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

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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 (≈ 25 min for LP against ≈ 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) (Baek and Kim, 2020). Reducing GHGE can be achieved by better insulating houses and buildings, switching from polluting (albeit cheap) coal to natural gas or renewable energy sources (Lazarus and van Asselt, 2018), and developing intelligent applications to efficiently integrate such renewables resources with flexible storage systems (Ahmed et al., 2021). 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.) (Al-Shahri et al., 2021).

A number of charging and discharging optimization models of storage units have been proposed in the literature (Hannan et al., 2021). 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.

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Figure 1: Nanogrid main technological constituents

Heuristic methods to solve LP's can combat the computation issue, but the trade off is in solution quality 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 Hannan et al. (2021). To overcome these limitations, an innovative sliding grid carbon intensity threshold approach, developed as part of a European project named RED WoLF¹ (Rethink Electricity Distribution Without Load Following), has been presented initially in (Shukhobodskiv and Colantuono, 2020), modified in (Ortiz et al., 2021) and extended with (Wiesheu et al., 2021), 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 (Munir et al., 2019), 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 (2020) 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 Overall, the present paper differs from our previous papers in several respects:

- first, an in-depth analysis and comparison between two approaches (rule-based *vs.* Linear programming) aiming at reducing carbon emission in residential houses are carried out. To the best of our knowledge, no study has ever conducted such an analysis in the field of low greenhouse gas emission houses.
- second, in order to allow for fair comparison between the two approaches, an extension of the initial Olivieri's model is proposed to integrate PV systems;
- third, even if the prime objective is to reduce CO₂, an in-depth analysis and comparison analysis of how the two models behave in terms of the battery lifespan and computational time needed to solve the problem are carried out.

2. Scope, Definition and Positioning

Section 2.1 gives the context of our contribution focusing on 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 (Saleem et al., 2019). The present research falls within the scope of energy management at the consumption stage, and more exactly in residential nanogrids (Burmester et al., 2017). Energy management in nanogrids usually consists of four equipment categories, as depicted in Figure **[**, namely:

¹https://www.nweurope.eu/projects/project-search/red-wolfrethink-electricity-distribution-without-load-following/

- *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 (Georgiou et al., 2019), 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 [] 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,





Figure 2: Literature review process

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).

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 such as (Fodhil et al., 2019), as it allows for simulating and

		Optimization Goals				Storage/Shiftable			Production									
	Lifecycle Phase	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	Method
Tooryan et al. $(2020a)$ Tooryan et al. $(2020b)$ Das et al. $(2020b)$ Yazan M. et al. (2019) Ashraf et al. (2019) Ashraf et al. (2019) Fondhil et al. (2019) Fonseca et al. (2021) Ayse Fidan and Muhsin (2020) Bingham et al. (2019) García-Vera et al. (2019) García-Vera et al. (2019) García-Vera et al. (2020) Aziz et al. (2019) Pandžid (2018) O'Shaughnessy et al. (2018) Nguyen et al. (2014) Borra and Debnath (2019) Arévalo et al. (2020) Haidar et al. (2020) Haidar et al. (2018) Liu et al. (2020) Nagapurkar and Smith (2019) Olivieri and McConky (2020) Schram et al. (2018) Terlouw et al. (2018) Mahmud et al. (2018) Terlouw et al. (2019) Moradi et al. (2019) Moradi et al. (2019) Moradi et al. (2019) Moradi et al. (2019) Mulleriyawage and Shen (2020) Litigens et al. (2019) Aziz et al. (2019) Aziz et al. (2019) Mulleriyawage and Shen (2020) Litigens et al. (2019) Aziz et al. (2019) Schram et al. (2019) Mulleriyawage and Shen (2020) Lithow et al. (2019) Aziz et al. (2019) Aziz et al. (2019) García-Triviño et al. (2017) González-Briones et al. (2018) Luo et al. (2021) Shukhobodskiy and Colantuond (2020); Ortiz et al. $(2021)Georgiou et al. (2020)Shukhobodskiy and ColantuondGeorgiou et al. (2020)$	D D <td< td=""><td></td><td></td><td></td><td></td><td></td><td>•</td><td></td><td></td><td>•</td><td>-</td><td>•</td><td>• • •</td><td></td><td></td><td></td><td></td><td>MH MH MH MCDA MH MH MH MH MH MB MH MB MH MB MH MP MB MH MP MB MH MP MP MP MP MP MP MP MP MP MP MP MP MP</td></td<>						•			•	-	•	• • •					MH MH MH MCDA MH MH MH MH MH MB MH MB MH MB MH MP MB MH MP MB MH MP MP MP MP MP MP MP MP MP MP MP MP MP
		39	27	2	18	20	5	3	38	2	2	5	6	18	28	31	14	

Table 1: Classification of the scientific articles reviewed throughout Section

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 II all the reviewed articles adopt a multi-objective optimization model, aiming at first – *in* 85% of the reviewed articles – reducing the electricity bill, second – 54% – at reducing GHGE, third – 46% – 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. The reason for this is twofold: (i) fuel reduction and peak shaving are often formulated as overarching objectives when there is no connexion



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

to the electrical grid; and (ii) there are partly tackled implicitly when addressing the GHGE reduction and bill reduction problems (fuel reduction being mainly linked to GHGE and peak shaving to financial costs).. From an energy production and storage viewpoint, a significant proportion of the reviewed articles -65%- 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 (Murty and Kumar, 2020). Another interesting point is that a couple of approaches propose to combine different types of storage such as BESS and EV (Mahmud et al., 2018), BESS and hydrogen storage (Bhavo et al., 2020), or still BESS and thermal storage (e.g., water cylinder) (Terlouw et al., 2019b), which provides additional flexibility for energy management. Looking at the optimization techniques used for problem-solving, most of the approaches - in 73% 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 by Feng et al. (2021).

