy. The methodology we developed starts by first solving the problem of energy production optimization using the analytical method as well as machine learning method; Artificial Neural Network (ANN) and Support Vector Regression (SVR) in order to satisfy a random demand of energy during a finite horizon. The obtained results are considered as input in developing maintenance strategy by considering the impact of the variation of the energy production on the degradation level on the wind turbine and the solar PV panel. We also studied the influence of environmental and operational condition of the systems and then validated the models by numerical examples and sensitivity studies proving the robustness of the developed models.

This manuscript is therefore organized as follows:

The first chapter consists of bibliographical study including research work on maintenance strategies, machine learning and its application in optimization, the renewable energy production and maintenance strategies for both solar PV and wind energy systems. This state of the art allows us to situate our contribution and our problem in relation to existing work in the literature. We also highlighted the problem as well as the objectives of our research work.

The problem of developing an optimal production plan integrated into maintenance was considered in the second chapter. In this chapter, we developed model that optimizes the production plan in order to determine the optimal numbers of solar panels, wind turbines and battery storage required to satisfy load demand during each production period. In case the quantity of energy produced and stored is not sufficient to supply the demand (shortage), an extra parameter for the cost of shortage is introduced to take care of the economic losses associated with the shortage. ANN and SVR techniques as well as analytical techniques of electricity generation were considered. A maintenance strategy model is then developed integrating the optimal results

from production plan into the maintenance strategy with the aim of determining the total maintenance cost and to determine which technique presents the best optimal plan.

In the third chapter, we consider a priority selective maintenance strategy with the hope of achieving maximum availability from the energy generating system. Furthermore, our model takes into account the influence of production rate, environmental (as environmental constraint) and operational conditions (operational constraint) into the maintenance strategy. The strategy consists of selecting components for maintenance at preventive maintenance time based on reliability of the components so that reliability threshold is imposed. A perfect maintenance strategy is applied on the components selected during each preventive maintenance time. This is to minimize the maintenance downtime and maximize availability and reliability of the system.

The fourth and last chapter of this thesis consists of developing an integrated production and maintenance model to minimize the total life cycle cost of the renewable systems. The developed algorithm is aimed at simultaneously minimizing the total life cycle cost and maximizing the system availability while respecting the customer service rate. In this model also, energy production from all three techniques (ANN, SVR and analytical) are considered, it is a joint optimal production and maintenance strategy to determine the economic plan minimizing the total life cycle cost, the optimal number of preventive maintenances to be performed as well as the optimal periodicity between 2 preventive maintenance sessions. Thus, minimizing production and economic losses for both solar PV and wind energies systems. This method/strategy is a combined perfect/imperfect priority selective maintenance strategy in which a component is selected for maintenance if its reliability falls below a minimum reliability threshold, thus evaluating the maintenance cost and time it takes for the preventive maintenance to be performed.

For each chapter, we carried out numerical analysis on our case study and proposed the best solution among the three techniques. We also implemented a sensitivity analysis on the algorithm to demonstrate its robust fullness for all the techniques applied in the work.

We then ended the manuscript with a general conclusion commenting on the results obtained generally and also presented a research perspective for continuity of the thesis.

CHAPTER 1: Production and Maintenance Strategies in the renewable energy sector (Photovoltaic, Wind): State of the art

This chapter discusses the bibliographic study of the thesis establishing the importance of the work in relation to the identified gap. This study is to develop production integrated into maintenance strategy for optimizing renewable (solar PV and wind) energy systems. The chapter first discusses maintenance, its categories and types of actions from their early starts. We then discuss production strategies in general ranging from analytical approaches to the advanced methods of machine learning techniques. A general overview of optimization applied to production as well as maintenance in renewable energy is studied. This is followed by the global description of the thesis problem and also, the main objectives of the work. The notation used for the work are also presented at the end of the chapter.

1.1 Introduction

The persistence in climate change, global warming and its impact on the world gets a lot of attention, despite the surprisingly opposition in some countries. Nonetheless, with economic challenges, increase in power prices and energy demand, CO₂ emissions continue to grow. Conference of Parties (COP) have been organized annually by United Nations Framework Convention on Climate Change (UNFCCC) getting industrialized countries commit to limit and reduce greenhouse gas emissions. This is however done in accordance with agreed individual party target since the commencement of the Kyoto protocol in 1997. In 2015, Part of the agreements of the COP 21 is to limit the temperature well below 1.5°C to minimize the impact of climate change to achieve a sustainable environment by 2050. To reach this target by 2050, CO₂ emissions must decrease by 3.3% yearly (UN, 2015). But the current emission trends are not on the path to meet that goal allowing fossil fuels to continue to dominate the global mix.

To limit the use of fossil fuels, major transformation is therefore required on the means of energy generation in order to develop a sustainable economy capable of providing useful services to the public and also maintain a friendly environment by means of effective support instruments to climate change alleviation (International Energy Agency, 2012). Rapid depletion of fossil fuel, increase in oil prices, climate change and global warming necessitate seeking alternative energy sources which requires development and utilization of renewable energy sources. Renewable energy is environmentally friendly and clean alternatives to fossil fuel power generation technologies. It plays an important role in environmental protection and less dependence on fossil fuels for energy production. These renewable technologies include wind, photovoltaic (PV), micro hydro (MH), biomass, geothermal, ocean wave and tides. On another hand, to ensure the sustainability of these renewable power generating plants, it has become necessary to perform maintenance on the machinery of the generating units. Energy produced by renewable sources is fast gaining recognition with solar and wind systems becoming the most widely used renewable energy sources in the world (*Global Energy Review 2021*). Therefore, the focus of this work is on

solar PV and wind energy generation systems. Availability of the solar and wind resources globally is the main driving factor for the rapid development of these industries. This thesis therefore, seeks to contribute to the development of integrated maintenance strategies for solar and wind energy systems.

Fossil fuel was used as the major source of electricity since industrial revolution from the early 19th century till date. The world energy generation chart presented in figure 1.1 shows that fossil fuel contributes 73% of the world energy sources (International Energy Agency, 2021) with all other sources taking up the remaining 27%. This source however, is limited to specific geographical zones and is also fast depleting since it is non-renewable in nature.

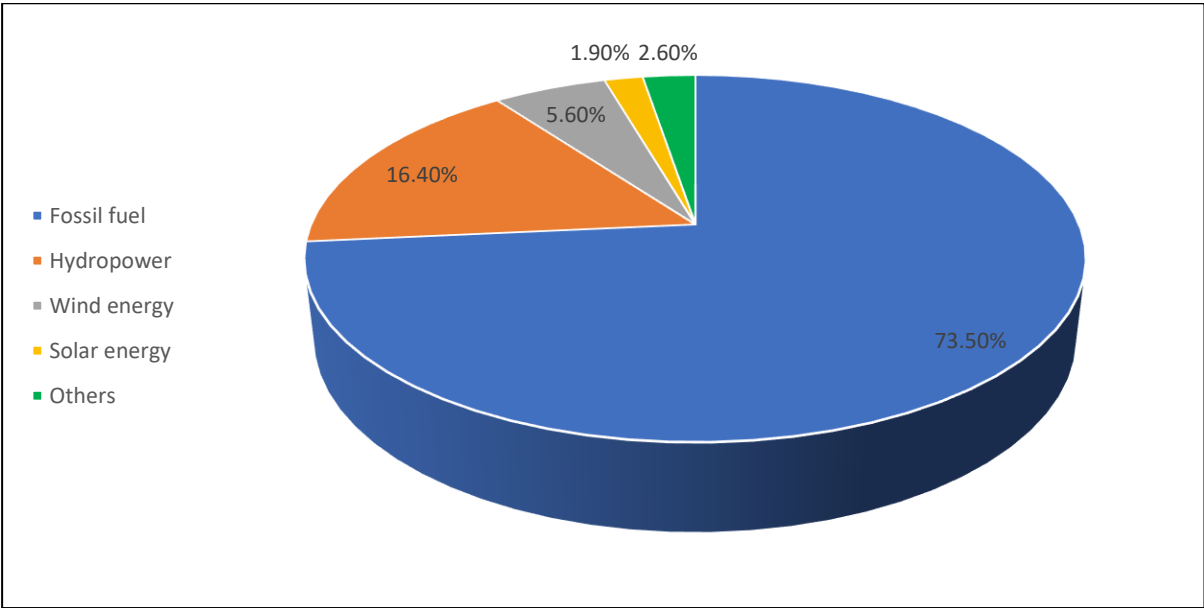


Figure 1.1: World energy generation, (International Energy Agency, 2021)

The ever-growing global economy and energy demand, it is nearly impossible to rely solely on these fossil fuel resources for a long period. With the current depletion rate, fossil fuel reserves will be exhausted within few years. This calls for search of new technologies such as nuclear fission and renewable energy. However, the only naturally occurring and spontaneously fissionable source of energy is uranium 235. But nuclear energy produces spent fuel, which is extremely hazardous and can leak radiations if not stored properly. Another key motivation for alternate energy resources is that non-renewable sources are environmentally unfriendly and hazardous by increasing the carbon footprint in the atmosphere. The resultant effect of climate change and global warming have forced us to think about alternatives. Primary energy is more efficiently used by renewable energy technologies such as hydropower, wind power, biogas, and PV (Opiyo, 2018) especially in developing nations.

Developing nations are considered “developing” because development takes place primarily in urban areas, whereas rural areas are highly under-developed. About one billion people are living in remote scattered areas of developing countries all around the world. These people are trapped in an unbearable combat between geography and development. The increasing covets for better standard of living along with extremely slow opportunity growth in rural areas also forced

rapid and massive rural-to-urban migration. This results in an explosive growth and plenteous slum areas around larger metropolises. Hence, steps must be taken to improve the basic living environment to meet the energy requirements and other necessities of the rural areas which must be treated as a top priority (Ramakumar, 1983).

Similar to other industrial equipment, wind turbines and solar panels are subject to failures, thereby disrupting energy production plans. Aging, failure and time for maintenance are all examples of random phenomena often observed in energy production systems. Within few years, "maintenance" function has become one of the strategic functions for any risky production system, in particular energy production systems. Indeed, it has transformed from "traditional maintenance function" considered as a financial burden to a "necessary" activity considered for generating profit, minimizing maintenance costs and maximizing availability of production systems. An increasing competitive energy production has confronted companies with an enormous challenge, prompting them to continually search for new methods and strategies to satisfy external constraints such as meeting deadlines, quality service, and cost reduction.

In this chapter therefore, we conducted a bibliographic study of the main work related to the problem of the thesis in order to position our study in relation to literature and work previously carried out. Therefore, the chapter is structured as follows; A general introduction to "maintenance" function, its different types and its different strategies and optimization of maintenance strategies are presented in section 1.2. In section 1.3, the concept of machine learning and its optimization techniques are presented. We present the renewable energy industry focusing on solar and wind energy systems, where we present the energy production components, their functionality and types of failure occurring on those components in 1.4. Having highlighted production and maintenance, we proceeded to present an integrated production and maintenance strategies related to PV and wind systems in section 1.5. This section highlighted the optimization techniques related to PV and wind energy systems. A general description of the thesis problem and the notations used is discussed in 1.6 with a conclusion presented in 1.7.

1.2 Maintenance

The aeronautical information manual (AIM) defined maintenance as "set of activities performed to help keep an industrial plant, a machinery or other facilities and equipment in good operating and working condition. It is also capable of enhancing the smooth and efficient working of an equipment which also improves its productivity and extends its life/age" (U.S. Department of Transportation, 2017). Maintenance is an important parameter for sustainable production in industrial systems by ensuring continuous operations through reliability, plant and machines/components failures routine checks. As a result of the importance of maintenance in industries, manufacturers and researchers decided that we cannot restrict ourselves to ordinary curative actions, carried out on equipment in the event of failure or simple maintenance carried out arbitrarily. The concept of maintenance has been in existence dating as far back as 1960s (Barlow & Hunter, 1960). Since then, many researchers have been working on updating and improving industrial maintenance strategies as presented in the works (Bouzoubaa, 2021a; Nakagawa, 1979, 1980, 1986; Tsai et al., 2001). It is estimated that maintenance cost represents about 15 to 40 % of total production expenses (Walford, 2006). Therefore, maintenance management must

occupy an increasingly important place in business. Indeed, the current maintenance activity plays a key role for the successful achievement of the objectives of productivity, quality, profitability and growth of the company, taking into account environmental and operational constraints. In fact, maintenance has become an essential and strategic component for production systems within company, improving availability by minimizing failures, cost of production and losses incurred. The following subsections explain types of maintenance, actions performed and different types of strategies developed.

1.2.1 Types of maintenance

Maintenance is generally categorized into two main types viz:

1.2.1.1 Preventive maintenance (PM)

This is a periodically planned maintenance performed at specific time according to prescribed criteria to reduce the probability of failure and sudden breakdowns of a machine or an industrial system (Nakagawa, 1979). Based on the definition, three (3) forms of preventive maintenance can be drawn which are:

i. Systematic PM:

This type of maintenance is performed at predefined time interval or according to a defined number of units used but without prior check on the condition of the components.

ii. Conditional PM:

This is based on monitoring of component's operation or significant parameters of the operation such as reliability evaluation. This type of maintenance is mainly applied when the failure condition of the component or sub-component can be monitored.

iii. Predictive PM:

This is a conditional maintenance carried out following a forecast obtained through repeated analysis or evaluation of the characteristics of significant parameters in the degradation of a component.

1.2.1.2 Corrective maintenance (CM)

Corrective maintenance is a remedial action performed because of failure or deficiencies found during preventive maintenance. In other words, it is an action performed when a sudden failure occurs. Corrective maintenance can be performed in ways such as mechanical service, repair or replacements (Tsai et al., 2004). There are two (2) types of corrective maintenance:

i. Deferred corrective maintenance:

It is a type of corrective maintenance which is not carried out immediately after the fault detection but is delayed in accordance with given maintenance rules.

ii. Emergency corrective maintenance:

This is a type that is carried out without delay after detection of a failure in order to avoid unacceptable consequences.

1.2.2 Maintenance actions

This section describes maintenance type that defines the state in which an equipment can perform its intended function. The state of the equipment after a maintenance action gives us an idea of the type of action performed. In the literature related to maintenance reliability, there are mainly three types of maintenance actions. Perfect, imperfect and minimal maintenance (or minimal repair). These types of maintenance, based on literature studies, are detailed below:

i. Perfect maintenance:

It is a maintenance action which restores a system's operating condition to be as good as new (AGAN). That is, upon performing perfect maintenance, a system has the same lifetime distribution and failure rate function as a brand-new system. It occurs when all subcomponents of a system or the whole system is replaced.

ii. Minimal repair:

Also referred to as "palliative maintenance" in some books. It was first studied by Barlow and Proshan in early 1960s. It consists of restoring system to an operational state, and more precisely, the state that preceded the failure. In literature, this state is often called 'As Bad As Old' (ABAO). In this regard, failure rate returns to the same state it was when the system failed (Banerjee, 1965)

iii. Imperfect maintenance:

This type of maintenance does not make a system as good as new, but makes it younger. In literature, imperfect maintenance has been treated by many researchers presenting several analytical methods used to mathematically model this type of maintenance. The methods can be classified into three categories:

- a) based on failure rate reduction
- b) based on equipment age reduction and
- c) hybrid models which represent a combination between the two methods above.

Usually, it is assumed that imperfect maintenance restores the system operating state somewhere between as good as new (AGAN) and as bad as old (ABAO).

1.2.3 Maintenance strategies

Maintenance strategy is a guide developed to help maintenance managers in decision making towards achieving their set goals. It involves applying technical and administrative actions during the life cycle of a machine/system in order to retain certain operational conditions.

Thousands of maintenance models have been published. Yet there is a limited number of maintenance strategies which all maintenance models can be based on. This section therefore explains the most widely based maintenance strategies adopted by most maintenance managers categorized into the following.

1.2.3.1 Age type maintenance strategies

Age replacement strategy is the most common and popular type of strategy dated back as early 60s. In the age replacement strategy, components are replaced when they reach a certain age measured from the time of the last replacement or first usage. The age type strategy developed well after consideration of imperfect maintenance. Several modifications have been proposed to result in a considerable number of interesting extensions. This strategy now consists of carrying out a preventive maintenance action at predetermined age T or a repair action in the event of failure. It is important to mention that perfect maintenance actions at age T while corrective maintenance actions in the event of failure can be minimal, perfect or imperfect. The age type strategy is more economical but presents some difficulties in scheduling (Barlow & Hunter, 1960).

1.2.3.2 Block type maintenance strategies

Block type or block replacement was initially performed where a component is replaced at specific time according to a schedule even if the component has not failed. Block replacement tends to reduce the number of minimal repair and works without considering the age of the system/component and its failure history initially proposed by (Nakagawa, 1979). An extension of this strategy is known as "Block-Type Strategy with Minimal Repair". This strategy consists of replacing a unit at a fixed periodicity and in the event of failure, a minimal or palliative repair is carried out, with the appearance of the concept of minimal repair and imperfect maintenance (Barlow & Hunter, 1960). The block-type strategy is less economical compared to the age-type strategy and also easy from an industrial scheduling point of view.

1.2.3.3 Strategy based on failure rate

Under this type of strategy, maintenance is performed only when the failure rate or other reliability indices of a unit reach a fixed level in which interceding failures are corrected by repairs. This strategy makes a unit work at or above a minimum acceptable level of reliability threshold. Generally, the problem with this type of strategy is that it requires much computing efforts. Many maintenance strategies have been built on this type of strategy such as the works of Hajej et al. (2017)

1.2.3.4 Strategy based on cost or duration

This strategy is based on limited amount of resources available; mainly time and cost. They form a major decision on which type of action should be performed and at what time. A selective strategy is usually formed in order to select the part or component on which maintenance should be performed upon. Cassady et al. (2001) developed a strategy of maintenance selection based on the limited time resource available for maintenance. In 1982, Beichelt (1982) used this strategy as a decision criterion for a system repair cost such that it does not exceed a predefined limit otherwise

the system will be replaced. Nakagawa & Osaki (1974) based their strategy on limiting the duration of repair. If the duration of a repair exceeds a limit, a replacement action will be performed. Otherwise, the system will be serviced (Khatab et al. 2014).

1.2.3.5 Strategy based on the number of repairs

According to Makabe & Morimura (1963), the number of repairs will be a decisive criterion for this type of strategy. In their study, the decision variable is the value of k . Indeed, after the first $(k-1)$ failures, a minimal repair action will be performed. And after the k th failure, a replacement action will take place. Several works dealt with the issue of maintenance strategies based on limiting the number of repairs and several extensions have been proposed. Morimura (1970) proposed an extension by adding a new variable T (reference time). According to this new strategy, and like the basic strategy, the first $(k-1)$ failures will be corrected with minimal repair action. If the k th failure occurs before the cumulative good operating time T , it will be corrected with a minimal repair action and a replacement action will be carried out after the next failure $((k+1)$ th). But if the k th failure occurs after the cumulative good operating time T , a repair action will be carried out. The decision variables of this strategy are therefore k and T .

1.2.4 Optimization of maintenance strategies

Maintenance is a value-adding activity which comes with necessary expenses, (Ben-Daya & Duffuaa 1995). However, to contain the expenses and avoid waste of resources both financial and material, a balance has to be created also keeping in mind the objective of the maintenance. Therefore, maintenance control plays an important role in maintenance optimization (Al-Sultan & Duffuaa 1995). Earlier, researchers were using optimization criteria for minimizing system maintenance cost rate, ignoring other factors such as reliability and availability. Therefore, optimal maintenance strategies are not only based on cost but also on other set objectives such as reliability and availability (Sharma et al. 2011). Maintenance optimization generally consists of establishing an optimal maintenance plan based on a systematic preventive maintenance frequency or optimal inspection instances in the case of predictive maintenance to minimize maintenance costs or maximize availability. For more details, optimization is explained in section 1.3. The effects of the frequency of preventive and corrective maintenance actions on the total cost is presented in figure 1.2 below. The goal is to determine an equilibrium allowing to obtain a minimum operating cost.

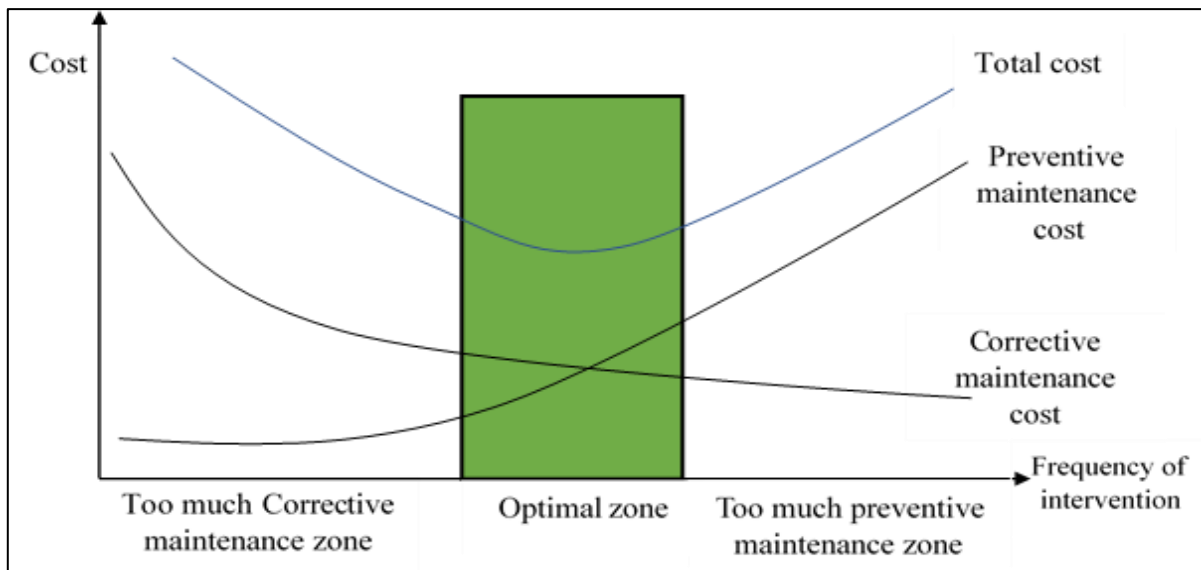


Figure 1.2: Influence of maintenance frequency on cost (Bouzoubaa, 2021a)

Maintenance models are generally of two (2) classes distinguished as

i. Maintenance models with known lifetimes

These models are based on the knowledge of uptime and reliability function of a system. Age and block type strategies are two families of strategies based on the knowledge of time to failure. A predictive maintenance planning for a turbofan engine was carried out based on the remaining useful lifetime of the machine by Mathew et al. (2017). The authors observed and concluded that performing predictive maintenance reduces lost production time and maintenance costs. Jonge et al. (2015) studied the effect of parameter uncertainty on the optimum age-based maintenance strategy assessed by considering both a theoretical uniform lifetime distribution and a Weibull lifetime distribution on a production unit. Age replacement type of preventive maintenance was considered by Cha et al. (2017) on components considered in a random industrial environment modelled by a Poisson process of shocks. Their strategy was to replace a component/unit either on predetermined time or at failure depending on the circumstance.

ii. Maintenance models known to degrade

These models are based on the knowledge of degradation, more particularly based on the knowledge of system degradation level in order to make maintenance decisions. Development of maintenance strategies has gained recognition since early 1950s. A Preventive Maintenance model with imperfect continuous condition monitoring of a wind turbine components was presented by Raza & Ulansky (2019). The model is aimed at for calculating the expected cost of maintenance per unit time and the average lifetime maintenance cost which are derived for an arbitrary distribution of time to degradation failure. Another maintenance strategy model was formulated using neural network in Hameed & Wang (2012) where optimization of the turbine system was performed by clustering mapping similar turbines to obtain maximum power while minimizing cost. Nourelfath et al. (2016) integrated the deterioration of quality in the integration of production and maintenance problem for an imperfect maintenance process. An opportunistic preventive maintenance (PM) strategy was developed for a 2-unit system where inspection was considered both periodically

every time T or when failure occurs on the first unit (Yang et al. 2018). When a defect is detected, replacement is performed on the system. In Merizalde et al. (2019), a mathematical model for maintenance based on the effective age of the components, determined after periodic inspections also considering replacement during PM intervention.

Modern approaches to business management within the framework of an integrated vision ensure that planning and management of maintenance activities can no longer be done independently of other business activities. Consequently, several works were carried out to develop new integrated maintenance strategies taking into account other functions such as quality, production and inventory management. More recently, several researchers have noted that the close link between maintenance and other functions such as production, inventory management and quality should no longer go unnoticed (Matsuoka & Muraki, 2007). The following sub-section therefore, focuses on the integration of maintenance with production.

1.2.5 Integrated maintenance strategies

An integrated maintenance strategy boils down to simultaneous management of maintenance with other functions, mainly production (Bajestani et al. 2014). In the industry, when there is miscommunication and lack of harmonisation between production and maintenance divisions, a conflict usually erupts resulting in unexpected shutdowns in the production line due to the increase in rate of failure. This causes loss of productivity as well as equipment/machine availability at an appropriate time, which is a necessary condition for smooth running of production and for meeting delivery deadlines. Therefore, this attracted the interest of several researchers being that maintenance and production are two main functions for any type of production industry. In practice, these two functions are often managed separately even though they are closely related and have been widely treated in the literature. But in recent years particular attention has been paid to maintenance strategies integrated into production. This trend is motivated by the fact that integration strategies can improve productivity and significantly reduce costs.

In literature, several works are directed essentially towards the integration of preventive maintenance and production strategies but with different points of view. This collaboration can be defined according to two approaches: restricted approach and global approach. For the case of the restricted approach, the problem study relates to only one machine, while the global approach studies the case of many machines whose number is defined and known over a time horizon. In single-machine problems, a single disjunctive resource which can perform only one operation at a given time, is available to perform multiple jobs. Thus, this type of problem aims to determine an optimal sequence of number of tasks (n) available at time (t).

Several researches have been carried out to deal with the problem of the joint optimization of production and maintenance by considering the case of many machines. In this context, we can cite the work of Brandolese et al. (1996) who looked at the relationship between production and maintenance by considering the case of many machines. This approach considers a fixed execution date for each task and the workstation on which this task must be executed. We can also talk about the work of Hafidi & Barkany (2019), who proposes a stochastic production and maintenance

planning optimization for multi-parallel machine. The authors proposed an optimal method minimizing the maintenance cost while considering the production rate with the possibility of subcontracting. Ben-Salem et al. (2015) tackled the problem of joint production, maintenance and control of emissions, including a potentially degrading production system. The aim of their work is to simultaneously control the production rate, emission rate and maintenance rate in order to mitigate the effects of system degradation by minimizing the total cost over an infinite horizon. Due to the numerous research studies, we can classify the work carried out previously on the optimization of maintenance integrated into production into two main categories as follows:

1.2.5.1 Simultaneous optimization model of production rate and maintenance frequency

This model, mainly developed by Ouali et al. (2001), adopted and improved by Kenne et al. (2003) is based on the problem of optimal production flow control. The particularity of this model is that the production ratio and the maintenance date represent the decision variables for technical and economic optimization. Kenne et al. (2003) based their model on the control of a system's production of a system, composed of m identical machines capable of producing n types of products subject to recovery periods after troubleshooting. The main objective of their research work is to minimize the expression of the total cost under the two decision variables.

Ouali et al. (2001) proposed a simultaneous optimization of production flow and preventive maintenance. Their work takes into account the interaction between these two services. In fact, the system performance indicators, which are the stock level and the age of the production system, are used to develop a maintenance strategy. The production system of the study was based on a single machine producing only one type of product to satisfy a constant demand over time. A safety stock must be accumulated and this can be done when the machine has a production rate higher than the demand. Indeed, during preventive or corrective maintenance, the demand is drawn from the safety stock. In this model, the maintenance and production strategies were first studied independently. Then, they combined the two activities to consider a global cost function simultaneously integrating the costs of maintenance, inventory, as well as the costs of unsatisfied demands. Thus, an optimal safety stock is achieved by minimizing the average total cost.

More recently, the interests of many researchers have been drawn to the study of scheduling and maintenance strategies for wind power plants (Dawid et al. 2015). Hassoine et al., (2021) investigated the optimal placement of wind turbines in a large offshore wind farm in order to determine the effect of wind turbines spacing layout on power production output of the system. Tawfiq et al. (2020) proposed a model based on Markov chain to enable them assess and evaluate the reliabilities of an electrical transmission system components to analyse the impact of outage rate from each turbine in a wind farm and to improve the turbine stability and other performance factors. Levitin & Lisnianski, (2000) developed a model that generalizes a preventive maintenance optimization problem to multi-state systems having a range of performance levels. The possible preventive maintenance actions are characterized by their ability to affect the effective component age. A universal generating function technique and genetic algorithm were used to solve the problem with respect to system performance by the minimum maintenance cost.

1.2.5.2 Simultaneous optimization of production and maintenance under constraint

We start by presenting work on the integration of maintenance and production for a degradation-prone manufacturing system in a stochastic context. In this context, Dehayem Nodem et al. (2011) developed optimal production and maintenance strategies for a manufacturing system subject to degradation. They proposed a replacement/repair switching strategy depending on the state of the system that degrades with the repair actions. In order to improve the reliability of the equipment, the authors considered preventive maintenance actions. They proposed a semi-markov process model using a stochastic dynamic programming method to find the decision variables such as production rate, preventive maintenance rate, and repair/replacement actions that minimize the total cost over an infinite horizon. In the same context of degraded system, Nourelfath et al. (2012) formulated an optimization model for a joint strategy of redundancy and imperfect preventive maintenance for a degraded system of multi-components. The system consists of a series-parallel component where each component degrades according to use. The objective of the study is to determine an optimal preventive maintenance to guarantee maximum availability of the system under budgetary constraints. To evaluate the system availability and the cost function, they used a markov process model and a universal moment generation function.

Aramon Bajestani et al. (2014) developed an integrated maintenance and production model for a production system subject to deterioration over several periods. They proposed a markov process model correlated with an integer programming model to determine the optimal maintenance and production schedule that minimizes total maintenance cost and production loss. Recently, Nourelfath et al. (2016) incorporated quality degradation into the production and maintenance problem for an imperfect process. The studied production system is composed of a machine which is characterized by two states under control or out of control and where the machine produces a part of non-conforming articles. They proposed an optimization model and a resolution algorithm in order to determine the optimal production and maintenance plans that minimize the total cost taking into account, quality-related costs. Aghezzaf et al. (2016) studied the problem of production-integrated maintenance for stochastic systems. They modelled an imperfect maintenance strategy based on the age reduction approach. They proposed a mixed integrated linear optimization problem model of the integration of maintenance into production. Even more recently, concerning the integrated maintenance strategy for a multi-machine system, Hajej et al. (2018) dealt with a forecasting problem for a manufacturing system composed of several parallel machines to meet the random demand. To achieve so, the authors proposed a production strategy that obtains the optimal number of machines in operation for each production period.

In order to maintain reliability, maximize availability and minimize economic losses of a production system, an optimal maintenance strategy is proposed in this work. The aim is to determine an optimal preventive maintenance plan for each generating source considered according to its production rates.

1.3 Machine learning and Optimization

This section explains the concept of artificial intelligence (which gives birth to machine learning), the different machine learning tools and their applications.

1.3.1 Machine learning tools

Before we discuss machine learning, we have to begin from its stem, which is the concept of artificial intelligence. Artificial intelligence (AI) is defined as the ability of the computer to think and act humanly and to also to think and act rationally (Russell et al. 2010). More generally, it is the science and engineering of making intelligent machines, especially intelligent computer programs that can be best described as using computers to understand human intelligence. AI was conceptualised as far back 1950s from a scientist called Turin after the WWII where he tried to answer the question “can machines think like humans?”. And since then, AI has been evolving with improvements and different classes of AI were established. The reader can refer to Russell et al. (2010) for further reading on the history of AI. Its goal is to produce better, more efficient and effective computing systems which may sometimes require adding features associated with human intelligence such as learning and the ability to interpolate from current knowledge. The appropriate use of intelligent technologies leads to useful systems with improved performance or other characteristics that cannot be achieved through traditional methods (Medsker, 1996). Today, AI has two main sub-fields; machine learning and deep learning, which are frequently mentioned in conjunction with artificial intelligence. These fields are comprised of algorithms that typically make predictions or classifications based on input data. In this work, our main focus is the machine learning. While AI and machine learning are very closely connected, they’re not the same. Machine learning is considered a subset of AI.

Machine learning is an application of AI which involves the process of using mathematical models of data to help a computer learn without direct instruction. This enables a computer system to continue learning and improving on its own, based on experience. It has numerous applications in the field of health care, renewable energy, cybersecurity and banking, etc.

1.3.1.1 Machine learning approaches

There are three distinct approaches to using machine learning which correspond to the learning patterns depending on the nature of the response available to the machine/system (Mellit, 2007). These categories of the ML approach are:

a. Supervised learning

The algorithm is presented with example inputs and their desired outputs, otherwise known as "response". The aim is to train the computer to learn and understand a general rule that maps inputs to outputs. Supervised learning algorithms include linear regression, logistics regression, support vectors machines and artificial neural networks etc. They are mainly applied for classification and regression problems. An example of this application is forecasting/prediction. You can predict a weather based on humidity, temperature and wind speed values.

b. Unsupervised learning

In this case, no labels or input/output feature are given to the learning algorithm, it therefore devices its own methods of finding its structure. Unsupervised learning can be a goal in itself by discovering hidden patterns in data. Unsupervised learning can be used to classify objects by

identifying some of the features from the learning data. Some of this type of learning approach are K-means clustering, hierarchical clustering, principal component analysis (PCA) etc. and are generally used for clustering and association problems. For example, a customer agent can use this method to group customers according to their likes and preferences.

c. Reinforcement learning

A computer program interacts with a dynamic environment in which it must perform a certain goal. As it navigates its problem space, the program is provided feedback that's analogous to rewards, which it tries to maximize in a particular situation. It uses an agent and environment to produce actions and the rewards. The agent has a start and end state with no predefined path to achieving the result (end). An example of this is to train a machine to identify an object based on a given set of data. Some of the algorithms used for this type of learning are Q-learning, Monte-Carlo etc. This is mostly applied in the gaming industry to develop games and also in training robots.

1.3.1.2 Machine learning models

Executing machine learning involves creating a model, which is trained on some training data that can process additional data to make predictions/forecasts. In literature, there are several machine learning tools and models used which we will mention few of them below.

a) Artificial Neural Network (ANN)

ANN are computing systems ambiguously inspired by the biological neural networks found in human brains. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. The main aim of the ANN is to solve problems in the same way that a human brain would. However, over time, attention moved to performing specific tasks, leading to deviations from biology. Artificial neural networks have been used on a variety of tasks, including computer vision, speech recognition, machine translation, social network filtering, and energy forecasting.

b) Support Vector Machines (SVR)

SVR are a set of related supervised learning methods used for classification and regression. Given a set of training examples, each marked as belonging to one of two categories, a SVR training algorithm builds a model that predicts whether a new example falls into one category or the other. In addition to performing linear classification, SVR can efficiently perform complex non-linear classification task using what is called the kernel trick by implicitly mapping their inputs into high-dimensional feature spaces.

c) Regression Analysis

Regression analysis involves a large variety of statistical methods to estimate the relationship between input variables and their associated features. Its most common form is linear regression, where a single line is drawn to best fit the given data according to a mathematical criterion such as ordinary least squares. The latter (linear regression) is often extended by regularization methods to lessen overfitting such as in ridge regression. When dealing with non-linear problems, go-to

models include polynomial regression, logistic regression or even kernel regression are used. These models introduce non-linearity by taking advantage of the kernel trick to implicitly map input variables to higher-dimensional space.

d) Bayesian Networks

A Bayesian network model is a probabilistic graphical model that represents a set of random variables and their conditional independence. For example, a Bayesian network could represent probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Efficient algorithms exist which perform inference and learning. Bayesian networks that model sequences of variables, like speech signals or protein sequences, are called dynamic Bayesian networks. Generalizations of Bayesian networks that can characterize and solve decision problems under uncertainty are called influence diagrams.

e) Genetic algorithm (GA)

The GA is a method for solving optimization problems that is based on natural selection- the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals from the current population (data sample size) to be parents and uses them to produce children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. GA can be applied to solve a variety of optimization problems which are not well suited for standard optimization algorithms.

1.3.2 Optimization using machine learning

Optimization is a process aimed to find best solution of a problem by minimizing or maximizing an objective function. It is required where multiple feasible solution exists in the search space which determines the input that results to the best possible outcome of the problem. It solves:

- Minimization problem; minimizing power losses in energy, minimizing operational maintenance of microgrid.
- Maximization problem; maximizing the availability of operational equipment or a system, maximizing efficiency of the generation plant.

There are different optimization techniques as detailed in figure 1.3 below:

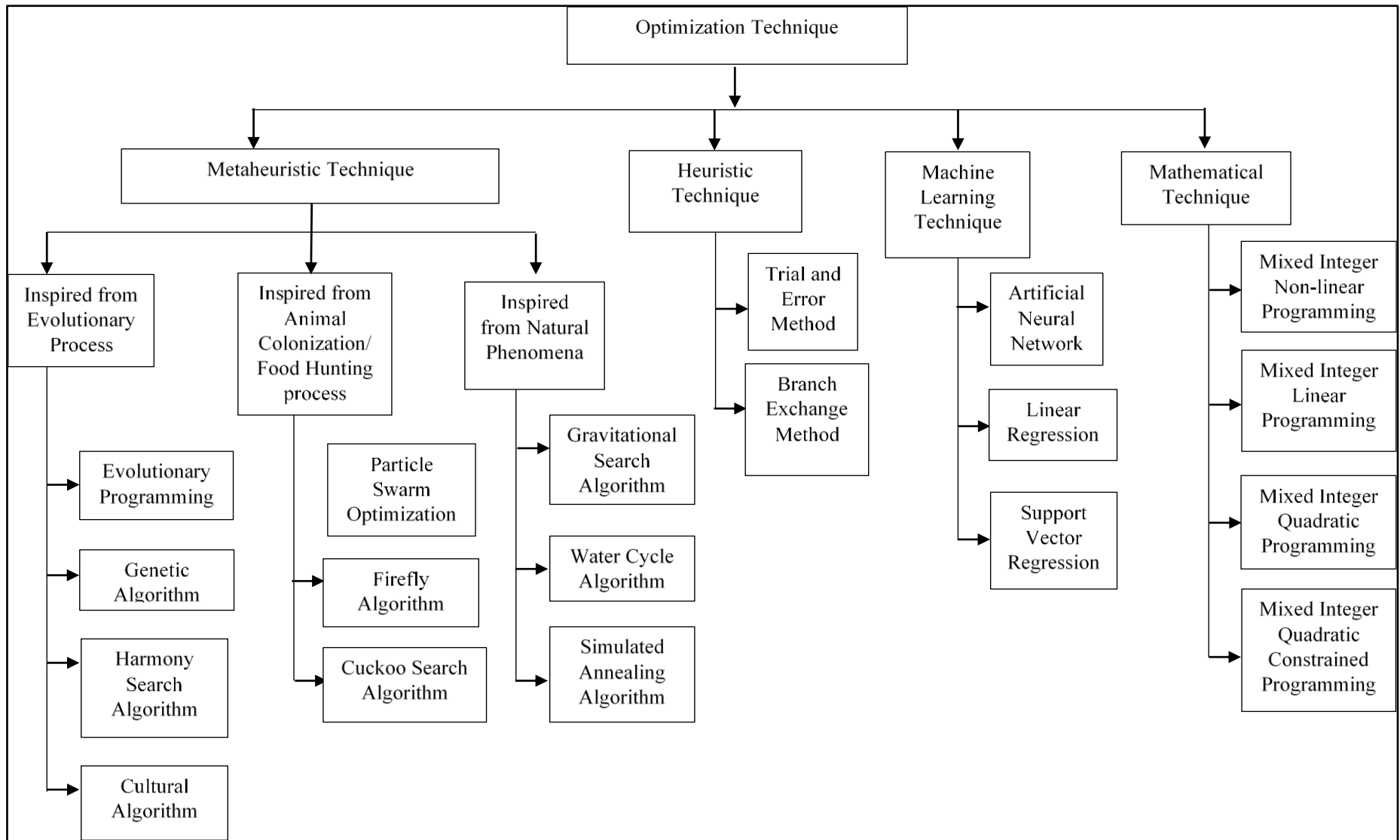


Figure 1.3: Optimization Techniques

Let us summarize the important characteristics of the different optimization techniques from the figure above as follows:

- Heuristic techniques
 - Optimal solution is determined based on greedy rules.
 - It has the capability to attain near optimal solution in short span of time.
 - It is problem dependent and the solution obtained does not always guarantee optimal solution.
- Metaheuristic techniques
 - Search for the best solution based on intrinsic parameter (called particles).
 - It is used as black box which mean that this method is independent of specific problem.
 - It has the capability to achieve optimal solution. However, it requires longer time compared to other approaches.
- Mathematical techniques
 - Similar to heuristic technique, mathematical approach is also problem dependent.
 - Problem is specifically modelled in terms of objective function and constraints.
 - Constraints used in mathematical model ensure that the global optimum solution lies inside the feasible region.
- Machine learning techniques
 - Similar to metaheuristic technique, machine learning techniques are black box techniques.
 - In machine learning technique, solution of the problem requires historical input and targeted data.
 - Based on the historical data, there technique predict the optimize solution for future dataset.

Optimization using machine learning techniques have been used in numerous researches for solving different problems such as in the works of Faker et al. (2021) . Mellit (2003) developed an ANN model for the estimation of sizing parameters of stand-alone PV-systems. In their model, the inputs are: latitude, and longitude of the site, while the output are the sizing parameters functions. These parameters allow the designers of PV-systems to determine the number of solar PV modules and the storage capacity of the batteries necessary to satisfy a given consumption. In addition, several AI-based sizing of PV systems has been developed in order to select the optimal sizing parameters of PV system in remote areas (Mellit et al., 2004), and the results obtained have been compared and tested with experimental values. A methodology for optimal sizing of stand-alone PV/wind-generator systems was developed by Koutroulis et al. (2006), where the proposed methodology was based on GA and compared with linear programming. The simulation results verify that hybrid PV/wind-generator systems feature lower system cost compared to the cases where either exclusively wind-generator or exclusively PV sources are used. Senjyu et al. (2007) developed an optimal configuration of power generating systems in isolated islands using GA. This methodology can be used for determining the optimum number of solar panels array, wind turbine generators, and batteries configurations. A novel strategy, optimized by genetic

algorithms, to control stand-alone hybrid renewable electrical systems with hydrogen storage is presented in Hernández et al. (2007). The optimized hybrid system composed of renewable resources (wind, PV and hydro), batteries, fuel cell, AC generator and electrolyser.

1.4 The energy industry

In this part, we review the renewable energy sector with a particular focus on solar and wind energy industry. Introduction to the energy industry is discussed in section 1.4.1 and particularly renewable energy is 1.4.2. We outlined the functionality and the design of solar panels and wind turbines in section 1.4.3 where we then proceeded to outline the identified failure characteristics and failure causes of solar PV and wind turbines systems in section 1.4.4. section 1.4.5 discusses about energy production from PV and wind system while maintenance strategies related to the PV and wind systems are presented in 1.4.6

1.4.1 General introduction

The global conventional energy sources based on oil, coal, and natural gas have been recognized to be highly effective drivers of economic progress, at the same time detrimental to the environment and to human health. These long-standing fossil fuel-based energy sources also known as non-renewable sources are facing increasing pressure on the environmental fronts, posing serious challenge on the future use of coal. This is a great challenge being discussed at the Kyoto protocol with the aim of reducing greenhouse gas (GHG) emission (mostly CO₂) to a level below 550 parts per million (ppm). In the light of GHG emission reduction, renewable energy gained a lot of attention for heating and electricity generation. The prospect of renewable energy sources is enormous as they can supply the world's energy demand. Renewable energy sources such as wind, solar, hydropower, biomass, and geothermal can provide sustainable energy services, based on the availability of indigenous resources. They currently supply somewhere between 15 percent and 20 percent of world's total energy demand. The supply is dominated by traditional biomass, mostly fuel wood used for cooking and heating, especially in developing countries of Africa, Asia and Latin America. A major contribution is also obtained from the use of large hydropower; with nearly 20 percent of the global electricity supply being provided by this source. New renewable energy sources (solar energy, wind energy, modern bio-energy, geothermal energy, and small hydropower) are currently contributing about two percent. A number of scenario studies have investigated the potential contribution of renewables to global energy supplies (*Global Energy Review 2021*, 2021).

1.4.2 Renewable energy

Renewable energy is the energy obtained from sources that are continually replenished by nature; solar, wind, hydro, geothermal (the Earth's heat), and biomass (plants). Renewable energy technologies convert these fuels into functional kinds of energy; mostly electricity, but also heat, chemicals, or mechanical power (National Renewable Energy Laboratory (NREL), 2015). Figure 1.4 shows some of the global renewable energy mix by percentage of each sources' contribution from

2019 to 2021. An outstanding level of renewable energy capacity additions is expected to be maintained, with 270 GW becoming operational in 2021 and 280 GW in 2022 such that renewables are expected to account for 90% of total global power capacity increase in both 2021 and 2022. Continuous growth in solar PV additions, spurred by lower investment costs and ongoing policy support, partly compensates for lower wind capacity additions. Annual solar PV expansion is expected to reach 162 GW in 2022, breaking records and accounting for almost over 55% of all renewable energy expansion in 2022. An acceleration of hydropower additions through 2022 is driven by the commissioning of mega-scale projects in China. Meanwhile, expansion in other renewables, led by bioenergy, remains stable and represents 3% of total new renewable capacity additions.

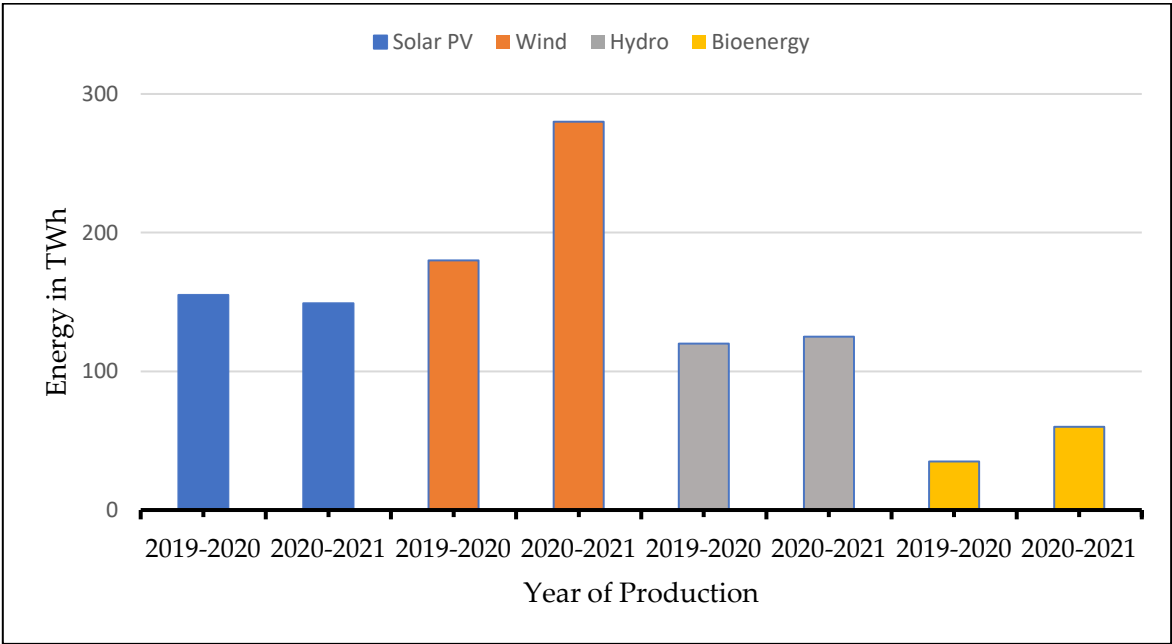


Figure 1.4: Global renewable energy yearly growth from 2019 to 2021. (Global Energy Review 2021, 2021)

Benefits of renewable energy include;

- Reliable, distributed power supplies and fuel diversification, which enhance energy security for both individual facilities and the nation.
- More power for peak-use periods
- Fewer (or no) greenhouse gases emission associated with energy use
- Lower risk of fuel spills in environmentally sensitive, remote locations- less pollution
- Less need for imported fuels
- Lower utility bills
- Reduced operation and maintenance (O&M) costs
- Greater price stability in an uncertain energy economy.
- Reduction of greenhouse gas emissions.

1.4.3 Component functionality, material design of PV and wind systems

This section treats the types and explains the different components of solar PV and wind turbine systems

1.4.3.1 Components of PV system

The main components of a PV system are:

- i. **Panels:** These are the large and most visible part of the PV system shown in figure 1.5. It comprises of solar cells shown in figure 1.6, connected in series to be able to generate substantial amount that can be able to power a bulb or charge phone. These cells are made up of semiconductor crystalline silicon particles which can be either monocrystalline or polycrystalline in nature. When sunlight hits a solar cell, the electrons in the semiconductor get energized and create an electric field in the cell causing electric current to flow from cell to cell. A panel generates direct current (DC) which are non-consumable.

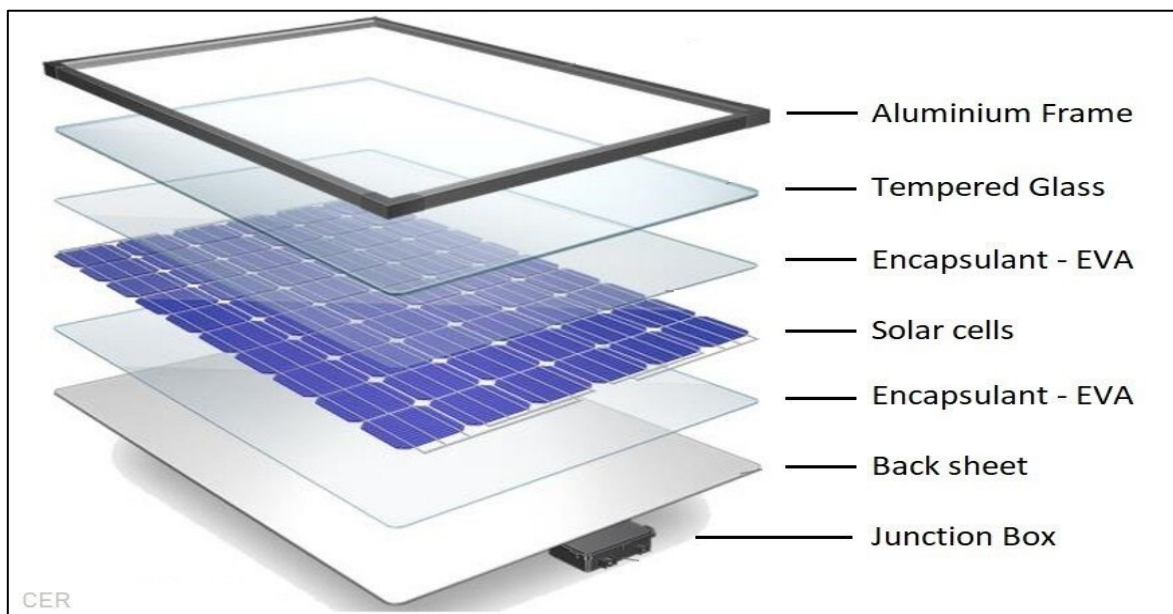


Figure 1.5: Detailed diagram of a solar panel [<https://www.cleanenergyreviews.info/blog/solar-panel-components-construction>]

- ii. **EVA:** which stands for 'ethylene vinyl acetate', is a specially designed polymer highly transparent (plastic) layer used to encapsulate the cells and hold them in position during manufacture. The EVA material must be extremely durable and tolerant of extreme temperature and humidity, it plays an important part in the long-term performance by preventing moisture and dirt ingress.
- iii. **Junction box:** The junction box is a small weatherproof enclosure located on the rear side of the panel. It is needed to securely attach the cables required to interconnect the

panels. The junction box is important as it is the central point where all the cells interconnect and must be protected from moisture and dirt.

- iv. **Bypass diode:** The bypass diodes are needed to prevent back current which occurs when cells are shaded or dirty. Diodes only allow current to flow in one direction. A typical 60-cell panel is divided into 3 groups of 20 PV cells, each with a bypass diode for preventing reverse current. Unfortunately, bypass diodes can fail over time and may need to be replaced, so the cover of the junction box is usually able to be removed for servicing, although many modern solar panels now use more advanced long-lasting diodes and non-serviceable junction boxes.



Figure 1.6: Solar cell (Gorjian, 2017)

- v. **Inverter:** This is an important component in the PV system because its main function is to convert a DC current to a consumable form known as an alternating current (AC) used in residential and commercial properties.
- vi. **Battery:** This component is used to store excess unused energy
- vii. **AC/DC cables:** They are the media through which electricity flows from the panels to converter (DC cables) and from the converter to the load (AC cables).

1.4.3.2 Components of a wind turbine

A wind turbine is considered as a multi-component system with a series-parallel structure as shown in figure 1.7. Wind power output is stochastic due to its dependence on wind speed. Thus, the correlation between wind turbine production and maintenance is emphasized through

the influence of the production rate of the wind turbine on its failure rate. In this section, we will briefly discuss some of the most important components of a wind turbine.

- i. **Blade:** This is the aerodynamic component of the turbine that generates aerodynamic torque from the wind.
- ii. **Bearing:** Wind turbine bearing serves as a lubricant to reduce the frictional resistance between blades, main shaft and gearbox when in motion. It is usually self-aligned spherical roller designed with two (2) sets of rollers which allows the absorption of loads; both radial and axial.
- iii. **Main shaft:** Also known as the low-speed shaft is the connecting rod which transmits rotating force from the blades to the gear.
- iv. **Gearbox:** This component of the turbine increases the rotational speed from the main shaft to a higher torque required to drive the turbine generator.
- v. **Brakes:** This component is used for braking the wind turbine when turbulence occurs
- vi. **Generator:** The generator converts mechanical energy from the rotating blades into electrical energy.
- vii. **Tower:** Holds the nacelle and blades up in the wind.
- viii. **Foundation:** It is the base on which the turbine is fixed firm in the ground.

