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RED WoLF Hybrid Storage System: Adaptation of Algorithm and Analysis of Performance in Residential Dwellings

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Abstract

The manuscript proposes the innovative energy storage technology which will allow reducing the load from the grid during peak time consumption, as a result, less CO2 will be generated by electrical grid or renewable energy such as wind energy will not be wasted but rather stored in each household. We do not manage the household consumption, but we store the energy whenever it is "greenest" and can be used in the future and at the same time avoid the usage of the grid during the peak time, thus there is no effect on the dweller lifestyle. Although the technologies used in the article are well known and are ready to use, such a unique combination was never proposed before. We combine photovoltaic arrays, storage heaters and batteries. The inclusion of storage heaters allows us not to use the battery to heat the dwelling and consequently dramatically reduce the battery size needed for the storage. The article also shows the success in avoiding peak times of such combination during numerical simulation test of the control algorithm. These results become exceptionally interesting since this algorithm will be later tested on various pilot sites across North Europe and thus innovate the energy sector.

Keywords: Hybrid Energy Storage, Battery, CO2 emissions, AI, Photovoltaic

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1. Introduction

Global warming is a significant challenge for the environment and human civilisation. The paramount influence in hasting the such an unfortunate sce-

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CCS	Carbon Capture and Sequestration
DHW	Domestic Hot Water
EU	European Union
GHG	Green House Gases
HSS	Hybrid Storage System
NWE	North West Europe
PV	Photovoltaic
RED WoLF	Rethink Electricity Distribution Without Load Following
SHs	Storage heaters
The Grid	Electric Grid
The UK	The United Kingdom of Great Britain and Northern Ireland

List of Acronyms

nario is greenhouse gases (GHG). CO_2 is one of such gases that are emitted from fossil fuel power stations. Furthermore, association of electric grid (The Grid) CO_2 emission level to produced kWh of energy is uneven throughout a day. In more details for each kWh produced by the electric grid the amount of CO_2 in grams emitted by the grid is given by the CO_2 intensity index. That phenomena is illustrated in figure 1. The reason behind uneven energy generation throughout a day is mainly due to uneven energy consumption, which triggers on demand fossil fuel power plants to satisfy the momentary consumption. This is due to renewable power plants corresponding to solar, hydro and wind energy as well as nuclear power stations are very limited in their flexibility to modulate energy generation. In order to fix the problem and reduce the dependency on "dirty" on demand power plants, the energy storage must be implemented either on the side of power generator or on the side of the final consumer. Furthermore, the residential sector in Europe produces 30% of total GHG emission. Therefore, tackling this sector is of utmost importance for achieving sustainability.

Significant amount of research was produced in order to solve such an issue throughout recent years. Potential strategies of a battery storage were excessively studied in [1]. The effects of changing climate on daytime peak hours of power demand are discussed in [2]. In the work [3] it was shown that battery storage technologies can provide significant peaking capacity contributions on example of the case of 18 regions in the United States. Optimisation of the discharging/charging process of electrical storage is investigated as a cost-effective way to benefits through load shifting in [4]. Microgrids control management for batteries was discussed in [5]. The aticle [6] presents the latest achievements in thermal storage for the time period between 2009 and 2017. In the [7] the authors suggested that financial benefit might be achieved by smartly combining heat pump and thermal storage. Furthermore, another scenario was studied in [8], where both heat pump and domestic hot water cylinder (DHW cylinder) are joined together. Later that idea was developed by adding electrochemical storage further and analysed theoretically in [9] and experimentally in [10]. Such a configuration could lead to reduction of an operational cost. Intriguingly, such systems could lead to significant increase of the construction costs. In opposition to the aforementioned articles, this work was performed with the aim of both

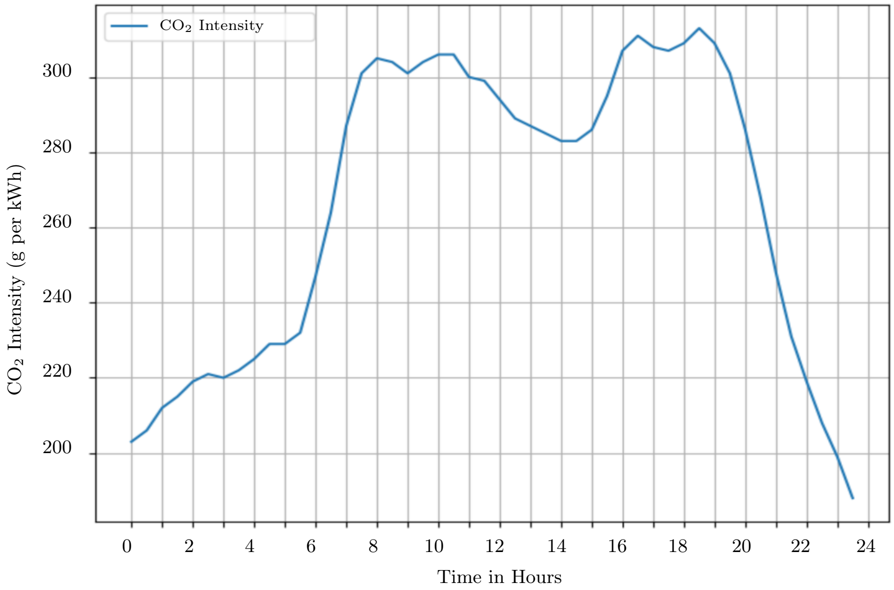


Figure 1: Exemplary data of the CO$_2$ Grid intensity level over a day.

optimising the financial expenditure and reducing the environmental impact. In the [11] the authors provided excessive review of strategies in order to improve PV generated energy self-consumption. To reduce peak demand, an approach based on storing energy during off-peak periods or during periods of solar energy availability and then using it during peak periods was proposed in [12]. Peak demand shifting was discussed with the aid of batteries in [13]. [14] achieves similar results by cleverly managing the equipment within the dwelling. In the work [15] the authors coupled the Grid, with a battery and thermal storage other than Storage Heaters (SHs) to minimise the intake from the Grid. The smart combination of SHs, a Battery, a PV array and DHW cylinder allows to achieve similar results in the absence of pipework associated with central heating and heat pumps. In [16] and [17] the authors produced comprehensive reviews of pathways to CO$_2$ reduction. In [18] the authors suggested that the demand management could be added on top of storage systems to improve the latter performance. Furthermore, in [19] the authors reviewed the advances in AI control for renewable energy systems.