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 (Shukhobodskiy and Colantuono, 2020). Section 3 recalls the infrastructure and logic underlying RED WoLF, but also proposes an extension of the LPbased algorithm introduced by Olivieri and McConky (2020) with the aim to integrate PV into the model.

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 introduced in (Shukhobodskiy and Colantuono, 2020) and further in (Ortiz et al., 2021), highlighting the power flow, monitoring flow (i.e., monitored devices) and control flow (controllable devices from 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 highlighted 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:

	Class	Variable	Units	Description
	Real-time	A _{cur}	kW	Appliances present consumption
	Real-time	CO_{2cur}	gCO ₂ /kWh	Grid present CO_2 load
	Real-time	PV_{cur}	kW	PV present production
	Real-time	B_{lev}	kWh	Battery state of charge
	Real-time	C_{lev}	kWh	Cylinder state of charge
	Real-time	H_{lev}	kWh	Storage heater state of charge
	Predicted	A_{pre}	kW	Appliances predicted consumption
	Predicted	PV_{pre}	kW	PV predicted production
les	Predicted	CO_{2pre}	gCO ₂ /kWh	Grid predicted CO ₂ load
iab	Predicted	D_{ED}	kWh	Appliances predicted consumption until the end of the day
Var	Predicted	G_{PU}	kW	Grid predicted available mean drawable power
al	Static	B_C	kWh	Battery capacity
ern	Static	B_{Imax}	kW	Battery maximum admissible power
Int	Static	C_{Imax}	kW	Cylinder maximum admissible power
Š	Static	C_{set}	kWh	Cylinder setpoint
put	Static	D_{Imax}	kW	Grid power drawing limit (set by utility provider)
In	Static	H_{Imax}	kW	Storage heater maximum admissible power
	Static	H_{set}	kWh	Storage heater setpoint
	N/A	C_{dem}	kW	Cylinder present power demand
	N/A	B_{dem}	kW	Battery present power demand
	N/A	$D_{ImaxAPV}$	kW	Grid and PV power available for HSS
	N/A	H_{dem}	kW	Storage heater present power demand
	N/A	P_{bal}	kW	Remaining power after supplying appliances and HSS
	N/A	CO_{2thr}	gCO ₂ /kWh	Control CO ₂ threshold
	N/A	T_I	min	Smallest time to supply HSS considering appliances
	Real-time	B_{con}	kW	Power to be drawn from the battery
/ar.	Real-time	B_{inj}	kW	Power to be stored in the battery
ut 🗸	Real-time	C_{cur}	kW	Power to be stored in the water cylinder
ıtpı	Real-time	G_{con}	kW	Power to be drawn from the grid
Õ	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

Table 2: Variables used in the RED WoLF optimization system

- 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 (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 CO₂ 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 CO₂ 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).

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

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

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

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

Several system constraints and state variables are



Figure 4: RED WoLF's CO2 threshold computation example

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 is greater than 0, False (0) otherwise.

The minimum time length (T_I) to charge equipment is further computed from $D_E D$, G_{PU} , H_{dem} and C_{dem} , as given in Eq. (5).

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

The CO₂ threshold (CO_{2thr}), which identifies the best intervals for drawing electricity from the grid, is then computed using Eq. (7), $CO_{2preSort}$ referring to the CO₂ prediction vector sorted in ascending order, as given in Eq. (6).

$$CO_{2preSort} = sort(CO_{2pre})$$
 (6)

The ceil function used in Eq. (7) allows for getting an integer value, which represents the drawing time (in minutes) that is used as index in the sorted CO_2 vector to determine the CO_2 threshold.

$$CO_{2thr} = CO_{2preSort} \left(\left\lceil T_I \right\rceil \right) \tag{7}$$

Figure 4 illustrates 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 CO2 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 "CO2 threshold computation" in Figure 5, the steps refer to the reading of sensor data 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



Figure 5: Overall RED WoLF logic

(Differ of Variables used in the Orivier of optimization of stein (Orivier and The Control, 2020)	Table 3: Variables used in the Olivie	ri's optimization system	Olivieri and McConky,	2020)
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	Class	Var.	Unit	Description
	Predicted	d _i	kW	Power required to supply appliances over the time interval <i>i</i>
s	Predicted	M_i	gCO ₂ /kWh	Grid CO_2 load over the time interval <i>i</i>
ble	Predicted	pv_i	kW	Power provided by PV over the time interval <i>i</i>
aria	Real-time	Cap	kWh	BESS max capacity
Ň	N/A	ppv _i	kW	Power from PV used by appliances over the time interval <i>i</i>
nal	N/A	bpv _i	kW	Power from PV injected to BESS over the time interval <i>i</i>
nter	N/A	gpv _i	kW	Power from PV sent back to grid over the time interval <i>i</i>
z Ir	N/A	$CO2_i$	gCO ₂	CO_2 emitted over the time interval <i>i</i>
ıt &	N/A	SOC_i	kWh	BESS state of charge read over the time interval <i>i</i>
ndu	N/A	Ι	hrs	Length of each time interval
i i i	N/A	Т	N/A	Set of discrete time intervals
	N/A	inef	%	Inefficiency factor (0 to 1)
ut.	N/A	pc_i	kW	Power charged in BESS over interval <i>i</i>
Ó	N/A	pd_i	kW	Power discharged from BESS over <i>i</i>

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:

- if CO_{2cur} < CO_{2thr}, appliances and the hybridenergy 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.