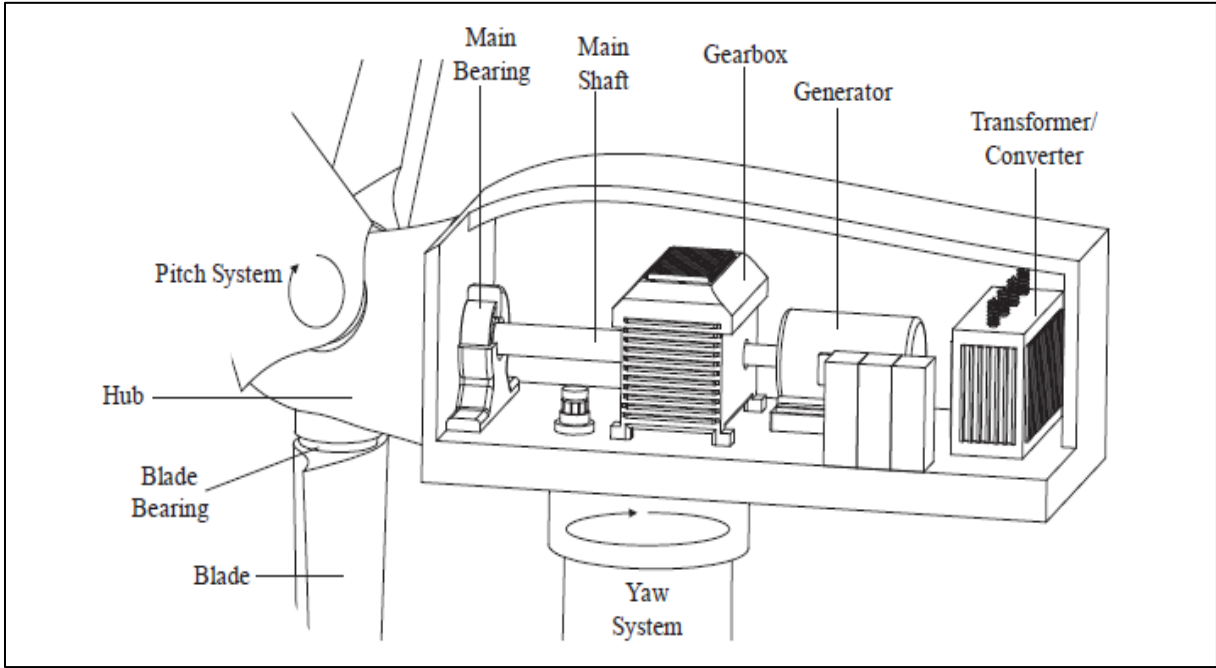


Figure 1.7: Wind turbine (Sa’ad et al., 2022)

Note: Nacelle is the component that houses the bearings, shafts, gearbox, brakes, generators and the brakes.

1.4.4 Causes of failures and failure characteristics

The first step towards improving a system's reliability is to detect the root causes of systems' failures. In this context, Failure Mode Effect Criticality Analysis (FMECA) (Ozturk et al. 2018), is used to analyse the failure causes of systems. It focuses mainly on identifying the possible failure causes. Basically, there are four main causes of equipment or material asset failure:

1. Human error: the gap between what is done and what should have been done such as improper installation of components, etc
2. Natural events: refers to events that cannot reasonably be foreseen or avoided, e.g. thinning.
3. Design flaws
4. Failure of related components: deterioration of the equipment in its normal operating context such as fatigue, wear, etc.

In this section, we will discuss the different types of failures on both solar system and wind system.

1.4.4.1 Failure causes and effects in a PV system

A PV system is divided into two main subsystems; PV modules and a Balance of System (BoS) subsystems. The major failure modes for crystalline silicon PV panel are:

- i. **Interconnector's failure:** In a PV panel, a series of cells are connected to form higher voltage. this series of interconnected cells is called a string and the cell strings itself are typically interconnected in series or sometimes in parallel by string interconnecting ribbons. In such conventional interconnected PV modules, we sometimes find weakened cell or string interconnect ribbons and following disconnections. Especially the ribbon link between the cells and the joint between the cell interconnect ribbon and the string interconnect are prone for fatigue breakage (Köntges et al. 2014). There may be several possible causes of this failure. Poor soldering in PV module production process between cell interconnect ribbon and string interconnect is the most important reason for disconnections. A narrow distance between cells is another possibility of cell interconnect ribbon breakage.
- ii. **Broken or cracked cells:** Many semiconductors are brittle, so cell cracking is a concern for PV modules. Cell cracks can be initiated during manufacturing due to residual stresses from thermal processing, soldering, and lamination (Budiman et al. 2014). They can also arise during transportation and installation, and from static or cyclic mechanical loads during operation. Depending on the number and size of cracks, module power may be only slightly affected, or hotspots and dead areas may form. However, once present their severity is likely to increase over time due to mechanical or thermomechanical stresses, which would open and propagate cracks.
- iii. **Corrosion:** Corrosion is caused when moisture enters a PV panel through the laminate edges. Moisture retention in the housing of the module increases electrical conductivity of

the material. Indeed, corrosion attacks the metallic connections of PV cells causing a loss of performance by increasing leakage currents. Corrosion also degrades the adhesion between cells and metallic frame. Kato (2011) studied the impact of humidity and temperature on PV module degradation and found out that corrosion appeared after 1000 h of exposure of PV module under 85°C and 85% of relative humidity.

- iv. **Delamination of encapsulants:** This occurs due to manufacturing imperfections, harsh outdoor conditions or a combination of both. Poor lamination process during production is one of the main causes of delamination. This causes non-uniform distribution of temperature, pressure and presence of impurities inside the laminator. During the service exposure, the adhesive bonds between encapsulant solar cells of PV module become weak by the moisture intrusion from the corners and back-sheet of the module (Sinha et al. 2016).
- v. **Discoloration:** This results from degradation of the encapsulant module, EVA (Ethylene Vinyl Acetate) or adhesive material between the glass and the PV cells. Module discoloration is a change in color of material which turns yellow and sometimes brown. It modifies transmittance of light reaching PV cells and therefore, power generated by the module is reduced. Oreski & Wallner (2005) claim that the main causes of degradation are ultra-violet (UV) rays combined with water under temperatures higher than 50 C. Discoloration may appear in different and not neighbouring zones of a PV module; this may be due to the polymers used with different characteristics. This could mean that discoloration comes from the encapsulating polymer instead of the adherent element such as EVA in general.
- vi. **Solder bond failure:** Solder bond failures can be caused by thermal fatigue (Köntges et al. 2014). The failures may be hastened because of the increased resistance and associated heating as the joint begins to fail and current still flows through it.
- vii. **Broken glass:** Glass breakage is an important degradation factor of PV modules. They occur in most of the cases during installation, maintenance, and especially during transportation of modules to their installation sites. The broken modules or modules with cracks may keep functioning correctly. However, the risk of an electrical shock and that of moisture infiltration increases. Breakages and cracks are usually followed by other degradation types such as corrosion, discoloration and delamination (Kato, 2011).
- viii. **Hot spots:** A hot spot is an area of a PV module that has a very high temperature which could damage a cell or any other element of the module. A hot spot cause could be a variety of cell failures, including partial shadowing, cells mismatch or failures in the interconnection between cells (Molenbroek et al. 1991).
- ix. **Junction box failures:** The junction box is typically located on the backside of a PV module, and less commonly on the edge. It protects the connections of the strings, external wiring, and often the bypass diodes. The box is typically made from polycarbonate, and adhered to the backside of the module. In literature, the junction box failure is a fairly common problem (Köntges et al. 2014). The main failure modes for junction boxes include detachment (from the module backsheet), poorly sealed or closed boxes, corrosion, and arcing due to bad or degraded wiring. Degradation and failure of junction box components can lead to major performance losses and safety hazards because of the high current leakage.

- x. **Bypass diode failures:** Bypass diodes are protective components intended to minimize module losses during reverse bias operation by providing a path for the current of good cells to bypass bad cells. When there is a large mismatch in short-circuit current between several cells, the cell or cells with lowest current may become reverse biased and then overheat. This can occur temporarily during shading or permanently when a cell or the internal electric circuit is compromised. Bypass diodes are usually integrated into the junction box, and are a somewhat common source of issues in underperforming or failed modules (Aghaei et al. 2022). Catastrophic failure modes of bypass diodes include electrostatic discharge, and thermal runaway, and can lead to severe performance losses.
- xi. **Potential induced degradation (PID):** In recent years potential induced degradation (PID) has been identified as a major concern in field modules (Luo et al. 2017). This occurs when there is a high electrical potential between the module frame and solar cells, which generates leakage of currents through the module packaging.

A percentage of average proportional failures of a PV systems' components is pictorially explained on figure 1.8. We can see that hotspot failure occurs most with a 33% occurrence, followed by ribbon discoloration 20%, then glass breakage 12%, encapsulant discoloration occurring 10%, cell breakage -9%, PID 8% and others (Kim et al. 2021).

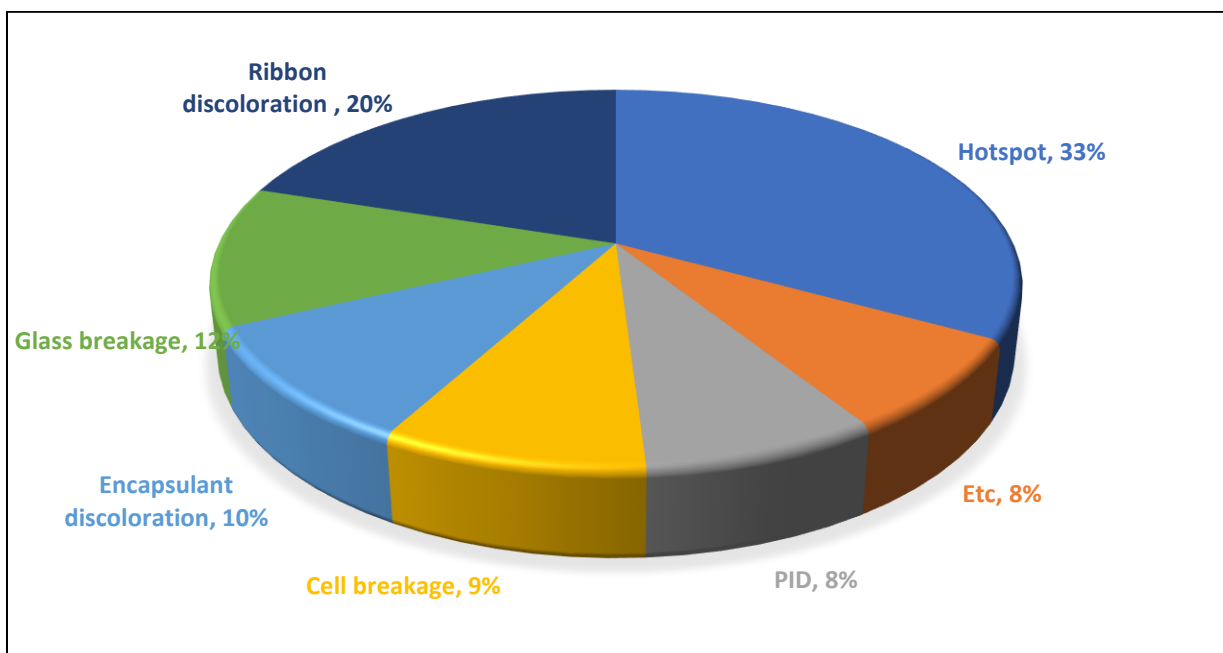


Figure 1.8: Failures of a PV system (Kim et al. 2021)

1.4.4.2 Failure causes and effects in a wind system

In the wind turbine, the major components reported to fail frequently, their causes and effects are outline as follows:

- i. **Main bearing failure:** Main bearings are usually designed specifically to ensure that wind turbines withstand high loads during gusts and during braking. However, poor

lubrication, wear, pitting, deformation of the outer race and rolling elements are known to cause main bearing failures (Duarte et al. 2006). One of the most critical problems in preventive maintenance is the determination of optimum frequency to perform preventive maintenance in equipment, in order to ensure its availability. In this paper, we propose an algorithm to solve the previous problem for equipment that exhibit linearly increasing hazard rate and constant repair rate. Based on this algorithm, we have developed another one to solve the problem of maintenance management of a series system based on preventive maintenance over the different system components. We assume that all components of the system still exhibit linearly increasing hazard rate and constant repair rate and that preventive maintenance would bring the system to the as good as new condition. We define a cost function for maintenance tasks (preventive and corrective) for the system. The algorithm calculates the interval of time between preventive maintenance actions for each component, minimizing the costs, and in such a way that the total downtime, in a certain period of time, does not exceed a predetermined value.

- ii. **Gearbox failure:** Among the major causes of failure in a wind turbine is the universal gearbox; main causes of failure are poor lubrication, bearings and gear tooth failures. Ragheb & Ragheb (2010) carried out detailed research on gearbox problems, and listed some common causes of their failure.
- iii. **Generator Failure:** Bearings are known to be the main cause of failure of a squirrel cage induction generator. Thus, the maintenance of a SCIG (Squirrel Cage Induction Generator) is mainly limited to the lubrication of the bearings. Muljadi et al. (1999) observed that at high power frequencies, the SCIG is inherently stable, but when connected to a weak network with an unbalanced three-phase load, overheating and torque pulsation can occur. A comprehensive detail of the generic causes of Induction motor failure is discussed in Muljadi et al. (1999).

The International Electro-Technical Commission on Wind Turbine Standards presented comprehensive design tests for the various components of a wind turbine (IEC61400-22,2010). However, these design tests cannot accurately predict all actual environmental factors which vary from site to site, or all possible causes of failure that may occur during service life of the wind turbine (Bi et al. 2014). It is therefore essential to assess the failure characteristics of wind turbines in the field to understand the likely failure behaviour of turbines when exposed to the natural environment. In Germany, the field failure behaviour of wind turbines was evaluated based on reported 1261 cases to determine all causes of failure. The result, shown in Figure 1.9 shows that 43% of the total failure was caused by component failure (gear, generator etc), while 22% was caused by control system failure, grid failure accounts for 7%. Etc (Troskie, 2021).

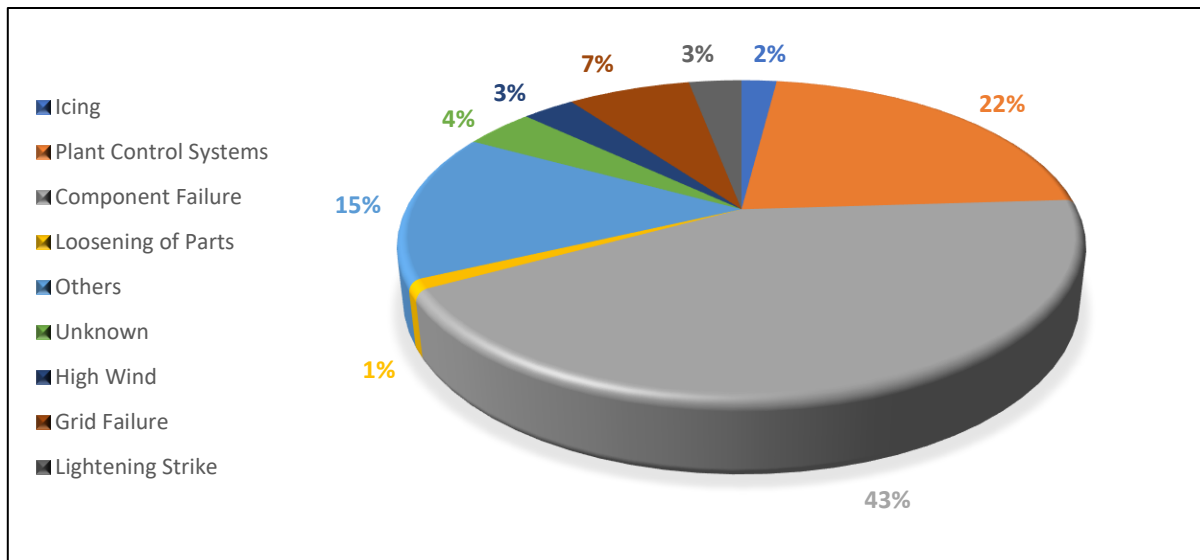


Figure 1.9: Main causes of failure in a wind turbine

(<https://www.engineeringworldchannel.com/wp-content/uploads/2020/08/Wind-turbines-failure-analysis.jpg?x16490>)

1.4.5 Energy production optimization: PV and wind

In renewable energy system, the production units' efficiency depends on climatic factors. Wind speed in the case of wind energy and solar radiation in the case of solar energy are the most important factors or determinants of the energy production and these elements are intermittent in nature. Harnessing these sources require appropriate and efficient planning in order that energy can be made available even when the source produces less than the required demand since these sources depend on weather conditions for their availability. In order to deal with the fluctuation problem and to ensure a more reliable supply of energy, energy planning has been an important subject of study for several researchers (Zhou et al. 2010). In order to deal with the fluctuations and have stability of energy supply, many researchers studied and developed algorithms to estimate the capacity of renewable generating units capable of supplying energy reliably at low cost by different approaches.

Borowy & Salameh (1996) presented an iterative method for determining the optimal number of generating as well as the storage units in an autonomous PV/wind hybrid energy system in their model. Wind turbines of different sizes and capacities were considered, and for each of the turbine, a combination of the number of PV panels and storage units required to satisfy the demand at minimal cost. A model to estimate the levelized cost of energy was developed by Diaf et al. (2007) which properly sizes the dimensions of the generating units in a stand-alone PV/wind hybrid energy system. In their work, the authors believed that appropriate selection of the battery storage system plays an important role in minimizing the cost. Hence, five (5) different types of storage capacities were considered to determine the optimal storage capacity that guarantees the loss of power supply probability (LPSP) reliability at an optimal cost.

Hosseinalizadeh et al. (2016) simulated the behaviour of several combinations of PV, wind turbines, fuel cells and battery storage systems. For the conditions analysed, they concluded that the PV/WT system with battery bank has lower costs of energy than other configurations. Furthermore, Singh et al. (2017) examined the optimal solution for the electrification of Kavaratti island in India based on minimizing the cost of energy. They stated that PV-wind system with batteries is the best option for reducing the cost of each kWhr of electricity. Additionally, Maatallah et al. (2016) investigated the economic and technical feasibility of a hybrid PV/wind system with batteries in Bizerte, Tunisia where they used Hybrid Optimization of Multiple Energy resources (HOMER) software. They claimed that adding batteries to the hybrid wind/PV system reduces the net present cost by 85%. Bahramirad et al. (2012) estimated the optimal capacity of energy storage system (ESS) in a microgrid system where the objective was to minimize the cost of investment of the ESS in addition to the levelized cost of energy (LCOE) of the microgrid where their constraint was the reliability of the grid represented by the loss of load expectation. They found that larger ESS capacities do not always have larger economic benefits where the optimal size of the ESS should be found to ensure the economic feasibility of the ESS.

Yang et al. (2007) developed a model on a sizing optimisation problem for a hybrid solar wind system with a battery bank. They obtained the most economical value by varying the numbers of PV panels, the wind turbine and the battery. A review of various optimization techniques was presented Chehouri et al. (2015). The authors pointed main factors to consider in optimising the performance of wind turbines. In their recent work, Chehouri et al. (2016) presented the fundamental principles of multi-objective optimisation in the design of wind turbines. Al-Shamma'a & Addoweesh (2014) developed an optimization model using genetic algorithms in order to assess the techno-economic feasibility of several configurations of PV, wind, batteries and diesel generator systems. Their optimization was based on achieving zero loss of power supply probability with the lowest cost. They concluded for the analysed conditions that the PV/ wind-battery with diesel generator is the optimal configuration and that the integration of the battery reduced the capacity of the required diesel generator. Furthermore, Balali et al. (2017) wrote a review paper in which they reviewed the literature on the environmental and economic aspects of grid-connected hybrid PV/wind systems with ESS for microgrid applications. It can be concluded from their review paper that none of the studies analysed the economic effects of the integration of ESS with RES. Sandhu & Mahesh (2016) proposed a new approach for sizing battery storage systems to reduce the fluctuations in the energy generation by PV/wind hybrid systems. The optimization model was developed using particle swarm optimization where their objective was to meet the smoothing power level requirements with the two constraints of maintaining within the limits the energy loss and the state of discharge of the battery. Sa'ad et al. (2018) developed model for wind energy generation considering taking into account the environmental influence on a direct driven horizontal axis wind turbine (HAWT).

1.4.6 Maintenance strategies generally applied to PV and wind energy

Maintenance is an important factor for sustainable production in industrial systems to ensure continuous operations by considering reliability, plant and machines/components failures (Sa'ad

et al. 2021a). The functionality of any system becomes reduced with aging components and increased usage. This also affects the economic benefits associated with the production system. Therefore, performing preventive maintenance is often implemented to improve the system efficiency and to minimize losses associated with costs. However, when maintenance is rarely performed, failure rate increases which leads to excessive economic losses due to frequent repairs. When performed too often, it leads to material wastage also having an impact on the economic implication of the production system. It is therefore important to find a balance by developing optimal maintenance strategy for minimizing the cost of maintenance. To ensure smooth running of a manufacturing system, an important concept of service rate was discussed in (Bouzoubaa, 2021a). The service rate is expressed in various forms; probability that a component ruptures, frequency of rupture or failure, estimated time between failure, etc. In this context, this work adopts the service rate as the probability that the system does not fail. This sub-section therefore discusses maintenance strategies used on PV and wind energy systems as they are assumed to have similar approach.

Solar energy is one of the most abundant renewable energy source and appeared to be one of the most exploited renewable energy sources especially for electricity generation globally García et al. (2010), reaching approximately 227 GW plant installations worldwide (Kalogirou, 2018). The increased growth rate of the PV exploitation increased the attention of investors, researchers, government organizations and other stakeholders for financial investment and technical development (Sa'ad et al. 2021), whose aim is to ensure that a PV system should reliably and cost-effectively generate energy while being sustainable. Solar energy production will be explicitly explained in chapter 2.

Although the PV reliability notion was recognized about four decades ago, its significance over an entire PV generation system remains vague due to the complex nature of PV systems (Stember et al.1982). Therefore, reliability analysis represents a decisive issue for the system planning. Majority of the existing literature focused on the reliability assessment of different subsystems, such as the inverter (Alonso et al., 2012), PV module (Dhere et al. 2013), and balance of systems (BOS) (Cristaldi et al. 2015). Much fewer literature discusses the reliability evaluation for entire PV system. Simplified, system-level models for PV system reliability using a Markov modelling concept was presented by Dhople et al. (2010). Periodic preventive maintenance schedule for the service life of a mechanical series system was optimized by Tsai et al., (2001) where they defined a formula to calculate the redundant life of the series and was used as the criterion for replacement selection.

Preventive maintenance action model was developed by Tsai et al. (2004) to maximize system availability during each interval by formulating a constant value used as an improvement factor. Their model was based on the assumption that the time interval for a component with least life in a series system to be considered the maintenance interval period. This however was considered uneconomical because of high maintenance cost and material wastage. Vaurio, (1997) explored the time-dependent unavailability of sporadically tested aging components under

different testing and repair strategies. Age diagnostic based renewal strategy was determined by Legát et al. (1996) for an optimal preventive maintenance strategy defined over finite time horizon.

1.5 Integrated production and maintenance of PV and wind energy

This section explains optimization in the renewable energy sector (solar and wind in our case) in relation with production and maintenance strategies. First in 1.5.1, we discuss optimization of energy production. This is followed by optimization of maintenance under constraint for both PV and wind energy systems under operational and environmental constraints in section 1.5.2. In section 1.5.3, we discuss about maintenance optimization techniques adopted in the PV/wind systems and lastly, in section 1.5.4, we present integrated maintenance strategies with and without constraints.

1.5.1 Optimization of energy production

Renewable energy production as well as the energy efficiency depends on climatic factors which makes it volatile in dealing, hence, to ensure that each production period is secured regardless of the climatic condition, a service level must be implemented. However, the efficiency of green energy production units depends on climatic factors (wind speed and solar radiation). A level of service must be provided at each period regardless of climatic fluctuations. To deal with this challenge, energy production planning has become an important subject of study by several researchers. Kiran, (2019) defined production planning as ‘a method concerned for a required level of production in a specified time horizon dealing with the allocation of finite resources to meet the customer demand. It helps to develop the expected power output and the energy storage over a finite production horizon. In this regard, different techniques for wind energy production were presented in (Hajej et al. 2017; Pohekar & Ramachandran, 2004). In Pohekar & Ramachandran (2004), the authors stated that ‘Analytical Hierarchy Process’ is the most suitable methodology for energy planning since it considers the intermittency of the renewable energy sources which can decrease the availability of the energy production systems.

To optimize and stabilize the volatile renewable energy system, several researchers worked on several energy production optimization problems. (Habib et al. 1999) considered hybrid systems composed of photovoltaic panels and different types of wind turbines having different power ratings. These are used to establish to establish the optimal rate of produced power by the system that insures the constant energy demand. In Borowy & Salameh (1996), iterative numerical method to minimise the total cost of production and storage for a renewable energy system was proposed. The objective is to determine the optimal combination of the number of batteries, wind turbines and photovoltaic arrays corresponding to the least cost of stand-alone hybrid PV/wind system and successfully satisfies the system reliability. As part of the efforts to better understand the principles of wind energy production optimization technique, (Chehoury et al. 2015) presented the fundamental principles by developing a multi-objective optimization model for wind turbines in two stages; first, they identified constraints and objective functions mainly targeted by designers,

and then, developed optimisation model by emphasizing the emergence of the use of population-based techniques, GA in particular.

Optimization of renewable energy have also been dealt with using several methodologies such as SVR (Sa'ad et al. 2020), ANN (Sa'ad et al. 2022), and long short-term memory (LSTM) Alzahrani et al. (2017), to predict wind speed and solar irradiance. These predictions can be considered as the first step in renewable energy production. Gensler et al. (2016) developed power production forecasting model for a PV system using Auto Encoder (AE) and LSTM neural network. The authors used the encoding side of the AE to realize the most effective features for learning and attached it to the LSTM network. Accordingly, the LSTM uses the learned encoding data as an input to predict the solar power generation of a PV plant. The proposed model showed powerful results compared to multilayer perceptron's (MLP), LSTM, deep belief networks, and AE. In contrast with Gensler et al. (2016), Hsu (2018) combined the AE with LSTM to establish an augmented long short-term memory (A-LSTM) forecasting model. The algorithm was tested on different datasets, and it performed well on time series datasets. Wang et al., (2018) proposed a GRU based short-term PV power forecasting algorithm. GRU model is used to reduce the long training time compared to LSTM model as well as improve the accuracy of the output. They concluded that GRU outperformed the traditional ML models such as SVR, autoregressive integrated moving average model (ARIMA), LSTM, and back propagation neural network (BPNN). In summary, many ML algorithms have been used to predict the solar power generated from distinct PV plants. The ML techniques are gaining more attention in the recent years as against the statistical traditional techniques of forecasting energy. The ML techniques are gaining more attention in the recent years as against the statistical traditional techniques of forecasting energy.

1.5.2 Optimization of maintenance strategies

Maintenance optimization is “a process that attempts to balance the maintenance requirements (legislative, economic, technical, etc.) and the resources used to carry out the maintenance program (human, spare parts, consumables, equipment, facilities, etc.)” (Andrawus, 2008). A maintenance strategy that is appropriate and optimal may not be optimal in the very near future due to the intermittent nature of input variables such as interest rate, component cost, failure behaviour, etc. Thus, maintenance optimization is not a one-time procedure but an ongoing process that requires periodic performance evaluation and improvement of past achievements. A good maintenance and inspection strategies is essential for improving the financial viability of a system. To describe the actual influence of maintenance, imperfect maintenance models such as age reduction coefficient, hazard rate adjustment factor and hybrid have been applied in various applications (Wang et al. 2020). Availability maximization algorithm was developed by Duarte et al. (2006) for a system composed of n-components by considering the components' linearly increasing hazard and constant repair rate of previous similar equipment. Tsai et al. (2001, 2004) developed different models and maintenance strategies with the aim of attaining optimal preventive maintenance actions by means of cost optimization and selective preventive maintenance strategy.

In order to increase the probability of successfully completing production mission without failure, Khatab et al. (2014) developed Selective PM model for multi-component system. The model was based on hybrid hazard rate approach aimed at improving the reliability of the component for the next production mission. This model has the benefit of combining age reduction and adjustment coefficient which helps in exposing the system degradation as well as the effect of PM actions. Taking into account the benefits from the model, Khatab et al. (2017) developed PM strategy to determine optimal number of PM that maximizes system availability while also considering the impact of reliability threshold on the system availability. A binary state strategy for selective maintenance was built by Maaroufi et al. (2013) for a multi-component system where reliability was calculated and gauged for each mission to determine the components due for maintenance. The authors applied Markov process in the selection while calculating the optimal cost for performing such actions. To minimize maintenance makespan, Hadjaissa et al. (2016) developed a bi-objective optimization model that minimizes the makespan (time for maintenance) while also maximizing training time. A derringer function was used as the tool to determine an optimized trade-off between the two objective functions. In Bukala et al. (2019), a maintenance optimization model was developed for complicated case (guy-wired masts) such as small wind turbines to minimize the periodicity of power generation from the turbines

Vatn et al. (1996) optimized the maintenance of energy production system taking into account safety and environment by minimizing production/maintenance costs. Further studies have treated both predictive and preventive maintenance using multi-objective optimization model to power distribution networks. Reliability and availability of PV system by means of general reliability analysis methods were studied by (Ahadi et al. 2014; Li et al. 2012). Fault tree method with an exponential probability distribution function was used to analyse the components of 7 large-scale PV systems in Ahadi et al. (2014), the method serves as a suitable tool for identifying the most critical components of PV systems and helps in identifying areas that planned maintenance should be focused on. Quantitative risk analysis technique was used by Li et al. (2012) on 20 kW grid-connected PV system over a 25-year period to analyse the system and to assist in developing better maintenance strategies, and thus to realize maximum benefit of photovoltaic power.

In accordance with machine deterioration factor, Kahrobaee & Asgarpoor (2013) established an optimum maintenance strategy for a wind turbine taking into account the degradation influence, where they proposed different maintenance optimisation methods based on analytical methods considering several factors such as weather conditions, and resource availability. The authors first used a hybrid analytical-simulation method to determine the optimum maintenance strategy. Then thereafter, they modified the model to investigate the effects of maintenance and repair activities on the system's availability as well as the costs. Lu et al. (2017) developed an opportunistic maintenance strategy for an electrical and electronic system of wind turbine taking into account the durations of imperfect preventive maintenance. The proposed planning of maintenance during the mission horizon taking into account the changed and uncertainty of information with time, respecting a threshold of reliability and reducing the total maintenance cost. Using the data mining concept for wind farm, Hahn et al. (2017) have presented a brief overview

of the main results concerning the data collection and reliability assessment for O&M optimisation of wind turbines.

1.5.3 Optimization of PV/WT maintenance under constraints (operational and environmental)

We begin by presenting some works concerning the optimization of production and maintenance taking into account the degradation of wind turbines, since our study is situated in this context. Using a stochastic model, Carlos et al. (2013) proposed a new maintenance strategy taking into account the influence of the stochastic load, experienced by the wind turbine, on the degradation process of the wind turbine. The optimal maintenance strategy characterized by the date of carrying out a maintenance action, the frequency of maintenance and the duration of this activity, has a great influence on operational costs and aims to minimize the total cost and maximize the annual energy produced. Kahrobaee & Asgarpour (2013) studied the optimal maintenance strategy for wind turbine equipment subject to deterioration. They proposed a variety of maintenance optimization methods based on analytical approaches taking into account several factors such as weather conditions or resource availability affecting the operation and maintenance of wind power equipment. First, they used a hybrid simulation and analytical approach to determine the optimal maintenance strategy, then they studied the effects of maintenance and repair activities on system availability and costs.

Due to the faster degradation processes of wind turbines in onshore compared to the offshore environment, operation and maintenance (O&M) activities are more complex and costly and account for a considerable portion of the energy cost. In this context, Santos et al. (2015) studied the wind turbine performance problem by identifying the factors that affect the performance the most, i.e. availability, overall cost and cost of the wind turbine, so that measures can be taken to minimize their effects. They addressed these issues by presenting a parametric study on the impact of variation in failure and repair patterns, logistics delays, weather conditions and waiting times on wind turbine performance. They proposed an optimization model and simulation for the operation and maintenance strategy based on generalized stochastic Petri net with Monte Carlo simulation. Carroll et al. (2016) studied the importance of failure rates and resource requirements for the repair of offshore wind turbines on modelling and reducing operating and maintenance costs and on minimizing energy costs. First, they provided the failure rates based on runtime, cost category, and failure modes of the overall wind system and its subassemblies. Second, they proposed a new contribution regarding decision-making for managers by modelling the problem of offshore wind operation and resources, and compared the failure rate of onshore and offshore generators.

Recently, other significant works, concerning the reliability analysis of offshore wind turbines taking into account the complexity of the system and the negative impacts in operating conditions, have been presented in the literature. Walford (2006) highlighted the issues regarding wind system reliability by describing and identifying the various costs associated with the operation, maintenance and availability of the wind farm. A new optimization strategy is proposed

to deal with the different causes of uncertainty in estimating the reliability of wind turbine components and to minimize operating and maintenance costs. Failure event can be accepted within a maintenance strategy aiming at global cost minimization. If a preventive maintenance is approached, failure can eventually bring an occasional use of opportunistic strategies. For example, Wildeman et al. (1997) dealt with the problem of grouping the Maintenance activities in order to save set-up costs, since the Execution of a group of maintenance activities requires a single set-up. The authors propose a rolling horizon approach that takes the long-term tentative plan as the basis for the next adaptation according to the short-term information, as the component failure. This yields a dynamic grouping strategy, which assists the maintenance manager when planning job. In the following sub-section, we will discuss some of the integrated maintenance strategies carried out.

1.5.4 Integrated maintenance optimization strategies under constraints

It is important that when establishing a maintenance strategy, the manager has specific targeted objectives to fulfil. These can be cost optimization, availability maximization, ensuring equipment reliability, asset preservation, enhanced safety, compliance, and product quality. Thus, the preventive maintenance models must align with the objectives. An optimization model dealing with integrated production and maintenance strategy for a single machine over a finite horizon in an industry was proposed by (Hajej et al. 2017). In this problem, the production plan was first modelled analytically and then sequentially integrated to maintenance planning to minimize the total production cost. Wang et al. (2020) showed that a well-developed steady-state availability using the appropriate model is an important performance parameter in repairable systems. The authors also tried to compare the traditional exponential method of determining availability to probabilistic method where they scheduled an imperfect PM by developing a steady-state availability model to help determine the optimal PM strategy that maximizes the system availability.

An integrated preventive maintenance strategy was developed by Faker et al. (2021) which factors turbine degradation and spare part sourcing as the constraints in their work. Their main aim was to determine the optimal total cost related to production, maintenance and spare parts considered as three-threshold strategy over a fixed finite horizon. Rationalized over a fixed periodicity (interval), Wang (2012) planned a preventive maintenance to successfully and effectively for an optimized spare part inventory. Hajej et al. (2017) presented an integrated maintenance economic plan related to wind turbines 'energy production by minimizing the total costs of production and maintenance considering the production rate and the degree of deterioration of the turbine over the horizon. Sobolewski et al. (2019) established a choice model of optimal maintenance plan of wind turbines system considering the maintenance duration, the order of wind turbines system maintenance (selecting different turbines at PM time) and the maintenance starting time.

An optimization model was developed by Mansour & Djallel (2017) for optimizing a solar/wind/battery hybrid energy system to optimize power generation from a wind turbine used

for implementing battery energy control system. (Kahla et al. 2017) presented an optimization model that maximizes the wind turbine power production under. Lachichi (2014) analysis a modular multi-level converter with integrated energy storage batteries highlighting the influence of injecting energy from the grid for balancing the voltage in the capacitor. An optimization model for determining the best technical approach of maintenance was presented by Hossain Lipu et al. (2017) for a hybrid energy system. The aim is to determine the cost-effective approach for the stand-alone system. In Okinda & Odero (2016), a mathematical model using the genetic algorithm method was developed in order to optimize and obtain the best formation for a solar wind hybrid energy system. For an independent microgrid operating with hybrid solar/wind renewable energy system, Atia & Yamada, (2015) developed an optimization model for sizing the components considering the stochastic distribution of the generating sources.

To develop optimal joint production and maintenance planning, Fitouhi & Nourelfath (2014) presented an integrated model of preventive maintenance production and planning for multi-state systems. First, the model generated the quantity of inventory and the delivery time for each product over the production planning horizon. Then an integrated model for the system was developed to determine the type of action and proposed time optimal time for preventive maintenance action for each component over the horizon. Cheng et al. (2016) focused on developing an integrated modelling method which simultaneously determined production planning and maintenance planning in a machining system, bearing in mind replacement of the machine's failure tool, taking into account the constant demand and possibility of shortage. Built on a linear mixed number programming model, Alaoui-Selsouli et al. (2012) planned production and maintenance activities jointly. The model considered the reliability and expected number of failures of production costs, maintenance, shortages and demand. Preventive maintenance was scheduled on programmed dates while corrective maintenance was performed to restore the system to an operating state without altering the failure rate function.

Keeping in mind the aim of integrating production and maintenance planning, Aghezzaf et al. (2007) proposed a model for scheduling maintenance for a multi-product batch production system with faulty equipment. Xiang et al. (2014) proposed joint production and maintenance models considering the uncertainty of yield, which helped avoid shortage of inventory and loss of customers. The problem was formulated using the Markov decision process. Additionally, they established that optimal production and maintenance strategies had a control limit structure. A joint model of production and maintenance planning for a production system subject to random failures was presented by (Najid et al. 2011). The model reduced shortage of demand and gave more flexibility to preventive maintenance actions. Interaction between the environment and the machine were considered when planning production and maintenance in (Bouslah et al. 2013). The authors investigated the issue in respect with the machine degradation and proposed three control strategies for the maintenance activities.

In line with the above, we propose to develop integrated maintenance strategy taking into account the influence of the environmental elements, the operational condition as well as the

degradation factors of the machines (solar panels and wind turbine) with the aim of achieving maximum availability and optimizing the cost.

1.6 Problem Description and Notation Presentation

In this section, the global problem of this thesis is explained which brings out the main problems to be addressed. We have highlighted their importance by making them the specific objectives to be achieved chapter by chapter in this work. We also present all the notation used regarding all the mathematical modelling in the work.

1.6.1 General description of the thesis problem

The recent evolution and increased attention gained by the renewable energy industry caused high exploitation rate especially in the area of solar and wind energy. Energy exploitation from these sectors encompass various activities such as generation, transmission and storage of the energy system. It has therefore become necessary to constantly improve the energy system condition in order to satisfy customers demand, maximize the system availability and to minimize cost of energy production as well. Therefore, to successfully improve the system condition, and have it to perform its intended tasks until the end of its lifespan (reliability), periodic planned preventive maintenance actions are necessary.

Renewable energy generation systems (Solar and wind in our case) generally, are subject to unexpected breakdowns (failure), the frequency of this failure increases as non-compliance with performing preventive maintenance on the components increases. Other factors that increase the rate of failure include machine/component age and production rate. The frequent shutdowns caused by increased failure rate of the system are considered sources of disruptions and loss of productivity since availability of the system is necessary for reliable and constant energy supply to customers. Therefore, it is necessary to optimize maintenance planning to reduce the rate of failure on the machine components to barest minimum in order to keep it up and running.

In renewable energy, there are several risks observed in the industry especially in the wind and solar energy system. In solar energy profession, the main risks originate from mismatch between the workers' capabilities and workplace factors. Reports by Bakhiyi et al.,(2014); White & Doherty (2017) shows that high risks associated with the solar industry emanates from installations and maintenance of the system. In wind industry, injuries and falling objects especially during installations are identified as the main risks associated with the industry. In this regard, it has become highly necessary to effectively plan maintenance in order to reduce the risks maintenance personnel can encounter as well as to achieve the optimization goal.

In this context, our proposed research work is to develop an integrated maintenance strategy factoring the effect of energy production on the generating unit (wind turbine and solar panels) to maximize the system availability at optimal cost. We developed strategies to optimize the number and costs associated with maintenance actions, maximize system availability and to minimize losses due to market demand and the risks of operations. In order to fully account for all losses and

improve productivity, it is essential to plan and integrate energy generation (production). We also analysis the influence of environmental constraints on both solar and wind systems. An additional considered factor of operational constraints is considered in the wind energy system since it encompasses some moving parts that are prone to mechanical wears, vibrations, shocks and loading etc.

1.6.2 General objectives

Having identified the problem, this thesis is built on the following main objectives;

- i. To develop an improved strategy that determines the optimal number of components and battery capacity that successfully ensures fluctuating customer demand is satisfied over a finite horizon.
- ii. To develop a priority selective maintenance that improves and maintains high system reliability and availability.
- iii. To also optimize the system by minimizing its economic losses incurred as a result of non-production due to maintenance under reliability constraints.

To achieve the said objectives, we first proposed energy generation models based on two approaches: analytical method and the use of 2 machine learning techniques; ANN and SVR for both solar and wind energy generations to effectively plan so that the customer random demand is met at all times. First, we carry out an optimal production plan determining the optimal number of PV panels and wind turbines as well as the number of batteries required at minimal cost. The strategy presents power produced and the quantity of energy stored per production period. We then develop an availability maximization selective maintenance strategy considering reliability threshold as the constraint and criteria for component selection during preventive maintenance.

Reliability of turbine or solar components were evaluated and the decision to perform maintenance is placed on a minimum amount of reliability obtained from each component/subcomponent, hence a selection decision process is made on the component on which maintenance should be performed on. This is to aid in selecting the optimal number of preventive maintenance actions that minimizes the downtime which in turn maximizes availability, this process is known as imperfect/combined maintenance strategy. In doing so, a set of constraints is imposed depending on the system: environmental in the case of solar energy system, and both environmental and operational in the case of wind energy system. Lastly, we combine the above-mentioned process in an integrated production and maintenance strategy to determine the optimal number of maintenance actions that minimizes the total production cost (which also maximizes system reliability based on the two energy generation approaches selected and then a comparison is made between the three approaches.

1.6.3 Notation

a Weibull shape parameters

AEC	Available energy capacity of battery
c	Weibull scale parameters;
C_b	Battery capacity
C_{t1}	Cost of production
C_{t2}	Cost of storage
C_{t3}	Cost of shortage
C_{bat}	Cost of purchasing battery
C_{pv}	Cost of purchasing PV panel
C_{wt}	Cost of purchasing a wind turbine
C_{sell}	Cost of selling 1 kW
DOD	Depth of discharge
H	Operation horizon
H_{system}	Cost index of the system
H_{cap}	Capital cost of the system
H_{ope}	Operational cost of the system
k	Production period index ($k = 1, 2, \dots, H$)
N_{PV}	Number of PV panels
N_{wt}	Number of wind turbine
P_b	Power stored in the battery
P_k	Power generation during period k
P_L	Power load demand
P_S	Power from solar energy
P_{wt}	Power from wind energy
P_r	Rated Power of the wind turbine
P_{max}	Maximum power production level over the horizon

SOC	State of charge of battery
TCb	Total battery capacity of the system
V_b	Voltage capacity of battery
Δt	Duration of each production period
θ	Service level rate

Maintenance

Chapter 2

N	Number of preventive maintenance actions
M_c	Maintenance cost
C_{pm}	Cost of preventive maintenance
C_{cm}	Cost of corrective maintenance
$\bar{Y}(P_k, N)$	Average number of failures depending on N and power production within k

Chapters 3 and 4

A	Availability
C_i	Criticality coefficient of failure of the system
N	Number of preventive maintenances to be performed
NC	Number of subcomponents
R^*	Minimum required reliability threshold
T	Production horizon
$T_{maintenance}$	Total maintenance duration
$\varphi(N)$	Number of Average failure rate
β_j	Criticality coefficient vector for component j
$\lambda_{j/i}$	Constant failure rate of components/subcomponents
μ_p	Preventive maintenance time
μ_c	Corrective maintenance time

$\beta_{i,j}$ Criticality coefficient for component i under environmental influence j

$\beta_{o,j}$ Criticality coefficient under nominal environmental condition

λ_n Nominal Failure rate

Solar PV

a/b_{cause} Failure cause constant under chemical influence

$a/b_{corrosion}$ Corrosion coefficient constant under chemical influence

$a/b_{discoloration}$ Discoloration coefficient constant under chemical influence

$C_{o,j}$ Criticality coefficient of j^{th} component

$R(t)$ System reliability at t

$R_{equipment}$ Reliability function of equipment

R_{cause} Reliability function of cause of failure for a component

R_j Reliability of the j^{th} component under the effect of environmental condition

$R_{o,j}$ Reliability of the j^{th} component under nominal condition

Z_i : Vector of environmental conditions

Z^{EC} Environmental condition representation

AC and DC wires

R_{DC} Reliability function of DC wire

R_{AC} Reliability function of AC wire

R_{wire} Reliability function of wire

R_{cut} Reliability function of cut

$R_{corrosion}$ Reliability function of corrosion

$C_{corrosion}$ Corrosion coefficient for wires

$C_{corrosion-wire}$ Corrosion coefficient of wire

$\lambda_{cut-wire}$ Failure rate related to wire cut

n_{AC} : Number of AC wires

n_{DC} : Number of DC wires

Inverter

$R_{inverter}$ Reliability function of inverter

$\lambda_{inverter}$ Inverter Failure rate

$n_{inverter}$: Number of inverters

PV panel/module

R_{PV} Reliability function of PV system

R_{series} Reliability function of series

R_{panel} Reliability function of panel

n_{series} Number of Series components

n_{panels} Number of PV panels

Junction box

$R_{junction}$ Reliability function of junction box

$\lambda_{junction}$ Junction box Failure rate

Glass

R_{glass} Reliability function of glass

λ_{glass} Glass Failure rate

Bye-pass diode

R_{bypass} Reliability function of bypass diode

λ_{bypass} Bye-pass diode Failure rate

PV cell

R_{cell} Reliability function of cell

λ_{cell} PV cell Failure rate

Interconnectors

$R_{interconnect}$ Reliability function of interconnectors

$\lambda_{interconnect}$ Interconnection Failure rate

Delamination

$R_{delamination}$ Reliability function of delamination

$\lambda_{delamination}$ Delamination Failure rate

Hot spot

$R_{hotspot}$ Reliability function of hotspot

$\lambda_{hotspot}$ Hotspot Failure rate

Discoloration

$R_{discoloration}$ Reliability function of discoloration

$\lambda_{discoloration}$ Discoloration Failure rate

Ribbon

R_{ribbon} Reliability function of ribbon

λ_{ribbon} Ribbon Failure rate

Wind energy

R_{wt} Reliability of wind turbine

Z^{CC} Climatic condition representation

Z^P Power rate representation

η Weibull scale parameter for nominal condition

β Weibull shape parameter for nominal condition

Main bearing

R_{mb} Reliability of main bearing

η_{mb} Weibull scale parameter for main bearing

β_{mb} Weibull shape parameter for main bearing

Main shaft

R_{ms} Reliability of main shaft

η_{ms}	Weibull scale parameter for main shaft
β_{ms}	Weibull shape parameter for main shaft
Z_1^i	i^{th} variable for operational condition of the main shaft
b_1^i	i^{th} variable for environmental condition of the main shaft

Gearbox

R_{gb}	Reliability of the gearbox
η_{gb}	Weibull scale parameter for gearbox
β_{gb}	Weibull shape parameter for gearbox
Z_2^i	i^{th} variable for operational condition of the gearbox
b_2^i	i^{th} variable for environmental condition of the gearbox

HSS Bearing

R_{hss}	Reliability of HSS bearing
η_{hss}	Weibull scale parameter for HSS bearing
β_{hss}	Weibull shape parameter for HSS bearing

IMS Bearing

R_{ims}	Reliability of IMS bearing
η_{ims}	Weibull scale parameter for IMS bearing
β_{ims}	Weibull shape parameter for IMS bearing

Keyway

R_{keyway}	Reliability of keyways
η_{keyway}	Weibull scale parameter for keyways
β_{keyway}	Weibull shape parameter for keyways

Gearbox gears

R_{gear}	Reliability of gearbox gears
η_{gear}	Weibull scale parameter for gearbox gear

β_{gear} Weibull shape parameter for gearbox gear

Generator

R_{gen} Reliability of the generator

η_{gen} Weibull scale parameter for generator

β_{gen} Weibull shape parameter for generator

Z_3^i i^{th} variable for operational condition of the generator

b_3^i i^{th} variable for environmental condition of the generator

Generator bearing

$R_{bearing}$ Reliability of generator bearing

$\eta_{bearing}$ Weibull scale parameter for generator bearing

$\beta_{bearing}$ Weibull shape parameter for generator bearing

Generator windings

$R_{winding}$ Reliability of generator windings Structure

$\eta_{winding}$ Weibull scale parameter for generator windings

$\beta_{winding}$ Weibull shape parameter for generator windings

1.7 Conclusion

Today, integrated maintenance in the field of renewable energy is considered one of the most sensitive technical functions given its risk and importance in the stability of energy production and improvement of renewable energy especially solar and wind system profitability. Therefore, optimization and proper maintenance planning have become a necessity in decision-making. In the first part of this chapter, we presented a detailed bibliographic study of the different types and strategies of maintenance in the industrial field as well as the different maintenance optimization strategies; this study is also concerned with various works making the coupling of production and maintenance under different constraints such as environmental constraints and service rate. In a second part, we introduced machine learning and discussed extensively on its types and applications. We also presented the different type of optimization techniques using the machine learning approach and their characteristics. In the third part after the presentation of a state of the art concerning the field of renewable energy (solar and wind energy) production, then its interest at the economic, social and environmental levels. We also presented a more in-depth study on current designs, the different components that make up a solar and a wind system, their function

and their cause of failure. In the fourth and last part, we presented the different production and maintenance optimization strategies applied to the solar and wind energy systems.

In the rest of this chapter, we have presented the main problem by illustrating the contribution in relation to what already exists in this field of research; we have mainly focused our participation on the level of operating conditions and environmental and industrial constraints, and their influence on production and maintenance optimization strategies for a renewable energy production system (solar and wind system). These operating conditions are related to the influence of variations in the energy production rate on the degradation of the generating equipment, as well as on the production strategy and the maintenance strategy.

CHAPTER 2: Developing and optimizing a renewable energy production and maintenance strategy

This chapter develops a production and maintenance planning model for solar and wind energy systems. The main aim is to develop optimal production plan and integrate it into maintenance strategy in order to reduce both production and maintenance costs. The methodology is performed by first determining the optimal numbers of solar panels, wind turbines and batteries required to satisfy the customer demand for each of the selected case studies (Sokoto solar power plant and Katsina wind farm, Nigeria). We developed three methods of energy production models; ANN, SVR and an analytical technique for the power production optimization strategy. The optimal production plan is integrated into the maintenance plan to determine the optimal number of preventive maintenance (N^) to be performed over a finite chosen horizon and the cost related with it. A numerical example was presented where we compared the results from the three production techniques for both solar and wind energy systems.*

2.1 Introduction

The function of energy and more particularly electricity, is of essence for growth in rural areas. Installation of modern energy systems improves access to potable water through pumping and distribution system. In medical field, cold storage of medicines and access to modern healthcare technologies is one way of reducing diseases which is more tenable with sustainable energy supply thereby reducing children and maternal mortality rates. In educational sector, energy supply aids education and welfare of rural regions by providing adequate electricity and smooth flow of communication. With modern renewable energy systems, it is feasible to achieve abundant access to power supply in the near future (Mosbah & Iqbal 2018)

In recent years, a significant shift in the interest of utilizing renewable energy resources is represented in figure 2.1. More so, the gap between interests and implementation of renewables is yet to be bridged. This gap is caused by the absence of large and effective infrastructure to generate renewable energy in rural areas (Hoogwijk & Graus 2008). One way to bridge this gap is by effectively and efficiently utilizing the resources that are readily available in those areas such as solar and wind resources. Availability of open spaces in rural areas provides an edge for easy solar PV and wind energy systems set-up.

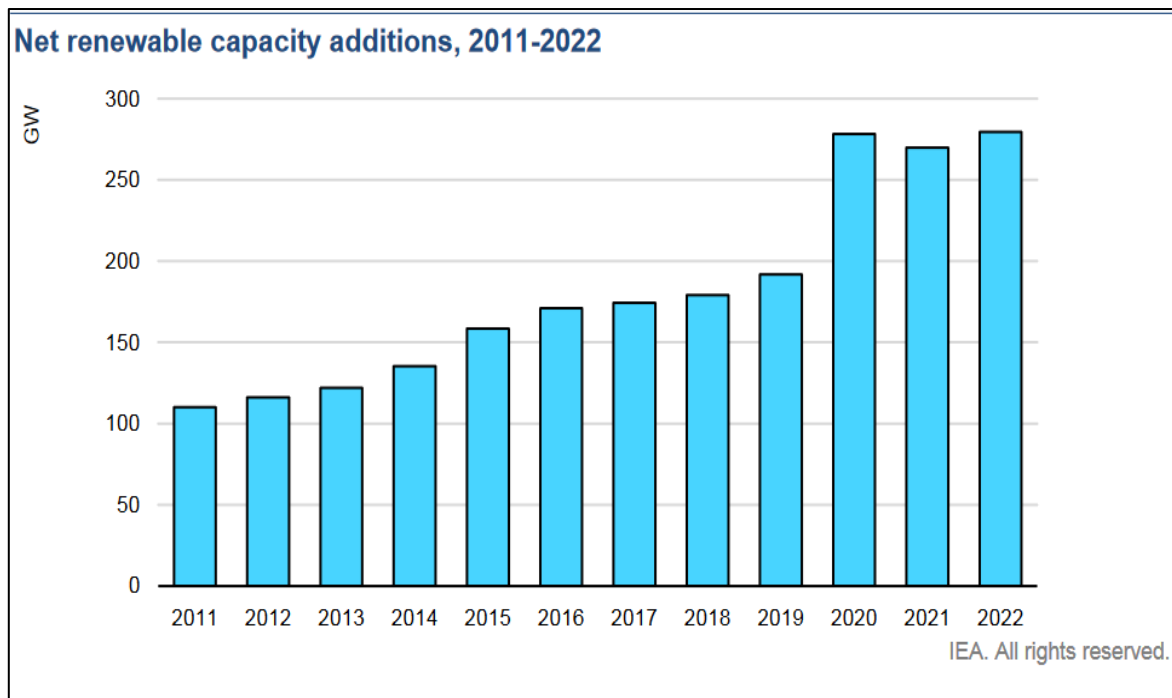


Figure 2.1: Average net renewable capacity installations (International Energy Agency 2021)

The ever-growing demand of increasing world population inspired us to contemplate alternatives to supply quality energy in a sustainable manner. Furthermore, the need for sustainability has caused ample research growth in the area of renewable energy. The current renewable industry is characterised by strong competition to satisfy the needs of a client that is often demanding in terms of energy availability, and cost. However, due to the stochastic nature of the renewable source, appropriate planning must be carried out to ensure customers' needs are met. To remain competitive, renewable energy companies must control operating costs and optimise the production facilities to be able to supply energy and at minimum levelized cost of energy (LCOE) since generation cost invariably affects the selling cost of the energy.

