Greenhouse Gas Emission Reduction System in Photovoltaic Nanogrid with Battery and Thermal Storage Reservoirs

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

[a] *Université de Lorraine, CNRS, CRAN, F-54000, France*
[b] *Leeds Beckett University, Leeds, United Kingdom.*

Abstract

The residential sector accounts for 30% of the total green house gas emissions in Europe, which can be reduced either by switching to low-carbon technologies or reducing the amount of fossil fuel energy consumed. In this work, a new greenhouse gas emission (GHGE) reduction system at the house (nanogrid) level is investigated. The originality of the proposed system and underlying algorithm lies in the fact that it acts in a proactive manner, by continuously controlling and optimizing energy flows between on-site local power production systems (photovoltaics - PV - array in our case), loads, and storage units (combining battery and thermal storage reservoirs). This system/algorithm is evaluated based on real-life input datasets from the United Kingdom (UK) and France, and compared with traditional house energy infrastructures, namely (i) a house not fitted with battery, and (ii) a house fitted with battery but without additional "smart" software layer. Results show that it performs better in terms of CO_2 (capacity of the algorithm to reduce the amount of non carbon-free energy consumed from the grid), Power to Grid (capacity to maximize the use of local green energy), and financial cost (capacity to reduce the overall electricity bill), respectively improving performance by up to 8%, 10% and 37%.

Key words: Greenhouse Gas Emission, Carbon footprint, Energy efficiency, Photovoltaics, Battery, Nanogrid

1. Introduction

Buildings account for a significant proportion of global energy demand, GHGE, waste generation and resource demands. According to the results of the 21^{st} Conference of the Parties on Climate Change (COP21), held in Paris in 2015, the building sector is responsible for 40% of worldwide energy consumption and 30% of GHGE (Baek and Kim, 2020; Wang et al., 2020). Reducing GHGE can be achieved by either switching to low-carbon technologies or reducing the amount of fossil fuel energy consumed (Holdren, 2006; Blackburn et al., 2017; Lazarus and van Asselt, 2018).

The scope and focus of this research is on the latter, namely the investigation of innovative solutions to reduce fossil fuel energy consumption at the house/building level. Such an objective can be achieved at several

March 31, 2021

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

phases of the energy lifecycle, as depicted in Figure 1. At the generation phase, research usually focuses on the design of weather dependent power generators, along with high capacity energy storage systems (Li et al., 2020; Lai et al., 2020). At the transmission and distribution phases, "smart grid" is an omnipresent topic (Dileep, 2020; Rahim et al., 2019), which is tightly coupled with the digital information flow allowing for both continuous monitoring of the demand, and control of the grid itself. Then, a large research community focuses on in-house solutions, spanning from the design of demand side management strategies (Wen et al., 2020; Mendes et al., 2020) to advanced metering and/or nanogrid architectures (Burmester et al., 2017; Kalair et al., 2020). The research work presented in this manuscript, which is developed as part of the RED WoLF project (standing for: *Rethink Electricity Distribution Without Load Following*) funded by the European Union (EU) programme Interreg North-West Europe (NWE), focuses on and contributes to the latter topic (i.e., nanogrid). Although definitions of what a nanogrid are discussed later in this paper, let us emphasize that the proposed system acts for a single home without gas connection, continuously controlling on-site local power production systems and loads, with the option of using green energy stored locally. The originality of the proposed RED WoLF system and underlying algorithm, compared with state-of-the-art solutions, is threefold:

i. RED WoLF introduces an innovative CO_2-based progressive threshold approach, based on an optimization algorithm which is developed to decide when non carbon-free energy (from the grid) should be drawn to supply/charge in-house equipment;

ii. RED WoLF includes battery and thermal storage reservoirs, including storage heaters and water cylinders;

iii. RED WoLF system/algorirthm is continuously executed, whose decisions are taken in real-time using on-site monitored data (via sensors) and predicted data (PV, CO_2, home consumption).

Section 2 provides background information about the scope and focus of this research. Section 3 introduces the proposed RED WoLF's GHGE reduction system and underlying algorithm, which first and foremost focuses on CO_2. Section 4 provides experimental evidence that the proposed system performs better than traditional ones in terms of CO_2 (capacity to reduce the amount of consumed non carbon-free energy), power to grid (capacity to maximize the use of local green energy), and financial (capacity to reduce the electricity bill). In this respect, real-life datasets from UK and France are considered for evaluation purposes (i.e. PV generation, house consumption). Conclusion and research perspectives are discussed in section 6.

2. Scope, Definition and Positionning

Section 2.1 provides the necessary background information to understand where our contribution stands in the energy field. Section 2.2 discusses the extent to which our research is different from the existing literature.

2.1. Scope and Definition

Figure 1 based on (Saleem et al., 2019), provides a cartography of the power life cycle, which consists of: *(i) power systems:* corresponding to the physical infrastructure; *(ii) Power flow:* representing the power exchanges occurring from its generation to its consumption; *(iii) Information flow:* symbolizing the size of the underlying networks infrastructures, from wide area networks to home area networks. The research work presented in this work falls within the scope of Home Area Network (Consumption) phase, and more specifically in the scope of “Nanogrid”. One may wonder why we talk about Nanogrid and not Microgird ? Although there is nothing in the microgrid definition to say it cannot be confined to a single home/building, we adopt, as suggested by Burmester et al. (2017), that single home microgrids should adopt the term nanogrid for three reasons: (i) nanogrids play a different role to microgrids in the power hierarchy (e.g., by connecting multiple nanogrids a microgrid can be formed); (ii) the potential markets for nanogrids are different to that of microgrids. A nanogrid allows a power structure to be obtained at a relatively low cost compared to microgrids, thus shifting the interest from large/multiple investors to small ones; (iii) as the nanogrid structure is confined to a single home, the technical goals, hardware and software often vary from that of a microgrid.

A wide range of scientific and technological challenges related to nanogrid are addressed in the literature, spanning from the design of new DC converters for nanogrid (Xie et al., 2020; Wu et al., 2016), new appliance task scheduling optimization and demand-side management strategies (Kalair et al., 2020; Sahin et al., 2019), to innovative plug-in electric vehicle optimization strategies (Wu et al., 2017; Shamshirband et al., 2018). Despite this wide scope of research, they all rely on a common set of technological constituents (or building blocks), which can be declined into three main categories, as illustrated in Figure 2:

- *Local energy generator(s):* including both/either renewable generators (e.g., Solar PV arrays, wind) or non-renewable ones (e.g., diesel, gas, stirling):
- *Residential loads:* referring to home equipment that consume energy (e.g., appliances, car);
- *Local energy storage units:* referring to equipment able to store energy for later use, including batteries, storage heaters, water cylinders, or still electrical vehicles;

In the next section state-of-the-art studies that focus on similar objectives as RED WoLF (i.e., reduction of GHGE in PV nanogrid) are discussed, along with the extent to which they differ from RED WoLF.

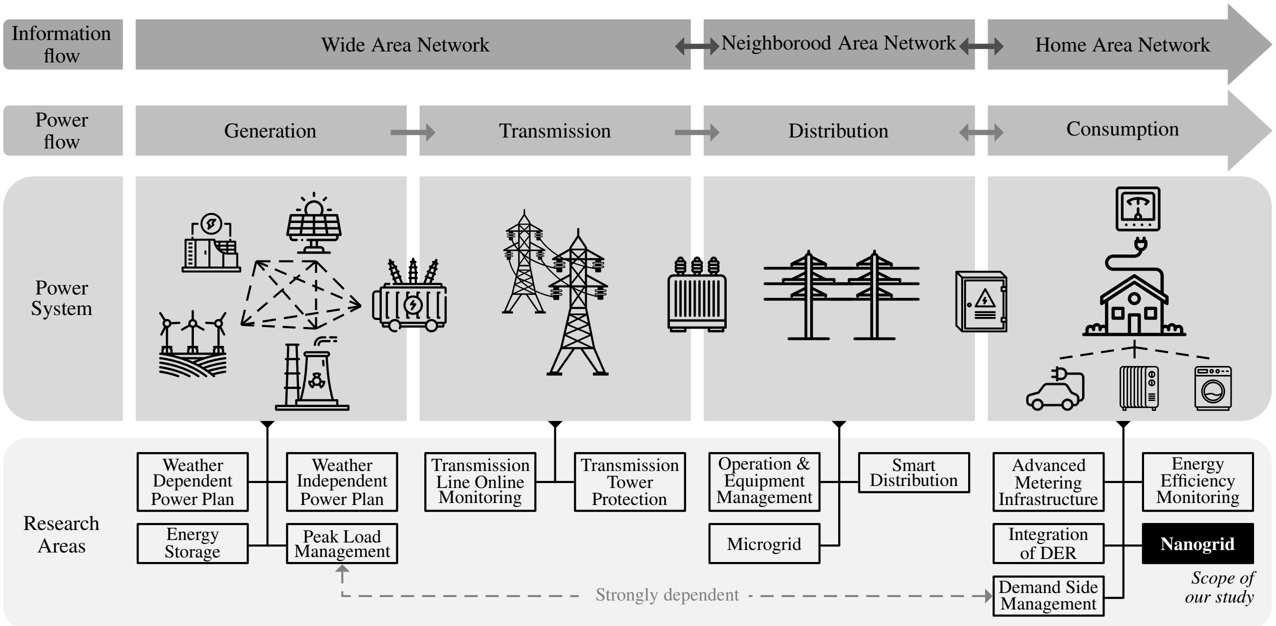


Figure 1: Power system overview (adapted from (Saleem et al., 2019))