Wholesale energy has a potential to reach negative price [20]. Moreover, on demand energy in case of time of use tariff has the similar ability [21]. Unfortunately wind energy generation [22, 23, 24] could produce a mismatch between power generation and the consumption. A similar phenomena could be also observed in the case of the solar energy called a *duck curve* [25, 26]. As a result, it is paramount to develop a system which would be able to improve the usability of renewable system through smart storage. Different types of energy storage systems were investigated in recent years. Depending on their storage methods the systems can be divided into 4 groups with mechanic, electrochemical, electromagnetic and phase change energy storage modes [27, 28, 29, 30]. One such system is the RED WoLF Hybrid Storage System (HSS) first mentioned in [31]. The system consists of smart coupling of the SHs, a DHW Cylinder, a battery and a PV array. There are both physical and financial reasons for such a choice of components. First of all, these components remove all associated costs with plumbing work related to central heating systems, allowing the additional budget to be used for the installation of the system components. Secondly, the presence of SHs allows to reduce the capacity of a battery in order to achieve peak shifting. SHs are not only significantly cheaper than a battery, with high end state-of-the-art models costing at least ≈ 10 times less, but also to convert 100% of the Grid energy into heat. Finally, the multiple countries start to phase out domestic gas usage from heating applications. For example the Netherlands has a plan to phase out gas heating by 2050 [32] and the UK by 2025 [33]. This leads to high level of demand for fully electrical dwellings as proposed by the RED WoLF.

Interestingly, SHs are not well represented throughout the world. Despite that SHs significantly improved their performance throughout multiple years and could produce significant impact in the era of renewable and sustainable energy. In some countries where such heating devices are common are the UK, Republic of Ireland, France and Australia. In the UK, Republic of Ireland and Australia the rise of the storage heaters is related to deindustrialisation, where excess energy produced by inflexible coal power plants was needed to be stored in order to sustain the Grid operation. Such a solution was successful, however was later phased out by gas central heating due to coal plants decommissioning. In France such a solution is related to the overabundance of nuclear energy generation, which could be modulated, however not on the scale of fossil fuels power plants.

The RED WoLF HSS is planned to be installed throughout 100 dwellings in 6 pilot sites within North-West Europe (NWE) under regional development project [34]. These pilot sites are located within 3 different countries, namely France, the Republic of Ireland and the UK. These countries have different wiring and the Grid standards, which add additional level of complexity for system designs throughout the testing stage. Nevertheless, such differences are providing the unique opportunity to test the design and control throughout with multiple possible setups. The pilot sites would provide the unique data that would be later compared and enhanced with the numerical simulation presented in current work.

1.1. Novelty

The basic RED WoLF system [31] is an important step towards a more sustainable future. Achieving carbon emission reduction secures a more lively environment, and changes the direction our society is heading in. The core purpose of this work is to improve the performance of progressive threshold approach and adapt the controlling logic for international applications, in order to minimise the CO_2 output.

Instead of trying to reduce the operation cost or energy consumption, the RED WoLF system achieves significant savings in CO_2 by shifting the energy peak demand to times of low CO_2 Grid intensities. As decarbonisation of the electricity system is an immediate goal of several countries, replacing the wet heating system and using the Grid for heating purposes are important steps to fulfil CO_2 reduction targets and attain independence from fossil fuels.

In this manuscript we expand the idea of progressive threshold approach described in [31] and employed for systems equipped with battery only in [35]. Two new algorithm strategies recursive strategy and normalisation strategies are proposed in order to boost the performance of the algorithm. The limitations and benefits of these approaches are tested in a numerical simulation performed in two different countries France and the UK, for systems with various battery capacities and PV arrays.

2. RED WoLF hybrid storage system

In order to reduce the dependencies from the Electric Grid, the system must be able to satisfy the demand for heating, hot water and electric energy for household appliances. Therefore the RED WoLF components consist of storage heaters (SHs) for space heating, a DHW cylinder for hot water storage and a battery for electricity supply. For efficiency reasons, a PV array is also included as a component in the RED WoLF system. The power distribution is coordinated by the In-house Programmable Logic Controller (PLC), which uses predictions for the PV output and the home demand for heat, hot water and electricity. Further predictions are made for the CO_2-intensity, updated and adjusted to the real data every hour. In this way, the electrical demand that cannot be covered by the PV array itself is adjusted to the time interval when the CO_2-intensity of the Grid is the lowest (except for the appliances which are powered on demand). In the case of energy excess, the PV array will also supply the Grid after fully loading the system components.

After determining the estimated energy demand and production, the RED WoLF system handles the energy distribution of the dwelling. The schematic energy flow is shown in Figure 2.

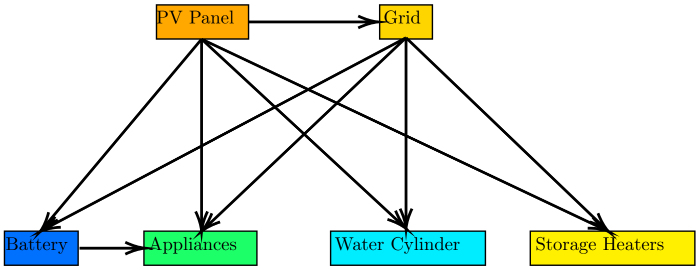


Figure 2: Schematic representation of the energy flow in a dwelling using the RED WoLF System (based on representation presented in: [31])

2.1. The basic RED WoLF Algorithm

In this subsection we will carefully explain how does the base RED WoLF algorithm function. We ought to explain the decision making, and showcase the procedure. Firstly, a list of all variables that our system uses is provided in Table 1.

Notice that some of the parameters are predefined locally, and are depending on the house equipment (H_{IMax}, $\widetilde{H}_{\text{IMax}}$, B_{IMax}, C_{IMax} and B_{Max}). Others, for example H_{Setup} and C_{Setup}, are adjustable by the dwellers or automatically set up for a fixed period of time. Necessary inputs for a legitimate simulation are the 24h PV generation forecast (P_{PV}), household consumption forecast (P_{P2A}) and the 24h CO_2 intensity from the Grid forecast (Q). The base system will operate in the time span of 24h, which we will later optimise to work for multiple days. In what follows we write Grid intake, for power intake from the grid to the dwelling. Heat, battery and cylinder demand are defined in the following way:

$$\widetilde{H}_D = \widetilde{H}_{\text{Imax}} \cdot \Theta(\widetilde{H}_{\text{Setup}} - \widetilde{H}_{\text{level}}), \tag{1}$$

$$B_D = B_{\text{Imax}} \cdot \Theta(B_{\text{Setup}} - B_{\text{level}}), \tag{2}$$

$$C_D = C_{\text{Imax}} \cdot \Theta(C_{\text{Setup}} - C_{\text{level}}), \tag{3}$$

where $\Theta(x) = \begin{cases} 1 & \text{if } x > 0, \\ 0 & \text{if } x \leq 0. \end{cases}$ and $\Theta(x)$ is dimensionless Heaviside step function.