It should be noted that the RED WoLF algorithm is inspired by the ARIMA (Autoregressive Integrated Moving Average) model (Siami-Namini et al., 2018), which in our case (considering the input data of our problem) adds non-linearity and other levels of complexity to the system. This is due to RED WoLF algorithm takes as the input the prediction values and current state of storage reservoirs, however the execution is done on current physical state of the system.

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 (Olivieri and McConky, 2020). 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 361



Figure 6: Olivieri's hardware architecture

 CO_2 emissions produced to meet the household's energy demand during a time interval denoted by *i*.

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

subject to

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

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

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

$$(pc_i + bpv_i) \le Cap/2.7, \forall i \in T$$
(12)

$$SOC_{i} = \sum_{t=0}^{i} (pc_{t} + bpv_{i}) \cdot inef \cdot I$$
$$-\sum_{t=0}^{i} pd_{t} \cdot I, \forall i \in T$$

$$-\sum_{t=0} pd_t \cdot I, \forall t \in I$$
(13)

$$SOC_i \ge 0, \forall i \in T$$
 (14)

$$SOC_i \le Cap, \forall i \in I$$
 (15)

$$gpv_i + ppv_i + ppv_i = pv_i, \forall i \in I$$
(10)

 $gpv_i, ppv_i, bpv_i \ge 0, \forall i \in T$ (17)

 CO_2 emissions are computed using Eq. 9 while



Figure 7: Comparison Infrastructure

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 infrastructure² for fair comparison with RED WoLF. Please note that the variables highlighted in **bold** in Eq. (8) to (17) represent the extensions of Olivieri's model in order to integrate the solar production into the optimization model, which was not proposed in the initial model; all variables being summarized in Table 3

The complexity of Olivieri's model is given through Table 4 which provides information related to decision variables and constraints for different model sizes, which all consider 7 decision variables and 393 11 constraints per time period, as well as a time period length of 1 min. Furthermore, Pyomo modeling 395 language with GLPK solver was used under the following configuration: 2,3 GHz Intel Core i7 quad core 397 with 32 Go RAM

4. Experimental evaluation

To evaluate the performance of RED WoLF, three 402 scenarios are defined and compared, as illustrated in 403 Figure 7 In the first scenario (denoted by "Baseline" in Figure 7, the carbon footprint in terms of kg equiv- 405 alent CO₂ emissions (denoted by kg eq. CO_2 in the 406 rest of the paper) is computed for a given residential 407 house and a given energy consumption demand. As 408 energy supply sources, the considered house has a PV 409

Table 4: Complexity of Olivieri's model related to decision variables and constraints for different model sizes (7 decision variables, 11 constraints per time period, period length of 1 min).

Horizon (hours)	Total Time Periods	Number of de- cision variables	Number of constraints
4	240	1680	2640
8	480	3360	5280
12	720	5040	7920
24	1440	10080	15840
36	2160	15120	23760
48	2880	20160	31680
60	3600	25200	39600
72	4320	30240	47520

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 hybridenergy storage system is implemented and compared against the Baseline and Olivieri scenarios. Let us stress the fact that the comparison between RED WoLF or Olivieri's algorithms is established on a fair basis, as the two algorithms consider similar input data (PV energy production, energy storage system connected to a battery, house electricity demand, grid carbon intensity) and seek to optimize the same criterion (i.e., carbon emission reduction). The other results that will be compared in the rest of the study, such as electricity bills or battery lifespan correspond to side effects on other parameters.

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

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²The average electricity consumption of the thermal heating and 412 hot water are computed (respectively being equal to 1.04 kW + 0,167 kW) and added to the total house demand. 413

Table 5: Datasets used as experimental inputs

Dataset	Loc.	Name	Period	URL
House demand	UK FR	UKDALE IHEPCDS	Oct. Oct.	(UKDALE, 2015) (IHEPCDS, 2010)
PV production	UK FR	N/A N/A	Oct. Oct.	(NREL, 2020) (Eur. 2020)
Grid carbon	UK	N/A	Oct.	(CIA, 2020)
intensity	FR	N/A	Oct.	(RTE, 2022)
Energy price	UK FR	N/A N/A	N/A N/A	(Statista, 2021)

4.1. Experimental setup

As illustrated in Figure $\overline{7}$ the three scenarios are going to be compared on the basis of three performance indicators, namely (i) CO_2 emissions: CO_2 458 equivalent greenhouse gas emissions produced for 459 supplying house electrical power demand in kg eq. 460 CO₂; (ii) Computational time: time needed to gen- 461 erate the recommended set of commands to be exe- 462 cuted; (iii) Battery lifespan: amount of time a battery 463 lasts until it needs to be replaced. In terms of input 464 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 (Monacchi et al., 2014) (see Table 5 for further details). The reason for considering these two datasets is twofold: (i) as of the pilots (currently being setting up) of the RED WoLF project are located in these two countries; (ii) these two countries have different ways of generating elec-478 tricity (nuclear in France, natural gas in UK), 479 which have direct impact on the grid's carbon intensity. This study considers the October month;
- 2. PV production: to the best of our knowledge, there is no platform in France providing real- 482 time PV production, while in UK the NREL (Na-483 tional Renewable Energy Laboratory) web plat-484 form makes available both historical and predicted PV datasets. A simulator developed by the European Commission (*cf.*, Table **5**) 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 101 via the NREL platform) was increased by 15.4% 10. for the French experiments;
- 3. Grid carbon intensity: two distinct web plat-493 forms making carbon intensity available for 494 France and UK were used, namely RTE for 495 France and Carbon Intensity for UK (cf., Ta- 496 ble 5).