2.2. Positionning of RED WoLF in the Literature

Many scientific studies have addressed the subject of GHGE reduction and electricity consumption optimization at the nanogrid level[1]. These studies span from the implementation of basic mechanisms based solely on temperature readings (TAŞTAN, 2019; Marinakis and Doukas, 2018) to the integration of predictive models considering meteorological information or still inhabitant behaviors (Ngarambe et al., 2020; Goudarzi et al., 2019). With the problems related to global warming, the optimization criterion is changing, increasingly focusing on the consumption of renewable energies for carbon dioxide emission reduction (Adams and Nsiah, 2019; Kahia et al., 2019).

In this respect, a comprehensive economic evaluation of a residential building with solar PV and battery energy storage systems is carried out by Akter et al. (2017) considering an Australian use case. The evaluation compares different scenarios, which can be divided into two categories: (1) savings/benefits resulting from the use of solar PV unit only; (2) savings/benefits resulting from the use of solar PV unit combined with a battery-based energy storage system. From a CO_2 perspective, in both cases the reduction of emissions increases along with the size of the solar PV units, however PV units with smaller capacities are more viable options from a return on investment perspective. Although the results of this study are interesting to understand how a given PV and a battery design could impact on savings/benefits, the study remains at

[1] Given the definition adopted earlier (*cf.,* section 2.1), i.e. that single home micro-grids are referred to as nanogrid.

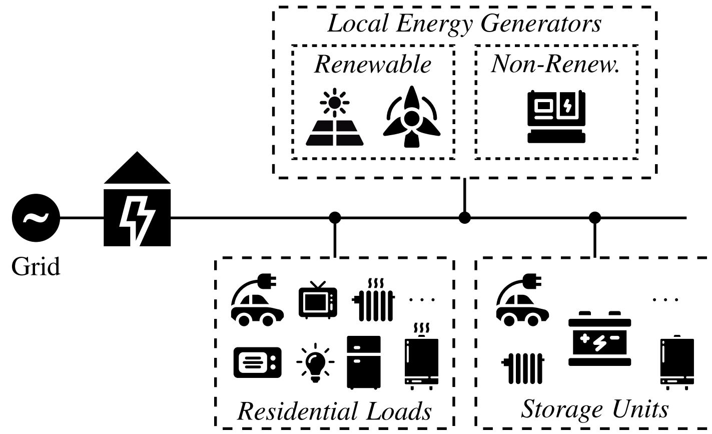


Figure 2: Nanogrid main technological constituents : figure adapted from (Ahmed et al., 2019)

the evaluation stage and does not propose any new optimization layer (e.g., to reduce CO_2, bills, *etc.*).

Other research works do introduce such optimization models. Ban et al. (2019) formalize a capacity planning problem, along with an algorithm seeking to determine the optimal sizing of PV generation and batteries for nanogrid. This optimization minimizes the investment cost, while guaranteeing the desired level of reliability in the energy supply. This work is interesting as it allows system designers to select the best suited PV and battery sizes, however, such an analysis is carried out off-line (i.e. in the design phase of the systems), while, in RED-WoLF, the goal is to achieve continuous optimization in an on-line and continuous mode.

Several studies have developed on-line (real-time) optimization solutions. Among others, Leonori et al. (2016) presented an approach to enhance energy trading tasks and maximize the prosumer gain from an electricity price viewpoint (by deciding when to charge/discharge the battery). Arun and Selvan (2017) propose an online algorithm to minimize the electricity bill by taking advantage of low electricity pricing intervals. Ock et al. (2016) introduce a conceptual framework that takes into account weather data changes in order to adjust the energy used for lighting or still HVAC (Heating, Ventilation, Air-Conditioning) operational scheduling. A weakness of these last three presented works is the non-consideration of the CO_2 impact in the optimization function.

Several studies have proposed multi-objective optimization models to balance the competing goals of minimizing electricity costs for the home owner as well as minimizing CO_2 emissions. Huang et al. (2012) propose an algorithm maximizing the amount of energy produced locally (via PV) to the grid. However, in our opinion, selling energy is not always the best solution (or not allowed by energy provider), as it could be, in some cases, better to save this energy for future use when purchased energy price will increase. Olivieri and McConky (2020) present an innovative optimization model used to develop optimal battery charge and discharge schedules under three different objectives: minimize time dependent energy costs, minimize carbon emissions, and a multi-objective model that considers both energy costs and carbon emissions by including a social cost of carbon. In the same vein, Haidar et al. (2018) propose a real-time consumer-dependent energy management system for smart buildings, which is designed to find a trade-off between the energy cost (either renewable or non-renewable) and its carbon impact. One limitation from these last two presented works is the non-consideration of forecasts, which somehow hinders the system's ability to react to non-expected behaviors (e.g., in terms of CO_2 emission, energy price, PV generation, home consumption) over the forthcoming hours or days. Such forecasting is being considered by Moradi et al. (2016), where a 24 hours ahead optimization of PV-Wind hybrid systems with battery storage is performed in order to meet the load requirements. Nonetheless, the authors do not take into account CO_2 forecasts (only PV, wind and load forecasts being considered). Let us add that all the previously introduced research works do not consider thermal reservoirs as storage units in their model, which prevents to increase (i) the storage capacity of the overall system; and (ii) the flexibility in the optimization process. RED WoLF and the present study are committed to overcome these limitations.

One may also point out studies considering both stationary and mobile batteries (e.g., electric vehicle) in the optimization process (Mahmud et al., 2018; Gomes and Suomalainen, 2020), with the possibility to add specific constraints (e.g., *"allow for discharging the mobile battery but yet maintain a range of* 25 *km"*). However, the use of mobile battery systems is out of scope of RED WoLF.

3. RED WoLF's GHGE Reduction System

The RED WoLF's GHGE reduction system consists of three steps. First, the necessary input data sources to run the proposed optimization algorithm are collected/accessed. Second, a CO_2 threshold used for later optimization stages is computed. Third, a GHGE reduction logic is specified based on the computed CO_2 threshold. These three steps are respectively detailed in sections 3.1, 3.2 and 3.3. Note that a primary version of the threshold computation was formalized in (Shukhobodskiy and Colantuono, 2020).

3.1. Input data sources

Several input data sources must be accessed/monitored in order run the proposed GHGE reduction logic. These data sources can be divided into three categories, as depicted in Figure 3, namely:

i. *Pre-defined parameter values:* this category corresponds to fixed parameters such as manufacturers' data (e.g., maximum battery capacity and power intake);

ii. *Real-time monitored values:* this category corresponds to data monitored on-site, which includes smart meter-, heater-, cylinder- (water tank-), PV- and home appliance-related data;

iii. *Predicted dataset values:* this category corresponds to predicted dataset patterns, and particularly the predicted CO_2 generated by the grid for a given forthcoming period of time, as well as the predicted PV and home consumption.

