An optimisation algorithm for distributed energy resources management in micro-scale energy hubs

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Abstract

In this paper, a new algorithm for optimal management of distributed energy resources in facilities with distributed generation, energy storage systems and specific loads – energy hubs – is shown. This method consists of an iterative algorithm that manages optimal energy flows to obtain the minimum energy cost based on availability of each resource, prices and expected demand. A simulation tool has been developed to run the algorithm under different scenarios. Eight different scenarios of an energy hub have been simulated to illustrate the operation of this method. These scenarios consist of a demand curve under different conditions related to the existence or absence of renewable energy sources and energy storage systems and different electricity tariffs for grid supply. Partial results in the iterative process of the developed algorithm are shown and the results of these simulations are analysed. Results show a good level of optimisation of energy resources by means of optimal use of renewable energy sources and optimal management of energy storage systems. Moreover, the impact of this optimised management on carbon dioxide emissions is analysed.

Keywords: distributed energy resources, renewable energy sources, energy management system, energy resources management, energy hub operation.

Highlights:

An iterative optimisation algorithm for energy hub resources management is proposed.

A fast and simple method for resources allocation in smart facilities is tested.

A simulation tool has been developed to test strategies in energy hubs.

Savings greater than 50% in energy hubs with distributed resources are simulated.

The algorithm allows taking advantage of tariffs with hourly discrimination.

Nomenclature

Acronyms

DER	distributed energy resource
DEROP	distributed energy resources optimisation (name of the proposed algorithm)
DG	distributed generation
DSM	demand side management
ESS	energy storage system
LabDER	Laboratory of distributed energy resources
MILP	mixed integer linear programming
PV	photovoltaic
RES	renewable energy source
UPV	Universitat Politècnica de València

Superscripts

(i)	iteration in the DEROP algorithm. From (0) to (f)

Subscripts

j	time index in the simulation period. From 0 to $N-1$
k	energy resource index. From 1 to n

Parameters, variables, and functions

T	Duration of the simulation period
N	Number of intervals in which the simulation period is divided
n	Number of energy resources in the energy hub (generation and storage resources)
f	last iteration of DEROP algorithm
τ	simulation step size, length of each simulation interval
t_0	initial time in the simulation period

t_j instant in which the jth simulation interval ends ($j > 0$)

d_j total power demand at instant t_j

p_{jk} power provided by resource k at instant t_j

q_{jk} associated cost of resource k at instant t_j

Q_j total cost of generated power at instant t_j

S schedule consisting of a $N \times n$ binary matrix that indicates the state of each resource at each simulation interval

C_j total cost of supplied energy during the interval $\lfloor t_j, t_{j+1} \rfloor$

C total cost of energy during the simulated period

A_{jk} mean available power of resource k during the interval $\lfloor t_j, t_{j+1} \rfloor$

p_{in} effective power that batteries receive when they are charged

A available power used to charge batteries

η_c efficiency of the battery charging process

$W_{st(j)}$ total energy stored in batteries at instant t_j

p_{out} effective power that is extracted from batteries when they are discharged

p_{bat} net power that batteries lose when they are discharged

η_d efficiency of the battery discharging process

$W_{out[t_j, t_{j+1}]}$ energy received by loads from battery during interval $\lfloor t_j, t_{j+1} \rfloor$

1 Introduction

Energy consumption has been growing over recent decades. In order to minimise the dependence on fossil fuels, new energy resources are being integrated in energy systems [1], such as renewable energy sources (RESs) e.g. wind, solar, biomass and so on, and energy storage systems (ESSs). Also, new regulations have to be developed to support this integration [2]. Optimal management and control of the available resources is a key issue to be addressed and many research studies have been developed. Some of these works study optimal planning for new generation facilities [3]. In other works, optimal management is studied focusing on management of loads [4], i.e. demand side management (DSM). Some research studies are focused on DSM of individual facilities [5]. Conversely, in other studies, management of loads is studied at aggregator level, to optimise the global benefit [6]. Nevertheless, the optimisation problem may be studied from the perspective of energy generation facilities management [7], since modern facilities include more and more distributed energy resources (DERs) that must be managed to get the maximum benefit from them, i.e. the lowest energy costs.

A facility with multiple energy sources that has energy production, conversion and storage technologies (RESs, batteries, ice storage, hydrogen cells and so on) to supply electricity (and other services such as heating or cooling) is widely called an energy hub [8]. From the perspective of end users in energy hubs, optimal management of their available resources consists of controlling all energy flows in their facilities (between power grid, distributed generation resources, ESSs and loads) to minimise the total energy costs. Therefore, these facilities require reliable energy management systems (EMS) with real-time data acquisition and processing from energy resources and external variables (e.g. temperature, wind speed or energy purchase prices) and sophisticated algorithms to achieve an optimal management of the available resources along the time.

Over the past years, various algorithms to find an optimal solution of energy operation in energy hubs have been proposed. For example, [9] shows a multi-objective optimisation method applied to manage several generators in a microgrid. So, some algorithms have been developed to optimise overall costs by managing ESSs to purchase energy for microgrids with several available sources [10]. Many studies indicate that the impact of RESs is greater when ESSs are installed, as the unpredictability of these resources has a lower impact on the optimal solution [11]. In fact, ESSs are key elements to reduce energy costs in facilities by reducing peak load or to help successfully incorporate distributed generation (DG) as shown in [12].

However, despite the interest of researchers in finding an optimal solution to systems operation, most of the developed optimisation methods are focused on DSM as in [13], by developing demand response programs and efficient management of loads. Others are focused on optimal planning for smart grids, in which some aspects might be relevant, such as topology, energy transmission, reliability of supply, and so on. For example, [14] shows an algorithm to optimise the capacity of batteries to be installed and diesel generators in an energy hub. [15] shows an optimisation algorithm to compute the economic dispatch in a grid with several energy hubs. [16] describes an algorithm to achieve optimal management of energy resources and loads along a day. However, only linear functions are used in this algorithm.

