# Greenhouse Gas Emission Reduction in Residential Buildings: A Lightweight Model to be Deployed on Edge Devices

Paul Ortiz[a,*], Sylvain Kubler[a,b], Éric Rondeau[a], Katie McConky[c], Alexander Alexandrovich Shukhobodskiy[d], Giuseppe Colantuono[d], Jean-Philippe Georges[a]

[a]*Université de Lorraine, CNRS, CRAN, F-54000, France*
[b]*Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, L-1359 Esch-sur-Alzette, Luxembourg*
[c]*Department of Industrial and Systems Engineering, Rochester Institute of Technology, 81 Lomb Memorial Drive, Rochester, NY 14623, United States*
[d]*School of Built Environment, Engineering and Computing, Leeds Beckett University, Leeds, LS1 3HE, UK*

**Abstract**

Electricity produced and used in the residential sector is responsible for approximately 30% of the greenhouse gas emissions (GHGE). Insulating houses and integrating renewable energy and storage resources are key for reducing such emissions. However, it is not only a matter of installing renewable energy technologies but also of optimizing the charging/discharging of the storage units. A number of optimization models have been proposed lately to address this problem. However, they are often limited in several respects: (i) they often focus only on electricity bill reduction, placing GHGE reduction on the backburner; (ii) they rarely propose hybrid-energy storage optimization strategies considering thermal and storage heater units; (iii) they are often designed using Linear Programming (LP) or metaheuristic techniques that are computational intensive, hampering their deployment on edge devices; and (iv) they rarely evaluate how the model impacts on the battery lifespan. Given this state-of-affairs, the present article compares two approaches, the first one proposing an innovative sliding grid carbon intensity threshold algorithm developed as part of a European project named RED WoLF, the second one proposing an algorithm designed based on LP. The comparison analysis is carried out based on two distinct real-life scenarios in France and UK. Results show that both algorithms contribute to reduce GHGE compared to a solution without optimization logic (between 10 to 25%), with a slight advantage for the LP algorithm. However, RED WoLF makes it possible to reduce significantly the computational time ($\approx$ 25 min for LP against $\approx$ 1 ms for RED WoLF) and to extend the battery lifespan (4 years for LP against 12 years for RED WoLF).

*Keywords:* Greenhouse Gas Emission, Energy efficiency, Photovoltaics, Battery, Edge computing, Linear Programming

## 1. Introduction

Globally, the residential sector accounts for a substantial part of the consumed energy and greenhouse gas emission (GHGE) [1, 2]. Reducing GHGE can be achieved by better insulating houses and buildings, switching from polluting (albeit cheap) coal to natural gas or renewable energy sources [3], and developing intelligent applications to efficiently integrate such renewables resources with flexible storage systems [4]. Indeed, it is not only a matter of installing renewable energy technologies (e.g., PV array, wind or biomass), but also of optimizing the charging/discharging of the storage units (e.g., battery, thermal storage, electric vehicles, etc.) [5].

A number of charging and discharging optimization models of storage units have been proposed in the literature [6]. Although these models may differ in terms of required infrastructure (e.g., different renewable energy sources, loads), targeted fitness goals, they are often limited in three-respects. First, they are often designed based on Linear Programming (LP), which can quickly become complex and time consuming with the increase in the number of constraints and variables. Significant computation requirements of LP can have negative environmental impacts due to computational energy consumption. Heuristic methods to solve LP's can combat the computation issue, but the trade off is in solution quality

*Corresponding author
*Email addresses:* paul.ortiz@univ-lorraine.fr (Paul Ortiz), s.kubler@univ-lorraine.fr (Sylvain Kubler), eric.rondeau@univ-lorraine.fr (Éric Rondeau), ktmeie@rit.edu (Katie McConky), A.Shukhobodskiy@leedsbeckett.ac.uk (Alexander Alexandrovich Shukhobodskiy ), G.Colantuono@leedsbeckett.ac.uk (Giuseppe Colantuono), jean-philippe.georges@univ-lorraine.fr (Jean-Philippe Georges)

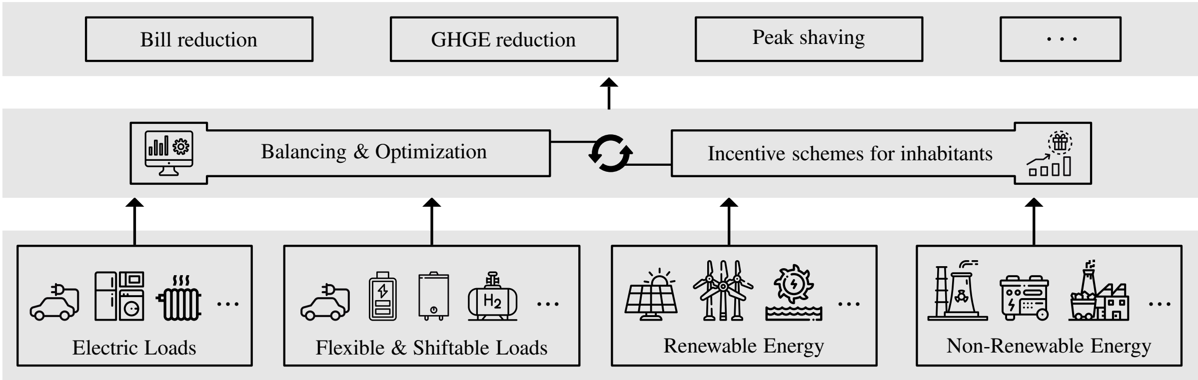



Figure 1: Nanogrid main technological constituents

with heuristics providing sub-optimal solutions. Second, they often focus on cost – *electricity bill* – reduction, placing environmental goals such as GHGE reduction, maximization of the system's lifespan, on the backburner. Third, they often consider a single storage unit (mostly Battery Energy Storage System - BESS) and rarely propose hybrid-energy storage optimization strategies (e.g., combining BESS with thermal storage, storage heaters, *etc.*). Such limitations have been stressed and discussed in the recent survey published by [6]. To overcome these limitations, an innovative sliding grid carbon intensity threshold approach, developed as part of a European project named RED WoLF[1] (Rethink Electricity Distribution Without Load Following), has been presented in our previous research work [7, 8, 9], which can act on any dwelling. In the present article, the goal is to study the extent to which RED WoLF outperforms LP or heuristic-based algorithms in terms of GHGE reduction efficiency, battery lifespan maximization, and computational complexity. The latter (computational complexity) is of particular importance with the advent of Edge Computing in the energy sector [10, 11], which pushes the frontier of computation applications away from centralized nodes (Cloud) to the communication network's extremes (Edge).

In section 2, a review of existing energy storage optimization strategies is carried out, based on which research trends and gaps are discussed. Section 3 presents the RED WoLF system and underlying logic, but also proposes an extension of the algorithm introduced by Olivieri and McConky [12] with the aim of integrating PV energy resources into their model. Both algorithms are evaluated and compared in section 4 considering two real-life scenarios (houses) from France and UK, the conclusion follows in section 5.

[1] https://www.nweurope.eu/projects/project-search/red-wolf-rethink-electricity-distribution-without-load-following/

## 2. Scope, Definition and Positioning

Section 2.1 provides the necessary background information to understand where our contribution stands in the energy field. Section 2.2 discusses how our research progresses the current state-of-the-art.

### *2.1. Scope and Definition*

The energy life cycle consists of several stages, spanning from its generation and transmission to its distribution and consumption [13]. The present research falls within the scope of energy management at the consumption stage, and more exactly in residential nanogrids [14]. Energy management in nanogrids usually consists of four equipment categories, as depicted in Figure 1, namely:

- *Electric Loads:* referring to house equipment that consume energy such as appliances, Electric Vehicle (EV), HVAC equipment, *etc.*;
- *Flexible & Shiftable Loads:* referring to equipment able to store energy for later use (incl., batteries, storage heaters, water cylinders, or stationary electrical vehicles) or to shift consumption from the peak of the utility provider's demand curve, when energy is most precious, to another most appropriate time (e.g., by delaying the start time of the washing machine or the charging start time of the EV);
- *Renewable energy sources:* referring to energy sources that can be regenerated and sustainably utilized from nature including non-fossil energy such as wind energy, solar energy, biomass energy, geothermal energy or kinetic ocean energy;
- *Non-renewable energy sources:* referring to energy sources that have finite supplies and cannot be restored or regenerated in short periods of time (incl., coal, natural gas, oil, nuclear energy).

Depending on the type of nanogrid architecture (i.e., presence or not of renewable energy sources, flexible loads, *etc.*) and the targeted objectives (e.g., reducing energy bills and/or GHGE and/or extending device lifetimes, *etc.*), the Energy Management System (EMS) integrates different logics [6, 4], as reviewed and discussed in the next section.

### 2.2. *Current state-of-affairs*

This section presents an overview of the current state-of-affairs, along with the trends and gaps in the literature. The methodology applied for reviewing the literature is detailed in Figure 2. Sources such as doctoral dissertations, master's theses, textbooks and unpublished papers were ignored. A first filter, denoted by (1) in Figure 2, has been applied, consisting in selecting articles based on the abstract content. This led us to keep 202 articles. A second filter, denoted by (2), has then been applied to keep papers dealing with energy storage optimization (147 articles were identified). A final third filter denoted by (3), was applied to keep only papers proposing approaches at the residential level only. This led us to review 43 articles, which have been classified in Table 1 based on the following criteria/categories:

- *Lifecycle phase:* highlights whether the proposed approach deals with an optimization problem at the Design (D) phase (e.g., for battery sizing) or at the Operational (O) one (i.e., for deciding when to consume/store/release energy);

- *Optimization goal(s):* highlights what objective(s) is/are targeted by the proposed approach, which are categorized as follows: (i) bill reduction; (ii) GHGE reduction; (iii) peak shaving; (iv) sustainability; (v) grid independency; (vi) fuel reduction;

- *Energy storage:* highlights what storage systems are considered/used, which are categorized as follows: (i) BESS (battery energy storage system) to (ii) hydro, (iii) Electric Vehicle (EV), (iv) thermal or heating, and (v) fuel cell storage. This category also emphasizes whether the approach takes advantage of (vi) shiftable loads;

- *Energy production:* highlights what production systems are considered/used, which are categorized as follows: (i) fossil fuel, (ii) electrical grid; (iii) PV array; (iv) wind turbine;

- *Method:* highlights the type of methods used for optimization: (i) Heuristic (H); (ii) Metaheuristic (MH); (iii) Mathematical Programming (MP); (iv) Rule-Based (RB); (v) Multi-Criteria Decision Attribute (MCDA).