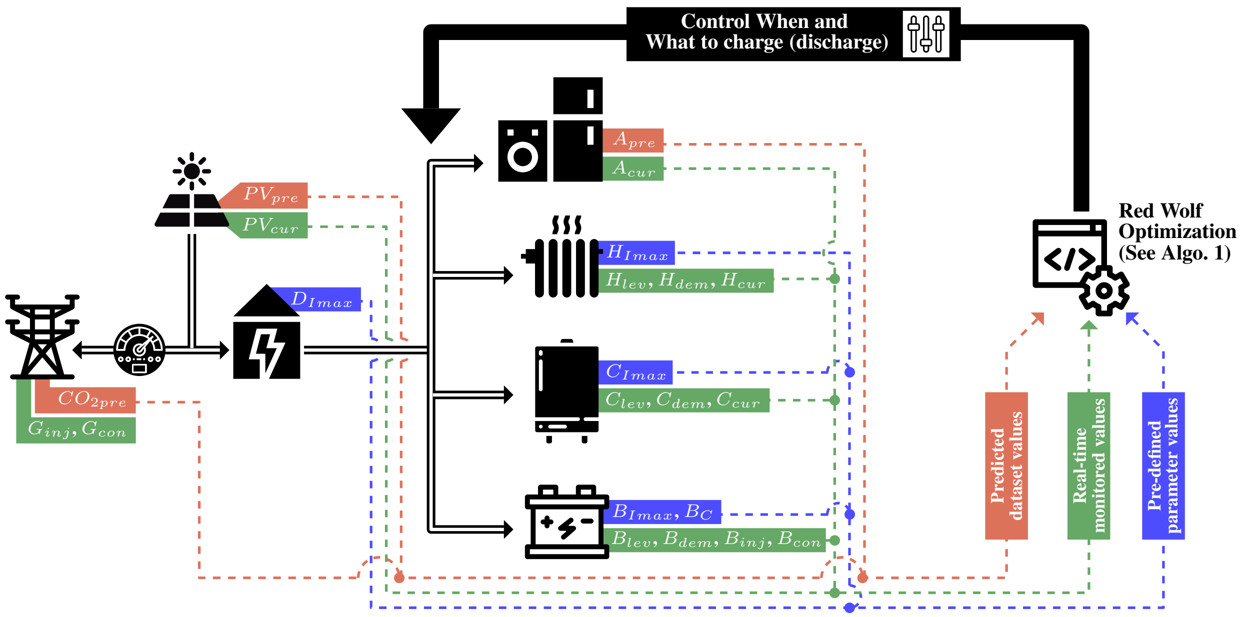


Figure 3: RED WoLF's GHGE reduction system overview

Table 1 provides the list of data sources that need to be accessed/monitored for each of the above categories, as well as the algorithm outputs and internal algorithm variables. In the next section, the notion of "CO_2 threshold" is introduced and formalized, which is key to the proposed GHGE reduction logic.

3.2. CO_2 Threshold identification

To compute what is referred to as CO_2 threshold, denoted by CO_{2thr}, several computational steps must be conducted.

First, the predicted average remaining power drawable from the grid (denoted by G_{PU}) and the predicted energy consumed by appliances and thermal reservoirs until the end of the day (denoted by D_{ED}) must be estimated. The former (G_{PU}), which can be understood as the available amount of instantaneous power to charge home storage reservoirs (i.e., storage heaters and cylinder), is computed based on Eq. (1), where D_{Imax}, A_{pre} and B_{Imax} respectively refer to the maximum house power intake allowed by the energy provider, the estimated forthcoming power consumed by appliances, and the maximum battery's intake limitation. The latter (D_{ED}), which represents the remaining amount of energy required to reach the setpoint for the next day, is computed based on Eq. (2), where H_{dem} and C_{dem} respectively refer to heater and cylinder current power demands (which are computed based on Eq. (3) and (4)), and H_{lev} and C_{lev} to the current

Table 1: Variable definitions

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

level of energy still available in the heater and cylinder. The "Heavi" (Heaviside step function) function represents is defined as "1" if the input parameter is positive, "0" otherwise.

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

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

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

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

Based on G_{PU} and D_{ED}, the minimum time length to charge equipment in parallel of supplying home appliances, is computed based on Eq. (5) (denoted by T_I).

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

Finally, the CO_2 threshold (CO_{2thr}), which identifies when it is optimal to draw energy from the grid, is computed based on Eq. (7), where $CO_{2preSort}$ corresponds to CO_2 prediction vector sorted in descending order as given in Eq. (6). Note that the ceil function is required here in order to obtain an integer, which refers to the drawing time (in minutes) that represents the index of the CO_2 threshold in the sorted CO_2 vector.

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

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

Figure 4 provides a graphical representation of what the above-introduced equations result in. Overall, once T_I is obtained/computed (which is equal to 7h in this example), a threshold that meets this charging duration is identified. In our example, the first threshold (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 $[2pm; 6pm]$.

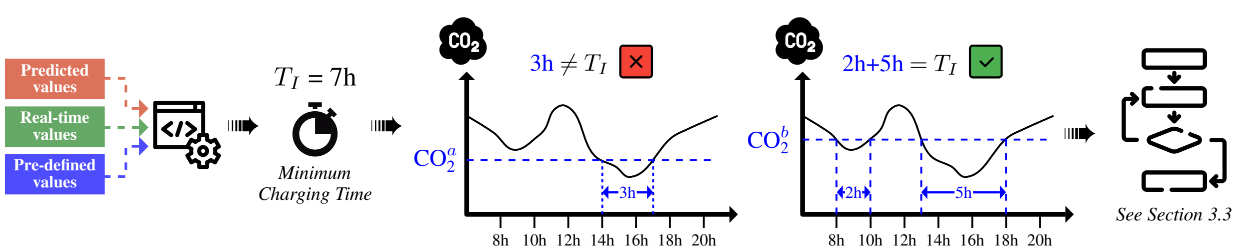


Figure 4: Illustration of the CO_2 threshold computation used in the RED WoLF's GHGE reduction system

Algorithm 1: GHGE Reduction Logic

input : A_{cur}, A_{pre}, $CO2_{cur}$, $CO2_{pre}$, PV_{cur}, PV_{pre}

output: B_{con}, B_{inj}, C_{cur}, G_{con}, G_{inj}, H_{cur}

begin
 for *each* t **do**
  read B_{lev}, H_{lev}, C_{lev}
  compute B_{dem}, H_{dem}, C_{dem} // See Eq. (3),(4)
  for *each* t_{pred} **do**
   read CO_{2pre}, A_{pre}, PV_{pre}
   compute CO_{2thr} // See Eq. (7)
  read CO_{2cur}, A_{cur}, PV_{cur}
  if $CO_{2cur} \geq CO_{2thr}$ **&** $A_{cur} \geq PV_{cur}$ **then**
   $\alpha \leftarrow A_{cur} - PV_{cur}$ // Missing PV power to cover appliances' demand
   $B_{con} \leftarrow \min(B_{lev}, \alpha, B_{Imax})$
   $G_{con} \leftarrow \min(\alpha - B_{con}, D_{Imax})$
  else if $CO_{2cur} \geq CO_{2thr}$ **&** $A_{cur} < PV_{cur}$ **then**
   $\beta \leftarrow PV_{cur} - A_{cur}$ // Remaining PV power after covering appliances' demand
   if $\beta < C_{dem}$ **then**
    $C_{cur} \leftarrow \beta \times Heavi(C_{set} - C_{lev})$
   else if $\beta \geq C_{dem}$ **&** $\beta < C_{dem} + H_{dem}$ **then**
    $C_{cur} \leftarrow C_{dem}$
    $H_{cur} \leftarrow (\beta - C_{dem}) \times Heavi(H_{set} - H_{lev})$
   else if $\beta \geq C_{dem} + H_{dem}$ **&** $\beta < C_{dem} + H_{dem} + B_{dem}$ **then**
    $C_{cur} \leftarrow C_{dem}$
    $H_{cur} \leftarrow H_{dem}$
    $B_{inj} \leftarrow \min\left((\beta - C_{dem} - H_{dem}), B_{Imax}\right) \times Heavi(B_C - B_{lev})$
   else
    $C_{cur} \leftarrow C_{dem}$
    $H_{cur} \leftarrow H_{dem}$
    $B_{inj} \leftarrow B_{dem}$
    $G_{inj} \leftarrow \beta - (C_{cur} + H_{cur} + B_{con})$
  else
   $D_{ImaxAPV} \leftarrow D_{Imax} + (PV_{cur} - A_{cur})$
   $B_{inj} \leftarrow \min(B_{dem}, D_{ImaxAPV} \times Heavi(B_C - B_{lev}))$
   $H_{cur} \leftarrow \min(H_{dem}, (D_{ImaxAPV} - B_{inj}) \times Heavi(H_{\mathrm{set}} - H_{lev}))$
   $C_{cur} \leftarrow \min(C_{dem}, (D_{ImaxAPV} - (B_{inj} + H_{cur})) \times Heavi(C_{set} - C_{lev}))$
   $P_{bal} \leftarrow A_{cur} - PV_{cur} + C_{cur} + H_{cur} + B_{inj}$
   if $P_{bal} \geq 0$ **then**
    $G_{con} \leftarrow P_{bal}$
   else
    $G_{inj} \leftarrow -P_{bal}$

3.3. GHGE reduction logic

Based on the computed threshold, a logic is applied to decide which equipment need to be charged (or not) depending on the threshold value, but not only, it also depends on current PV production, the current demands of the storage heater, cylinder, battery, and so forth. Algorithm 1 provides the applied logic, which is run based on a two time intervals (see rows 2 and 3 in Algorithm 1), namely: (i) every t_{pred} (every hour in our case), the CO_{2thr} is computed based on A_{pre} and PV_{pre}; (ii) every t (every minute in our case), the program monitors the current input values in order to perform the following logic:

- *Case 1 (row 9 to 11 in Algorithm 1):* when the current grid CO_2 level (CO_{2cur}) is higher than the CO_2 threshold (CO_{2thr}), and that the PV production is not sufficient to supply the home appliances, energy from the battery (if any) is consumed, and then (if not sufficient) from the grid;
- *Case 2 (row 12 to 27):* if the PV production is sufficient to supply the appliance power demand, the extra power (if any) is used to charge the thermal storage reservoirs (cylinder, then heaters), and then (if extra power still available) the battery. If some extra power is still available, it is then re-injected to the grid;
- *Case 3 (row 28 to 36):* if CO_2 is lower than CO_{2thr}, everything is charged (to the extent possible) by drawing power from the grid if PV is not sufficient to cover the demand.