This means that unless the storage fulfils the daily required energy, the power demand for the storage is the maximum rate of intake, otherwise, it is zero. Next, we will make an introduction to the integral balance of the system:

$$\begin{aligned} \mathbb{I} &= \tfrac{1}{60} \int_{\hat{t}}^{\mathbb{T}} (P_{P2A}(t) - P_{PV}(t))dt + C_{\text{Setup}} - C_{\text{Level}} \\ &\quad + \widetilde{H}_{\text{Setup}} - \widetilde{H}_{\text{Level}}. \end{aligned} \tag{4}$$

Variable t represents time, $\hat{t}$ is the current time and $\mathbb{T}$ is the time up to which the prediction is made (in minutes). We should also note that division by 60 in the right-hand side of Equation (4) is needed to transform kWmin to kWh. This integral defines the difference between the total energy demand and the energy generated by the PV array. Hence, $\mathbb{I}$ is an energy quantity in kWh and describes the accumulation of energy in the considered period of time. In the case when $\mathbb{I} \leq 0$, the amount of generated energy is larger than what is needed for consumption. However, if $\mathbb{I} > 0$, the predicted generated energy is lower than the required energy. Consequently, we can modify the time we supply the house with the Grid energy based on forecasts. In other words, when PV generation forecast is high, the Grid is used a lot less. The rate of power intake

B_{IMax}	Maximum rate of battery intake in kW
B_{Max}	Maximum battery capacity in kWh
C_{IMax}	Maximum rate of Cylinder intake in kW
H_{IMax}	Maximum rate of house intake from Grid in kW
$\widetilde{H}_{\text{IMax}}$	Maximum rate of heat intake in kW
B_D	Battery demand in kW
B_{level}	Battery level in kWh
B_{setup}	Energy required to be stored in a battery in 24h in kWh
C_D	Cylinder demand in kW
C_{level}	Cylinder level in kWh
C_{Setup}	The energy required by user to be obtained in 24h in kWh
E	Excess of power generation in kW
$\widetilde{H}_D$	Heat demand in kW
$\widetilde{H}_{\text{level}}$	Heat level in kWh
$\widetilde{H}_{\text{Setup}}$	The energy needed for SHs to obtain in 24 h in kWh
$\mathbb{I}$	The integral balance of the system
P_{P2A}	Predicted power to appliance in kW
P_{PV}	Predicted power from PV in kW
$\hat{t}$	Current time in min
T_{PV}	Actual power from PV in kW
T_{P2B}	Actual power to battery in kW
T_{PFB}	Actual power from battery in kW
T_{P2H}	Actual power for heating in kW
T_{P2C}	Actual power to Cylinder in kW
T_{PFG}	Actual power from Grid in kW
T_{P2G}	Actual power to Grid in kW
T_{P2A}	Actual power to Appliances in kW
$\mathbb{T}$	Duration of forecast in min
$\mathbb{T}_{\text{int}}$	Time of the Grid energy intake in min
Q	CO_2 intensity level prediction in gCO_2/kWh
Q_{sort}	Sorted in monotonically increasing order array of CO_2 intensity level predictions in gCO_2/kWh
δ	CO_2 intensity threshold in gCO_2/kWh
Θ	The Heaviside step function.

Table 1: Predefined parameters and variables

is defined as:

$$\tilde{\omega} = \min(\omega, H_{\text{IMax}}), \tag{5}$$

where,

$$\omega = \int_{\hat{t}}^{\mathbb{T}} P_{P2A}(t)dt/\mathbb{T} + \widetilde{H}_{\text{IMax}} + C_{\text{IMax}} + B_{\text{IMax}}. \tag{6}$$

where $min(x_1, x_2, ..., x_n)$ is the a function which chooses the minimum values between $x_1 \wedge x_2 \wedge ... \wedge x_n \; \forall \; x_1,x_2,...,x_n \in \mathbb{R}$ ($\wedge$ is logical and, $\forall$ is for all, $\in$ means belongs to the set), with dimensions being preserved. The power intake is the sum of the storage demands and the average appliances intake and therefore a power quantity.

Time for which we are allowed to intake power is the following:

$$\mathbb{T}_{int} = 60\left[max\left(\tfrac{\mathbb{I}}{\tilde{\omega}}, \tfrac{C_{\text{Setup}} - C_{\text{Level}}(\hat{t})}{C_{\text{IMax}}}, \tfrac{H_{\text{Setup}} - H_{\text{Level}}(\hat{t})}{H_{\text{IMax}}}\right)\right], \tag{7}$$

where $max(x_1, x_2, ..., x_n)$ is the a function which chooses the maximum values between $x_1 \wedge x_2 \wedge ... \wedge x_n \; \forall \; x_1,x_2,...,x_n \in \mathbb{R}$ and multiplication by 60 is used to make dimensions of T_{int} minutes.

Q is the array of predicted values of CO_2 intensity level for the next 24 hours period with one minute step resolution. Rearranging Q in monotonically increasing order grants us a monotonically increasing array Q_{sort}. By doing so, it is possible to define the CO_2 threshold, above which we are not allowed to take energy from the Grid to charge the components:

$$\delta = Q_{sort}(\mathbb{T}_{\text{int}}) \text{ for } \mathbb{I} > 0, \text{ or } \delta = 0 \text{ for } \mathbb{I} \leq 0. \tag{8}$$

In other words, if $\delta \leq Q(t)$, we won't supply from the Grid. In that case, if $T_{P2A} \geq T_{PV}$ (the power from PV does not cover the demand), power is drawn from the battery to supply the appliances. However if the battery is insufficient, we rely on the Grid. Thus:

$$T_{PFG} = (T_{P2A} - T_{PV}) \cdot \Theta(\tfrac{T_{P2A}}{60} - \tfrac{T_{PV}}{60} - B_{\text{level}}), \tag{9}$$

$$T_{PFB} = (T_{P2A} - T_{PV}) \cdot \Theta(\tfrac{T_{P2A}}{60} - \tfrac{T_{PV}}{60} - B_{\text{level}}). \tag{10}$$

Here we divide by 60 within the Heaviside step function in order to transform power in kW to energy in kWh used in one minute. On the other hand, if $T_{P2A} \leq T_{PV}$, there is excess PV power: $E = T_{PV} - T_{P2A}$. This excess can be spent on different ways, based on its quantity.

Case 1. $E < C_D$.

In this case we transfer all of the surplus power to the water cylinder. Thus:

$$T_{P2C} = E \cdot \Theta(C_{\text{Setup}} - C_{\text{level}}). \tag{11}$$

Case 2. $E \geq C_D \wedge E < C_D + \widetilde{H}_D$.
Here,

$$T_{P2C} = C_D, \tag{12}$$

$$T_{P2H} = (E - C_D) \cdot \Theta(\widetilde{H}_{\text{Setup}} - \widetilde{H}_{\text{level}}). \tag{13}$$

This would mean that the water cylinder is our priority, since we supply it first.

Case 3. $E \geq C_D + \widetilde{H}_D \wedge E < C_D + \widetilde{H}_D + B_D$.
Therefore our algorithm is as follows:

$$T_{P2C} = C_D, \tag{14}$$

$$T_{P2H} = \widetilde{H}_D, \tag{15}$$

$$\begin{aligned} T_{P2B} = min((E - C_D - \widetilde{H}_D), B_{\text{IMax}})\cdot \\ \cdot\Theta(B_{\text{Max}} - B_{\text{level}}). \end{aligned} \tag{16}$$

This is done with the intention to charge the battery as much as possible.

