

CANO: A lightweight CARbon emission and inhabitants' energy Needs Optimisation model

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Abstract: Greenhouse gas emissions (GHGE) can be attributed at 30% to the residential sector in Europe. Several solutions are possible to reduce these emissions, whether by improving the insulation of houses or by increasing the efficiency of the integration of renewable energy and storage resources. The research presented in this paper falls within the scope of the last alternative (i.e., management of renewable energy and storage resources). Most of today's energy management systems rely on mathematical programming or metaheuristics to optimize the storage and release of energy. While they provide high-quality optimum or near-optimal solutions, they are computational-intensive and time-consuming, which make them non-suitable to be deployed at edge architecture. To overcome this limitation, this paper suggests adopting a rule-based optimization approach, proposing a lightweight model seeking to reduce GHGE, while meeting the inhabitants' energy needs. This new model, which is an evolution of the model proposed by the European project RED WoLF, is called CANO (standing for "lightweight CARbon emission and inhabitants' energy needs optimization model"). This paper presents, evaluate, and compares CANO to the RED WoLF algorithms based on two real datasets from two different countries (UK and France). The results evidence that CANO outperforms RED WoLF, and most importantly that it can satisfy all heating demands, which was not the case with the initial version of RED WoLF (only satisfying 80% and 96% of the demands respectively in France and the UK scenarios).

Keywords: Distributed Energy Resource Integration and Coordination, Smart grids, Intelligent control of power systems, Control of renewable energy resources, Renewable Energy System Modeling and Integration

1. INTRODUCTION

In Europe, the residential sector is responsible for a significant part of the greenhouse gas emissions (GHGE) causing global warming (Baek and Kim, 2020). This problem is mainly due to three factors (i) poor insulation of houses and buildings; (ii) a weak integration of distributed energy resources (DER) or the use of polluting production means in the national grid energy source mix (Lazarus and van Asselt, 2018); (iii) a lack of optimization algorithms for reducing GHGE while maintaining inhabitant comfort and budget (Wang et al., 2017).

Different solutions can be envisioned such as improving houses and buildings insulation, increasing renewable energy generator proportion (e.g., wind turbin, biomass) (Ahmed et al., 2022). Other solutions such as the one investigated in this research article, propose to power houses with distributed energy resources (e.g., photovoltaic array, battery system) to produce and store locally green energy (Hannan et al., 2021). However, it is not only a matter of installing PV arrays and storing solar power in a battery, but also a matter of optimizing the charging/discharging strategy of local storage units (Al-Shahri et al., 2021), knowing that green local production may not be sufficient to meet the house demand. In other words, the total energy generated locally may not be sufficient to meet the

inhabitant needs, thus requiring to draw electricity from the electrical grid, which is often not carbon free. There is thus a need to design optimization algorithms to search for optimal time intervals for drawing electricity from the grid, while taking into account the overall IT (hardware and software) infrastructure (i.e., avoiding to deploy computational intensive optimization algorithms). To achieve this objective, an algorithm named RED WoLF (Rethink Electricity Distribution Without Load Following) has been proposed in previous research by the European Interreg NWE RED WoLF (2019) project. Although the algorithm foundation and philosophy are promising, some improvements are necessary to ensure that the energy needs are always met. To overcome those limitations, a new algorithm named CANO (standing for house CARbon emission and inhabitant Needs Optimisation) is proposed in this article.

Section 2 provides a brief state of the art of existing optimization algorithms for energy management considering RES (standing for Renewable Energy Sources) and storage systems, along with explanations why the RED WoLF philosophy is interesting to reduce the computational burden traditional algorithms (making it suitable to be deployed at the Edge of the electrical grid such as on smart meters) and what limitations still remain to be solved. The proposed CANO algorithm is then introduced in Section 3, while section 4 focuses on the comparison

analysis between RED WoLF and CANO algorithms. This comparison study is performed using real-life datasets from France and UK. Conclusion is given in section 5.