In the next section, the proposed RED WoLF's GHGE reduction system is evaluated based on real-life datasets.

4. Experiments

In order to evaluate the benefits from implementing our proposal, three distinct scenarios have been analyzed and compared, as summarized in Figure 5:

A. *PV:* it consists of a single home fitted with PV array. Energy is consumed, first and foremost, from PV (when possible), otherwise from the grid. Note that the storage heaters and the water cylinder are considered as loads and storage units without optimization (i.e., charging at a given point in time, regardless of the CO_2 level or energy price);

B. *PV & battery:* it consists of a single home fitted with PV system and a battery. Energy is consumed, first and foremost, from PV array (when possible), then from the battery (when possible), otherwise from the grid. As before, storage heaters and a water cylinder are considered as loads and storage without optimization yet;

C. *PV & battery & RED WoLF:* it consists of a single home fitted with PV arrays, a battery and thermal storage reservoirs (heaters and water cylinders). Unlike the previous two scenarios, thermal storage reservoirs are taken into account, along with the battery, into the optimization process. Energy is consumed, first and foremost, from PV arrays (when possible), then from the battery (when possible), otherwise from the grid.

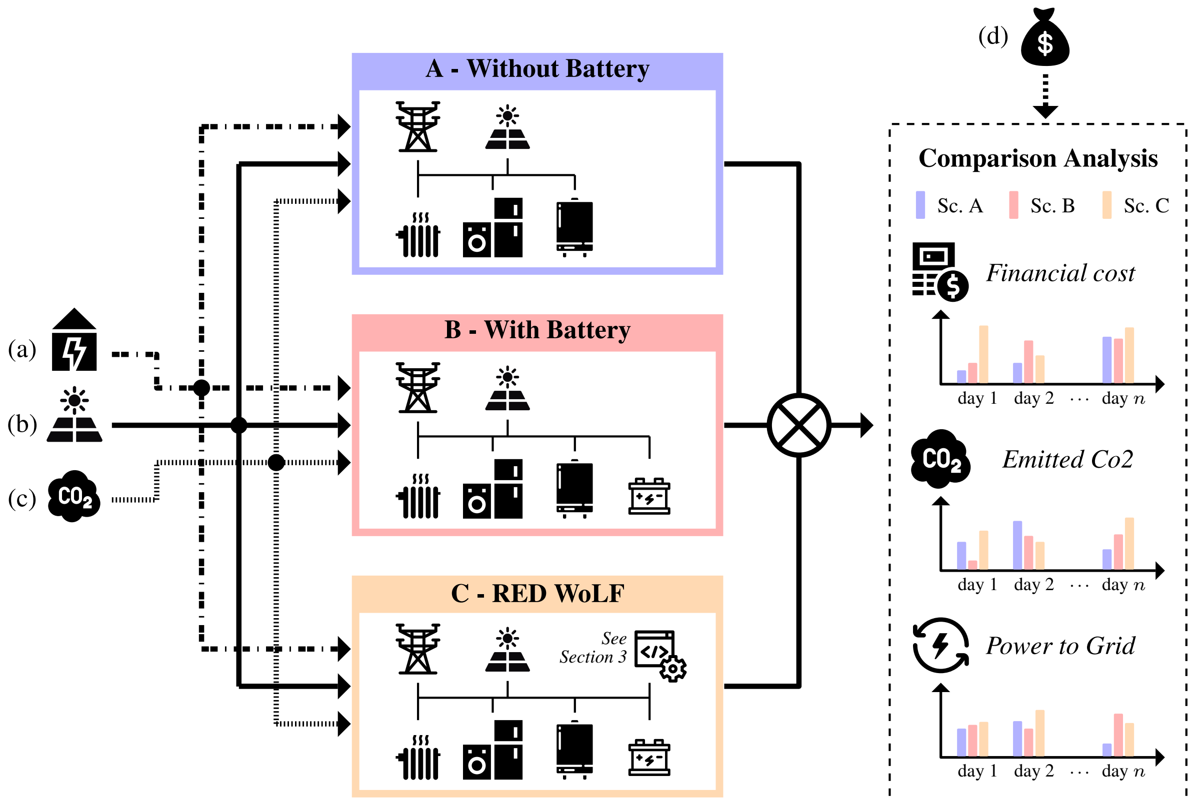


Figure 5: Benchmarking study to evaluate the benefits of the RED WoLF system/algorithm

Figure 5 provides a graphical overview of both the inputs and outputs of our study. In this respect, a distinction has to be drawn between inputs needed to feed the proposed system/algorithm, namely inputs (a) house electricity consumption, (b) electricity produced by PV arrays, (c) grid-related CO_2, and an input not needed to run the algorithm but used for comparison purposes, namely (d) electricity price. Regarding the performance indicators considered, three indicators are defined:

1. *CO_2 Emission (gCO_2/kWh):* corresponds to the amount of grams of CO_2 (per kWh) emitted to produce the electrical energy consumed by the house (i.e., energy from the grid);

2. *Financial cost (euros):* corresponds to the electricity bill related to the energy consumed from the grid;

3. *Power to Grid (kW):* corresponds to the algorithm's ability to maximize PV self-consumption.

The experimental setup (incl., datasets used as inputs of the carried out experiments) is detailed in section 4.1. Experimental results are presented and discussed in section 4.2. Finally, a sensitivity analysis of the impact of the battery size on the overall system performance is carried out in section 4.3.

4.1. Experimental Setup

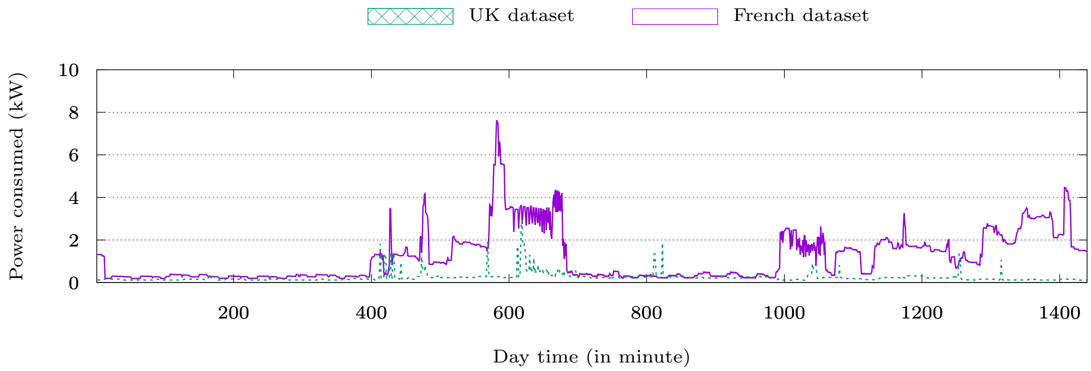
In the following, the four input data sources briefly mentioned previously – *i.e. (a), (b), (c), (d) in Figure 5* – are further detailed in this section.

Home consumption (a): several scientific datasets can be found in the literature, as reported in (Monacchi et al., 2014). In this study, two of them, namely the UKDALE (UK Domestic Appliance-Level Electricity) for UK-related experiments and IHEPCDS (Individual Household Electric Power Consumption Data Set) for French-related ones, are considered (Table 2 provides further details about those datasets). These two datasets have been selected and are of interest for us because (i) these are popular benchmark datasets in the housing sector; and (ii) as part of the RED WoLF project, pilots located in these two countries are currently being set up. Furthermore, choosing these two countries is interesting from an experimental viewpoint, as they have different ways of generating electricity (mostly nuclear-based in France, while UK mostly uses natural gas), which makes it possible to evaluate the performance of the proposed algorithm under different grid conditions. The October month is considered in this study. Figure 6(a) gives insight into the energy consumption patterns over a day from these two datasets, showing that a similar trend is observed, corresponding to period of times where inhabitants are at home.