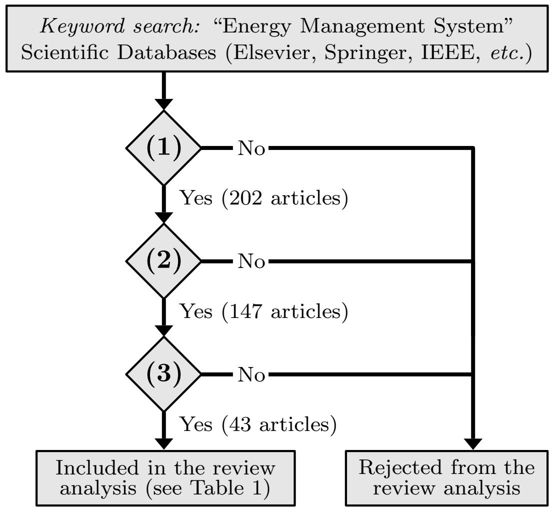



Figure 2: Literature review process

A first interesting finding from this review is that there is a similar proportion of articles dealing with optimization problems at the design (D) phase and at the operational (O) one. In the former (D), articles mainly focus on optimizing the hardware constituents (battery size, installation cost, self-consumption capabilities, *etc.*) as well as the equipment configuration to meet the various possible objectives (e.g., total cost of the installation, environmental impact, self-consumption). The HOMER (Hybrid Optimization Model for Electric Renewable) software, developed by the National Renewable Energy Laboratory (NREL), appears in several of these articles [22, 21, 28], as it allows for simulating and analyzing different types of renewable energy infrastructures. Although our article focuses on the operational phase (optimizing energy storage over time), our review evidences that optimization also plays a key role at the design phase.

Regarding the articles at the operational (O) phase, most of the literature focuses on optimizing charging/discharging cycles of the energy storage systems to shift the consumption from peak to off-peak hours. As evidenced in Table 1, all the reviewed articles adopt a multi-objective optimization model, aiming at first – *in 95% of the reviewed articles* – reducing the electricity bill, second – *48%* – at reducing GHGE, third – *42%* – at improving sustainability aspects (e.g., extending the battery lifespan) and/or grid interdependency, while peak shaving and fuel reduction have been considered infrequently in the reviewed papers. From an energy production and storage viewpoint, a significant proportion of the reviewed articles – *62%* – consider a combination of electrical grid, PV and BESS technologies, which can be explained by the fact that it is often the most economical configuration, as analyzed in [57]. Another interesting point is that

Table 1: Classification of the scientific articles reviewed throughout Section

| | Lifecycle Phase | Optimization Goals | | | | | | Storage/Shiftable | | | | | | Production | | | | Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Bill reduction | GHGE reduction | Peak Shaving | Sustainability | Grid Independency | Fuel reduction | Shiftable Load | BESS | Hydro | EV | Thermal / Heating | Fuel Cell | Fosil Fuel | Electrical Grid | PV Array | Wind Turbine | |
| Tooryan et al. [15] | D | ■ | ■ | | ■ | ■ | ■ | | ■ | | | ■ | ■ | ■ | ■ | ■ | ■ | MH |
| Tooryan et al. [16] | D | ■ | ■ | | ■ | ■ | ■ | | ■ | | | | | ■ | | ■ | ■ | MH |
| Das et al. [17] | D | ■ | ■ | | ■ | ■ | | ■ | | | ■ | | | | ■ | | | MCDA |
| Yazan M. et al. [18] | D | ■ | ■ | | ■ | | | | | | | | | | | | | MH |
| Awan et al. [19] | D | ■ | ■ | | ■ | | | | ■ | | | | ■ | ■ | | ■ | ■ | MH |
| Ashraf et al. [20] | D | ■ | ■ | | | ■ | | | | | | | | | | | | MH |
| Awan [21] | D | ■ | ■ | | | ■ | | | ■ | | | | | ■ | | ■ | ■ | H |
| Fodhil et al. [22] | D | ■ | ■ | | | ■ | | | ■ | | | | | ■ | | ■ | | MH |
| Fonseca et al. [23] | D | ■ | ■ | | | ■ | | | ■ | | | | ■ | ■ | ■ | ■ | | MP |
| Ayse Fidan and Muhsin [24] | D | ■ | ■ | | | | ■ | | | | | | | | | | | MH |
| Bingham et al. [25] | D | ■ | ■ | | | | | | ■ | | | | | | ■ | ■ | | MH |
| Salehi et al. [26] | D | ■ | ■ | | | | | | ■ | | | ■ | | ■ | ■ | | ■ | RB |
| García-Vera et al. [27] | D | ■ | | | ■ | | | | ■ | | | | | ■ | | ■ | ■ | MH |
| Aziz et al. [28] | D | ■ | | | | | | | ■ | ■ | | | | ■ | | ■ | | RB, H |
| Pandžić [29] | D | ■ | | | | | | | ■ | | | | | | ■ | | | MP |
| O'Shaughnessy et al. [30] | D | ■ | | | | | | | ■ | | | | | | ■ | ■ | | H |
| Nguyen et al. [31] | D | ■ | | | | | | | | | | | | | ■ | | ■ | MP |
| Borra and Debnath [32] | D | | ■ | | | | ■ | | | | | | | ■ | | | | MH |
| Arévalo et al. [33] | D | | | | | | | | | | | | | | | | | RB |
| Bhayo et al. [34] | D | | | | | | | | ■ | ■ | | | | | | ■ | | MH |
| Haidar et al. [35] | O | ■ | ■ | | | | | | ■ | | | | | ■ | ■ | | | MP |
| Mahmud et al. [36] | O | ■ | ■ | | | | | | ■ | | ■ | | | | ■ | ■ | | RB |
| Liu et al. [37] | O | ■ | ■ | | ■ | | | | ■ | | | | | | ■ | ■ | | RB |
| Nagapurkar and Smith [38] | O | ■ | ■ | | ■ | | | | ■ | | | | ■ | ■ | | ■ | ■ | MH |
| Olivieri and McConky [39] | O | ■ | ■ | | | | | | ■ | | | | | | ■ | | | MP |
| Schram et al. [40] | O | ■ | ■ | | ■ | ■ | | | ■ | | | | | | ■ | | | H |
| Stepaniuk et al. [41] | O | ■ | ■ | | | ■ | | | ■ | | | | | | ■ | ■ | ■ | RB |
| Terlouw et al. [42] | O | ■ | ■ | | ■ | | | | ■ | | | | | | ■ | ■ | | MP |
| Terlouw et al. [43] | O | ■ | ■ | | | ■ | | ■ | ■ | | | ■ | | | ■ | ■ | | MP |
| Moradi et al. [44] | O | ■ | ■ | | | | | | ■ | | | | | ■ | ■ | ■ | ■ | MP |
| Nottrott et al. [45] | O | ■ | | ■ | | ■ | | | ■ | | | | | | ■ | ■ | | MP |
| Yadav et al. [46] | O | ■ | | ■ | | | | | ■ | | | | | ■ | | | | MP |
| Mulleriyawage and Shen [47] | O | ■ | | | ■ | ■ | | | ■ | | | | | | ■ | ■ | | MP |
| Litjens et al. [48] | O | ■ | | | ■ | ■ | | | ■ | | | | | | ■ | ■ | | RB |
| Adefarati et al. [49] | O | ■ | | | ■ | | | | ■ | | | | | ■ | | ■ | ■ | MH |
| Aziz et al. [50] | O | ■ | | | ■ | | | | ■ | | | | | ■ | | ■ | | RB, H |
| García-Triviño et al. [51] | O | ■ | | | ■ | | | | ■ | | | | ■ | | | ■ | ■ | MH |
| Marzband et al. [52] | O | ■ | | | | ■ | | | ■ | | | | | | ■ | ■ | | MH |
| Marzband et al. [53] | O | ■ | | | | ■ | | | ■ | | | | | | ■ | ■ | ■ | MP |
| González-Briones et al. [54] | O | ■ | | | | | | ■ | | | | | | | ■ | | | RB |
| Luo et al. [55] | O | ■ | | | | | | | ■ | | | | ■ | ■ | ■ | ■ | ■ | MH |
| Shukhobodskiy and Colantuono [9], Ortiz et al. [7] | O | | ■ | | | ■ | | | ■ | | | ■ | | ■ | ■ | ■ | ■ | RB |
| Auñón-Hidalgo et al. [56] | O | | | | | ■ | ■ | | ■ | | | ■ | | ■ | ■ | ■ | | RB |
| | | **38** | **24** | **2** | **15** | **17** | **5** | **3** | **35** | **2** | **2** | **5** | **6** | **18** | **25** | **28** | **14** | |

a couple of approaches propose to combine different types of storage such as BESS and EV [36], BESS and hydrogen storage [34], or still BESS and thermal storage (e.g., water cylinder) [9, 56, 43], which provides additional flexibility for energy management. Looking at the optimization techniques used for problem-solving, most of the approaches – *in 80% of the reviewed articles* – rely on optimization solvers or heuristic algorithms, which require a certain amount of time to find optimal solutions, often growing exponentially along with the increase of constraints and variables. This constitutes a serious impediment for the development of Edge Computing solutions in the energy sector, as thoroughly discussed in [10].

Given the lack of approaches combining different types of storage systems, and the fact that most of them are computationally intensive, a new hybrid storage system for GHGE reduction in residential houses/dwellings is being developed by the Interreg NWE RED WoLF consortium, as originally presented in [9]. Section 3 recalls the infrastructure and logic underlying RED WoLF, but also proposes an extension of the LP-based algorithm introduced by Olivieri and McConky [12] with the aim to integrate PV into the model.

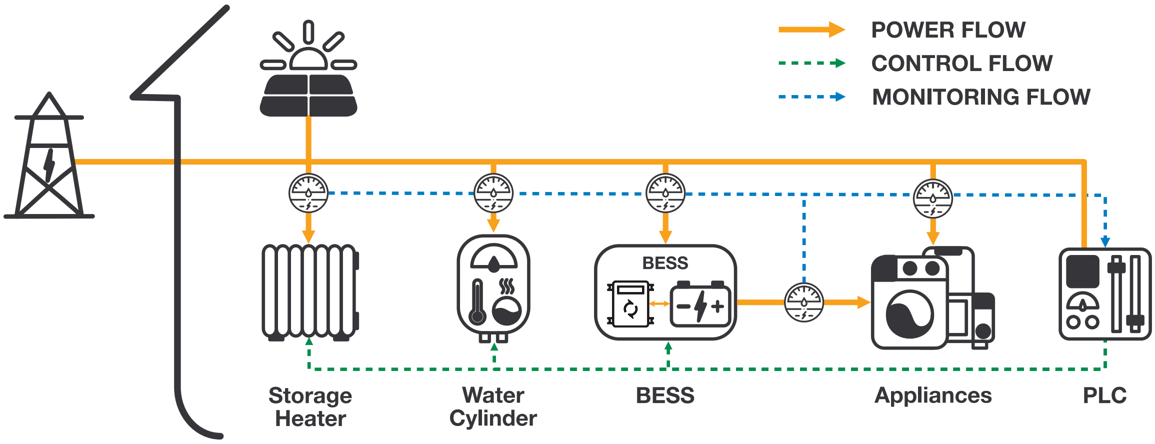



Figure 3: Overview of the RED WoLF's hardware architecture, along with the underlying power, data monitoring and control flows

## 3. GHGE reduction systems

The hybrid-energy storage strategy proposed in RED WoLF is detailed in section 3.1. The extension of Olivieri's model is then presented in section 3.2.