Contemporary manufacturing processes are now more sophisticated in many advanced industries leading to upsurge in internal uncertainties in the manufacturing systems. The use of contemporary technology, intricate equipment, complex tooling requirements, are all factors that make it difficult to maintain a predictable level of output (Hwang & Singh 1998). Often times, newer and more profitable products face even greater uncertainty because the industry has not yet accumulated enough learning experience with the equipment and processes to reduce the variance. Nevertheless, production needs to be carried out in an economic manner, despite the inherent variabilities in the system. In fact, the fundamental objective of production systems is the systematic elimination of waste by focusing on production costs, product quality and delivery, and Personnel.

Until recent, one of the first actions in industrial decision making is the determination of optimal production plan which minimizes total production cost. This forms the base for decision-making hierarchy where optimal inventory and lost demands are considered. To minimize the mentioned industrial problem and determine optimal production plan, many researchers

developed optimization models to minimize production costs under various constraints. For a stochastic manufacturing system comprising of a single machine subjected to constant demand, Sethi et al. (1997) defined an optimal production plan taking into account the rate of production over a finite time in order to minimize wastage of over production and the total average production cost. More recently, using a heuristic approach, Dahane et al. (2012) considered a single randomly failing and repairable manufacturing system producing two products by GA. The strategy is to simultaneously determine the optimal production rate of first product and the optimal duration of production interval of the second product to maximize the expected profit. Hajej et al. (2015) developed a production strategy on a manufacturing system comprising several identical machines arranged in parallel under withdrawal and leasing constraint. In their work, the authors modelled the problem such that a best combination of number of leased machines, production rate and inventory level is made which minimize the total production and holding costs. An optimal cost model of production system comprising of several identical machines considering the reparation periods and the production rate of the machines (Kenne & Nkeungoue 2008). In Hajej et al. (2015), economical production planning also considering subcontracting and leasing of machines was modelled using a quadratic model to satisfy random demand. Nonetheless, the case of renewable energy is not far from the industrial set-up since they both comprise of manufacturing units and product/service delivery to satisfy customer demand. In the renewable energy especially solar and wind energies, the main challenge faced by the industry is the intermittent nature of the resource. Therefore, many works have dealt with the production optimization process by considering different optimization strategies.

In this context, we can cite the work of (Mansour et al. 2017) who studied the procedure for optimizing a wind farm operation. They applied an experimental management for the control of the energy stored in the batteries. Kahla et al. (2017) presented an optimization model maximizing the power of the wind turbine. Multi-objective functions are developed to solve the wind energy conversion system by finding the optimal parameters of the control methodology. Hossain Lipu et al. (2017) studied an optimization design of hybrid renewable energy systems by a hybrid optimization model developed to determine the most viable, autonomous and cost-effective technique. Omondi Okinda et al. (2016) examined the problem of optimal sizing of a hybrid renewable energy system; wind and solar. A linear mathematical model and genetic algorithms are developed for optimization and to obtain the optimal configuration of the system.

This chapter consists of developing and optimizing an optimal maintenance strategy integrated into an economic production plan by comparing between ANN, SVR and analytical method. It is organized as follows: Problem statement and motivation for this work is presented in section 2.2. In section 2.3, renewable energy (Solar and wind energies) was studied. Analytical, ANN and SVR methods of production are explained in 2.4 for both solar and wind energy systems. In section 2.5, the maintenance strategy developed for this chapter was discussed and we formulated the maintenance planning showing the algorithm developed. This is then followed by numerical example in 2.6 and a conclusion is drawn in 2.7.

2.2 Problem Statement

According to World Bank report, (2021), 940 million (about 13%) of the world population do not have access to basic electricity with more than 90% of this figure being from sub-Saharan Africa. Despite the efforts made by the Nigerian government to provide electricity, there are about 89.63 million people (44.6%) still lacking access to electricity most of which are found in the remote and rural areas across the nation. With the current energy situation, there are still many challenges and weaknesses affecting the energy sector in Nigeria. Some of the challenges are: Lack of modern facilities that can generate and distribute energy, low access to modern energy for cooking, increase in population leading to increase in energy demand, high cost of energy, high cost of rural electrification from the grid, frequent power outage and high dependence on petroleum products. Since Nigeria is a developing country with constant power outage, then it is necessary for energy decentralization from national grid to enable rural areas access basic amenity. The rural electrification agency (REA) of Nigeria has proposed ways of decentralizing energy from the grid to generate few watts or kW such as rooftop solar to power homes and pump water in the rural areas. There are other mega projects capable in MW capacity such as the Sokoto power plant and Katsina wind farm capable of supplying energy to the locals around the plant location as well as cities in the geographical zones.

In order to improve the efficiency and performance of the mega projects, several approaches to optimize the power plants' power generation were developed and the results presented for both solar and wind energy. However, most of the work did not pay attention to the maintenance strategies suitable for the optimization. In that case, we have proposed an integrated maintenance strategy to optimize Sokoto solar power plant and Katsina wind farm in Nigeria as our case study. The methodology we developed starts by first solving the problem of energy production optimization using analytical, ANN and SVR to satisfy energy demand over a finite horizon. Thus, considered as the first sub-problem of the optimization problem. Then the obtained results are considered as input in the second sub problem of maintenance by considering the impact of the variation of the energy production on the degradation level of the wind turbine and the solar PV.

2.3 Renewable (Solar and Wind) energy study (Reminder)

Renewable energy as an alternative source is green, abundant and hazard-free. Solar, wind, biomass and ocean wave current are some examples of the renewable energy sources. In this work, we limit our study to solar energy and wind energy.

2.3.1 Solar energy

Solar energy is one of the abundant available sources of renewable energy. It can be converted to electric energy through a variety of established technologies. One way is to convert the sunlight directly into heat by use of solar thermal technologies. Heat collected can be used for space heating or can be stored in a thermal medium such as water or molten salt. Dependence of electric grid can be reduced when solar energy replaces electricity in such applications. According

to (Global Wind Energy Council Report, 2019), global solar energy has a cumulative installed capacity of about 633.7 GW by the end of 2019 and expected to reach 1TW by 2023 which increases the global solar penetration capacity by 23%. This means that electricity generated from solar energy has grown by nearly 400% from its inception since early time of the century which occurred when Germany launched feed-in tariff law on grid-connected solar plants (Solar Power Europe, 2020). In figure 2.3, the cumulative global installed solar PV capacity from 2000 to 2020 is shown.

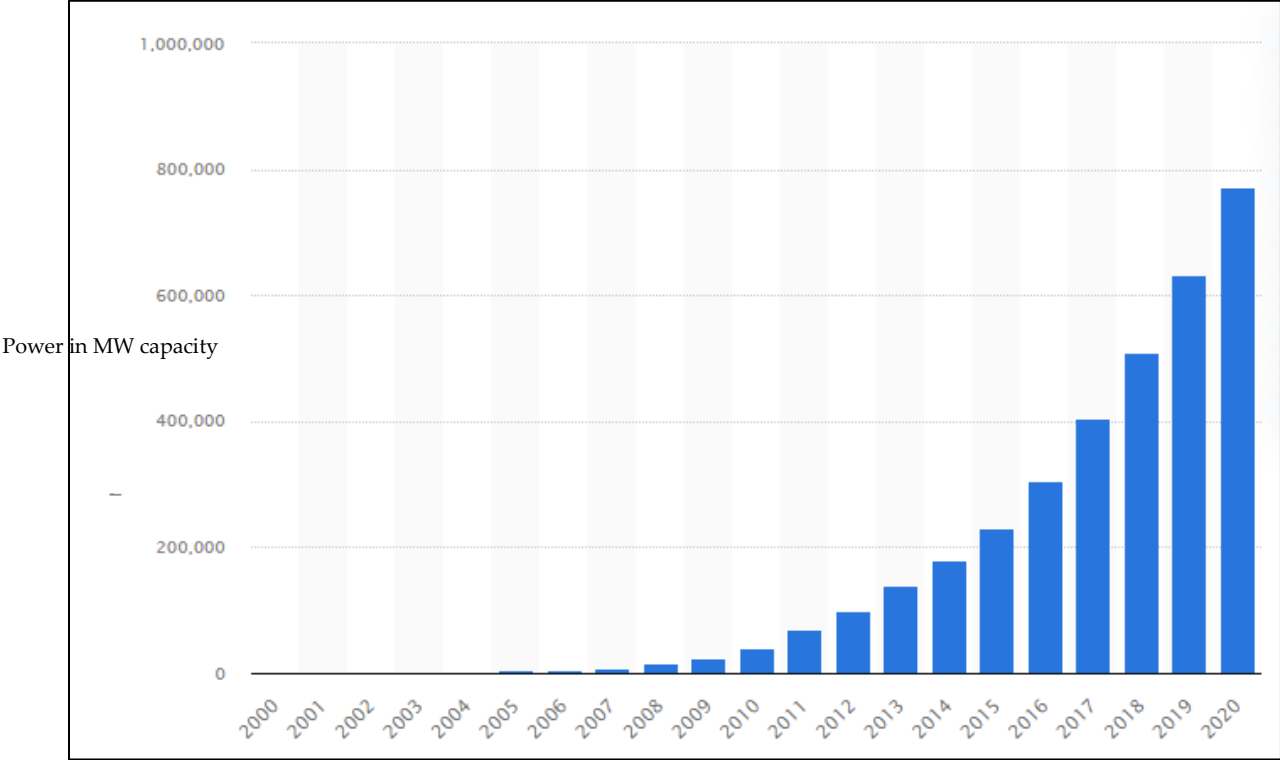


Figure 2.2: Cumulative installed PV capacity worldwide from 2000 to 2020 in GW (statistica.com)

Concentrating Solar Power (CSP) is one of the most promising technologies for harvesting solar energy. CSP technology is poised to take its place as one of the major contributors to future clean energy. It is a simple technology in which very large quantity of sunlight is focused onto a very small area, generating heat that can be transformed into electricity. CSP, unlike conventional photovoltaic technology, it stores heat rather than electricity. Figure 2.3 shows a typical CSP setting where reflections from the solar panels are concentrated to an angle. Another way of using solar energy is through PV technologies. PV directly absorb incident photons (particles of light acting as individual units of energy) without complete conversion to heat. It is either converted to DC electricity as in PV cell or stored as chemical energy through a chemical reaction such as dissociation of water into hydrogen and oxygen (US departments of the interior, 2006).



Figure 2.3: A CSP setup (Gorjian, 2017)

This work concentrates on solar PV generation using solar panels. A PV panel consists of a number of cells connected in series to generate electricity as shown on figure 1.6 in the previous chapter. The effect of a PV is the process through which a PV cell converts energy from the sun into electricity. Sunlight is composed of photons (light energy particles) containing various amounts of energy corresponding to the different wavelengths in the solar spectrum. When photons hit a solar cell, the energy from the photons is transferred to an electron in the semiconductor (usually silicon) solar cell atoms. The energized electron becomes loose and set in motion thereby forming electricity in an electric circuit. A PV generated electricity is in the form of a direct current (DC). DC is not the type of consumable power by the load, therefore, converting it to an alternating current (AC) which can be usable in homes is necessary. To convert DC to AC, an inverter is connected to the solar generating units. In modern solar systems, these inverters can be configured as one inverter for the entire system or as individual micro-inverters attached behind the panels (*Solar Photovoltaics*, 2003).

2.3.2 Wind energy study

Wind is air in motion in simple terms. Uneven heating of the Earth's surface causes it by radiant energy from the sun. People have harnessed wind energy since ancient times. Ancient Egyptians used wind to sail ships on the Nile River as early as 5000 B.C. Later, windmills were

developed to grind wheat and other grains. Early windmills looked like paddle wheels. Centuries later, people in Holland improved the windmill. They gave it propeller- type blades, still made with sails. By about the 19th century, windmills were used to pump water, grind grains and generate electricity. Although they lost their significance in 1950’s because of cheap oil and low energy prices, they re-entered the market around the 1970’s when there was oil crisis all around the world (Shahan, 2014). Wind energy is the conversion of kinetic energy from the wind into electricity through a wind turbine. Wind turbines are either horizontal axis (HAWT) or vertical axis (VAWT), but we focus on the HAWT. A typical wind turbine (HAWT) consists of blades, the hub, pitch system, main shaft gearbox generator and transformers as shown in figure 1.7 in the previous chapter.

The wind turbine converts the kinetic energy from the rotating wind around the blades into mechanical energy which is converted into electrical energy by the use of the electric generator in the turbine (Sa’ad et al. 2021b). Over the years, both offshore and onshore wind energy has received tremendous attention thereby causing annual increase in electricity generation from the wind as shown in figure 2.4. According to the 2019 Global Wind Energy Outlook (GWEC) report (*Global Wind Energy Council Report, 2019*), a global installed capacity of 60.4 GW in 2015 was injected, which marks the second largest year in history and close to the bumper year of 2015 (63.8 GW) thereby totalling the installed capacity to 651 GW. The GWEC Market Intelligence experts forecasted that 355 GW of new capacity will be added by the year 2024 (71 GW annually averagely).

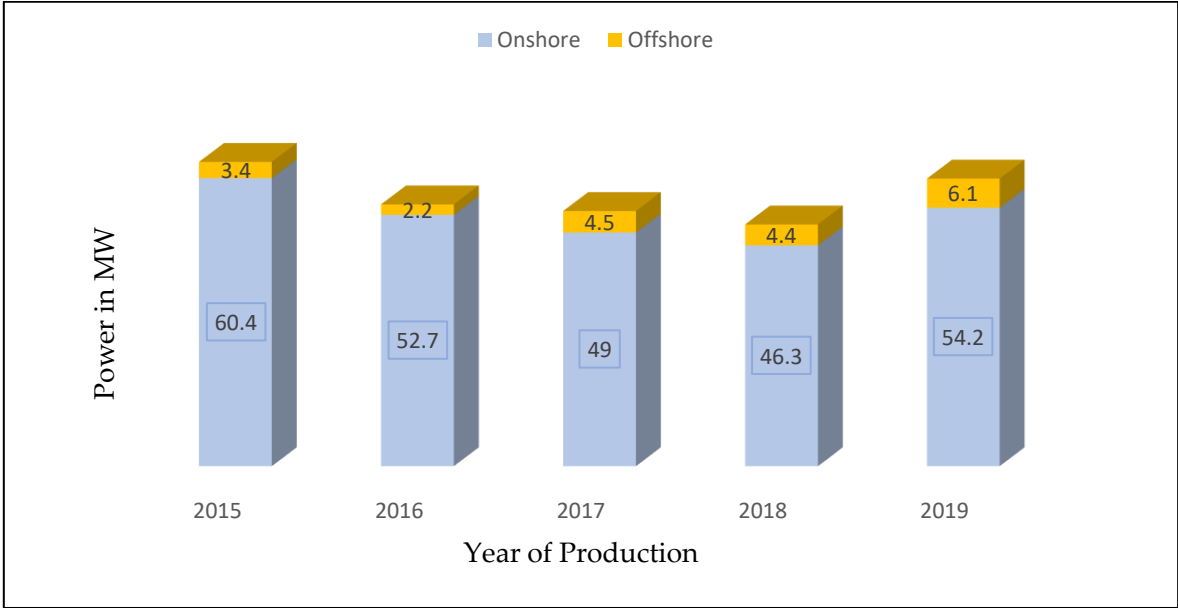


Figure 2.4: Annual wind energy injection (Solar Power Europe, 2020)

2.4 Production problem formulation by machine learning and analytical methods

The problem of power production is formulated for both solar and wind energy in the following sub-sections using ANN, SVR and analytic method.

2.4.1 Production problem on PV system

The power production system consists of solar panels and battery bank. Battery is not a generating unit but an energy storage system that supplies the load when there is lack of electricity. It also stores the surplus when the power generated exceeds the load. In some cases, shortage of energy to satisfy the demand occurs. Therefore, our design considered the cost implication of shortage in the system optimization. Optimization process can be defined by finding values of variables that minimize or maximize an objective function and satisfy the constraints. The optimization problems are centred on three main factors which are: i) objective function which is to be minimized or maximized, ii) a set of unknown variables that have effect on the objective function, and iii) a set of constraints that allow the unknown to take on certain values. The main aim of this work is to minimize the PV system production cost; determining the optimal number of PV panels required (N_{pv}) and the battery capacity (C_b). In literature, there are various ways to calculate system costs (Bernal-Agustín et al. 2006; Dufo-López et al. 2007). Based on (Li et al. 2012), this work adopts the lifecycle cost (LCC) analysis, of determining the total production cost of the system represented by C_{system} . The optimization problem is presented as:

$$\text{Min } C_{system}(N_{pv}, C_b)$$

Subject to:

$$\begin{aligned} N_{pv} * P_{pv}(t) + V_b * SOC(t) &\geq P_L(t) \\ AEC_{min} &\leq AEC(t) \leq AEC_{max} \\ N_{pvm} &\leq N_{pv}(t) \leq N_{pvM} \end{aligned}$$

The total system cost (H_{system}) is the sum total of initial capital cost (H_{cap}) and the operational cost (H_{ope}) expressed in equation 2.1. Furthermore, the initial capital cost comprises of cost of purchasing and installing the units explained in equation 2.2 while the operational cost is in equation 2.3.

$$C_{system} = C_{cap} + C_{ope} \quad 2.1$$

$$C_{cap} = \sum_{t=1}^H N_{pv}(t) * C_{pv} + C_b(t) * C_{bat} \quad 2.2$$

$$C_{ope} = C_{t1} + C_{t2} + C_{t3} \quad 2.3$$

Conventionally, the operational cost is evaluated as a percentage of the capital cost in relation to the lifespan of the considered component for maintenance. In order to minimize waste that could result from such, we modified the operational cost analysis as shown in equation 2.3 where C_{t1} is the cost of producing 1kW of energy, C_{t2} is the cost of storing 1kW of energy and C_{t3} is the cost of shortage of 1 kW of energy. Explicitly, the operational costs are evaluated as follows:

$$C_{t1} = \sum_{t=1}^H \left(C_p \times \sum_{j=1}^{N_{pv}} P_{js}(t) \right) \quad 2.4$$

$$C_{t2} = \left(C_s^+ \times \Delta t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)>0}) \right) \quad 2.5$$

$$C_{t3} = \left(C_s^- \times t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)<0}) \right) \quad 2.6$$

With the storage condition on the battery's state of charge being

$$1_{SOC(t)>0} = \begin{cases} 1 & \text{if } SOC(t) > 0 \\ 0 & \text{otherwise} \end{cases}$$

and that of shortage condition on the battery's state of charge being

$$1_{SOC(t)<0} = \begin{cases} 1 & \text{if } SOC(t) < 0 \\ 0 & \text{otherwise} \end{cases}$$

Here, C_p is the cost of production per unit kW, C_s^+ is the cost storage per unit kW, C_s^- is the cost of shortage per unit kW and P_k is the total power generation within production period k (determined by the analytical and machine learning approach). We assume that the quantity produced in period k is added to the inventory at the end of the period which satisfies the demand P_L . Accordingly, the inventory evolves as shown in figure 2.5 below

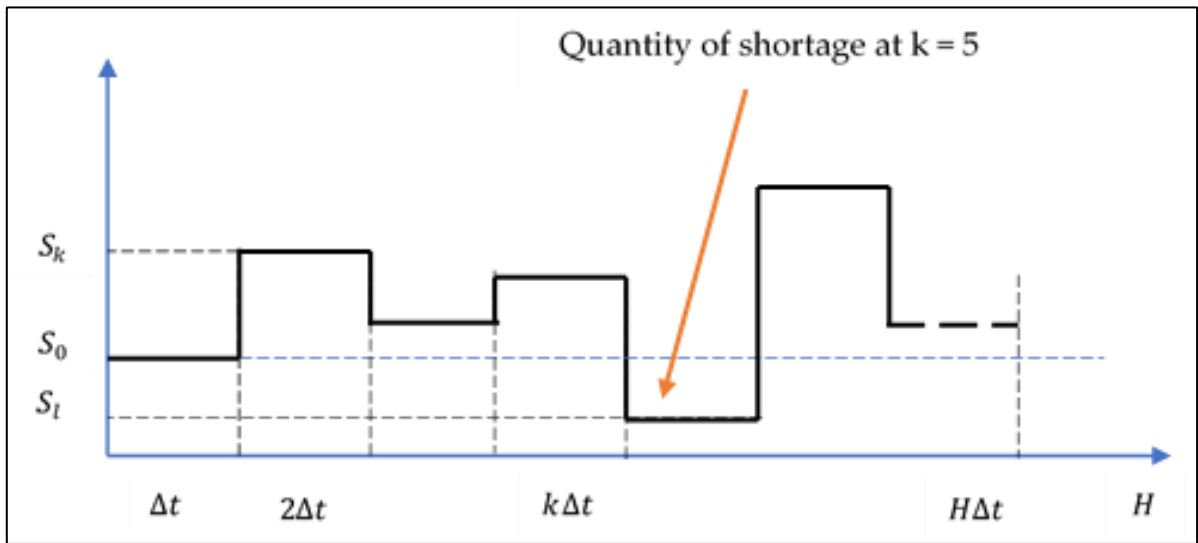


Figure 2.5: Evolution of storage inventory

2.4.1.1 Storage sizing problem

The battery storage behaviour is characterized by its state of charge (SOC) (Piller et al. 2001). The SOC depends on the past data and the power in the battery system which is the difference between the generated power $P_G(t)$ and the power load demand $P_L(t)$ at every time instance t. Therefore,

$$SOC(t) = SOC(t-1) + \frac{P_G(t) - P_L(t)}{V_b \cdot TC_b} \quad 2.7$$

Given that

$$P_G(t) = \sum_{t=1}^H N_{pv} \times P_S(t) \quad 2.8$$

Where V_b and TC_b are the battery voltage and battery capacity respectively.

To ensure good performance of the battery bank, a new concept of cycle invariance criterion is introduced (Li et al. 2012). The cycle invariance criterion is such that, the battery SOC returns to its initial state at the end of each production period which implies that

$$SOC(t) = SOC(t - 1) \quad 2.9$$

This criterion helps in proper sizing to determine the number of panels required, hence equation 2.9 is remodelled into

$$\sum_{t=1}^H (N_{pv} \times P_S(t) - P_L(t)) = 0 \quad 2.10$$

Therefore,

$$N_{pv} = \frac{\sum_{t=1}^H P_S(t)}{\sum_{t=1}^H P_L(t)} \quad 2.11$$

After N_{pv} is determined, the battery capacity is obtained by calculating the energy flowing into and out of the battery bank ($P_b(t)$) at time t by

$$P_b(t) = P_G(t) - P_L(t) \quad 2.12$$

At present, the total battery capacity (TC_b) is undetermined, then we let $AEC(t)$ denote the available energy capacity of battery bank at t expressed as

$$AEC(t) = AEC(t_0) + \sum_{t=1}^H \frac{P_b(t)}{V_b} \quad 2.13$$

We assume that the initial condition $AEC(t_0) = 0$ which means the battery is empty at the initial condition. This causes, the energy in the battery bank to be less than zero (0) and is not technically feasible. To overcome this, a suitable initial condition is proposed such that the $AEC(t)$ at each period is characterized by the SOC variation which is expressed as

$$AEC(t) = SOC(t).C_b \quad 2.14$$

To determine the total battery bank capacity TC_b over a finite time horizon H, the TC_b must satisfy the following condition in order not that the battery capacity does not become negative

$$TC_b \geq AEC_{max} - AEC_{min} \quad 2.15$$

where

$$AEC_{max} = \max (AEC(t)) \text{ and } AEC_{min} = \min (AEC(t)) \quad \ni t = 1 \dots H$$

If $P_G(t) > P_L(t)$, the battery becomes in a charging state and if otherwise when $P_G(t) < P_L(t)$, the battery gets into a discharge state. The $AEC(t)$ of the battery during the charging and discharging states are expressed in the following form

$$AEC(t) = AEC(t - 1) \cdot (1 - \sigma) + \left(PG(t) - \frac{PL(t)}{\eta_{inv}} \right) \cdot \eta_{bat} \quad 2.16$$

$$AEC(t) = AEC(t - 1) \cdot (1 - \sigma) - \left(\frac{PL(t)}{\eta_{inv}} - PG(t) \right) \quad 2.17$$

Where σ is the battery self-discharge rate given as 25% by battery manufacturers, η_{inv} is the inverter efficiency considered as constant, (92%) and η_{bat} is the battery efficiency is set to 1 during discharge process and 0.65 during charge state. On another hand, to improve the battery efficiency, the battery energy flow within the battery must be limited within a certain range and then the maximum absorbable energy (Capata, 2011) must be considered as

$$TC_b \geq \frac{|P_b(t)|}{V_b}, \quad \exists t = 1 \dots H \quad 2.18$$

Each battery cycle is characterized by its depth of discharge (DOD) so as to guarantee the battery cycle and minimize deep cycle, which means that the amount of capacity withdrawn from a battery is expressed as a percentage of its maximum capacity. Therefore, the allowable DOD must be taken into account so as to extend the working life of the battery. Hence, the TC_b is maximum of the combination of equation 2.15 and 2.18 becomes:

$$TC_b = \max((AEC_{max} - AEC_{min}), |P_b(t)|/V_b)/DOD \quad 2.19$$

Having defined and formulated the optimization problem, the power generated is then modelled based on the following chosen techniques.

2.4.1.2 Artificial neural network (ANN)

An ANN is an array network of uncomplicated processors called neurons. A typical ANN architecture is shown in Figure 2.6. The ANN consists of an input layer, one or more hidden layers and an output layer. Each layer engages numerous other neurons and each neuron in a layer is connected to the neurons in the adjacent layer with different numerical values known as the weights. These weights are the core processors for performing the neural computations for the output. Data fed into the input layer, pass through the hidden layers, and reach the output layer to make prediction. With the exception of the input layer, each neuron receives data from the neurons of the previous layer linearly weighted by the weight between the neurons. The neuron then produces its output by passing the summed signal through an activation function. For example, a total of P sets of training data is assumed to be available. Inputs of P (i_1, i_2, \dots, i_p) are the learning features and are imposed on the input layer. The ANN is trained to respond to the corresponding target output vectors, Y (y_1, y_2, \dots, y_n) at the output layer. The training continues until a certain stop-criterion is satisfied. Typically, training is halted when the average error between the desired and actual outputs of the neural network over the P training data sets is less than a predetermined threshold. The training time required is dictated by various elements including the

complexity of the problem, the number of data, the structure of the network, and the training parameters used.

In this paper, we applied the delta rule (Hanson, 1990) to train the ANN model using the neural network tool (nn toolbox) in MATLAB 2021b. According to the difference between the produced and target outputs, the network's weights ($w_{i,j}$) are adjusted to reduce output error. For the purpose of this work, we train a model comprising of input layer with 2 features (temperature and solar irradiance), single hidden layer comprising of 20 neurons and a single output for predicting our power production.

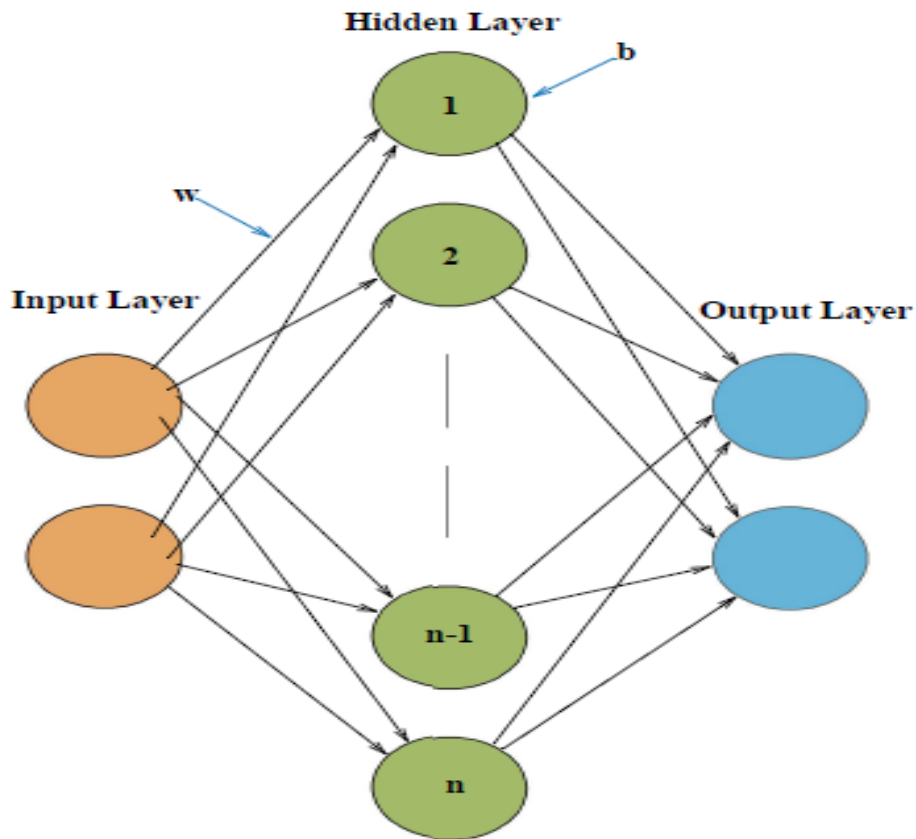


Figure 2.6: ANN architecture

The output, from neuron i , is connected to the input of neuron j through the interconnection weight $w_{i,j}$. The input to neuron j is defined as

$$k_{j,\text{input}} = \sum_{i=1}^m w_{i,j} x_i + b_{\text{input}} \quad 2.20$$

x_i is the i^{th} input node, $k_{j,\text{input}}$ is the input of the j^{th} hidden node, $w_{i,j}$ is the weight assigned to the i^{th} input node that is mapped to the j^{th} hidden node and b_{input} is the input layer bias.

The output from the hidden layer is activated by an activation function and in our case, we selected the sigmoid function because of its adaptability with even complex data. The output therefore is obtained as

$$k_{j,output} = f(k_{j,input}) \quad 2.21$$

$k_{j,output}$ is the output of the j^{th} hidden node while f is the activation function of the model expressed as $1/(1 + e^{-x})$. Through the computations and mathematical manipulations, the output prediction from the j^{th} hidden node of the hidden layer is

$$y_p = \sum_{j=1}^n k_{j,output} + b_{\text{hidden}} \quad 2.22$$

b_{hidden} is the hidden layer bias and y_p is the output of the model.

2.4.1.3 Support vector regression (SVR)

An SVR is a nonlinear kernel-based machine learning technique used for regression as well as classification. The kernel functions as activation power which makes the model exhibit good prediction ability. It consists of creating or mapping training data into hyper-planes to gaudily discriminate predictions from training data in the feature space as shown in figure 2.7 which deals efficiently with nonlinear regression problem. Given a set of data points represented by $\{x_i, y_i\}_i^n$ where x_i is the input space vector from the sample, y_i is the target value and n , is the total sample size. A support vector machine output prediction is calculated in the following form

$$f(x) = w\varphi(x) + b \quad 2.23$$

where φ is the transfer function, x is an input data point, w is a normal vector and b is a scalar. They are estimated by minimization of regularized risk function by introducing regularized risk function solved as (Cortes & Vapnik, 1995).

$$\begin{aligned} \text{minimize } L_p &= \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) & 2.24 \\ \text{Subject to } & \begin{cases} y_i - \varphi(x_i) - b \leq \epsilon + \xi_i \\ \varphi(x_i) + b - y_i \leq \epsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0 \quad i = 1, 2, \dots, n \end{cases} \end{aligned}$$

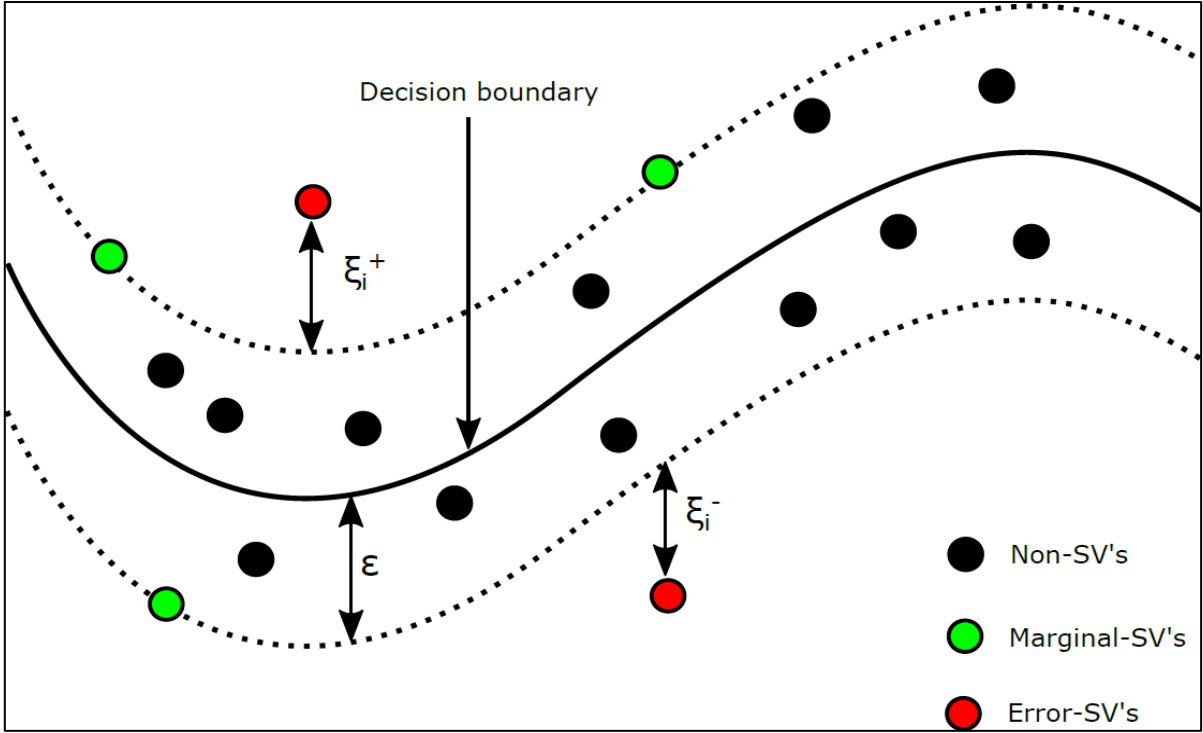


Figure 2.7: An SVR hyperplane representation

where $\frac{1}{2} \|w\|^2$ represents the regularization term, y_i is the i^{th} target and C is the error penalty factor used to control the trade-off between the regularization term and empirical risk, ϵ is the deviation threshold of the function f , and ξ_i is the slack error that guarantees the solution by coping the infeasible constraints and n is the number of elements in training data sample. Equation 2.23 can be solved by introducing Lagrange multiplier and optimality constraints, hence obtaining a generic function given by

$$f(x) = \sum_{i=1}^n (\beta - \beta^*) K(x_i, x_j) + b \quad 2.25$$

where $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$ and the term $K(x_i, x_j)$ is called the kernel function, which is a product of the two vectors x_i and x_j in the feature space $\varphi(x_i)$ and $\varphi(x_j)$, respectively. This product associates each pair of vectors in the space with a scalar quantity known as the inner product of the vectors. Inner products allow the rigorous introduction of intuitive geometrical notions such as the length of a vector or the angle between two vectors (Olatomiwa et al. 2015). The main purpose of SVRs is to carry out data correlation via non-linear mapping. Kernel methods enables it to operate in a higher dimensional feature space without ever computing the coordinates of the data in that space, but rather by simply computing the inner products between the metaphors of all pairs of data in the feature space. This operation is often computationally cheaper than the explicit computation of the coordinates. This approach is known as a direct computation method of a kernel function, denoted by K . The results obtained in the higher-dimensional feature space correspond to the results of the original, lower-dimensional input space.

There are four basic kernel functions provided by SVR, namely, linear, sigmoid, polynomial, and radial basis functions. But over the years, radial basis function (RBF) has been proven to be the best kernel function due to its computationally efficiency, simplicity, reliability, ease of adaptation to optimization and other adaptive techniques as well as its adaptability in handling parameters that are very complex (H. Yang et al. 2009). RBF kernel function only needs the solution of a set of linear equations instead of the lengthy and computationally demanding quadratic programming problem for its training. The RBF kernel function is defined as

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \quad 2.26$$

where x_i and x_j are vectors in the input space, i.e. vectors of features computed from training or test samples.

The three parameters associated to RBF Kernels are γ , ϵ and C . The accuracy of SVR model is principally dependent on model parameter selection. In our work we used the default value of $\epsilon = 0.1$ which seemed to perform well. To select user-defined parameters (i.e. γ , ϵ and C), a large number of trials were carried out with different combinations of C and γ for the radial basis function kernel. It is worthy of mention that SVRs are effective with limited samples which also minimizes structural risks of the regression problem. Furthermore, SVRs have a wide application range such as solar irradiance prediction (Voyant et al. 2017), energy generation predictions (Sa'ad et al. 2020), anomaly detection (Harrou et al. 2021) and road traffic prediction (Zeroual et al. 2021).

2.4.1.4 Analytical method for PV system

Due to the intermittent nature of solar PV and its dependent on weather elements and climatic condition for power generation the solar power output from a panel is modelled based on the temperature and solar irradiance, thus obtained by the following equation;

$$P_s(G, \Delta T) = k_1 \times A_s \times G \times (1 - k_T \Delta T) \quad 2.27$$

However, due to other insolation phenomena such as dust and cloud cover, solar irradiance is represented as random variable (Li et al., 2012) characterised by beta distribution function with α and β parameters expressed in the following form;

$$f(G) = \frac{\Gamma(\alpha + \beta)}{(\Gamma\alpha)\Gamma(\beta)} \left(\frac{G}{G_{max}}\right)^{\alpha-1} \left(1 - \frac{G}{G_{max}}\right)^{\beta-1} \quad 2.28$$

A PV panel consists of several solar cells as described in section 1.4.3, therefore, the total obtainable power output from a panel could be expressed as

$$P(S) = \int_0^{G_{max}} \left(k_1 \times A_s \times G \times (1 - k_T \Delta T) \times \frac{\Gamma(\alpha + \beta)}{(\Gamma\alpha)\Gamma(\beta)} \times \left(\frac{G}{G_{max}}\right)^{\alpha-1} \times \left(1 - \frac{G}{G_{max}}\right)^{\beta-1} \right) d(G) \times \Delta t \quad 2.29$$

where G is the solar radiation for each generating period, G_{max} is the maximum solar radiation over the production horizon in W/m^2 , k_1 is the PV panel generating efficiency, A_s is the panel area in

m^2 , k_T is the cell temperature coefficient, $\Delta T = T_c - T_{cref}$ representing the error between the cell temperature and the chosen reference cell temperature in $^{\circ}\text{C}$, α and β are the beta function parameters.

2.4.1.5 PV production planning algorithm

The flow chart for the above formulated problem is presented in figure 2.8. The input data for this algorithm is the monthly average temperature, solar irradiance and the load demand for a horizon of 1 to 12. Firstly, the configuration of the system (N_{pv} and C_b) to satisfy the demand calculated by the algorithm after which C_{system} is calculated so as to obtain the optimal solutions.

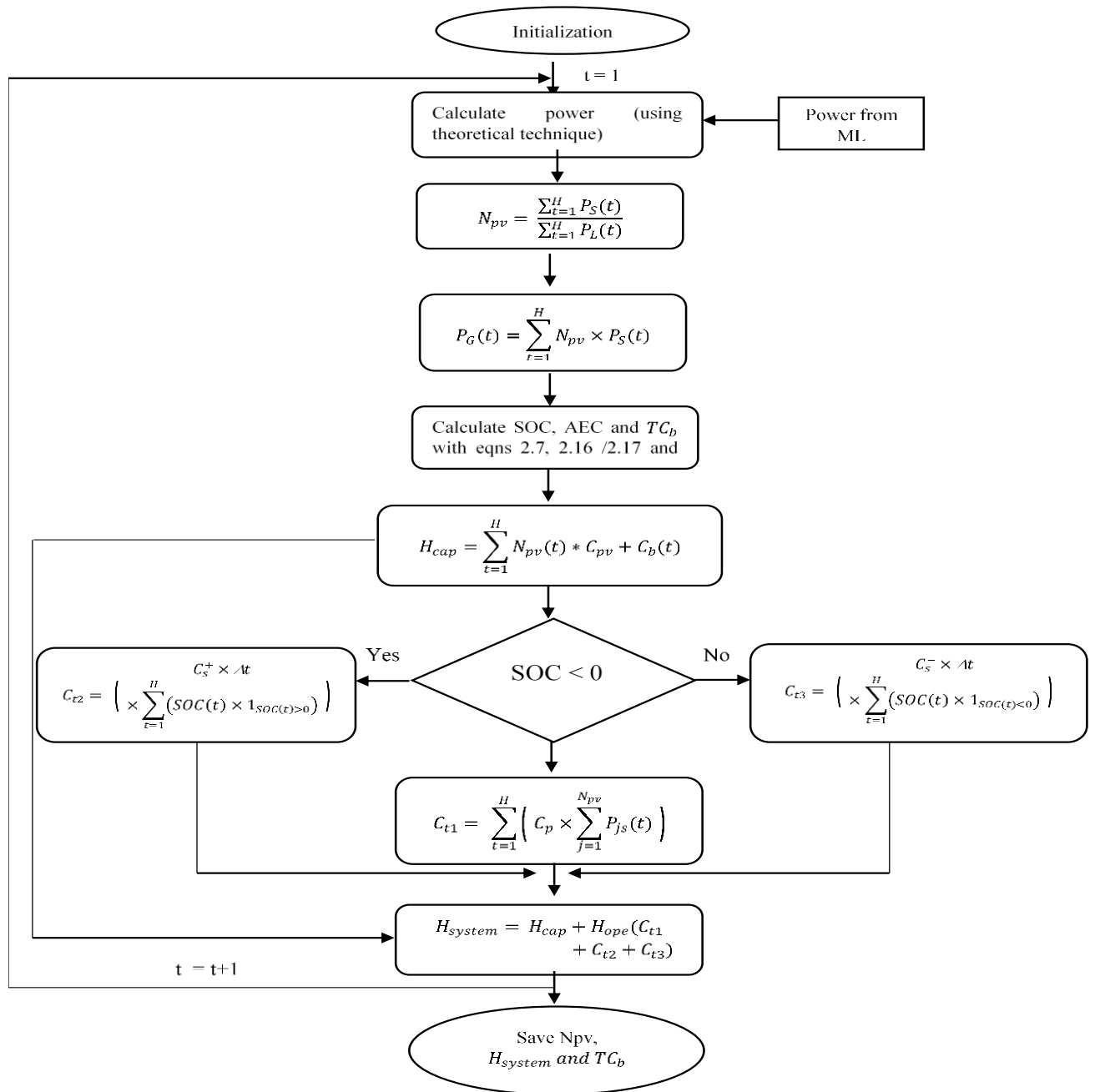


Figure 2.8: Solar production planning algorithm

2.4.2 Production problem on wind energy

In this subsection, the mathematical modelling is performed similar to the solar PV analysis as follows

$$\text{Min } C_{system}(N_{wt}, C_b)$$

Subject to:

$$\begin{aligned} N_{wt} * P_{wt}(t) + V_b * SOC(t) &\geq P_L(t) \\ AEC_{min} &\leq AEC(t) \leq AEC_{max} \\ N_{wtm} &\leq N_{wt}(t) \leq N_{wtM} \end{aligned}$$

The system cost is then expressed as

$$C_{system} = C_{cap} + C_{ope} \quad 2.30$$

$$C_{cap} = \sum_{t=1}^H N_{wt}(t) * C_{wt} + C_b(t) * C_{bat} \quad 2.31$$

$$C_{ope} = C_{t4} + C_{t5} + C_{t6} \quad 2.32$$

The operational cost is the costs of production (C_{t4}), cost of storage (C_{t5}) and cost of shortage (C_{t6}). These costs are evaluated as follows:

$$C_{t4} = \sum_{t=1}^H \left(C_p \times \sum_{j=1}^{N_{wt}} P_k(t) \right) \quad 2.33$$

$$C_{t5} = \left(C_s^+ \times \Delta t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)>0}) \right) \quad 2.34$$

$$C_{t6} = \left(C_s^- \times \Delta t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)<0}) \right) \quad 2.35$$

With the storage condition on the battery's state of charge being

$$1_{SOC(t)<0} = \begin{cases} 1 & \text{if } SOC(t) < 0 \\ 0 & \text{otherwise} \end{cases}$$

and that of shortage condition on the battery's state of charge being

$$1_{SOC(t)<0} = \begin{cases} 1 & \text{if } SOC(t) < 0 \\ 0 & \text{otherwise} \end{cases}$$

2.4.2.1 Battery storage sizing problem for wind energy

The battery storage sizing is formulated similar to the case of PV. Therefore, to refresh the reader's mind, the formulation is expressed as follows:

$$SOC(t) = SOC(t-1) + \frac{P_G(t) - P_L(t)}{V_b \cdot TC_b} \quad 2.36$$

Given that

$$P_G(t) = \sum_{t=1}^H N_{wt} \times P_{wt}(t) \quad 2.37$$

Where V_b and TC_b are the battery voltage and capacity respectively.

To ensure good performance of the battery bank, a new concept of cycle invariance criterion (Li et al. 2012) is introduced. The cycle invariance criterion is such that, the battery SOC returns to its initial state $SOC(t_0)$ at the end of each production period which implies that

$$SOC(t) = SOC(t - 1) \quad 2.38$$

This criterion helps in proper sizing to determine the number of panels required, hence equation 2.36 is remodelled as

$$\sum_{t=1}^H (N_{wt} \times P_{wt}(t) - P_L(t)) = 0 \quad 2.39$$

Therefore,

$$N_{wt} = \frac{\sum_{t=1}^H P_{wt}(t)}{\sum_{t=1}^H P_L(t)} \quad 2.40$$

After determining N_{wt} , battery capacity is obtained by calculating the energy flowing into and out of the battery bank $P_b(t)$ at time t by

$$P_b(t) = P_G(t) - P_L(t) \quad 2.41$$

At present, the total battery capacity TC_b is undetermined, then we let $AEC(t)$ denote the available energy capacity of battery bank at t expressed as

$$AEC(t) = AEC(t_0) + \sum_{t=1}^H \frac{P_b(t)}{V_b} \quad 2.42$$

We assume that the initial condition $AEC(t_0) = 0$ which means the battery is empty at the initial condition. This causes, the energy in the battery bank to be less than zero (0) which is not technically feasible. To overcome this, a suitable initial condition is proposed such that the $AEC(t)$ at each period is characterized by the SOC variation which is expressed as

$$AEC(t) = SOC(t).C_b \quad 2.43$$

In order to determine the total battery bank capacity TC_b over a finite time horizon H, the TC_b must satisfy the following condition in order not to be negative

$$TC_b \geq AEC_{max} - AEC_{min} \quad 2.44$$

where

$$AEC_{max} = \max(AEC(t)) \text{ and } AEC_{min} = \min(AEC(t)) \ni t = 1 \dots H$$

If $P_G(t) > P_L(t)$, the battery becomes in a charging state and if otherwise when $P_G(t) < P_L(t)$, the battery gets to a discharge state. The $AEC(t)$ of the battery during the charging and discharging states are expressed in the following form:

$$AEC(t) = AEC(t-1) \cdot (1 - \sigma) + \left(PG(t) - \frac{PL(t)}{\eta_{inv}} \right) \cdot \eta_{bat} \quad 2.45$$

$$AEC(t) = AEC(t-1) \cdot (1 - \sigma) - \left(\frac{PL(t)}{\eta_{inv}} - PG(t) \right) \quad 2.46$$

Where σ is the battery self-discharge rate given as 25% by the battery manufacturer, η_{inv} is the inverter efficiency considered as constant, (92%) and η_{bat} is the battery efficiency is set to 1 during discharge process and 0.65 during charging state.

On another hand, to improve the battery efficiency, the battery energy flow within the battery must be limited within a certain range and then the maximum absorbable energy (Capata, 2011) must be considered as

$$TC_b \geq \frac{|P_b(t)|}{V_b} \ni t = 1 \dots H \quad 2.47$$

Each battery cycle is characterized by its depth of discharge (DOD) so as to guarantee the battery cycle and minimize deep cycle, which means that the amount of capacity withdrawn from a battery expressed as a percentage of its maximum capacity. Therefore, the allowable DOD must be taken into account so as to extend the working life of the battery. Therefore, the TC_b is maximum of the combination of equation 2.42 and 2.45 expressed in the following form:

$$TC_b = \max((AEC_{max} - AEC_{min}), |P_b(t)|/V_b)/DOD \quad 2.48$$

After successful formulation of the optimization problem, the power generated is then modelled based on ANN, SVR and analytical techniques. Both ANN and SVR are modelled same as solar PV, therefore, we will only discuss the analytical approach.

2.4.2.2 Analytical method for wind energy

Estimating wind energy from the wind turbine is an essential aspect of wind energy management. It enables the manager to estimate the quantity of wind energy to be produced per period. However, generating energy from the wind depends on several factors: the directional profile characterised by the probabilistic tendency of wind direction, the speed profile that characterised by the probabilistic tendency of speed and the annual and daily variation of average speed (Hajej et al. 2020). Wind speed is often treated as a random variable characterized by Weibull distribution function expressed as follows:

$$f(v) = \frac{a}{c} \left(\frac{v}{c} \right)^{a-1} \exp \left(- \left(\frac{v}{c} \right)^a \right) \quad 2.49$$

where v is the wind speed (m/s), c is the scale parameter of Weibull distribution with unit of speed and a is the shape parameter of Weibull distribution. Different methods of calculating the two parameters of Weibull distribution of wind speed are available in literature (Celik 2004). From Xiang et al. (2012), the obtainable average wind power P_{wind} from the turbine is estimated by

$$P_{wind}(v) = \begin{cases} P_r \frac{(v^a - v_{ci}^a)}{(v_{ci}^a - v_r^a)} & \text{for } v_{ci} \leq v \leq v_r \\ P_r & \text{for } v_r \leq v \leq v_{co} \\ 0 & \text{Otherwise} \end{cases} \quad 2.50$$

where P_r is the rated power of the turbine, v_r is the rated wind speed and v_{ci} is the cut-in wind speed, v_{co} is the cut-out wind speed represents respectively the starting and the stop of generating power and depends on the type of wind turbine, a is the Weibull shape parameter.

In line with the wind speed variation distribution functions, the average power output from a turbine whose specifications are provided by the manufacturer per period is calculated using the following equation:

$$P_{wt}(v) = \int_{v_{ci}}^{v_r} \left(\frac{a}{c} \left(\frac{v}{c} \right)^{a-1} \exp \left(- \left(\frac{v}{c} \right)^a \right) \times P_r \times \frac{(v^a - v_{ci}^a)}{(v_{ci}^a - v_r^a)} \right) dv + \int_{v_{ci}}^{v_r} \left(\frac{a}{c} \left(\frac{v}{c} \right)^{a-1} \exp \left(- \left(\frac{v}{c} \right)^a \right) \times P_r \right) dv \quad 2.51$$

However, wind energy production can only be achieved when the wind speed exceeds a threshold (Sa'ad, et al. 2020). Presented in figure 2.9, there is no power output generation in region 1 because the wind speed in that region is below the cut-in speed. The cut in speed ($v_{cut\ in}$) represents the minimum amount of wind speed required for the turbine to start generating electricity. With increase in wind velocity, in region 2, the power output increases until the velocity reaches the turbine rated velocity (v_{rated}), an amount sufficient to generate rated turbine power output which becomes steady in region 3 despite increase in the wind speed. At cut-off speed ($v_{cut\ off}$), the turbine shuts down to avoid being damaged with high wind speed or under turbulence, as such there is no power is generated in region 4 also.

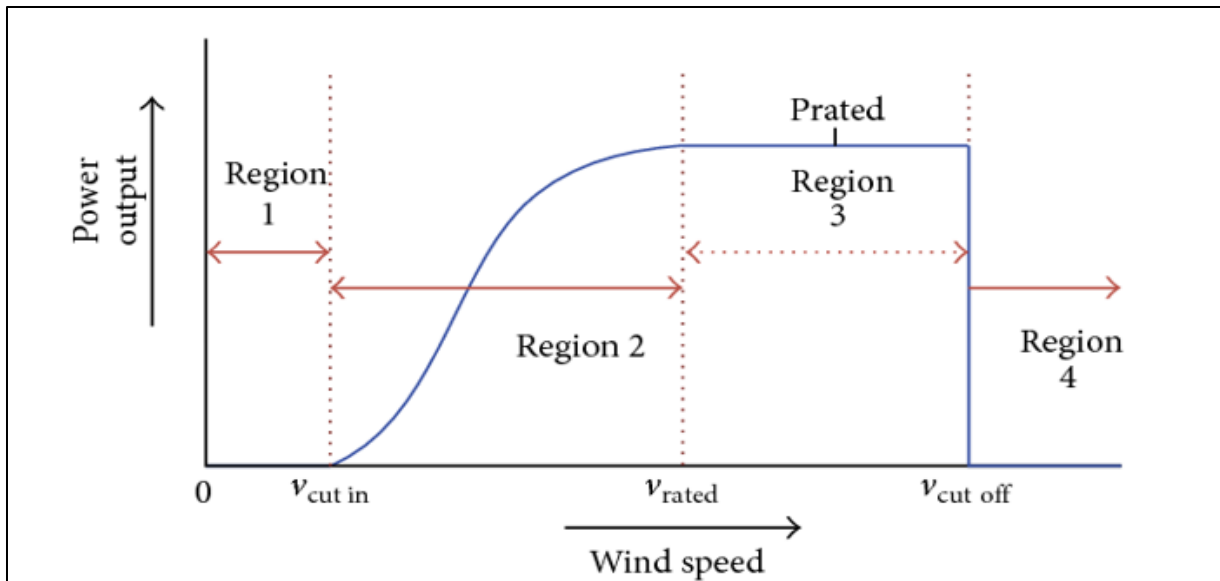


Figure 2.9: Power output extraction from a wind turbine

2.4.2.3 Wind production algorithm

The flow chart for the above formulated problem is presented in figure 2.10. The input data for this algorithm is hourly data summed into monthly average for wind speed and the load demand for a horizon 12 months. Firstly, the configuration of the system (N_{wt} and C_b) to satisfy the demand calculated by the algorithm after which C_{system} is calculated so as to obtain the optimal solutions.