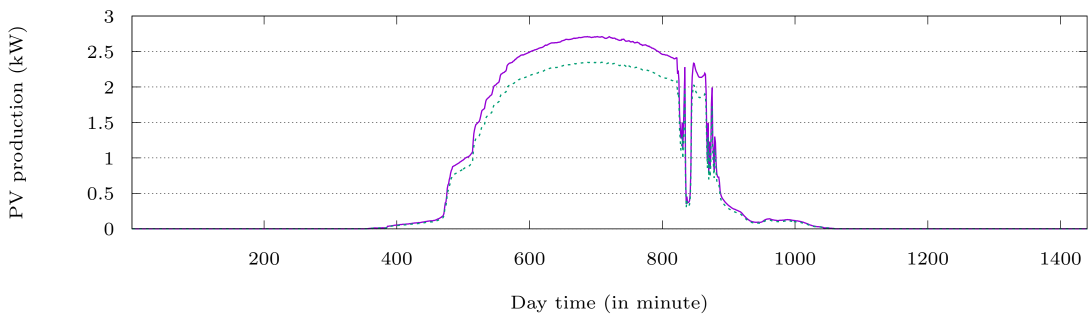
Table 2: Input dataset-related information

Input dataset	Location	Name	Period	URL
(a) Home consumption	UK	UKDALE	October	(NSD, 2021)
	France	IHEPCDS	October	
(b) PV production	UK	N/A	October	(NRE, 2020)
	France	N/A	October	(PVG, 2020)
(c) Grid-related CO_2	UK	N/A	October	(NGE, 2021)
	France	N/A	October	(RTE, 2021)
(d) Energy price	UK	N/A	N/A	(STA, 2021)
	France	N/A	N/A	

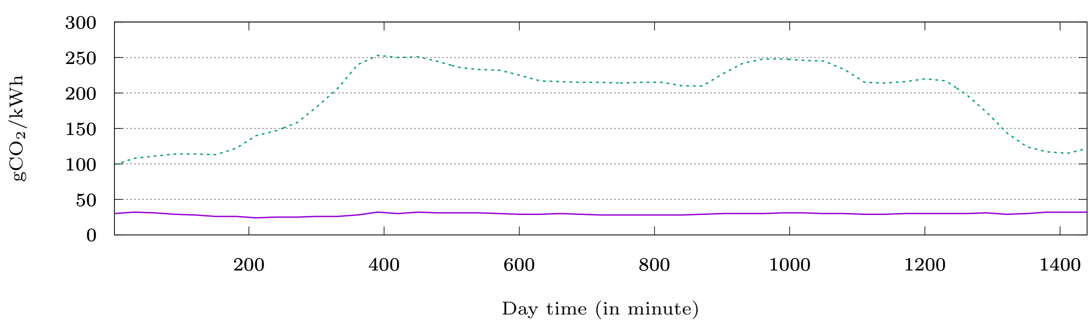
PV production (b): No platform providing real-time PV production data in France exists, to the best of our knowledge, while in UK the NREL (National Renewable Energy Laboratory) web platform provides access to both historical and predicted PV datasets. Noentheless, a simulator developed by the European Commission (*cf.*, Table 2) shows that there is a difference of 15.4% between UK and France (in favour of France). As a result, the PV production dataset obtained for UK via the NREL web platform was increased of 15.4% for the French experiments (see Figure 6(b)).



(a) Input: Home power consumption



(b) Input: PV power production



(c) Input: CO_2 load emitted by the grid

Figure 6: Input datasets

Grid-related CO_2 (c): two distinct web platforms providing APIs (standing for: Application Programming Interface) to access carbon intensity variation of the FR and UK grids were used, namely the RTE

APIs (Réseau de Transport d'électricité) for France and the carbon intensity website for UK (*cf.*, Table 2). Figure 6(c) gives insight into the carbon intensity variation patterns over a day for the two considered countries. It can be observed that the energy is much less greener in UK than in France (3 to 5 times less green), adding that UK is subject to significant CO_2 variations compared with France. This can be explained by the fact that, in France, most electricity is produced by nuclear power plants. Obviously, such political factors have a direct impact on the proposed solutions, and subsequently on the decisions taken, whether at the grid, microgrid, or nanogrid levels.

Energy price (d): even though prices could vary during the day, a fixed average electricity price obtained from Eurostat[2] is considered, namely 0.2122 and 0.1765 euros per kWh in UK and France respectively.

Finally, let us note that a battery of capacity (B_C) 7 kWh and of maximum power intake (B_{Imax}) of 14 kW is considered for the experiments, which corresponds to a mid-range battery product on the market. However, a more in-depth analysis of the impact of the battery size impact on the overall system performance is carried out in section 4.3.

4.2. Experimental Results

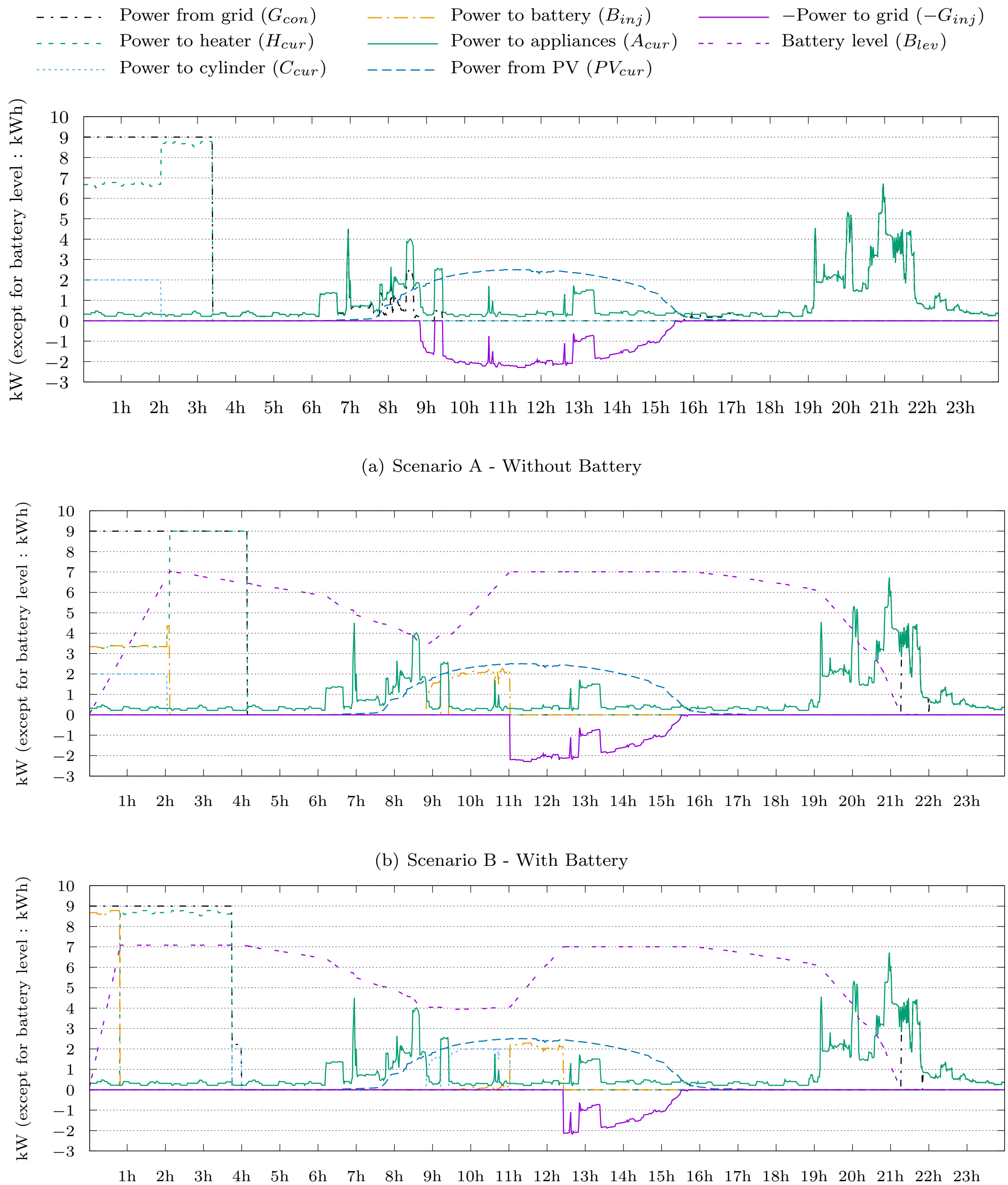
The presentation of the experimental results is divided into two parts. In section 4.2.1, results for a 1-day timeframe are presented, while results for a 1-month timeframe are analyzed in section 4.2.2.