In this paper, a new algorithm to achieve an optimal management of the available energy resources in energy hubs is proposed. The main target of the new DERs optimisation algorithm (DEROP) is to minimise energy costs by maximising RESs generation and optimising the management of ESSs. Some advantages of DEROP are that it allows considerable energy cost reductions, with a simple procedure and a fast computation algorithm. DEROP is flexible to be used under a wide range of situations with many different DERs and with different purposes, including non-linear functions for costs and efficiency of each resource. So, DEROP is easy to be implemented as an online service for end users.

This paper is organised as follows. Section 2 describes DEROP algorithm, which has been developed to achieve an optimal control of the available resources in energy hubs. All aspects related to DEROP algorithm and its features are shown in this section. Section 3 defines the scenarios to be simulated in order to show the performance of DEROP algorithm and the simulation tool. Section 4 shows the results of multiple simulations carried out with DEROP algorithm and the developed tool. These results are compared, analysed and discussed in this section. Finally, some conclusions to this work are drawn in section 5.

2 Methodology

As aforementioned, most algorithms to optimise management of energy resources are focused on DSM. Others are focused on DG resources management, but they assume linearity in costs and efficiencies. Due to this reason, this paper shows DEROP algorithm, which optimises DG and ESSs management allowing non-linear functions. Figure 1 shows the concept of an energy hub where DEROP algorithm would enable energy cost minimisation to meet a fixed demand curve.

DEROP algorithm calculates the cost of the total consumption from grid supply under a set of conditions and it iterates with some modifications in the energy supply schedule attempting to reduce this cost until reaching an optimal situation where no improvement is possible. Each generation resource has a different cost depending on the raw material and time. The aim of this algorithm is to optimise the operation of energy resources in an existing facility. As the main goal is not to plan the installation of generation or storage systems, in this experiment, only energy costs are taken into account. Therefore, for PV panels and wind generator, only costs for maintenance operations are considered since these resources do not need any raw material. This guarantees that the algorithm will maximise the use of these sources. As regards ESSs, a variable cost may be associated with these systems, depending on the charging and discharging profiles.

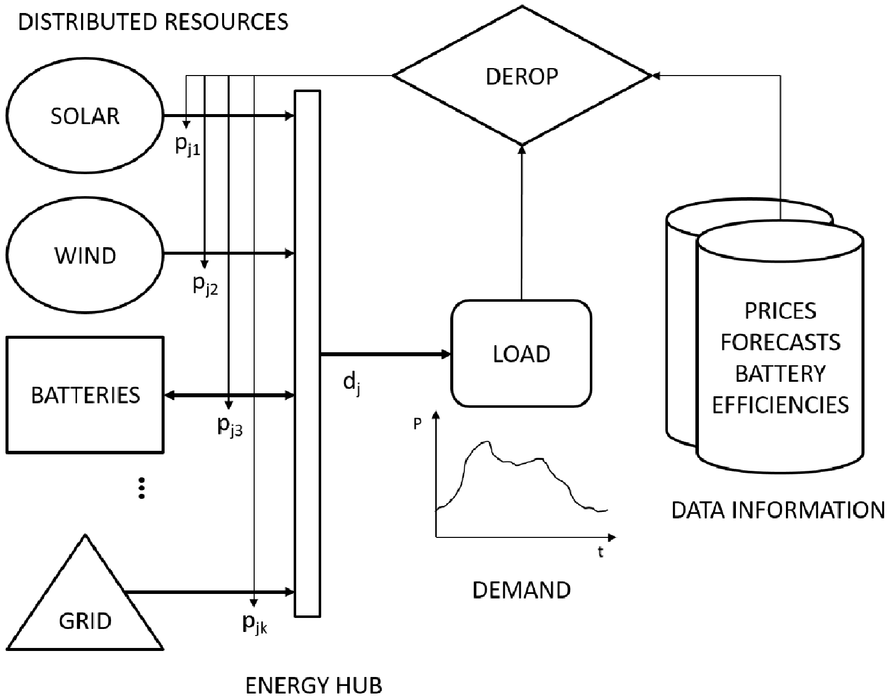

Figure 1. Energy hub concept to implement DEROP algorithm in order to optimise DERs.

For a simulation of length T, a simulation step size τ is chosen and a set of N identical intervals are taken of a length

$$\tau = \frac{T}{N} \tag{1}$$

The resulting intervals are $\{[t_j, t_{j+1}], j \in [0, N-1] : t_{j+1} = t_j + \tau\}$. At each instant t_j, the total power demand d_j is satisfied as

$$d_j = \sum_{k=1}^{n} p_{jk} \tag{2}$$

p_{jk} being the total power provided by resource k in a set of n available resources.

At each interval $\lfloor t_j, t_{j+1} \rfloor$, each resource k has an associated cost q_{jk}. Therefore, total cost of generated power in iteration i for that interval $\lfloor t_j, t_{j+1} \rfloor$ will be

$$Q_j^{(i)} = \sum_{k=1}^{n} p_{jk}^{(i)} \cdot q_{jk} \tag{3}$$

Under certain simplifications, expression (3) could be linearised and a mixed integer linear programming (MILP) method would provide an accurate solution, as proposed in other studies [17]. MILP algorithms have been used at microgrid level [18] and at district-scale level [19] by other researchers. However, due to the low value of n in real cases, the authors use an iterative algorithm that provides an optimal solution with little computational effort, allowing non-linear functions for costs or efficiencies.