2. STATE-OF-THE-ART

Section 2.1 defines the energy subfield in which our contribution is situated. Section 2.2 explains the different links between our research and the state of the art.

2.1 Positioning

Saleem et al. (2019) describe the life cycle of electrical energy as a succession of the following phases: 1. *production*, 2. *transmission*, 3. *distribution* and 4. *consumption*. This article contribute in the consumption management phase and more specifically in a residential nanogrid (Burmester et al., 2017). As denoted by Fig. 1, a nanogrid is usually composed of five categories:

- *Distributed Energy Resource*: corresponds to local energy production sources that can be installed at the house to provide additional energy, often renewable (e.g., photovoltaic array, wind turbine, etc.);
- *Conventional Energy Resources*: corresponds to national power plants from renewable or non-renewable sources, often of significant size (e.g., nuclear power plant, hydroelectric dam, solar farm, etc.);
- *Electrical Loads*: corresponds to all devices that consume energy (e.g., appliances, HVAC, etc.);
- *Storage Equipment*: corresponds to all the equipment having the capacity to store energy in any form to release it at more convenient time (e.g., Battery Energy Storage System (BESS), storage heater, water cylinder, etc.);
- *Control/Monitoring equipment*: corresponds to all the equipment for charging, measuring, transferring, processing, executing energy-related data and commands (e.g., meter, communication network, switch, etc.);

2.2 State-of-the-art

This section introduces state-of-the-art research articles dealing with the optimization of energy storage systems, along with their *pros* and *cons*. In the literature, two categories of optimization can be defined: (1) mathematical and metaheuristic optimization; and (2) rule-based optimization. In the following, key research articles falling within each of these categories are discussed, with a particular focus on assessing the extent to which the proposed

algorithms are suitable to be deployed/run at the Edge of the network/grid (Feng et al., 2021).

Mathematical and metaheuristic programming provide optimal solution(s) or highly accurate optimum(s) demonstrating that this choice is legitimate for the optimization of energy storage systems. Olivieri and McConky (2020) propose a linear optimization model to find the optimal solution to charge/discharge a battery with the national grid as the only energy source. The fitness function can be defined using one or more objectives: (1) minimizing GHGE; (2) minimizing financial cost; (3) minimizing emissions and financial costs. The control strategy is computed based on 48h appliances consumption and grid carbon load prediction and performed by a smart meter with processing capabilities. Likewise, Haidar et al. (2018) propose a linear optimization model, which differs from the previous one, as the authors consider three distinct energy sources: (1) non-renewable energy; (2) renewable energy; (3) local generator. The proposed optimization model seeks to find the best combination of energy sources and the best time slots to charge/discharge the battery, with the overall objective to reduce carbon emissions and/or financial costs, while meeting the inhabitant's energy needs. Furthermore, this research paper introduces a parameter sets by the inhabitant aiming at fixing the acceptable additional financial cost to further reduce his carbon emission. Nevertheless, even though they provide extremely powerful solutions, the computational resource needed to run the algorithm is still very high, which hampers its deployment using Edge computing solutions.

Rule-based optimization provides computationally lightweight strategies, thus making it an interesting choice for an edge computing based architecture. Mahmud et al. (2018) proposes a rules based optimization to control the charging/discharging of a stationary battery and an electric vehicle (EV) with vehicle to grid (V2G) capability, which is considered as both an electrical load and a storage system to increase the overall system capacity. This algorithm deals with two energy sources: national energy grid and local PV system in order to reduce the peak load, and indirectly the carbon emission and financial costs. To go along the smart meter with processing capabilities there is a monitoring infrastructure in order to execute the decision tree strategy, formalized in this research article. The model proposed by Shukhobodskiy and Colantuono (2020) and Ortiz et al. (2021) introduces a hybrid energy storage system (HSS) based on a BESS (standing for Battery Energy Storage System) and thermal reservoirs. A two-step approach is defined to generate the HSS charge/discharge strategy: (1) every hour a CO₂ threshold limit is calculated; (2) every minute, a command is generated based on a rule system (e.g., if current CO₂ is lower than CO₂ threshold then HSS charging is allowed). This model allows a fast execution of the command but requires a constant internet connection in order to access the appliances, solar production and grid carbon load predictions and current value. While the underlying philosophy is interesting, we realize that the proposed model does not fully meet the inhabitants' energy needs. To illustrate this state-of-the-affaire we analyzed in Fig. 3b the extent to which the initial RED WoLF model is meeting the houses' energy demand considering the two use case scenarios/datasets