4.2.1. 1-day analysis

Figures 7(a) and 7(c) give insight into the power exchanges occurring at a given day between the grid, the home appliances, the battery and thermal storage reservoirs, and the PV units, with regard to the three considered scenarios. For the conducted experiments, let us note that the sum of the power supplied to indoor equipment (incl., appliances, battery and thermal storage reservoirs), minus the power generated by PV must not exceed the limit fixed by the electricity provider, which is set to 9 kW. Looking at results in Figures 7(a) and 7(c), an interesting observation is that, for this specific day, less power is re-injected to the grid when using our system (scenario C) compared with scenarios A and B (see curve denoted by *-Power to grid*). Indeed, when looking at the first scenario, almost all the energy generated by PV is re-injected (see period 9h to 16h), while in our system, it only starts around 12:30. Although this observation is only valid for this specific day, it is worth noting it as the following consideration is made: the higher the amount of energy re-injected to the grid, the less this energy source is valued at the local level. This has a twofold consequence: (1) the inhabitant does not take advantage of her/his own energy, which goes against one of the ecological principles (namely "shop locally" (Benyus, 1997)), adding that she/he remains grid-dependent[3],

[2] https://fr.statista.com/infographie/11825/comparaison-cout- electricite-en-europe/

[3] Grid independency is a sustainability measure which is usually used to see how the house will perform if there will be no energy supply from the main grid (Akter et al., 2017).

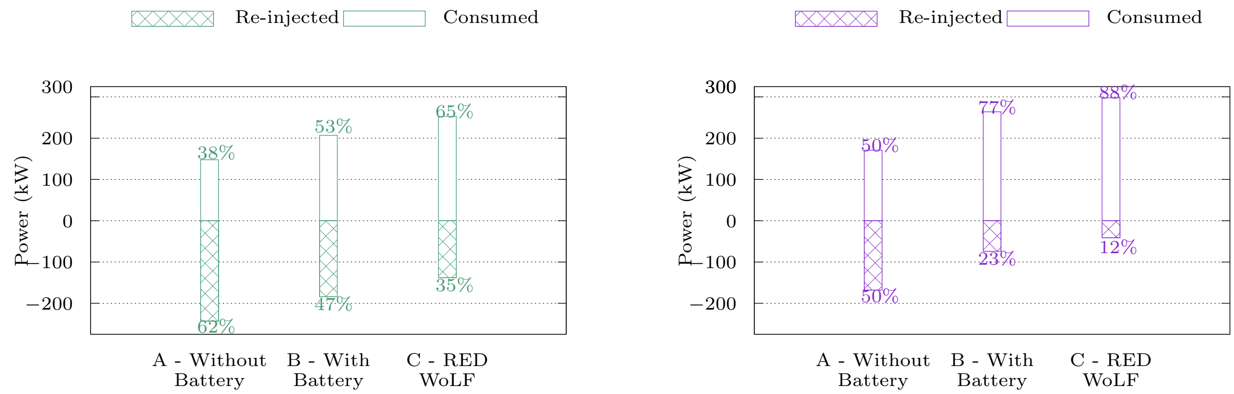


(a) Scenario A - Without Battery

(b) Scenario B - With Battery

(c) Scenario C - Red WoLF

Figure 7: 1-day analysis regarding the three scenarios compared in our experiments



(a) UK (b) France

Figure 8: Power to Grid

and (2) energy losses will likely occur during energy transmission phases on the grid. Having said that, it cannot be concluded at this stage (i.e., based on a single day) whether our approach leads to better results on long term runs. As a result, a longer period of time is studied in the next section.

4.2.2. 1-month analysis

In the following, a full month (October) is analyzed with respect to the three performance indicators introduced in Figure 5.

Power to Grid: Figures 8(a) and 8(b) provide insight into how much local energy (i.e., produced by PV) is re-injected to the grid (in the UK and French cases), or locally consumed. Let us note that the sum of the re-injected and locally consumed energies is equal to the total amount of energy produced by PV. For example, considering scenario B in Figures 8(a), 53% refers to the part of the energy generated by PV that is locally consumed, while the remaining 47% is re-injected to the grid. Having in mind that the objective of RED WoLF is to maximize local energy consumption (as discussed in the section 4.2.1), it can be noted, as a first comment of Figures 8(a) and 8(b), that more than half of the energy produced locally is re-injected to the grid in scenario A ("Without battery"), while this effect is significantly reduced when adding a battery and/or thermal storage reservoirs to the infrastructure (scenarios B and C). Indeed, the implementation of storage units enables to mitigate the re-injection of energy produced locally to the grid up to 23% in France, against 47% in the UK. When using the RED WoLF's GHGE reduction system, this reduction goes down to 12% and 35% respectively in France and UK. This difference between both countries is mainly due to the energy consumption patterns, as in the French house, the consumption is higher than in the UK's house (821 kWh against 269 kWh), adding that the solar energy can be almost fully used locally with the proposed system/algorithm (i.e., scenario C). Furthermore, by examining the house energy consumption patterns (see Figure 6(a)), it can be seen that the energy produced by PV takes mainly place outside daylight periods,

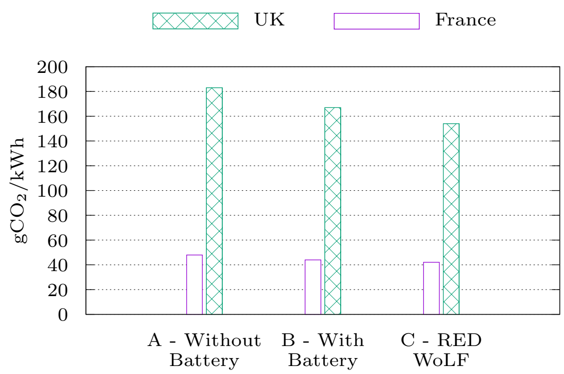


Figure 9: Emitted CO_2

which is why a smart procedure for optimizing the use of the storage units based on inhabitant needs and habits is relevant.

CO_2 Emission: Let remind ourselves that this metric is the most important from a RED WoLF project perspective, as the main goal of the project is to increase renewables' usage and reduce CO_2 emission. Figure 9 gives insight into the experimental results related to the three considered scenarios (A, B, C). It can be observed that a similar trend is obtained, with a decrease of around 9% between scenarios A and B (i.e., without battery *vs.* with battery), and around 7% between scenarios B and C (i.e., with battery *vs.* RED WoLF). These results show to what extent it could be beneficial to add some "smart" (software) logic to battery products available on the market. Indeed, up to 16% of gCO_2/kWh could be saved using the proposed solution compared with a basic installation integrating only PV. However, it should be noted that such a reduction could be more or less significant according to the country. In our case (see Figure 9), the monthly gain for the UK house is almost four times higher than for the French one (29000 gCO_2/kWh *vs.* $\approx$ 5500 gCO_2/kWh). This somehow proves that the actions to be taken to in-house GHGE not only required smart solutions at the house level, but also appropriate political decisions and measures, which is obviously out of scope of this study.

Financial Cost: If the use of "smart" storage system is interesting from an environmental viewpoint, its societal impact should not be neglected by analyzing the cost of the implemented solution. Figure 10 gives insight into the electricity bill resulting from each solution/scenario. It can be observed that the bill is reduced by around 10% percent in the UK case and 7% in the French one when the RED WoLF system is used (i.e., scenario A *vs.* C). When comparing scenarios B and C, RED WoLF makes it possible to reduce the monthly bill by 12 euros for the UK case, and 3 euros for the French one. A simple explanation is that the optimization of local energy usage results in price-free energy. Compared to the current literature studies (*cf.*, section 2) that consider both CO_2 and energy price in their optimization process, the proposed algorithm allows to implicitly optimize both criteria (CO_2 and price). Given that the home energy consumption over