Case 4. $E \geq C_D + \widetilde{H}_D + B_D$
Finally:

$$T_{P2C} = C_D, \tag{17}$$

$$T_{P2H} = \widetilde{H}_D, \tag{18}$$

$$T_{P2B} = B_D, \tag{19}$$

$$T_{P2G} = E - (C_D + B_D + \widetilde{H}_D). \tag{20}$$

Here we export the excess power to the Grid, as we have sufficient energy. Now, lets assume that $Q < \delta$. The maximum power that can be directed into the house is

$$M_{HPV} = H_{\text{IMax}} + T_{PV}. \tag{21}$$

As the CO$_2$ level is below the threshold, we are allowed to use the Grid energy. Our equations now become:

$$\begin{aligned} T_{P2C} = \min(C_D, (M_{HPV} - T_{P2A})\cdot \\ \cdot\Theta(C_{\text{Setup}} - C_{\text{level}})), \end{aligned} \tag{22}$$

$$\begin{aligned} T_{P2H} = \min(\widetilde{H}_D, (M_{HPV} - T_{P2A} - T_{P2C})\cdot \\ \cdot\Theta(\widetilde{H}_{\text{Setup}} - \widetilde{H}_{\text{level}})), \end{aligned} \tag{23}$$

$$\begin{aligned} T_{P2B} = \min(B_D, (M_{HPV} - T_{P2A} - T_{P2C} - T_{P2H})\cdot \\ \cdot\Theta(B_{\text{Max}} - B_{\text{level}})) \end{aligned} \tag{24}$$

In the case of PV energy surplus, we are able to feed all the excess power into the Grid. We update the CO_2 intensity threshold only if the demand of SHs and the water cylinder is not satisfied as a result of it deviating from the starting predictions. This can be beneficial when the original predictions differ from the actual energy generation and consumption.

Below in Figure 3 is the plot of the CO_2 intensity along with the generated thresholds based on the power of the PV. We could notice how the threshold is getting higher, the weaker the PV is. That means, if the PV has more power, the system will supply from the Grid less, and rely more on the photo-voltaic array.

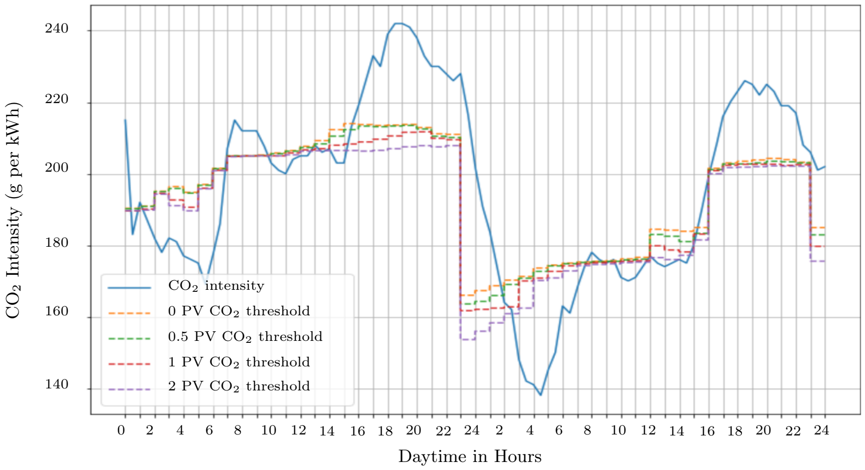


Figure 3: Different CO_2 thresholds based on the power of PV.0, 0.5, 1, 2 correspond to the variation of the original PV array by multiplication on the mentioned values.

2.2. Progressive threshold approach - the normalised version

One major problem with the basic version of the RED WoLF algorithm is, that the introduction of a CO_2 threshold does not guarantee that space heating and hot water are always available. Since the CO_2 intensity is usually low in the morning and in the afternoon, the intervals, when the Grid is used, are set accordingly. With an especially low CO_2 intensity level in the afternoon, it can happen, that the storage is not loaded in the morning, despite the need for heat or hot water. Therefore it is not guaranteed that the energy levels of the SHs or the Hot Water Cylinder do not decrease to zero due to the consumption of heat or hot water. In the worst scenario, the CO_2 intensity minimum at the end of the day are always below those of the previous day and the new global minimum is selected for loading the storage. This could result in unheated houses for numerous days, until the CO_2 intensity level rises again.

We are proposing two approaches to correct this problem. The first one is advance the calculation method for the CO_2 threshold. There are always two days compared by the algorithm, so we use the energy consumption and generation predictions for at least the next 25 hours. The hours before 12 o'clock at night are considered the first day, the hours after the second day. This method consists of four steps, that are visualised in Figure 4:

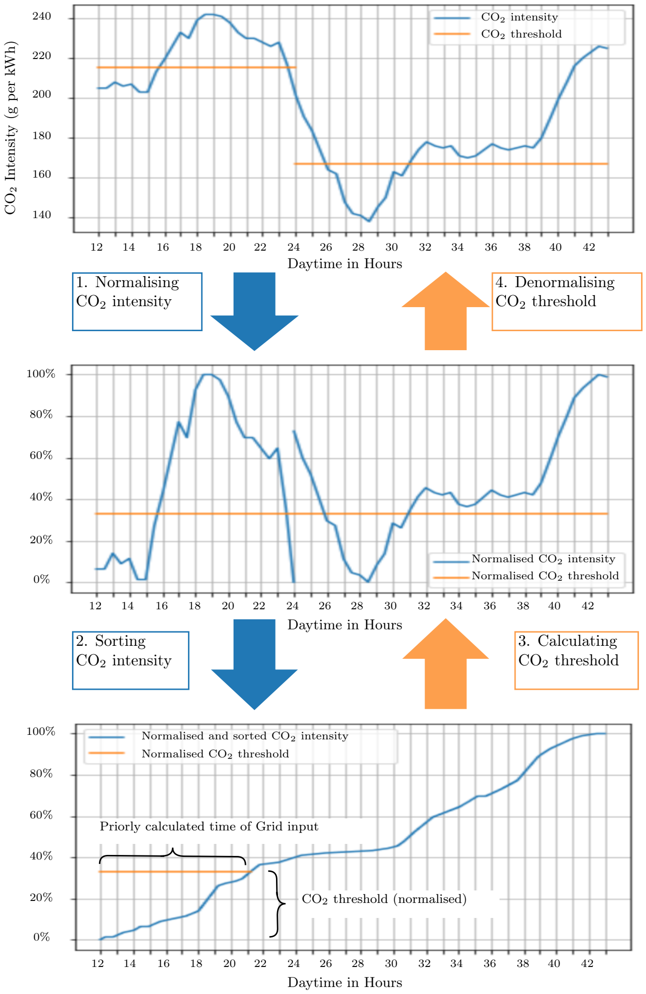


Figure 4: Process of calculating the CO_2 threshold by normalising two consecutive days and denormalising the CO_2 threshold.