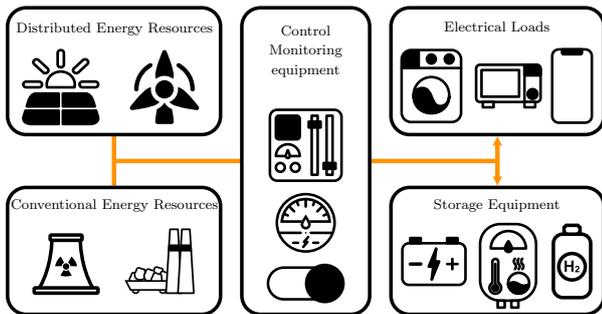


Fig. 1. Nanogrid architecture

defined in Ortiz et al. (2021) (namely a house from UK and France). Results show that in both cases the house energy demand is not fully satisfied (only satisfying 80% and 96% of the demands respectively in France and UK scenarios). To address this problem, a new model called CANO is formalized and proposed in the next section.

3. CANO STRATEGY

In this section, the CANO strategy will be presented in further details. Section 3.1 deals with the hardware infrastructure used for the reduction of greenhouse gas emissions, while section 3.2 will provide an overview of the software part that controls the system.

3.1 Hardware

The Fig. 2 shows three different types of equipment: the *energy sources* that will power the house and whose carbon intensity is more or less important depending on the type of source and the time of day (e.g., utility grid, solar array, etc.); the *appliances* that cannot be controlled and will have to be powered based on demand of the inhabitant (e.g., TV, oven, computer, etc.); Finally, the *energy storage* that offer the capacity to store energy in different forms to release it at more opportune times during the day (e.g., water cylinder, storage heater, electrochemical storage, etc.).

This figure also provides a high level view of the hardware architecture. Three flows are highlighted in this figure: the *power flow* representing the high voltage network coming from the grid to supply the equipments (e.g., hybrid storage system, appliances, etc.); the *monitoring flow* schematizing the network infrastructure necessary to retrieve the different local data (e.g., solar production, appliances consumption, etc.); the *control flow* representing the sending of the charging/discharging commands from the PLC to the controllable equipments (e.g., BESS discharging, charge storage heater, etc.)

3.2 Software

The table 1 provides the list of variables used by the algorithm, their units associated with a description as well as their types indicated by the *Class* column (e.g.,

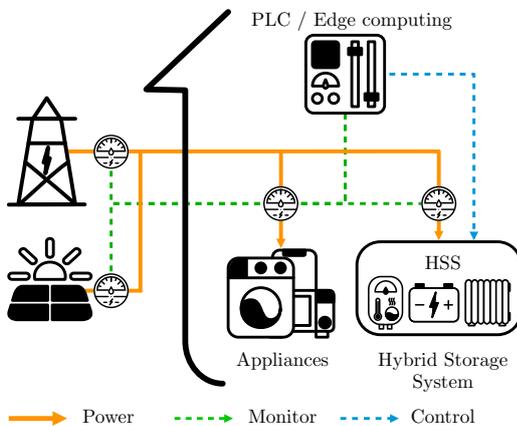


Fig. 2. Hardware infrastructure

Output). The variable C represents the prediction of the carbon intensity of the electricity supplied by the national grid. Like variable C , the vector E represents the prediction of the instantaneous power available over the current minute for charging the hybrid energy storage system. E is computed by subtracting the predicted consumption of the appliances from the maximum available power (sum of the limit set by the energy provider and the instantaneous solar production). The scalar L is defined by the sum of energy based on the heating setpoints of the storage heater, the cylinder and the capacity of the battery. It thus ensures that the required comfort level is reached. The transfer matrix M allows the ascending sorting of the vectors C and E according to the carbon intensity (C). Finally, the Boolean vector S represents the best moments to consume the energy supplied by the electrical network.