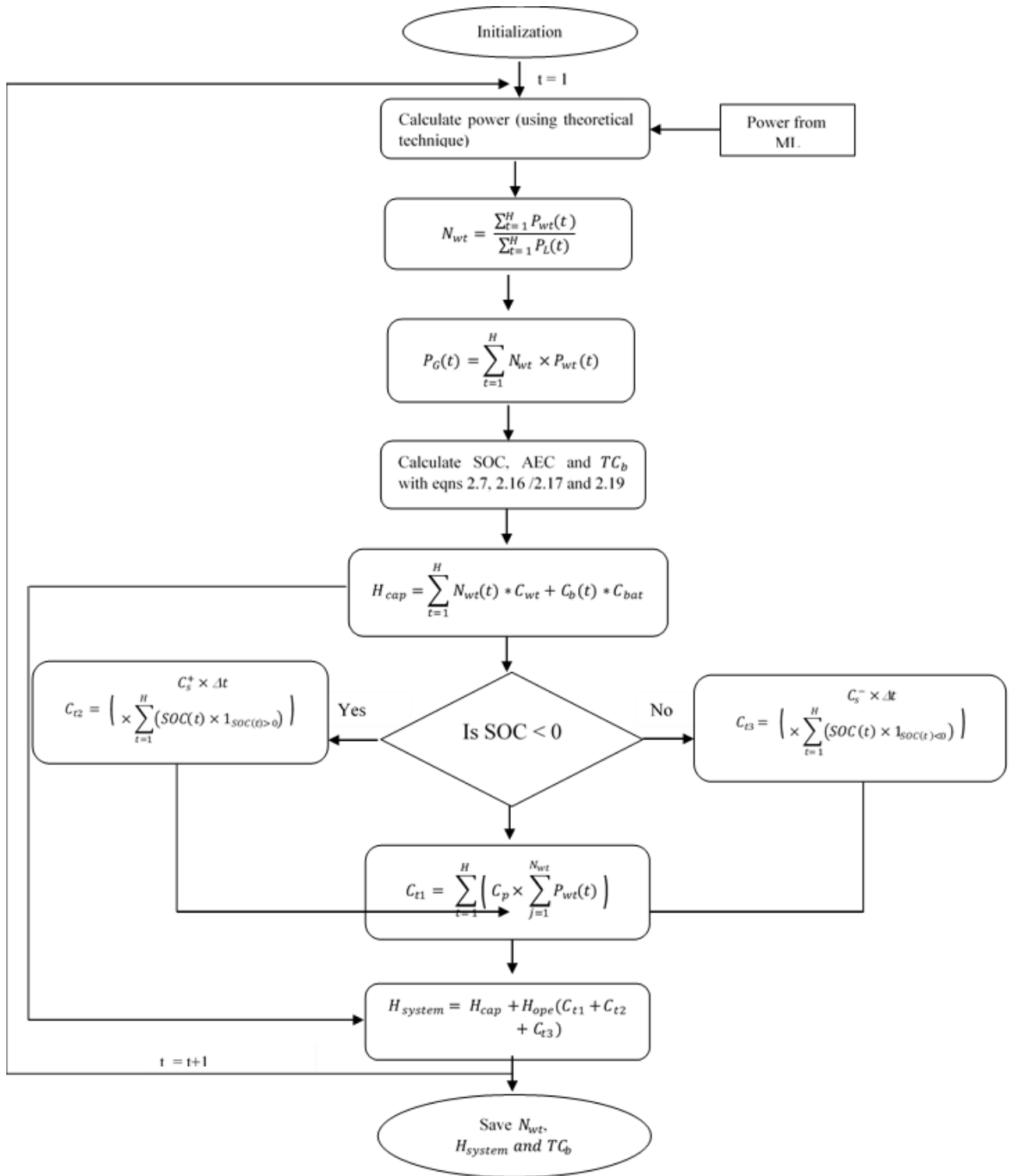


Figure 2.10: Wind power production planning algorithm

2.5 Maintenance strategy

Maintenance is an important factor for sustainable production in industrial systems to ensure continuous operations by considering reliability, plant and machines/components failures. The functionality of any system becomes reduced with aging components and increased usage. This also affects the economic benefits associated with the production system. Therefore, performing preventive maintenance is often implemented to improve the system efficiency and to minimize losses associated with costs. However, when maintenance is rarely performed, failure rate increases which leads to excessive economic losses due to frequent repairs. When performed too often, it leads to material wastage also having an impact on the economic implication of the production system. It is therefore important to find a balance by developing optimal maintenance strategy for minimizing the cost of maintenance.

We can recall that our problem combines two strongly related sub problems; production and maintenance. Thus, after optimizing the production problem, we must include the results obtained in the maintenance problem in order to solve the maintenance planning problem. The solution to the maintenance scheduling problem is to determine the minimal optimal cost of preventive and corrective maintenance. To do this, the objective of this section is to determine the optimal period to perform preventive maintenance actions on the wind turbine or solar panels, which is characterized by the optimal number of preventive maintenance actions. In this case therefore, we must keep in mind that the degradation state of the wind turbine or solar panel depends on its energy production rate. Consequently, it is necessary to consider the influence of the production on the degradation of the system and in the planning of the maintenance subsequently. Thus, sequential approach was selected for this optimization which can be justified by the above explanation. In our case, to simplify the model, we assume that the realization of a preventive action corresponds to the end of a production period. Preventive maintenance actions must be scheduled periodically over the production horizon $H.\Delta t$. However, between successive preventive maintenance interventions, failures may occur and corrective actions with minimal repair should be implemented. These actions cannot be planned in advance but one can simply estimate the failure rate which aids in estimating the number of corrective maintenance interventions on $H.\Delta t$ accordingly.

2.5.1 Maintenance planning problem formulation for solar and wind energy system

All industrial companies desire to increase their profitability and this can particularly be achieved by optimizing production costs. This necessarily requires reducing the costs of maintenance activities by adopting the most appropriate planning. Creating a routine maintenance plan can be easy to accomplish. But creating a comprehensive and effective maintenance program that takes into account the degradation of machines over time as well as their rate of production over all previous periods poses interesting challenges. In order to reach our sequential resolution for the combined production and maintenance planning, this section is dedicated to the

optimization of the maintenance planning taking into account various assumptions after successful optimization of the production planning.

The general idea of the maintenance problem is presented by illustrating the main objective and the major hypothesis necessary to formulate the whole problem (costs involved). Then a numerical test is performed by considering the approximate solution obtained by solving the production problem as inputs data. After having determined the economic production plan described in the previous section, and following the sequential resolution approach, we are interested in determining the maintenance strategy adapted to each of the generating source mentioned above. Thus, we study the impact of the various parameters at the level of the production plan on the degradation rate of the system.

The maintenance strategy developed in this section makes it possible to establish an optimal maintenance plan characterized by the optimal number of preventive maintenance actions, to reduce the average number of failures and consequently, corrective maintenance actions. Indeed, corrective maintenance actions are subject to unforeseen breakdowns and require interventions in the middle of the production cycle, which is more expensive. While preventive maintenance actions are scheduled within a finite production horizon, it is applied at specific times in order not to disrupt the production cycle and minimize the total cost.

The maintenance strategy proposed in this study is a preventive maintenance strategy with minimal repair which is characterized by the optimal number of preventive maintenance actions (N^*) and the most adequate time between them T^* . Over a finite time, horizon H , after production periods T^* , a preventive maintenance action must be carried out on the system at periods $k.T$ where $k \in \{1, 2 \dots N^*\}$. After each preventive maintenance action, the equipment is restored to new condition (AGAN: As good as new). When between two successive preventive maintenance actions, some equipment fail, minimal repairs must be carried out on the damaged equipment to restore it to its old operating state (As Bad As Old). The relationship between T^* and N^* is given by:

$$T^* = \left[\frac{H}{N^*} \right] \quad 2.52$$

where $[.]$ is the integral part.

The proposed maintenance plan takes into account two types of activities: preventive and corrective activities. While preventive activity should be scheduled to be performed at specific times, corrective activity is performed at unscheduled times as it is caused by sudden and unexpected breakdown. In addition, through preventative action, equipment is restored to AGAN condition. On the other hand, corrective actions generally consist of minimal repairs to restore the machines to an ABAO condition without modifying the evolution of the failure rate of the system, as shown in figure 2.11:

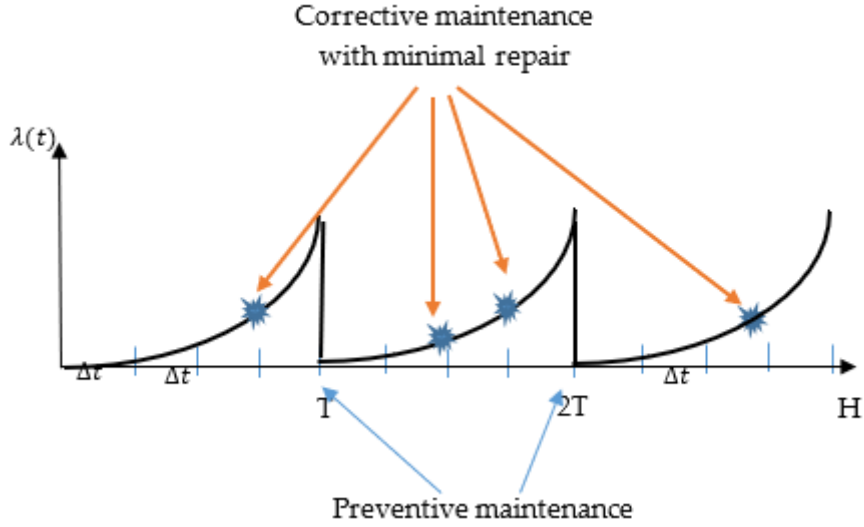


Figure 2.11: Evolution of the failure rate during perfect maintenance with minimal repairs

2.5.2 Failure rate estimation

In this study, the maintenance strategy depends on the level of degradation of the wind turbine or solar PV. Similarly, the degradation of the wind turbine is influenced by the amount of time it works as well as by the amount of energy produced. Thus, the joint optimization as well as the sequential method of solving the energy production and the maintenance of the system are justified. In this study, we assume that the various preventive maintenance actions are always planned at the end of the production period. Recall that the main objective of this study is to jointly optimize production and maintenance by adopting a sequential resolution method. Undeniably, in the present work, we have only studied the influence of the operating factor (energy production) on the degree of degradation of the generating components as well as on its reliability function. Using a parametric relationship between the operating and failure risk factors, failure rate of the wind turbines/solar panels progress during each production period as a function of both time and variation in production rate (operating factor). In order to consider the impact of the production rate on the system degradation, we establish a parametric relationship between the nominal failure rate $\lambda_n(t)$ which depends only on time and the energy production function $f(P_k) = \frac{P_k}{P_{max}}$ for each production period k ($k: 1 \dots H$) (Hajej et al., 2011). The function of the instantaneous failure rate at each period k was presented by the following relationship:

$$\Delta\lambda(t, P_k) = f(P_k) \cdot \lambda_n(t) \quad t \in [0, \Delta t] \quad 2.53$$

Where $\lambda_n(t)$ is the failure rate for nominal operating condition modelled with Weibull distribution which corresponds to the rate of failure with maximum production rate:

$$\lambda_n(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad 2.54$$

2.5.3 Maintenance cost formulation

Having briefly considered some of the literature on maintenance costs, our maintenance problem is therefore formulated taking into account the influence of the equipment degradation on the system by determining the expected average number of failures between successive preventive maintenance periods as presented in the following form (Bouzoubaa, 2021a)

$$M_C(P_k, N) = C_{pm} \cdot N + C_{cm} \cdot \bar{Y}(P_k, N) \tag{2.55}$$

where $\bar{Y}(P_k, N)$ is the average failure rate over the horizon H, and we can say that $N = \lfloor \frac{H}{T} \rfloor$ from equation 2.52.

As we already stated, the maintenance strategy adopted in our problem is a strategy of perfect maintenance with minimal repair, then the average number of breakdowns during the preventive maintenance interval T characterized by the production rate (P_k) is determined by calculating the integral of the function rate of the failure which must be a monotonically increasing function shown in Figure 2.12. Considering the production rate variation (P_k) during each production period (Δt), we establish the average failure rate from the figure below by defining the area under the curve for each production period shown by the shaded portion.

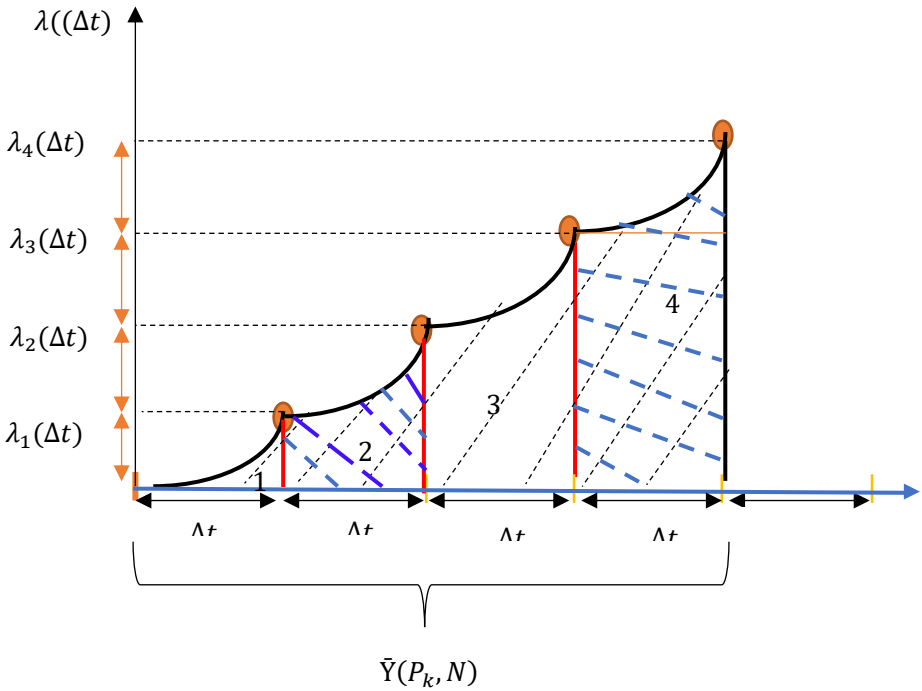


Figure 2.12: Average number of failures for perfect maintenance with minimal repairs

We can mathematically derive it by solving each production period (Δt) separately from between 0 and T. As explained from equation 2.53, the failure rate is a function of the nominal failure rate, we calculate the area therefore as follows:

$$S_1 = \int_0^{\Delta t} \frac{P_1}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.56$$

From the 2nd period up, the area is calculated area of the rectangular part + the area of the triangular part. As expressed from equation 2.53, the failure rate $\lambda_1(\Delta t)$ is therefore expressed as a function of $\lambda_n(\Delta t)$. The above expression is therefore expanded as:

$$S_2 = \lambda_1(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_2}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.57$$

$$= \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_2}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.58$$

$$S_3 = \lambda_1(\Delta t) \cdot \Delta t + \lambda_2(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_3}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.59$$

$$= \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_2}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_3}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.60$$

$$= \left(\frac{P_1}{P_{max}} + \frac{P_2}{P_{max}} \right) \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_3}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.61$$

$$S_4 = \lambda_1(\Delta t) \cdot \Delta t + \lambda_2(\Delta t) \cdot \Delta t + \lambda_3(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_4}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.62$$

$$= \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_2}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_3}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_4}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.63$$

$$= \left(\frac{P_1}{P_{max}} + \frac{P_2}{P_{max}} + \frac{P_3}{P_{max}} \right) \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_4}{P_{max}} \cdot \lambda_n(t) \cdot dt \quad 2.64$$

The total area is therefore expressed as

$$S(T) = S_1 + S_2 + S_3 + S_4 \quad 2.65$$

$$\begin{aligned}
S(T) = & \int_0^{\Delta t} \frac{P_1}{P_{max}} \cdot \lambda_n(t) \cdot dt + \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_2}{P_{max}} \cdot \lambda_n(t) \cdot dt \\
& + \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_2}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \int_0^{\Delta t} \frac{P_3}{P_{max}} \cdot \lambda_n(t) \cdot dt \\
& + \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_2}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + \frac{P_3}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t \\
& + \int_0^{\Delta t} \frac{P_4}{P_{max}} \cdot \lambda_n(t) \cdot dt
\end{aligned} \tag{2.66}$$

It is therefore summed and generalized as shown in equations 2.67

$$\begin{aligned}
S(T) = & \sum_{i=1}^4 \int_0^{\Delta t} \frac{P_i}{P_{max}} \cdot \lambda_n(t) \cdot dt + 3 \frac{P_1}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t + 2 \frac{P_2}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t \\
& + \frac{P_3}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t
\end{aligned} \tag{2.67}$$

$$(T) = \sum_{i=1}^{\frac{T}{\Delta t}} \int_0^{\Delta t} \frac{P_{i,T}}{P_{max}} \cdot \lambda_n(t) \cdot dt + \sum_{i=2}^{\frac{T}{\Delta t}} \left(\frac{T}{\Delta t} - (i-1) \right) \cdot \left(\frac{P_{i-1,T}}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t \right) \tag{2.68}$$

In General, the overall expected failure for every T preventive maintenance time to be performed over the horizon from k=1.....H, the formulation is then transformed as follows:

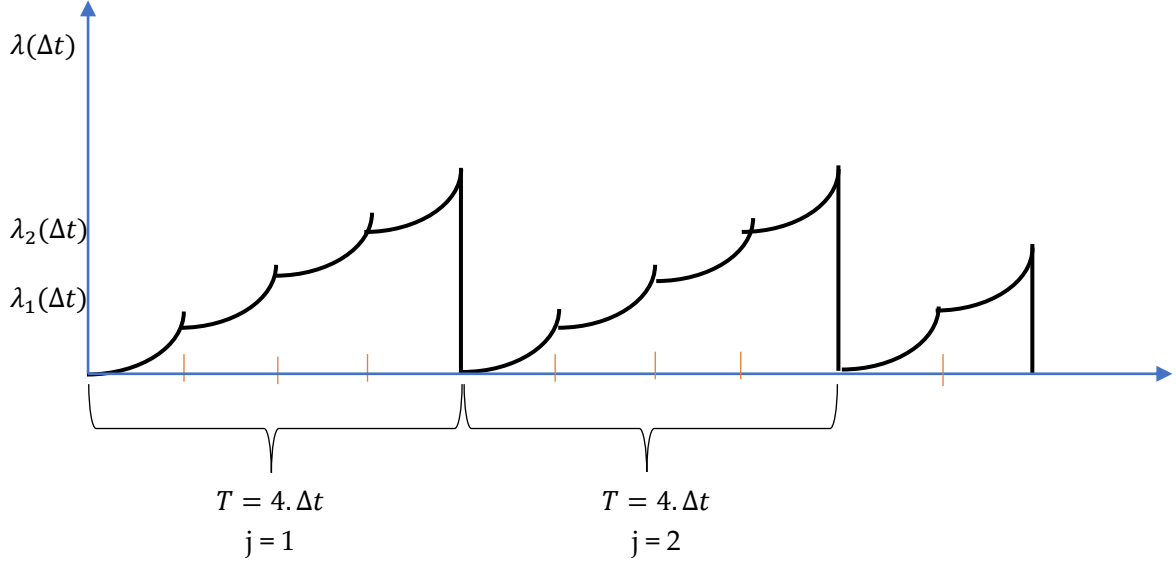


Figure 2.13: Illustration of the generalized failure rate

Since $T = \left\lfloor \frac{H}{N} \right\rfloor$, the total average number of failures for j(1,2,3...N) maintenance sessions over a finite horizon $H \cdot \Delta t$ as shown in fig 2.13 above is expressed as

$$\begin{aligned}
\bar{Y}(P_k, N) = & \sum_{j=1}^{\frac{H}{\Delta t}} \left[\sum_{i=1}^{\frac{T}{\Delta t}} \int_0^{\Delta t} \frac{P_{i,T}}{P_{max}} \cdot \lambda_n(t) \cdot dt + \sum_{i=2}^{\frac{T}{\Delta t}} \left(\frac{T}{\Delta t} - (i-1) \right) \cdot \left(\frac{P_{i-1,T}}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t \right) \right] \\
& + \left(\sum_{i=\left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor + 1}^H \int_0^{\Delta t} \frac{P_i}{P_{max}} \cdot \lambda_n(t) \cdot dt + \sum_{i=\left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor + 2}^H \left(H - \left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor \cdot T \right) \right. \\
& \left. - \left(i - \left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor \cdot T - 1 \right) \cdot \frac{P_i}{P_{max}} \cdot \lambda_n(\Delta t) \cdot \Delta t \right)
\end{aligned} \tag{2.69}$$

2.5.4 Maintenance algorithm

In order to determine the optimal number of preventive maintenance actions, we propose the following simple numerical procedure. We will calculate the maintenance cost corresponding to $N \in \{1, \dots\}$. The N^* will correspond to the cheapest maintenance cost M_C^* . The numerical procedure is detailed on figure 2.14. From the beginning of the algorithm, for each N , the associated cost M_C is calculated. In two successive computations, M_C with minimal amount automatically becomes the optimal cost M_C^* which is stored until a lesser cost is obtained, in that case, it automatically becomes the optimal.

After having found the economic plan of energy production and by using the results obtained, we seek to determine the optimal number of actions of preventive maintenance to be carried out on the wind turbine/solar panel during the horizon H as well as the intervals which separate them. The maintenance strategy adopted is perfect maintenance with minimal repair at failure as explained as follows; Wind turbine/solar panel repair is carried out every $k.T$ period ($1, 2, \dots, kN$). Preventive maintenance actions are considered as replacements allowing to restore the system to AGAN. After a perfect maintenance action, the distribution of lifetimes and the function of the failure rate are the same as those of a new unit. When a failure occurs between two successive preventive maintenance actions, a minimum repair is then carried out. We assume that the durations of repair or replacement are considered negligible. The change in the amount of energy produced by the wind turbine or solar PV during the production horizon H acts on the failure rate of the system. The above maintenance strategy is applied to both solar and wind energy assessments. Since all the wind turbines and solar panels have the same power ratings in this work, we assume that they have the same power output. Therefore, maintenance planning is considered for one (1) solar panel and one (1) wind turbine for both solar and wind energy maintenance.

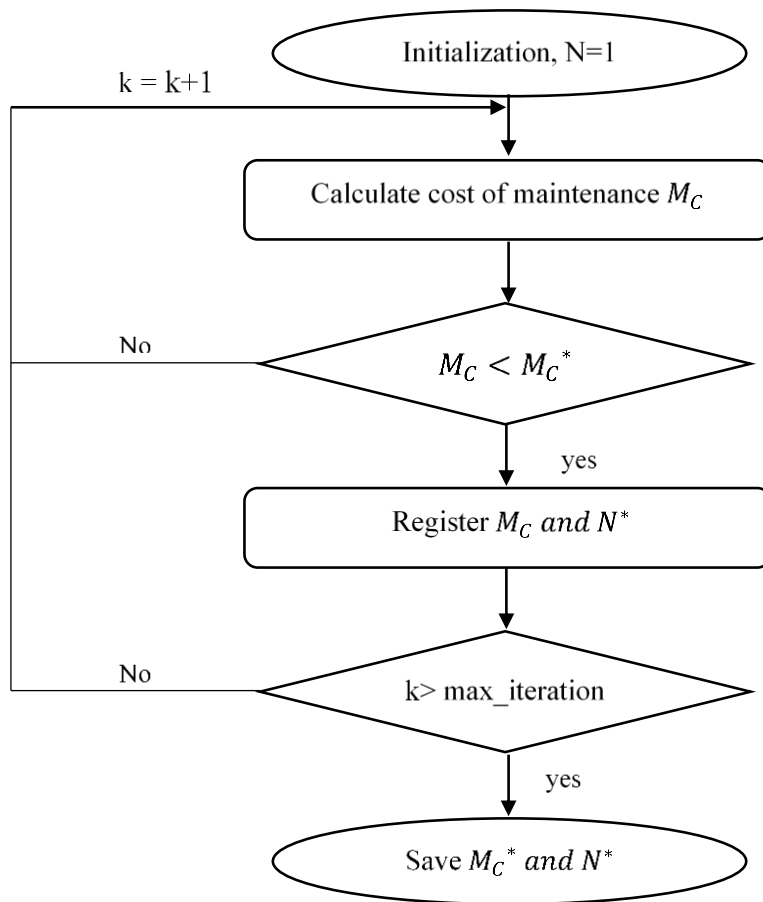


Figure 2.14: Numerical procedure to determine the optimal number of maintenance N^* , within the framework of a perfect integrated maintenance strategy

2.6 Case study

Nigeria is a developing nation in the sub-Saharan region in Africa with a population of about 200 million people. From statistics, about 44.6% of the population lack access to electricity most of which are found in the remote and rural areas across the nation (World Bank report, 2021). The rural electrification agency (REA) of Nigeria has proposed ways of decentralizing energy from the grid to generate few watts or kW such as rooftop solar to power homes and pump water in the rural areas. With the current energy situation, there are still many challenges and weaknesses affecting the energy sector in Nigeria. Some of the challenges are: Lack of modern facilities that can generate and distribute energy, low access to modern energy for cooking, increase in population leading to increase in energy demand, high cost of energy, high cost of rural electrification from the grid, frequent power outage and high dependence on petroleum products. Since Nigeria is a developing country with constant power outage, then it is highly necessary for energy decentralization from the grid to enable the rural areas access the basic amenity. As efforts to further decentralize the system, mega projects capable of generating energy in MW capacity such

as the Sokoto power plant and Katsina wind farm to supply some locals around the plant location as well as cities in the geographical zones. This section is therefore aimed at demonstrating the viability of our developed algorithm using a solar power plant and a wind farm in Nigeria.

2.6.1 Sokoto Solar PV power plant case

Sokoto is a state in the north western part of the federal republic of Nigeria located on 13° 44'N and 5° 02'E. It is characterized by dry Sahel savannah and sandy hills. The state is usually hot and arid with annual mean temperature is about 28.3 °C, and maximum daytime temperature of about 40 °C. It has daily average sunshine hours of 12 hours 53 minutes and daily average solar irradiance of 258.51 W/m² all year-round, thus making the location suitable for harnessing solar energy Adejumo et al. (2017). The periodic average solar irradiance and average temperature over the 12 periods (months) is presented on figure 2.15 and 2.16. The considered case study is the 55MW solar power plant operating where we aim to consider the power plant as stand-alone expected to supply energy the host community of Yabo town and its environs. For the purpose of this work, we consider only the host community of Yabo town for the analysis. The average estimated load demand from the case study (Yabo town) is presented on figure 2.17.

In Nigeria, it is estimated that the cost of energy production and storage from the solar power plant is 12 NGN and 15 NGN respectively. NGN is the Nigerian currency known as Nigerian Naira (1 Euro = 508.224 NGN). When load demand is not met and energy has to be sourced from the grid, the cost of this shortage is obtained at 25 NGN. The cost of purchasing a PV panel and a battery storage component is assumed to be 30,000 NGN and 700,000 NGN. As expressed above, Weibull distribution was considered for modelling the failure rate, hence table 2.1 provides details of the maintenance parameters for this work.

Table 2.1: Maintenance parameters for solar energy

β	η	Cpm (NGN)	Ccm (NGN)
2	10	3000	12000

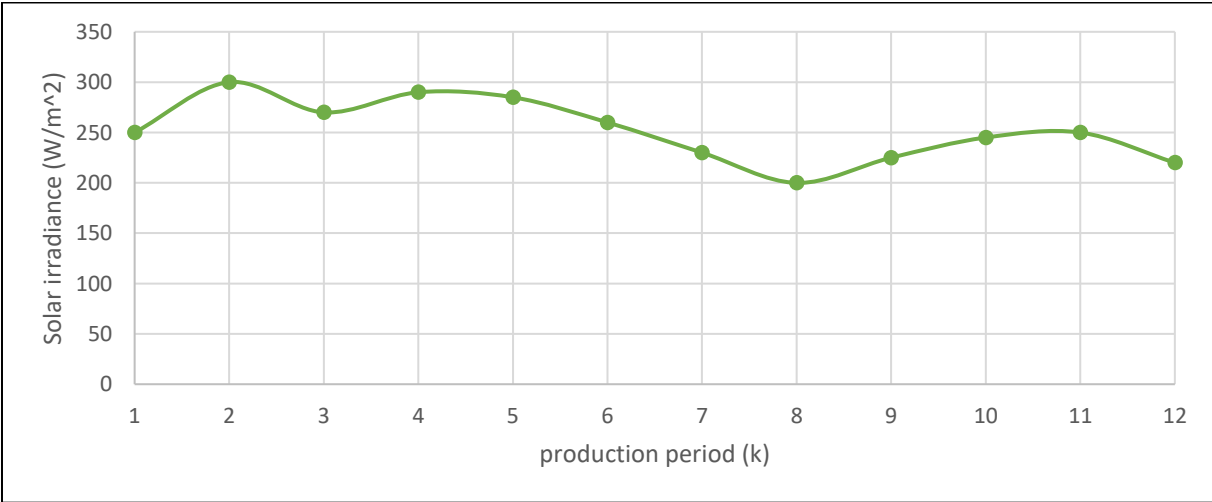


Figure 2.15: Solar irradiance of Sokoto

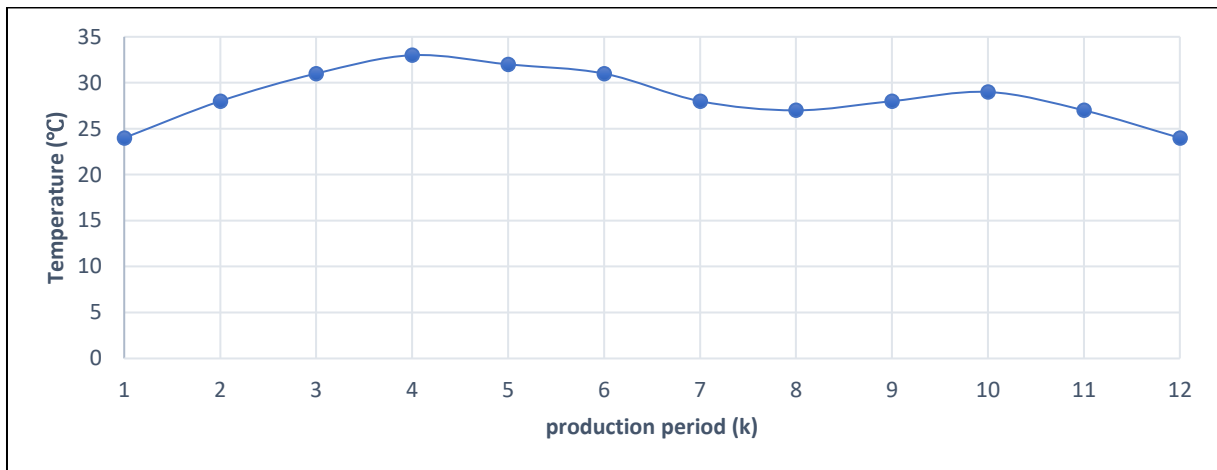


Figure 2.16: Temperature of Sokoto

A polycrystalline PV module AE215P6-72 solar panel was found suitable for this site having considered the characteristics. It consists of 72 cells with a 30-year performance life span. The characteristics of the panel is shown on table 2.2 while the battery characteristics is presented on table 2.3. The average monthly load demand of Yabo town for the year 2020 is presented in figure 2.16. Having obtained the above data and processed them using the proposed techniques discussed above, the available energy in the battery characterized by the SOC invariance criterion as well as the obtained period by period optimized results are presented in figure 2.17.

Table 2.2: Solar panel characteristics

Parameter	Value
Nominal Power (W)	215
Max power voltage (V)	37.18
Max power current (A)	9.28
Module efficiency (%)	17.78
Operating temperature (°C)	-40 to +85
NOCT (°C)	45 ± 2
Module dimensions (mm ²)	1956 x 992

Table 2.3: ALFA-0125A Li-ion battery

Nominal charge (A)	Capacity (Ah)	Voltage (v)	Energy Stored (Watt-hour)	Cycle Life (cycles)
20	125	12	1500	2000+

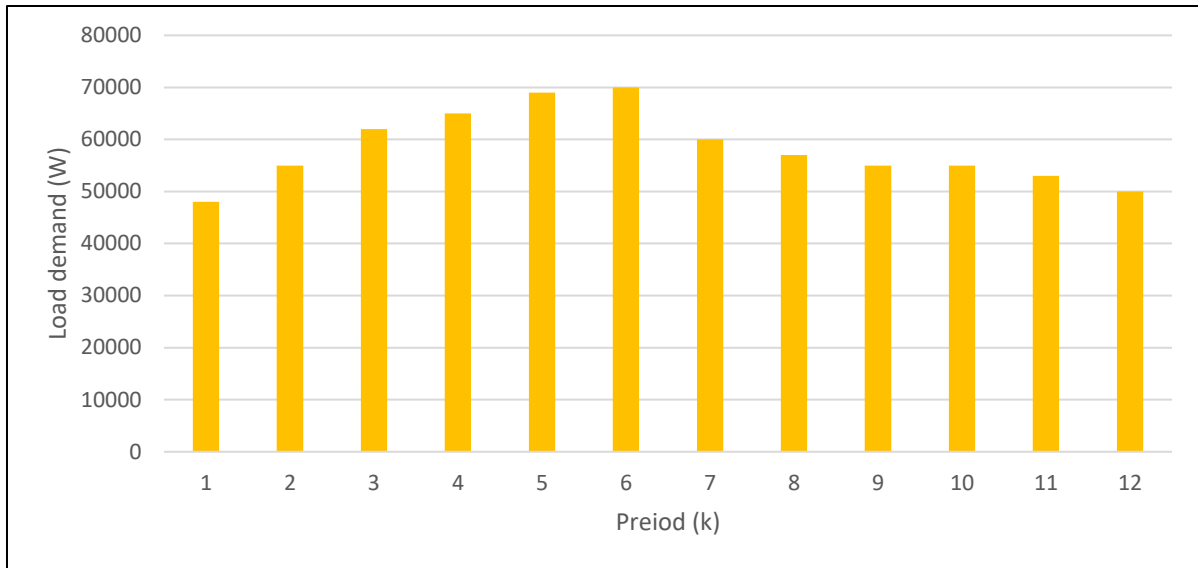


Figure 2.17: Average load characteristics of the Yabo town (Sokoto State, Nigeria)

2.6.1.1 Solar production results and discussion

The results for the optimal number of PV panels as well as the battery capacity required for storing excess energy at minimal cost considering all the power generation methods are presented.

i. Analytical approach

Having considered the inputs, the available power in the battery at each period is presented on figure 2.18.

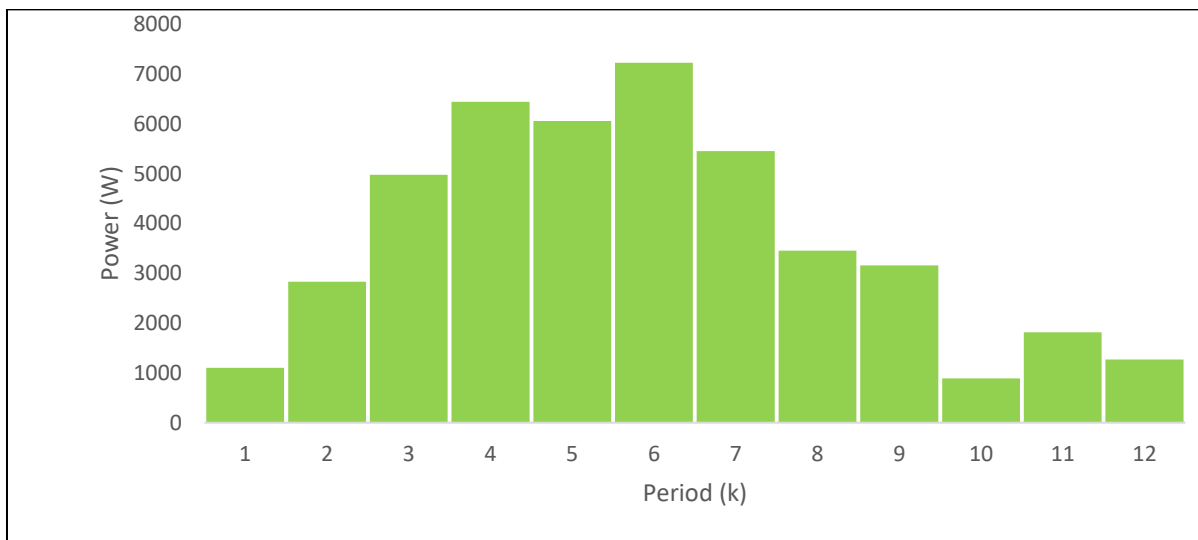


Figure 2.18: Available power in the battery

Table 2.4, provides the optimal number of panels that generate energy per production period. The power generated and the battery capacity for storing the energy and the optimal cost associated with it is also represented. From the table, the optimal cost of producing and supplying

electricity to the consumers when estimated using the analytical method is found to be 18.05 million NGN.

Table 2.4: Optimal production plan using the analytical approach

Total cost = 18.05 x10 ⁶ (NGN)				
Period	Optimal cost x10 ⁶ (NGN)	Number of panels (PV)	Battery capacity (x10 ⁴ Ah)	Generated power (x10 ⁵ W)
1	1.4880	634	0.5183	1.174
2	1.4930	660	2.8951	2.277
3	1.4931	710	2.9496	3.263
4	1.4931	770	2.9496	3.274
5	1.4949	741	2.7882	3.089
6	1.5374	897	2.8843	9.869
7	1.5005	856	3.7292	8.961
8	1.5119	837	3.3224	8.213
9	1.5006	752	3.2679	1.031
10	1.5050	787	3.9722	6.232
11	1.5223	767	3.7625	7.723
12	1.5102	647	2.7383	1.184

Machine learning and artificial intelligence has proved to be useful in the energy, economic and financial institutes. The results obtained from the ML techniques are presented below;

ii. ANN method

The power available in the battery generated using the ANN is presented in figure 2.19 showing the quantity of energy stored during each production period.

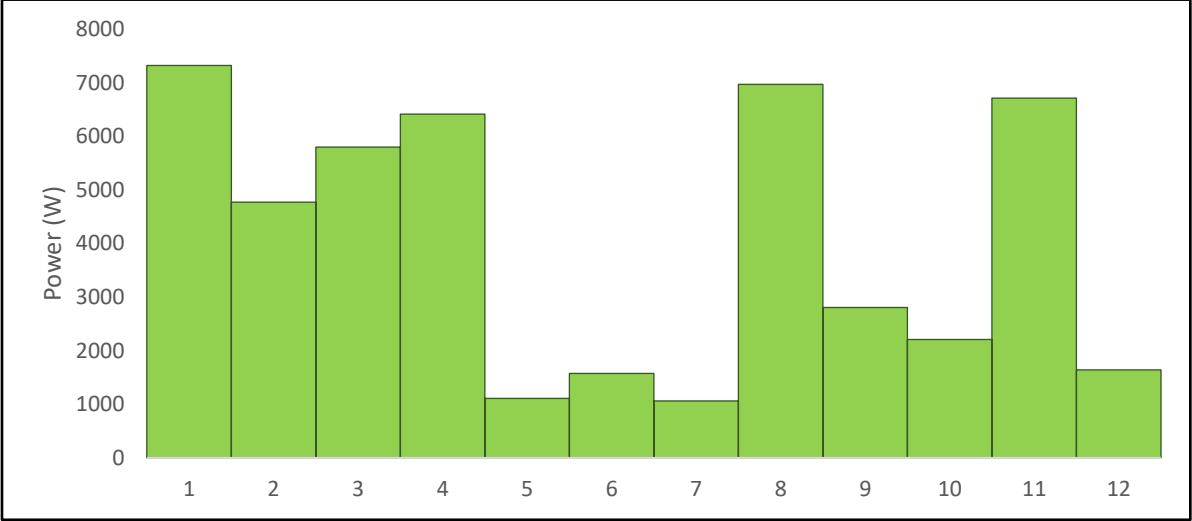


Figure 2.19: Power available in the battery

The optimal production plan is presented on table 2.5 with the periodic optimal cost presented for each period alongside the optimal number of components required. In this case, the total optimal cost is obtained to be 15.453 million NGN.

Table 2.5: Optimal production plan using the ANN approach

Total cost = 15.453 x10 ⁶ (NGN)				
Period	Optimal cost x10 ⁶ (NGN)	Number of panels (PV)	Battery capacity (x10 ⁴ Ah)	Power generated (x10 ⁵ W)
1	1.0750	571	1.0435	5.922
2	1.2317	685	1.0435	5.806
3	1.3699	635	1.3478	5.719
4	1.4291	689	1.4288	5.660
5	1.4291	604	1.5633	5.690
6	1.5277	663	1.7832	5.720
7	1.3304	749	1.3422	5.810
8	1.2317	861	1.6490	5.835
9	1.2317	766	1.6660	5.810
10	1.2712	703	1.4284	5.777
11	1.1922	782	1.3799	5.835
12	1.1333	593	1.0412	5.920

iii. SVR approach

With this method, the power available in the battery is presented in figure 2.20 and the optimal plan presented on table 2.6. An amount of 15.59 million Nigerian Naira was found to be the total optimal cost.

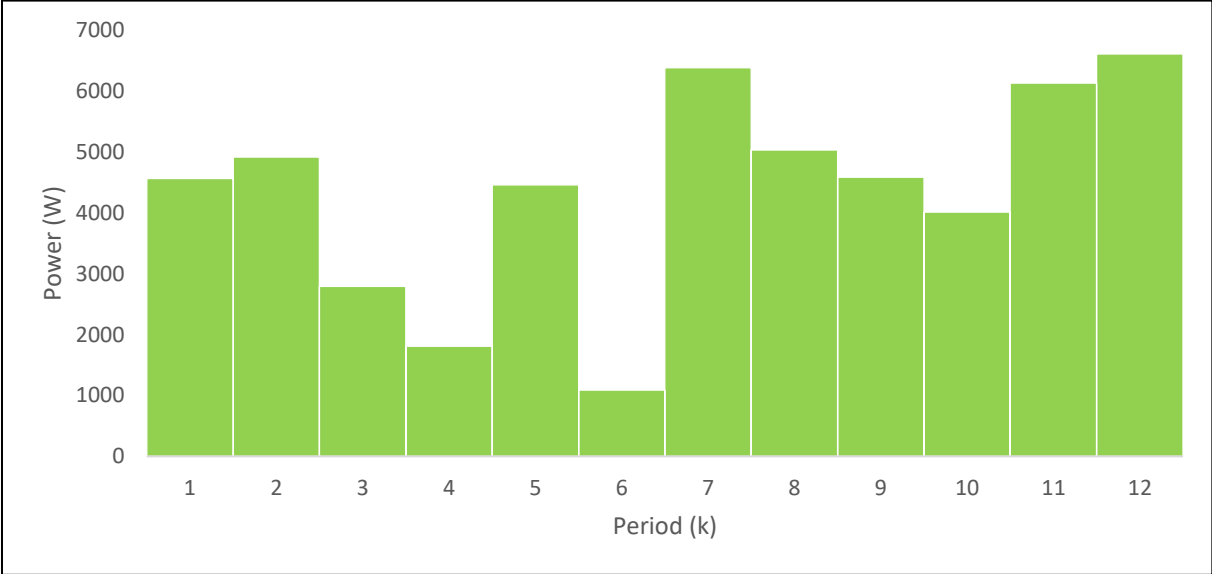


Figure 2.20: power available in the battery storage

Table 2.6: Optimal production plan using the SVR approach

Total cost = 15.5924 x10 ⁶ (NGN)				
Period	Optimal cost x10 ⁶ (NGN)	Number of panels (PV)	Battery capacity (x10 ⁴ Ah)	Power generated (x10 ⁵ W)
1	1.3005	517	0.5378	5.2562
2	1.3006	522	0.6378	5.9915
3	1.3177	672	1.4780	6.4794
4	1.3329	621	1.9200	6.3193
5	1.3444	601	2.5800	6.0545
6	1.3743	599	4.2800	5.9110
7	1.3740	558	3.8300	5.3620
8	1.3812	503	3.6500	4.9972
9	1.3282	582	2.2800	5.4541
10	1.3809	618	3.3700	6.1011
11	1.3783	583	3.5200	5.9129
12	1.3805	529	3.6300	5.6607

Considering the three approaches above, the best economical plan is seen to be in the ANN approach whose value is 15.45 million Nigerian Naira (NGN) then followed by the SVR method which presented 15.59 million NGN while 18.05 million NGN for the analytical approach. Applying the machine learning approach appears to be most viable approach for the solar energy optimization.

We can see from these tables that the ANN technique presented the best optimal result followed by the SVR and analytical techniques. We can say that the simplicity of the ANN model makes it to adapt well with the parameters given that machine learning techniques deal with more realistic values and doesn't depend on random numbers as in the case of the analytical technique. Comparing the 2 machine learning techniques, SVR is more complex because it deals with other random variables (such as lagrangian multiplier and error penalty selection) in addition to kernel function selection while in the ANN, the only problem is determining the right value for the activation function. Using the analytical technique as our datum, we can see that there is a 14.39% gain in the ANN cost while a 13.62% in the SVR cost for the solar energy analysis.

2.6.1.2 Solar maintenance planning results

Having considered the power production plan from the above, the optimal number of preventive maintenances estimated to be performed on the solar energy system is presented on table 2.7. An optimal maintenance plan of 2 is obtained across the three selected techniques employed. This means that maintenance actions should be performed every 6 months. However, when choosing the best technique that yields minimal cost, the analytical approach presents the best value of 9,912.70 NGN. This is followed by the SVR and then finally the ANN. It is worthy of note that the maintenance strategy is opted considering the production plan of one (1) panel to represent the system since all panels are considered identical having the same power output.

Table 2.7: Optimal PM actions for solar energy

Technique	N*	Cost (NGN)
ANN	2	10,377.40
SVR	2	10,355.90
Theoretical	2	09,912.70

2.6.1.3 Sensitivity analysis for solar PV system

In this section, we seek to study the influence of the change of some parameters on the maintenance plan. To do this, we study the variation in the values of the unit costs of preventive maintenance (Cpm) and corrective maintenance (Ccm) and their effect on the optimal number of preventive maintenance actions to be carried out on the solar energy system. In this case, we vary the difference between the corrective maintenance costs and the preventive maintenance costs by increasing the difference from NGN12,000 to NGN50,000, NGN100,000 and NGN 1500,000 while maintaining the preventive maintenance cost at NGN3000 in order to study the effect of corrective maintenance on the optimal number of PM actions.

The optimal maintenance plan is presented on table 2.8 for all the three techniques and the chosen corrective maintenance costs. When the corrective maintenance cost is at NGN 50,000, the N* is increased to 3. Further increase in the cost changes the optimal value from three to five with the SVR technique but remains the same for the other two (2) techniques. When increased to NGN 150,000, the optimal N* shifts further requiring more maintenance to be performed on the system. Five maintenance actions are required with the ANN, and six with the SVR and the analytical methods. This variation is explained by the impact of the generated power on the failure rate of the system as well as a good choice of the Weibull parameters.

Table 2.8: Optimal number of PM (N*) with varying cost of CM on solar energy

Ccm (NGN)	Technique	N*	Cost (NGN)
50,000	ANN	3	21476.10
	SVR	3	21691.10
	Theoretical	3	19312.10
100,000	ANN	3	33952.20
	SVR	5	30891.20
	Theoretical	3	29624.20
150,000	ANN	5	38460.30
	SVR	6	38815.50
	Theoretical	6	35887.40

The findings of this comparative study should serve as a foundation for decision-making for the energy power plant. Having obtained the best optimal maintenance plan in terms of the maintenance cost with the analytical technique, the manager can use this method to prioritize critical components, and plan maintenance tasks efficiently. However, the cost difference is quite insignificant compared with the ML technique and therefore, it can be neglected considering the total LCC of the system. From our previous LCC analysis, using the ANN technique is the best and

the cost difference between ANN and the analytical technique is much. With this finding, the ANN model can be integrated into the plant’s asset management systems. This ensures coordination between maintenance planning, asset tracking, inventory management, and work order management. It is also important to invest in training programs and skill development initiatives to equip the maintenance teams with the necessary knowledge and capabilities of using this technique.

2.6.2 Katsina wind farm

Katsina is the capital of Katsina state in the federal republic of Nigeria which is geographically located at 13° 01'N latitude and 07° 41'E longitude, north western Nigeria. The city is at an average altitude of 480 m above sea level and has a mean maximum annual temperature of 39°C. We consider the pilot 10 MW wind farm installed in Katsina as the case study of our work with the location’s average monthly wind speed presented on figure 2.21. It is estimated that an average of 29.6 kWh/month of energy can be produced monthly, thus making the site very suitable for wind turbine applications in power generation (Balarabe et al. 2014). The wind system is considered as a stand-alone wind/battery energy system supplying a remote area of Lambar Rimi community characterized by a monthly average load demand shown of figure 2.22. Data was obtained for the year 2020 from January to December and the following results were obtained. As expressed above, Weibull distribution was considered for modelling the failure rate, hence table 2.9 provides details of the maintenance parameters for this work.

Table 2.9: Maintenance planning for wind energy

β	η	Cpm (NGN)	Ccm (NGN)
1.5	5	50,000	300,000

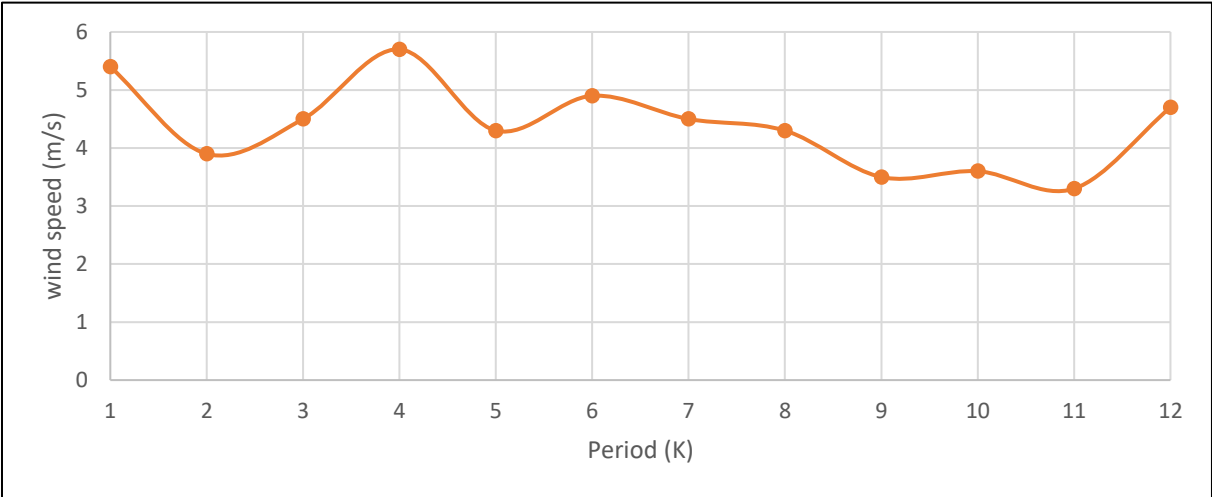


Figure 2.21: Average monthly wind speed for Katsina 2020

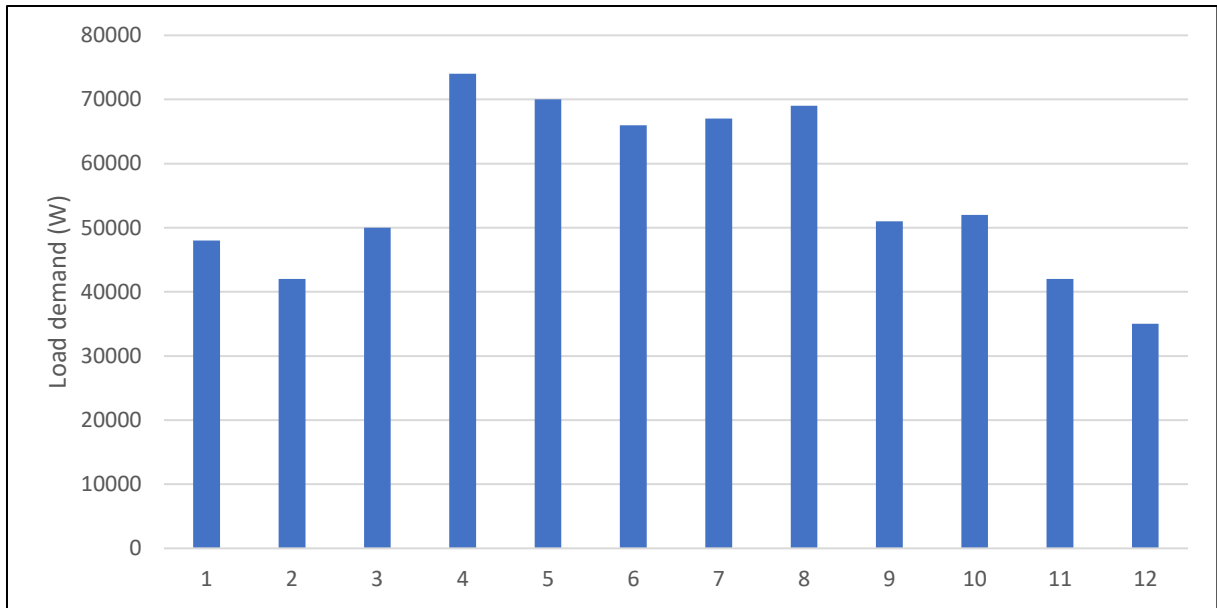


Figure 2.22: Average monthly load demand for Rimi (Katsina State, Nigeria)

2.6.2.1 Wind production result

i. Analytical approach

In this analysis, the wind turbine used for the analytical method varies from the one used with the machine learning method. The turbine is a NEG Micon 1MW wind turbine whose characteristics is presented in table 2.10. It is estimated that the cost of energy production and storage from the wind power plant is 15 NGN and 17 NGN respectively. When load demand is not met and energy has to be sourced from the grid, the cost of this shortage is obtained at 25 NGN. The cost of purchasing a wind turbine and a battery storage component is assumed to be NGN2,500,000 and NGN700, 000.

Table 2.10: NEG Micon 1MW wind turbine characteristics

Rated Power (kW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Rotor diameter (m)	Hub height (m)
1000	3	14	26	60	50

Production planning for each of the methods discussed above showing the number of wind turbines, the battery capacity as well as the power generated during each period is presented on table 2.11 with the battery power in figure 2.23. This method estimated the optimized cost to be 452 million Nigerian naira.