1. **Normalising the CO_2 intensity:** By normalising the CO_2 intensity data for each day, local CO_2 intensity minimum, that occur on the current

day, are as equally important as global minimum on the next day. This avoids long time intervals without energy intake from the Grid.

2. **Sorting the CO_2 intensity:** This step is the same as calculating the CO_2 threshold for the basic algorithm. The only difference is that the normalised CO_2 intensities are used instead of the real ones.
3. **Calculating the normalised CO_2 threshold:** The normalised CO_2 threshold is the value at the calculated time of Grid intake $\mathbb{T}_{int}$, as explained in the previous subsection. The calculation for $\mathbb{T}_{int}$ did not change.
4. **Denormalising the CO_2 threshold:** With the known maximum and minimum CO_2 intensity levels for each day, the normalised CO_2 threshold is being denormalised for the current and the next day, resulting in a different CO_2 thresholds for each day.

This normalisation technique creates scenarios that are much more stable compared to a calculation method with a single CO_2 threshold.

Nevertheless, while normalising the CO_2 intensity levels balances the usage of the Grid, it is still not guaranteed, that the heat or cylinder level falls to zero. Due to unforeseen circumstances, the energy consumption and generation will always differ from the predictions. So the second idea we introduce here is force charging. Heating and hot water should be always available, so if the energy level of the SH or the water cylinder decreases to zero, it will be forced charged one hour until the CO_2 threshold is updated again, no matter the CO_2 intensity. This limits the efficiency of the system for the rare case of exceptionally high energy demands, but at this point assuring energy supply is more important than saving CO_2.

2.3. Progressive threshold approach - the recursive version

The basic RED WoLF algorithm calculates the optimal time for Grid usage, but it is not verified, that the scenario is possible without empty storage reservoirs. So another method to stabilise the algorithm, is to check, if the scenario works with simplified assumptions (evenly distribution of heat and hot water demand), and recalculate the simulation with less prediction time, if the heat or hot water level falls below zero. This is where the idea of ‘recursive’ comes from: If the scenario is not feasible, retry it with less prediction time, until it works. If the standard RED WoLF algorithm fails due to low CO_2 intensities in the future, the enhanced recursive algorithm successively removes the future predictions, which lead to infeasible results.

The recursive method also starts with 24 hours of prediction, as the standard algorithm does. If the feasibility check works, then the CO_2 threshold from the standard algorithm is used. If this is not the case, then one hour less of prediction will be used, so 23 hours in this case. This continues, until a CO_2 threshold is found, that minimises the used CO_2 Grid intensities without the danger to run out of storage capacity or need to force charge. If there is no CO_2 threshold found for one hour of prediction, the maximum CO_2 intensity of that interval is returned, such that the system is allowed to charge.

Figure 5 shows how the recursive system works. We can see that in the first iteration heat levels drop below zero. Therefore, we calculate the optimal threshold once again with one hour shorter predictions. At one point, when the threshold gets high enough, the heat levels stabilise, as we are allowed to use the grid more often.

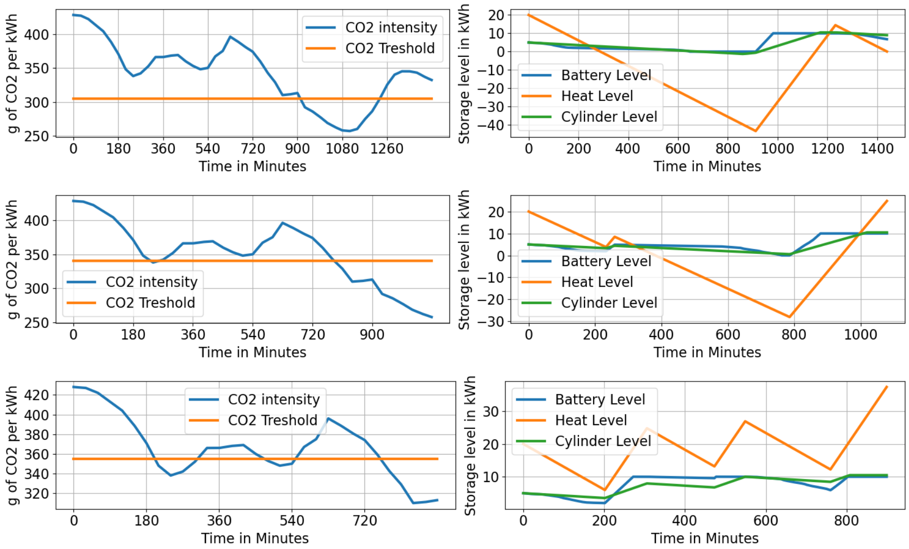


Figure 5: Three steps of the recursive enhancement for the REDWoLF algorithm. Panels on the left correspond to creation of optimal thresholds the avoids force charges. Panels on the right represents storage levels, with top two failing to achieve point in order to avoid force charging.

This method still needs the ability to force charge, as the predictions for heat, hot water and appliances consumption will differ from reality, but as the algorithm combines the ‘perfect’ threshold from the standard algorithm with a reality check to avoid force charging in times of high CO_2 intensities, the results are both very stable and effective. A drawback compared to the normalising method is that it is computationally more expensive because of the recursive iterations. But this should not be much of a problem in the real application, because the computations only need to be performed once every hour.

2.4. Adapting the RED WoLF Algorithm for different environments

Further adapting energy distribution for storage may result in better system performance. Different countries have different housing infrastructures, thus our strategy may not be the most efficient one in some parts of the world. However, we are able to adapt the system, and make it work optimally in various regions. Namely, the maximum rate of house intake (H_{IMax}) deviates in European countries, hence the energy spending priorities must change. For example, in the UK we know that: $H_{\mathrm{IMax}} = 25kW$, while in Belgium it is usually much lower: $H_{\mathrm{IMax}} = 9kW$.

We propose that for countries with relatively low maximum house intake the battery has to be charged first, whether we are above or below the threshold. When the CO_2 intensity is above the threshold and we have excess PV energy, we should examine whether that surplus is larger than the battery demand (instead of the cylinder demand, as we did before). After supplying the battery, the cylinder, SHs and the Grid are provided with the power respectively.