Table 1. Variables

Class	Variable	Unit	Description
Input	C	g eq. CO ₂	grid carbon load
	E	kW	power available prediction
	L	kWh	sum of HSS setpoint
Internal	M	/	transfert matrix
	C_T	g eq. CO ₂	sorted grid carbon load
	E_T	kWh	sorted energy available
Output	H	hrs	interval time length
	S	/	solution vector $\{1,1... 0,0\}$

The algorithm presented in this research article is a threshold-based computational strategy inspired from the algorithm proposed by Shukhobodskiy and Colantuono (2020) as it used the same hardware infrastructure and computational philosophy (e.g., threshold-based). The generic problem addressed by the strategy proposed in this article is expressed by the equations 1 and 2. The objective being to minimize the greenhouse gas emissions, the optimization will aim at finding the vector S which minimizes the product expressed in the equation 1 while satisfying the load set point of the equipments (cf., equation 2).

$$\text{minimize} \quad C^t S, S \in \mathbb{B}^{24/H} \quad (1)$$

$$\text{subject to} \quad E^t S H \geq L \quad (2)$$

The computational resources provided by the PLC being limited (e.g., edge computing), equations 3 to 5 model the proposed heuristic to reduce the computational time/load required to generate the control strategy. The assumption on which this heuristic is based is : "by consuming the least amount of time on the grid and at the least carbon intensive times possible, a satisfactory optimum can be found". Thus, by sorting in ascending order the vectors C and E using the transfer matrix M (cf., equation 5), it is possible to simplify the initial optimization model by searching for the minimum time sum needed to reach the HSS setpoints by supplying with electricity grid (e.g., sum of the S vector) computed using equations 3 and 4.

$$\text{minimize} \quad C_T^t S, S \in \mathbb{B}^{24/H}, S = (1, \dots, 1, 0, \dots, 0) \quad (3)$$