### 3.1. RED WoLF optimization system

Figure 3 gives an overview of the hardware, electrical and communication architecture underlying the RED WoLF system [9, 7], highlighting the power flow, monitoring flow (i.e., monitored devices) and control flow (devices that can be controlled by the algorithm). As a first category of equipment, home appliances comprise all devices that consume electrical power and do not have any storage capability (e.g., TV, oven, light, *etc.*). It should be noted that, as of today, RED WoLF does not consider shiftable loads as an additional flexibility resource. From an energy supply perspective, RED WoLF considers two electrical power sources to supply the home appliances, namely (i) the national electrical grid, which is a non-renewable energy source as it has a carbon intensity, and (ii) a PV array, which is a renewable (non-polluting) source. In terms of flexible energy-storage devices, RED WoLF proposes a hybrid-energy storage system, combining electrochemical and thermal storage systems, as illustrated in Figure 3 (BESS, water cylinder and storage heaters). Finally, from a control viewpoint, the RED WoLF algorithm is executed in a PLC (see Figure 3), generating commands at different times to either store or draw a certain amount of power in/from the above described hybrid-energy storage system.

Based on the hardware constituents, several data are collected for use by the RED WoLF algorithm. These data can be categorized in three classes:

i. *Static parameter values:* referring to fixed parameters such as manufacturers' data (e.g., maximum battery capacity);

ii. *Real-time data values:* referring to live data monitored at the hardware layer (e.g., data coming from smart meters, sensors in the battery, *etc.*);

iii. *Predicted data values:* referring to predicted data such as predicted grid carbon intensities, predicted PV generation and house consumption.

Table 2 (column denoted by class) reports what system variables belong to what class. It should be noted that some system parameters are both predicted (using ML) and monitored in real-time (e.g., via sensors), such as house appliance demand (respectively denoted by $A_{pre}$ and $A_{cur}$), the output power produced by PV ($PV_{pre}$, $PV_{cur}$), or the grid carbon intensities ($CO_{2cur}$, $CO_{2pre}$). Based on the input data, the RED WoLF algorithm follows a two-step approach. First, a $CO_2$ threshold applied on the (predicted) grid intensity signal is computed, which identifies when it is optimal to draw energy from the grid to meet – *at minimum* – the house demand. Based on this threshold, a rule-based strategy is applied to decide the charging/discharging actions to be executed. These two steps are further described in the following paragraphs.

To compute the $CO_2$ threshold, the average available electrical power to supply the thermal storage system ($G_{PU}$), the energy required to reach the setpoint until the end of the day ($D_{ED}$), the heater and cylinder power demands ($H_{dem}$ and $C_{dem}$) must be computed, as respectively given from Eq. (1) to (4). Several system constraints and state variables are used in this respect, such as the maximum charging power of the battery, cylinder and heater (respectively denoted by $B_{Imax}$, $H_{Imax}$, $C_{Imax}$), the maximum power drawable from the grid ($D_{Imax}$), or still the current level of charge of the heater and cylinder ($H_{lev}$ and $C_{lev}$). Note that the Heaviside step function (*Heavi*) is defined as `True` (1) if the input parameter is positive,

Table 2: Variables used in the RED WoLF optimization system

| | Class | Variable | Units | Description |
|---|---|---|---|---|
| Input & Internal Variables | Real-time | $A_{cur}$ | kW | Current power injected to appliances |
| | Real-time | $CO_{2cur}$ | $gCO_2/kWh$ | Current grid $CO_2$ load |
| | Real-time | $PV_{cur}$ | kW | Current PV production |
| | Real-time | $B_{lev}$ | kWh | State/Level of charge of the battery |
| | Real-time | $C_{lev}$ | kWh | State of charge of the water cylinder |
| | Real-time | $H_{lev}$ | kWh | State of charge of the storage heater |
| | Predicted | $A_{pre}$ | kW | Predicted power to be injected to the appliances |
| | Predicted | $PV_{pre}$ | kW | Predicted PV production |
| | Predicted | $CO_{2pre}$ | $gCO_2/kWh$ | Predicted grid $CO_2$ load |
| | Predicted | $D_{ED}$ | kWh | Predicted energy consumed by appliances until the end of the day |
| | Predicted | $G_{PU}$ | kW | Predicted average remaining power drawable from the grid |
| | Static | $B_C$ | kWh | Charging capacity of the battery |
| | Static | $B_{Imax}$ | kW | Maximum battery intake power |
| | Static | $C_{Imax}$ | kW | Maximum water cylinder's power intake |
| | Static | $C_{set}$ | kWh | Setpoint of cylinder |
| | Static | $D_{Imax}$ | kW | Maximum equipment usable power set by the electricity provider |
| | Static | $H_{Imax}$ | kW | Maximum storage heater's power intake |
| | Static | $H_{set}$ | kWh | Setpoint of storage heater |
| | N/A | $C_{dem}$ | kW | Current water cylinder's power demand |
| | N/A | $B_{dem}$ | kW | Current battery's power demand |
| | N/A | $D_{ImaxAPV}$ | kW | Maximum equipment usable power including PV and appliances |
| | N/A | $H_{dem}$ | kW | Current storage heater's power demand |
| | N/A | $P_{bal}$ | kW | Power balance after powering appliances and equipment supply |
| | N/A | $CO_{2thr}$ | $gCO_2/kWh$ | $CO_2$ threshold over which grid electricity is not allowed to be drawn |
| | N/A | $T_I$ | min | Minimum time to supply equipment and appliances |
| Output Var. | Real-time | $B_{con}$ | kW | Power to be drawn from the battery |
| | Real-time | $B_{inj}$ | kW | Power to be stored in the battery |
| | Real-time | $C_{cur}$ | kW | Power to be stored in the water cylinder |
| | Real-time | $G_{con}$ | kW | Power to be drawn from the grid |
| | Real-time | $G_{inj}$ | kW | Power to be injected to the grid |
| | Real-time | $H_{cur}$ | kW | Power to be stored in the storage heater |

`False` (0) otherwise.

$$G_{PU} = D_{Imax} - \int_t^T \frac{A_{pre}(t)}{(T-t)} dt - B_{Imax} \quad (1)$$

$$D_{ED} = \int_t^T \frac{A_{pre}(t)}{60} dt + \sum_{i=H,C} (i_{dem} - i_{lev}) \quad (2)$$

$$H_{dem} = H_{Imax} \times Heavi(H_{set} - H_{lev}) \quad (3)$$

$$C_{dem} = C_{Imax} \times Heavi(C_{set} - C_{lev}) \quad (4)$$

The minimum time length to charge equipment is further computed, as given in Eq. (5).

$$T_I = \max\left(\frac{D_{ED}}{G_{PU}}, \frac{H_{dem} - H_{lev}}{H_{Imax}}, \frac{C_{dem} - C_{lev}}{C_{Imax}}\right) \quad (5)$$

The $CO_2$ threshold ($CO_{2thr}$), which identifies the best intervals for drawing electricity from the grid, is then computed using Eq. (6), $CO_{2preSort}$ referring to the $CO_2$ prediction vector sorted in ascending order, as given in Eq. (7). The ceil function used in Eq. (6) allows for getting an integer value, which represents the drawing time (in minutes) that is used as index of the $CO_2$ threshold in the sorted $CO_2$ vector.

$$CO_{2thr} = CO_{2preSort}\,(\lceil T_I \rceil) \quad (6)$$

$$CO_{2preSort} = sort(CO_{2pre}) \quad (7)$$

Figure 4 illustrate the output when applying the above equations. Assuming a $T_I$ equals to $7h$, the threshold that meets this charging duration should be identified. The first threshold example (denoted by $CO_2^a$ in Figure 4) does not meet this requirement, while the second threshold ($CO_2^b$) does, resulting in two "low $CO_2$ periods": $[8am; 10am]$ and $[2pm; 6pm]$. Based on the computed threshold, a specific rule-based logic is applied, which is detailed in the form of a flowchart in Figure 5 using the UML activity diagram formalism. This flowchart shows that two parts are run in parallel. On the first part (see frame denoted by "$CO_2$ threshold computation" in Figure 5), the steps refer to the reading of sensor data

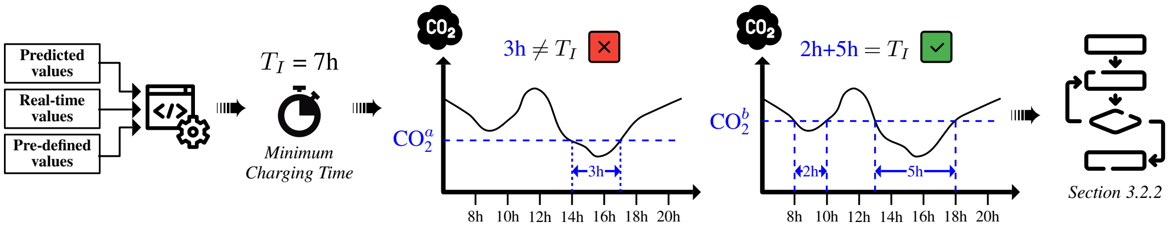



Figure 4: Illustration of the $CO_2$ threshold computation used in the RED WoLF's GHGE reduction system

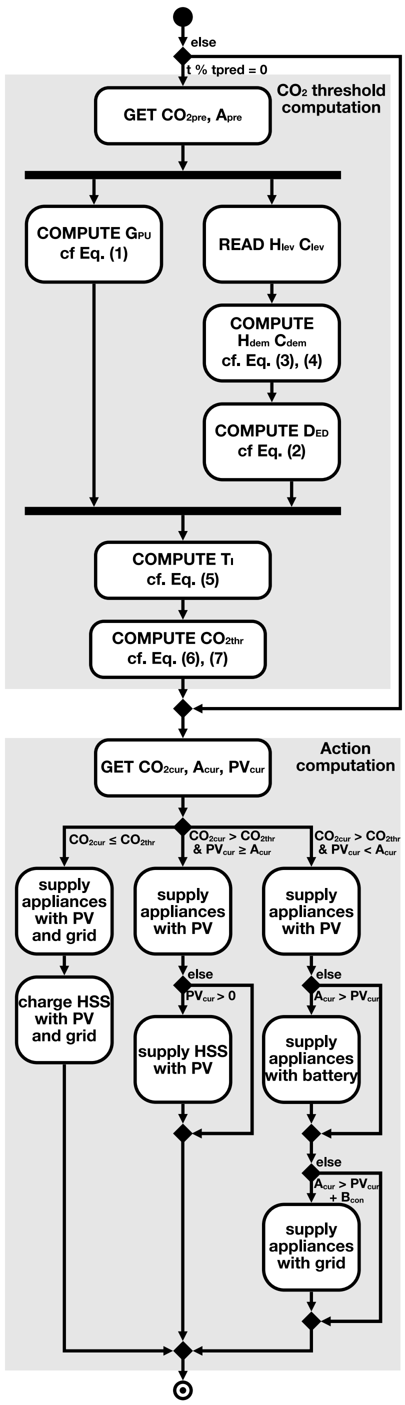



Figure 5: Overall RED WoLF logic

needed to compute the $CO_2$ threshold ($CO_{2thr}$). Such data is either locally accessed (e.g., state of charge of the battery) or remotely (e.g., appliance consumption forecasts or grid carbon intensity forecasts that are computed at the Cloud level). On the second part (see frame denoted by "Actions computation" in Figure 5), the steps refer to the decisions about the actions to be executed in terms of energy storage and release depending on the threshold value ($CO_{2thr}$), namely:

1. if $CO_{2cur} < CO_{2thr}$, appliances and the hybrid-energy storage system are powered by the grid and PV array;
2. if $CO_{2cur} > CO_{2thr}$ but PV is sufficient, appliances are powered through PV and extra-power (if any) is used to load the hybrid-energy storage system;
3. if $CO_{2cur} > CO_{2thr}$ and PV is insufficient, appliances are powered through PV; if not sufficient, through battery; if not yet sufficient, then through the grid.