In the case when the intensity is bellow the threshold, the algorithm is as follows:

$$\begin{aligned} T_{P2B} = \min(B_D, (M_{HPV} - T_{P2A})\cdot \\ \cdot\Theta(B_{\text{Max}} - B_{\text{level}})), \end{aligned} \tag{25}$$

$$\begin{aligned} T_{P2C} = \min(C_D, (M_{HPV} - T_{P2A} - T_{P2B})\cdot \\ \cdot\Theta(C_{\text{Setup}} - C_{\text{level}})), \end{aligned} \tag{26}$$

$$\begin{aligned} T_{P2H} = \min(\widetilde{H}_D, (M_{HPV} - T_{P2A} - T_{P2B} - T_{P2C})\cdot \\ \cdot\Theta(\widetilde{H}_{\text{Setup}} - \widetilde{H}_{\text{level}})) \end{aligned} \tag{27}$$

The idea behind these changes is that the battery now charges the appliances most of the time, and it is used more often than in the previous version of the system. The savings are now higher when the PV panels are weak, as we are distributing energy efficiently with this improved algorithm (it would have been much lower with the old system). In Figure 6, we demonstrate how our algorithm functions for multiple days in the UK case. The storage levels, the CO_2 data and the power flow for the components are plotted. In order to simulate the performance of the system we take PV power generation and appliance consumption from [36] and [37], respectively. These data was previously used in [38] and [31]. We should note that [37] data were detrended from seasonal effects, which may contribute to heating and normalised to 5 MWh annual consumption for electric appliance in the UK and France in accordance to [39].

The main area of application of the RED WoLF algorithm is the regions with climates, where the heating is necessity, but cooling is not present. Nevertheless the initial algorithm could work in different circumstances as well. [35] concluded that the original RED WoLF algorithm, is stable even in presence of PV panel and battery only and could lead to savings in CO_2 emissions up to 37 %. Furthermore, the system as it is has potential to accommodate cooling. The one of the possible solutions is to add the prediction of cooling consumption to the prediction appliance consumption in order to calculate CO_2 threshold. It is also possible to add new section to the algorithm responsible for cooling. The exact strategy would depend on the implemented cooling technology.

The RED WoLF system is designed to separate thermal storage and storage required for appliance consumption. This would allow to reduced the financial expenditure required for the system installation. The cost reduction is achieved by employing SHs instead of batteries for the space heating and domestic hot water. SHs with the same amount of energy capacity are significantly cheaper than batteries. Low-tier SHs could cost as low as ≈ 200 GBP per 15 kWh. Mid-tier and high-tier have prices significantly higher and could cost from ≈ 500 GBP to ≈ 1000 GBP with ≈ 24 kWh capacity. Nevertheless, the price is significantly lower, than the one of the batteries where price for 1 kWh capacity is around 1000 GBP. Furthermore, storage heaters are 100 % efficient and all the energy input is transformed directly to heat. As a result the price of an average system with 4 kW PV array, 5 SHs, 2 kWh battery and a water cylinder is around 7050 GBP (installation cost included). Moreover, we should note that SHs could be connected to the power socket directly without any additional work. Thus, making them easy substitution for high capacity batteries, for space heating applications.

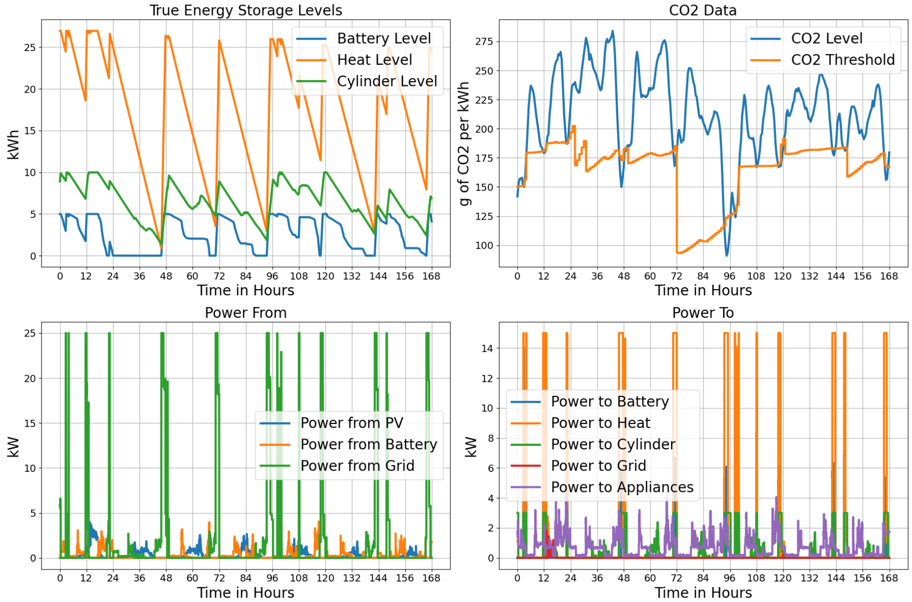


Figure 6: Power flow and CO_2 threshold for one week in spring in the UK. Recursive version is used for threshold calculation.

2.5. *Application of the RED WoLF Algorithm using existing data as input*

At this point, the progressive threshold approach implemented in the RED WoLF is ready for different countries and seasons. Additional scenarios with different PV array sizes will also be tested (half size, double size and no PV). To date, there is no detailed data for the daily consumption of hot water and space heating, for the systems composed of the RED WoLF elements, so some assumptions are necessary for the distribution of the yearly demand, which is known. So we assume that most of the space heating (75%) is needed in winter, there is no space heating in summer and the remaining heating is equally distributed to spring and autumn. The yearly need for heat in kWh for certain countries is shown in table 2. With the aid of [40] and [41], the maximum rate of house intake from the grid is for different countries is considered, although the exact rate might vary for some specific energy providers and tariffs.

country	Yearly heat demand [kWh]	Max rate of house intake [kW]
Spain	4291	5.5
Italy	9595	15
UK	12037	25
Poland	12084	25
France	12305	12
Germany	13572	34
Ireland	15816	25
Belgium	16630	9

Table 2: Yearly energy demand per dwelling and maximum rate of house intake for specific countries.

3. Results

In the previous chapter we introduced two methods in order to improve the standard RED WoLF algorithm and create stable scenarios for multiple days. The two techniques proposed are Normalising of the CO_2 intensities and Recursive solving. Furthermore, we introduced the origin of main data used in the numerical experiment.

To determine the performance of each algorithm, different scenarios were simulated with each version using historical data from 2018 in the UK (figure 7) and France. Table 3 lists the relative savings for different PV and battery sizes for the Standard, Normalise and Recursive version of the RED WoLF algorithm obtained with the aid of the numerical experiment. During this study it was assumed that the power input to all system components could vary from 0 to maximum nominal power continuously. Moreover, the heat and hot water consumption is spread throughout the day evenly. The later assumption could underestimate the positive impact of the algorithm on CO_2 reduction due since in majority of standard dwellings the main consumption occurs in day and "peak" hours [42]. However, as such system has not being tried to be implemented before, these results could provide sufficiently good estimates of systems performance and guarantees safety before it could be tested in pilot sites that would be occupied with residents. Similarly to [31], we assume that power flow in each minute is different to the one predicted by adding white noise to historical one. Such a process allows to present the system stability. That could differ to the planned pilot sites case, where all the predicted consumption and the grid CO_2 intensity index would be generated via machine learning techniques and would be unique for each single dwelling. The percentage savings refer to a dwelling without storage reservoir but electric heating on demand that emits 4 tons of CO_2 over the year. Moreover, the main assumptions are as follows. The hot water consumption is the same for both the France and the UK. The heating pattern is the same, however the overall heat consumption is normalised for the yearly demand provided by table 2, to take into account the difference between two countries. Furthermore, we assume the dwellings in both countries have the same size of the PV array and a battery capacity, which is then scaled in the numerical investigation. The appliance consumption is the same for both cases, and the prediction for appliance consumption is different for the same white noise. The PV generation and prediction for the UK and France are different, since the countries have different geographical locations.