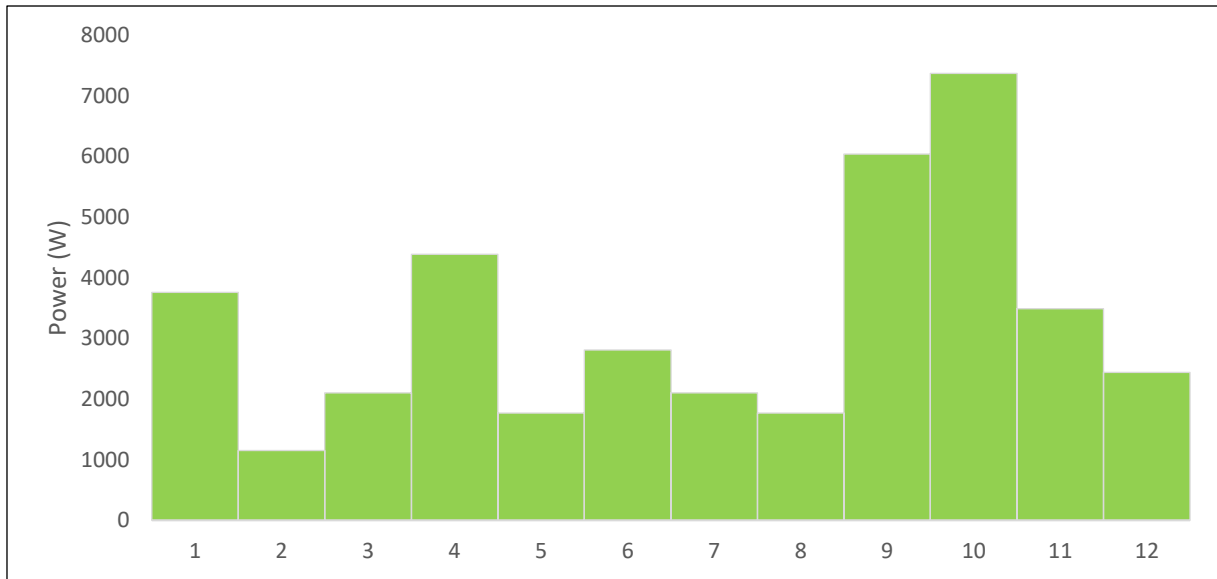


Figure 2.23: Power in the battery for theoretical

Table 2.11: Optimal wind production planning for analytical approach

Total cost = 45.2808 x10 ⁷ (NGN)				
Period	Optimal cost x10 ⁷ (NGN)	Number of wind turbines (wt)	Battery capacity x10 ⁵ (Ah)	Power generated (x10 ⁶ W)
1	4.4433	4	0.536	3.770
2	3.2552	3	0.552	1.160
3	4.5162	4	0.687	2.110
4	5.3534	5	1.080	4.390
5	3.8721	3	1.090	1.770
6	3.2887	3	1.080	2.810
7	3.6561	4	1.210	2.110
8	3.6554	3	1.120	1.770
9	2.6547	3	1.080	0.608
10	2.6547	3	0.699	0.742
11	2.6539	3	0.801	0.354
12	5.2771	4	2.120	2.450

The machine learning and artificial intelligence has proved to be useful in the energy, economic and financial institutes. As discussed above, the results from the ML techniques are presented below

ii. ANN

Table 2.12 provides the turbine information for the 100kW Hummer H25-100kW turbine for the machine learning approach. The costs of production and storage remain the same with the previous approach except the cost of purchasing wind turbine which is NGN1,800,000 Nigerian Naira.

Table 2.12: Hummer H25-100kW wind turbine characteristics

Rated Power (kW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Rotor diameter (m)	Hub height (m)
100	2.5	10	20	25	50

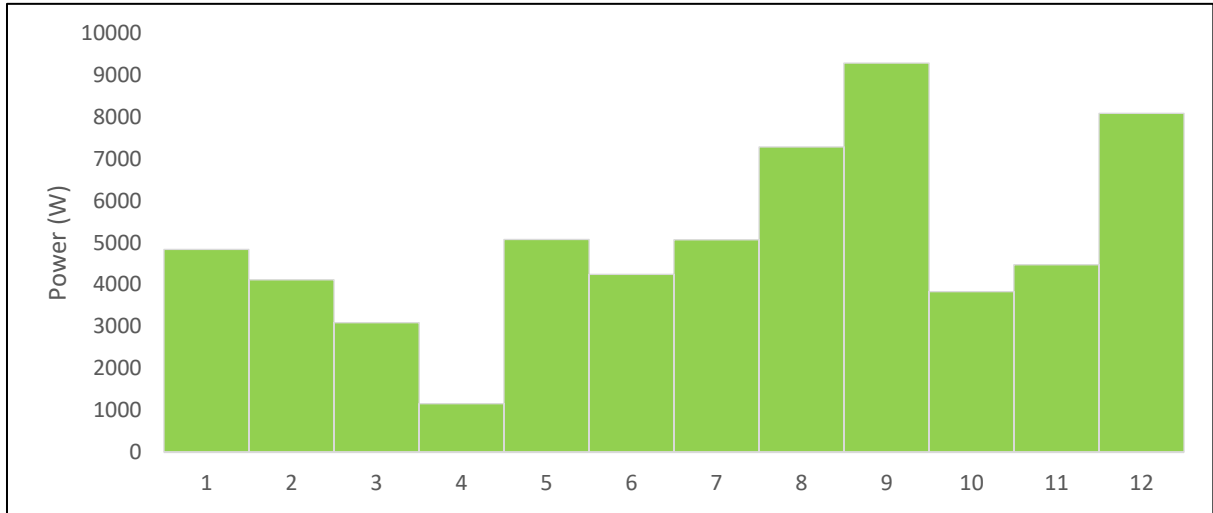


Figure 2.24: Power available in the battery

The optimal cost of generating electricity with the machine learning approach for the ANN is presented on table 2.13 and the available power stored in the battery is shown on figure 2.24. The total optimal cost is found to be about 395 million Nigerian naira and the period with the least optimal cost is found to be when $k = 11$.

Table 2.13: Optimal wind production planning for ANN approach

Total cost = 39.5659×10^7 (NGN)				
Period (k)	Optimal cost $\times 10^7$ (NGN)	Number of wind turbines (wt)	Battery capacity $\times 10^4$ (Ah)	Power generated ($\times 10^5$ W)
1	3.2713	2	0.8434	1.2238
2	3.2789	2	1.6052	1.1111
3	3.2865	2	2.5333	1.5661
4	3.2941	3	1.3560	1.5803
5	3.3017	2	2.3090	1.4624
6	3.3092	2	2.9136	1.5834
7	3.3168	2	2.4349	1.3508
8	3.3243	2	2.9351	1.0183
9	3.3318	2	2.9358	1.2787
10	3.3393	1	2.9403	0.9576
11	3.2509	1	1.9413	0.7727
12	3.2611	2	2.9403	1.4688

iii. SVR approach

The optimal cost of generating electricity with the machine learning approach for the SVR is presented on table 2.14. The total optimal cost is found to be about 423.2 million Nigerian naira while the quantity of energy available in the battery storage per period is presented on figure 2.25.

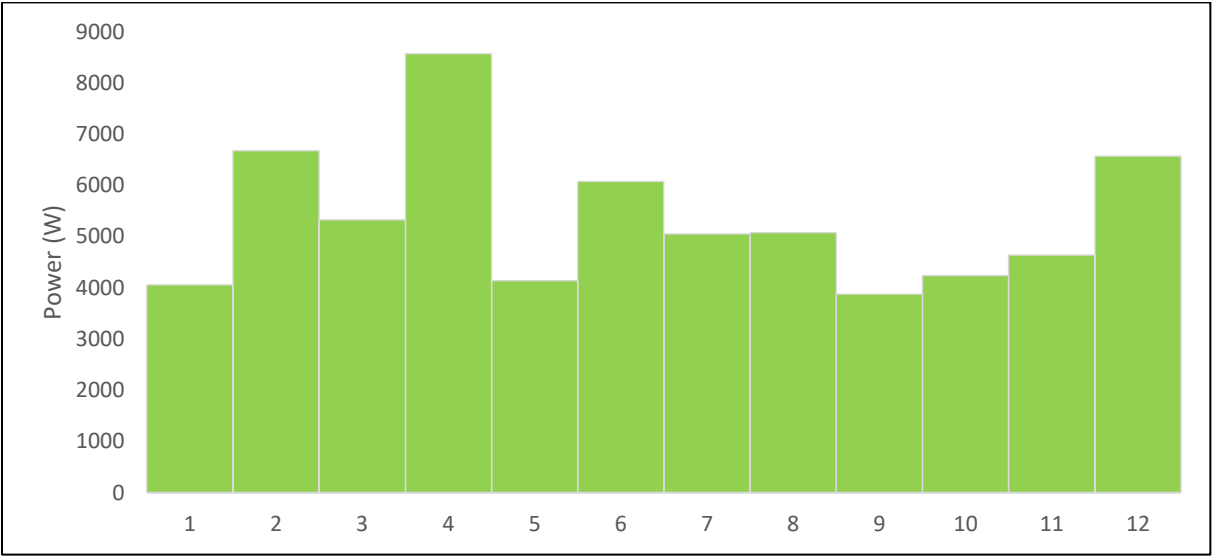


Figure 2.25: Power available in the battery

Table 2.14: Optimal wind production planning for SVR approach

Total cost = 42.3162 x10 ⁷ (NGN)				
Period (k)	Optimal cost x10 ⁷ (NGN)	Number of wind turbines (wt)	Battery capacity x10 ⁴ (Ah)	Power generated x10 ⁵ (W)
1	3.7639	3	1.49	2.300
2	3.6241	2	1.99	1.730
3	3.5484	2	2.34	1.880
4	3.5428	3	2.99	2.760
5	3.3136	2	2.21	1.840
6	3.4313	3	2.76	2.110
7	3.3976	3	2.99	2.030
8	3.3678	2	2.81	1.990
9	3.3766	2	2.57	1.490
10	3.3956	2	2.65	1.570
11	3.4884	2	1.89	1.460
12	4.0661	3	2.07	2.180

Similar to the PV analysis, ANN presents the best optimal result followed by the SVR and the analytical method. Using the analytical technique as our datum, we can see that there is a 12.61% gain in the ANN cost while a 06.54% with the SVR technique.

2.6.2.2 Wind maintenance planning result

The proposed optimal maintenance plan for the wind energy is presented on table 2.15 where the optimal values for the maintenance costs as well as the number of PM actions for ANN, SVR and analytical techniques applied are stated. It is worthy of note that all the wind turbines are assumed to have the same power output, therefore, maintenance planning is performed considering the production of only one (1) wind turbine. From the table, it is seen that the optimal maintenance to be performed on the system is 2 to be performed every 6 months for all techniques. The ANN presenting the minimal cost making it the most suitable method for this system costing 172,346.00 NGN followed by analytical at 198,901 NGN and lastly the SVR which would cost about 207,316 NGN.

Table 2.15: Optimal number of PM for wind energy

Technique	N*	Cost (NGN)
ANN	2	172,346.00
SVR	2	207,316.00
Theoretical	2	198,901.00

2.6.2.3 Sensitivity analysis for wind energy

In this section, we seek to study the influence of the change of some parameters on the maintenance plan. We therefore study the variation in the values of the unit costs of preventive maintenance C_{pm} and corrective maintenance C_{cm} and their effect on the optimal number of preventive maintenance actions to be carried out on the wind energy system. Here, we vary the difference between the corrective maintenance costs and the preventive maintenance costs by increasing the difference from 300,000 NGN to 500,000 NGN, 700,000 NGN and 900,000 NGN keeping the preventive maintenance cost at 50,000 NGN.

Table 2.16: Optimal number of PM (N*) with varying cost of CM on wind energy

Ccm (NGN)	Technique	N*	Cost (NGN)
500,000	ANN	2	220,576.00
	SVR	3	266,600.00
	Theoretical	3	250,295.00
700,000	ANN	2	268,806.00
	SVR	3	313,240.00
	Theoretical	3	290,413.00
900,000	ANN	3	303,677.00
	SVR	3	359,880.00
	Theoretical	3	330,531.00

By varying the maintenance costs, the optimal number of actions to be performed are 2 for ANN to be performed every 6 months, and 3 for SVR and the analytical approach to be performed every 4 months. With further increase to 700,000 NGN and 900,000 NGN, it yields the similar result

which mean that the cost increases by reducing the effect of failure rate on the system. Having obtained the best optimal maintenance plan in terms of the maintenance cost with the ANN technique, the manager can use this method to prioritize critical components, and plan maintenance tasks efficiently. With this finding, the ANN model can be integrated into the plant's asset management systems. This ensures coordination between maintenance planning, asset tracking, inventory management, and work order management. It is also important to invest in training programs and skill development initiatives to equip the maintenance teams with the necessary knowledge and capabilities of using this technique.

2.7 Conclusion

In this chapter, we developed methodologies for optimizing solar power plant and a wind farm. A case study of Sokoto solar power plant and Katsina Wind farm in Nigeria were considered in sub-Saharan Africa. Nigeria is a developing country with constant power outage, hence highly necessary for energy decentralization from the grid. Several approaches were developed and the results presented for both solar and wind energy. For each period over one-year horizon, the optimal number of components (solar panels or wind turbines), battery capacity required and the quantity of energy produced were obtained. This presents the periodic optimal cost for that period. The total cost is the presented over the horizon for all techniques presented in the text. For the best approach of obtaining the optimal cost of generating energy the ANN has proven to be most effective in both solar energy and wind energy production analysis. From this analysis, we can deduce that the machine learning approach yields the best results. Maintenance planning scheduling was also proposed to determine the optimal number of maintenance actions to be performed considering each of the techniques and the optimal cost associated with it. From this analysis, we could conclude that ANN fits well for both the solar and wind energy production and maintenance planning proposed.

For the solar analysis, the approach which presents the least cost is the ANN with NGN15.4 million. With this amount, a total of about 8301 panels, battery capacity of 26.71×10^4 Ah which generates 69.49×10^5 W. The number of panels required by SVR analysis was found to be 8905 panels which required 31.71×10^4 Ah generating about 69.50×10^5 W while the power generation by analytical method required 9058 panels, 35.78×10^4 Ah battery capacity. The variation between the two (2) machine learning techniques was insignificant in terms of the power generation, but the panels required and the battery capacity for the SVR technique were higher than the ANN which explains the fare difference.

Similarly, the wind energy presents the optimal production result with the ANN being the best optimal plan for the production plan. The optimal production cost for the ANN is NGN395 million requiring 21 turbines and 27.69×10^4 Ah battery. Then this is followed by the SVR which yields NGN423 million which estimates the usage of 29 turbines and 28.76×10^4 Ah battery. The analytical technique over-estimated number of wind turbine thereby estimating that a total of 42 turbines and 12.06×10^4 Ah battery capacity requirements.

Maintenance for both solar and wind energy systems were proposed for each of the approach. In the solar energy study, the analytical method presents the minimal costs considering the total or overall maintenance cost. With the wind energy however, the ANN method is the considered the optimal in terms of cost minimization. Having studied the production and maintenance planning of solar and wind energy systems in this chapter, we can conclude that the ANN approach is the best form for power estimation and maintenance for wind energy. This can be explained by the ability of the ANN to learn relevant features from the data and is capable of fitting well with the data after training. The SVR however, there is a problem of dimensionality which has poor generalization property because it is easy for the algorithm to draw a good boundary on the training set.

CHAPTER 3: Developing and optimizing an integrated maintenance strategy maximizing availability under operational and environmental constraints

This chapter presents an optimal integrated maintenance plan for maximizing the power plant availability of both solar and wind energies. In this chapter, we developed a maintenance strategy to maximize the plant availability by reducing maintenance downtime over the production horizon. The strategy is a priority selective maintenance strategy that selects a component for maintenance during preventive maintenance sessions based on reliability criteria. A reliability threshold is placed such that any component's reliability that falls under the threshold is selected for maintenance. A perfect maintenance (replacement) is adopted on the component and a perfect maintenance on the system when all components are replaced, otherwise, an imperfect maintenance is considered. We also considered the influence of environmental and operational conditions on the system in planning the maintenance. We presented numerical examples and also performed sensitivity analyses to validate the developed strategy and the results obtained are discussed.

3.1 Introduction

Renewable energy generation systems are considered a set of industrial system and are treated as such. Therefore, they consist of different components connected in order to deliver a desired output (energy) that satisfies customers' demands. Hence, exploitation of such sources requires strategically planned and effective maintenance strategies to keep up with satisfying customers while minimizing losses. Failures of critical assets are sometimes catastrophic and result in extended downtime which are disadvantageous for the financial outcome of the investment, client satisfaction, safety, and sustainability. Maintenance is an important parameter for sustainable production in industrial systems for ensuring continuous operations through reliability, plant and machines/components failures.

In renewable energy, there are several risks observed in the industry especially in the wind and solar energy system. In solar energy profession, the main risks originate from mismatch between the workers' capabilities and workplace factors. Most of the occupational risks from equipment management result from electrocution, fire and ergonomic risks (Sen et al., 2021). Fatigue from long hours of work, extreme temperature/ weather condition of the site, working under typhoons and/or near water are all examples of work environment risks. Exposure to long hours of intense sunlight by the workers causes serious health challenge (mostly affects eyes and skin) to the workers thereby limiting their work ability and also a reduced lifespan. Report by White & Doherty, (2017) shows that high risks associated with the solar industry emanates from installations and maintenance of the system. Maintenance personnel face serious hazards that leads

to potential death during cleaning and replacement of components especially panels because the panel cannot be turned off and may generate electricity during the activity.

Maintenance personnel are also exposed to risks from the microclimate, which might present extreme temperatures, exposure to toxic chemicals, excessive noise, and vibration from the use of tools/equipment. Cleaning of solar panels during maintenance and repair/replacement of floaters involves prolonged work with water. In addition, scheduling of installation and maintenance jobs should consider the weather forecast data to provide for emergency evacuation during such events. Proper planning of preventive measures such as design interventions are adopted at the project sites, the workers can be provided with a safe working environment at different locations in spite of many challenges. Hence, in this work, maintenance planning is done under both nominal and environmental conditions.

In wind industry, injuries and falling objects especially during installations are identified as the main risks associated with the industry. In order to address the concerns of the energy institute published comprehensive guidelines about works at height in the offshore wind industry with detailed references to design, construction, protection and maintenance requirements (EI, 2018). Furthermore, there is limited literature about risks associated with the transport phase, including wind turbine loading and transportation. Additionally, driver fatigue could be a significant hazard, as many wind farms are located in isolated areas where excessive distances are required to be travelled (Webster et al.2013). As an example of the level of risk, the Caithness Wind-farm Information Forum (CWIF) reported 230 accidents during transportation activities in the United Kingdom alone (Karanikas et al. 2021). Once wind farms are operational, they are basically unmanned facilities. Personnel access them only to perform maintenance and repairs. Notwithstanding whether a wind turbine is onshore or offshore, once a technician is inside the turbine, the operational and maintenance tasks are exactly the same. When a wind turbine is operational, there are a number of ways in which it could fail and affect the operational safety of personnel working on it such as tower collapse, blade failure, lightning strike etc. Weather is another key operational feature that creates risks for workers on both onshore and offshore wind farms. Work plans should therefore consider information from national meteorological offices.

To ensure maximum system functionality, reliability, availability, and maintainability (RAM) assessment is usually implemented. It is important in measuring the effectiveness of industrial systems. The functionality of all equipment and components of an industrial system tend to depreciate with usage and age. Thus, PM action is often implemented to improve the reliability and availability of the overall system (Sa'ad et al. 2021a). PM scheduling plays a very important role in the successful, economical, and reliable operation of engineering systems. When rarely performed especially imperfect maintenance, frequent system failures occur resulting in long downtime which affects the availability as well as the financial benefit of the system. However, when performed too often, it can cause material wastage and considerable increase in maintenance cost. therefore, it is necessary to develop an optimal plan to balance between maintenance cost, material usage as well as reducing downtime to maximize availability. These are critical decision variables for any preventive maintenance strategy and as such, criteria such as priority selection of

components enables maintenance manager to determine components that need maintenance during preventive maintenance session. Selective maintenance was introduced by Cassady et al. (2001a) where they defined it as the process of selecting the right maintenance actions under certain conditions such as system reliability, time and cost during each maintenance period. It enables the manager to determine the trade-offs between maintenance risks.

This chapter therefore focuses on developing an optimal maintenance strategy that maximizes the system availability for both solar and wind energy systems taking into account the influence of environmental and operational conditions on the system. In the wind energy analysis, the influence of energy degradation caused by the production rate is also considered and integrated in to the reliability estimation. The remainder of this chapter after the introduction is organized as follows: Motivation of the study is discussed in section 3.2. Maintenance strategies for maximizing system availability are presented in sections 3.3 and 3.4 for solar and wind energy systems respectively. Section 3.5 presents numerical example demonstrating the viability of our developed algorithms from the 2 previous sections and conclusion is given in section 3.6.

3.2 Description of the problem

All industries aim to maximize profit and ensure customer satisfaction which is subject to strong competition with the customer expectations seemingly increasing daily in terms of quality of product, delivery time and cost. The technological progress we have experienced over the past few decades has been the main driver of economic development and increased competition. To remain competitive with the hope to occupy a leading position in the industrial market, companies must manage their resources and operating costs more effectively to optimize their means of production. But given the risks that various industrial equipment can suffer, it is also important to optimize their operation by carrying out preventive and corrective maintenance actions when necessary. Preventive maintenance scheduling requires proper and effective planning of resources: time, cost, material and human resource availability. The priority in this work is to seek how to improve the system availability by managing the time resource to minimize downtime due to maintenance.

Wind turbines and solar panels are subject to random failure which can be described by the probability density function of time to failure $f(t)$ and for which the failure rate $\lambda(t)$ increases with time. Therefore, preventive maintenance is planned to improve the system reliability as well as the availability. Inspired by the work of Cassady et al. (2001a) we develop a priority selective maintenance model that selects components for maintenance during preventive maintenance activity. We want to determine the optimal number of preventive maintenance actions that improves the system (PV and wind) reliability and maximizes its availability. This is achieved by systematically replacing certain number of components at different time units depending on the component's reliability during maintenance. We also explore the influence of environmental and operational condition on the system to observe its effect on the optimal number of preventive maintenance actions.

3.3 PV maintenance strategy: maximizing availability

This section discusses the PV system, its main components and the types of failure occurring on each component. It also highlights the important functions of the components.

3.3.1 PV study

A typical photovoltaic plant is a complex system composed of different electronic devices predominantly photovoltaic modules and inverters as shown in figure 3.1. The photovoltaic modules are usually either connected in series, in parallel or a combination of both. When connected in series, it improves the voltage while in parallel improves the current. Different series are connected in series to improve the intensity to form the photovoltaic field. As the output of the photovoltaic field is a direct current (DC), the series are connected via DC wires to the inverters which convert the output to an alternative current (AC). The output of the inverters then feeds the load via AC wires.

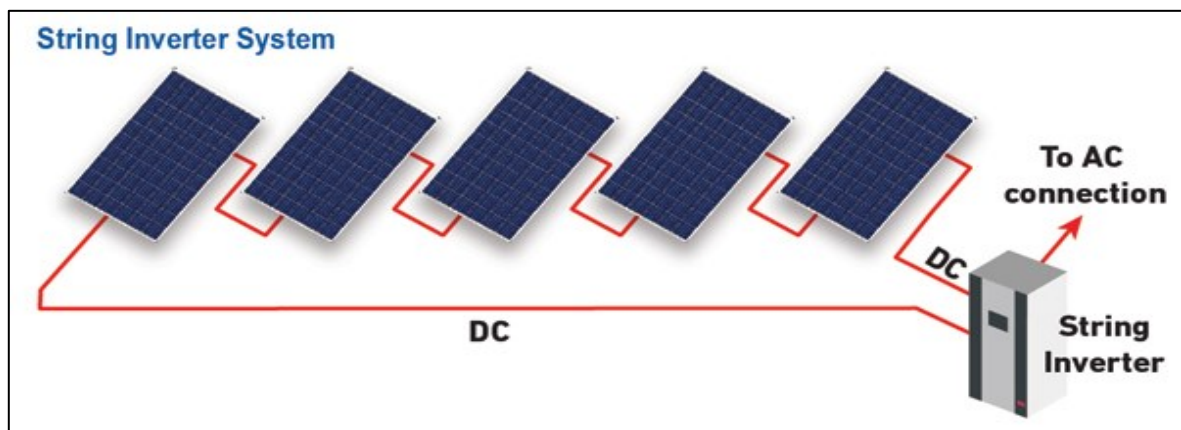


Figure 3.1: A PV field layout

The main components of a PV system are:

- i. **Panels:** These are the large and most visible part of the PV system. It comprises of solar cells connected in series to be able to generate substantial amount that can be able to power a bulb or charge phone. These cells are made up of semiconductor crystalline silicon particles which can be either monocrystalline or polycrystalline in nature. When sunlight hits a solar cell, the electrons in the semiconductor get energized and create an electric field in the cell causing electric current to flow from cell to cell. The panel generates a DC.
- ii. **Inverter:** This is an important component in the PV system because its main function is to convert a DC to a consumable form known as AC used in residential and commercial properties.
- iii. **Battery:** This component is used to store excess unused energy
- iv. **AC/DC cables:** They are the media through which electricity flows from the panels to converter (DC cables) and from the converter to the load (AC cables).

3.3.2 Types of failure, and the environmental elements affecting the PV components

Failure refers to malfunctioning of a component or a system. According to Blache and shrivastava, failure is defined as “the termination of the ability of an item to perform a required function”, (Blache & Shrivastava, 1994). It occurs when the function of a system cannot be performed or has a performance that falls outside its performance requirement. For a PV system, failures most often occur in inverters and other electronic devices (Yang, 2015). However, it occurs in other components such as the panel and the wires over the production horizon. In a panel, failures are mostly caused by breakage or cracks o the cells causing low cell conversion rate, delamination caused by extreme heat and humidity, burnt solder joint, discoloration of the cells due to overheating, bad or degradation of bypass diode performance. When there is high current flow in a de-energized state, degradation occurs on the cells causing current leakage to the ground. This potentially induced degradation is termed the hotspot. Other forms are due to improper wire sizing or termination, galvanic corrosion with incompatible metals, materials installed in environments beyond their rating and improperly installed components. As mentioned earlier, the objectives of this work are to maximize the system availability and to explore the environmental influence on the reliability of the photovoltaic system. Thus, table 1 identifies the environmental element influencing each type of failure on the system.

Table 3.1: Matches each failure with the weather elements influencing its failure cause

Component	Failure	Te	I	Hu	P
Photovoltaic Panel	Hotspots		x		
	Junction box	x		x	
	Broken glass	x	x		x
	Diode bypass		x		
	Delamination	x		x	
	Broken cells	x			x
	Welding ribbons	x		x	
	Interconnections	x		x	
	Discoloration		x		
	Corrosion	x		x	
DC/AC Wires	Cut or melt	x			
	Corrosion	x		x	
Inverter	Failure	x		x	

Where Te refers to Temperature, I to Irradiance, Hu to Humidity and P to Pressure

3.3.3 Description of solar PV maintenance strategy

The aim of our work is to develop maintenance strategy that minimizes maintenance downtime by selecting priority components onto which maintenance would be performed at the PM period. As part of the goals of this work, we also determine the optimal number of PM (N*)

actions that would yield the maximum availability over a chosen finite horizon without discontinuity. This is done by developing a priority selective maintenance model that chooses the components to be replaced during each maintenance so as to guarantee maximum reliability and availability. The photovoltaic system is considered as a multi-component system whose components are only maintained in the predetermined maintenance periods N . Our strategy therefore, combines preventive and selective maintenance strategy to decide the best combination which provides optimal number of preventive maintenance action. At each selective maintenance period $k=1,2,\dots, N^*$, the objective of priority selective maintenance is to select the right components $i=1,2,\dots, N_c$ to be maintained, so that a required reliability level is guaranteed until the next shutdown. The selection is based on reliability criteria such that a minimum acceptable reliability threshold is set on which each component is gauged against at the end of each production period. when the component reliability falls short of the threshold (R^*), it is automatically selected for maintenance. With this technique, the time duration for maintenance is minimized since not all components could be selected at preventive maintenance time.

Consequently, when all the components are selected for maintenance, a perfect preventive maintenance is considered. This implies that all components will be replaced and the system is restored to “as good as new (AGAN)” state with near zero failure rate shown in figure 3.2 and 100% reliability. Conversely, when one, two or three components are selected, an imperfect maintenance is performed. This reduces the failure rate of the system but does not make the system as good as new. This work also discerns the influence of environmental factors on a PV system by considering the effect on each component of the system.

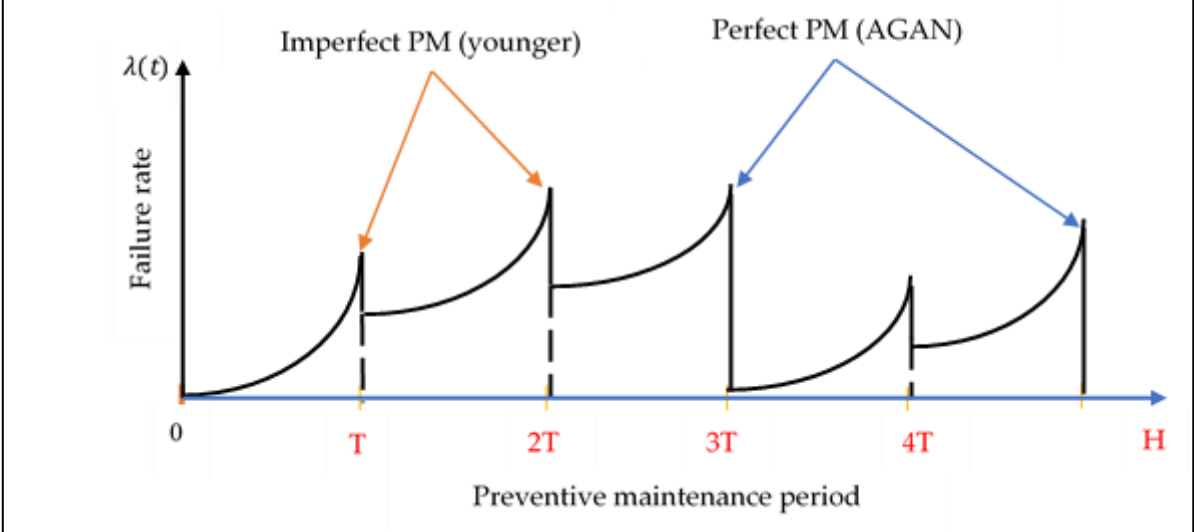


Figure 3.2: Failure rate evolution with maintenance

The evolution of reliability on a system which preventive maintenance is performed on is illustrated in figure 3.3. When the reliability of a system falls below a certain minimum threshold R^* , maintenance is performed on the components depending on the required maintenance type. If for example as in figure 3.3, when maintenance is carried out at T , some components only require servicing and/or repairs, in that case, imperfect maintenance is carried out. This increases the

system reliability by making it younger but not completely making it new. At $2T$, the type of maintenance carried out is a perfect maintenance which occurs when all components are replaced as explained earlier.

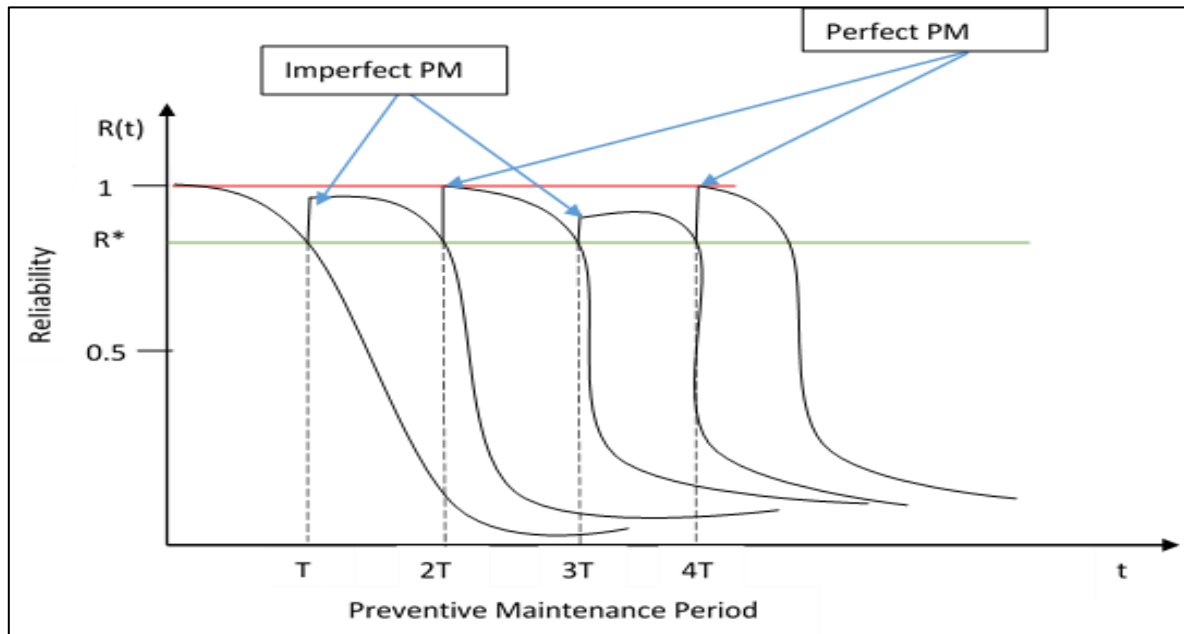


Figure 3.3: Reliability evolution when maintenance is performed

Assumptions

1. The system and its components are in a binary state, that is, they are either working or failed.
2. Minimal repair is performed as soon as a component fails during a mission.
3. After replacement, a component is "as good as new." When minimal repair is performed, it becomes "as bad as old."
4. All failures are assumed to be random and independent
5. For the electrical components' failure, the reliability is exponentially distributed with a constant failure rate while Weibull distribution was used for other types of failures.
6. The failure rate of the same components is the same.
7. For equipment having various causes, the reliability was assumed to be the product of the reliabilities of all the causes.

3.3.4 Formulation of maintenance strategy

The objective of this work is optimal scheduling of maintenance actions for a photovoltaic plant. For this purpose, the problem of the availability maximization constrained to the reliability threshold was considered. In this section, a mathematical model was developed to express the availability of photovoltaic system as a function of the decision variables: the optimal number of preventive maintenance actions N^* and the component to be replaced if it is to be maintained based on reliability threshold. The availability of the system is expressed as follows:

$$\text{Max } A = \frac{H - T_{\text{maintenance}}}{H} \quad 3.1$$

Where

$$T_{\text{maintenance}} = \mu_p + \mu_c$$

Here, the preventive maintenance time (μ_p) can be defined as the sum of the duration of the following jobs:

- i. **Access time (t₁):** This is the time required to gain access to and identify the failed component to be maintained by disassembling the system.
- ii. **Inspection time (t₂):** The time required to determine and diagnose the cause of failure.
- iii. **Replacement (or repair) time (t₃):** Once the component has been identified and inspected, this is the actual time of carrying out the main PM activity of either repair or replacement depending on the manager's decision.
- iv. **Assembling time (t₄):** This is the last stage consisting of verification, alignment and assembling the dismantled system to get it back up into operation.

Furthermore, the Corrective Maintenance time (μ_c) in addition to the above mentioned time incurs additional time since the failure occurs unexpectedly (Tsai et al. 2004). The additional times are stated as follows:

- v. **Supply delay time (t₅):** the time delay in obtaining necessary spare parts or components.
- vi. **Maintenance delay time (t₆):** the time spent waiting for the maintenance personnel, resources and facilities to be in place.

Mathematically, that the availability is inversely proportional to the maintenance duration therefore the problem is remodelled as:

$$\min T_{\text{maintenance}} \quad 3.2$$

subject to

$$R(t) > R^* \quad \forall t$$

The aim of this work is to maximize the availability of the system having in mind that the reliability of the photovoltaic system should be greater than a fixed minimum value called R^* . Thus, the problem is formulated as follows:

$$\text{Max } A = \frac{H - T_{\text{maintenance}}}{H} \quad 3.3$$

where

$$T_{\text{maintenance}}(N) = \underbrace{\sum_{k=1}^N \sum_{i=1}^{NC} [\mu_{P_i} \times m_i(k)]}_{\text{preventive maintenance duration}} + \underbrace{\mu_c \times \varphi(N)}_{\text{corrective maintenance duration}} \quad 3.4$$

Subject to

$$m_i(k) = \begin{cases} R_{PV}(k, T, Z^{EC}) \geq R^* & \text{if the component is to be maintained} \\ 0 & \text{otherwise} \end{cases}$$

$m_i(k)$ is a binary vector string for the components such that it equals 1 if the component is to be replaced and 0 if maintenance is not to be performed. The average number of failures is expressed as follows;

$$\varphi(N) = \sum_{k=0}^{N-1} \left[\int_{k.T}^{(k+1).T} \lambda_{PVk}(t) dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{PVk}(t) dt \quad 3.5$$

where:

$$\lambda_{PV,k}(t) = -\frac{dR_{PV,k}(t)}{R_{PV}(t) dt} \quad 3.6$$

3.3.5 Reliability estimation

Let T be a random variable referring to the time to failure of an equipment and P the probability of its failure. Having in mind the assumptions made above, the reliability of the equipment at t is defined as the probability that the system will not fail before or at that instant. R is then the probability that T is greater than t . This is explicated as follows:

$$R(t) = P(T > t) \quad 3.7$$

$$R(t) = P(T_1 > t_1, T_2 > t_2, \dots, T_n > t_n) \quad 3.8$$

The PV system is complex and contains a large number of sub-assemblies that may be connected in series, parallel or even a combination of both. When the sub-assemblies are connected in series, the overall system will be interrupted in case of failure of one sub-assembly. However, all sub-assemblies must fail in order to interrupt the overall system in the parallel connected system. For components associated in series, the reliability of the group is assumed to be the product of each component reliability as shown in the following equation

$$R(t) = R_1(t).R_2(t) \dots R_n(t) = \prod_{i=1}^n R_i(t) \quad 3.9$$

For equipment composed of different components associated in series, unreliability function Q is used to define the reliability of the group. The unreliability of the equipment is the products of each component unreliability (Mahani et al. 2019):

$$Q(t) = 1 - R(t) = 1 - P(T > t) \quad 3.10$$

$$Q(t) = Q_1(t).Q_2(t) \dots Q_n(t) = \prod_{i=1}^n Q_i(t) \quad 3.11$$

$$Q(t) = (1 - R_1(t)).(1 - R_2(t)) \dots (1 - R_n(t)) \quad 3.12$$

$$R(t) = 1 - \prod_{i=1}^n (1 - R_i(t)) \quad 3.13$$

$$R(t) = 1 - \prod_{i=1}^n (1 - P_i(T_i > t_i)) \quad 3.14$$

The reliability of the equipment having various failure causes is assumed to be the product of the reliability functions established for each failure cause. Therefore,

$$R(t) = R_{\text{cause } 1}(t) \cdot R_{\text{cause } 2}(t) \dots R_{\text{cause } n}(t) \quad 3.15$$

Equation (3.15) is summed into equation (3.16)

$$R(t) = \prod_{i=1}^n R_{\text{cause } i}(t) \quad 3.16$$

3.3.6 Photovoltaic plant reliability

The reliability of each of the subcomponents is detailed in this subsection given that the overall system reliability is expressed as the product of the main considered components; photovoltaic field, Dc Wires, inverters and AC Wires associated in Series as in equations (3.17) and (3.18), respectively.

$$R_{\text{system}}(t) = \prod_{i=1}^4 R_{\text{component},i}(t)^{n_{\text{component},i}} \quad 3.17$$

$$R_{\text{system}}(t) = R_{\text{PVfield}}(t) \cdot R_{\text{DC Wire}}(t)^{n_{\text{DC Wires}}} \cdot R_{\text{Inverters}}(t)^{n_{\text{Inverters}}} \cdot R_{\text{AC Wires}}(t)^{n_{\text{AC Wires}}} \quad 3.18$$

The reliability of each of the subcomponents is expressed below:

➤ Photovoltaic Field Reliability:

The photovoltaic field is composed of n_{series} number of photovoltaic components associated in series. Its reliability has then this form:

$$R_{\text{PVfield}}(t) = 1 - \prod_{i=1}^{n_{\text{series}}} (1 - R_{\text{serie},i}(t)) \quad 3.19$$

As the series are identical, their reliability functions are also identical. Thus, the field reliability is shown in equation (3.20) which is further broken down to show the sub components of the PV field in equations (3.21-3.25):

$$R_{\text{PVfield}}(t) = 1 - (1 - R_{\text{serie},i}(t))^{n_{\text{series}}} \quad 3.20$$

The PV field consists of n number of panels (n_{panels}) linked in series expressed in the following form:

$$R_{\text{serie},i}(t) = \prod_{j=1}^m R_{\text{panel},j}(t) \quad 3.21$$

$$R_{\text{serie},i}(t) = \left(R_{\text{panel}}(t) \right)^{n_{\text{panels}}} \quad 3.22$$

On the panel, there are a number of subcomponents that are prone to failure such as the cell, glass, ribbons e.t.c which constitute to the panel reliability function as follows is expressed as follow;

$$R_{\text{panel}}(t) = R_{\text{panel components}}(t) \cdot R_{\text{causes}}(t) \quad 3.23$$

$$= R_{\text{junction box}}(t) \cdot R_{\text{glass}}(t) \cdot R_{\text{bypass Diode}}(t) \cdot R_{\text{cells}}(t) \cdot R_{\text{ribbons}}(t) \cdot R_{\text{interconnectors}}(t) \quad 3.24$$

$$R_{\text{causes}}(t) = R_{\text{delamination}}(t) \cdot R_{\text{hotspot}}(t) \cdot R_{\text{discoloration}}(t) \cdot R_{\text{corrosion}}(t) \quad 3.25$$

➤ DC/AC wires Reliability:

The DC Wires and the AC Wires reliability functions are of the same form, as such they are treated in a similar way:

$$R_{\text{wire}}(t) = R_{\text{cut}}(t) \cdot R_{\text{corrosion}}(t) \quad 3.26$$

➤ Inverter Reliability:

The inverter is a complex and expensive component of a photovoltaic system. The main causes of failure in inverters are mainly design problems, manufacturing defects and poor management practices even though temperature and humidity can affect the functionality of the inverter (Realini, 2003). Thus, low inverter reliability contributes to an unreliable system and a loss of confidence in the renewable technology. The reliability function described by an exponential distribution and will be explicitly expressed in the next subsection. More explicitly, the reliability of components is often characterized by failure rate λ and is expressed as in the equation thus:

$$R = e^{-\lambda t} \quad 3.27$$

The reliability functions of each component depend only on time and independent of atmospheric conditions. Hence, for each component, the explicit reliability functions are given as follows;

▪ PV Panels

For the PV Panels, the components and the causes for failure $R_{\text{junction box}}(t)$, $R_{\text{glass}}(t)$, $R_{\text{bypass Diode}}(t)$, $R_{\text{cells}}(t)$, $R_{\text{ribbons}}(t)$, $R_{\text{hotspot}}(t)$, $R_{\text{delamination}}(t)$, and $R_{\text{interconnectors}}(t)$ have the same form given as:

$$R_{\text{equipment/cause}}(t) = e^{-\lambda_{\text{equipment/cause}} \cdot t} \quad 3.28$$

Thus, the reliability of the panel components is expressed by;

$$R_{\text{panel components}}(t) = e^{-(\lambda_{\text{junction box}} + \lambda_{\text{bypass Diode}} + \lambda_{\text{cells}} + \lambda_{\text{ribons}} + \lambda_{\text{interconnectors}}) \cdot t} \quad 3.29$$

The reliability functions related the discoloration and corrosion failures $R_{\text{discoloration}}(t)$, $R_{\text{corrosion}}(t)$ are expressed as follows:

$$R_{\text{cause}}(t) = e^{-b_{\text{cause}} \cdot t + a_{\text{cause}}} \quad 3.30$$

Thus, R_{cause} is expressed by:

$$R_{\text{discoloration/corrosion}}(t) = e^{-(b_{\text{discoloration}} + b_{\text{corrosion}}) \cdot t + a_{\text{discoloration}} + a_{\text{corrosion}}} \quad 3.31$$

Those failures are due to chemical reactions and this is the reason for using different probability distribution.

$$R_{\text{panel}}(t) = e^{-(\lambda_{\text{junction box}} + \lambda_{\text{bypass Diode}} + \lambda_{\text{cells}} + \lambda_{\text{ribons}} + \lambda_{\text{interconnectors}}) \cdot t} \cdot e^{-(b_{\text{discoloration}} + b_{\text{corrosion}}) \cdot t + a_{\text{discoloration}} + a_{\text{corrosion}}} \quad 3.32$$

- DC/AC wires:

The Wires have two failure causes; cut and corrosion. For each cause, the reliability function has a different form:

$$R_{\text{cut}}(t) = e^{-\lambda_{\text{cut}} t} \quad 3.33$$

$$R_{\text{corrosion}}(t) = 1 - C_{\text{corrosion}} \cdot t^{a_{\text{corrosion}}} \quad 3.34$$

The reliability of the AC and DC wires is then:

$$R_{\text{wire}}(t) = (1 - C_{\text{corrosion-wire}} \cdot t^{a_{\text{corrosion-wire}}}) \cdot e^{-\lambda_{\text{cut-wire}} \cdot t} \quad 3.35$$

- Inverter:

The reliability function of the inverter is described by an exponential distribution:

$$R_{\text{inverter}}(t) = e^{-\lambda_{\text{inverter}} t} \quad 3.36$$

The overall PV system reliability is therefore expressed as;

$$R_{\text{pv}}(t) = R_{\text{panel}}(t) \cdot R_{\text{AC-wire}}(t) \cdot R_{\text{DC-wire}}(t) \cdot R_{\text{inverter}}(t) \quad 3.37$$

Which is explicitly expressed as:

$$R_{\text{pv}}(t) = e^{-(\lambda_{\text{junction box}} + \lambda_{\text{bypass Diode}} + \lambda_{\text{cells}} + \lambda_{\text{ribons}} + \lambda_{\text{interconnectors}}) \cdot t} \cdot (e^{-(b_{\text{discoloration}} + b_{\text{corrosion}}) \cdot t + a_{\text{discoloration}} + a_{\text{corrosion}}}) \cdot \left((1 - C_{\text{corrosion-DC}} \cdot t^{a_{\text{corrosion-DC}}}) \cdot e^{-\lambda_{\text{cut-DC}} \cdot t} \right) \cdot \left((1 - C_{\text{corrosion-AC}} \cdot t^{a_{\text{corrosion-AC}}}) \cdot e^{-\lambda_{\text{cut-AC}} \cdot t} \right) \cdot e^{-\lambda_{\text{inverter}} \cdot t} \quad 3.38$$

Consequently, the reliability of PV power plant is given by:

$$R_{\text{pvplant}}(t) = \left(1 - \left(1 - \left(R_{\text{panel}}(t) \right)^{n_{\text{panels}}} \right)^{n_{\text{series}}} \right) \cdot R_{\text{DC Wire}}(t)^{n_{\text{DC Wires}}} \cdot R_{\text{Inverters}}(t)^{n_{\text{Inverters}}} \cdot R_{\text{AC Wires}}(t)^{n_{\text{AC Wires}}} \quad 3.39$$

Subsequently the reliability is elaborated as:

$$\begin{aligned}
R_{pvplant}(t) = & \left(1 - \left(1 - \left(e^{-(\lambda_{junction\ box} + \lambda_{junction\ box} + \lambda_{cells} + \lambda_{ribons} + \lambda_{interconnectors}) \cdot t} \right. \right. \right. \\
& \cdot e^{-(b_{discoloration} + b_{corrosion}) \cdot t + a_{discoloration} + a_{corrosion}} \left. \right)^{n_{panels}} \left. \right)^{n_{series}} \\
& \cdot \left((1 - C_{corrosion-DC} \cdot t^{a_{corrosion-DC}}) \cdot e^{-\lambda_{cut-DC} \cdot t} \right)^{n_{DC\ Wires}} \\
& \cdot \left((1 - C_{corrosion-AC} \cdot t^{a_{corrosion-AC}}) \cdot e^{-\lambda_{cut-AC} \cdot t} \right)^{n_{AC\ Wires}} \\
& \cdot \left(e^{-\lambda_{inverter} \cdot t} \right)^{n_{inverter}}
\end{aligned} \tag{3.40}$$

Moreover, if a maintenance action is applied at the instance $k.T$ with $(k: 1,..,N)$, the reliability of the Photovoltaic plant is expressed:

$$\begin{aligned}
R_{pvplant}(k.T) = & R_{panel}(k.T)^{(1-m_i(k))} \cdot R_{ACwire}(k.T)^{(1-m_i(k))} \\
& \cdot R_{DCwire}(k.T)^{(1-m_i(k))} \cdot R_{inverter}(k.T)^{(1-m_i(k))}
\end{aligned} \tag{3.41}$$

$$\begin{aligned}
R_{pv}(k.T) = & e^{-(\lambda_{junction\ box} + \lambda_{bypass\ Diode} + \lambda_{cells} + \lambda_{interconnectors}) \cdot k \cdot T \cdot (1-m_i(k))} \\
& \cdot \left(e^{-(b_{discoloration} + b_{corrosion}) \cdot k \cdot T + a_{discoloration} + a_{corrosion}} \right)^{(1-m_i(k))} \\
& \cdot (1 - C_{corrosion-DC} \cdot (k \cdot T)^{a_{corrosion-DC}})^{(1-m_i(k))} \\
& \cdot e^{-\lambda_{cut-DC} \cdot k \cdot T \cdot (1-m_i(k))} \\
& \cdot (1 - C_{corrosion-AC} \cdot (k \cdot T)^{a_{corrosion-AC}})^{(1-m_i(k))} \\
& \cdot e^{-\lambda_{cut-AC} \cdot k \cdot T \cdot (1-m_i(k))} \cdot e^{-\lambda_{inverter} \cdot k \cdot T \cdot (1-m_i(k))}
\end{aligned} \tag{3.42}$$

And consequently, the reliability of photovoltaic power plant:

$$\begin{aligned}
R_{pvplant}(k.T) = & \left(1 - \left(1 - \left(R_{panel}(k.T)^{(1-m_i(k))} \right)^{n_{panels}} \right)^{n_{series}} \right) \cdot \left(R_{DCwire}(k.T)^{1-m_i(k)} \right)^{n_{DCwire}} \\
& \cdot \left(R_{ACwire}(k.T)^{1-m_i(k)} \right)^{n_{ACwire}} \cdot \left(R_{inverter}(k.T)^{1-m_i(k)} \right)^{n_{inverter}}
\end{aligned} \tag{3.43}$$

3.3.7 Photovoltaic plant reliability under environmental condition influence

In this section an in-depth study of the reliability estimation of photovoltaic components as a function of environmental conditions using a parametric relationship between environmental and risk factors was carried out. Each climatic factor z_i is associated with a weighting coefficient $\beta_{i,j}$ that quantifies the influence of climatic conditions on the photovoltaic system. A multiplicative regression model for survival data known as Cox regression model was used to establish the relationship between the reliability function established under nominal climatic conditions $(R_{0,j}(t))$ and the criticality function $C_j(Z)$ of j climatic conditions. Cox model is a statistical tool that was first developed in the medical industry to formulate a relationship between the survival of a patient and several other variables by estimating the effect of treatment on patients and the risks of death after the treatments. To integrate the environmental impact on the reliability function, the criticality

coefficient (C) for each failure was defined. The coefficient is the product of the frequency (F), detectability (D) and severity (S) of each failure.

$$C = F \times D \times S \quad 3.44$$

Based on the indication of the environmental elements that stimulates each failure type as shown in Table I, different values of the criticality coefficient were defined based on the weather data. The environmental data was explored by assigning a value between 0 and 5 to each element according to its real value. The mathematical expression of the criticality coefficient as a function of the weather elements is established as in equation (3.45) and shown in figure 3.4. The idea is to amplify the degeneration of reliability if the environmental conditions were more critical and recompense if otherwise.

$$C_j(Z) = e^{\sum \beta_{i,j} Z_i} \quad 3.45$$

$\beta_{i,j} = (\beta_{0,j}, \beta_{1,j}, \beta_{2,j}, \beta_{3,j}, \beta_{4,j})$ is the vector of parameters for $C_j(Z)$

where $\beta_{0,j}$ is the constant of criticality for each component, $\beta_{1,j}, \beta_{2,j}, \beta_{3,j}, \beta_{4,j}$ are the criticality values for Temperature, Humidity, Irradiance and Pressure as shown in appendix I. Equation 3.45 is reconstructed to equation (3.46) by dividing C_j by $\beta_{0,j}$ to show the final criticality coefficient $c_j(Z)$ given as:

$$c_j(Z) = \frac{C_j(Z)}{\beta_{0,j}} = \frac{e^{\sum \beta_{i,j} Z_i}}{\beta_{0,j}} \quad 3.46$$

The criticality factor (Cj) was integrated into the reliability function equation yielding equation (3.47). $R_j(t)$ denotes the reliability function of the i^{th} component/cause depending only on time while $R_{0,j}(t)$ is the reliability for nominal environmental conditions. Given that $R_j(t, Z)$ must imperatively decrease over time, we opted for the integration of the previous value of this function. Accordingly, the following expression was developed for each reliability function related to each failure/component:

$$R_j(t, Z) = R_j(t - 1, Z_{t-1}) - \left(R_{0,j}(t - 1) - R_{0,j}(t) \right) * c_j \quad 3.47$$

where:

Z_{t-1} : is the vector of environmental elements corresponding to the time instant (t - 1).

