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Multi-vector energy management system including scheduling electrolyser, electric vehicle charging station and other assets in a real scenario

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ABSTRACT

Today, in the field of energy, the main goal is to reduce emissions with the aim of maintaining a clean environment. To reduce energy consumption from fossil fuels, new tools for micro-grids have been proposed. In the context of multi-vector energy management systems, the present work proposes an optimal scheduler based on genetic algorithms to manage flexible assets in the energy system, such as energy storage and manageable demand. This tool is applied to a case study for a Spanish technology park (360 kW consumption peak) with photovoltaic and wind generation (735 kW generation peak), hydrogen production (15 kW), and electric and fuel cell charging stations. It provides an hourly day-ahead scheduling for the existing flexible assets: the electrolyser, the electric vehicle charging station, the hydrogen refuelling station, and the heating, ventilation, and air conditioning system in one building of the park.

A set of experiments is carried out over a period of 14 days, using real data and performing computations in real time, in order to test and validate the tool. The analysis of results show that the solution maximises the use of local renewable energy production (demand is shifted to those hours when there is a surplus of generation), which means a reduction in energy costs, whereas the computational cost allows the implementation of the tool in real time.

1. Introduction

In the modern world, the use of fossil fuels such as coal or gas gives rise to significant concern due to their environmental footprint, as they release greenhouse gases like CO_2 and other gases into the atmosphere and cause global warming (Association et al., 2022). The planet's climate emergency requires the effective and rapid decarbonisation of the ways the energy is produced and consumed. This energy transition involves several actors, as new policies and circular economy (Magazzino and Falcone, 2022) or reconversion of existing energy installations, such as refineries (Falcone et al., 2021). The energy sector, including transport, industry, and heating & cooling, is responsible for around 72% of the European Union's greenhouse gas emissions. As a consequence, renewable energy sources are being introduced into electrical energy systems to decrease dependence on conventional resources (Maris and Flouros, 2021).

Although renewable energy sources such as solar and wind energy do not emit greenhouse gases, this type of generation involves uncertainty due to the variable and intermittent nature of the primary energy sources, i.e., sunlight and wind. This inherent uncertainty and intermittence causes difficulties in terms of planning the daily operation of a local energy system (LES) or micro-grid (MG). The goal of this planning is to ensure that the maximum proportion of the energy consumed is generated locally. With increasing the use of local generation the energy that needs to be supplied by the utility is reduced. Energy supplied by utilities is not always generated using conventional primary energy sources. Moreover, the market prices for energy depend on when the energy is consumed, or the maximum amount of energy consumed. Planning for an MG also aims to minimise the operational cost in terms of energy costs. In order to tackle these challenges, there is a need to develop an optimal scheduler (OS) module inside a multi-vector energy management system (MVEMS) that can optimise the use of local renewable generation, increase the autonomy of the system, and reduce the overall energy costs, peak loads and CO_2 emissions, among other optimisation criteria.

Nowadays, the management of an energy system must consider different types of power systems, such as managing heating, ventilation and air conditioning (HVAC), electricity-to-hydrogen conversion, solar thermal and geothermal systems. Moreover, new technologies such as electrical, thermal and hydrogen storage, electric and fuel cell electric vehicles (EVs, FCEVs) have arisen, as has the problem of flexible demand. These assets have to be managed together, and decisions must be made on when to consume or store energy, or when to charge an

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Table 1
State-of-the-art schemes for multi-vector energy management systems.

Year	Author	Name	Controllable assets	Non-controllable loads	Non-controllable generation	Real data	Solver	Ref
2014	Mousa Marzband	Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for micro-grids in islanded mode	EES, MT, RLD	NRL	PV	No	Gravitational search algorithm	Marzband et al. (2014)
2014	Mehdi Motevasel	Expert energy management of a micro-grid considering wind energy uncertainty	EES, MT, FC		WT, PV	No	Bacterial foraging optimisation	Motevasel and Seifi (2014)
2014	E.E. Sfikas	Simultaneous capacity optimisation of distributed generation and storage in medium voltage micro-grids	EES, BM	NRL	WT, PV	Weather	Non-linear programming	Sfikas et al. (2015)
2015	Christos-Spyridon Karavas	A multi-agent decentralised energy management system based on distributed intelligence for the design and control of autonomous poly-generation micro-grids	EES, FC, HT, PWT, ROD	NRL, PEM	WT, PV	No	Multi agent system	Karavas et al. (2015)
2015	G.R. Aghajani	Presenting a multi-objective generation scheduling model for pricing demand response rate in micro-grid energy management	EES, FC, MT	NRL	WT, PV	No	Multi-objective particle swarm optimisation	Aghajani et al. (2015)
2015	Walied Alharbi	Probabilistic coordination of micro-grid energy resources operation considering uncertainties	EES, CG		WT, PV	No	Multi-scenario mixed integer linear programming	Alharbi and Raahemifar (2015)
2015	Saber Talari	Stochastic-based scheduling of the micro-grid operation including wind turbines, photovoltaic cells, energy storages and responsive loads	EES, FC, MT	NRL	WT, PV	No	Linear programming	Talari et al. (2015)
2018	Chee Lim Nge	A real-time energy management system for smart grid integrated photovoltaic generation with battery storage	EES		PV	No	Lagrange multipliers	Nge et al. (2019)
2019	Makbul A.M. Ramli	Efficient Energy Management in a Micro-grid with Intermittent Renewable Energy and Storage Sources	EES, CHP	NRL	WT, PV	No	Most valuable player algorithm	Ramli et al. (2019)
2020	Sizhou Sun	Multi-Objective Optimal Dispatching for a Grid-Connected Micro-Grid Considering Wind Power Forecasting Probability	EES, MT, FC		WT, PV	No	Improved multi-objective bat algorithm	Sun et al. (2020)