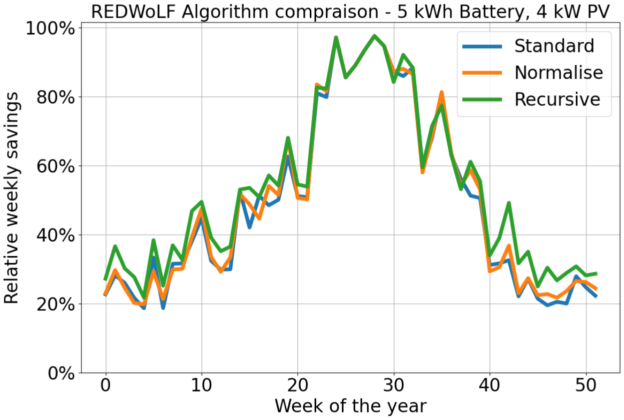


Figure 7: Simulated weekly relative savings of CO_2 of the REDWoLF System in the UK for the different types of algorithms with a 5 kWh battery and a 4 kW PV array.

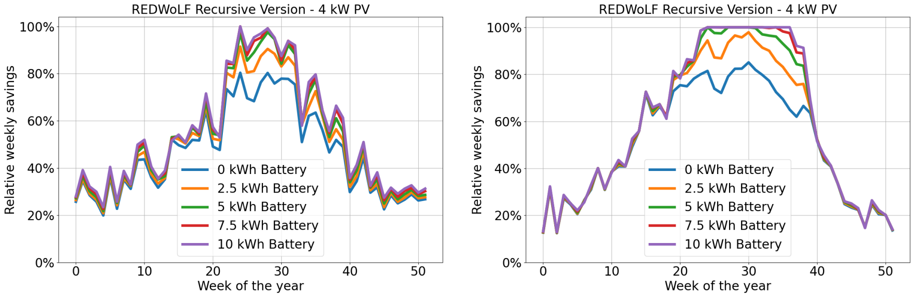
The first discovery follows from figure 7. We can conclude the recursive version is very stable in operation and performs best for all scenarios. The normalisation of CO_2 intensities usually yields better results compared to the standard algorithm, but the improvement is much lower than expected. While normalisation is advantageous if force charging is avoided, the use of local minima seems to be a disadvantage when it is not needed.

Since the recursive algorithm clearly outperforms the other versions, it will be used in the following analyses. In figure 8 different battery sizes are used with a 4 kW PV array. Again the relative savings of CO_2 are compared to a dwelling that uses the Grid for heating and appliances on demand. The relative savings fluctuate for each week, depending on the CO_2 intensities, PV generation and electric demand, but the overall trend becomes clear: Low PV generation and high heat demand result in lower savings in winter months, whereas high PV generation and low heat demand result in high relative savings in summer months. The larger the battery size, the greater the savings, which is also to be expected. The difference in relative savings is most evident in the summer months, as the battery is charged only by PV.

Battery	0 kWh Battery			2.5 kWh Battery			5 kWh Battery			7.5 kWh Battery			10 kWh Battery		
Version*	S	N	R	S	N	R	S	N	R	S	N	R	S	N	R
0 kW PV	14.9	15.4	20.0	15.8	16.2	21.4	17.1	17.6	22.9	18.2	18.7	24.1	19.1	19.5	25.2
2 kW PV	24.5	24.7	29.4	25.5	25.7	30.9	26.7	27.1	32.3	27.7	28.0	33.4	28.5	28.8	34.2
4 kW PV	31.3	31.8	36.2	33.0	33.6	38.2	34.3	35.0	39.8	35.3	36.0	41.0	36.0	36.7	41.7
8 kW PV	40.5	40.4	44.6	42.7	42.8	47.2	44.4	44.7	49.1	45.4	45.7	50.3	46.1	46.4	51.0

Table 3: Relative percentage savings of CO_2 comparison for the UK depending on the PV and battery size

**, S, N and R stand for standard, normalising and recursive REDWoLF system respectively*



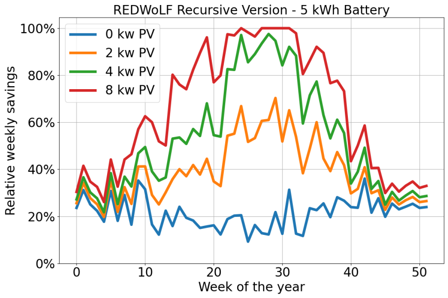
a) b)

Figure 8: Simulated weekly relative savings of CO_2 of the RED WoLF System in the UK (a) and France (b) compared to a house with electric heating on demand. The standard 4 kW PV array is compared with varying battery sizes.

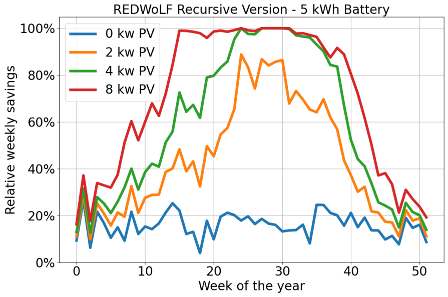
The same observation can be made comparing different PV array sizes. The weekly savings are shown in figure 9a for a 5 kWh battery. Again the relative savings fluctuate for each week primarily due to different CO_2 intensities and PV generation. One major difference is that varying the PV size also significantly changes the savings, much more compared to the battery size. This is also expected as Solar provides carbon free electricity, whereas the battery redistributes the Grid usage. Having a large PV array even results in 100 percent of savings in certain weeks in summer, making the dwelling independent from the Grid.

As gas and oil heating is still common in different regions throughout the EU, we eventually compare a RED WoLF-dwelling with different heating systems (equipped with 5kWh Battery and 4kW PV). The absolute CO_2 emission for each week is shown in figure 10. With 650 grams of CO_2 equivalents per kWh, heating with oil results in more than 10.1 tons of CO_2 over the year. Heating with gas is better than oil, but with 490 grams of CO_2 equivalents per kWh and about 7.9 tons of CO_2 yearly still extremely bad, considering 4 and 2.4 tons of yearly CO_2 emissions for electric heating and the RED WoLF system. Abstaining from oil and gas for heating purposes is necessary in order to meet the CO_2 reduction goals.