To clarify this, when battery is being charged, the effective power that it receives (p_{in}) is not 100% of the available power (A):

$$p_{in} = \eta_c \cdot A \tag{4}$$

This has a direct impact on the energy stored in battery at the end of interval $\lfloor t_j, t_{j+1} \rfloor$, $W_{st(j+1)}$, that will be:

$$W_{st(j+1)} = W_{st(j)} + \int_{t_j}^{t_{j+1}} p_{in} \cdot dt \tag{5}$$

Similarly, when battery is being discharged, the effective power extracted from it (p_{out}) is not 100% of the power that it gives (p_{bat}):

$$p_{out} = \eta_d \cdot p_{bat} \tag{6}$$

In this case, the amount of energy received by loads from battery during interval $\lfloor t_j, t_{j+1} \rfloor$, $W_{out[t_j, t_{j+1}]}$, will be:

$$W_{out[t_j, t_{j+1}]} = \int_{t_j}^{t_{j+1}} p_{out} \cdot dt \tag{7}$$

And the energy stored in battery at the end of interval $\lfloor t_j, t_{j+1} \rfloor$, $W_{st(j+1)}$, will be:

$$W_{st(j+1)} = W_{st(j)} - \int_{t_j}^{t_{j+1}} \frac{p_{out}}{\eta_d} \cdot dt \tag{8}$$

In expressions (4), (6) and (8), real efficiencies would not be constant:

$$\eta_c = \eta_c(A) \tag{9}$$

$$\eta_d = \eta_d(p_{out}) \tag{10}$$

To calculate the optimal schedule through an iterative procedure, in each iteration i, a proposed schedule $S^{(i)}$ is simulated, and its energy cost $C^{(i)}$ is calculated as explained below. The simulated schedule consists of a $N \times n$ binary matrix that indicates the state of each resource at each simulation interval. That is, each schedule has for each interval $\left[t_j^{(i)}, t_{j+1}^{(i)}\right]$, $j \in [0, N-1]$ a state (ON/OFF) associated with each element of the simulated facility. These states, along with the operating rules programmed into the software, determine energy flows. With the prices of each resource at these intervals, cost $C_j^{(i)}$ is computed (11).

$$C_j^{(i)} = \int_{t_j}^{t_{j+1}} Q_j^{(i)} \cdot dt \approx \sum_{k=1}^{n} p_{jk}^{(i)} \cdot q_{jk} \cdot \tau \tag{11}$$

Note that these prices are not necessarily linear functions.

Throughout the entire simulation period the total energy cost $C^{(i)}$, is obtained as

$$C^{(i)} = \int_0^T Q_j^{(i)} \cdot dt \approx \sum_{j=0}^{N-1} \left(\sum_{k=1}^{n} p_{jk}^{(i)} \cdot q_{jk} \cdot \tau \right) = \sum_{j=0}^{N-1} C_j^{(i)} \tag{12}$$

Assuming the step size τ is constant (intervals may occasionally have different durations), the problem is formulated as follows:

$$\text{minimise } \sum_{j=0}^{N-1} C_j\left(p_{j1}, p_{j2}, \ldots, p_{jn}\right) \tag{13}$$

$$\text{subject to } p_{jk} \le A_{jk},\ \forall k \in [1, n],\ \forall j \in [0, N-1] \tag{14}$$

and the constraint addressed in (2), A_{jk} being the available power of resource k during interval $\left[t_j, t_{j+1}\right]$.

DEROP algorithm begins with the steps in which the greatest potential savings may be obtained and it analyses possible alternatives, only accepting those that reduce $C^{(i)}$. Therefore, with DEROP algorithm, starting from an initial schedule $S^{(0)}$, in which all energy is provided by power grid, this schedule is modified step by step, resulting in new schedules $S^{(i)}$, with the purpose of gradually reducing initial cost $C^{(0)}$ up to a situation where schedule $S^{(f)}$ has the minimum possible associated cost $C^{(f)}$ where f is the last iteration of the algorithm. DEROP consists of two separated stages. At the beginning of the iterative process, the algorithm attempts to exploit all RESs charging batteries with surplus generation (surplus selling is considered because it is not covered by current Spanish regulation related to self-consumption [20] and electricity sector laws [21]). In this stage, the algorithm optimises the usage of RESs by managing ESSs. During the second stage, in each iteration i, power supplied by grid is decreased during the most expensive available interval $\left[t_j^{(i)}, t_{j+1}^{(i)}\right]$ and battery power is supplied during that time period. If battery requires more charge to meet demand at some point, it is charged in the cheapest available interval $\left[t_b^{(i)}, t_{b+1}^{(i)}\right]$ with $b < j$. When demand is successfully supplied, a new schedule proposal $S^{(i+1)}$ is reached. If $C^{(i+1)} < C^{(i)}$, then $S^{(i+1)}$ is accepted. Otherwise, the grid power reduction attempted in $t_j^{(i)}$ does not produce any benefit, so the algorithm goes back to the previous state (schedule $S^{(i)}$) undoing the last changes and interval $\left[t_j^{(i)}, t_{j+1}^{(i)}\right]$ is cancelled (marked as not available) for next iteration. DEROP algorithm ends when in iteration $i = f + 1$ there are no available times to reduce power that enable a new state with a schedule $S^{(f+1)}$ such that $C^{(f+1)} < C^{(f)}$, leaving schedule $S^{(f)}$ as the optimal one, with associated cost $C^{(f)}$ being the minimum possible cost for that scenario. The diagram of DEROP algorithm is shown in figure 2.