Figure 8: Overview of the Computational Time and associated performance in terms of total emitted CO2 with Olivieri's system

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.

4.2. Experimental results

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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 (Shukhobodskiy et al., 2021). In opposition, Olivieri's algorithm processing time varies exponentially according to the length of 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 6h with a 72*h*-prediction time window (*cf.*, Figure \bigotimes). As a complementary information, the total CO_2 emitted



(c) Grid carbon intensity evolution, along with a representation of when and what proportion of power the RED WoLF and Olivieri systems should be drawn from the electrical grid. In this scenario, RED WoLF draws power from the grid in an intensive manner from 0:00 (midnight) to \approx 3:30am (i.e., drawing power in a range of \geq 7kW, as indicated in the Legend frame), while Olivieri's algorithm generates charging orders all over the day (i.e., in a continuous manner) in a less intensive manner (in a range of [0; 3.5kW[). To understand the impact of such behavior on the battery state of charge, the reader shall refer to Figures 9(a) and 9(b)

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

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with the Olivieri's algorithm over the October month 526 498 is depicted in Figure 8 showing that beyond a 24h- 527 499 prediction time window, the optimization does not 528 500 lead to better performance. As a consequence, a 24h- 529 501 prediction time window is chosen for running the ex- 530 502 periments conducted in the rest of the paper, bear- 531 503 ing in mind that in this configuration Olivieri requires 532 504 ≈ 25 min for generating the optimal solution against 533 505 < 1 ms with RED WoLF. 506

4.2.2. Daily analysis 507

Before presenting the monthly comparison analy-508 sis, which is the subject of section 4.2.3, we suggest 509 to analyze how RED WoLF and Olivieri algorithms 510 behave with respect to the system inputs considering 511 three specific days. Let us note that, in the conducted 512 experiments, the battery capacity for both algorithms 513 is 6.5 kWh and the maximum intake/outtake power is 514 4.2 kW. Furthermore, two assumptions differ between 515 RED WoLF and Olivieri: (i) maximum grid intake: 516 RED WoLF defines a constraint defining the maxi-517 mum power that can be drawn from the grid by the 518 sum of house consumption minus the power generated 519 by the PV system. This limit is fixed by the energy 520 provider and set to 9 kW. Olivieri's algorithm does 521 not include such a constraint; (ii) Thermal charging 522 using battery: In Olivieri, space heating and hot wa-523 ter needs are considered as appliances and therefore 524 553 could be supplied by the battery, unlike RED WoLF 525

where thermal reservoir must be supplied by the grid or PV unit sources (this constraint has been added to avoid energy losses during energy conversion). 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 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



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

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lower - even if it remains high - than the rest 585 555 of the day. Figure 9(b) shows that RED WoLF 586 556 draws power from the grid in an intensive manner 587 557 to charge all storage systems (i.e., battery, water 588 558 cylinder and storage heaters); 589 559

- in the morning (likely because residents get up), 560 In 592 batteries are discharged in both models. 56 Olivieri, the battery is almost completely dis-562 593 charged, which is mostly due to the fact that it is 563 not possible to store energy in the heater and/or 564 water cylinder, unlike RED WoLF in which both 565 storage systems have been charged during the 566 night (at the same time as the battery); 567
- 599 • batteries are then charged during sunshine hours. 568 600 However, as the battery's SOC in RED WoLF 560 is always high, the battery quickly becomes full 570 and solar energy produced locally is redirected to 571 the grid. For that day 62% of the PV production 572 in RED WoLF (eq. to 8,4 kWh) is fed back to 573 the grid, while all the PV production is adsorbed 574 by the battery with Olivieri; 575
- at the end of the day, when the house electricity 608 576 demand increases, the RED WoLF system is self- 609 577 sufficient (operating solely on its battery), while 610 578 Olivieri's schedule draws power from the grid. 611 579 In this respect, RED WoLF, which keeps a high 580 battery's SOC, has an advantage in the event of a 581 grid failure or disconnection; 582

Let's remind ourselves that the primary objective 583 of RED WoLF and Olivieri is to reduce GHGE. For 584

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 $(3.2 \text{ kg eq. } CO_2)$ 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 (Karamov and Suslov, 2021). 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 concern; (iii) increasing costs due to the battery purchase leads to social concerns. Overall, Olivieri results in twice more charging/discharging phases³ (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

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

³A 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.