It has become clear, that the RED WoLF system is able to reduce the CO_2



(a) UK



(b) France

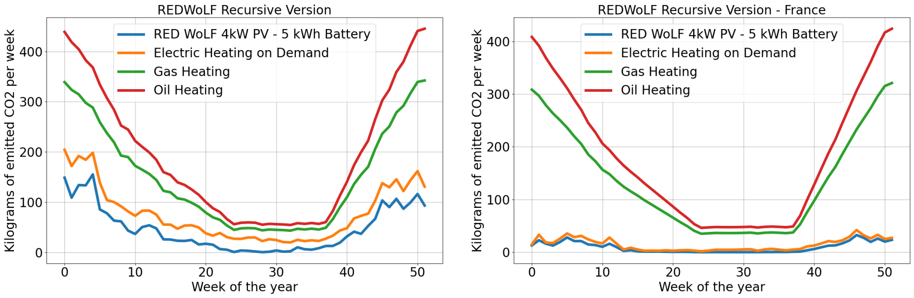
Figure 9: Simulated weekly relative savings of CO_2 of the REDWoLF System in the UK (a) and France (b) compared to a house with electric heating on demand. The standard 5 kW PV array is compared with varying battery sizes.

emissions for a dwelling in the UK drastically. The RED WoLF system with a 4 kW PV array and a 5 kWh battery saves from about 40 % (compared to direct heating) to 69 % (compared to gas heating) and even 76 % (compared to oil heating).

As circumstances differ for every country, we also test the RED WoLF system for a different country: France. The data sets for CO_2 intensity, heating and PV generation are taken from [43]. The uniqueness of France is the low CO_2 Grid intensities due to high use of nuclear energy. Table 4 provides the relative savings over a year for France. The results are similar to the UK, where the recursive RED WoLF algorithm performs best and Normalising is slightly better than the Standard version. The reference is again a house with electric heating on demand, but the CO_2 emissions for this dwelling in France are about 740 kilograms.

The relative weekly savings for different battery sizes for France are shown in figure 8b. These values are higher compared to the UK mainly due to higher PV production in France. The overall trend is the same.

Emissions with the RED WoLF systems are drastically lowered, as Figure 10 shows. Depending on the type of heating, the carbon footprint we leave varies



a) b)

Figure 10: Simulated weekly absolute CO_2 emissions for different heating systems in the UK (a) and France (b)

Battery	0 kWh Battery			2.5 kWh Battery			5 kWh Battery			7.5 kWh Battery			10 kWh Battery		
Version*	S	N	R	S	N	R	S	N	R	S	N	R	S	N	R
0 kW PV	11.5	10.8	13.3	12.1	11.5	14.1	12.8	12.1	14.9	13.4	12.5	15.5	13.9	12.7	16.0
2 kW PV	24.7	23.9	26.3	25.5	24.7	27.2	26.1	25.1	27.7	26.5	25.3	28.1	26.9	25.5	28.5
4 kW PV	32.6	31.9	34.3	34.2	33.4	35.9	35.1	34.2	36.8	35.6	34.5	37.3	35.9	34.7	37.6
8 kW PV	44.8	44.1	46.2	46.6	45.7	48.1	47.6	46.7	49.1	48.1	47.1	49.6	48.2	47.2	49.7

Table 4: Yearly relative percentage savings of CO_2 comparison for France depending on the PV and battery size
**, S, N and R stand for standard, normalising and recursive RED WoLF system respectively*

a lot. We can notice that using the RED WoLF, the carbon discharge is much lower compared to the traditional systems. Specifically, compared to the yearly emissions for direct heating on demand (740 kg CO_2), gas heating (7.1 tons CO_2) and oil heating (9.3 tons CO_2) the RED WoLF system (468 kg) with 4 kW PV and 5 kWh battery saves about 37 %, 93 % and 95 % respectively. It is clear that heating with fossil fuels is so much worse, as the CO_2 Grid intensity is low in France.

The simulations performed are based on measured data for PV generation, real electricity and real CO2 intensity thus although the results are estimates, they are close to the real life case. These assumptions are based on understanding of possible operational capabilities of the equipment. SHs are able to store up to 80% of heat withing 3 day period. However, this heat is not lost as it makes the dwelling warmer. The operation time frame of the system is 24 hours, that makes the SHs technology appropriate and not prone to large errors in the estimates. The same holds truth for the hot water cylinder. The water boiler insulation is sufficient to keep water hot within required time frame of the system operation. The heating requirements for both water and space heating during that period could outweigh the requirements in appliances consumption for up to 10 times. Furthermore, white noise was added to the consumption profiles, in order to guarantee that even in the wrong consumption prediction the system would operate. Thus, the results of numerical simulation, coincides with expectation of the system performance. Therefore, they could be used as a guidance for the system operation.

4. Conclusions

The ability to find the adequate threshold, which serves as an indicator to change the energy supplier and store heat, is the key feature of the RED WoLF algorithm. It is worth noticing that thermal demand is not to be satisfied with the battery output, due to conversion losses and relatively large amount of energy required for heating. However, during simulation phase there was found a limitation in original RED WoLF algorithm for cases with low power supply from the grid. Thus we introduced additional logic for such cases. Moreover on top of that two different techniques were developed in order to improve the performance of progressing threshold approach. The first one includes normalisation techniques which on average slightly outperforms by $\approx 1\%$ the original RED WoLF algorithm. The second techniques include recursive action, which leads to more significant savings of $\approx 5\%$.

The performed numerical simulation are promising with the system equipped with 5 kWh battery and 4 kW PV array the system could save 39.8% of CO_2 in the UK and 36.8% of CO_2 in France. Furthermore, the total energy consumption of the RED WoLF system produces by far less CO_2 than the one that would only be spent on space heating by gas and oil systems. That statement holds to be true even in the UK, where high penetration of fossil fuel plants is present. Furthermore, there is a difference that is hard not to notice in the UK case between systems equipped with the RED WoLF or not. In France there is even greater margin between electric heated houses and ones equipped with gas or oil. In terms of CO_2 the difference between the RED WoLF and conventional electric house is not that great in absolute values. That could be explained by high nuclear power plant penetration, which lowers the electrical grid CO_2 emissions. Thus for France the best recommendation is to adapt the progressive threshold approach to time of use tariff signal. More intriguingly, for some system configurations significant period of time corresponding to 100% CO_2 savings, making the system self sufficient both for France and the UK. Which shows the ultimate potential of such system configuration.

The fact that the cost of electrical energy usually follows the CO_2 intensity levels introduces an alternative motive for pursuing changes the RED WoLF offers. Namely, the benefit of the system is therefore not only the reduction of CO_2 emissions, but also the decrease of the heating cost, which accounts for more than 10% of the household income in certain regions [44]. Nevertheless, a more detailed study is needed to be done in order to estimate the potential of the system in cost reduction. As the number of renewable energy providers supplying the electrical grid increases, the system also stabilises the Grid. Overall, it can be said that the system has numerous advantages and is in many ways superior to traditional heating systems.

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