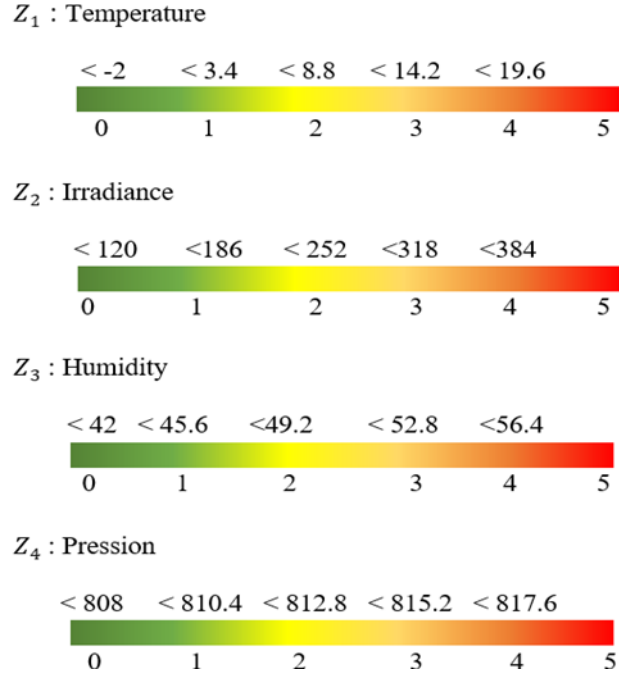


Figure 3.4: Criticality coefficient of the weather elements

And $H_j = R_j(t, Z) - R_j(t - 1, Z_{t-1})$

$$\text{Thus: } \begin{cases} c_j < 1 : H_j < R_{0,j}(t) - R_{0,j}(t - 1) \\ c_j = 1 : H_j = R_{0,j}(t) - R_{0,j}(t - 1) \\ c_j > 1 : H_j > R_{0,j}(t) - R_{0,j}(t - 1) \end{cases}$$

The reliability of the plant at t under condition Z becomes

$$\begin{aligned} R_{pvplant}(t, Z) &= R_{pvplant}(t - 1, Z_{t-1}) \\ &- \left(\left(- \left(1 - \left(R_{panel}(t - 1) \right)^{n_{panels}} \right)^{n_{series}} \right) \cdot R_{DC\ Wire}(t - 1)^{n_{DC\ Wires}} \cdot R_{Inverters}(t - 1)^{n_{inverters}} \cdot R_{AC\ Wires}(t - 1)^{n_{AC\ Wires}} \right) \\ &- \left(\left(- \left(1 - \left(R_{panel}(t) \right)^{n_{panels}} \right)^{n_{series}} \right) \cdot R_{DC\ Wire}(t)^{n_{DC\ Wires}} \cdot R_{Inverters}(t)^{n_{inverters}} \cdot R_{AC\ Wires}(t)^{n_{AC\ Wires}} \right) \times \frac{e^{\sum \beta_{i,k} z_i}}{C_{0,k}} \end{aligned} \quad 3.48$$

More explicitly, equation (3.48) becomes

component at that time. A binary vector is constructed for the selection of the component for the maintenance action, which is a finite integer of string m over the planning horizon. Each element of m is one of a possible number of maintenance actions available in the case where one, two, or three components are to be replaced at a time, in which an imperfect maintenance action is performed. In the case where all 4 components are to be replaced, the maintenance action on the system becomes a perfect maintenance. The algorithm calculates the reliability of each component to determine if maintenance should be performed or not. If the verification condition is met, i.e., if the reliability of the component has fallen below the reliability threshold, a string corresponding to the condition of the components is drawn such that the $m_i(k)$ of the components selected for maintenance action is assigned a value 1. It is possible to find two identical strings of solution during the planning horizon. Therefore, the vector is constructed in a way that strikes out all duplicates of the string so that maintenance is carried out on each component once during a maintenance action period.

With the solution string constructed, the number of preventive maintenance action (N) was set to N_{max} and the threshold of reliability. The algorithm was set in such a way that for each N ($1:N_{max}$) selected, the maintenance time is evaluated using equation 3.4. The total maintenance time takes care of both the planned preventive and corrective maintenance times. The availability estimation, as in equation 3.3, was subsequently followed. The availability achieved was stored and used as the threshold for the next availability estimation, and if the value of the availability obtained was less than the previous value, the previous value remains the intended availability until a greater value is obtained. In other words, it stores only the maximum availability of the system.

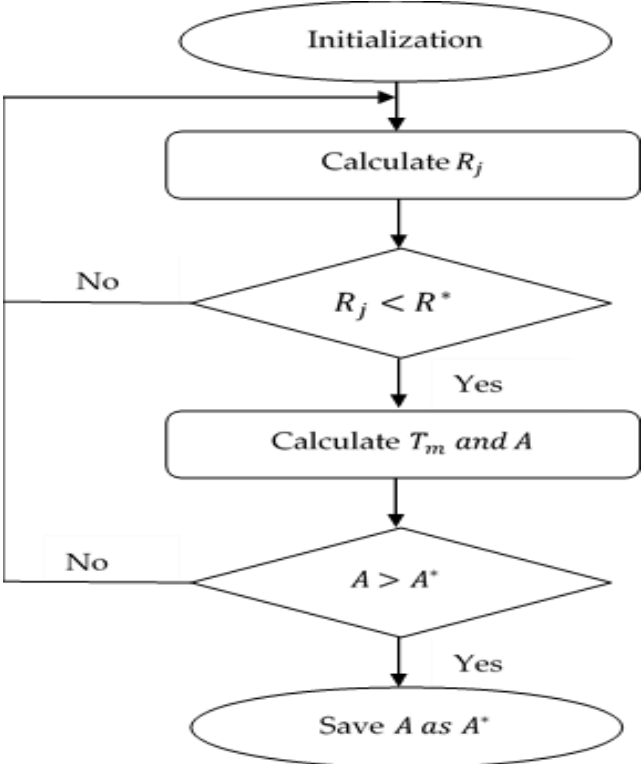


Figure 3.5: Maintenance flow chart algorithm

3.4 Integrated maintenance strategy for wind turbine; maximizing availability

Maintenance of wind energy system integrated with the wind turbine production rate is considered in this section. We therefore develop a production plan using machine learning techniques and integrate into maintenance strategy to determine the optimal maintenance plan yielding maximum availability of the wind energy system.

3.4.1 Wind energy study

The wind turbine is considered as a multi-component system with a series-parallel structure as shown in figure 3.6. Wind power output is stochastic due to its dependence on wind speed. Thus, the correlation between wind turbine production and maintenance is emphasized through the influence of the production rate of the wind turbine on its failure rate. In this section, we will briefly discuss some of the most important components of the wind turbine.

- i. **Blade:** This is the aerodynamic component of the turbine that generates aerodynamic torque from the wind.
- ii. **Bearing:** Wind turbine bearing serves as a lubricant to reduce the frictional resistance between blades, main shaft and gearbox when in motion. It is usually self-aligned spherical roller designed with two (2) sets of rollers which allows the absorption of loads; both radial and axial.
- iii. **Main shaft:** Also known as the low-speed shaft is the connecting rod which transmits rotating force from the blades to the gear.
- iv. **Gearbox:** This component of the turbine increases the rotational speed from the main shaft to a higher torque required to drive the turbine generator.
- v. **Brakes:** This component is used for braking the wind turbine when turbulence occurs
- vi. **Generator:** The generator converts mechanical energy from the rotating blades into electrical energy.
- vii. **Tower:** Holds the nacelle and blades up in the wind.
- viii. **Foundation:** It is the base on which the turbine is fixed firm in the ground.

Note: Nacelle is the component that houses the bearings, shafts, gearbox, brakes, generators and the brakes.

In this work, we limit the scope to four (4) of the turbine components based on the work of Hajej et al., (2022) because they were identified to be the most sensitive components that fail more often. Since in this chapter, we are studying the reliability of the turbines, these components make up the most crucial components of the turbine that impacted the reliability of the turbine. Those components are also the components where electricity generation and transmission are performed. The reliability of these components will be detailed in section 3.4.3.2

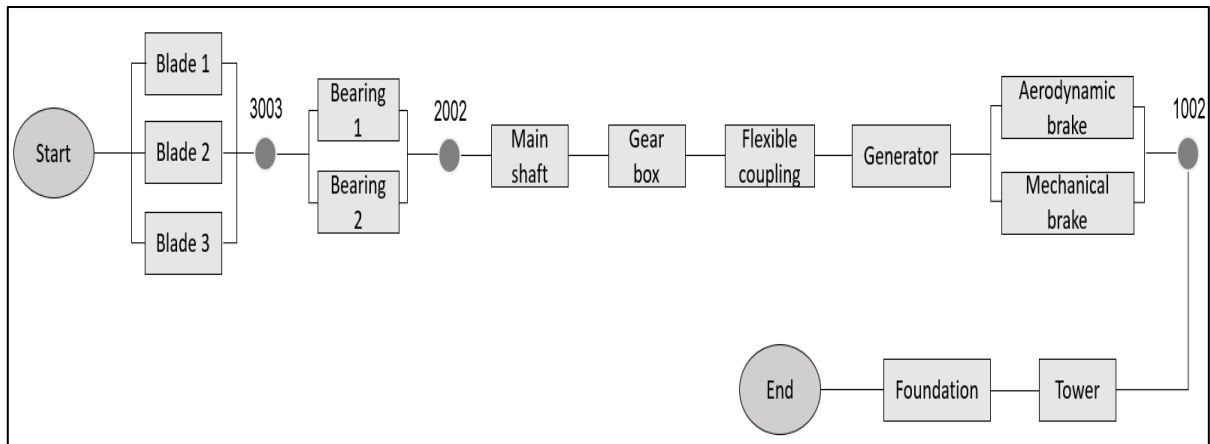


Figure 3.6: Schematic Components of a wind turbine

We recall that the purpose of this work is to develop an optimal maintenance strategy integrated with the energy production of a wind turbine to maximize availability, therefore, the subsequent sub-sections describe the maintenance of the wind turbine.

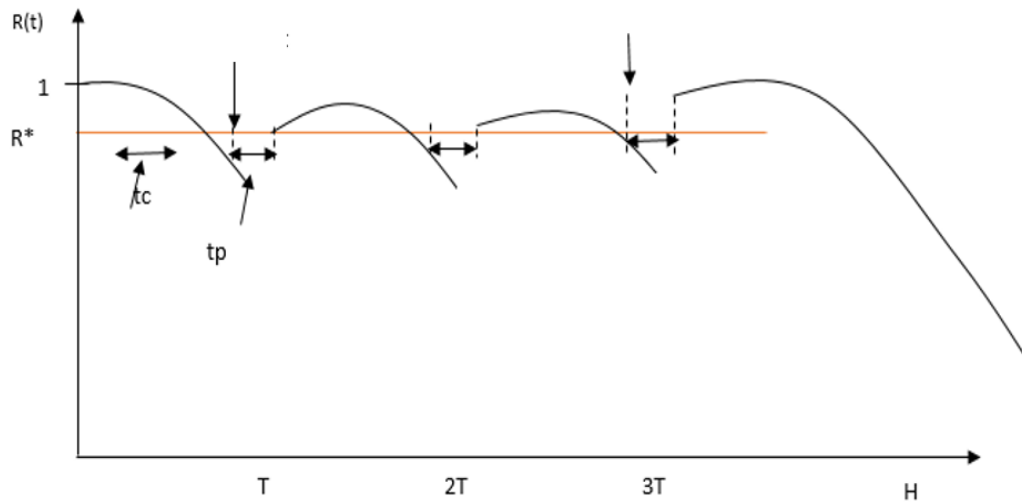
3.4.2 Description of the wind turbine maintenance strategy

This section is aimed at establishing the optimal preventive/selective maintenance with a high reliability level as well as a high maximum availability to ensure that the next energy production periods run without discontinuity, considering the obtained component reliability estimation of the wind system under operating and environmental conditions. For this purpose, the wind turbine system is considered a multicomponent system that is periodically maintained in the predetermined optimal preventive/selective maintenance periods (N) that was determined in the maintenance strategy. At each preventive/selective maintenance period ($k = 1, 2, \dots, N^*$), the objective of priority selective maintenance is to select the right components ($i = 1, 2, \dots, N_c$) to be maintained, so that a required reliability level is guaranteed until the next shutdown and a maximal availability during the whole production horizon.

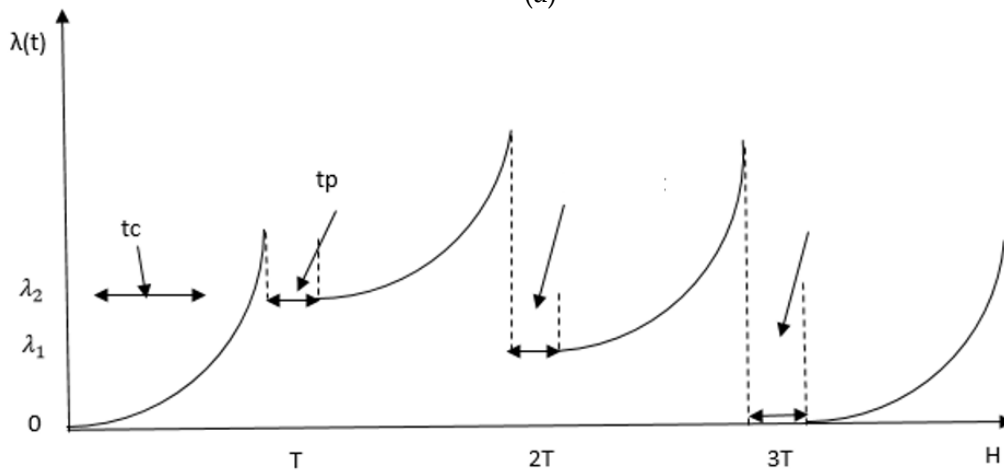
Figure 3.7(a) illustrates the typical reliability system evolution of preventive maintenance where at each preventive maintenance action time, we verify if the reliability of a system falls below a certain minimum margin R^* , perfect maintenance activity by using replacing action is performed on the components depending on the required maintenance type. The type of maintenance carried out is the perfect maintenance for each component which will be maintained during each preventive maintenance interval. At this point, the component becomes completely as good as new (AGAN) and the reliability of wind turbine system exceeds the given reliability margin. A minimal repair is performed on the wind turbine system for each failure which occurs between two successive preventive maintenance actions. The failure rate, however, decreases with an increase in the system reliability as function to the reliability/failure relationship, as illustrated in Figure 3.7(b).

Assumptions

1. Reliability function of the wind turbine mechanical components is modelled with Weibull pdf.
2. The windings are considered as electrical components where the reliability function is modelled with exponential pdf.
3. Blades, flexible coupling, tower and foundation are assumed as non-failure components hence their reliability equal 1.
4. The horizon considered is finite (H)
5. PM has equal time intervals at $T, 2T$, up to H.
6. The system, and the components within, are in a binary state, that is, they are either working or failed.
7. Minimal repair is performed as soon as a component fails during a mission.
8. After replacement, a component is "as good as new". When minimal repair is performed, it becomes "as bad as old".
9. All failures are assumed to be random and independent.



(a)



(b)

Figure 3.7: Illustration of the PM action on (a) reliability and (b) failure rate evolution

3.4.3 Formulation of wind maintenance problem

Based on the optimization strategy developed in Chapter 2, ranging from production to storage through the maintenance of a wind turbine, we consider the same system subject to operational and environmental constraints. Hence it is an improved maintenance strategy which factors the variation of the energy production rate incorporated with the reliability in order to develop maximum availability while satisfying customer demand.

3.4.3.1 Formulation of production problem (reminder)

The amount of energy produced by wind turbines essentially depends on the wind speed, which is very random. Periodically quantifying the output power of wind turbines requires an in-depth study considering several uncertain factors so as to be able to satisfy customer demands. To

this end, this section recalls the fundamental elements of the energy production planning strategy developed in the chapter 2. From the chapter, it can be recalled that we used machine learning techniques; ANN and SVR to develop optimal production plan. But to refresh the readers mind, we state the machine learning techniques here.

a) ANN

ANN is an AI algorithm inspired from the human brain neurons arrangement. In the brain, the dendrites receive all the inputs, sums them and produces output if the sum is greater than a threshold value. A simple model of an ANN was illustrated in figure 2.6 of the previous chapter. The inputs are connected to the neurons of the next layer which is the first layer of the hidden layer through channels. Each of the channels is assigned a numerical value known as weight; the inputs are multiplied to the weights and the result is sent to the hidden layer, each of these neurons is associated with a numerical value called bias which is added to the input sum. The model can be mathematically explained in the following form (Meenal & Selvakumar, 2017)

$$P_k = f \left[\sum_{i=1}^n I_i w_i + b \right] \quad 3.51$$

where I_i is the input, w_i is the weight associated with it, b is the bias and f is the activation function. The above equation is for a single output single input layer. For the purpose of this work, a single hidden layer comprising of 20 neurons is selected with a radial basis function for the activation function.

b) SVR

The SVR approximates predictions using a function f that has a fixed deviation threshold from actual targets (Cortes & Vapnik, 1995). The function is generally expressed in the following form:

$$f(x) = w\varphi(x) + b \quad 3.52$$

Where φ is the transfer function, x is an input data point and the parameters w and b are estimated by solving the following optimization problem.

$$\begin{aligned} \text{minimize } L_p &= \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) & 3.53 \\ \text{Subject to } & \begin{cases} y_i - \varphi(x_i) - b \leq \epsilon + \xi_i \\ \varphi(x_i) + b - y_i \leq \epsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned}$$

Where y_i is the i^{th} target, n is the of training samples, ϵ is the deviation threshold of the function f , C is the penalty parameter and ξ_i is the slack error that guarantees the solution by coping the in-feasible constraints (Vapnik, 1995). For the purpose of our work, the Radial Basic Function (RBF) is selected. A simple illustration of the SVR hyperplane was shown in figure 2.7.

3.4.3.2 Formulation of maintenance problem

The main objective of this work is the optimal maintenance planning for a wind turbine system. Maintenance planning, in this context, is the determination of the time interval (periodicity) of preventive maintenance action to be performed during the energy production horizon. In this case, we are considering a perfect maintenance for each maintained component. For this purpose, the problem of the availability maximization constrained to the reliability threshold was considered. In this section, a mathematical model is developed to express the availability of the wind turbine system as a function of the decision variables, the optimal number of preventive maintenance actions N^* , and the component to be replaced if it is to be maintained based on the reliability threshold. The availability maximization problem of the wind turbine system is expressed as follows:

$$\max A = \frac{H - T_{\text{maintenance}}}{H} \quad 3.54$$

Subject to

$$m_i(k) = \begin{cases} 1 & \text{if } i\text{th component is to be replaced during period } k \\ 0 & \text{otherwise} \end{cases}$$

From the above equation, maximizing A can be achieved when T_m is minimum, thus, the minimization is expressed as:

$$\min T_{\text{maintenance}} \quad 3.55$$

Subject to

$$m_i(k) = \begin{cases} 1 & \text{if } i\text{th component is to be replaced during period } k \\ 0 & \text{otherwise} \end{cases}$$

Where

$$T_{\text{maintenance}} = \mu_p + \mu_c \quad 3.56$$

And

$$T_{\text{maintenance}} = \sum_{k=1}^N \sum_{i=1}^{NC} [\mu_{pi} \times m_i(k)] + (\mu_c \times \varphi(N)) \quad 3.57$$

With $\varphi(N)$: The average number of failures which is expressed as

$$\varphi(N) = \sum_{k=0}^{N-1} \left[\int_{k.T}^{(k+1).T} \lambda_{wt}(t) dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{wt}(t) dt \quad 3.58$$

$$\lambda_{wt}(t) = \frac{-dR_{wt}(t)}{R_{wt}(t) dt} \quad 3.59$$

The maintenance time (T_m) thus comprises of preventive (t_p) and corrective (t_c) maintenance time which takes into account; access time to check for the failure, diagnostic time which enables

the maintenance officer diagnose and ascertain the actual problem, replacement/repair time and alignment time. However, in the case of corrective maintenance, additional time could be needed since it is a sudden break-down. In case the problem encountered can't be solved by some in-house maintenance personnel, personnel out sourcing may be required or the case of non-availability of spare part at the time of break-down which requires additional time.

Considering the stated details in section 3.4.1 where we mentioned that four components are considered in this work, we establish the reliability of the wind turbine and its components affected by operating and environmental conditions based on cox model. These selected components are: the bearings, main shaft, gearbox and the generator connected in series and the reliability is expressed in equation (3.60).

$$R_{wt}(t) = R_{mb}(t) \cdot R_{ms}(t) \cdot R_{gb}(t) \cdot R_{gen}(t) \quad 3.60$$

The reliability of each component/subcomponent is modelled based on Weibull distribution depending on time(t) and is discussed below.

i. Main bearings

The reliability of a wind turbine bearing is calculated as

$$R_{mb}(t) = e^{-\left(\frac{t}{\eta_{mb}}\right)^{\beta_{mb}}} \quad 3.61$$

ii. Main shaft

The reliability of the main shaft is calculated as

$$R_{ms}(t) = e^{-\left(\frac{t}{\eta_{ms}}\right)^{\beta_{ms}}} \quad 3.62$$

iii. Gearbox

The reliability of gearbox is calculated in equation (3.67). The component encompasses 4 subcomponents; Intermediate shaft (IMS) bearing, High speed stage (HSS) bearing, keyways and gears. Hence, the overall reliability of the gearbox is calculated in equation 3.67 with the reliability of each of the subcomponents expressed in the equations 3.63 - 3.66;

- HSS bearing

$$R_{hss}(t) = e^{-\left(\frac{t}{\eta_{hss}}\right)^{\beta_{hss}}} \quad 3.63$$

- IMS bearing

$$R_{ims}(t) = e^{-\left(\frac{t}{\eta_{ims}}\right)^{\beta_{ims}}} \quad 3.64$$

- Keyways

$$R_{keyway}(t) = e^{-\left(\frac{t}{\eta_{keyway}}\right)^{\beta_{keyway}}} \quad 3.65$$

- Gears

$$R_{gear}(t) = e^{-\left(\frac{t}{\eta_{gear}}\right)^{\beta_{gear}}} \quad 3.66$$

The overall gearbox reliability is expressed as

$$R_{gb}(t) = e^{-\left[\left(\frac{t}{\eta_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\eta_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{\eta_{keyway}}\right)^{\beta_{keyway}} + \left(\frac{t}{\eta_{gear}}\right)^{\beta_{gear}}\right]} \quad 3.67$$

- iv. Generator

The generator also encompasses 2 subcomponents; bearings and windings. Its reliability is the product of the subcomponents.

- Generator bearing

$$R_{bearing}(t) = e^{-\left(\frac{t}{\eta_{bearing}}\right)^{\beta_{bearing}}} \quad 3.68$$

- Generator winding

$$R_{winding}(t) = e^{-\left(\frac{t}{\eta_{winding}}\right)^{\beta_{winding}}} \quad 3.69$$

The overall generator reliability is calculated as

$$R_{gen}(t) = e^{-\left[\left(\frac{t}{\eta_{bearing}}\right)^{\beta_{bearing}} + \left(\frac{t}{\eta_{winding}}\right)^{\beta_{winding}}\right]} \quad 3.70$$

3.4.4 Wind turbine components' operating condition

Let us consider the operating conditions of the turbine. Each component/subcomponent undergoes a different kind of operating condition such as wear, loading and heating depending on the component's operation.

- i. Main bearing

The bearing is a mechanical component and thus not affected by operating condition and as such, the reliability of the bearing under operating condition remains unchanged from equation 3.61 which we recall was expressed as:

$$R_{mb}(t, Z) = e^{-\left(\frac{t}{\eta_{mb}}\right)^{\beta_{mb}}}$$

- ii. Main shaft

The operation of the main shaft is influenced by 2 operating conditions: Alignment and Loading, hence the operating condition is expressed as;

$$g(Z) = e^{(b_1^1 z_1^1 + b_2^1 z_2^1)} \quad 3.71$$

Condition 1: Alignment has 2 levels of severity defined by;

$z_1^1 = 0$ under normal condition and

$z_1^1 = 1$ when misaligned

Condition 2: Loading which is also defined by 2 levels of severity;

$z_1^2 = 0$ if applied load is less than maximum load

$z_1^2 = 1$ if applied load is greater than maximum load

The overall shaft reliability under operating condition is calculated as

$$R_{ms}(t, Z) = e^{-\left(\frac{t}{\bar{\eta}_{ms}}\right)^{\beta_{ms}} \cdot [e^{b_1^1 z_1^1 + b_2^1 z_2^1}]} \quad 3.72$$

iii. Gearbox

The gearbox is influenced by 4 conditions: shock, wear, load and heating based on Cox model as shown in the equation below:

$$g(Z) = e^{(b_2^1 z_2^1 + b_2^2 z_2^2 + b_2^3 z_2^3 + b_2^4 z_2^4)} \quad 3.73$$

Shock: this is defined by 3 levels of severity such that

$z_2^1 = 0$ if the shock is normal

$z_2^1 = 1$ if the shock is strong

$z_2^1 = 2$ if the shock is severe

Wear: This has 2 levels

$z_2^2 = 1$ if abrasive

$z_2^2 = 2$ if corrosive

Loading

$z_2^3 = 0$ if load applied is less than maximum

$z_2^3 = 1$ if the load is greater than maximum

Thermal Heating

$z_2^4 = 0$ if the temperature is less than the maximum

$z_2^4 = 1$ if the temperature is greater than maximum

The gearbox reliability under operational condition is then expressed as

$$R_{gb}(t, Z) = e^{-\left[\left(\frac{t}{\bar{\eta}_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\bar{\eta}_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{\bar{\eta}_{keyway}}\right)^{\beta_{keyway}} + \left(\frac{t}{\bar{\eta}_{gear}}\right)^{\beta_{gear}}\right]} \cdot e^{(b_2^1 z_2^1 + b_2^2 z_2^2 + b_2^3 z_2^3 + b_2^4 z_2^4)} \quad 3.74$$

iv. Generator

The generator is influenced by 2 operational conditions namely vibration and heating. This was adopted from the work of (Bouzoubaa, 2021b) where the authors specified two (2) factors (vibration and thermal heating) as the factors that highly influence the operational condition of the generator. The influence of operating conditions on generator degradation is modelled according to the risk function of the Cox model:

$$g(Z) = e^{(b_3^1 z_3^1 + b_3^2 z_3^2)} \quad 3.75$$

Vibration

$$z_3^1 = 0 \text{ if normal}$$

$$z_3^1 = 1 \text{ if severe}$$

Thermal Heating

$$z_3^2 = 0 \text{ if it's less than maximum}$$

$$z_3^2 = 1 \text{ if it's greater than maximum}$$

The generator reliability under operational condition is therefore expressed as;

$$R_{gen}(t) = e^{-\left[\left(\frac{t}{\bar{\eta}_b}\right)^{\beta_b} + \left(\frac{t}{\bar{\eta}_{winding}}\right)^{\beta_{winding}}\right]} \cdot e^{(b_3^1 z_3^1 + b_3^2 z_3^2)} \quad 3.76$$

The overall reliability under operating condition is shown in equation 3.77:

$$R_{wt}(t, Z) = R_{mb}(t, Z) \times R_{ms}(t, Z) \times R_{gb}(t, Z) \times R_{gen}(t, Z) \quad 3.77$$

More explicitly, it is shown as

$$\begin{aligned} & R_{wt}(t, Z) \\ &= \left(2 - e^{-\left(\frac{t}{\bar{\eta}_{mb}}\right)^{\beta_{mb}}}\right) \\ & \times e^{-\left[\left(\left(\frac{t}{\bar{\eta}_{ms}}\right)^{\beta_{ms}} \cdot [e^{b_1^1 z_1^1 + b_1^2 z_1^2}]\right) + \left(\left[\left(\frac{t}{\bar{\eta}_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\bar{\eta}_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{\bar{\eta}_{keyway}}\right)^{\beta_{keyway}} + \left(\frac{t}{\bar{\eta}_{gear}}\right)^{\beta_{gear}}\right] \cdot e^{(b_2^1 z_2^1 + b_2^2 z_2^2 + b_2^3 z_2^3 + b_2^4 z_2^4)}\right) + \left(\left[\left(\frac{t}{\bar{\eta}_{bearing}}\right)^{\beta_{bearing}} + \left(\frac{t}{\bar{\eta}_{winding}}\right)^{\beta_{winding}}\right] \cdot e^{(b_3^1 z_3^1 + b_3^2 z_3^2)}\right)\right]} \end{aligned} \quad 3.78$$

3.4.5 Reliability of the wind turbine under the influence of climatic condition

The major climatic condition influencing wind turbine performance is the wind speed (Hajej et al., 2022). This constraint is modelled as

$$g(Z) = e^{bZ^{CC}} \quad 3.79$$

For the purpose of this work, the condition is set between a minimum and maximum bound of 3m/s to 10m/s, hence the severity is divided into 3 depending on the velocity (v) as shown below:

$$\begin{aligned} Z^{CC} &= 1 & \text{if } v \in [3 - 6\text{m/s}] \\ Z^{CC} &= 2 & \text{if } v \in [6 - 8\text{m/s}] \\ Z^{CC} &= 3 & \text{if } v \in [8 - 10\text{m/s}] \end{aligned} \quad 3.80$$

Therefore, the reliability considered under operational and climatic condition is calculated as following:

$$\begin{aligned} R_{wt}(t, Z, Z^{CC}) &= \left(2 - e^{-\left(\frac{t}{\bar{\eta}_{mb}}\right)^{\beta_{mb}}} \right) \\ &\times e^{-\left[\left[\left(\frac{t}{\bar{\eta}_{ms}}\right)^{\beta_{ms}} \cdot [e^{b_1^1 z_1^1 + b_1^2 z_1^2}] \right] + \left[\left(\frac{t}{\bar{\eta}_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\bar{\eta}_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{\bar{\eta}_{keyway}}\right)^{\beta_{keyway}} + \left(\frac{t}{\bar{\eta}_{gear}}\right)^{\beta_{gear}} \right] \cdot e^{(b_2^1 z_2^1 + b_2^2 z_2^2 + b_2^3 z_2^3 + b_2^4 z_2^4)} \right] \\ &\times e^{-\left[\left(\frac{t}{\bar{\eta}_{bearing}}\right)^{\beta_{bearing}} + \left(\frac{t}{\bar{\eta}_{winding}}\right)^{\beta_{winding}} \right] \cdot e^{(b_3^1 z_3^1 + b_3^2 z_3^2)}} \right] \quad 3.81 \\ &\times e^{bZ^{CC}} \end{aligned}$$

3.4.6 Reliability under the influence of the production

While performing the reliability assessment, it is important to factor the production and its effect on the reliability of the components. For this, we first establish a nominal failure rate developed on Weibull distribution with the following expression:

$$\lambda_n(t) = \frac{\beta}{\bar{\eta}} \cdot \left(\frac{t}{\bar{\eta}}\right)^{\beta-1} \quad 3.82$$

Then the production rate is shown as

$$e^{-\left(\frac{P_k}{P_{max}}\right) \cdot \lambda_n(t)} \quad 3.83$$

Therefore, the overall system reliability considered under operational and climatic condition as well as the influence of the production rate is calculated viz:

$$\begin{aligned} R_{wt}(t, Z, Z^{CC}, Z^P) &= \left(2 - e^{-\left(\frac{t}{\bar{\eta}_{mb}}\right)^{\beta_{mb}}} \right) \\ &\times e^{-\left[\left[\left(\frac{t}{\bar{\eta}_{ms}}\right)^{\beta_{ms}} \cdot [e^{b_1^1 z_1^1 + b_1^2 z_1^2}] \right] + \left[\left(\frac{t}{\bar{\eta}_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\bar{\eta}_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{\bar{\eta}_{keyway}}\right)^{\beta_{keyway}} + \left(\frac{t}{\bar{\eta}_{gear}}\right)^{\beta_{gear}} \right] \cdot e^{(b_2^1 z_2^1 + b_2^2 z_2^2 + b_2^3 z_2^3 + b_2^4 z_2^4)} \right] \\ &\times e^{-\left[\left(\frac{t}{\bar{\eta}_{bearing}}\right)^{\beta_{bearing}} + \left(\frac{t}{\bar{\eta}_{winding}}\right)^{\beta_{winding}} \right] \cdot e^{(b_3^1 z_3^1 + b_3^2 z_3^2)}} \right] \quad 3.84 \\ &\times e^{bZ^{CC}} \times e^{-\left(\frac{P_k}{P_{max}}\right) \cdot \lambda_n(t)} \end{aligned}$$

3.4.7 Algorithm

Based on the formulated problem, we built a maintenance algorithm integrated with the power production rate. The algorithm is a sequential technique on which production planning was

first performed with the mentioned production techniques (from chapter 2) as presented in figure 3.8 for both ANN and SVR techniques. The objective of the work is to find the optimal number of PM actions (N) that yields maximum availability under the environmental and operating conditions of the wind turbine. However, wind turbine is impacted by the influence of power generation degradation, we therefore consider the impact of the power production on the turbine. Additionally, there is no constraint on the number of components to be maintained during each maintenance period. This is because the life cycle as well as the degradation factors of some components are lower than others. At the beginning of the horizon, all the components are new and are assumed to have reliability of a new component/ machine (usually assumed to be 1). The maintenance scheduling is planned such that selective maintenance on the components is carried out at the time of the preventive maintenance action, depending on the reliability of the component at that time. A binary vector is constructed for the selection of the component for the maintenance action, which is a finite integer of string m over the planning horizon. Each element of m is one of a possible number of maintenance actions available in the case where one, two, or three components are to be replaced at a time, in which an imperfect maintenance action is performed.

In a case where all of the (4) components are to be replaced; the maintenance action then becomes a perfect maintenance. The algorithm calculates the reliability of each component to determine if maintenance should be performed or not. If the verification condition is met, i.e., if the reliability of the component has fallen below the reliability margin, a string corresponding to the condition of the components is drawn such that the $m_i(k)$ of the components selected for maintenance action is assigned a value 1. It is possible to find two identical strings of solution during the planning horizon. Therefore, the vector is constructed in a way that strikes out all duplicates of the string so that maintenance is carried out on each component once during a maintenance action period.

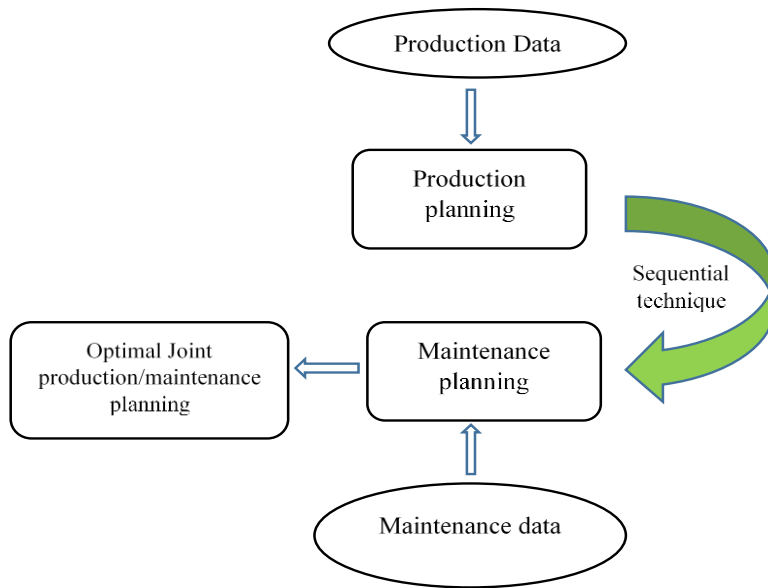


Figure 3.8: Sequential approach of solving the maintenance problem

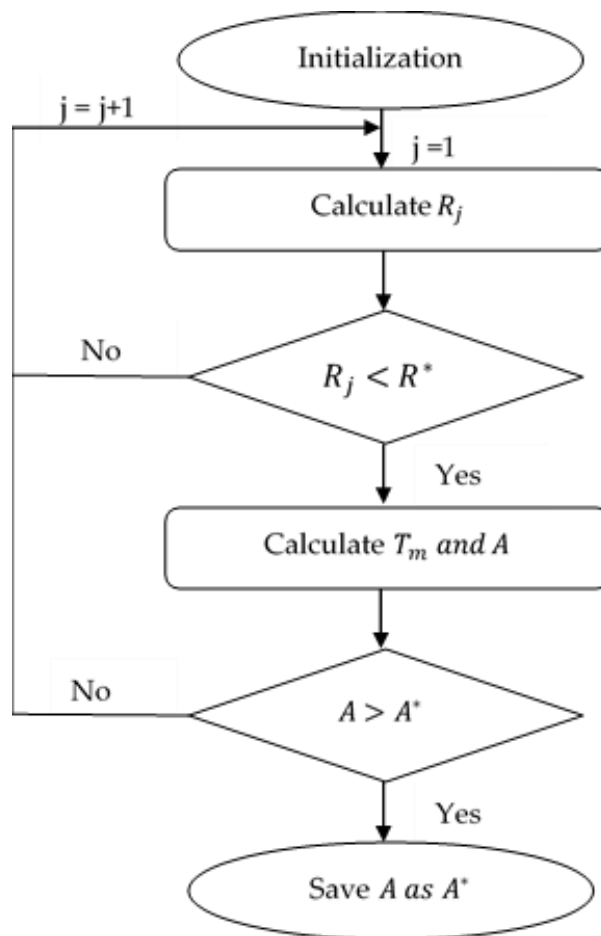


Figure 3.9: Maintenance flow chart algorithm

With the solution string constructed, the number of preventive maintenance action (N) was set to Nmax. The algorithm was built in such a way that for each value of N (1:Nmax) selected, the maintenance time was evaluated by equation 3.56. The total maintenance time takes care of both the planned preventive and corrective maintenance times. The availability estimation, as in equation 3.54, was subsequently followed. The availability achieved was stored and used as the margin for the next availability estimation, and if the value of the availability obtained was less than the previous value, the previous value remains the intended optimal availability until a greater value is obtained. In other words, it stores only the maximum availability of the system.

3.5 Numerical analysis

In this section, we implement the above developed algorithms for both solar and wind energy systems in order to determine the optimal number of preventive maintenance actions yielding maximum availability for each system.

3.5.1 PV system

Following the optimization procedure based on the algorithm we determined the optimal maintenance plan on the PV system with the following numerical values for a finite. The constant failure rates of the PV system components and subcomponents are tabulated in table 3.2. Following the PV system developed in chapter 2 (Sokoto PV power plant), we consider a PV system consisting of one (1) PV modules connected in series, the output is connected to one (1) inverter via one (1) DC cable. The inverter output is transmitted to the load via one (1) AC cable as well. The reparation rate for each component and the constant corrective maintenance time is also tabulated in table 3.3. Considering the environmental condition influencing the components/subcomponents, the criticality coefficient data is given in appendix 1 while the corresponding represented values were shown in Figure 3.4. The environmental condition parameters chosen for this purpose are 3,4,3,4 for temperature, humidity, irradiance and pressure respectively according to figure 3.4 and the chosen time horizon is 2000 units of time. Using this information, the system availability was determined under two scenarios mentioned as: (1) under nominal condition and (2) under environmental conditions.

Table 3.2: Component/subcomponent constant failure rate

Failure mode	Constant Failure rate (hr ⁻¹)
Hot spot	7.13×10^{-7}
Diode bypass	5.85×10^{-7}
Junction box	7.87×10^{-7}
Delamination	5.44×10^{-7}
Glass case (broken)	5.44×10^{-7}
Cell	7.13×10^{-6}
Soldering tape	4.84×10^{-6}
Interconnection box	4.68×10^{-6}
b-Discoloration	1.36×10^{-20}

a-Discoloration	3.08×10^{-20}
b-Corrosion	1.61×10^{-21}
a- Corrosion	3.08×10^{-20}
DC cable	4.83×10^{-8}
DC cable Corrosion coefficient	1.68×10^{-7}
AC cable	1.30×10^{-8}
AC cable Corrosion coefficient	8.82×10^{-8}
Inverter	9.51×10^{-6}

Table 3.3: PV system components' repair time(s)

Components	PM time (units)	CM time (unit)
PV Panel	0.3	15
DC wire	0.2	
AC wire	0.2	
Inverter	0.3	

3.5.1.1 Results and discussion for PV system

A solar power plant maintenance model was developed to determine the optimal maintenance plan that would yield maximum availability of the plant. This is performed under ideal situation without considering the influence of environment on the system (scenario 1) and when the environmental influence is considered (scenario 2). The maximum availability of the system results obtained for the PV maintenance optimization are presented on figures 3.10 and 3.11 for scenarios 1 and 2 respectively.

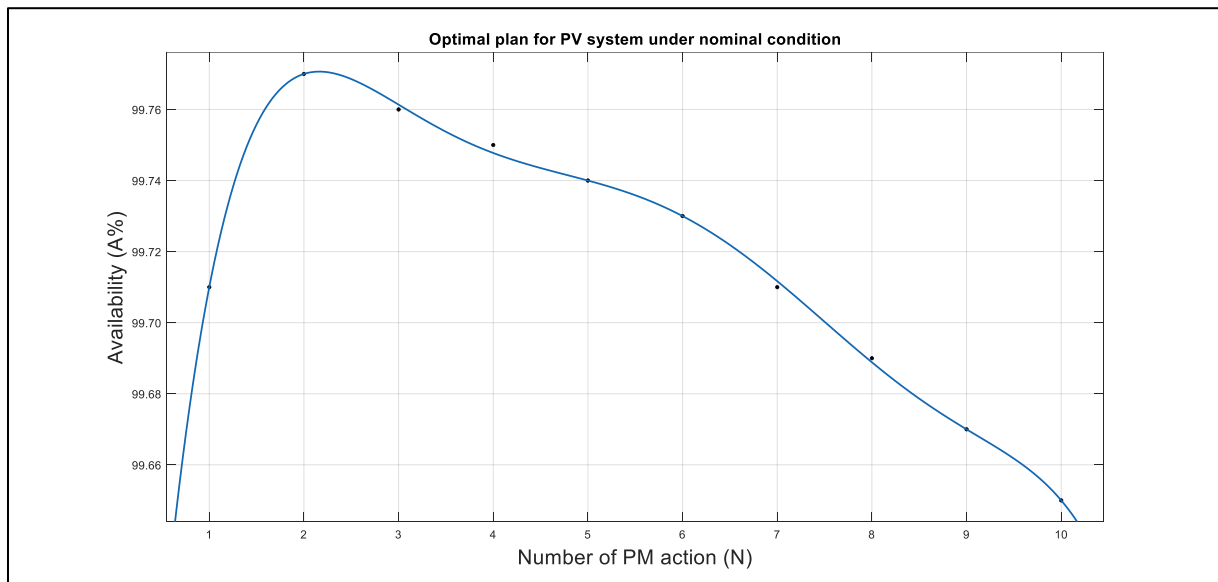


Figure 3.10: Optimal maintenance plan for scenario 1

From the above figure, maximum availability is achieved at 99.77%. The components selected for maintenance for the scenario 1 are shown on table 3.4 with only DC wire selected for

maintenance in the first maintenance round whereas all components are replaced at the end of the horizon.

Table 3.4: Components selected for maintenance during PM in scenario 1

Period	Panel	DC wire	AC wire	Inverter
1000	-	x	-	x
2000	x	x	x	x

In scenario 2, maximum availability is achieved at 99.72% at an optimal maintenance plan of 2, the graph of which is presented in figure 3.12. Table 3.5 shows the components selected for maintenance during each maintenance period under this condition. In the first period, the solar panel and the AC wires are the components selected.

Table 3.5: Components selected for maintenance during PM in scenario 2

Period	Panel	DC wire	AC wire	Inverter
1000	x	-	x	-
2000	x	x	x	x

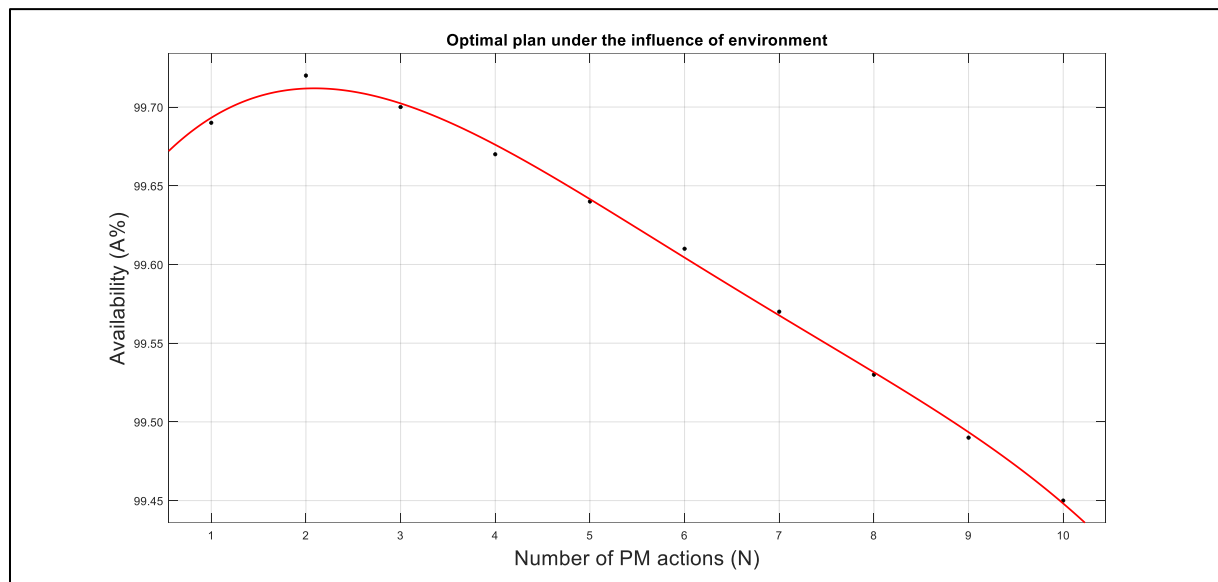


Figure 3.11: Optimal maintenance plan considered under environmental influence

3.5.1.2 Sensitivity analysis for the PV system

To understand the influence of some parameters on the system, we decided to vary the corrective maintenance time for each scenario as well as other parameters as follows:

- a) Influence of varying corrective maintenance time on the availability.

We have varied the corrective maintenance time to 10 and 20 accordingly while maintaining the original preventive maintenance time for each of the components. The results obtained are presented on table 3.6 where maximum availability of 99.89 % is achieved for 10 (tu) of corrective

maintenance at an optimal maintenance plan of 2. When the time is increased to 20 (tu), the optimal plan becomes 3 at 99.81% availability.

Table 3.6: Influence of corrective maintenance time on the availability for scenario 1

	CM = 10 (tu)	CM = 20 (tu)
N*	2	3
A* (%)	99.89	99.81

The components selected for maintenance as predicted from the algorithm is shown on tables 3.7 and 3.8 for the nominal condition (scenario 1). On table 3.7, three (3) components; panel, AC and DC wires are selected for in the first maintenance period when the CM time is 10 units.

Table 3.7: Components selected for maintenance in scenario 1 when CM = 10 (tu)

Period	Panel	DC wire	AC wire	Inverter
1000	x	x	x	-
2000	x	x	x	x

In the first period of maintenance when CM is 20 tu, DC wire and inverter are the selected component. While the panel, DC wire and inverter are the selected components in the second period as shown on table 3.8 and at the end of the production horizon, all components are replaced.

Table 3.8: Components selected for maintenance in scenario 1 when CM = 20 (tu)

Period	Panel	DC wire	AC wire	Inverter
666	-	x	-	x
1333	x	-	x	x
2000	x	x	x	x

For scenario 2, the results are presented on table 3.9. The optimal maintenance plan is obtained to be 3 when CM time is both 10- and 20-time units having availability of 99.79% and 99.65% respectively.

Table 3.9: Influence of corrective maintenance time on the availability for scenario 2

	CM = 10 (tu)	CM = 20 (tu)
N*	3	3
A* (%)	99.79	99.65

The components selected for maintenance are respectively presented on tables 3.10 and 3.11. When CM is 10-time units, AC wire and inverter are the components selected for the first period and Panel for the second period on table 3.10. On table 3.11, panel and DC wire are the selected components in the first period, while only inverter is selected on the second period and all the components are replaced at the end.

Reducing corrective maintenance time in scenario 1, the N* remains 2 but availability increases. However, increasing the time increases the N*. The availability increases from the initial condition of 99.77% to 99.81% which is higher but is not as much as the value obtained with decreased time.

Table 3.10: Components selected for maintenance in scenario 2 when CM = 10 (tu)

Period	Panel	DC wire	AC wire	Inverter
666	-	-	x	x
1334	x	-	-	-
2000	x	x	x	x

Table 3.11: Components selected for maintenance in scenario 2 when CM = 20 (tu)

Period	Panel	DC wire	AC wire	Inverter
666	x	x	-	-
1334	-	-	-	x
2000	x	x	x	x

In scenario 2, decreasing CM time increases the optimal maintenance plan (N^*) and the availability while increasing the time increases the N^* also but not so much with the availability. Therefore, we can say that it has no much influence on the availability since our strategy is a selective strategy and different components are selected at different maintenance periods.

b) Influence of varying the reliability threshold in scenario 1

We again varied the reliability threshold to 70%, 80% and then to 95%, in order that we understand its influence on the availability and subsequently the optimal number of maintenances to be performed. The optimal values are shown on table 3.12 with N^* being 2 at 99.68% availability at 70% reliability threshold. When the threshold is at 80%, the optimal N is 2 at 99.72% availability and when increased to 95%, the optimal is 3 at 99.82% availability. Reliability threshold is seen to influence the optimal number of preventive maintenances to be performed as it is seen to be increasing with increase in the reliability threshold.

Table 3.12: Influence of varying reliability threshold on availability for scenario 1

R^* (%)	70%	80%	95%
N^*	2	2	3
A (%)	99.68	99.72	99.82

Tables 3.13- 3.15 present the components selected for maintenance considering each of the reliability threshold presented on table 3.12 above. On table 3.13, only inverter is selected for maintenance in the first period, while AC and DC wires are selected for the second period. on table 3.14, when R^* is 80%, only DC wire is selected for the first period of maintenance. On table 3.15 for when R^* is 95%, DC wire and inverter are the components selected for maintenance.

Table 3.13: Components selected for maintenance during PM when $R^* = 70\%$

Period	Panel	DC wire	AC wire	Inverter
1000	-	x	x	-
2000	x	x	x	x

Table 3.14: Components selected for maintenance during PM when $R^* = 80\%$

Period	Panel	DC wire	AC wire	Inverter
1000	-	x	-	-
2000	x	x	x	x

Table 3.15: Components selected for maintenance during PM when $R^* = 95\%$

Period	Panel	DC wire	AC wire	Inverter
666	x	-	x	-
1334	-	x	-	x
2000	x	x	x	x

When the reliability threshold is decreased, N^* is still 2 but the availability increases, and further increase in the threshold increases N^* and also increases the availability. We can therefore say that reliability threshold influences both N^* and the availability.

c) Influence of varying the environmental factors in scenario 2

Since we are considering the influence of environment on our system, we have varied the condition of the elements to a harsher and a milder condition to determine its influence on the availability and to predict the number of possible preventive maintenance to be carried out. Therefore, we have constructed the following to represent the values of the environmental condition combination selected for this analysis. The values will be arranged as; temperature, humidity, irradiance and pressure respectively as shown below.

- I. $E1 = [5 \ 3 \ 5 \ 4]$
- II. $E2 = [4 \ 3 \ 3 \ 4]$
- III. $E3 = [2 \ 5 \ 3 \ 3]$

The optimal values of the result obtained for all the constructed vectors are presented on table

Table 3.16: Influence of varying environmental condition on availability for scenario 2

	E1	E2	E3
N^*	2	2	4
A (%)	99.83	99.70	99.67

From the table above, the optimal plans are 2, 2 and 4 respectively for the environmental conditions selected respectively. In this analysis, the influence is seen to have an impact on the availability such that the availability is seen to be decreasing. We can deduce that the temperature has the most influence on the systems and as such decreases the availability when decreased. When the influence of environmental condition is considered on the system, availability is seen to be decreasing. This can be explained by the increase in the frequency of the maintenance which increases maintenance downtime. For each of the environmental conditions of E1, E2 and E3, the selected components for maintenance according to the algorithms are presented on tables 3.17-3.19.

The components chosen for maintenance on table 3.17, panel and inverter are the components chosen at the first period. AC wire and inverter are the components for E2 shown on

table 3.18. On table 3.19, DC and AC wires are the selected components for the first period of maintenance, followed by the panel and DC wires during the second period. In the third period, AC wire and inverter are the chosen components and all components are replaced in the last period.

Table 3.17: Components selected for maintenance during PM for E1

Period	Panel	DC wire	AC wire	Inverter
1000	x	-	-	x
2000	x	x	x	x

Table 3.18: Components selected for maintenance during PM for E2

Period	Panel	DC wire	AC wire	Inverter
1000	-	-	x	x
2000	x	x	x	x

Table 3.19: Components selected for maintenance during PM for E3

Period	Panel	DC wire	AC wire	Inverter
500	-	x	x	-
1000	x	x	-	-
1500	-	-	x	x
2000	x	x	x	x

3.5.2 Wind energy system

This section presents a numerical analysis of the developed algorithm based on the strategy developed in this paper, which consist of the optimal imperfect / priority maintenance plans. A wind turbine operates 8 hours averagely daily, consequently, 2000-time units maintenance horizon was considered for this purpose. The PM time (μ_p) for each component under investigation as well as the CM time (μ_c) presented on table 3.20. Katsina is located in the north western part of Nigeria at 13.0070N and 07.6610E with an altitude of 5060.0 m and air density 1.18 kg/m³. The average wind speed of the location at 50m height was found to be in the range of 3.5-5.5 m/s and an average power density of 160.6 W/m². It was estimated that an average of 29.6 kWh/month of energy can be produced monthly, thus making the site very suitable for wind turbine applications in power generation (Balarabe et al. 2014).

Table 3.20: PM and CM time for the components

Component	μ_p (time units)	μ_c (time units)
Bearing	0.10	10
Main Shaft	0.30	
Gear	0.50	
Generator	0.20	

Since the reliability of the components/system was modelled based on Weibull law, table 3.21 provides the Weibull scale and shape factors of each component considered. For the purpose of this paper, an average wind speed of 4m/s was chosen for the climatic and operational condition

of the turbine as well as the environmental conditions which are shown on table 3. We also assumed that the maximum heat generated within the gearbox and the generator does not exceed 100J. The weight associated with the index (b) was analysed and adopted from the work of (Bouzoubaa, 2021b) and included on table 3.22.

Table 3.21: Weibull parameters of the component/subcomponent

Component	Sub-component	β_i	η_i
Main Bearing	-	1.43	6389
Main Shaft	-	1.09	3835
Gearbox	Gears	2.50	5715
	HSS Bearings	1.52	7244
	IMS Bearings	3.63	4694
	Keyways	0.84	101790
Generator	Bearings	1.39	4956
	Windings	-	7158

Table 3.22: Operating condition of the turbine

Component	Type of operating condition	Severity index (z)	Weight associated with the index (b)
Main Bearing	-	-	
Main Shaft	Alignment	0	-0.189
	Loading	0	1.143
Gearbox	shock	0	-1.164
	wear	1	0.921
	loading	0	-0.425
	Thermal heating	0	-0.689
Generator	Vibration	0	0.231
	Thermal heating	0	-1.462

3.5.2.1 Wind production results and discussion

Production planning shows the quantity of energy produced per period by a turbine and the optimal number of turbines required per period. In the second subsection, availability maximization of the power plant is presented showing the optimal maintenance plan for the system with maximum availability and optimal number of maintenances and the results presented in this section. We can recall the optimal production plan for wind energy from the machine learning techniques in chapter 2 are presented. Based on the optimal plan, we developed the availability maximization maintenance plan in this chapter. To refresh the readers mind, we present the optimal production plan on tables 3.23 and 3.24 below for ANN and SVR techniques respectively.