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

using RED WoLF and Olivieri (see Figures 10(a) and 644 612 10(b)) is quite similar to the one analyzed in Oct. 3rd 645 613 (battery's SOC remaining high and part of the PV pro- 646 614 duction -8,7 kWh – being fed back to the grid). One 647 615 difference lies in the fact that RED WoLF is no longer 648 616 self-sufficient in the morning (from 8am to 10am), as 649 617 it draws power from the grid to first charge the bat- 650 618 tery and then power the appliances (*cf.* Figure 10(c)). 619 The reason for this is twofold: (i) the carbon grid in- 652 620 tensity is low during that period (≈ 100 g eq. CO_2), 653 621 and (ii) RED WoLF predicts that the intensity will 654 622 significantly increase within the following 12h. With 655 623 Olivieri, the charging pattern differs from Oct. 3rd; 656 624 the battery starts with a half SOC, while it was full in 657 625 Oct. 3rd. In a similar way as RED WoLF, Olivieri's 626 algorithm takes the opportunity to both satisfy the 627 house electricity demand and charge the battery when 628 the carbon intensity is low (until 4 pm). From this 629 time onwards, the battery in Olivieri becomes the only 630 source of supply until 8 pm (when the grid electricity 631 662 becomes cleaner again). As on Oct. 3rd, Olivieri's 632 663 system uses all the PV production, while RED WoLF 633 re-injects part of this production into the grid. Re-634 garding now the number of charge/discharge phases, 635 666 5 phases are identified in RED WoLF against 12 in 636 667 Olivieri, which is mostly due to the greater variability 637 in the carbon intensity. 638

Day 5 of October: The grid carbon intensity of this 670 639 third day is given in Figure 11(c), which is relatively 67 640 high at the beginning of the day, and then progres-641 sively decreases. Looking at Figures 11(a) and 11(b), 642 it can be observed that the RED WoLF is charging 674 643

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).

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 (ignored into account in Fig-

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



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

Table 6: 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. <i>CO</i> 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

⁶⁷⁵ ure 12, or still the computational complexity of each ⁷⁰⁵

algorithm. Table 6 provides such complementary in- 706

⁶⁷⁷ formation for both scenarios (France and UK).

Firstly, let us compare the results obtained with 708 678 RED WoLF and Olivieri with the Baseline scenario 709 679 (cf., Figure 7). Table 6 reports that in both cases $_{710}$ 680 (France and UK), the monthly CO₂ emissions is re-711 681 duced by 10% (France) and 30% (UK) when imple-712 682 menting RED WoLF's or Olivieri's system, with a 713 683 slight advantage for the latter. However, as previously 714 684 mentioned, this result does not take into considera- 715 685 tion the PV electricity re-directed to the grid. Table 6 716 686 reports that Olivieri is consuming 100% of the lo-717 687 cal PV production, while RED WoLF consumes only 688 86% (France) and 58% (UK). Although it is preferable 719 689 to consume locally the electricity (to avoid electricity 720 690 losses during transmission), the results given and dis-72 691 cussed in Figure 12 need to be put into perspective. 692 722

Secondly, looking at the electricity bills, Olivieri 723 693 outperforms RED WoLF with a difference of more 724 694 than 50€ in the UK scenario and 10€ in the French 725 695 one. This can be explained by the fact that Olivieri 726 696 consumes all the local PV production, unlike RED 727 697 WoLF that re-injects part of the production to the grid, 728 698 as previously discussed. Here again, some revenue 729 699 could be generated in that case, which has not been 730 700 taken into account in this study. Although the objec-73 701 tive of reducing the electricity bill has not been de-702 fined as the prime objective in RED WoLF, nor in 733 703 Olivieri (the focus being given to GHGE reduction), it 734 704

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 6 are obtained. It can be noted that RED WoLF reduces by 60% (France) and 50% (UK) the number of cycles 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

Table 7: Total CO₂ emitted over the month of October using batteries of different capacities/sizes

		Blue	etti	LG	3.3	LG	6.5	Tes	la
		CO_2 kg eq. CO_2	PV to Grid <i>kWh</i>	CO ₂ kg eq. CO ₂	PV to Grid <i>kWh</i>	CO ₂ kg eq. CO ₂	PV to Grid <i>kWh</i>	CO_2 kg eq. CO_2	PV to Grid <i>kWh</i>
FR	RED WoLF Olivieri	42.13 42.53	140.16 17.87	40.50 41.28	138.47 0.59	39.48 40.04	137.41 0	37.70 40.04	137.73 0
UK	RED WoLF Olivieri	152.80 157.57	90.38 12.96	147.34 148.57	61.33 3.08	146.21 140.79	50.60 0	146.32 128.35	44.23 0

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have limited computational capabilities such as smart 773 735 meters. 774 736

4.2.4. Impact of different batteries on the optimiza-737 tion performance 738

To study the impact of how a battery with differ-739 ent characteristics may impact on the algorithm per-740 formance, we consider four different technologies to-778 741 day available on the market, namely Bluetti, LG3.3, 779 742 LG6.5 and Tesla, whose respective characteristics are 743 780 summarized in Table 8 (battery capacity and maxi-744 mum power intake). Table $\boxed{7}$ reports the total CO_2 745 782 emission (in kg eq. CO₂) and power re-injected to the 746 783 grid (in kWh) obtained when running the RED WoLF 747 784 and Olivieri algorithms with these four batteries. 748

Table 8: 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 UK scenario, It can be noted that increas-749 793 ing the size and power intake of the battery leads to 794 750 a significant reduction of CO₂ emission in Olivieri, 795 751 which is not true for RED WoLF. The reason for 796 752 this is highly correlated to the amount of energy re-797 753 injected into the grid, as Olivieri is better than RED 798 754 WoLF in maximizing the consumption/storage of lo-755 cal PV production (*cf.*, PV to grid values in Table 8). 756 Interestingly, RED WoLF outperforms Olivieri when 757 using the smallest (Bluetti) battery, while the trend 758 801 is reversed with the three other battery technologies. 750 Overall, the LG3.3 is sufficient in RED WoLF, as 760 803 larger batteries do not lead to a substantial improve-761 804 ment in CO₂ reduction, while the bigger the battery 762 805 the better in Olivieri. This obviously has a financial 763 impact. 764

In the FR scenario, RED WoLF always outperforms 765 Olivieri, adding that the total CO₂ emission decreases 766 along with the increase of the battery size, which does 767 not apply for Olivieri. One reason for this lies in 768 the RED WoLF logic that gives as much importance 769 to low-carbon grid periods as local PV production, 770 which may prove to be an effective strategy when the 771 national grid is of low carbon, as is the case in France. 772

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 & Research implications

5.1. A European willingness to primarily focus on **GHGE** reduction

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. This is in line with the commitments of the signatory countries of the Paris conventions (COP21), whose objective is to reduce carbon emissions from various human activities by 2030 (housing being one of the key focus).