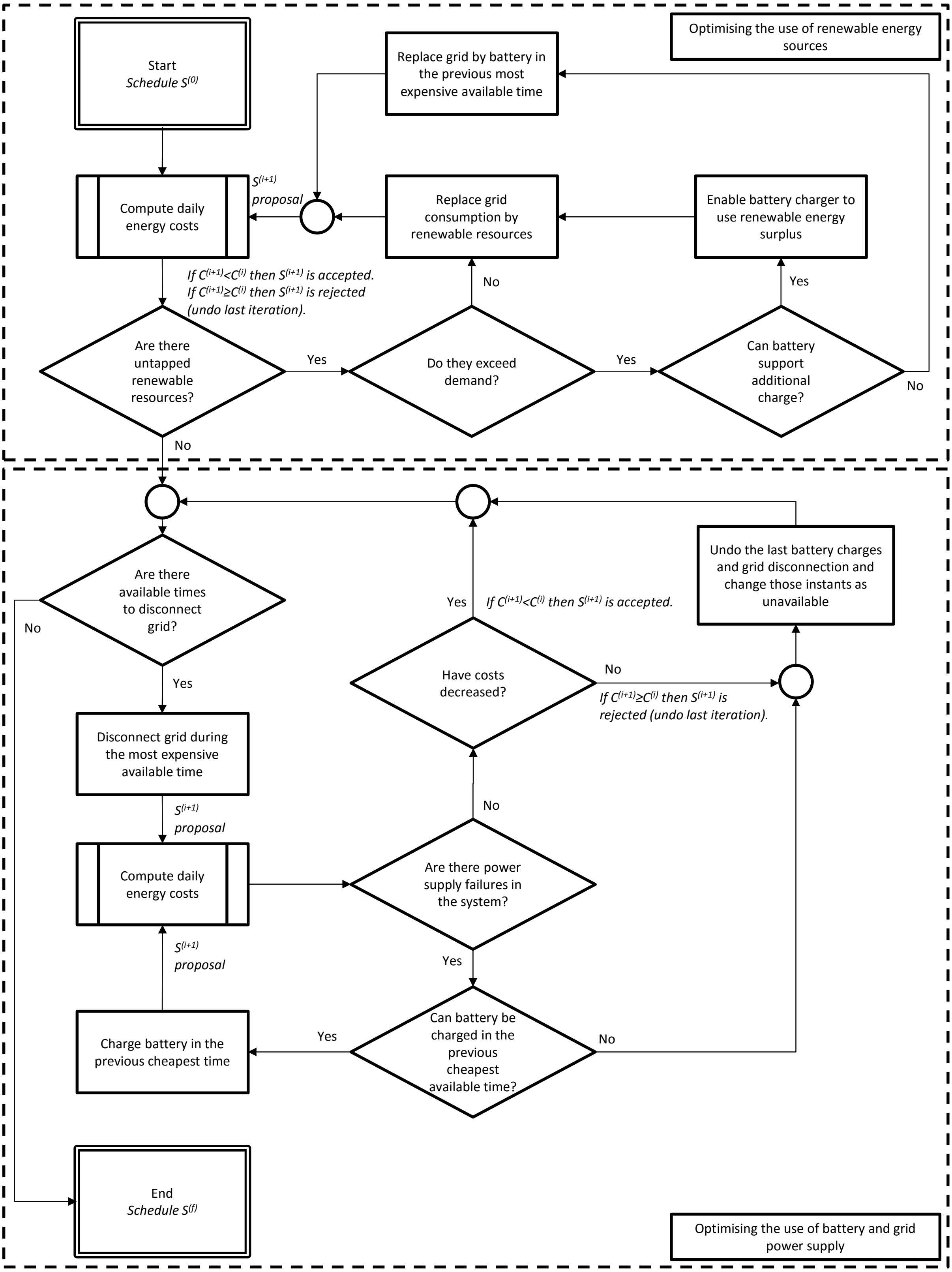

Figure 2. DEROP algorithm diagram.

2.1 Implementation features

The algorithm has been tested in the Laboratory of DERs (LabDER) at Universitat Politècnica de València. LabDER is a laboratory with various DERs (solar, wind power, a generator that works with fuel or biogas, batteries and grid supply) and some loads such as heaters or other consumption of the laboratory (e.g. lighting) [22]. The EMS of this energy hub was developed to design experiments related to management of available resources in order to establish the basis of a control strategy that optimises energy costs, among other purposes.

In order to facilitate the task of proposing and simulating this algorithm, the authors have developed a tool to simulate energy flows, costs and emissions in a facility with several DG resources, ESSs and power grid connection. This tool is based on MS Excel Worksheets to show graphical results and handle all the data, VBA code to execute DEROP algorithm and SQL Databases connections to read real data from an energy hub control system. This program calculates the use of each DER and its cost in each simulation step. Using this simulation tool, several real buildings with some RESs, an ESS and grid supply have been simulated under different situations and some of these simulations carried out in LabDER are presented in this paper to test and show the performance of DEROP algorithm. The simulations selected for this work show that, if the forecasts of all resources and demand are accurate, energy costs are significantly reduced.

Electricity prices are obtained from the System Operator's website [23] every day. All the data related to costs, planning of demand needs for the selected facility during the simulated period (e.g. a quarter-hourly energy curve for a whole day) and the expected availability of each energy source (solar, wind, grid, generator, initial state of ESSs) are the inputs to the developed simulation software. This software uses a set of rules of installed equipment operation (panels, wind generator, inverter, charger, generator, and grid) through which it computes actual energy flows and overall costs associated with energy supply and executes DEROP to optimise these costs.

To calculate CO_2 emissions associated with the proposed schedule, mean values in kg/kWh have been taken from [23] in peak, shoulder and valley periods.

To reach this algorithm certain assumptions that reduce the complexity of the problem and do not affect the optimality of DEROP algorithm have been taken. These assumptions are explained below.

a) First, only operating costs of the facility are considered, so only the purchase price of energy for every moment of the day and DERs costs are used when computing the total costs. Thus, other concepts of electricity bills, such as the cost associated with the contracted power or rental of measuring equipment are not covered, although they are taken into account when analysing the results to draw some conclusions.

b) Secondly, all the simulations have been carried out with real data (solar power and wind power generation curves in LabDER, real consumption curve shapes of a building simulated with the controllable loads in LabDER, real hourly purchase prices of energy from [23]). When this methodology is implemented for an energy hub's management, forecasts might be inaccurate. However, the aim of this study is to achieve a methodology to control available resources optimally, which will be effectively achieved only if good forecasts are available. Some methodologies to improve forecasts have been developed in other studies [24]. Running DEROP algorithm in continuous mode, every new measured value, both in consumption and generation systems, may be used to improve forecasts during the next time intervals, thus achieving highly accurate results. Similarly, running DEROP every step, energy will be optimally managed for the next hours, no matter how inaccurate the forecasts have been in the previous hours.