Since all turbines are assumed to have similar output, maintenance planning was done considering one (1) wind turbine which can then be applied to the rest of the turbines in the system.

For each of the production techniques, an availability maintenance is proposed factoring the environmental and operational condition and the results are presented.

Table 3.23: Optimal wind production planning for ANN approach

Period (k)	Number of wind turbines (wt)	Power generated (x10 ⁵ W)
1	2	1.2238
2	2	1.1111
3	2	1.5661
4	3	1.5803
5	2	1.4624
6	2	1.5834
7	2	1.3508
8	2	1.0183
9	2	1.2787
10	1	0.9576
11	1	0.7727
12	2	1.4688

Table 3.24: Optimal wind production planning for SVR approach

Period (k)	Number of wind turbines (wt)	Power generated x10 ⁵ (W)
1	3	2.300
2	2	1.730
3	2	1.880
4	3	2.760
5	2	1.840
6	3	2.110
7	3	2.030
8	2	1.990
9	2	1.490
10	2	1.570
11	2	1.460
12	3	2.180

3.5.2.2 Wind maintenance planning result and discussion

We evaluated the maximum availability of the system based on the already discussed methods of production plan based on machine learning- the ANN and SVR. In figure 3.12, maximum availability based on SVR is presented. From the analysis performed, we obtained that when two maintenance procedures should be carried out in order to achieve maximum availability throughout the production horizon. In this case, an availability of 99.87% is achieved when 2 maintenances are planned.

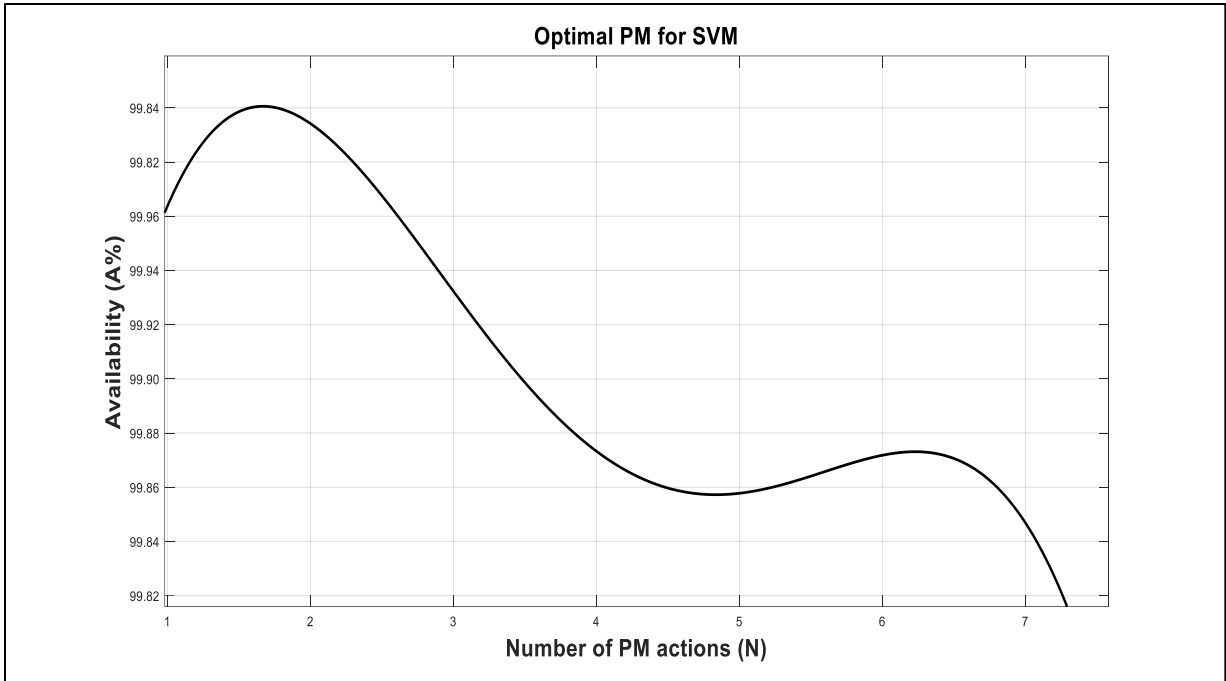


Figure 3.12: Optimal maintenance plan with SVR

With the ANN, three maintenance procedures should be planned to achieve maximum availability. In this case, availability of 99.92% is the maximum achieved availability at optimal plan of 3 as represented in figure 3.13. The components selected for maintenance during each maintenance period for both ANN and SVR are presented on tables 3.25 and 3.26.

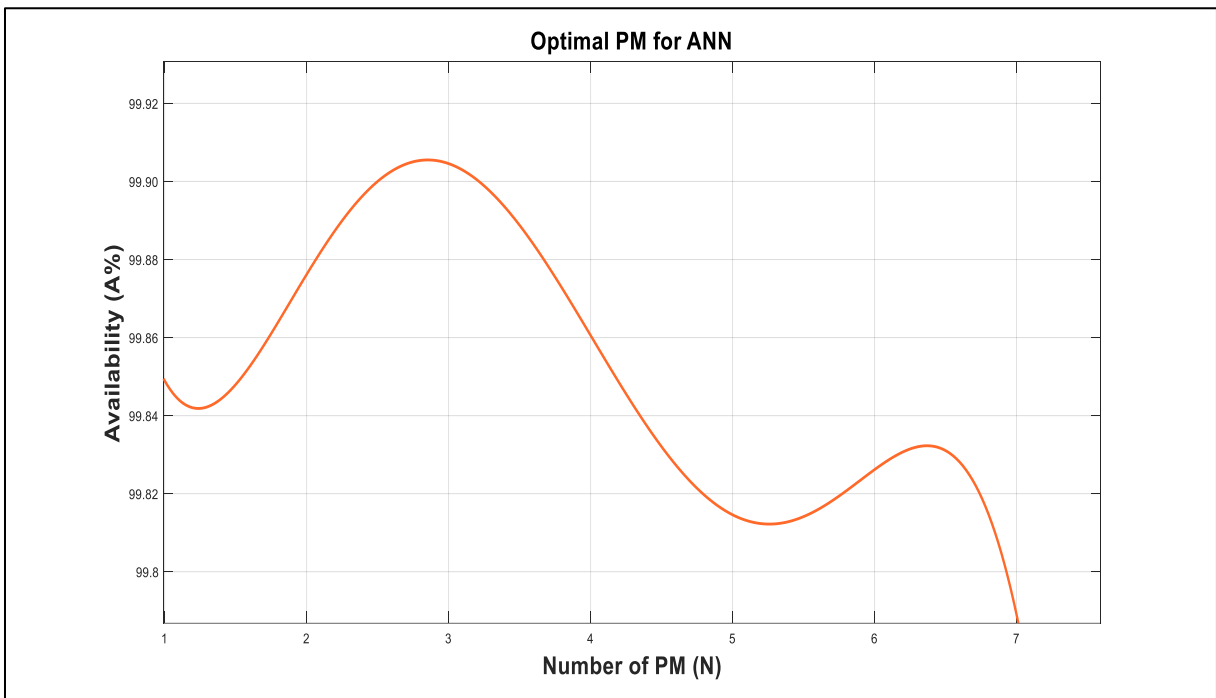


Figure 3.13: Optimal maintenance plan ANN

The components selected considering the ANN are bearing, gearbox and generator are the components selected for maintenance during the first maintenance plan. Only gearbox is selected during the second maintenance plan, while at the end, all components are to be replaced as seen on table 3.25. From table 3.26 for the SVR, the Main shaft and Gearbox for the first maintenance period while all components are replaced to mark the beginning of a new production horizon.

Table 3.25: Components selected for maintenance during PM with ANN

Period	Bearing	Main shaft	Gearbox	Generator
666	x	x	-	x
1333	-	-	x	-
2000	x	x	x	x

Table 3.26: Components selected for maintenance during PM with SVR

Period	Bearing	Main shaft	Gearbox	Generator
1000	-	x	x	-
2000	x	x	x	x

We can establish that in addition to power production rate influence on maintenance plan, selective maintenance also has an influence because different components are selected during PM session and each component has a different maintenance time.

3.5.2.3 Sensitivity analysis for wind energy system

We determined the optimal plan by varying some parameters so that we can determine their various effects on the optimal maintenance plan based on availability. First, we make very large time difference between the preventive and corrective maintenance time, we also check the influence when the difference is minimal and finally, we determine the influence of selecting a good reliability threshold.

a) Influence of large difference between corrective and preventive maintenance times

This analyses the impact that a wide time difference between the 2 maintenances time has on the optimal maintenance plan. From table 3.27, when the corrective maintenance time is increased to 20-tu, the optimal maintenance plan (N*) for both ANN and SVR are obtained to be 3, when increased to 30-tu, it remains 3 with SVR but increases to 4 with the ANN technique. Further increase in the corrective time to 40 and 50-tu, the optimal N is further increased to 5 for both techniques. This shows that the further the difference between corrective and preventive maintenance time, the more maintenance is required.

Table 3.27: Optimal PM plan for large time difference between CM and PM time

CM time (tu)	N* (ANN)	N* (SVR)
20	3	3
30	4	3
40	5	5
50	5	5

When the time difference between PM and CM is large ($\times 10^2$), further increasing the CM time increase N^* for both techniques. Considering the result on table 3.27, tables 3.28-3.31 expatiates the selected components for maintenance for each of the chosen CM time.

Table 3.28: Selected components when μ_c is 20-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	666	-	x	-	-
	1334	x	-	x	x
	2000	x	x	x	x
SVR	666	x	-	-	x
	1334	-	x	x	-
	2000	x	x	x	x

On table 3.28, only Main shaft is selected for maintenance in the first streak with the ANN. While bearing, gearbox and generator are all to be replaced at the second maintenance streak. The case is different with the SVR technique in which bearing and generator are the components for replacement in the first streak while main shaft and gearbox are to be replaced in the second maintenance streak.

Table 3.29: Selected components when μ_c is 30-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	500	-	x	x	-
	1000	x	x	-	-
	1500	-	x	x	x
	2000	x	x	x	x
SVR	666	x	-	x	-
	1334	-	x	-	x
	2000	x	x	x	x

From table 3.29, main shaft and gearbox are to be replaced for the first maintenance, bearing and main shaft in the second then, main shaft, gearbox and generator are the components for the third maintenance session with the ANN method. Considering the SVR, the generator is the first to be replaced, followed by bearing and main shaft, then shaft, gearbox and generator and finally shaft and generator. Here, it is expected that the generator reliability drops more often than the rest of the components.

Table 3.30 is when the corrective maintenance time unit is increased to 40, main shaft is the first to be replaced, then bearing and generator for the second session. In the third session, main shaft, gearbox and generator are to be replaced and bearing, main shaft and gearbox are the components selected for the fourth maintenance session. In the last part, when the corrective maintenance time is 50-time units, main shaft and bearing are to be replaced more often (3 times) while the other components; gearbox and generator are to be replaced twice with the ANN technique as shown on table 3.31. For the SVR analysis, bearing is to be replaced twice, main shaft twice, gearbox three times while the generator only once.

Table 3.30: Selected components when μ_c is 40-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	400	-	x	-	-
	800	x	-	-	x
	1200	-	x	x	x
	1600	x	x	x	-
	2000	x	x	x	x
SVR	400	-	-	-	x
	800	x	x	-	-
	1200	x	-	x	x
	1600	-	x	-	x
	2000	x	x	x	x

Table 3.31: Selected components when μ_c is 50-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	400	x	x	-	-
	800	x	-	-	x
	1200	-	x	x	x
	1600	x	x	x	-
	2000	x	x	x	x
SVR	400	x	-	-	-
	800	-	x	x	-
	1200	-	x	x	-
	1600	x	-	x	x
	2000	x	x	x	x

b) Influence of small difference between corrective and preventive maintenance times

Considering minimal difference between corrective and preventive maintenance as shown on table 3.32. In this analysis, we can spot some variation in optimal maintenance plan with the 2 techniques. For both ANN and SVR, the optimal is 3 when the corrective time is 2-tu, when increased to 3 and 4-time units, the SVR optimal remains 3 while the ANN reduces to 2, at 5-time units, the optimal for SVR techniques reduces to 2 while the ANN remains 2 as well. The shows that very little time difference between corrective and preventive maintenance times could lead to increased unnecessary maintenance plans while larger difference could also lead to the same wastages. We can say that when the difference is small (x10), increasing the CM time reduces N* for both ANN and SVR.

For this analysis, the components selected for maintenance based on the above table are presented on tables 3.33-3.36. When corrective time unit is 2, each component is replaced once during maintenance in both methods as shown on table 3.33. In 3.34 however, three components out of the four components with the exception of main shaft are replaced during maintenance

considering the ANN method. With the SVR, each component is replaced once until the end of the production horizon.

Table 3.32: Optimal PM plan for varying the maintenance time

CM time (tu)	N* (ANN)	N* (SVR)
2	3	3
3	2	3
4	2	3
5	2	2

Table 3.33: Selected components when μ_c is 2-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	666	-	x	-	-
	1334	x	-	x	x
	2000	x	x	x	x
SVR	666	x	-	-	x
	1334	-	x	x	-
	2000	x	x	x	x

Table 3.34: Selected components when μ_c is 3-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	1000	x	-	x	x
	2000	x	x	x	x
SVR	666	x	-	-	x
	1334	-	x	x	-
	2000	x	x	x	x

When the time unit is 4, 2 bearing and generator are the components to be replaced considering the ANN technique, but with the SVR, bearing and main shaft are selected for the first maintenance session and main shaft, gearbox and generator are to be replaced in the second session as seen on table 3.35. On table 3.36, only generator is to be replaced with the ANN but with the SVR method, main shaft, gearbox and generator are the components selected for replacement.

Table 3.35: Selected components when μ_c is 4-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	1000	x	-	-	x
	2000	x	x	x	x
SVR	666	x	x	-	-
	1334	-	x	x	x
	2000	x	x	x	x

Table 3.36: Selected components when μ_c is 5-time units

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	1000	-	-	-	x
	2000	x	x	x	x
SVR	1000	x	-	x	x
	2000	x	x	x	x

c) Influence of reliability threshold

Reliability analysis of the components is an important factor in keeping the system safe with high dependence. For this, we varied the reliability threshold to 80, 90 and 95% respectively in order that we achieve the optimal maintenance plan for each. From table 3.37, considering the 2 production techniques, when the threshold is at 80%, the optimal maintenance is expected to be 2 for ANN techniques with a maximum availability of 99.90% and 2 maintenances at 99.69% availability for SVR. When the threshold is increased to 85%, the optimal is seen to increase to 3 at 99.87% with the SVR technique while remain 2 with the ANN technique at 99.92% availability. At 95% reliability, there is further increase in the optimal maintenance plan for both ANN and SVR. An optimal of 3 at 99.96% and 5 with 99.93% availability respectively for both cases. We can say that to guarantee maximum reliability, it is logical to increase the optimal number of preventive maintenances which at the same time increases maximum availability as can be seen in both cases.

Table 3.37: Optimal PM plan for varying the reliability threshold (R^*)

R^* (%)	ANN		SVR	
	N^*	A (%)	N^*	A (%)
80	2	99.90	2	99.69
85	2	99.92	3	99.87
95	3	99.96	5	99.93

In the following tables, for each of the reliability threshold presented, the components selected for maintenance are presented. On table 3.38 when the corrective maintenance time unit is 2, the bearing and gearbox are expected to be replaced once during the maintenance period with the ANN technique while main shaft and generator are to be replaced during maintenance period with the SVR. Generally, considering the components selection, either of the techniques is a good choice since the optimal for both is the same. Nonetheless, since our consideration is based on availability, we would say that using the ANN production technique for maintenance is our optimal.

Table 3.38: Selected components 80% reliability threshold

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	1000	x	-	x	-
	2000	x	x	x	x
SVR	1000	-	x	-	x
	2000	x	x	x	x

For the 85% reliability threshold, table 3.39 presents the components selected for each of the techniques. Two maintenance sessions are required with the ANN while three are required with the SVR. From the table, mains shaft and Gearbox are expected to be replaced during the first maintenance session for the ANN. Using the SVR technique, gearbox and generator are the components for the second session for maintenance during the first maintenance session. Bearing. In the second maintenance, main shaft, bearing and the generator are the components selected for replacement.

Table 3.39: Selected components for 85% reliability threshold

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	1000	-	x	x	-
	2000	x	x	x	x
SVR	666	-	-	x	x
	1334	x	x	-	x
	2000	x	x	x	x

On the last analysis shown on table 3.40 for 95% reliability, the optimal for ANN is three and that of SVR is five. For the ANN, main shaft is the only component for maintenance in the first maintenance streak, and the other remaining 3 components; bearing, gearbox and generator are the selected components to be replaced in the second session. With the SVR, the gearbox is expected to fail and be replaced in the first session. During the subsequent sessions, bearing and main shaft are selected twice, gearbox once during the fourth maintenance while the generator is selected 3-times during all the sessions except the first.

Table 3.40: Selected components for 95% reliability threshold

Technique	Period	Bearing	Main shaft	Gearbox	Generator
ANN	667	-	x	-	-
	1334	x	-	x	x
	2000	x	x	x	x
SVR	400	-	-	x	-
	800	x	-	-	x
	1200	x	x	-	x
	1600	-	x	x	x
	2000	x	x	x	x

From the above sensitivity analysis, we understand that the production rate has a strong influence on the turbine because more components are replaced during maintenance considered with the SVR technique than with the ANN technique. By highlighting the superiority of the ANN, we recommend that companies should adopt this technique during decision-making to integrate the implementation when designing a new project. It is also a base for continuous performance evaluation to evaluate the model impact on energy optimization by comparing actual energy consumption with predicted values, and assess the achieved benefits, such as energy savings, cost reductions, or environmental impact.

3.6 Conclusion

In this chapter, we developed maintenance planning models for solar power plant and wind farm which maximizes each of the system's availability. For each of the model, the algorithm calculates and selects the minimum maintenance time (i.e minimum downtime) in order to maximize availability. Selective maintenance process was imbibed in order to select components during maintenance based on a prescribed criterion; reliability threshold. We set a minimum reliability for each system on which the selection is based such that during maintenance, the reliability of each component is calculated and gauged with the threshold. When the reliability of a component falls below the threshold, the component would be replaced in order that it improves the reliability of the system.

The novelty of this work is that, the reliabilities of both solar and wind energies were modelled based on environmental and operational conditions. In the solar study, the major environmental condition affecting each of the considered component was stated and maintenance was planned considering the influence of those climatic condition on the overall system. We determine the optimal maintenance plan first under nominal condition (ideal) and then we did the same considering the environmental influence on the components. From the result we obtained, the optimal maintenance plan for both conditions are found to be 2. However, availability of 99.77% is maximum under ideal condition as expected, while reduced with the consideration of the environmental impact having availability of 99.72%.

In the analysis of the wind energy, the influence of the operational condition was considered in addition to the climatic condition. This is because a wind turbine comprises of rotating parts from the turbine blades, the shafts and the gears. Due to that, wears and other mechanical properties of the turbine components can deteriorate and reduce the turbine efficiency. Another factor we considered in the wind maintenance planning was the impact of the production rate on the maintenance. We modelled the maintenance strategy such that all the production was integrated into the maintenance plan. The maintenance plan was based on the two (2) production planning techniques by machine learning considered in this manuscript; ANN and SVR. For each of the production technique, a maintenance plan was established. We found that with the SVR technique, the optimal maintenance plan is two (2) and that of the ANN, the optimal plan is three (3). When considering the maximum availability, the ANN presents the system with maximum availability of 99.92% while the availability under the with the SVR production plan was 99.87%. From this, we could see that the production rate has an influence on the maintenance plan. The SVR has lower availability percentage despite of it having the lower optimal number of maintenances to be performed. As mentioned in chapter 2, ANN has better capability of fitting well with the data because of its ability to learn and adjust its learning rate easily without dimensionality problem which is often encountered with the SVR.

We also performed sensitivity analysis on each of the system by varying the difference between the corrective maintenance and preventive maintenance times to understand its effect on maintenance, by varying the climatic condition as well as the reliability threshold on the systems.

We can conclude that; for solar analysis, corrective maintenance time influences the N^* but not so much on the availability since the process is a selective strategy. We can also say that reliability threshold influences both the N^* and the availability, and when considering the environmental impact, it causes a decrease in availability. With the wind energy, when the time difference between PM and CM is large ($\times 10^2$), further increasing the CM time increase N^* for both techniques. However, where, the difference is small ($\times 10$), increasing the CM time reduces N^* for both ANN and SVR. Considering the reliability threshold selection, increase in the threshold increase N^* but has no much influence on the availability.

CHAPTER 4: Development and optimization of an integrated energy production and maintenance strategy minimizing the Economic Losses under reliability constraints

In this chapter, we present optimal integrated production - maintenance strategies for a solar power plant and wind farm. We developed an optimised maintenance cost model applied to both solar plant (Sokoto power plant, Nigeria) and wind farm (Katsina wind farm, Nigeria) combining each of the maintenance strategies developed in the previous chapters (perfect, then combined imperfect/selective). Our goal is to simultaneously determine the optimal energy production and maintenance plan characterized by the quantity of energy stored and the losses incurred when the energy demand is unmet. Our strategy is to minimize the expected total lifecycle cost of the energy production system (generation, storage and shortage) as well as maintenance over a limited time horizon. Thus, determining the economic plan of energy production and the optimal number of maintenances to be performed that yields maximum reliability associated with the cost. To that effect, a reliability threshold constraint was imposed on the model in order that maximum reliability is achieved to the maintenance cost model. Hence, developing relationship based on reliability to minimize the downtime, and the failure rate as well. At the end, a numerical example is presented to validate the developed model for both cases; Sokoto solar power plant and Katsina wind farm in Nigeria.

4.1 Introduction

Rural electrification programs especially in developing nations is an important challenge that has to be dealt with. According to International Energy Agency (IEA), in 2020, there were about 7.8 billion people around the world, having about 15% of world population living without electricity out of which 85% live in rural areas in developing countries (Dalla Longa & van der Zwaan, 2021). Enormous number of private utility companies, which provide electricity are unwilling to electrify the isolated areas because it is too expensive to pass electric lines to the inaccessible parts characterized with low load factors. Additionally, some utility companies also claim that, the people living in these areas are too poor to be able to afford electricity. Development in the urban areas takes place on social, political and economic grounds whereas development in rural areas is neglected and overlooked. More than one-thirds of the populations of developing countries live in rural areas where there is a lack of access to the national grid and funds for the development of these areas are limited. Hence, importing the needed resources makes the situation financially unsustainable. Supplying electricity from a central grid is also inefficient and unfeasible because these areas are isolated with low loads leading to high transmission and distribution costs (Ramakumar, 1977). The difficult topography in many rural regions also increases costs of infrastructural development significantly.

Energy supply aids education and welfare of rural regions by providing adequate electricity and communication. With modern renewable energy systems, it is feasible to achieve abundant access to power supply in the near future (Mosbah & Iqbal, 2018). The current renewable industry is characterised by strong competition to satisfy the needs of a client often demanding in terms of energy availability, and cost. However, due to the stochastic nature of the renewable source, appropriate planning must be carried out to ensure customers' needs are met and satisfied. To remain competitive, the renewable energy companies must control operating costs and optimise the production facilities to be able to supply energy and at minimum cost of energy (COE) since generation cost invariably affects the selling cost of the energy.

Modern-day manufacturing processes are now more refined in many advanced industries which lead to upsurge in internal uncertainties in the manufacturing systems. The use of contemporary technology, intricate equipment, complex tooling requirements, are all factors that make it difficult to maintain a predictable level of output (Hwang & Singh, 1998). Often times, newer and more profitable products face even greater uncertainty because the industry has not yet accumulated enough learning experience with the equipment and processes to reduce the variance. However, production needs to be carried out in an economic manner, despite the integral variabilities in the system. In fact, the fundamental objective of production systems is the systematic elimination of waste by focusing on production costs, product quality and delivery, and personnel. Until recent, one of the first actions in industrial decision making is the determination of optimal production plan which minimizes total production cost. This forms the base for the decision-making hierarchy where optimal inventory and lost demands are considered. To minimize the above-mentioned industrial problem and determine optimal production plan, many researchers developed optimization models to minimize production costs under various constraints. For a stochastic manufacturing system comprising of a single machine subjected to constant demand, Sethi et al., (1997) defined an optimal production plan taking into account the rate of production over a finite time in order to minimize wastage of over production and the total average production cost. More recently, using a heuristic approach, Dahane et al., (2012) considered a single randomly failing and repairable manufacturing system producing two products by genetic algorithm. The optimal production rate of first product and the optimal duration of the production interval of the second product were determined simultaneously during each production period in the production horizon to ensure maximum the expected profit. Hajej et al., (2015) developed a production strategy on a manufacturing system comprising several identical machines arranged in parallel under withdrawal and leasing constraint.

Nonetheless, the case of renewable energy is not far from the industrial set-up since they both comprise of manufacturing units and product/service delivery to satisfy customer demand. In the renewable energy especially solar and wind energies, the main challenge faced by the industry is the intermittent nature of the resource. Therefore, many works have dealt with the production optimization process by considering different optimization strategies. In this context, we can cite the work of Mansour & Djallel, (2017) who studied the procedure for optimizing a wind farm operating in solar, wind and battery storage. Kahla et al., (2017) presented an optimization model maximizing the power of the wind turbine. Hossain Lipu et al., (2017) studied the

optimization design of hybrid renewable energy systems. From the point of view of reliability, in recent years, renewable energy has become an effective way to achieve sustainable development, and is influenced by several factors in terms of reliability degradation. In this context, wind variability is considered to be an important factor that has a major effect on the availability of wind power equipment and the consideration of climatic variation as a constraint for the application of maintenance actions (preventive and corrective maintenance). In this study, the renewable energy development concept is established in terms of modelling and optimization. A stand-alone renewable system makes isolated rural areas self-sufficient for basic needs such as cooking, pumping water and electricity in a cost effective and efficient manner, without the need for central grid. In order to optimize the sources, the manager needs to efficiently optimize the number of components (solar panels, wind turbines and batteries) required to satisfy the demand. This work considers the case where there is generation and storage shortage on the system. In this case, outsourcing or buying energy from another company or grid becomes necessary.

Implementation of the renewable energy system is therefore proposed and the system is optimized to minimize cost and improve reliability. Energy production is generally associated with losses especially maintenance losses. To minimize these economic losses, Wang et al., (2022) developed strategy for optimal cleaning of a PV system. The authors proposed a risk-taking tendency (RTT) factor to reduce the uncertainty in energy production forecasting to minimize economic losses of cleaning the system. Also in Tanesab et al., (2018), PV cleaning solution was proffered considering different scenarios for dust accumulation on the PV panels and its effect on the PV production. However, the effect of maintenance time and its consequential energy and economic losses were not taken into account. On another hand, wind energy is a highly capital-intensive technology, it also requires highly skilled economic evaluation especially for its maintenance. In that framework, Blanco, (2009) presented strategies for both onshore and off-shore wind farms solving the problem of production cost minimization taking into account the operational and maintenance costs and minimizing the economic losses associated with it. Efforts were also made by Kerres et al., (2015) to minimize the economic losses by developing a stochastic strategy for wind turbine maintenance presenting an optimal life-cycle cost analysis for the system where the suggested that the cost benefit of the maintenance increases the price of electricity. In this context, we developed a new integrated maintenance strategy for minimizing the total production cost of solar/wind systems.

Thus, our developed strategy takes into account the implication of shortage and loss of production costs. In this case, the energy production and battery storage are not able to meet the load demand due to the loss of production throughout the significant and non-negligible duration of preventive and corrective maintenance actions. The main objective of this chapter therefore, is to simultaneously optimise production and maintenance in order to minimise the total cost of production, storage, shortage and loss of production taking into account the implication of time for preventive and corrective maintenance. Conclusively, this work consists of developing and optimizing maintenance strategy integrated constrained to reliability threshold into an economic production plan by comparing between ANN, SVR and analytical method.

This chapter is organized as follows: Problem statement and motivation for this work is presented in section 4.2. In section 4.3, integrated maintenance strategy for solar PV was discussed. Wind energy maintenance strategy is discussed on 4.4. To validate the algorithm, numerical example is developed and the results discussed in section 4.5 while conclusion is drawn in section 4.6.

4.2 Description of the problem

In order to improve the efficiency and performance of our case study, we have proposed an integrated maintenance strategy to optimize the systems. The maintenance strategy developed makes it possible to establish an optimal maintenance plan defined by optimal number of preventive maintenance sessions (N^*) to be performed, to reduce the average number of failures. Indeed, corrective maintenance actions are subject to unforeseen breakdowns which require interventions in the middle of the production cycle, which is more expensive. While preventive maintenance actions are scheduled within the finished production horizon, so as to be applied at specific times in order not to disrupt the production cycle and minimize the total cost while also improving the reliability. Thus, we solve the problem of energy production optimization by using ANN, SVR and analytical methods, taking into account an optimal maintenance plan constrained to reliability maximization, in order to satisfy a random demand of energy over a finite horizon and minimizing the production and economic losses for wind and solar PV

4.3 Maintenance strategy integrated into PV and wind energy; minimizing costs

This section deals with developing maintenance strategy for solar PV and wind energy as described below:

4.3.1 Description of the strategy

In this section, we develop a maintenance strategy integrated with production planning for both solar PV and wind energy systems. Based on the observation of the impact of long durations of preventive and corrective maintenance actions on production, failure to meet demands and generate loss of production costs increases. On this account, we developed an integrated production and maintenance model that minimises the total life cycle cost (of production, storage, shortage and loss of production) of the renewable systems. The maintenance strategy considered is the perfect maintenance with minimal repair. This is to determine the optimal number of preventive maintenance (N^*) at minimal cost over a chosen finite horizon. It is an optimization problem constrained to reliability, service rate and power generation of the system such that the reliability as well as the service rate exceed a minimum set threshold. Therefore, it is a priority selective algorithm to select the most critical components to be maintained during preventive maintenance such that its reliability falls below the reliability threshold (R^*) which at the same time minimizes the maintenance downtime to maximize the availability. The PV is considered as a

multi-component system whose components are only maintained in the predetermined maintenance periods N .

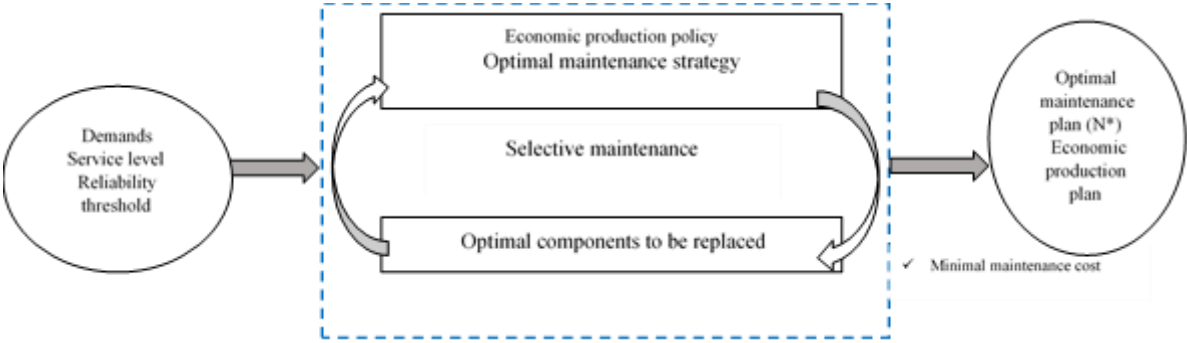


Figure 4.1: Integrated maintenance strategy

Our strategy therefore, combines preventive and selective maintenance strategy to decide the best combination which results optimal number of preventive maintenance action at minimal cost. Figure 4.1 represents a simple scheme of the strategy. At each selective maintenance period $k = 1, 2, \dots, N^*$, the objective of priority selective maintenance is to select the right components $i = 1, 2, \dots, N_c$ to be maintained, so that a required reliability level is guaranteed until the next shutdown. While doing so, the algorithm also selects the best combination that ensures that the system reliability is greater than the reliability threshold (R^*), satisfies the service rate and at minimal cost. With this technique, the time duration of maintenance is minimized since not all components could be selected at preventive maintenance time. Consequently, when all the components are selected for maintenance, a perfect preventive maintenance is considered. This implies that all components will be replaced and the system is restored to AGAN condition with near zero failure rate shown in figure 4.2 and maximum reliability. Conversely, some components are selected, an imperfect maintenance is performed. This reduces the failure rate of the system but does not make the system AGAN.

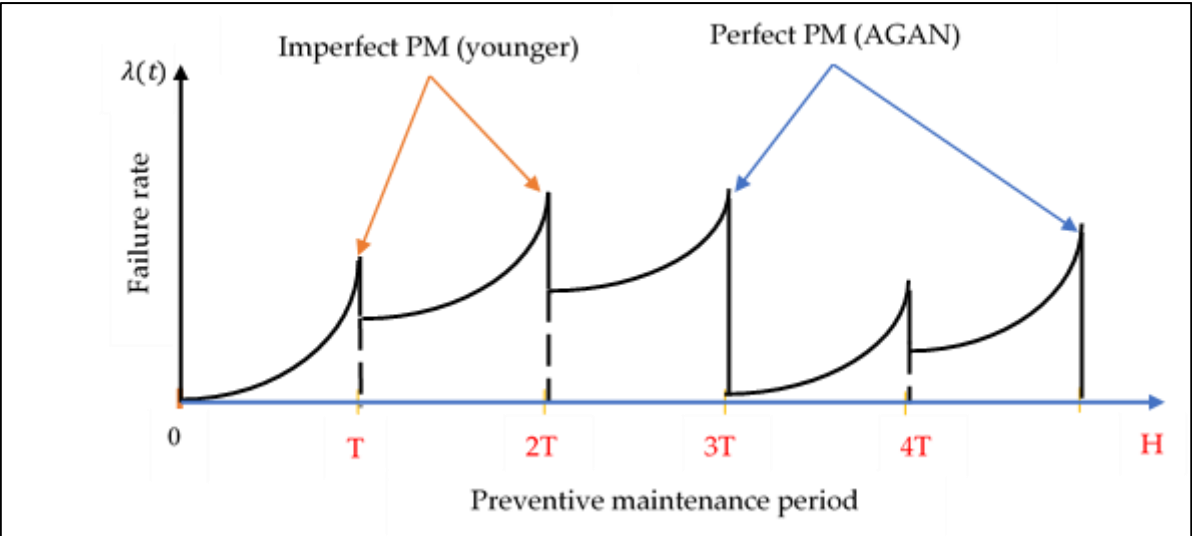


Figure 4.2: Evolution of failure rate with maintenance

Assumptions

1. The maintenance strategy involved in this work is preventive maintenance with minimal repair.
2. Maintenance is performed over a finite horizon H.
3. The time interval between successive preventive maintenance is equal time.
4. During preventive maintenance, perfect maintenance is considered on the component.
5. Imperfect maintenance on the PV or wind system is otherwise considered when fewer components are replaced
6. Minimal repair is performed at failure.

4.3.2 Optimization model of production and maintenance cost

In this section, we propose an optimization production and maintenance model applied for the PV or wind system in order to minimize the total cost of production, storage, shortage and loss. In this case, the loss cost is characterized by lost production during periods of system downtime due to maintenance periods. The decision variables are the economic production plan and the optimal number of preventive maintenance as well as the replaced components minimizing the total cost. The mathematical model for maintenance cost minimization of both PV and wind system is expressed below:

$$\min C = \min \sum_{k=1}^H \left(\underbrace{C_p \cdot P_k + C_s \cdot S_k + C_l \cdot S_l}_{\text{production+storage+shortage costs}} \right) + \underbrace{C_{post}}_{\text{loss cost}} \quad 4.1$$

S_k is the quantity of energy stored in the battery and S_l is the quantity of energy lost that needs to be outsourced in order to satisfy the demand. C_{post} is the production loss cost due to the maintenance actions duration expressed by the following:

$$C_{post} = C_{sell} \times \frac{\sum_{k=1}^H P_k \times (T_{\text{maintenance}}(N))}{H} \quad 4.2$$

With the $T_{\text{maintenance}}(N)$ characterized by the maintenance actions duration is expressed by the following equation:

$$T_{\text{maintenance}}(N) = \underbrace{\sum_{j=1}^N \sum_{i=1}^{NC} [\mu_{P_i} \times m_i(j)]}_{\text{preventive maintenance duration}} + \underbrace{\mu_c \times \varphi(N)}_{\text{corrective maintenance duration}} \quad 4.3$$

Subject to

$$\begin{aligned} & 0 < P_k < P_{max} \\ & (P(S(k) > 0) > \theta \\ & R_{PV}(t) > R^* \text{ for the PV system} \\ & R_{WT}(t) > R^* \text{ for the WT system} \\ m_i(k) &= \begin{cases} 1 & \text{if the } i^{\text{th}} \text{ component is to be replaced} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

$i \in \{1, 2, \dots, NC, \}$: i^{th} Subcomponent;

NC : Number of subcomponents;

$k \in \{1, 2, \dots, N\}$: Maintenance period

$m_i(k)$ is a binary vector string for the components such that it equals 1 if the component is to be replaced and 0 if maintenance is not to be performed. The average number of failures and the failure rate is expressed in equations 4.4-4.7 for wind and PV systems respectively;

$$\varphi(N) = \sum_{k=0}^{N-1} \left[\int_{k.T}^{(k+1).T} \lambda_{wt}(t) dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{wt}(t) dt \quad 4.4$$

$$\lambda_{wt}(t) = \frac{-dR_{wt}(t)}{dt} \quad 4.5$$

And

$$\varphi(N) = \sum_{k=0}^{N-1} \left[\int_{k.T}^{(k+1).T} \lambda_{PVk}(t) dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{PVk}(t) dt \quad 4.6$$

$$\lambda_{PV,k}(t) = \frac{-dR_{PV,k}(t)}{dt} \quad 4.7$$

As explained in chapter 2, we consider that the storage and shortage are expressed in terms of the battery SOC as shown below:

$$C_s = \left(C_s^+ \times \Delta t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)>0}) \right) \quad 4.8$$

$$C_l = \left(C_s^- \times t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)<0}) \right) \quad 4.9$$

With the storage condition on the battery's state of charge being

$$1_{SOC(t)>0} = \begin{cases} 1 & \text{if } SOC(t) > 0 \\ 0 & \text{otherwise} \end{cases}$$

and that of shortage condition on the battery's state of charge being

$$1_{SOC(t)<0} = \begin{cases} 1 & \text{if } SOC(t) < 0 \\ 0 & \text{otherwise} \end{cases}$$

C_s^+ is the cost storage per unit kW, C_s^- is the cost of shortage per unit kW and P_k is the total power generation within production period k (determined by the analytical and machine learning approach). We assume that the quantity produced in period k is added to the inventory at the end of the period which satisfies the demand P_L .

To quickly recap the battery sizing problem formulation, we express the SOC in the following form:

$$SOC(t) = SOC(t - 1) + \frac{P_G(t) - P_L(t)}{V_b \cdot TC_b} \quad 4.10$$

The SOC depends on the past data and the power in the battery system which is the difference between the generated power $P_G(t)$ and the power load demand $P_L(t)$ at every time instance t . With V_b and TC_b are the voltage and total capacity of the battery respectively and $P_G(t)$ is expressed as

$$P_G(t) = \sum_{t=1}^H N_{pv} \times P_S(t) \quad (PV \text{ system}) \quad 4.11$$

$$P_G(t) = \sum_{t=1}^H N_{wt} \times P_{wt}(t) \quad (Wind \text{ system}) \quad 4.12$$

N_{pv} and N_{wt} are respectively the number of panels and wind turbines generating energy per period, and $P_S(t)$ and $P_{wt}(t)$ are the total power generated respectively per panel and wind turbine. Since all the panels and wind turbines are identical with similar power rating, it is assumed that the power generated per panel for the PV system and wind turbine for the wind system is the same. The reader can refer to chapter 2 for detailed explanation.

4.4 Formulation of the integrated maintenance strategy

This subsection deals with the development of integrated production maintenance strategy for solar power as well as wind energy plans taking into account the production cost, the storage as well as the shortage cost in to the maintenance planning constrained to reliability, power production and the service rate.

4.4.1 Production strategy formulation (reminder)

Having defined and formulated the optimization problem, the power generated is then modelled based on the machine learning and analytical techniques in the previous chapters. Due to the volatile nature of solar and wind energy, it is not always easy to plan simple activity because the sources are random and stochastic. Solar and wind power generation therefore is a challenging task that requires an understanding of the functionality and reliability of solar panels/ wind turbines and its components to ensure customer satisfaction. Facing all these tasks at the same time requires careful study and planning in advance. To solve the problem therefore, we propose a model to carefully plan the energy production considering the production rate and a level of storage. The objective of the production strategy is to optimize the production system by minimizing the costs linked to the production cycle over the finite time horizon H . Recall that our production horizon H is divided into k equal periods of length with $k:1, \dots, H$ as shown in the following figure:



Figure 4.3: Planning horizon

As for the battery storage system, it provides the electric power to supply the load demand when there is a power shortage from production and stores the surplus energy when the generated power exceeds the load. In this section, we mainly focus on the costs related to the production and storage of energy. It is possible to satisfy the demand during each period k in different ways:

- Using the quantity produced during period k ;
- Using the quantity stored in the battery if sufficient.
- When these are not sufficient, we consider buying from outside (incurs cost due to loss).

In this context, it can be said that storage is essential to ensure the smooth demand supply. This leads us to talk about an important concept in the industrial field, which is the concept of service level. In business, service level is a performance metric used to measure customer service satisfaction in supply organizations. In the manufacturing industry, the service level is almost the same defined and considered as a major factor used to describe business performance. In fact, it measures the ability of an industry to meet the demand and requirements of its customers in a timely manner. This service level can be expressed in several terms:

- probability of failure;
- estimated number of failure;
- time elapsed between successive cases of failure;

In this work therefore, we consider the first method consisting in expressing the service rate as the probability of non-failure between two successive periods. We illustrate the service rate as:

$$prob(S(k) > 0) > \theta \tag{4.13}$$

With θ minimum level of customer satisfaction (service level threshold)

As expressed in the previous chapters, we refresh the memory of the reader on the production estimation from the artificial neural network (ANN) and support vector regression (SVR). We will therefore refresh the reader of the analytical method considered for the PV and wind energy system as below:

4.4.1.1 Analytic method for PV system

This section talks about the estimation of PV energy from a solar panel as expressed earlier in section 2.4.1.4 of chapter 2. As a reminder, the intermittent nature of solar energy makes it dependent on weather elements for power generation. The solar power output from a panel is

modelled based on the temperature and solar irradiance obtained by the equation (2.27). However, due to other insolation phenomena such dust and cloud cover, solar irradiance is represented as random variable expressed in equation (2.28). A PV panel consists of several solar cells as described in section 2.4.1, therefore, the total obtainable power output from a panel is expressed in equation (2.29).

4.4.1.2 Analytic method for wind system

In this section, wind energy estimation from wind turbine is determined as in section 2.4.2.2 of chapter 2. Recall that wind speed is often treated as a random variable characterized by Weibull distribution function expressed by equation (2.49). The obtainable average wind power P_{wind} from the turbine is estimated by equation (2.51). As previously shown, the total obtainable power from one wind turbine is obtained by equation (2.52).

4.4.2 Maintenance strategy formulation

The maintenance strategy considered in this chapter is the optimization of maintenance cost considered under reliability constraints such that the reliability exceeds certain threshold (R^*). Maintenance is an important factor for sustainable production in industrial systems to ensure continuous operations by considering reliability, plant and machines/components failures and availability. The functionality of any system becomes reduced with aging components and increased usage. This also affects the economic benefits associated with the production system. Therefore, performing preventive maintenance is often implemented to improve the system efficiency and to minimize losses associated with costs. However, when maintenance is rarely performed, failure rate increases which leads to excessive economic losses due to frequent repairs. When performed too often, it leads to material wastage also having an impact on the economic implication of the production system. It is therefore important to find a balance by developing optimal maintenance strategy for minimizing the cost of production loss. We can recall that our problem combines two strongly related sub problems; production and maintenance. Thus, we optimize simultaneously the economical production plan as well as the optimal maintenance plan minimizing the total production, storage and loss cost. To do this, the objective of this section is to determine the optimal period to perform preventive maintenance actions on the solar energy as well as on wind energy system, which is characterized by the optimal number of preventive maintenance actions.

In this case therefore, we must keep in mind that the degradation state of the solar panel as well as that of the wind turbine depends on its energy production rate. Consequently, it is necessary to consider the influence of the production on the degradation of the system in planning of the maintenance subsequently. In our case, to simplify the model, we assume that the realization of a preventive action corresponds to the end of a production period. Preventive maintenance actions must be scheduled periodically over the production horizon $H.\Delta t$. However, between successive preventive maintenance interventions, failures may occur and corrective actions with minimal repair must be implemented. These actions cannot be planned in advance but one can

simply estimate the failure rate which aids in estimating the number of corrective maintenance interventions on $H.\Delta t$ accordingly.

4.4.2.1 Reliability estimation of PV system

We recall from chapter 3 that the reliability of the PV system is complex and contains a large number of sub-assemblies that may be connected in series, parallel or even a combination of both. Extracted from the work of Sa'ad et al., (2021) PV field, DC Wires, inverters and AC Wires are the most sensitive components whose reliability has a major impact on the PV system. Therefore, this work considers the mentioned components arranged in Series. Based on the study carried out in chapter 3, the Overall PV system reliability is expressed below:

$$R_{pv}(t) = R_{panel}(t) \cdot R_{AC-wire}(t) \cdot R_{DC-wire}(t) \cdot R_{inverter}(t) \cdot e^{-\left(\frac{P_k}{P_{max}} \cdot \lambda_n(t)\right)} \quad 4.14$$

Therefore, the reliability of the PV plant with n numbers of panels, wires and inverters is given by equation (3.39). Thus, the reliability estimation of photovoltaic components as a function of environmental conditions using a parametric relationship between environmental and risk factors is expressed as:

$$\begin{aligned} & R_{pvplant}(j, T, Z) \\ &= \left(\left(1 - \left(1 - (R_{panel}(j, T, Z))^{(1-m_i(j))} \right)^{n_{panels}} \right)^{n_{series}} \cdot (R_{DCwire}(j, T, Z))^{(1-m_i(j))^{n_{DCWires}}} \right. \\ & \quad \left. \cdot (R_{inverter}(j, T, Z))^{(1-m_i(j))^{n_{inverters}}} \cdot (R_{ACwire}(j, T, Z))^{(1-m_i(j))^{n_{ACWires}}} \right) \quad 4.15 \\ & \times \frac{e^{\sum \beta_{i,j} Z_i}}{C_{0,j}} \times e^{-\left(\frac{P_k}{P_{max}} \cdot \lambda_n(t)\right)} \end{aligned}$$

4.4.2.2 Reliability estimation of WT system

Referring to chapter 3, we considered the reliability of four turbine components identified to fail often as established by the work of (Bouzoubaa, 2021b; Hajej et al., 2022). Hence, these components make up the most crucial components of the turbine that impacted the reliability of the turbine. These selected components and their subcomponents are: the bearings, main shaft, gearbox and the generator connected in series and the reliability is expressed in equation (3.60). The overall system reliability considered under operational, climatic condition and the influence of the production rate is expressed

$$\begin{aligned} & R_{wt}(t, Z, Z^{CC}) \\ &= \left(2 - e^{-\left(\frac{t}{\Gamma_{mb}}\right)^{\beta_{mb}}} \right) \\ & \quad \left[\left(\left(\frac{t}{\Gamma_{ms}} \right)^{\beta_{ms}} \cdot [e^{b_1^1 z_1^1 + b_2^1 z_2^1}] \right) + \left(\left[\left(\frac{t}{\Gamma_{hss}} \right)^{\beta_{hss}} + \left(\frac{t}{\Gamma_{ims}} \right)^{\beta_{ims}} + \left(\frac{t}{keyway} \right)^{\beta_{keyway}} + \left(\frac{t}{\Gamma_{gear}} \right)^{\beta_{gear}} \right] \cdot e^{(b_2^2 z_2^2 + b_3^2 z_3^2 + b_4^2 z_4^2)} \right) \right. \\ & \quad \left. + \left(\left[\left(\frac{t}{\Gamma_{bearing}} \right)^{\beta_{bearing}} + \left(\frac{t}{\Gamma_{winding}} \right)^{\beta_{winding}} \right] \cdot e^{(b_3^1 z_3^1 + b_3^2 z_3^2)} \right) \right] \\ & \times e^{bZ^{CC}} \times e^{-\left(\frac{P_k}{P_{max}} \cdot \lambda_n(t)\right)} \quad 4.16 \end{aligned}$$

4.5 Algorithm

To achieve the goal of this work, which is determining optimal number of preventive maintenance sessions $N^* \in \{1 \dots\}$ at the same time the minimal total life cycle cost of the system, we therefore developed an algorithm based on the following simple numerical procedure shown on figure 4.7. We built the algorithm to propose an economical production plan by selecting the components whose reliability criticality falls under the set reliability threshold, and customer satisfaction of service rate in order to minimize the total life cycle cost (cost of production, storage, shortage and loss). We start the iteration after the initialization processes (setting maximum number of iterations, input of initial costs etc.) by calculating and optimizing the production process of producing the electricity in order to determine the optimal amount of electricity generated and stored per production period also taking into account the shortage as explained in chapter 2. The production evaluation is performed for both machine learning techniques (ANN and SVR) and the analytical techniques and are used as the input for the maintenance strategy.

An initial start for number of maintenances to be performed is set at 1. Then a binary maintenance vector is generated such that when a component is selected for maintenance, it is represented with 1 and when not, it is represented as zero. Using this vector, the total system reliability is calculated and gauged with the reliability threshold. If the reliability exceeds the threshold, then the total lifecycle cost of the system is calculated and if the reliability doesn't, the system re-iterates the reliability evaluation by re-selecting another vector from the generated vectors. The process is repeated for another value of N ($N = N+1$), this means that for each value of N , the algorithm computes the total lifecycle cost as well as the reliability and selects the critical components for maintenance while also respecting the minimum service rate of reliability threshold. The optimal number of maintenance (N^*) corresponds to the cheapest total lifecycle cost is the optimal cost (C^*) having the highest reliability.

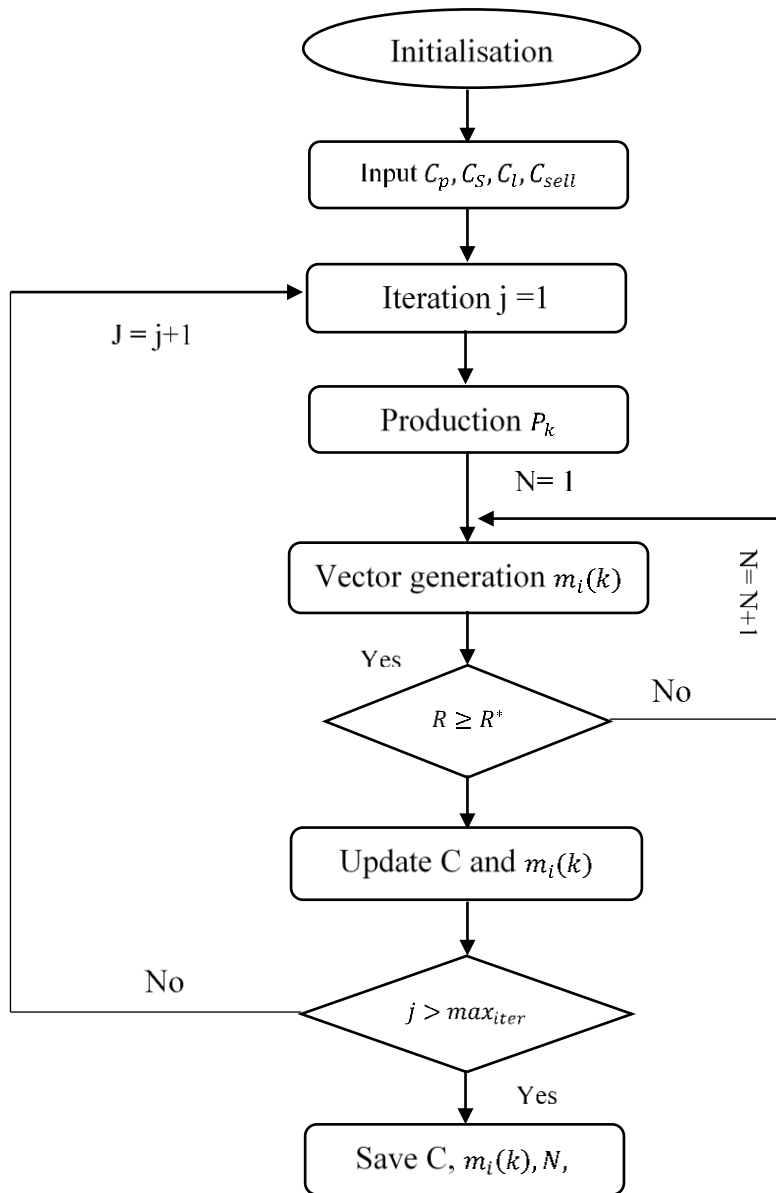


Figure 4.4: Production and Maintenance estimation algorithm

The maintenance strategy adopted is perfect maintenance with minimal repair at failure on the component as explained as follows; Solar or wind energy components maintenance is carried out every $i.T$ period $i(1,2\dots N)$. Preventive maintenance actions considered are replacements allowing to restore the component to AGAN. After a perfect maintenance action, the distribution of lifetimes and the function of the failure rate are the same as those of a new unit. When a failure occurs between two successive preventive maintenance actions, a minimal repair is then carried out. The change in the amount of energy produced by the solar PV and wind turbines during the production horizon H acts on the failure rate of the system. Since all units, (the solar panels and the wind turbines) have the same power ratings in this work, we assume that they have the same power output. Therefore, the maintenance planning is considered for one (1) solar panel and one (1) wind turbine.

4.6 Case study

This section is aimed at demonstrating the viability of our developed algorithm using a solar power plant and a wind farm in Nigeria as the case study. In this example, we recall from chapter 2, the details of the selected sites were established. Considering the customer service rate, we have chosen a threshold of 80% for this algorithm development.