The research conducted in this article - which is part of the RED WoLF Interreg NWE project - directly addresses the Interreg NWE's Low Carbon" Priority⁴, which is why the proposed solution is an all-carbon optimisation, while being aware that other factors can have an impact. In other terms, the carbon aspect is considered as a restrictive objective, which is aligned with a political will of the EU (COP21).

5.2. Comparison of two GHGE reduction models

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 (Feng et al., 2021) and the growing awareness of the the difficulty to

⁴Outline of the NWE's Low Carbon Priority available at: https://www.nweurope.eu/about-the-programme-2014-2020/the-themes/ last access June 1st 2022

manage and recycle renewable technologies such as 868 811 batteries and PV modules (Nain and Kumar, 2022). 869 812

To progress this state-of-affairs, an innovative CO_2 813 threshold-based strategy currently being developed 870 814 as part of a European project named RED WoLF 871 815 (Rethink Electricity Distribution Without Load Fol- 872 816 lowing) has been proposed in our previous research 873 817 work (Ortiz et al., 2021), which seeks to identify 874 818 the best periods of the day to charge and discharge 875 819 multiple types of storage units (incl., battery, stor-876 820 age heaters, water cylinder). In the present arti-821 877 cle, RED WoLF is evaluated and compared with a 878 822 second strategy proposed by Olivieri and McConky 879 823 (2020), which also aims at reducing GHGE but with 824 a slightly different infrastructure (only considering a 881 825 battery as flexible energy-storage) and algorithm de-826 signed based on Linear Programming (LP). The com-827 parison study brings evidence that the two strategies 884 828 (RED WoLF and Olivieri) contribute to significantly 885 829 reduce GHGE compared to a solution without any op-830 timization logic, although Olivieri has a slight advan-831 tage (11% of reduction with Olivieri against 8% with 832 RED WoLF). However, as analyzed in this article, the 889 833 behavior of the two algorithms is different in terms 890 834 of charging/discharging periods, resulting in different 891 835 pros and cons for the two strategies. Olivieri's algo-892 836 rithm has a more dynamic management of the bat-837 teries with a multitude of charging/discharging cycles 838 894 over the days, which has the advantage of maximiz-839 ing the consumption of local PV production, but, in 840 comparison to RED WoLF, is less self-sufficient in the 841 event of a power outage or of long periods of high 896 842 grid carbon intensity. Such an aspect could eventually 897 843 be of interest for distribution system operators dur-898 844 ing load shedding. RED WoLF also has the advan-845 tage of limiting the number of charging/discharging cycles compared with the Olivieri's algorithm, which 847 contributes in extending the battery's lifespan (in av-900 848 erage, 109 months with RED WoLF against 38 with 901 849 Olivieri's model), which has a direct impact on the 850 overall system cost and carbon footprint (i.e., reduc-851 904 ing maintenance costs, battery replacement, etc.). An-905 852 other pros of RED WoLF lies in the algorithmic com-906 853 plexity, which is very low compared to Olivieri (RED 854 WoLF requiring less than a second to find an optimal 855 solution, while Olivieri requires about 20 to 30min), 856 and this conclusion would be the same with any other 911 857 strategy using LP. This has a twofold consequence: (i) 858 RED WoLF can be extended with additional objec-859 914 tives and constraints without causing extra computa-915 860 tional burden; (ii) RED WoLF is lighter, resulting in 861 917 a lower GHGE and making it more suitable to be de-918 ployed on edge devices. 863 919 Overall, our study does not allow to derive generic 920 864 921 conclusions and findings, but still it brings interest-865

ing empirical evidence that two models designed on 866 two distinct theories lead to very different behaviors 867

and side effects (whether from a financial and battery lifespan perspective).

5.3. Further considerations in future research

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 negligble environmental impact considering the whole lifecycle of such technologies. The recent article of Sebestyén (2021) 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 sustainability of renewable energy systems/architectures, i.e. not only considering the operational phase, but also on the design phase (e.g., considering the quantity of available raw materials) and the recycling/disposal one. In this respect, forecasts about dynamics of raw materials (e.g., raw material reserves) released by EIT RawMaterials-like initiatives⁵ could be considered and integrated to such analyses.

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References

- 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.
- M. Lazarus, H. van Asselt, Fossil fuel supply and climate policy: exploring the road less taken, Climatic Change 150 (2018) 1-13.
- 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.
- 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
- 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.
- A. A. Shukhobodskiv, G. Colantuono, Red wolf: Combining a battery and thermal energy reservoirs as a hybrid storage system, Applied Energy 274 (2020) 115209.