c) The simulation tool has been designed to include several operation profiles for batteries, such as performance reduction due to losses or speed of cycles (i.e. when a battery is discharged too quickly it has lower efficiency). As previously stated, every resource (including battery) has been assigned a cost. In the simulations carried out to test the algorithm with real data, moderate costs have been assumed for ESSs assuming reasonable operation speed cycles. However, for RESs, only maintenance costs are taken into account, since the purpose of this research was to propose an algorithm for optimal management of an existing hub with specific RESs already installed.

d) To charge battery, three different speeds have been considered depending on the level of storage. If stored energy is less than 38% of the effective capacity, a charging rate of 20% of this capacity per hour has been assumed. When the charge level is between 38% and 77% of the effective capacity, the assumed charging rate is 13% per hour. Finally, when the charge level exceeds 77%, a charging rate of 3.7% per hour has been assumed. This charging profile has been proposed by means of real experiments data (although it can be controlled in LabDER). Under these conditions, it takes up to 10 hours to complete a full charge.

e) Related to emissions, three different values have been assumed depending on the time-of-use that defines peak, shoulder and valley. During peak period a value of 0.26 tons of CO_2 per MWh is assumed. During shoulder period, the assumed value is 0.25 tons of CO_2 per MWh. In valley period, the considered value is 0.22 tons of CO_2 per MWh. For the fuel generator, a value of 1 ton of CO_2 per MWh is estimated, although at first, this energy source is not used in these simulations due to the fact that it is much more expensive than the others. This source is reserved for situations where the price of energy is particularly high and for electric power supply problems. For RESs (PV panels and wind generator), no emissions are considered.

The developed tool is prepared to allow more generation resources (like the biomass generator or the hydrogen cell that are not being used at the moment) and more loads in parallel. When a new resource is defined, emissions and costs must be introduced for every simulation interval (they are null by default). Also, new rules and conditions may be added easily. These new features are expected to improve the results of the optimisation process [25].

3 Scenarios definition

To show the performance of DEROP algorithm, 8 scenarios have been defined and simulated. These scenarios correspond to a real curve shape of an academic building at UPV for a full day, simulated with the manageable loads in LabDER under different conditions, such as the availability or absence of RESs, ESSs (battery) and two different electric tariffs: a tariff with no time restrictions and a tariff with hourly discrimination. Table 1 shows the 8 scenarios. The optimal schedule of each scenario that provides the lowest energy cost has been obtained with the developed tool using DEROP algorithm.

Scenarios X1 (where X= A ,…, D) have a tariff with no time restrictions, whereas scenarios X2 have a tariff with hourly discrimination. A1 and A2 are base scenarios without RESs or ESSs, so its costs (reached in iteration $i = 0$) are used to be compared with other scenarios. Scenarios identified as B1 and B2 add the possibility of storing energy to the previous ones. These scenarios are intended to illustrate the second phase of the algorithm for the two types of tariff analysed in this study. This phase aims to optimise ESSs usage to minimise total costs of energy, which is a very important task in this kind of systems [10]. On the other hand, scenarios C1 and C2 add the existence of RESs to scenarios A1 and A2. Their simulation allows the analysis of the contribution of RESs to this facility, with no possibility of storing energy. Finally, scenarios D1 and D2 are complete scenarios, with all the resources, which illustrate the whole process of DEROP algorithm and allow the comparison of optimal costs and emissions with other scenarios.

Scenario name	Tariff with hourly discrimination	RESs	ESS
A1	No	No	No
B1	No	No	Yes
C1	No	Yes	No
D1	No	Yes	Yes
A2	Yes	No	No
B2	Yes	No	Yes
C2	Yes	Yes	No
D2	Yes	Yes	Yes

Table 1. Features of the simulated scenarios.

4 Scenarios simulation

The described scenarios have been simulated using the developed tool. As an example, the simulation of scenario D1 is detailed in this section. To perform this simulation the selected step size is 15 minutes.

In this scenario, there are RESs and an ESS (batteries). This scenario has an electricity tariff with no time restrictions.

At the beginning of the simulation, in iteration $i = 0$, the initial schedule $S^{(0)}$ consists of using grid supply for the entire simulation period (one day). Energy cost in this iteration is € 9.18, with a total demand of 71.87 kWh. The associated emissions are 17.9 kg of CO_2.

In iteration $i = 1$ the available RESs are used and the surplus generation is used to charge batteries. The result of this step is shown in Figure 3. The total cost of supplied energy in this case is € 5.96 and the total emissions are 11.7 kg of CO_2.