4.6.1 Sokoto PV power plant

For readers' purpose, we recap from chapter 2, the main data necessary for this analysis

- Cost of production = 12 NGN
- Cost of storage = 15 NGN
- Cost of shortage = 25 NGN

The results are presented as follows

4.6.1.1 Production planning

The aim is to carefully plan an optimal production system such that for each production period, an optimal cost of production and storage is determined. The problem formulation is similar to that carried out in chapter 2, with an improvement in this case, which is the introduction of the service rate constraint. From the algorithm shown on figure 4.4, the results obtained are presented on tables 4.1-4.3 for all considered techniques.

Table 4.1 provides the optimal production plan when we considered the analytical approach of energy production. The total cost incurred for the process involved is 4.4895×10^6 NGN. On tables 4.2 and 4.3, the optimal production planning results from using ANN and SVR is presented. For the ANN method on table 4.2, the optimal cost is forecasted to be 2.5246×10^6 NGN while the SVR approach presents an amount of 3.5150×10^6 NGN as shown on table 4.3. We could see that the machine learning presents the minimal costs as compared with the analytical method. This can be explained by the ability of the machine to easily learn from previous data and adapt to make a better prediction by adjusting the learning rates until minimal error is obtained. Among the two methods, the ANN is seen to present the optimal minimal cost among the two methods.

Table 4.1: Optimal production plan using the analytical approach

Total Cost (NGN) = 4.4895×10^6		
Period (k)	Generated power ($\times 10^4$ W)	Stored power ($\times 10^3$ W)
1	5.5322	3.3217
2	5.0230	4.7698
3	4.0796	4.7957
4	4.1437	6.4371
5	6.6110	1.1104
6	3.1578	1.5780

7	6.1064	1.0641
8	4.6035	7.9653
9	7.7806	2.8058
10	7.4934	2.2066
11	4.3289	7.7105
12	6.6399	1.6399

Table 4.2: Optimal production plan using the ANN approach

Total Cost (NGN) = 2.5246 x10 ⁶		
Period (k)	Generated power (x10 ⁴ W)	Stored power (x10 ³ W)
1	5.9223	1.0977
2	5.8062	2.8203
3	5.7191	4.9758
4	5.6610	6.4370
5	5.6901	8.0518
6	5.7191	1.2689
7	5.8062	1.8167
8	5.8352	3.4498
9	5.8062	3.1590
10	5.7772	0.8924
11	5.8352	5.4498
12	5.9223	8.2231

Table 4.3: Optimal production plan using the SVR approach

Total Cost (NGN) = 3.5150 x10 ⁶		
Period (k)	Generated power (x10 ⁴ W)	Stored power (x10 ³ W)
1	3.6302	4.4370
2	4.7415	5.0259
3	5.7802	5.6220
4	5.9102	5.9090
5	5.6625	5.9337
6	5.9535	6.4046
7	4.6290	5.5371
8	3.9547	5.1045
9	4.3162	5.0684
10	5.0038	5.1996
11	4.5091	4.8491
12	4.0725	4.5928

4.6.1.2 Sensitivity analysis

Since we considered the customer satisfaction probability in our model, we decided to vary the service rate to 60%, 70% and 90% in order to understand its influence on the production cost. The result of this variation is presented on table 4.4 where we observe that the production costs are seen to be increasing with increase in the customer satisfaction rate.

Table 4.4: Influence of service rate on production cost

Technique	Service rate (%)	Cost (x10 ⁶ NGN)
Theoretical	60	6.4880
	70	6.4931
	80	6.4985
	90	6.5032
ANN	60	1.3010
	70	1.4984
	80	1.5246
	90	1.6393
SVR	60	3.2988
	70	3.3910
	80	3.5150
	90	3.6000

4.6.1.3 Minimization of total production cost

In this section, we simultaneously minimize the total production cost of the system while determining the optimal number of preventive maintenances to be performed. The table 4.5, presents the maintenance inputs for maintenance planning. Since our maintenance strategy is an imperfect/ selective strategy, the table shows the cost and time of reparation for each component such that only the cost associated with the selected component is chosen for the evaluation of total maintenance cost analysis. Inspired from the work of Hajej et al. (2022), 90% reliability threshold was imposed for this illustration. All panels and other PV system components considered in this work are assumed to have similar ratings, therefore, maintenance action is illustrated for one (1) panel component which can be applied to many as considered

Table 4.5: Maintenance parameters for solar energy

Component	Panel	DC wire	AC wire	Inverter	CM
Cost (NGN)	25,000	10,000	10,000	70,000	120,000
Time (tu)	0.3	0.2	0.2	0.3	15

The objective of the maintenance strategy is to determine the optimal number of maintenance (N*) with minimal total cost and maximal reliability. Having defined this in the algorithm, the optimal N obtained for all techniques applied are presented below. Optimal number of maintenance sessions to be performed is 2 at a total cost of 4,598,409 NGN (sum of production and

maintenance costs) presented on figure 4.6. This means that maintenance should be performed twice every 1000-time units (tu) with the components selected for maintenance shown on table 4.5.

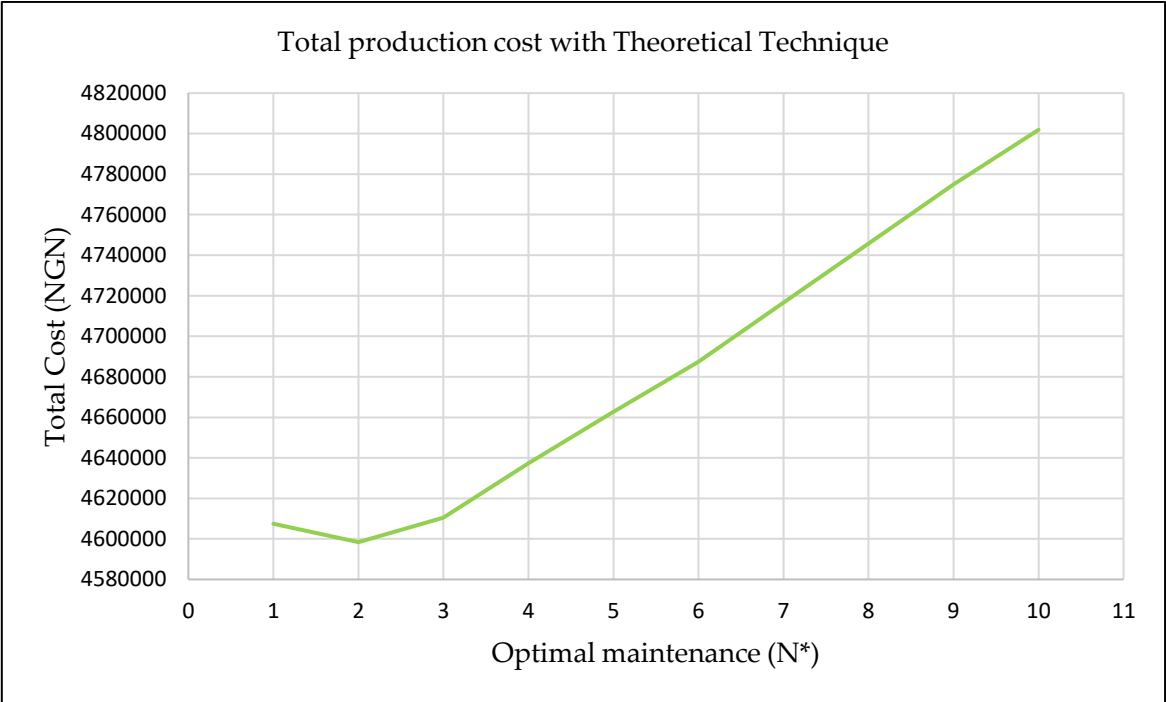


Figure 4.5: Optimal economic maintenance plan with the analytical technique

Table 4.6: Components selected for maintenance during PM for analytical method

Period	Panel	DC wire	AC wire	Inverter
1000	x	x	x	-
2000	x	-	-	x

Considering the machine learning, optimal number of maintenances of 2 and 3 are obtained for the ANN and SVR methods at 2,639,317 NGN and 3,629,449 NGN respectively represented on figures 4.6 and 4.7. Table 4.8 presents the selected components for replacement during the maintenance sessions. In the first session, panel, DC and AC wires are the selected components while the panel and inverter are selected for the second session.

Components selected during each preventive maintenance period are selected on tables 4.7 and 4.8. From table 4.7, DC wire is the chosen component for replacement in the first maintenance period while the panel and AC wire are selected during the second maintenance session. On table 4.8, inverter and DC wire are the chosen components during the first maintenance session. Again, inverter and AC wire are selected for the second streak while only the panel is selected for the last maintenance streak.

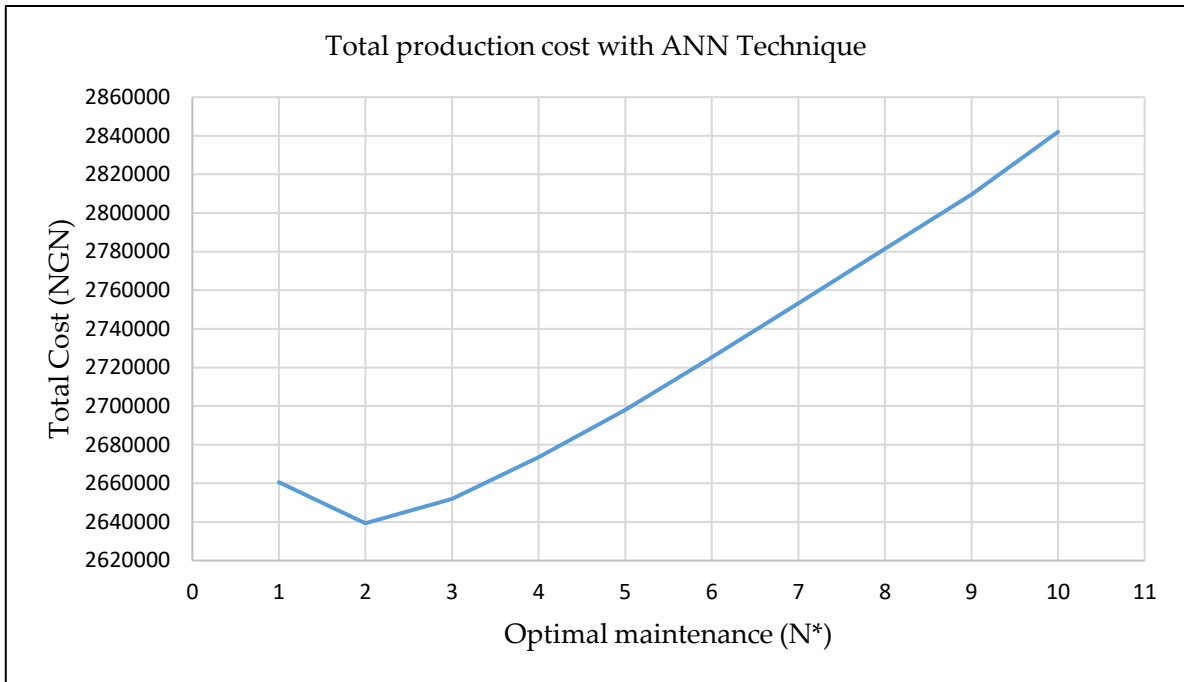


Figure 4.6: Optimal economic maintenance plan with the ANN technique

Table 4.7: Components selected for maintenance during PM for ANN

Period	Panel	DC wire	AC wire	Inverter
1000	-	x	-	-
2000	x	-	x	-

Table 4.8: Components selected for maintenance during PM for SVR

Period	Panel	DC wire	AC wire	Inverter
666	-	x	-	x
1334	-	-	x	x
2000	x	-	-	-

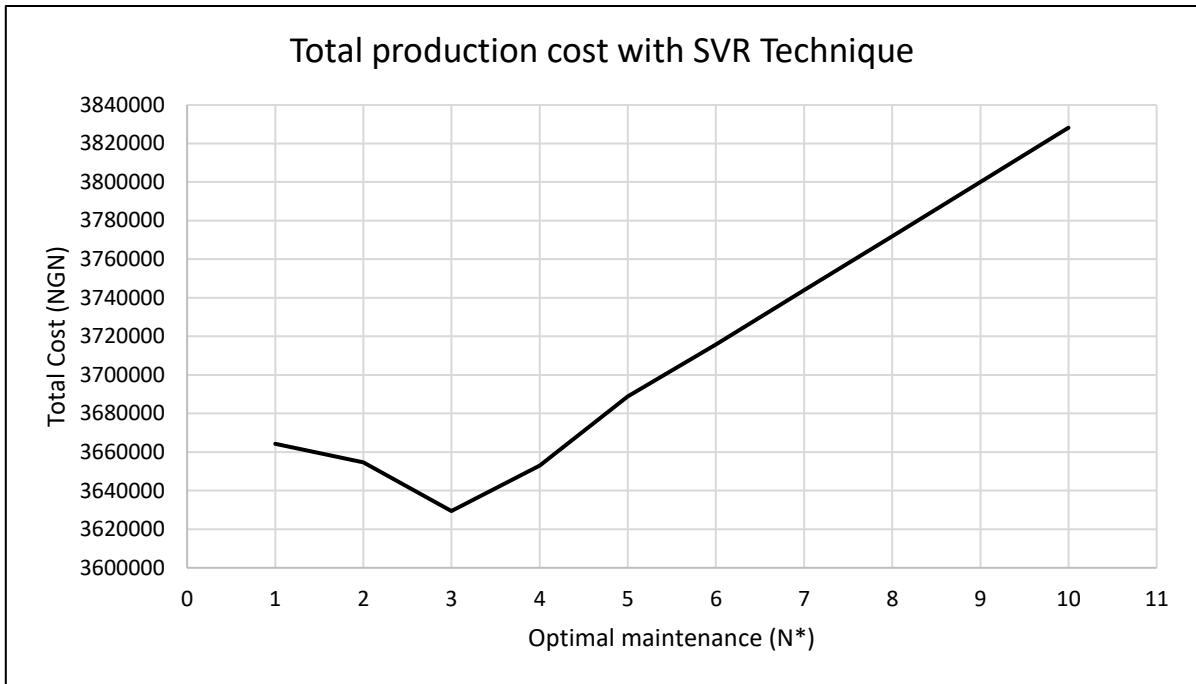


Figure 4.7: Optimal economic maintenance plan with the SVR technique

4.6.1.4 Sensitivity analysis

To better understand the influence of some parameters on the system, we varied the reliability threshold in this work. For each of the techniques, the optimal number of maintenance as well as the cost implication is obtained for each varied reliability threshold and the result of which is presented on table 4.9.

Table 4.9: Influence of reliability threshold on the optimal plan

Technique	R* (%)	N*	Total Cost (NGN)
Theoretical	80	2	4,590,820
	90	2	4,598,409
	95	3	4,620,642
ANN	80	2	2,654,541
	90	2	2,639,317
	95	2	2,657,849
SVR	80	2	3,635,459
	90	3	3,629,449
	95	3	3,664,057

From the above table, N* is seen to increase with increase in the reliability threshold. However, it has no influence on the cost as it is seen to fluctuate. For 80% reliability threshold, an optimal value of 2 is obtained for all the techniques. With this, the components selected during each maintenance streak is presented on table 4.10. As shown on table, the panel is to be replaced during the first maintenance streak, while inverter and Dc wire are the selected components for the second streak with the analytical technique. As with the ANN, only the DC wire is to be

replaced within the first maintenance whereas panel and AC wire are the selected components for the second streak. However, the SVR predicts DC wire, AC wire and the inverter all to be replaced during the first maintenance, and panel together with the inverter during the second maintenance period.

Table 4.10: Components selected for maintenance for 80% reliability threshold

Technique	Period	Panel	DC wire	AC wire	Inverter
Theoretical	1000	x	-	-	-
	2000	-	x	-	x
ANN	1000	-	x	-	-
	2000	x	-	x	-
SVR	1000	-	x	x	x
	2000	x	-	-	x

On table 4.11, a reliability threshold of 95% is considered. Here, it is expected that three (3) maintenance be performed with the analytical methods and the SVR while 2 with the ANN. The components selected for each method is displayed on the table. With the analytical method, the panel is replaced once during the last maintenance streak, the DC wire is also to be replaced one during the second streak. However, both AC wire and inverter are to be replaced twice with the AC replaced in the second and third streak while the inverter is to be replaced during the first and second streak.

With the ANN, inverter is not selected for replacement. The DC wire is selected during the first maintenance, while panel and the AC wire during the second maintenance session. With the SVR, panel is to be replaced during the second and third maintenance, DC wire during the first and third maintenance, while AC wire during the second streak and the inverter during the first and second maintenance. Thus, this explains the inconsistency in obtaining the optimal cost.

Table 4.11: Components selected for maintenance for 95% reliability threshold

Technique	Period (tu)	Panel	DC wire	AC wire	Inverter
Theoretical	666	-	-	-	x
	1334	-	x	x	x
	2000	x	-	x	-
ANN	1000	-	x	-	-
	2000	x	-	x	-
SVR	666	-	x	-	x
	1334	x	-	-	x
	2000	x	x	-	-

4.6.2 Katsina wind farm

4.6.2.1 Production results

In this section, we present the wind energy result carried out in a similar manner with the PV system analysis. The production optimization is performed with the aim of obtaining the right quantity of energy generated to satisfactorily supplies the customer demand and the quantity stored constrained to customer satisfaction service rate. Having modified the algorithm, the results obtained are presented as follows:

i. Analytical approach

In this analysis, the wind turbine used for the analytical method varies from the one used with the machine learning method. The turbine is a NEG Micon 1MW wind turbine whose characteristics is presented in table 4.12. It is estimated that the cost of energy production and storage from the wind power plant is 15 NGN and 17 NGN respectively. When load demand is not met and energy has to be sourced from the grid, the cost of this shortage is obtained at 25 NGN.

Table 4.12: NEG Micon 1MW wind turbine characteristics

Rated Power (kW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Rotor diameter (m)	Hub height (m)
1000	3	14	26	60	50

We have successfully conducted the production planning considering the customer satisfaction rate of 80% as constraint in order to be able to improve production from the system. Having done that, the results obtained with the modified algorithm are presented on tables 4.13 for the analytical technique.

Table 4.13: Optimal production plan using the analytical method

Total Cost (NGN) = 3.2660x10 ⁸		
Period (k)	Generated power (x10 ⁵ W)	Stored power (x10 ³ W)
1	3.7733	3.7649
2	1.1623	1.1553
3	2.1056	2.1008
4	4.3965	4.3923
5	1.7762	1.7723
6	2.8094	2.8060
7	2.1056	2.1028
8	1.7762	1.7733
9	0.6083	0.6048
10	0.7412	0.7373
11	0.3537	0.3486
12	2.4500	2.4434

The table, provides the optimal production plan when we considered the analytical approach of energy production. The total cost incurred for the process involved is 3.2660×10^8 NGN.

ii. Machine learning approach

The machine learning and artificial intelligence has proved to be useful in the energy, economic and financial institutes. Table 4.14 provides the turbine information for the 100 kW Hummer H25-100 kW turbine for the machine learning approach. The costs of production and storage remain the same with the previous approach. The results from the ANN and SVR techniques are presented below on tables 4.15 and 4.16:

Table 4.14: Hummer H25-100kW wind turbine characteristics

Rated Power (kW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Rotor diameter (m)	Hub height (m)
100	2.5	10	20	25	50

Table 4.15: Optimal production plan using the ANN approach

Total Cost (NGN) = 2.9145×10^6		
Period (k)	Generated power ($\times 10^5$ W)	Stored power ($\times 10^3$ W)
1	1.2238	1.1758
2	1.1117	1.0691
3	1.5661	1.5161
4	1.5803	1.5063
5	1.4624	1.3924
6	1.5834	1.5174
7	1.3508	1.2838
8	1.0183	0.9493
9	1.2787	1.2277
10	5.2777	0.7208
11	6.5760	0.9156
12	1.4688	1.4338

Table 4.16: Optimal production plan using the SVR approach

Total Cost (NGN) = 3.5138x10 ⁷		
Period (k)	Generated power (x10 ⁵ W)	Stored power (x10 ³ W)
1	1.1543	1.0563
2	7.1000	6.6800
3	7.0711	6.5711
4	6.0315	5.5747
5	4.8468	4.1468
6	6.7489	6.0889
7	6.1735	5.5035
8	5.7705	5.0805
9	4.3920	3.8820
10	4.7606	4.2406
11	5.0632	4.6432
12	1.3669	1.3319

4.6.2.2 Sensitivity analysis

Since we considered the customer satisfaction probability in our model, we decided to vary the service rate to 60%, 70% and 90% in order to understand its influence on the production cost. The results of this variation is presented on table 4.17 where we observe that the production costs are seen to be increasing with increase in the customer satisfaction rate.

Table 4.17: Influence of service rate on production cost

Technique	Service rate (%)	Cost (NGN)
Theoretical	60	2.9102x10 ⁸
	70	3.1940x10 ⁸
	80	3.2660x10 ⁸
	90	3.3580x10 ⁸
ANN	60	1.9617x10 ⁶
	70	2.5725x10 ⁶
	80	2.9145x10 ⁶
	90	3.1780x10 ⁶
SVR	60	3.3136x10 ⁷
	70	3.4298x10 ⁷
	80	3.5138x10 ⁷
	90	3.6064x10 ⁷

4.6.2.3 Total production optimization result

As explained in the PV result, the result for the optimized total cost of wind energy production is presented in this section. The table, 4.18 presents the maintenance inputs for

maintenance planning. Since our maintenance strategy is an imperfect/ selective strategy, the table shows the cost and time of reparation for each component such that only the cost associated with the selected component is chosen for the evaluation of total maintenance cost analysis. Inspired from the work of Hajej et al. (2022), 90% reliability threshold was imposed for this illustration. All wind turbines considered in this work are assumed to have similar ratings, therefore, maintenance action is illustrated for one (1) wind turbine which can be applied to many as considered.

Table 4.18: Preventive and corrective maintenance parameters for the wind turbine

Component	Main bearing	Main shaft	Gearbox	Generator	CM
Cost (NGN)	130,000	60,000	200,000	150,000	300,000
Time (tu)	0.10	0.30	0.50	0.20	10

The objective of the maintenance strategy is to determine the optimal number of maintenance (N^*) at minimal cost and maximal reliability. Having defined this in the algorithm, the optimal N obtained for all techniques applied are presented below. Optimal number of maintenance sessions (N^*) to be performed is 2 at 32,891,868 NGN presented on figure 4.8 for the analytical method. This means that maintenance should be performed twice every 1000-time units (tu) with the components selected for maintenance shown on table 4.19.

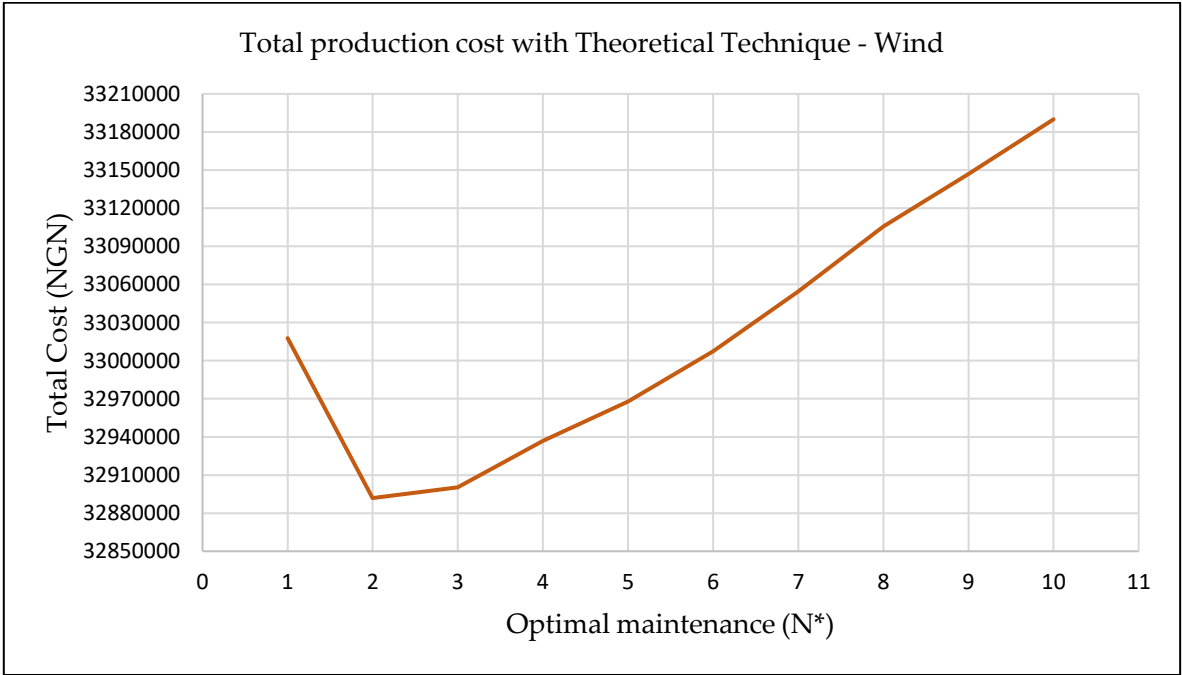


Figure 4.8: Optimal economic maintenance plan with the analytical technique

Table 4.19: Components selected for maintenance during PM with theoretical

Period (tu)	Bearing	Main shaft	Gearbox	Generator
1000	-	-	x	-
2000	x	-	-	-

Table 4.19 presents the selected components for replacement during the maintenance sessions. In the first session, only the gearbox is selected while the bearing is also the only selected

component for the second session. Considering the machine learning, optimal number of maintenances of 2 and 3 are obtained for the ANN and SVR methods at 29,341,461 NGN and 35,381,280 NGN respectively shown in figures 4.9 and 4.10.

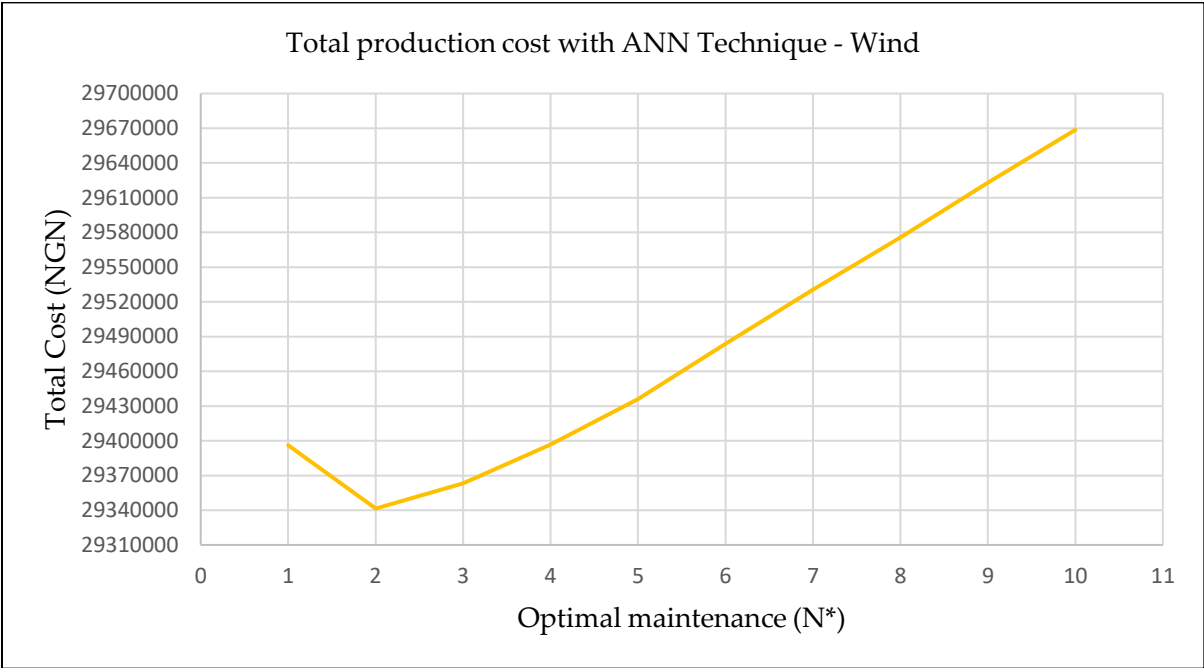


Figure 4.9: Optimal economic maintenance plan with the ANN technique

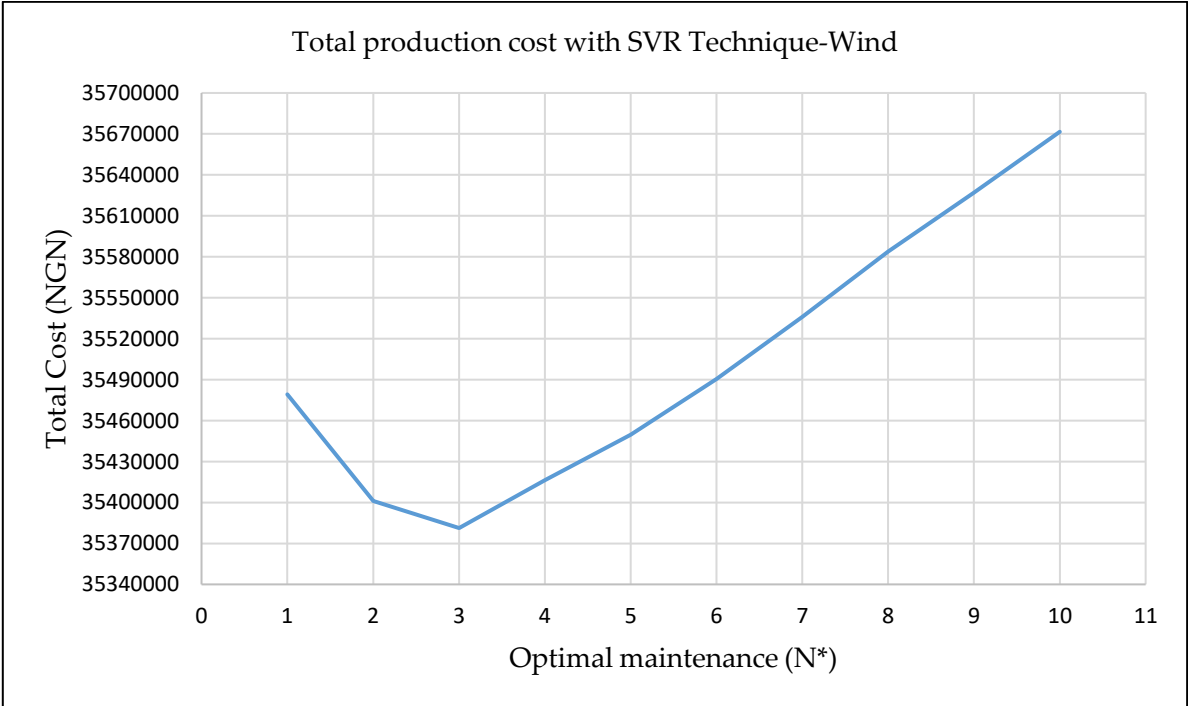


Figure 4.10: Optimal economic maintenance plan with the SVR technique

Components selected during each preventive maintenance period are selected on tables 4.20 and 4.21. From table 4.20, it is expected that bearing and generator are to be replaced in the first

maintenance period. during the second maintenance, the main shaft and the gearbox are the selected components. On table 4.21, bearing is selected for first and second maintenance session. Main shaft is selected only once during the first session and gearbox twice during the second and last sessions, the generator is also selected once during the second session.

Table 4.20: Components selected for maintenance during PM with ANN

Period (tu)	Bearing	Main shaft	Gearbox	Generator
1000	x	-	-	x
2000	-	x	x	-

Table 4.21: Components selected for maintenance during PM with SVR

Period (tu)	Bearing	Main shaft	Gearbox	Generator
666	x	x	-	-
1333	x	-	x	x
2000	-	-	x	-

4.6.2.4 Wind energy sensitivity analysis result

To better understand the influence of some parameters on the system, we varied the reliability threshold in this work. For each of the techniques, the optimal number of maintenance as well as the cost implication is obtained for each varied reliability threshold and the result of which is presented on table 4.22.

Table 4.22: Influence of reliability threshold on the optimal plan

Technique	R* (%)	N*	Total cost (NGN)
Theoretical	80	2	32,940,603
	90	2	32,891,868
	95	2	32,916,325
ANN	80	2	29,346,431
	90	2	29,341,461
	95	3	29,361,314
SVR	80	2	35,396,006
	90	3	35,381,280
	95	4	35,436,831

From the above table, N* is seen to increase with increase in the reliability threshold. However, it has no influence on the cost as it is seen to fluctuate. For 80% reliability threshold, an optimal value of 2 is obtained for all the techniques. With this, the components selected during each maintenance streak is presented on table 4.23. As shown on table, for the analytical method, gearbox and generator are selected during the first session, while bearing and main shaft during the second. With the ANN approach, bearing, gearbox and generator are to be replaced when performing the first maintenance while main shaft and gearbox are to be replaced again during the second session. The bearing and generator are selected during the first maintenance session

considering the SVR method and the main shaft and gearbox are to be replaced during the second session.

Table 4.23: Components selected for maintenance for 80% reliability threshold

Technique	Period	Bearing	Main shaft	Gearbox	Generator
Theoretical	1000	-	-	x	x
	2000	x	x	-	-
ANN	1000	x	-	x	x
	2000	-	x	x	-
SVR	1000	x	-	-	x
	2000	-	x	x	-

On table 4.24, a reliability threshold of 95% is considered. Optimal maintenance of 2 is expected with the analytical approach, 3 with the ANN approach and 4 with the SVR approach. The components selected for each method is displayed on the table. With the analytical method, in the first session, bearing and main shaft are the selected components and the other two components during the second maintenance. The ANN presented an optimal of 3 where the bearing is to be replaced in the second and third sessions, main shaft in the first and second session, gearbox in the first and third sessions whereas the generator is replaced once during the second session. For the SVR, the bearing is to be replaced twice, main shaft three times, gearbox twice and the generator also three times as shown on the table. Thus, the selection of different components during each maintenance period explains the inconsistency in obtaining the optimal cost.

Table 4.24: Components selected for maintenance for 95% reliability threshold

Technique	Period (tu)	Bearing	Main shaft	Gearbox	Generator
Theoretical	1000	x	x	-	-
	2000	-	-	x	x
ANN	666	-	x	x	-
	1334	x	x	-	x
	2000	x	-	x	x
SVR	500	x	x	x	-
	1000	x	-	x	x
	1500	-	x	-	x
	2000	x	x	-	x

Generally, from the analysis carried out, we observed that the execution time for all the three techniques is 0.003448s, 0.003761s and 0.006113s for ANN, SVR and analytical techniques respectively for the PV analysis. In the case of the wind energy system, the execution time elapsed after 0.00599s, 0.00623s and 0.007886s for the ANN, SVR and analytical approaches respectively. The adaptability ability of the machine learning with the data makes a faster computation. This can also be said that the fact that the machine learning is more suitable for the prediction and planning because it deals with real life data/problem rather than probability problem as in the case of the analytical techniques.

4.7 Conclusion

In this chapter, we developed an algorithm for an integrated production/ maintenance strategy optimizing the total lifecycle cost (cost of production system, storage, shortage and loss) of the system constrained to reliability as well as service rate. The approach is such that the power production plan; the optimal quantity of energy produced and stored per production period which determines the optimal cost of production is performed simultaneously with the total lifecycle cost. The main objective of this chapter is to minimize the total lifecycle cost of the production system, i.e minimizing the cost of production, storage, shortage and losses incurred for the maintenance while simultaneously determining the optimal number of maintenances (N^*) to be performed in order to achieve the said objective.

The maintenance strategy adopted is a priority selective maintenance strategy which selects components for maintenance based on reliability during a scheduled preventive maintenance time. This is to minimize the maintenance downtime which also maximizes the system availability as well as the cost of maintenance. The method is applied to both solar and wind energy systems which we used the Sokoto power plant and Katsina wind farm as case study. The results we obtained proved the real-life data works better with the ANN method of the power production technique, followed by the SVR and the analytical technique respectively, which can be explained as the ability of the machine learning techniques to learn and fit well with the complex system data.

As the obtained results show that the ANN presented the best results with a total minimal cost of 4,598,409 NGN for PV system and 32, 891,868 NGN for wind systems followed by the SVR and analytical techniques. We can also see that even the execution time taken by the machine learning approach is less compared to that taken by the analytical approach where the ANN also presents lesser time compared to the other approaches. Generally, we can say that applying a real-life data presents a more reasonable result compared to the analytical approach since the analytical approach is performed by computational probability using the Weibull distribution function.

GENERAL CONCLUSION

The main contribution of this research work is the implementation of energy production strategies and maintenance strategies for a renewable (solar PV and wind) energy system subject to certain constraints. In this thesis, our focus was on the development of new integrated maintenance strategies into the energy production system taking into consideration, the influence of environmental and operational conditions on the system degradation. Our developed model was subject to reliability and availability constraints while also ensuring successful satisfaction of costumers' demand.

In the first chapter, we compiled a bibliographical study on research works essentially relating to the production of solar and wind energy and to simple integrated maintenance strategies. This allowed us to situate our thesis problem in relation to existing work in the literature. From this bibliographic study, we spotted the existence of gaps in the literature. The study was made over a finite horizon. From the literature, we understand that very few works reported renewable energy production planning considering shortage of supply and the possibility of outsourcing. Also, the influence of variable production rate, environmental and operational conditions of the electricity generating system on the system's failure rate were not commonly discussed and considered when planning maintenance. Additionally, to the best of our knowledge, there are very few integrated maintenance strategies with in-depth study on the reliability of the solar PV and wind energy systems under economic, environmental and safety constraints. Therefore, in this study, we successfully identified gap in the area of integrating production and maintenance and highlighted the main objectives of the work together with a brief general intended methodology of the work.

In the second chapter, we defined our energy production system for both solar and wind energy systems. Considering our case study, we developed optimization model based on machine learning and analytical techniques, to optimize the production system and determined the optimal number of components required; solar panels, wind turbines and number of battery storage for each system with all the techniques. The aim of the production planning was to determine the optimal cost of production by determining the optimal power produced as well as the optimal number of components that satisfy the demand per period. The novelty of this work is that it considers the cost of shortage when planning the production such that economic losses associated to the production system is minimized. We then proceeded to develop maintenance model for one (1) wind turbine and one (1) solar panel system integrating the production planning result into the maintenance model to determine the maintenance cost. Since we are comparing between the machine learning (ANN and SVR) and analytical techniques, from the result we obtained, we realised that best optimal results are observed with the machine learning techniques especially with the ANN. The ANN is a good machine learning tool that adapts and fits very well with the nature of our input data.

We successfully developed an integrated maintenance model that maximizes the solar and wind energy systems' availability under environmental and operational constraints in the third chapter. For the solar PV system, first, we identified the components affected by environmental

conditions and from literature, assigned criticality coefficients on each one of them. This is taken into account when scheduling maintenance in order to determine the optimal number of maintenances to be performed over the chosen horizon. We performed the analysis under nominal condition and compared the results. In the wind energy analysis, the environmental condition affecting the wind turbine is the wind speed, therefore it was categorized according to severity. We also identified the operational conditions affecting each of the components and assigned severity levels to them as well. Since the turbine is a multi-component with moving parts, the influence of its production was significant and also taken into account. All these were integrated into the maintenance model, integrating production and maintenance to achieve maximum availability. Since the main aim of this work was to maximize availability which means minimizing maintenance down time, a priority selective imperfect maintenance strategy was adopted in order to select components for maintenance during preventive maintenance time. The idea was to minimize the maintenance downtime. The selection was done under reliability threshold constraints such that at each preventive maintenance time, the reliability of each component was calculated and gauged with the threshold. When the reliability falls below the threshold, it was selected for maintenance.

Chapter 4 is a combination of chapters 2 and 3. In this chapter, we developed an integrated production and maintenance model that minimizes the total production cost (lifecycle cost) ensuring maximum reliability. For each of the system, the model for optimal production plan from chapter 2 was adopted, where we determined the optimal cost of production, storage and shortage of energy. In this section, a service rate constraint was imposed in order to ensure maximum customer satisfaction. The optimal production plan result was simultaneously determined with the maintenance model to obtain maximum availability as from chapter 3. Furthermore, a reliability threshold was imposed to ensure maximum reliability is maintained. In summary, figure I presents an overview of the relationship between the three developed models.

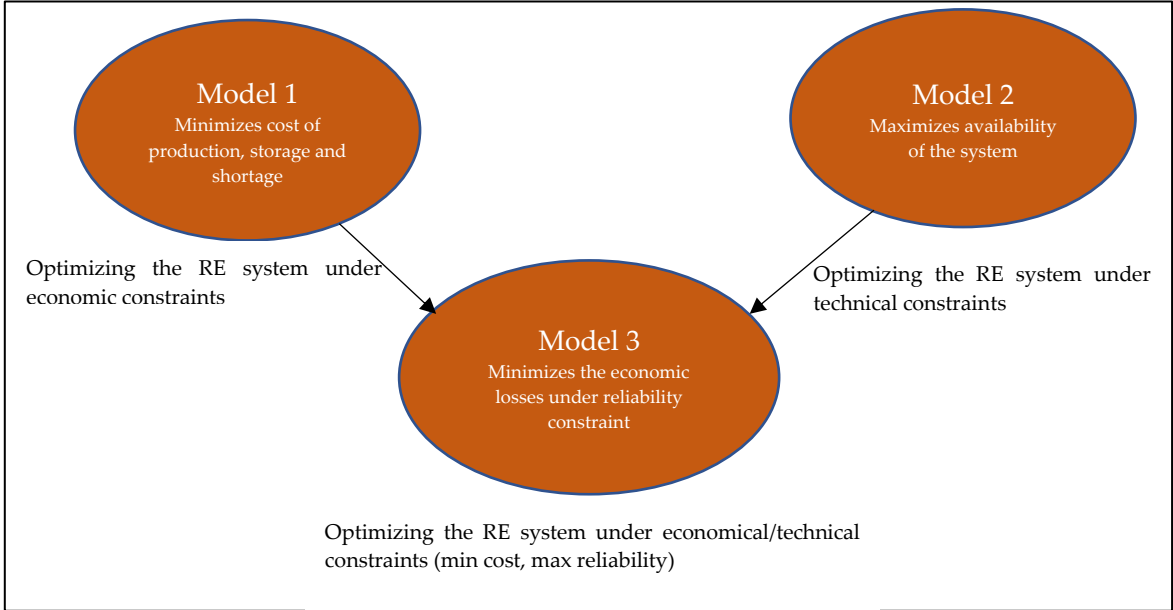


Figure I: Overview of the relationship between the three developed models

For each problem presented in chapters 2, 3 and 4 respectively, models were developed based on ANN and SVR and analytical techniques to determine the optimal number of preventive maintenances (N^*) to be performed which; minimizes cost, maximizes availability and a combination of both using different strategies. The viability of the developed models was illustrated by numerical analysis based on our case study and sensitivity analysis were also implemented to validate the models/algorithms. The integration of artificial intelligence and data-mining approaches is considered an interesting perspective in our problem because it deals with real-life situations which positively influences the decision concerning the production and maintenance of a solar/wind energy system. Additionally, the use of AI- based technique makes the computing time very short compared to the analytical technique.

The promising results obtained in this thesis can lead to interesting perspectives. Beyond this study, these contributions can be applied to other models. Our energy production system can be extended to a hybrid system consisting of wind and solar systems, and also with other renewable energy sources such as hydro and biomass. Following this study, and as a perspective, we can propose maintenance strategies by integrating the management of spare parts and possible out sourcing of maintenance personnel from maintenance companies. Also, using this comparative study can aid in constant improvement of these systems. With the incorporation of the future works mentioned, this strategy can be adopted by RE companies when designing a new production system. This eventually contributes to extensive adoption and utilization of sustainable energy resources.

ANNEX

The analysis for criticality weight index for PV system is assigned to the environmental condition is ranging from 1 to 5 is shown on table 1, while table 2 provides the criticality evaluation obtained from Sokoto solar energy research centre taking into account the influence of climatic condition. In table 3, the overall weight assigned to each failure is presented.

Table 1: Weight associated with environmental conditions

Irradiance		Humidity		Pressure		Temperature		Wind Speed	
146.9412	1	45.4057	1	812.2538	2	1.6324	1	5.1292	5
199.8563	2	56.3606	4	808.9660	1	-0.2681	1	3.7992	3
277.7092	3	44.8867	1	811.0436	2	5.2750	2	4.0070	4
322.1622	4	44.8571	1	810.3040	1	9.3224	3	3.4893	3
350.2139	4	54.2768	4	813.6064	3	13.6602	3	2.3967	1
432.0526	5	48.3996	2	813.1307	3	19.5112	4	2.4792	1
349.9464	4	53.3355	4	819.1665	5	22.2955	5	2.2653	1
324.1452	4	50.4359	3	817.0150	4	20.9718	5	2.1579	1
276.7991	3	55.3740	4	816.6191	4	17.8549	4	2.0596	1
225.0502	2	45.2796	1	815.5154	4	13.5199	3	2.3702	1
145.0498	1	44.0040	1	812.2964	2	5.6808	2	3.5633	3
129.6080	1	49.5488	3	814.5471	3	1.3585	1	2.2519	1

Table 2: Table of the criticality derivation for the failure types listed in the text

Hot Spot				Junction Box				Broken Glass				Bypass Diode				Delamination				Broken Cells				Soldering Tapes			
F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C
4	4	2	32	2	3	4	24	3	4	3	36	1	3	2	6	3	4	2	24	1	4	3	12	2	2	3	12
4	4	2	32	3	3	4	36	5	4	3	60	1	3	2	6	3	4	2	24	3	4	3	36	1	2	3	6
3	4	2	24	3	3	4	36	4	4	3	48	1	3	2	6	2	4	2	16	1	4	3	12	2	2	3	12
2	4	2	16	2	3	4	24	5	4	3	60	2	4	2	16	1	4	2	8	1	4	3	12	3	2	3	18
2	4	2	16	4	3	4	48	4	4	3	48	3	4	2	24	1	4	2	8	4	4	3	48	3	2	3	18
1	3	2	6	5	4	4	80	5	5	3	75	3	4	2	24	1	3	2	6	3	4	3	36	4	2	3	24
2	4	2	16	4	3	4	48	5	5	3	75	5	5	2	50	1	4	2	8	5	5	3	75	5	3	3	45
1	3	2	6	3	3	4	36	5	5	3	75	4	4	2	32	1	3	2	6	3	4	3	36	5	3	3	45
2	4	2	16	4	3	4	48	5	5	3	75	3	3	2	18	1	4	2	8	4	4	3	48	4	2	3	24
3	5	2	30	3	3	4	36	4	4	3	48	2	4	2	16	2	5	2	20	2	4	3	24	4	2	3	24
4	4	2	32	3	3	4	36	3	4	3	36	1	4	2	8	3	4	2	24	1	4	3	12	1	2	3	6
3	4	2	24	2	3	4	24	4	4	3	48	1	4	2	8	2	4	2	16	1	4	3	12	2	2	3	12
Interconnection				Discoloration				Corrosion				Cutting / Melting Cable				Cable Corrosion				Inverter							
F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C	F	S	D	C				
1	3	4	12	1	3	3	9	2	4	3	24	1	4	2	8	1	3	3	9	1	3	4	12				
1	3	4	12	4	4	3	28	4	4	3	48	1	4	2	8	2	3	3	18	2	3	4	24				
2	3	4	24	1	3	3	9	2	4	3	24	2	4	2	16	1	3	3	9	1	3	4	12				
3	3	4	36	2	4	3	24	2	4	3	24	1	4	2	8	1	3	3	9	3	3	4	36				
4	3	4	48	5	4	3	60	4	4	3	48	3	4	2	24	3	3	3	27	4	3	4	48				
4	3	4	48	3	4	3	36	4	4	3	48	4	4	2	32	2	3	3	18	4	3	4	48				
5	4	4	80	5	4	3	60	5	4	3	75	4	4	2	32	4	3	3	36	5	3	4	60				
5	4	4	80	5	4	3	60	4	5	3	48	4	4	2	32	3	3	3	27	5	3	4	60				
4	3	4	48	5	4	3	60	5	4	3	75	3	4	2	24	4	3	3	36	5	3	4	60				
3	3	4	36	2	4	3	24	3	4	3	36	2	4	2	16	1	3	3	9	2	3	4	24				
1	3	4	12	1	3	3	9	2	4	3	24	1	4	2	8	1	3	3	9	1	3	4	12				
2	3	4	24	2	4	3	24	2	4	3	24	1	4	2	8	2	3	3	18	1	3	4	12				

Table 3: Table of coefficients for each failure type affected by each environmental condition

	Hot Spot	Junction Box	Broken glass	Byepass Diode	Delamination	Broken cells	
Constant	3.99291	2.90727	1.33575	3.52084	1.7834	1.51668	
Temperature	0	0.141	0.46102	0	0.22828	0.29365	
Irradiance	-0.36987	0	0	-0.36099	0	0	
Humidity	0	0.1019	0	0	0.31899	0	
Pressure	0	0	0	0	0	0.17006	
	Soldering Tape	Interconnections	Discoloration	Corrosion	Cut	corrosion cable	Inverter
Constant	1.20737	1.74094	3.46308	2.70305	1.6918	1.59116	1.87358
Temperature	0.43783	0.21301	0	0.15279	0.3645	0.13266	0.35918
Irradiance	0	0	0.12771	0.20559	0	0	0
Humidity	0.08031	0.40773	0.07625	0	0	0.33833	0.17964
Pressure	0	0	0	0	0	0	0

Table 4: Overall criticality for all the failures, components and the climatic condition

Irradiance	Humidity	Pressure	Temperature	Wind Speed	Hot Spot	Junction Box	Glass case	Bypass Diode
1	1	2	1	5	32	24	6	24
2	4	1	1	3	32	36	6	24
3	1	2	2	4	24	24	6	16
4	1	1	3	3	16	24	16	8
4	4	3	3	1	16	48	24	8
5	2	3	4	1	6	80	24	6
4	4	5	5	1	16	48	50	8
4	3	4	5	1	6	36	32	6
3	4	4	4	1	16	48	18	8
2	1	4	3	1	50	36	16	20
1	1	2	2	3	32	24	8	24
1	3	3	1	1	24	24	8	16
Delamination	Broken Cells	Soldering Tape	Interconnection	Discoloration	Corrosion	Cut	Cable Corrosion	Inverter
12	12	12	9	36	24	8	9	12
36	6	12	48	60	48	8	18	24
12	12	24	9	48	24	16	9	12
12	18	36	24	60	24	8	9	36
48	18	48	60	48	48	24	27	48
36	24	48	36	75	48	32	18	48
75	45	80	60	75	75	32	36	60
36	45	80	60	75	48	32	27	60
48	24	48	60	75	75	24	36	60
24	24	36	24	48	36	16	9	24
12	6	12	9	36	24	8	9	12
12	12	24	24	48	24	8	18	12

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LIST OF PUBLICATIONS

- I. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ "Improved Preventive Maintenance Scheduling for a Photovoltaic Plant under Environmental Constraints" - *Sustainability* 2021, 13, 10472. <https://doi.org/10.3390/su131810472>
- II. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ "An Integrated Maintenance and Power Generation Forecast by ANN Approach Based on Availability Maximization of a Wind Farm"- *Energy Reports* Volume 8, Supplement 9, November 2022, Pages 282-301. <https://doi.org/10.1016/j.egyr.2022.06.120>
- III. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ "An Integrated Maintenance Scheduling Minimizing Economic Losses of Wind Turbine System"- *accepted at the 8th International Conference on Sustainable and Renewable Energy Engineering (ICSREE) Nice, France, May 11-13, 2023.*
- IV. **Aisha SA'AD**, Zied HAJEJ and Aime C. NYOUNGUE- **A Day-Ahead Multi-Approach Machine Learning Technique for Photovoltaic Power Forecasting-** *9th International Conference on Renewable Energy Research and Applications (ICRERA 2020) held in Glasgow, United Kingdom, September 27-30, 2020. DOI: [10.1109/ICRERA49962.2020.9242897](https://doi.org/10.1109/ICRERA49962.2020.9242897)*
- V. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ - **A Comparative Study of Hidden Layer Neurons and Delay Time for Wind Energy Forecasting Model Using NARX** - *10th International Conference on Renewable Energy Research and Applications (ICRERA 2021) held in Istanbul, Turkey, September 26-29, 2021. DOI: [10.1109/ICRERA52334.2021.9598743](https://doi.org/10.1109/ICRERA52334.2021.9598743)*
- VI. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ - **Bi-Objective Preventive Maintenance Scheduling Optimization of Photovoltaic System based on Availability** - *3rd International Conference on Energy and Sustainable Environment (ICESE 2021) held in Ogun, Nigeria October 26th – 28th, 2021. DOI: [10.1088/1755-1315/1054/1/012041](https://doi.org/10.1088/1755-1315/1054/1/012041)*
- VII. **Aisha SA'AD**, Aime C. NYOUNGUE and Zied HAJEJ - **Comparative Analysis of Wind Power Production Planning Based on Artificial Neural Network and Analytical Approach** – *12th Annual International Conference on Industrial Engineering and Operations Management to hold in Istanbul, Turkey, March 7 - 10, 2022.*
- VIII. **Aisha SA'AD**, Aime NYOUNGUE, Zied HAJEJ, Akilu YUNUSA-KALTUNGO and Cyril AMAGHIONYEODIWE - **Reliability Assessment and Maintenance Cost Optimization of Solar PV System Under Extreme Weather/Environmental Condition: A Case Study of Nigeria** - *8th International Symposium on Reliability Engineering and Risk Management (ISRERM) Hannover, 4 - 7 September 2022.*
- IX. **Aisha SA'AD**, Aime C. Nyounge and Zied Hajej- **An Optimal Integrated Production and Maintenance Scheduling Minimizing Economic Losses of Wind Energy System** - *Accepted in The 20th International Multi-Conference on Systems, Signals and Devices (SSD), Tunisia, February 20th-23rd, 2023.*
- X. **Aisha SA'AD**, Aime C. Nyounge and Zied Hajej- **An Optimal Integrated Maintenance Planning Minimizing Economic Losses of a Solar Photovoltaic (PV) System** – *accepted in MOSIM 23, Quebec, Canada 2023.*
- XI. **Aisha SA'AD**, Aime C. Nyounge and Zied Hajej- **Integrated Production and Maintenance Planning Optimization of a Photovoltaic System: A Case Study of Nigeria**–

presented in *The International Conference on Innovation and Technological Advances for Sustainability, Doha, Qatar, 1st-3rd March, 2023.*