$$\text{subject to} \quad E_T^t S H \geq L \quad (4)$$

$$\text{with} \quad C_T = C^t M \text{ and } E_T = E^t M \quad (5)$$

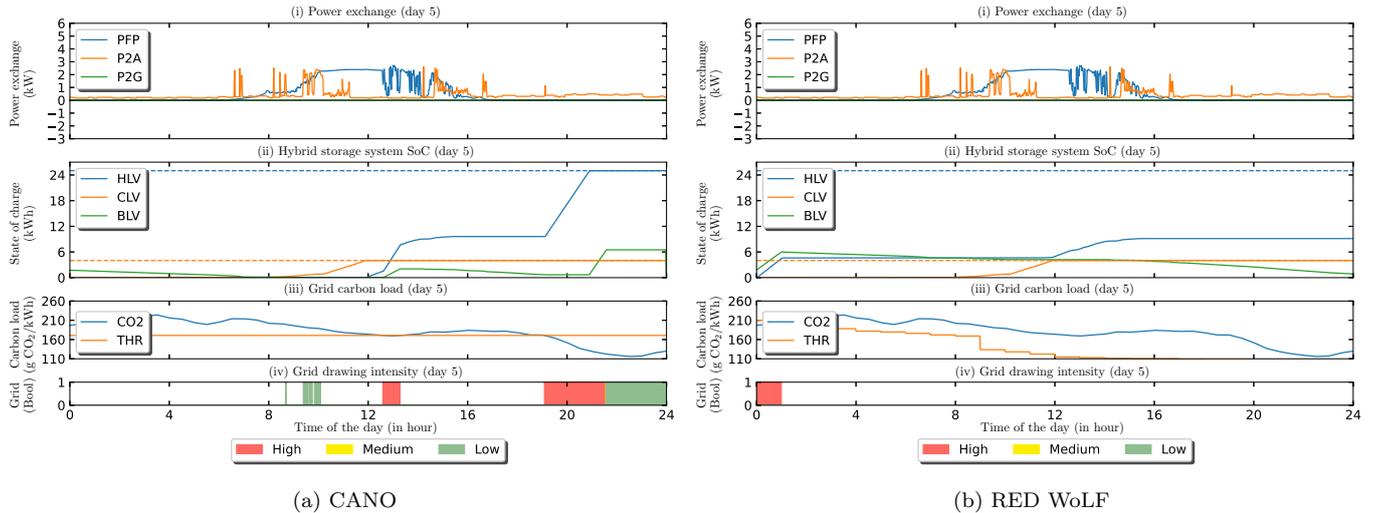


Fig. 3. Indicators overview

Finally, the CO_2 threshold can be obtained by using the sum of the S vector as an index of the C_T vector, thus giving the command value below which it will be possible to charge the HSS via the electrical network.

4. EXPERIMENTAL EVALUATION

This section is dedicated to the analysis of the results of the comparison between the algorithm used in the RED WoLF project Shukhobodskiy and Colantuono (2020) and Ortiz et al. (2021) and the model presented in Section 3. These two models use the same infrastructure and the same inputs as shown in Fig. 2. Both strategies use the same type of optimization, namely the use of a heuristic allowing the fast optimization (compared to a mathematical or metaheuristic optimization) of the different phases of charge/discharge of the equipments composing the hybrid energy storage system but CANO adds demand management constraint.

The datasets used to generate the results are detailed in Section 4.1. Section 4.2 presents the results obtained on a specific day for both models. Finally, Section 4.3 is dedicated to the analysis of the monthly results.

4.1 Input datasets

As illustrated in Fig. 3, both algorithms deal with appliances consumption, photovoltaic production and grid carbon load. For a fair comparison, both algorithms use the same state-of-the-art datasets and fully accurate prediction (e.g., real values use as predictions too). Four input data sources are used regarding the conducted experiments:

- *Appliances*: Two datasets are used, UK-DALE (UK Domestic Appliance-Level Electricity) and IHEPCDS (Individual Household Electric Power Consumption Data Set) which provide respectively the consumption of households in the United Kingdom and in France;
- *PV production*: in UK, real photovoltaic production is provided by NREL (National Renewable Energy Laboratory) web site while no such platform for

France was found during our research. Based on the simulator of the European Commission, it is possible to note a gap of 15.4% on the solar production in favor of France;

- *Grid carbon load*: grid carbon load is available through two web site for UK (Carbon Intensity) and France (RTE eCO2mix);
- *Energy price*: both UK and France electricity price are based on study which compare energy price a cross European Union.

4.2 1-day analysis

First of all, the results of the comparison of the CANO and RED WoLF algorithms will be compared over a one-day horizon from the whole October 2019 month with the UK dataset. This day has been selected to highlight a number of parameters that will be detailed later in this section. To perform these experiments, two parameters have been set: the physical characteristics of the battery (capacity: 6.5 kWh, maximum charge and discharge power: 4.2 kW), as well as the maximum power drawable from the grid set by the utility provider (9 kW). Fig. 3a (i) and 3b (i) provide quick view of power generate from PV array (PFP), power consume by appliances (P2A) and power send back to the grid (P2G) respectively for CANO and RED WoLF over the day. The two second graphs provide evolution overview of the storage equipment state of charge (HLV : storage heater level, CLV: cylinder level and BLV: battery level). The dashed lines of the same color as HLV and CLV (solid lines) show the level demanded by the inhabitants over the day on these two storage systems. If the dashed line does not reach the full line, this will result in an area of discomfort such as lack of hot water for a shower or other inconvenience. In the next section, each unsatisfied day will be counted over a month and given as a percentage as “daily needs filled” in Fig. 4. The grid carbon intensity (CO_2) and the CO_2 threshold (THR) are provided by the thirds graphs of the Fig. 3. Finally, the last graphs show the power consumed at each moment of the day, the color representing the power intensity range drawn from the grid (e.i., red ≥ 7 kW; 7 kW $>$ yellow ≥ 3.5 kW; green < 3.5 kW).