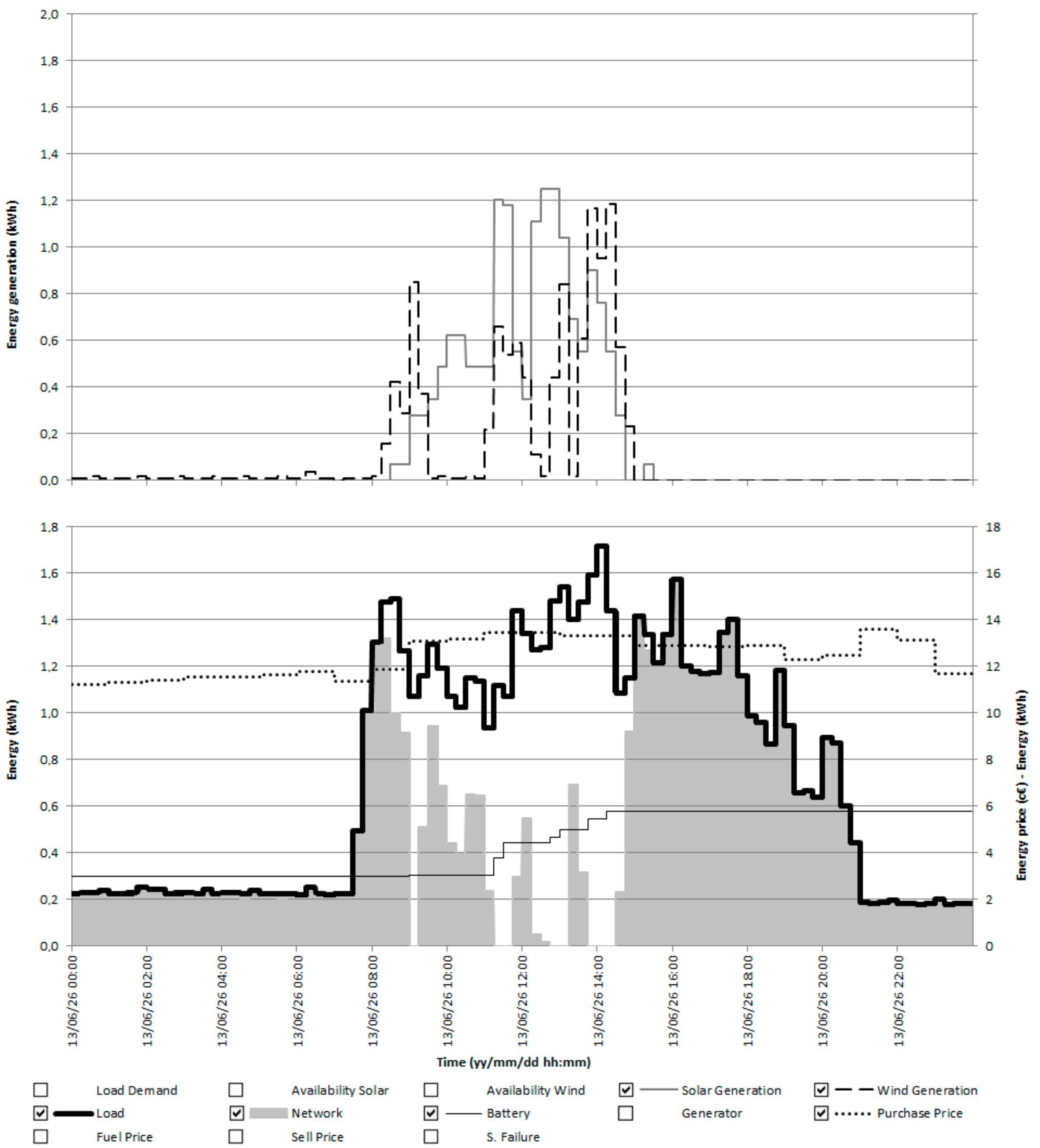

Figure 3. Results in iteration $i=1$ in scenario D1.

To complete the second iteration DEROP algorithm looks for interval the $\lfloor t_j, t_{j+1} \rfloor$ with the highest purchase price (which takes place during the interval 21:00-21:15) and grid supply is disconnected during that time interval. As a result of this iteration the energy cost has decreased until € 5.94 and total emissions are 11.6 kg of CO_2. In the next iterations new grid disconnections are scheduled in expensive intervals, until a moment when battery is not able to meet demand. In iteration $i=18$, if a new fraction of grid supply is disconnected (during the interval 10:45-11:00) battery cannot meet demand during the interval 21:15-21:30 and supply failures take place at that time. At this point, the total cost of energy has been reduced to € 5.22 and total emissions have decreased up to 10.3 kg of CO_2. Therefore, to complete iteration $i = 19$ a fraction of grid supply is disconnected during 10:45-11:00 and battery is charged during the cheapest interval (during 00:00-00:15). The result of this iteration is a total cost of € 5.21 and overall emissions of 10.2 kg of CO_2.

Continuing with this procedure the optimal situation is reached in the iteration $i = 35$ when there is no available time interval to disconnect grid supply and meet demand with batteries obtaining an economic benefit. The total cost is € 5.08 and the total emissions are 10 kg of CO_2. This situation is shown in Figure 4 and results are summarised in Table 2.

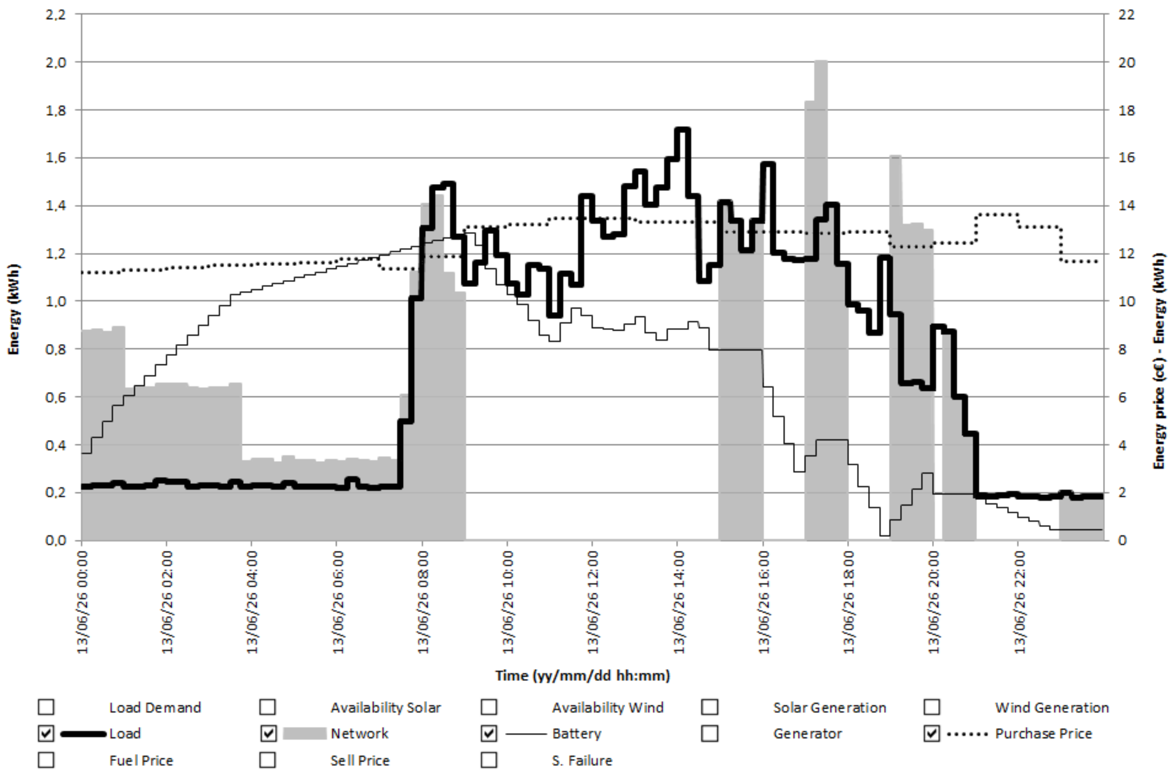

Figure 4. Simulation results in the final iteration ($i = 35$) in scenario D1.