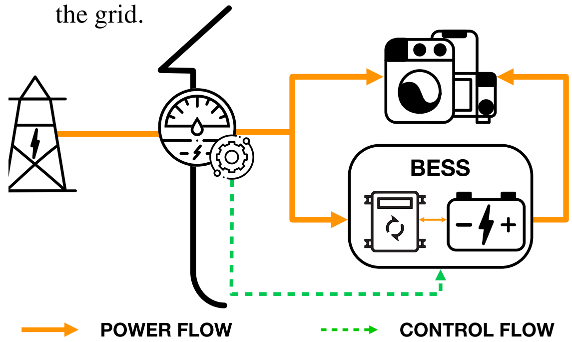



Figure 6: Olivieri's hardware architecture

### 3.2. Olivieri's optimization system

Olivieri's optimization model considers the infrastructure detailed in Figure 6, the algorithm being run on a smart meter that controls the battery [12]. The model uses a LP solver to reduce electricity bill, carbon emission, or both simultaneously. For a fair comparison with RED WoLF, only the model proposed for carbon emission reduction is considered in this study. This model is detailed through Eq. (8) to (17), which minimizes the $CO_2$ emissions produced to meet the household's energy demand during a time interval denoted by $i$. $CO_2$ emissions are computed using Eq. 9,

Table 3: Variables used in the Olivieri's optimization system [12]

| | Class | Var. | Unit | Description |
|---|---|---|---|---|
| Input & Internal Variables | Predicted | $d_i$ | kW | Power required to supply appliances over the time interval $i$ |
| | Predicted | $M_i$ | $gCO_2$/kWh | Grid $CO_2$ load over the time interval $i$ |
| | Predicted | $pv_i$ | kW | Power provided by PV over the time interval $_i$ |
| | Real-time | Cap | kWh | BESS max capacity |
| | N/A | $ppv_i$ | kW | Power from PV used by appliances over the time interval $i$ |
| | N/A | $bpv_i$ | kW | Power from PV injected to BESS over the time interval $i$ |
| | N/A | $gpv_i$ | kW | Power from PV sent back to grid over the time interval $i$ |
| | N/A | $CO2_i$ | $gCO_2$ | $CO_2$ emitted over the time interval $i$ |
| | N/A | $SOC_i$ | kWh | BESS state of charge read over the time interval $i$ |
| | N/A | I | hrs | Length of each time interval |
| | N/A | T | N/A | Set of discrete time intervals |
| | N/A | inef | % | Inefficiency factor (0 to 1) |
| Out. | N/A | $pc_i$ | kW | Power charged in BESS over interval $i$ |
| | N/A | $pd_i$ | kW | Power discharged from BESS over $i$ |

while Eq. (10) and (11) define the BESS charging and discharging constraints. Eq (12) represents the BESS maximum capacity to store energy, while the BESS state of charge (SOC) is computed using Eq. (13) to (15). Olivieri's model was slightly adapted to integrate the PV system to the infrastructure[2] for fair comparison with RED WoLF. The model extension corresponds to the variables highlighted in bold in Eq. (8) to (17); all variables being summarized in Table 3.

$$\min Emissions = \sum_{i \in T} CO2_i \tag{8}$$

subject to

$$CO2_i = (d_i + pc_i - pd_i \boldsymbol{-} \boldsymbol{ppv_i}) \cdot I \cdot M_i, \forall i \in T \tag{9}$$

$$pc_i \geq 0, \forall i \in T \tag{10}$$

$$pd_i \geq 0, \forall i \in T \tag{11}$$

$$(pc_i \boldsymbol{+} \boldsymbol{bpv_i}) \leq Cap/2.7, \forall i \in T \tag{12}$$

$$SOC_i = \sum_{t=0}^{i} (pc_t \boldsymbol{+} \boldsymbol{bpv_i}) \cdot inef \cdot I - \sum_{t=0}^{i} pd_t \cdot I, \forall i \in T \tag{13}$$

$$SOC_i \geq 0, \forall i \in T \tag{14}$$

$$SOC_i \leq Cap, \forall i \in T \tag{15}$$

$$\boldsymbol{gpv_i + ppv_i + bpv_i = pv_i, \forall i \in T} \tag{16}$$

$$\boldsymbol{gpv_i,\ ppv_i,\ bpv_i \geq 0, \forall i \in T} \tag{17}$$

## 4. Experimental evaluation

To evaluate the performance of RED WoLF, three scenarios are defined and compared, as illustrated in Figure 7. In the first scenario (denoted by "Baseline" in Figure 7), the carbon footprint in terms of kg equivalent $CO_2$ emissions (denoted by *kg eq.* $CO_2$ in the rest of the paper) is computed for a given residential house and a given energy consumption demand. As energy supply sources, the considered house has a PV installation and is connected to the grid, but it does not have any storage system nor optimization logic. In the second scenario (denoted by "Olivieri"), Olivieri's optimization algorithm is implemented and compared against the baseline scenario. In the third scenario (denoted by "RED WoLF"), the RED WoLF hybrid-energy storage system is implemented and compared against the Baseline and Olivieri scenarios.

Section 4.1 presents the datasets used as inputs of the conducted experimental evaluation. Section 4.2 presents the performance comparison analysis of the three scenarios.

### 4.1. Experimental setup

As illustrated in Figure 7, the three scenarios are going to be compared on the basis of three performance indicators, namely *(i) $CO_2$ emissions*: $CO_2$ equivalent greenhouse gas emissions produced for supplying house electrical power demand in kg eq. $CO_2$; *(ii) Computational time*: time needed to generate the recommended set of commands to be executed; *(iii) Battery lifespan*: amount of time a battery lasts until it needs to be replaced. In terms of input data, four data sources have been considered:

1. *Home consumption:* the state-of-the-art UK-DALE (UK Domestic Appliance-Level Electricity) and IHEPCDS (Individual Household Electric Power Consumption Data Set) datasets have been considered in this study, which provide real house consumption behaviors from houses located in UK and France respectively [58] (see

[2] The average electricity consumption of the thermal heating and hot water are computed (respectively being equal to 1.04 kW + 0,167 kW) and added to the total house demand.

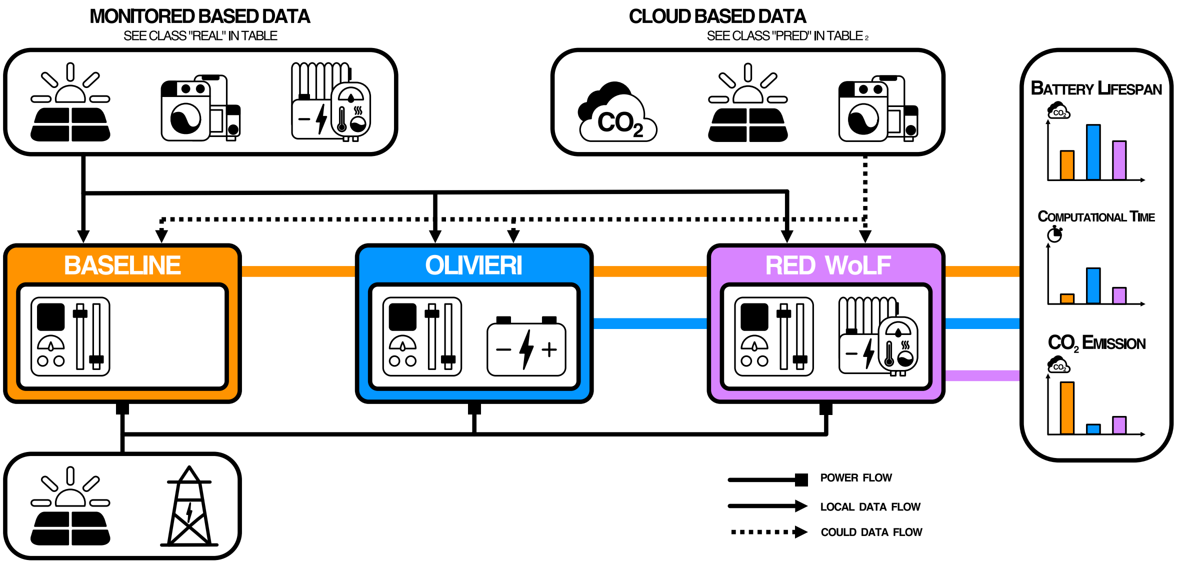



Figure 7: Comparison Infrastructure

Table 4 for further details). The reason for considering these two datasets is twofold: (i) as of the RED WoLF project, pilots located in these two countries are currently being set up; (ii) these two countries have different ways of generating electricity (nuclear in France, natural gas in UK), which have direct impact on the grid's carbon intensity. The October month is considered in this study;

2. *PV production:* to the best of our knowledge, there is no platform in France providing real-time PV production, while in UK the NREL (National Renewable Energy Laboratory) web platform makes available both historical and predicted PV datasets. A simulator developed by the European Commission (*cf.*, Table 4) nonetheless shows that there is a difference of 15.4% between UK and France (in favor of France). On this basis, the PV production dataset in UK (obtained via the NREL platform) was increased by 15.4% for the French experiments;

3. *Grid carbon intensity:* two distinct web platforms making carbon intensity available for France and UK were used, namely RTE for France and Carbon Intensity for UK (*cf.*, Table 4).

For a fair and consistent comparison between scenarios, the energy demands of the Baseline and Olivieri models have been slightly adjusted to include the power used for space and water heating in the RED WoLF scenario. It should also be noted that the time interval $i$ in Olivieri's algorithm has been set to 1 min in our experiments.