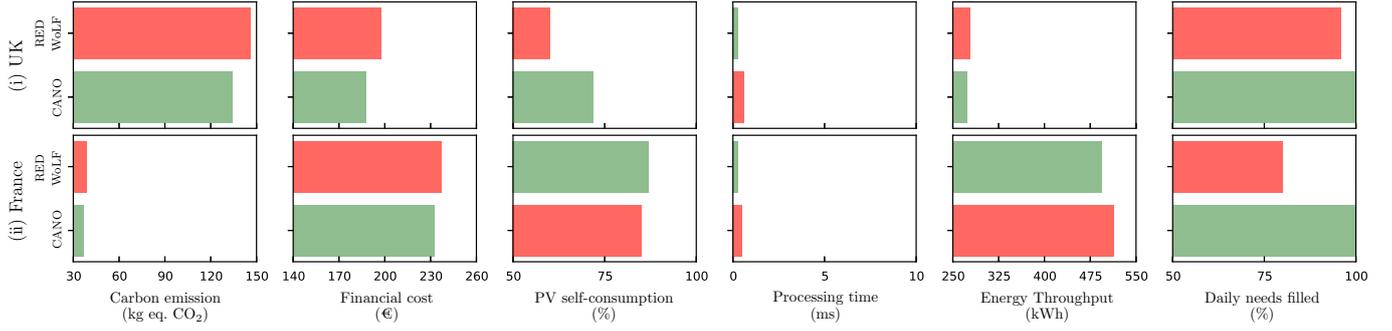


Fig. 4. Monthly indicators

Fig. 3a (i) and Fig. 3b (i) show that for both algorithms in the case of this particular day, the performances related to self-consumption are exactly the same (i.e., no injection to the grid). On the other hand, the times of the day when the grid is solicited are totally different. Indeed, we notice on Fig. 3b (iv) that the strategy adopted by RED WoLF is to charge the battery at the maximum at the beginning of the day to be able to isolate itself completely from the grid. The strategy presented in this article will divide the charge on periods where the carbon intensity is lower, even if it means to use the grid in case of peak consumption of the appliances. Moreover, it could be denoted that these behavior are tied to the CO₂ threshold command

Fig. 3a (ii) and 3b (ii) underline that in some cases, the thermal storage needs (e.g., storage heater and water cylinder respectively represented by blue and orange dashed line) are not satisfied until the end of the day with the algorithm proposed by Shukhobodskiy and Colantuono (2020) and Ortiz et al. (2021). This leads to a lack of energy for space heating and dwelling hot water, thus reducing the inhabitant’s comfort. On the other hand, this tendency is not present with the strategy proposed in this article. Finally, one last thing about the number of charges specific to each of the two solutions. Based on Fig. 3a (ii) and 3b (ii), it is possible to see that the CANO model on this particular day uses a larger amplitude of charge/discharge of the battery (e.g., about 3 charge/discharge against 2 for RED WoLF) which could reduce the lifetime of the battery on a longer horizon (Hu et al., 2020).

4.3 1-month analysis

In order to get a more representative view of the performance of the CANO and RED WoLF algorithms, this section aims to analyze the results over a month. Fig. 5 provides an overview of the energy flows into/out of the house. First, the energy produced by the photovoltaic panels (denote PFP) is common to both algorithms as it is an input to both optimization systems. The energy injected to the grid (denoted P2G) is the part of energy produced by the solar installation that can neither be used by the appliances nor stored in the storage system. Finally, the energy imported from the grid (denote PFG) is a variable controlled by the algorithms and therefore provides an indicator for comparison.

From the Fig. 5, two points can be highlighted: *first*, the results for each algorithm are quite close, with the exception of the 5th day, thus justifying the choice to

analyze this day specifically in Section 4.2; *second*, by comparing Fig. 5 (i) and (ii), It can be observed that CANO outperforms RED WoLF on the self-consumption indicator by injecting less locally generated energy to the national power grid.