Figure 5 shows the evolution of overall energy costs throughout the entire simulation.

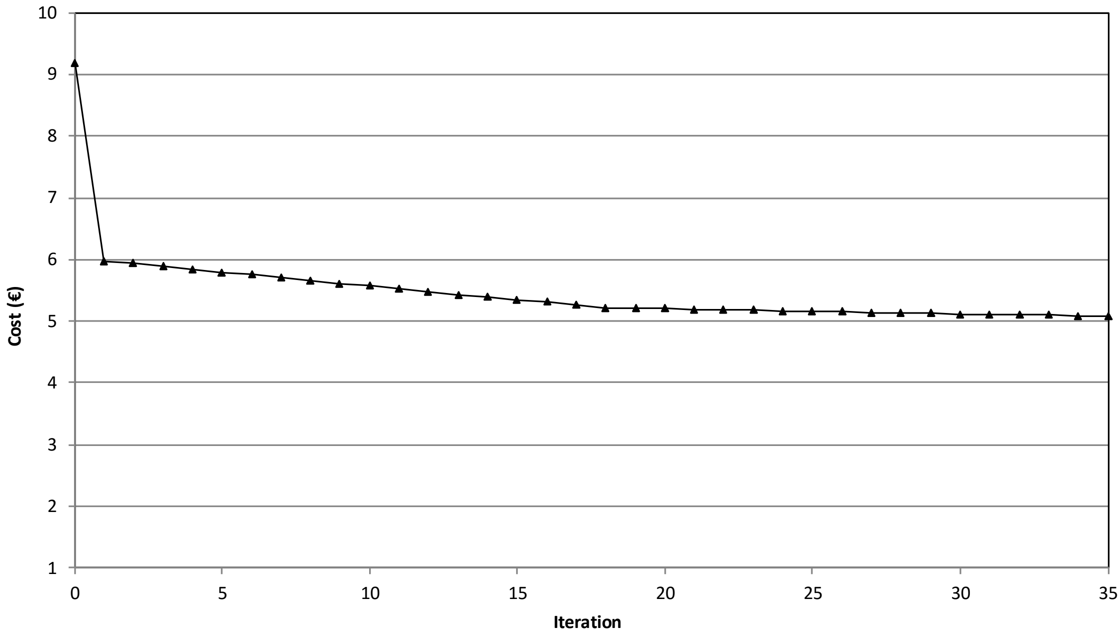

Figure 5. Evolution of costs in scenario D1.

Cost (€)	5.08
Emissions (kg CO_2)	10.03
Solar generation (kWh)	15.97
Wind generation (kWh)	11.11
Demand (kWh)	71.87
Power grid supply (kWh)	42.22

Table 2. Final simulation results in scenario D1.

So, as a result of the optimal management using DEROP algorithm, a significant economic saving is obtained in scenario D1, compared to results of scenario A1. In addition, there has been a great saving of CO_2 emissions. Results of all scenarios are compared below in order to analyse the performance of DEROP algorithm in different situations.

4.1 Scenarios results and discussion

Table 3 shows the results of all simulated scenarios. The greatest savings are achieved in D1 and D2, as it was expected. In D2 (Figure 6), savings up to 54.40% of the total energy costs are obtained in comparison with the energy supply from grid (scenario A2). As for emissions, the reduction obtained in C1 compared to A1 is 34.86%, due to the impact of RESs. When battery is used, a reduction of 44.06% is achieved (scenario D1).

The simulated building has a consumption profile in which the tariff with hourly discrimination is not profitable, due to the low night-time consumption. This is because the total energy cost in scenario

A1 is lower than the cost in A2. However, optimal management of resources through DEROP makes the tariff with hourly discrimination more profitable than the tariff with no time restrictions. This may be observed by comparing scenario D2 to A2 (which achieves savings of 54.40%) and D1 to A1 (which achieves savings of 44.66%).

It must be noted that scenarios that have all the resources (D1 and D2) provide greater savings than the sum of the savings obtained with each resource separately. That is, based on scenario A2, the batteries produce a saving of 14.05% (scenario B2) and the RESs produce a saving of 37.69% (scenario C2). However, scenario D2 achieves savings of 54.40%, which are higher than the sum of both savings. This is possible because batteries allow the storage of surplus generation and through an optimal management, a synergy between both resources takes place.

Scenario	A1	B1	C1	D1	A2	B2	C2	D2
Cost (€)	9.18	8.65	5.96	5.08	10.11	8.69	6.30	4.61
Emissions (kg CO_2)	17.93	16.93	11.68	10.03	17.93	16.85	11.68	9.95
Solar generation (kWh)	0.00	0.00	15.97	15.97	0.00	0.00	15.97	15.97
Wind generation (kWh)	0.00	0.00	11.11	11.11	0.00	0.00	11.11	11.11
Demand (kWh)	71.87	71.87	71.87	71.87	71.87	71.87	71.87	71.87
Power grid supply (kWh)	71.87	69.48	47.56	42.22	71.87	69.19	47.56	41.81
Number of iterations (N)	0	23	1	35	0	15	1	32

Table 3. Simulation results comparison between all scenarios.