Table 4: Datasets used as experimental inputs

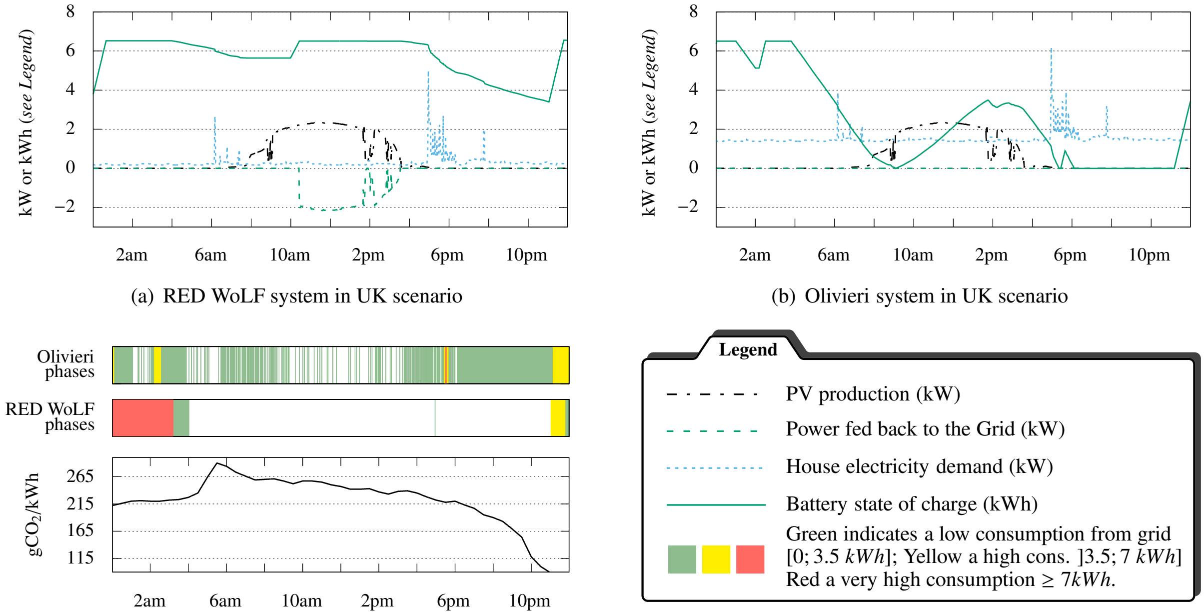
| Dataset | Loc. | Name | Period | URL |
|---|---|---|---|---|
| House demand | UK | UKDALE | Oct. | [59] |
| | FR | IHEPCDS | Oct. | |
| PV production | UK | N/A | Oct. | [60] |
| | FR | N/A | Oct. | [61] |
| Grid carbon intensity | UK | N/A | Oct. | [62] |
| | FR | N/A | Oct. | [63] |
| Energy price | UK | N/A | N/A | [64] |
| | FR | N/A | N/A | |

### 4.2. Experimental results

In this section, the three scenarios/algorithms (Baseline *vs.* Olivieri *vs.* RED WoLF) are compared over a 1-month period (October). However, before doing so, a pre-study is conducted in section 4.2.1 to determine the prediction horizon length to run the algorithms. Then, a comparison of the Olivieri and RED WoLF algorithms over three specific days is then conducted in section 4.2.2 to understand the behavior of each algorithm with respect to the different inputs, before conducting the 1-month comparison analysis in section 4.2.3. Finally, in section 4.2.4, we analyze to what extent a battery with different characteristics (different capacities, maximum power intake) may impact on the algorithm performance, along with what would be the best configuration (technology) to be selected.

#### 4.2.1. Prediction horizon length determination

Due to the low complexity in computing the threshold in RED WoLF, the scheduling process is almost instantaneous ($<$ 1 ms), as thoroughly analyzed in [65]. In opposition, Olivieri's algorithm processing time varies exponentially according to the length of




(a) RED WoLF system in UK scenario

(b) Olivieri system in UK scenario

(c) Grid carbon intensity evolution, along with a representation of when RED WoLF and Olivieri systems draw power from the electrical grid

Figure 9: October 3rd - One day analysis of how RED WoLF and Olivieri systems behave with respect to the different inputs

the prediction horizon. Figure 8 provides clear evidence of such an exponential behavior, showing that the longer the prediction horizon length ($x$-axis), the more exponential Olivieri's algorithm processing time ($y$-axis). Indeed, optimizing the energy storage and release with a 4$h$-prediction time window requires less than one second, while this processing time reaches 6$h$ with a 72$h$-prediction time window (*cf.*, Figure 8). As a complementary information, the total $CO_2$ emitted with the Olivieri's algorithm over the October month is depicted in Figure 8, showing that beyond a 24$h$-prediction time window, the optimization does not lead to better performance. As a consequence, a 24$h$-prediction time window is chosen for running the experiments conducted in the rest of the paper, bearing in mind that in this configuration Olivieri requires $\approx$ 25 min for generating the optimal solution against $<$ 1 $ms$ with RED WoLF.

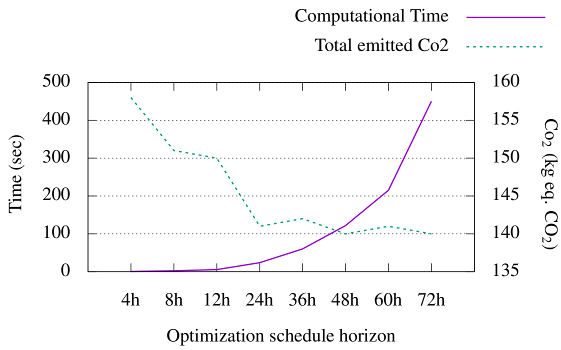
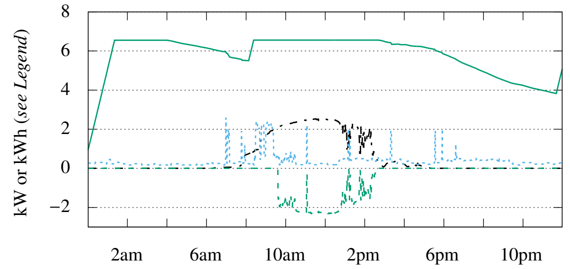



Figure 8: Overview of the Computational Time and associated performance in terms of total emitted $CO_2$ with Olivieri's system

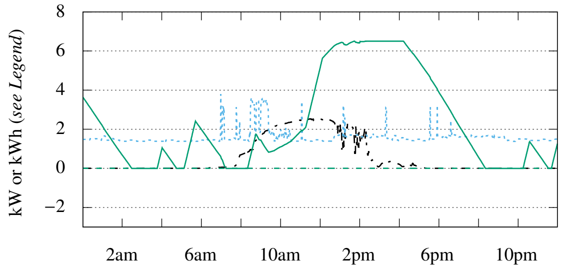
### 4.2.2. *Daily analysis*

Before presenting the monthly comparison analysis, which is the subject of section 4.2.3, we suggest to analyze how RED WoLF and Olivieri algorithms behave with respect to the system inputs considering three specific days. Let us note that, in the conducted experiments, the battery capacity for both algorithms is 6.5 kWh and the maximum intake/outtake power is 4.2 kW. Furthermore, two assumptions differ between RED WoLF and Olivieri: *(i) maximum grid intake:* RED WoLF defines a constraint defining the maximum power that can be drawn from the grid by the sum of house consumption minus the power generated by the PV system. This limit is fixed by the energy provider and set to 9 kW. Olivieri's algorithm does not include such a constraint; *(ii) Thermal charging using battery:* In Olivieri, space heating and hot water needs are considered as appliances and therefore could be supplied by the battery, unlike RED WoLF where thermal reservoir must be supplied by the grid or PV unit sources. This is why in Figure 9(b) the appliance demand in Olivieri is greater than in RED WoLF (*cf.*, Figure 9(a)).

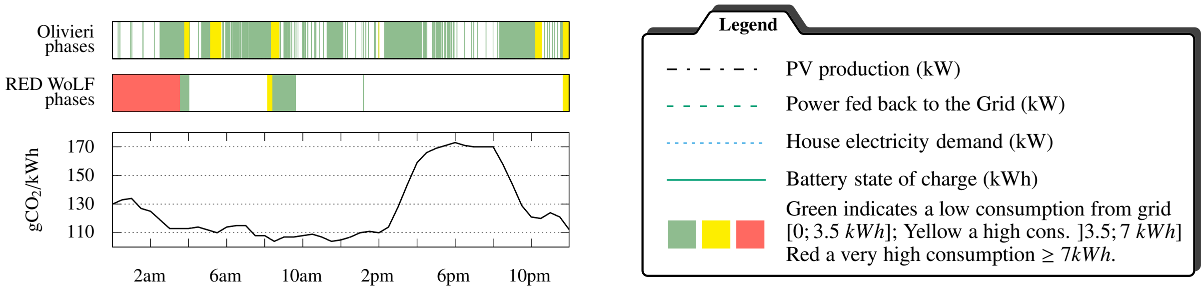
*October 3rd:* Power exchanges occuring between the grid, appliances, PV arrays and the hybrid energy storage system when using the RED WoLF and Olivieri strategies are plotted in Figures 9(a) and 9(b) respectively. A complementary plot of the amount of grid carbon intensity over that day is given in Figure 9(c), along with the periods when RED WoLF




(a) RED WoLF system in UK scenario




(b) Olivieri system in UK scenario



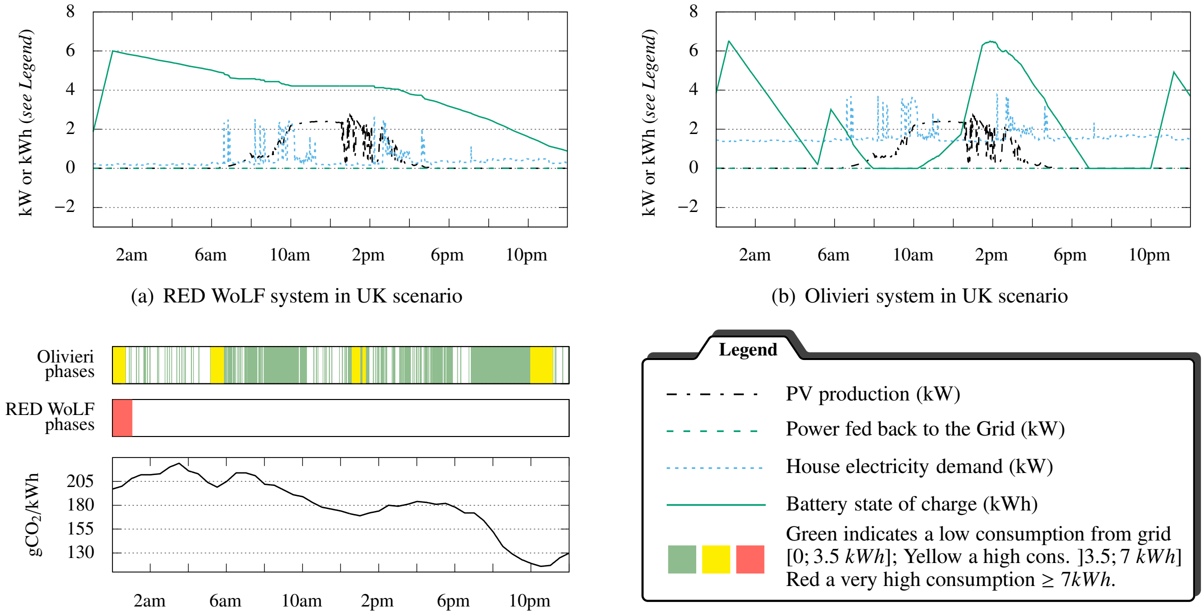

(c) Grid carbon intensity evolution, along with a representation of when RED WoLF and Olivieri systems draw power from the electrical grid