Until now the results presented in this paper were based only on the UK dataset, Fig. 4 provides a quick view of the results for both UK and France (Fig. 4(i) and (ii)). This figure allows to quickly identify which algorithm is the best with the color code (green corresponding to the best case) according to the parameter and the country of interest. First of all, it could be denoted that for the first two indicators (see Fig. 4 carbon emission and financial cost) and in both countries, the results are very close but in favor of CANO. Secondly, the computation time indicator denote that for both country, the RED WoLF strategy is twice less time consuming than the strategy propose in this article. This difference could be attributed to the rough cumulative sum action in the CANO process where RED WoLF use a numerical integration task. Then, the results given by the energy throughput indicator shows an inversion between the two datasets while remaining very close. The big difference between the results for France and the UK comes from the fact that the house chosen in the UK consumes less (about twice as much). Table 2 exposes a prediction of the battery life according to the use that the algorithms make of it. Note that the greater this indicator is the shorter the battery life will be. Then, on the Fig. 4, the PV self-consumption indicator shows the share of the local production used to power the appliances or stored in

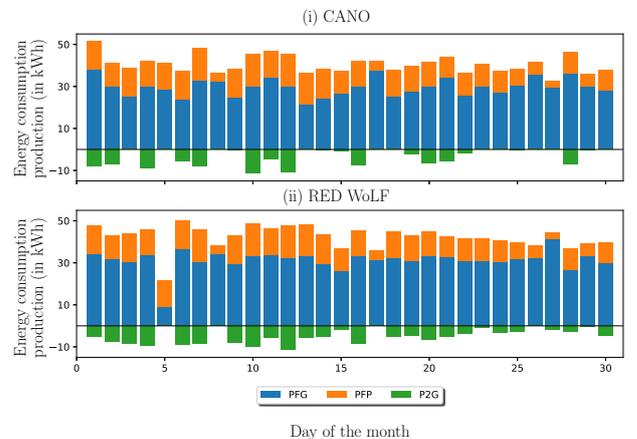


Fig. 5. day 5 – 1-day analysis

the hybrid energy storage system. Two comments could be made: (i) in France, the performance is very close between both algorithm but lower than in the UK; (ii) in the UK, the gap is larger in favor of the model proposed in this paper. Finally, the last but not the least, the daily needs filled indicator highlights probably the biggest advantage of the CANO model: capacity to always fulfill the heating needs. For both countries, CANO reaches the water cylinder and space heating setpoints whereas RED WoLF failed to do the same in one and four days respectively in UK and France.

Table 2. Battery lifetime

Algorithm	Country	Throughput	Warranty	Lifetime
CANO	FR	514 kWh	20 MWh	3.2 years
	UK	273 kWh	20 MWh	6.1 years
RED WoLF	FR	495 kWh	20 MWh	3.3 years
	UK	279 kWh	20 MWh	5.9 years

5. CONCLUSION

This research presents the CANO algorithm which is an evolution of the RED WoLF algorithm. Both algorithms are based on the same facility and therefore have an equivalent initial cost. They also have the advantage of being less demanding in terms of computer resources as the processing is simple compared to exact optimisation methods. The performance comparison between CANO and RED WoLF are relatively close but still to CANO's advantage in terms of reduced carbon emissions, lower electricity bills and increased battery life. On the other hand, CANO's strong point is that it always satisfies the needs of the inhabitants for energy storage, both HLC and CLV, and thus ensures optimal comfort throughout the day. This point is essential in the development of intelligent solutions in the environmental field. Indeed, it is important that the preservation of the planet is not done at the expense of people's comfort and to show that we can find win-win solutions, (i.e., win for the environment and win for the inhabitants). CANO is an algorithm that allows to have this sustainable vision from both a social (people's well-being) and environmental point of view. To go even further in a social direction, we are currently looking at extending CANO to eco- neighbourhoods for battery stored electricity sharing amongst a cluster of homes within the community.

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