⁵https://eitrawmaterials.eu, last access June 1st 2022

- 922 P. Ortiz, S. Kubler, E. Rondeau, J.-P. Georges, G. Colantuono, A. A. 993
- 923 Shukhobodskiy, Greenhouse gas emission reduction system in 994 photovoltaic nanogrid with battery and thermal storage reser- 995

997

1006

- voirs, Journal of Cleaner Production 310 (2021) 127347.
- 926 M. Wiesheu, L. Rutešić, A. A. Shukhobodskiy, T. Pogarskaia,
- A. Zaitcev, G. Colantuono, Red wolf hybrid storage system: 988 Adaptation of algorithm and analysis of performance in residential dwellings, Renewable Energy 179 (2021) 1036–1048.
- M. S. Munir, S. F. Abedin, N. H. Tran, C. S. Hong, When edge 1001
 computing meets microgrid: A deep reinforcement learning ap proach, IEEE Internet of Things Journal 6 (2019) 7360–7374. 1003
- Z. T. Olivieri, K. McConky, Optimization of residential battery 1004 energy storage system scheduling for cost and emissions reduc- 1005
- tions, Energy and Buildings 210 (2020) 109787.
- Y. Saleem, N. Crespi, M. H. Rehmani, R. Copeland, Internet of 1007 things-aided smart grid: Technologies, architectures, applica-1008 tions, prototypes, and future research directions, IEEE Access 7 1009
 (2019) 62962–63003. doi:10.1109/ACCESS.2019.2913984
- Burmester, R. Rayudu, W. Seah, D. Akinyele, A review of 1011
 nanogrid topologies and technologies, Renewable and Sustain- 1012
 able Energy Reviews 67 (2017) 760–775.
- able Energy Reviews 67 (2017) 760–775.
 G. S. Georgiou, P. Christodoulides, S. A. Kalogirou, Real-time 1014
- energy convex optimization, via electrical storage, in buildings- 1015
 a review, Renewable energy 139 (2019) 1355–1365.
- 946 F. Tooryan, H. HassanzadehFard, E. R. Collins, S. Jin, B. Ramezani, 1017
- Smart integration of renewable energy resources, electrical, and 1018
 thermal energy storage in microgrid applications, Energy 212 1019
 (2020a) 118716.
- F. Tooryan, H. HassanzadehFard, E. R. Collins, S. Jin, B. Ramezani, 1021
 Optimization and energy management of distributed energy re sources for a hybrid residential microgrid, Journal of Energy 1023
 Storage 30 (2020b) 101556. 1024
- R. Das, Y. Wang, G. Putrus, R. Kotter, M. Marzband, 1025
 B. Herteleer, J. Warmerdam, Multi-objective techno-economic- 1026 environmental optimisation of electric vehicle for energy ser- 1027 vices, Applied Energy 257 (2020) 113965.
- A. Yazan M., A. Alaa M., E. Abo Eleyoun, E.-W. Amged S., A. Al moataz Y., U. Vadim, U. Ali Arshad, Optimal configuration
 and energy management scheme of an isolated micro-grid using
 cuckoo search optimization algorithm, Journal of the Franklin
 Institute 356 (2019) 4191–4214.
- 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 1036 storage units, International Journal of Energy Research 43 1037 (2019) 6296–6321.
- M. A. Ashraf, Z. Liu, A. Alizadeh, S. Nojavan, K. Jermsittiparsert, 1039
 D. Zhang, Designing an optimized configuration for a hybrid 1040
 pv/diesel/battery energy system based on metaheuristics: A case 1041
 study on gobi desert, Journal of Cleaner Production 270 (2020) 1042
 122467. 1043
- A. B. Awan, Performance analysis and optimization of a hybrid 1044
 renewable energy system for sustainable neom city in saudi ara- 1045
 bia, Journal of Renewable and Sustainable Energy 11 (2019) 1046
 025905. 1047
- F. Fodhil, A. Hamidat, O. Nadjemi, Potential, optimization and 1048
 sensitivity analysis of photovoltaic-diesel-battery hybrid energy 1049
 system for rural electrification in algeria, Energy 169 (2019) 1050
 613–624. 1051
- 981 J. D. Fonseca, J.-M. Commenge, M. Camargo, L. Falk, I. D. Gil, 1052
- Multi-criteria optimization for the design and operation of dis tributed energy systems considering sustainability dimensions, 1054
 Energy 214 (2021) 118989.
- A. Ayse Fidan, K. Muhsin, Design and performance evaluation 1056
 based on economics and environmental impact of a pv-wind- 1057
 diesel and battery standalone power system for various climates 1058
 in turkey, Renewable Energy 157 (2020) 424–443. 1059
- in turkey, Renewable Energy 157 (2020) 424–443. 1059
 R. D. Bingham, M. Agelin-Chaab, M. A. Rosen, Whole building 1060 optimization of a residential home with pv and battery storage 1061
- in the bahamas, Renewable Energy 132 (2019) 1088–1103.
 J. Salehi, A. Namvar, F. S. Gazijahani, Scenario-based co- 1063

optimization of neighboring multi carrier smart buildings under demand response exchange, Journal of Cleaner Production 235 (2019) 1483–1498.

- 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.
- 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.
- H. Pandžić, Optimal battery energy storage investment in buildings, Energy and Buildings 175 (2018) 189–198.
- 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.
- 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.
- 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.
- P. Arévalo, D. Benavides, J. Lata-García, F. Jurado, Energy control and size optimization of a hybrid system (photovoltaichidrokinetic) using various storage technologies, Sustainable Cities and Society 52 (2020) 101773.
- 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.
- 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.
- 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.
- J. Liu, X. Chen, H. Yang, Y. Li, Energy storage and management system design optimization for a photovoltaic integrated lowenergy building, Energy 190 (2020) 116424.
- 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.
- Z. T. Olivieri, K. McConky, Optimization of residential battery energy storage system scheduling for cost and emissions reductions, Energy and Buildings 210 (2020) 109787.
- 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.
- 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.
- 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 (2019a) 356–372.
- 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 (2019b) 113580.
- H. Moradi, A. Abtahi, M. Esfahanian, Optimal operation of a multisource microgrid to achieve cost and emission targets, in: 2016 IEEE Power and Energy Conference at Illinois (PECI), IEEE, 2016, pp. 1–6.