Figure 10: October 6th - One day analysis of how RED WoLF and Olivieri systems behave with respect to the different inputs

and Olivieri algorithms draw power from the grid (a color code being used to indicate the intensity of consumption, as detailed in the “Legend” of Figure 9). A first reading of the graphs shows a different behavior of the battery management system. In RED WoLF, the battery has a constantly high level of charge (see Figure 9(a)), whereas the battery level is highly variable when using Olivieri’s algorithm, going from fully charged to empty several times over that day (see Figure 9(b)). It can also be noted that the battery is mainly charged by the local PV production in both cases, which can be partly explained by the grid carbon intensity that is consistently high that day (above 200g eq. $CO_2$ per kWh). From a more detailed examination of those plots, it can be noted that:

- during the night, batteries are fully charged in both algorithms as the grid carbon intensity is lower – *even if it remains high* – than the rest of the day. Figure 9(b) shows that RED WoLF draws power from the grid in an intensive manner to charge all storage systems (i.e., battery, water cylinder and storage heaters);
- in the morning (likely because residents get up), batteries are discharged in both models. In Olivieri, the battery is almost completely discharged, which is mostly due to the fact that it is not possible to store energy in the heater and/or water cylinder, unlike RED WoLF in which both storage systems have been charged during the night (at the same time as the battery);
- batteries are then charged during sunshine hours. However, as the battery’s SOC in RED WoLF is always high, the battery quickly becomes full and solar energy produced locally is redirected to the grid. For that day 62% of the PV production in RED WoLF (eq. to $8,4\ kWh$) is fed back to the grid, while all the PV production is adsorbed by the battery with Olivieri;
- at the end of the day, when the house electricity demand increases, the RED WoLF system is self-sufficient (operating solely on its battery), while Olivieri’s schedule draws power from the grid. In this respect, RED WoLF, which keeps a high battery’s SOC, has an advantage in the event of a grid failure or disconnection;

Let’s remind ourselves that the primary objective of RED WoLF and Olivieri is to reduce GHGE. For this specific day (Oct. 3rd), the latter (Olivieri) provides significantly lower emissions than RED WoLF as it makes use of the whole PV production, unlike RED WoLF that exports part of that production to the grid. In numerical terms, Olivieri emits half as much GHGE (3.2 kg eq. $CO_2$) than RED WoLF (6.9 $kg$ eq. $CO_2$). Another aspect that can be analyzed is the wear and tear of the battery as a result of charge/discharge cycles, which has a direct impact on the battery lifetime [66, 67]. Even if the maximization of the battery lifespan is not defined as an objective in RED WoLF or Olivieri, it is interesting to be analyzed, as replacing a battery has a threefold environmental impact: (i) producing new batteries results in depleting the earth’s resources; (ii) managing battery disposal today is a




(a) RED WoLF system in UK scenario

(b) Olivieri system in UK scenario

(c) Grid carbon intensity evolution, along with a representation of when RED WoLF and Olivieri systems draw power from the electrical grid

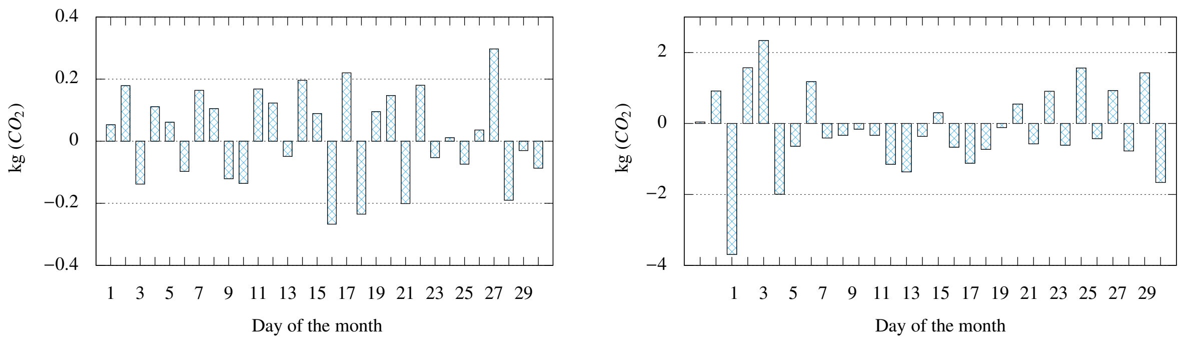
Figure 11: October 5th - One day analysis of how RED WoLF and Olivieri systems behave with respect to the different inputs

concern; (iii) increasing costs due to the battery purchase leads to social concerns. Overall, Olivieri results in twice more charging/discharging phases[3] (10 in total) than RED WoLF (5 in total).

*October 6th:* A second day is analyzed in Figure 10 in order to see whether a similar energy management behavior is observed. It can be first observed that unlike Oct. 3rd, the grid carbon intensity signal strongly varies over time (see Figure 10(c)), although it is globally cleaner than the signal of Oct. 3rd (see Figure 9(c)). Overall, the behavior of the house when using RED WoLF and Olivieri (see Figures 10(a) and 10(b)) is quite similar to the one analyzed in Oct. 3rd (battery's SOC remaining high and part of the PV production – *8,7 kWh* – being fed back to the grid). One difference lies in the fact that RED WoLF is no longer self-sufficient in the morning (from 8am to 10am), as it draws power from the grid to first charge the battery and then power the appliances (*cf.* Figure 10(c)). The reason for this is twofold: (i) the carbon grid intensity is low during that period (≈ 100 g eq. $CO_2$), and (ii) RED WoLF predicts that the intensity will significantly increase within the following 12h. With Olivieri, the charging pattern differs from Oct. 3rd; the battery starts with a half SOC, while it was full in Oct. 3rd. In a similar way as RED WoLF, Olivieri's algorithm takes the opportunity to both satisfy the house electricity demand and charge the battery when the carbon intensity is low (until 4 pm). From this time onwards, the battery in Olivieri becomes the only source of supply until 8 pm (when the grid electricity becomes cleaner again). As on Oct. 3rd, Olivieri's system uses all the PV production, while RED WoLF re-injects part of this production into the grid. Regarding now the number of charge/discharge phases, 5 phases are identified in RED WoLF against 12 in Olivieri, which is mostly due to the greater variability in the carbon intensity.

*Day 5 of October:* The grid carbon intensity of this third day is given in Figure 11(c), which is relatively high at the beginning of the day, and then progressively decreases. Looking at Figures 11(a) and 11(b), it can be observed that the RED WoLF is charging the storage units straight at the beginning of the day, which, combined with the PV production, is sufficient to meet the house electricity demand without consuming power from the grid, nor exporting surplus electricity. With Olivieri, several periods of battery charging/discharging can be observed. In total, 2 charging/discharging cycles are identified with RED WoLF, against 8 with Olivieri, where the total carbon emission for that day is estimated to 4.1kg eq. $CO_2$ for Olivieri, against 1.8kg eq. $CO_2$ for RED WoLF. The main reason leading to this result is the the non support (in Olivieri) of a hybrid-storage system (i.e., considering the water cylinder and storage heaters as storage units).

[3] A distinction between charge/discharge phases and cycles is made. One cycle is when we have charged or discharged an amount that equals 100% of the battery's capacity, but not necessarily all from one charge, while a phase refers to cases where we switch from charging to discharging command, or *vice-versa*.




(a) RED WoLF *vs.* Olivieri (France)

(b) RED WoLF *vs.* Olivieri (UK)

Figure 12: RED WoLF *vs.* Olivieri: a positive value indicating that RED WoLF outperforms Olivieri and *vice-versa*.

Table 5: Summary of key results obtained with the Baseline, RED WoLF and Olivieri systems over the whole month of October

| | | kWh from Grid | Elec. bill (euros) | kg eq. $CO_2$ from Grid | Local PV usage (%) | PV to Grid (kWh) | Nb. of Cycles | Battery life-span (months) | Comput. Time |
|---|---|---|---|---|---|---|---|---|---|
| FR | Baseline | 1454 | 257 | N/A | 100 | N/A | N/A | N/A | N/A |
| | RED WoLF | 1344 | 237 | 39 | 86 | 50.6 | 71 | 78 | $< 1ms$ |
| | Olivieri | 1296 | 227 | 40 | 100 | 0 | 190 | 31 | $25min$ |
| UK | Baseline | 1042 | 221 | 171 | 100 | N/A | N/A | N/A | N/A |
| | RED WoLF | 935 | 198 | 146 | 58 | 137.4 | 43 | 139 | $< 1ms$ |
| | Olivieri | 806 | 142 | 140 | 100 | 0 | 133 | 45 | $23min$ |

### *4.2.3. One Month analysis*

Figures 12(a) and 12(b) provide, for each day in October, the difference in $CO_2$ between the RED WoLF and Olivieri algorithms for France and UK datasets respectively; a positive value indicating that RED WoLF outperforms Olivieri, and *vice-versa*. It can be observed in Figure 12(a) that there is no clear outperforming algorithm and the difference in results is small (0.3 kg eq. $CO_2$ at most). This difference can be explained by the fact that France uses nuclear power for most of its electricity, which has a very low GHGE rate compared with UK. In the case of UK (see Figure 12(b)), Olivieri's algorithm outperforms RED WoLF in $\approx 60\%$ of the time. Nevertheless, in order to gain a full and complete comparison, other information such as the battery lifespan, the amount of energy redirected to the grid (not taken into account in the histogram values given Figure 12), or still the computational complexity of each algorithm. Table 5 provides such complementary information for both scenarios (France and UK).

Firstly, let us compare the results obtained with RED WoLF and Olivieri with the Baseline scenario (*cf.*, Figure 7). Table 5 reports that in both cases (France and UK), the total amount of $CO_2$ emissions is reduced by 10% (France) and 30% (UK) when implementing RED WoLF's or Olivieri's system, with a slight advantage for the latter. However, as previously mentioned, this result does not take into consideration the PV electricity re-directed to the grid. Table 5 reports that Olivieri is consuming 100% of the local PV production, while RED WoLF consumes only 86% (France) and 58% (UK). Although it is preferable to consume locally the electricity (to avoid electricity losses during transmission), the results given and discussed in Figure 12 need to be put into perspective.

Secondly, looking at the electricity bills, Olivieri outperforms RED WoLF with a difference of more than 50€ in the UK scenario and 10€ in the French one. This can be explained by the fact that Olivieri consumes all the local PV production, unlike RED WoLF that re-injects part of the production to the grid, as previously discussed. Here again, some revenue could be generated in that case, which has not been taken into account in this study. Although the objective of reducing the electricity bill has not been defined as the prime objective in RED WoLF, nor in Olivieri (the focus being given to GHGE reduction), it can be noted that ecology considerations are not systemically in contradiction with financial ones.