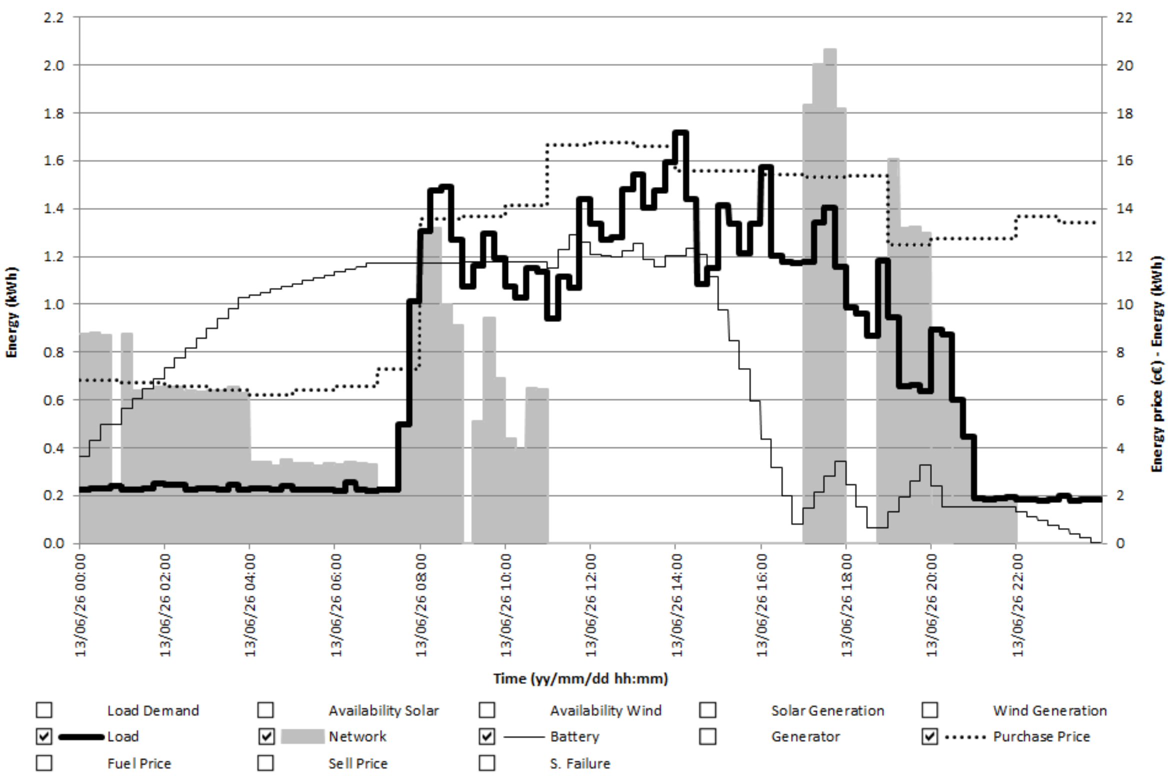

Figure 6. Simulation results in scenario D2 (tariff with hourly discrimination).

An additional algorithm called Basic Management 1 (BM1) has been used to compare the results with DEROP. The basis of BM1 is to charge ESS during the cheapest hours and disconnect the grid during the most expensive hours. Table 4 shows the results of both methods for scenario D2 compared to A2. DEROP achieves economic savings up to 18% higher than BM1. In addition, CO_2 savings are up to 14% higher with DEROP and energy savings from the grid are up to 10% higher.

Scenario	A2 (base)	D2 (BM1)	D2 (DEROP)
Cost (€)	10.11	6.41	4.61
Cost savings (%)	-	36.60	54.40
Emissions (kg CO_2)	17.93	12.52	9.95
Saved emissions (%)	-	30.17	44.51
Solar generation (kWh)	0	15.97	15.97
Wind generation (kWh)	0	11.11	11.11
Demand (kWh)	71.87	71.87	71.87
Power grid supply (kWh)	71.87	48.73	41.81
Grid supply savings (%)	-	32.20	41.83

Table 4. Comparison of results obtained with DEROP and BM1.

Regarding the number of iterations, scenario D1 has required 35 iterations to reach the optimum, while D2 has required 32 iterations. These differences are significantly increased with smaller simulation step sizes (the step used in this study is 15 minutes). This indicates that DEROP optimises faster with the tariff with hourly discrimination than with the tariff with no time restrictions. In any case, the algorithm is fast, since the simulations shown in this study take about 1 second in Matlab (in VBA they take a few seconds).

Logically, the results depend on the demand profile and the installed resources. However, it may be concluded that DEROP can manage resources in an energy hub and achieve significant savings. In addition, the described methodology allows to evaluate the economic and environmental impact of RESs. With the methodology shown in this study, different scenarios of an energy hub may be compared with different tariffs or resources. In addition, the algorithm is flexible because it allows you to introduce as many RESs as needed and use their cost and efficiency curves in the calculation.

5 Conclusions

In this paper, a new algorithm for optimal management of DERs (DEROP) is shown. The goal of DEROP is to minimise the cost of energy supply in energy hubs.

DEROP uses prices, efficiencies, generation forecasts of each resource and the expected demand as inputs. Through an iterative procedure, DEROP calculates optimal energy flows to obtain the minimum cost. The algorithm is fast, simple and easy to implement. In addition, it is flexible, since it allows the use of non-linear functions for costs and efficiencies during the calculation.

In addition, a tool has been developed to simulate DEROP in different types of facilities. As a case study, 8 scenarios of an energy hub under different conditions have been simulated. As a result of the simulations, it is concluded that significant cost savings (over 50%) may be achieved with the application of DEROP. In addition, the synergy between RESs and ESSs has been proven. Also, it has been observed that in situations where, a priori, the tariff with hourly discrimination is not profitable (for example, low night-time consumption) DEROP achieves higher savings than with the tariff with no time restrictions.

Finally, DEROP may be used for other purposes such as minimising CO_2 emissions, optimising contracted power, scheduling maintenance tasks, defining the size of RESs, and so on.

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