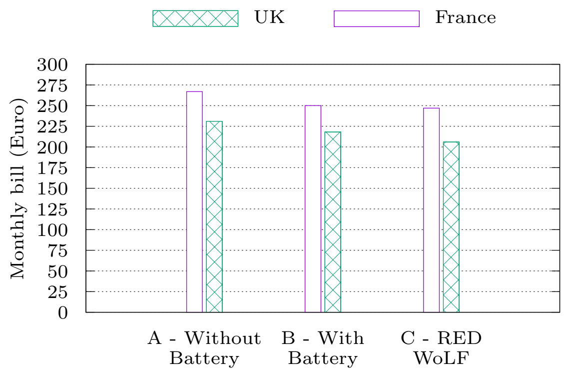


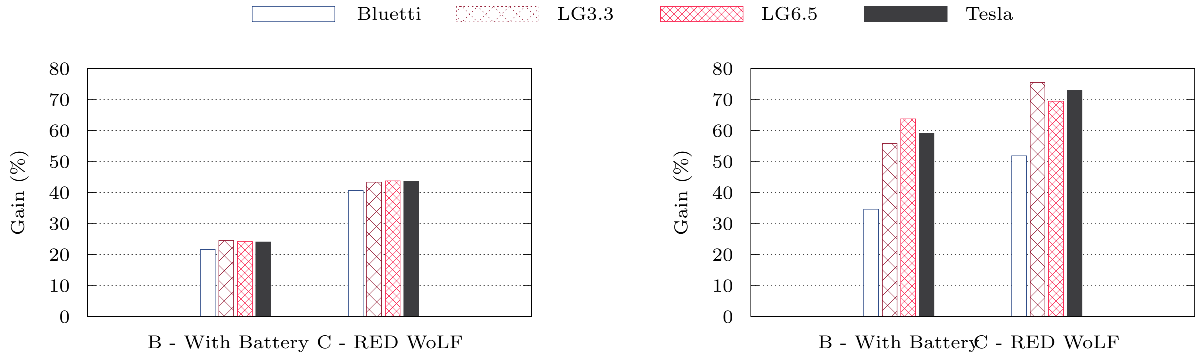
Figure 10: Electricity bill

the October month is of 821 kWh and 269 kWh respectively in France and UK, and that the electricity price in each country is different, it results in a saving of 0.38 euros per 100 kWh consumed in France, while in UK it reaches 1.46 euros per 100 kWh consumed. This is a non-negligible saving from a UK family viewpoint, while in France it is less significant, which confirms that it not that easy to come up with a "universal" GHGE reduction system proposal, as many external factors at the national level (incl., political, technological and societal ones) have direct impact on the efficiency of the proposed system. For example, in our case, just looking at Figure 6(c), it can quickly be noted that the RED WoLF algorithm will be less effective in France than in UK, as the CO_2 signal in France is both lower (average of 30 in France against 200 in UK) and subject to less variations (variation of 5 gCO_2/kWh in France against 100 gCO_2/kWh in UK).

4.3. Battery Capacity Analysis

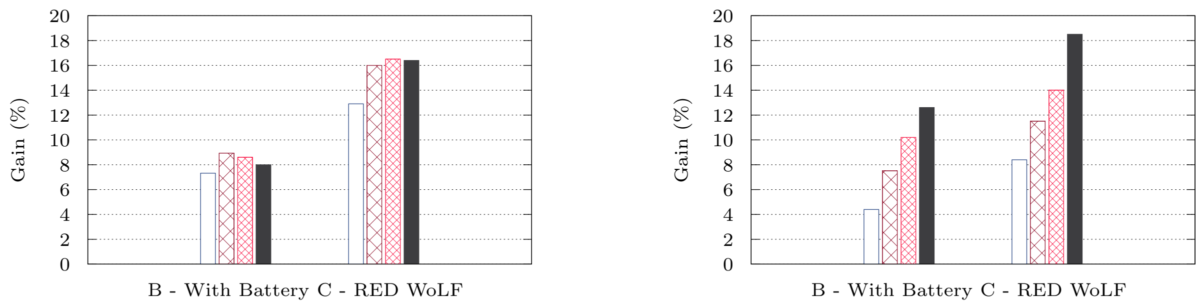
The previous section pointed out the fact that an optimized storage system makes it possible the reduction of GHGE, while reducing the electricity bill (even if the saving is more subtle in France than in UK). This analysis was done considering a battery capacity (B_C) of 7 kWh and a maximum power intake (B_{Imax}) of 14 kW. In this section, the goal is now to analyze the impact of these two parameters on the overall system performance when using the RED WoLF's GHGE reduction system. To this end, four types of batteries available on the market are considered, as synthesized in Table 3. In what follows the results of this analysis are discussed, but, unlike the previous section, results are now presented as an "improvement ratio" between storage-based solutions (i.e., scenarios B and C) with a reference scenario that corresponds to a infrastructure without battery (i.e., scenario A).

Figure 11 shows the improvement ratio related to the energy consumed locally. For clarification purposes, and to make sure that the "improvement ratio" has been correctly understood, let us consider the example of the LG6.5 battery in Figure 11(a): the result tells that scenario B is 23% more efficient than scenario A



(a) UK (b) FR

Figure 11: Improvement of local energy consumption



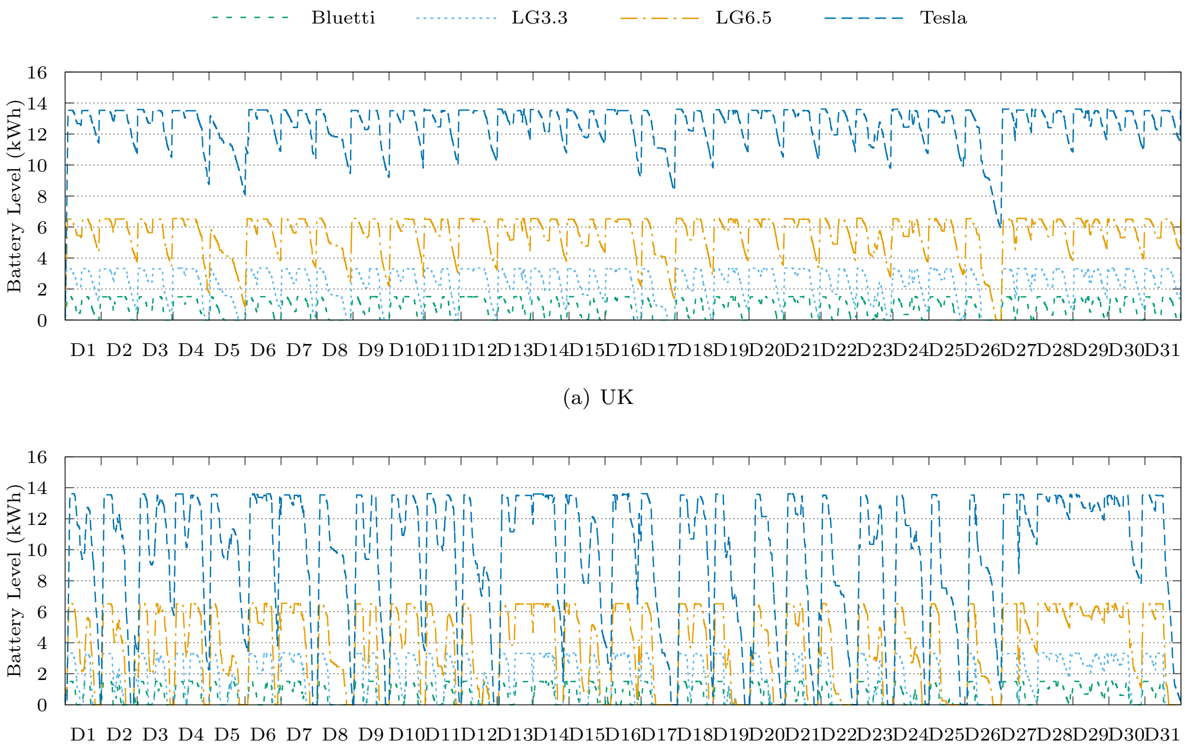
(a) UK (b) FR

Figure 12: Improvement of footprint impact (reduction of CO_2)

Table 3: 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

(which is considered as the reference), while scenario C is 43% more efficient than scenario A. Overall, when looking at all results in Figures 11(a) and 11(b), it can be concluded that, regardless of the battery size and whether a smart software layer is or not added, the use of storage units with a PV infrastructure is always beneficial (in the UK and France), reaching up to 75% of improvement in the French case with LG3.3. It can also be observed that the size of the battery has a lower impact in the UK case compared with the French one, which is due to the fact that the house electricity consumption is lower in UK. Given this, higher battery capacities are more beneficial in the French case. Furthermore, it can also be seen that, in France, RED WoLF provides the best results with the LG3.3 battery, which can be explained by the fact that the larger the battery capacity (e.g., LG6.5), the longer the charging times, which make the battery unusable during those periods, therefore impacting on the optimization performance. All in all, Figures 11(a) and 11(b) show that RED WoLF makes it possible to optimize the use of local energy sources with around 20% of improvement in UK between scenarios B and C, while this improvement ranges between 7% and 20% in France.