Thirdly, the total number of charge/discharge cycles of the battery over the month is calculated using the definition of a cycle, which consists of accumulating the energy charged in the battery by dividing it by its maximum capacity (in this case the battery has a capacity of 6.5 kwh), the same calculation being done for the discharge. Summing up the charge and discharge cycles, the values reported in Table 5 are obtained. It can be noted that RED WoLF reduces by 60% (France) and 50% (UK) the number of cycles

Table 6: Total $CO_2$ emitted over the month of October using batteries of different capacities/sizes

| | | Bluetti | | LG3.3 | | LG6.5 | | Tesla | |
|---|---|---|---|---|---|---|---|---|---|
| | | Co2 | PV to Grid | Co2 | PV to Grid | Co2 | PV to Grid | Co2 | PV to Grid |
| | | *kg eq. $Co_2$* | *kWh* | *kg eq. $Co_2$* | *kWh* | *kg eq. $Co_2$* | *kWh* | *kg eq. $Co_2$* | *kWh* |
| FR | RED WoLF | 42.13 | 140.16 | 40.50 | 138.47 | 39.48 | 137.41 | 37.70 | 137.73 |
| | Olivieri | 42.53 | 17.87 | 41.28 | 0.59 | 40.04 | 0 | 40.04 | 0 |
| UK | RED WoLF | 152.80 | 90.38 | 147.34 | 61.33 | 146.21 | 50.60 | 146.32 | 44.23 |
| | Olivieri | 157.57 | 12.96 | 148.57 | 3.08 | 140.79 | 0 | 128.35 | 0 |

compared with Olivieri. Considering now the battery specification, which is expected to operate for a total of 6000 cycles, it can be concluded that the battery will likely need to be replaced after 3 to 4 years with Olivieri, against 7 to 12 years with RED WoLF.

Fourthly, it is important to remind ourselves that the RED WoLF's optimization is almost instantaneous (less than $1ms$), while Olivieri's optimization takes about 25 min. This is not negligible as it has an indirect impact on the overall system carbon footprint (the higher the algorithm complexity, the heavier the computational load). Furthermore, if we consider extending Olivieri's model to integrate other storage units such as storage heaters, water cylinder, or any other type of storage unit, this would result in an even larger complexity. Finally, with the advent of the Edge Computing, RED WoLF algorithm turns to be more appropriate than Olivieri to be deployed on devices that have limited computational capabilities such as smart meters.

*4.2.4. Impact of different batteries on the optimization performance*

To study the impact of how a battery with different characteristics may impact on the algorithm performance, we consider four different technologies today available on the market, namely Bluetti, LG3.3, LG6.5 and Tesla, whose respective characteristics are summarized in Table 7 (battery capacity and maximum power intake). Table 6 reports the total $CO_2$ emission (in kg eq. $CO_2$) and power re-injected to the grid (in kWh) obtained when running the RED WoLF and Olivieri algorithms with these four batteries.

In the UK scenario, It can be noted that increasing the size and power intake of the battery leads to a significant reduction of $CO_2$ emission in Olivieri, which is not true for RED WoLF. The reason for this is highly correlated to the amount of energy re-injected into the grid, as Olivieri is better than RED WoLF in maximizing the consumption/storage of local PV production (*cf.*, PV to grid values in Table 7). Interestingly, RED WoLF outperforms Olivieri when using the smallest (Bluetti) battery, while the trend is reversed with the three other battery technologies. Overall, the LG3.3 is sufficient in RED WoLF, as larger batteries do not lead to a substantial improvement in $CO_2$ reduction, while the bigger the battery the better in Olivieri. This obviously has a financial impact.

Table 7: Battery products (from the market) analyzed

| | Bluetti | LG3.3 | LG6.5 | Tesla |
|---|---|---|---|---|
| $B_{Imax}$ (kW) | 1 | 3.3 | 4.2 | 7 |
| $B_C$ (kWh) | 1.5 | 3.3 | 6.5 | 13.5 |

In the FR scenario, RED WoLF always outperforms Olivieri, adding that the total $CO_2$ emission decreases along with the increase of the battery size, which does not apply for Olivieri. One reason for this lies in the RED WoLF logic that gives as much importance to low-carbon grid periods as local PV production, which may prove to be an effective strategy when the national grid is of low carbon, as is the case in France.

Overall, this study suggests that the choice of given strategy/algorithm and of a battery technology may depend on the country's strategic position in energy geopolitics.

## 5. Conclusion

Climate change and the continuous and rapid rise in temperature are forcing international political bodies to focus on reducing GHGE to save the planet. The housing sector is heavily contributing to global warming. Gone are the days where everyone tries to find optimal solutions to reduce financial costs, whatever the environmental cost. Better insulated house will have a positive impact on (reduction of) both electricity consumption and GHGE, but an additional step can take this positive change further. This step consists of using local renewable energy sources with flexible storage units.

The current state-of-affairs reviewed in this paper brings evidence that most of today's energy management systems primarily focus on electricity bill reduction, placing GHGE reduction on the backburner, they rarely propose hybrid-energy storage optimization strategies, neither evaluate how the proposed strategy impacts on the computational complexity nor on the battery lifespan. The two last impacts are of particular importance with both the advent of Edge Computing in the energy sector [10, 11] and the growing awareness of the the difficulty to manage and recycle renewable technologies such as batteries and PV modules [68, 69].

To progress this state-of-affairs, an innovative $CO_2$ threshold-based strategy currently being developed as part of a European project named RED WoLF (Rethink Electricity Distribution Without Load Following) has been proposed in our previous research work [7, 8, 9], which seeks to identify the best periods of the day to charge and discharge multiple types of storage units (incl., battery, storage heaters, water cylinder). In the present article, RED WoLF is evaluated and compared with a second strategy proposed by [12], which also aims at reducing GHGE but with a slightly different infrastructure (only considering a battery as flexible energy-storage) and algorithm designed based on Linear Programming (LP). The comparison study brings evidence that the two strategies (RED WoLF and Olivieri) contribute to significantly reduce GHGE compared to a solution without any optimization logic, although Olivieri has a slight advantage. However, as analyzed in this article, the behavior of the two algorithms is different in terms of charging/discharging periods, resulting in different *pros* and *cons* for the two strategies. Olivieri algorithm has a more dynamic management of the batteries with a multitude of charging/discharging cycles over the days, which has the advantage of maximizing the consumption of local PV production, but, in comparison to RED WoLF, is less self-sufficient in the event of a power outage or of long periods of high grid carbon intensity. Such an aspect could eventually be of interest for distribution system operators during load shedding. RED WoLF also has the advantage of limiting the number of charging/discharging cycles compared with the Olivieri's algorithm, which contributes in extending the battery's lifespan and thus reducing the overall system cost and carbon footprint (i.e., reducing maintenance costs, battery replacement, *etc.*). Another *pro* of RED WoLF lies in the algorithmic complexity, which is very low compared to Olivieri (RED WoLF requiring less than a second to find an optimal solution, while Olivieri requires about 20 to 30min), and this conclusion would be the same with any other strategy using LP. This has a twofold consequence: (i) RED WoLF can be extended with additional objectives and constraints without causing extra computational burden; (ii) RED WoLF is lighter, resulting in a lower GHGE and making it more suitable to be deployed on edge devices.

It should be noted that both RED WoLF and Olivieri strategies imply the integration of PV arrays, battery and ICT technologies, which have a non negligible environmental impact considering the whole lifecycle of such technologies. The recent article of [70] provides an interesting analysis in this regard, showing that in the case of wind, hydro-, geothermal, solar and biomass power plants falling ice, changes in the flow regime of rivers, noise, erosion caused by panels and the scale of harvesting, respectively, are the most critical environmental impacts. From a research perspective, further studies and tools for Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) should be developed to evaluate the overall carbon footprint of renewable energy systems/architectures, i.e. not only focusing on the operational phase, but also on the design phase (e.g., considering the quantity of available raw materials) and the recycling/disposal one.


## Acknowledgement

This work has been supported by the European Regional Development Fund and Interreg NWE, project RED WoLF, project number NWE847.


## References


[1] S. Baek, S. Kim, Potential effects of vacuum insulating glazing application for reducing greenhouse gas emission (ghge) from apartment buildings in the korean capital region, Energies 13 (2020) 2828.

[2] N. Wang, D. Satola, A. Houlihan Wiberg, C. Liu, A. Gustavsen, Reduction strategies for greenhouse gas emissions from high-speed railway station buildings in a cold climate zone of china, Sustainability 12 (2020) 1704.

[3] M. Lazarus, H. van Asselt, Fossil fuel supply and climate policy: exploring the road less taken, Climatic Change 150 (2018) 1–13.

[4] A. Ahmed, T. Ge, J. Peng, W.-C. Yan, B. T. Tee, S. You, Assessment of the renewable energy generation towards net-zero energy buildings: A review, Energy and Buildings (2021) 111755.

[5] O. A. Al-Shahri, F. B. Ismail, M. A. Hannan, M. S. H. Lipu, A. Q. Al-Shetwi, R. A. Begum, N. F. O. Al-Muhsen, E. Soujeri, Solar photovoltaic energy optimization methods, challenges and issues: A comprehensive review, Journal of Cleaner Production 284 (2021) 125465.

[6] M. A. Hannan, S. B. Wali, P. J. Ker, M. S. Abd Rahman, M. Mansor, V. K. Ramachandaramurthy, K. M. Muttaqi, T. M. I. Mahlia, Z. Y. Dong, Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues, Journal of Energy Storage 42 (2021) 103023.

[7] P. Ortiz, S. Kubler, E. Rondeau, J.-P. Georges, G. Colantuono, A. A. Shukhobodskiy, Greenhouse gas emission reduction system in photovoltaic nanogrid with battery and thermal storage reservoirs, Journal of Cleaner Production 310 (2021) 127347.

[8] M. Wiesheu, L. Rutešić, A. A. Shukhobodskiy, T. Pogarskaia, A. Zaitcev, G. Colantuono, Red wolf hybrid storage system: Adaptation of algorithm and analysis of performance in residential dwellings, Renewable Energy 179 (2021) 1036–1048.

[9] A. A. Shukhobodskiy, G. Colantuono, Red wolf: Combining a battery and thermal energy reservoirs as a hybrid storage system, Applied Energy 274 (2020) 115209.

[10] C. Feng, Y. Wang, Q. Chen, Y. Ding, G. Strbac, C. Kang, Smart grid encounters edge computing: Opportunities and applications, Advances in Applied Energy 1 (2021) 100006.

[11] M. S. Munir, S. F. Abedin, N. H. Tran, C. S. Hong, When edge computing meets microgrid: A deep reinforcement learning approach, IEEE Internet of Things Journal 6 (2019) 7360–7374.

[12] Z. T. Olivieri, K. McConky, Optimization of residential battery energy storage system scheduling for cost and emissions reductions, Energy and Buildings 210 (2020) 109787.

[13] Y. Saleem, N. Crespi, M. H. Rehmani, R. Copeland, Internet of things-aided smart grid: Technologies, architectures, applications, prototypes, and future research directions, IEEE Access 7 (2019) 62962–63003. doi:10.1109/ACCESS.2019.2913984.

[14] D. Burmester, R. Rayudu, W. Seah, D. Akinyele, A review of nanogrid topologies and technologies, Renewable and Sustainable Energy Reviews 67 (2017) 760–775.

[15] F. Tooryan, H. HassanzadehFard, E. R. Collins, S. Jin, B. Ramezani, Smart integration of renewable energy resources, electrical, and thermal energy storage in microgrid applications, Energy 212 (2020) 118716.

[16] F. Tooryan, H. HassanzadehFard, E. R. Collins, S. Jin, B. Ramezani, Optimization and energy management of distributed energy resources for a hybrid residential microgrid, Journal of Energy Storage 30 (2020) 101556.

[17] R. Das, Y. Wang, G. Putrus, R. Kotter, M. Marzband, B. Herteleer, J. Warmerdam, Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services, Applied Energy 257 (2020) 113965.