- A. Nottrott, J. Kleissl, B. Washom, Energy dispatch sched- 1135
 ule optimization and cost benefit analysis for grid-connected, 1136
 photovoltaic-battery storage systems, Renewable Energy 55 1137
 (2013) 230–240.
- M. Yadav, M. Jamil, M. Rizwan, Accomplishing approximately 1139
 zero energy buildings with battery storage using flann optimiza- 1140
 tion, in: 2018 International Conference on Advances in Com- 1141
 puting, Communication Control and Networking (ICACCCN), 1142
 IEEE, 2018, pp. 656–661. 1143
- U. Mulleriyawage, W. Shen, Optimally sizing of battery energy 1144
 storage capacity by operational optimization of residential pv- 1145
- 1075battery systems: An australian household case study, Renewable11461076Energy 160 (2020) 852–864.11471077G. Litjens, E. Worrell, W. van Sark, Assessment of forecasting1148
- G. Litjens, E. Worrell, W. van Sark, Assessment of forecasting 1148 methods on performance of photovoltaic-battery systems, Ap- 1149 plied Energy 221 (2018) 358–373.
- T. Adefarati, S. Potgieter, R. Bansal, R. Naidoo, R. Rizzo, P. San- 1151 jeevikumar, Optimization of pv-wind-battery storage microgrid 1152 system utilizing a genetic algorithm, in: 2019 International Con- 1153 ference on Clean Electrical Power (ICCEP), IEEE, 2019, pp. 1154 633–638. 1155
- A. S. Aziz, M. F. N. Tajuddin, M. R. Adzman, M. A. Ramli, 1156
 S. Mekhilef, Energy management and optimization of a 1157
 pv/diesel/battery hybrid energy system using a combined dis-1158
 patch strategy, Sustainability 11 (2019) 683.
- P. García-Triviño, L. M. Fernández-Ramírez, A. J. Gil-Mena, 1160
 F. Llorens-Iborra, C. A. García-Vázquez, F. Jurado, Optimized 1161
 operation combining costs, efficiency and lifetime of a hybrid 1162
 renewable energy system with energy storage by battery and hy-1163
 drogen in grid-connected applications, International Journal of 1164
 Hydrogen Energy 41 (2016) 23132–23144.
- M. Marzband, E. Yousefnejad, A. Sumper, J. L. Domínguez- 1166
 García, Real time experimental implementation of optimum 1167
 energy management system in standalone microgrid by using 1168
 multi-layer ant colony optimization, International Journal of 1169
 Electrical Power & Energy Systems 75 (2016) 265–274. 1170
- 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.
- 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.
- 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.
- 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.
- G. S. Georgiou, P. Christodoulides, S. A. Kalogirou, Optimizing
 the energy storage schedule of a battery in a pv grid-connected
 nzeb using linear programming, Energy 208 (2020a) 118177.
- G. S. Georgiou, P. Nikolaidis, S. A. Kalogirou, P. Christodoulides,
 A hybrid optimization approach for autonomy enhancement of
 nearly-zero-energy buildings based on battery performance and
 artificial neural networks, Energies 13 (2020b).
- H. Zhang, A. Davigny, F. Colas, Y. Poste, B. Robyns, Fuzzy logic
 based energy management strategy for commercial buildings in tegrating photovoltaic and storage systems, Energy and Build ings 54 (2012) 196–206.
- 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.
- 1133 C. Feng, Y. Wang, Q. Chen, Y. Ding, G. Strbac, C. Kang, Smart
- 1134 grid encounters edge computing: Opportunities and applica-

tions, Advances in Applied Energy 1 (2021) 100006.

- S. Siami-Namini, N. Tavakoli, A. Siami Namin, A comparison of arima and lstm in forecasting time series, in: 17th IEEE International Conference on Machine Learning and Applications (ICMLA), 2018, pp. 1394–1401. doi:10.1109/ICMLA.2018.00227
- 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.
- UKDALE, The uk-dale dataset, domestic appliance-level electricity demand and whole-house demand from five uk homes, 2015. URL: https://doi.org/10.1038/sdata.2015.7
- NREL, Pvwatts calculator, 2020. URL: https://pvwatts.nrel.gov/pvwatts.php
- Pvgis photovoltaic geographical information system, 2020. URL: https://ec.europa.eu/jrc/en/pvgis
- Carbon intensity api, 2020. URL: https://carbonintensity.org.uk.
- 2022. URL: https://www.rte-france.com/eco2mix
- Statista, Le prix de l'électricité en europe, 2021. URL: https://fr.statista.com/infographie/11825/
- 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.
- D. N. Karamov, K. V. Suslov, Structural optimization of autonomous photovoltaic systems with storage battery replacements, Energy Reports 7 (2021) 349–358.
- P. Nain, A. Kumar, A state-of-art review on end-of-life solar photovoltaics, Journal of Cleaner Production (2022) 130978.
- V. Sebestyén, Renewable and sustainable energy reviews: Environmental impact networks of renewable energy power plants, Renewable and Sustainable Energy Reviews 151 (2021) 111626.