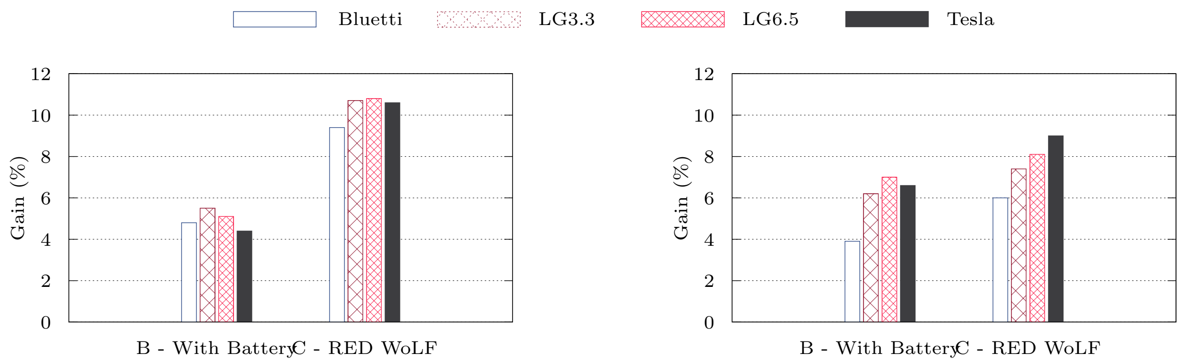


(a) UK

(b) France

Figure 13: Battery Level in scenario C (RED WoLF)

Figure 12 presents the improvement ratio, referring in this case to the extent to which GHGE are reduced. In the UK case, the following observation can be made: (i) RED WoLF makes it possible the reduction of emissions of around 8%, and (ii) there is no much difference in results when using different battery sizes. The reasons are the same as before, i.e. a lower house energy consumption than in the French house. Thus, above a certain battery size, the quantity of energy stored day by day in the battery will not be consumed. To better understand this effect, let us have a look at the battery levels over the whole October month, respectively in the UK case (see Figure 13(a)) and in the French one (see Figure 13(b)). It can be seen that the Tesla battery in the UK case remains almost full (it does not discharge much), while in the French case all batteries are fully discharged at the end of the day. This is why using high capacity batteries leads to better results in France (5% of improvement between scenarios C and B). One more comment about



(a) UK

(b) FR

Figure 14: Financial cost improvement

Figure 12(a) is that, when looking at scenario B, it can be observed a gradual increase in carbon emission for the two largest batteries. The reason for this is that, since there is no smart software layer, the battery charging is done over a single period of time and is not broken down into optimal charging periods (i.e., when the electricity is low carbon), as is the case with the RED WoLF algorithm. This may result in charging the battery during high carbon electricity periods, which will have the following consequence: the larger the battery size, the higher the amount of dirty electricity stored in the battery.

The impact of different battery sizes on the family budget is shown in Figure 14. This impact is tightly coupled with the the power to grid metric, as the higher the amount of PV-generated energy consumed locally, the lower the electricity bill. In UK, the proposed system makes it possible the reduction of the bill of about 10% compared with the reference scenario (i.e., without battery), while in France this reduction is about 8%.

As a concluding remark, these results prove that there is a benefit of combining batteries, thermal storage-like units, with additional software solutions, and this in three respects: (i) it contributes to increase the consumption of energy produced locally, thus making the house increasingly autonomous and self-sufficient energetically speaking; (ii) it contributes to reduce GHGE; and (iii) it contributes to reduce the electricity bill. This study also shows that the LG3.3 battery is sufficient in the UK case, while this is not the case in the French one. Indeed, the Tesla battery provides better results in terms of GHGE, but its high purchase price (due to its high storage capacity) has a non negligible impact oon the total budget.

5. Discussion

This work is part of the global effort that each sector of activity is asked to reduce GHGE by 20% by 2025, and by 40% to 50% by 2030 in order to comply with the Paris Climate Agreements. The political objective is clearly focused on GHGE without specifying constraints on adaptation costs. For example, in France, the economic impacts inherent to the new "Réglementation Environnementale 2020" standard (RE2, 2020) on decarbonisation applied to french dwellings are yet difficult to quantify. In our opinion, this is a bold but necessary gamble to move the lines in the construction, use and deconstruction of housing units. This study, and more generally the Interreg NWE RED WoLF project within which the research presented in this paper is developed, aligned with this move and does not yet take into account economical aspects, whether in terms of costs incurred by the system installation, or the dynamics in electricity prices. For the latter economical aspect (i.e., dynamics in prices), it can nonetheless be noted that the electricity CO_2 evolution is often correlated to the price evolution, so looking for low-carbon periods usually leads to lower the overall electricity bill, as was the case in the experiments carried out in section 4. Regarding the former aspect (i.e., system installation cost), the RED WoLF system can be approximately estimated at 6k€(±3k€) depending on the region, size of PV arrays, and the quality of the selected products/vendors, the main constituents and installation costs being (i) solar panels: about 800€/kW; (ii) battery: from 500-2000€/kWh; (iii) water boiler: between 500-1500€; (iv) storage heaters: between 200 and 1000€for around 15 kWh, and (v) microcontroller: about one hundred euros (e.g., arduino). All this to say that it should not be neglected that costly solutions can hamper the adoption of GHGE reduction systems by inhabitants, but this is not yet part of the research work presented this paper. To pursue the previous discussion about forthcoming moves and agreements envisioning the decarbonisation of electricity (e.g., Paris agreement plans to decarbonise it from 0.63 kg $eC0_2$/kWh in 2015 to 0.200 kg $eC0_2$/kWh by 2030), one may wonder whether RED WoLF-like systems will not be "obsolete" in a couple of years, as electricity decarbonisation will *de facto* lead to house decarbonisation. However, the figures given for 2030 are much higher for French production at present and globally equivalent to that of the UK. The execution of the RED WoLF-like algorithms show that electricity with less carbon than that produced worldwide brings a notable reduction and would be more interesting to apply outside Europe or in countries like Poland where coal is still widely used for electricity production.

In terms of next steps, our research aims at comparing the RED WoLF algorithm with other state-of-the-art algorithms, even though it is never a straightforward process to carry out such a comparison analysis, as the inputs and objectives functions underlying existing optimization algorithms often differ from one another (cf., section 2.2). For example, very few optimization functions from the literature do consider thermal storage equipment as storage units in their objective functions (McKenna et al. (2019)). It is therefore needed to carry out some adaptation steps to be able to compare our approache with existing ones. In this respect, a research collaboration with Dr. Katie McConky (Rochester Institute of Technology Industrial and Systems Engineering), who has proposed the optimization function presented in (Olivieri and McConky, 2020), has been initiated, whose results will be presented in a forthcoming paper.

6. Conclusion, Limitations & Perspectives

6.1. Conclusion

The residential sector accounts for a further 1/4 of EU final energy consumption, and for 30% of the total green house gas emissions. Within this context, the development of green energies in Europe comes with technological advances, cost decreases, process industrialisation, and efficiency improvement. Having said that, there is still work left to optimise the use of technologies such as PV, storage units (e.g., batteries) and so forth. This is the objective of the onging Interreg NWE RED WoLD project, which aims to increase renewables' usage and reduce CO_2 emission for homes with PV.

This research work presents a version of the RED WoLF system and the underlying GHGE reduction algorithm. Before developing technical solutions to achieve such a reduction, it is necessary to understand the benefit of such optimized energy systems. In this respect, first experimental studies carried out in this article, which rely on real-life input datasets, tend to show potential benefits that can be achieved. Overall, the conducted experiments, which rely on real-life datasets from UK and France, show that a "smart" (optimized) storage system makes it possible the reduction of about 5% (in France) of the GHGE compared with a off-the-shelf battery solution. To put the potential of this benefit into perspective, let us highlight the fact that the rehabilitation effort made by Paris over the last 6 years for the residential sector has led to a reduction of the GHGE of 25%[4]. These rehabilitation costs, yet necessary, are very high compared to the integration of RED WoLF-like solutions that lead to immediate gain (more than 5% in our case). Let us point out the fact that several real-life pilots are currently being setting up through the RED WoLF project, in France, UK and Ireland. Furthermore, the initial version of the RED WoLF algorithm (presented in this paper) is going to be improved in both iterative and recursive manner, both based on possible difficulties faced in real-life pilot settings and on innovative ideas, as discussed in the next section.

6.2. Research Limitations & Perspectives

As previously stated, the RED WoLF algorithm presented could be enhanced in several respects:

- first, one may wonder to what extent the implemented ICT (Information and Communication Technology) architecture impacts on the overall GHGE, and this would be a fair question (may be running a smart logic on the Cloud could result in high GHGE). In this respect, research will be carried out to estimate such impact and take it into account in future versions of the algorithm;

- second, it can be envisioned to combine several storage units (e.g., several batteries) into a single house in order to both (i) further optimize the storage and re-use of energy, as a battery in charging mode

[4]https://www.apc-paris.com/actualite/bilan-carbone-2018-paris -est-sur-bon-chemin

cannot be used to power appliances; (ii) propose innovative local electricity markets for the prosumer era (e.g., using blockchain), which could benefit from the proposed optimization system in the future;

- third, as previously discussed, other works in the field are multiplying in the literature, which could serve as benchmark studies for comparing RED WoLF with. The main challenge lies in the fact that the goals to be optimized often vary from one study to another (e.g., costs, energy mix, carbon emissions, electricity consumption), without speaking about the high heterogeneity in the input data sources. It could therefore be worth investigating a kind of generic (online) comparison framework to allow researchers to select various types of input data sources and performance indicators In this respect, collaborative work is underway with Rochester Institute of Technology Industrial and Systems Engineering, which could lead to a series of benchmarking studies and frameworks to be made available to the scientific community.

Acknowledgement

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

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