[18] A. Yazan M., A. Alaa M., E. Abo Eleyoun, E.-W. Amged S., A. Almoataz Y., U. Vadim, U. Ali Arshad, Optimal configuration and energy management scheme of an isolated microgrid using cuckoo search optimization algorithm, Journal of the Franklin Institute 356 (2019) 4191–4214.

[19] A. B. Awan, M. Zubair, G. A. S. Sidhu, A. R. Bhatti, A. G. Abo-Khalil, Performance analysis of various hybrid renewable energy systems using battery, hydrogen, and pumped hydro-based storage units, International Journal of Energy Research 43 (2019) 6296–6321.

[20] M. A. Ashraf, Z. Liu, A. Alizadeh, S. Nojavan, K. Jermsittiparsert, D. Zhang, Designing an optimized configuration for a hybrid pv/diesel/battery energy system based on metaheuristics: A case study on gobi desert, Journal of Cleaner Production 270 (2020) 122467.

[21] A. B. Awan, Performance analysis and optimization of a hybrid renewable energy system for sustainable neom city in saudi arabia, Journal of Renewable and Sustainable Energy 11 (2019) 025905.

[22] F. Fodhil, A. Hamidat, O. Nadjemi, Potential, optimization and sensitivity analysis of photovoltaic-diesel-battery hybrid energy system for rural electrification in algeria, Energy 169 (2019) 613–624.

[23] J. D. Fonseca, J.-M. Commenge, M. Camargo, L. Falk, I. D. Gil, Multi-criteria optimization for the design and operation of distributed energy systems considering sustainability dimensions, Energy 214 (2021) 118989.

[24] A. Ayse Fidan, K. Muhsin, Design and performance evaluation based on economics and environmental impact of a pv-wind-diesel and battery standalone power system for various climates in turkey, Renewable Energy 157 (2020) 424–443.

[25] R. D. Bingham, M. Agelin-Chaab, M. A. Rosen, Whole building optimization of a residential home with pv and battery storage in the bahamas, Renewable Energy 132 (2019) 1088–1103.

[26] J. Salehi, A. Namvar, F. S. Gazijahani, Scenario-based co-optimization of neighboring multi carrier smart buildings under demand response exchange, Journal of Cleaner Production 235 (2019) 1483–1498.

[27] Y. E. García-Vera, R. Dufo-López, J. L. Bernal-Agustín, Optimization of isolated hybrid microgrids with renewable energy based on different battery models and technologies, Energies 13 (2020) 581.

[28] A. S. Aziz, M. F. N. Tajuddin, M. R. Adzman, A. Azmi, M. A. Ramli, Optimization and sensitivity analysis of standalone hybrid energy systems for rural electrification: A case study of iraq, Renewable energy 138 (2019) 775–792.

[29] H. Pandžić, Optimal battery energy storage investment in buildings, Energy and Buildings 175 (2018) 189–198.

[30] E. O'Shaughnessy, D. Cutler, K. Ardani, R. Margolis, Solar plus: Optimization of distributed solar pv through battery storage and dispatchable load in residential buildings, Applied Energy 213 (2018) 11–21.

[31] C.-L. Nguyen, H.-H. Lee, T.-W. Chun, Cost-optimized battery capacity and short-term power dispatch control for wind farm, IEEE Transactions on Industry Applications 51 (2014) 595–606.

[32] V. S. Borra, K. Debnath, Comparison between the dynamic programming and particle swarm optimization for solving unit commitment problems, in: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), IEEE, 2019, pp. 395–400.

[33] P. Arévalo, D. Benavides, J. Lata-García, F. Jurado, Energy control and size optimization of a hybrid system (photovoltaic-hidrokinetic) using various storage technologies, Sustainable Cities and Society 52 (2020) 101773.

[34] B. A. Bhayo, H. H. Al-Kayiem, S. I. Gilani, F. B. Ismail, Power management optimization of hybrid solar photovoltaic-battery integrated with pumped-hydro-storage system for standalone electricity generation, Energy Conversion and Management 215 (2020) 112942.

[35] N. Haidar, M. Attia, S.-M. Senouci, E.-H. Aglzim, A. Kribeche, Z. B. Asus, New consumer-dependent energy management system to reduce cost and carbon impact in smart buildings, Sustainable Cities and Society 39 (2018) 740–750.

[36] K. Mahmud, M. J. Hossain, G. E. Town, Peak-load reduction by coordinated response of photovoltaics, battery storage, and electric vehicles, IEEE Access 6 (2018) 29353–29365.

[37] J. Liu, X. Chen, H. Yang, Y. Li, Energy storage and management system design optimization for a photovoltaic integrated low-energy building, Energy 190 (2020) 116424.

[38] P. Nagapurkar, J. D. Smith, Techno-economic optimization and environmental life cycle assessment (lca) of microgrids located in the us using genetic algorithm, Energy Conversion and Management 181 (2019) 272–291.

[39] Z. T. Olivieri, K. McConky, Optimization of residential battery energy storage system scheduling for cost and emissions reductions, Energy and Buildings 210 (2020) 109787.

[40] W. L. Schram, T. AlSkaif, I. Lampropoulos, S. Henein, W. G. Van Sark, On the trade-off between environmental and economic objectives in community energy storage operational optimization, IEEE Transactions on Sustainable Energy 11 (2020) 2653–2661.

[41] V. Stepaniuk, J. Pillai, B. Bak-Jensen, Battery energy storage management for smart residential buildings, in: 2018 53rd International Universities Power Engineering Conference (UPEC), IEEE, 2018, pp. 1–6.

[42] T. Terlouw, T. AlSkaif, C. Bauer, W. Van Sark, Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies, Applied energy 239 (2019) 356–372.

[43] T. Terlouw, T. AlSkaif, C. Bauer, W. van Sark, Optimal energy management in all-electric residential energy systems with heat and electricity storage, Applied Energy 254 (2019) 113580.

[44] H. Moradi, A. Abtahi, M. Esfahanian, Optimal operation of a multi-source microgrid to achieve cost and emission targets, in: 2016 IEEE Power and Energy Conference at Illinois (PECI), IEEE, 2016, pp. 1–6.

[45] A. Nottrott, J. Kleissl, B. Washom, Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems, Renewable Energy 55 (2013) 230–240.

[46] M. Yadav, M. Jamil, M. Rizwan, Accomplishing approximately zero energy buildings with battery storage using flann optimization, in: 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), IEEE, 2018, pp. 656–661.

[47] U. Mulleriyawage, W. Shen, Optimally sizing of battery energy storage capacity by operational optimization of residential pv-battery systems: An australian household case study,

Renewable Energy 160 (2020) 852–864.
[48] G. Litjens, E. Worrell, W. van Sark, Assessment of forecasting methods on performance of photovoltaic-battery systems, Applied Energy 221 (2018) 358–373.
[49] T. Adefarati, S. Potgieter, R. Bansal, R. Naidoo, R. Rizzo, P. Sanjeevikumar, Optimization of pv-wind-battery storage microgrid system utilizing a genetic algorithm, in: 2019 International Conference on Clean Electrical Power (ICCEP), IEEE, 2019, pp. 633–638.
[50] A. S. Aziz, M. F. N. Tajuddin, M. R. Adzman, M. A. Ramli, S. Mekhilef, Energy management and optimization of a pv/diesel/battery hybrid energy system using a combined dispatch strategy, Sustainability 11 (2019) 683.
[51] P. García-Triviño, L. M. Fernández-Ramírez, A. J. Gil-Mena, F. Llorens-Iborra, C. A. García-Vázquez, F. Jurado, Optimized operation combining costs, efficiency and lifetime of a hybrid renewable energy system with energy storage by battery and hydrogen in grid-connected applications, International Journal of Hydrogen Energy 41 (2016) 23132–23144.
[52] M. Marzband, E. Yousefnejad, A. Sumper, J. L. Domínguez-García, Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization, International Journal of Electrical Power & Energy Systems 75 (2016) 265–274.
[53] M. Marzband, H. Alavi, S. S. Ghazimirsaeid, H. Uppal, T. Fernando, Optimal energy management system based on stochastic approach for a home microgrid with integrated responsive load demand and energy storage, Sustainable cities and society 28 (2017) 256–264.
[54] A. González-Briones, J. Prieto, F. De La Prieta, E. Herrera-Viedma, J. M. Corchado, Energy optimization using a case-based reasoning strategy, Sensors 18 (2018) 865.
[55] L. Luo, S. S. Abdulkareem, A. Rezvani, M. R. Miveh, S. Samad, N. Aljojo, M. Pazhoohesh, Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty, Journal of Energy Storage 28 (2020) 101306.
[56] J. A. Auñón-Hidalgo, M. Sidrach-de Cardona, F. Auñón-Rodríguez, Performance and co2 emissions assessment of a novel combined solar photovoltaic and thermal, with a stirling engine micro-chp system for domestic environments, Energy Conversion and Management 230 (2021) 113793.
[57] V. V. V. S. N. Murty, A. Kumar, Optimal energy management and techno-economic analysis in microgrid with hybrid renewable energy sources, Journal of Modern Power Systems and Clean Energy 8 (2020) 929–940.
[58] A. Monacchi, D. Egarter, W. Elmenreich, S. D'Alessandro, A. M. Tonello, Greend: An energy consumption dataset of households in italy and austria, in: IEEE International Conference on Smart Grid Communications, 2014, pp. 511–516.
[59] 2022. URL: https://www.nature.com/sdata/.
[60] 2022. URL: https://pvwatts.nrel.gov/pvwatts.php.
[61] 2022. URL: https://ec.europa.eu/jrc/en/pvgis.
[62] 2022. URL: https://carbonintensity.org.uk.
[63] 2022. URL: https://www.rte-france.com/eco2mix.
[64] 2022. URL: https://fr.statista.com/infographie/11825/comparaison-cout-electricite-en-europe/.
[65] A. A. Shukhobodskiy, A. Zaitcev, T. Pogarskaia, G. Colantuono, Red wolf hybrid storage system: Comparison of co2 and price targets, Journal of Cleaner Production 321 (2021) 128926.
[66] D. N. Karamov, K. V. Suslov, Structural optimization of autonomous photovoltaic systems with storage battery replacements, Energy Reports 7 (2021) 349–358.
[67] N. Narayan, T. Papakosta, V. Vega-Garita, Z. Qin, J. Popovic-Gerber, P. Bauer, M. Zeman, Estimating battery lifetimes in solar home system design using a practical modelling methodology, Applied energy 228 (2018) 1629–1639.
[68] M. A. Pellow, H. Ambrose, D. Mulvaney, R. Betita, S. Shaw, Research gaps in environmental life cycle assessments of lithium ion batteries for grid-scale stationary energy storage systems: End-of-life options and other issues, Sustainable Materials and Technologies 23 (2020) e00120.
[69] P. Nain, A. Kumar, A state-of-art review on end-of-life solar photovoltaics, Journal of Cleaner Production (2022) 130978.
[70] V. Sebestyén, Renewable and sustainable energy reviews: Environmental impact networks of renewable energy power plants, Renewable and Sustainable Energy Reviews 151 (2021) 111626.