EV or produce cold. As a result, there is a need for an MVEMS, and more specifically an OS, that can optimise the operation of the MG as a whole.

In previous years, several OSs for MVEMSs have been proposed in the literature. Some of these works deal with MGs with a reduced numbers of dimensions and features, for example the scheme in Zhao et al. (2015) in which a photo-voltaic (PV) plant and a thermal system in a small building were optimally scheduled. In Jung et al. (2020), a residential building with PV and electric energy storage (EES) were managed using an OS. An OS was also applied to a battery bank in a system consisting of a PV, wind turbine (WT), diesel generator and one small building (Forough and Roshandel, 2017). At house level, a system with several assets (photovoltaic generation, micro fuel cell, solar thermal collectors, electrical and thermal storage) is controlled in Muthalagappan (2021).

As a summary of state-of-the-art MVEMSs for MGs for MGs with considerable dimensions, Table 1 shows which assets are controlled by the energy management system (flexible), demand and generation, non-controllable consumption assets (non-flexible demand), and non-dispatchable generation installations. The table also includes information on the use of real data and the nature of the tests done in real installations. Finally, it contains information on the solver (that is, the algorithm) employed to calculate an optimal scheduling plan for the controllable assets.

From a review of the controllable assets considered in the literature, all of the works in Table 1 include control of the EES (Marzband et al., 2014; Motevasel and Seifi, 2014; Sfikas et al., 2015; Karavas et al., 2015; Aghajani et al., 2015; Alharbi and Raahemifar, 2015; Talari et al., 2015; Nge et al., 2019; Ramli et al., 2019; Sun et al., 2020), whereas others forms of control, such as micro turbine (MT) (Marzband et al., 2014; Motevasel and Seifi, 2014; Aghajani et al., 2015; Talari et al., 2015; Sun et al., 2020) or responsive loads (RLDs) (Marzband et al., 2014), are used in only some of them. In addition, hydrogen tanks (HTs) (Marzband et al., 2014; Karavas et al., 2015), potable water tanks (PWTs) (Karavas et al., 2015), reverse osmosis desalination (ROD) (Karavas et al., 2015) and combined heat and power (CHP) (Ramli et al., 2019) are controllable assets that appear in some of these works. In regard to the non-controllable loads, non-responsive loads (NRLs) (Marzband et al., 2014; Sfikas et al., 2015; Karavas et al., 2015; Aghajani et al., 2015; Talari et al., 2015; Ramli et al., 2019) are considered in 64% of the works, and the remainder do not contain any non-controllable loads. There is one work (Karavas et al., 2015) in which the non-controllable load is defined as a proton-exchange membrane fuel cell (PEM). Finally, concerning the non-controllable generation, it is seen that all the works contain a PV, a WT, or both.

From an implementation point of view, there is only one work (Sfikas et al., 2015) in which real weather data were used in order to create the models. The rest of the works do not include real data or a real implementation in the case of an MVEMS. In regard to the way that the optimisation problem is solved, a wide variety of solvers have been implemented. Solvers that use linear programming (Sfikas et al., 2015; Karavas et al., 2015), Lagrange multipliers (LM) (Nge et al., 2019), nonlinear programming (Sfikas et al., 2015) and multi-agent systems (Karavas et al., 2015) have been applied, while the remainder have used stochastic methods such as the most valuable player algorithm (MVPA) (Ramli et al., 2019), the improved multi-objective bat algorithm (IMOBA) (Sun et al., 2020) and the gravitational search algorithm (GSA) (Marzband et al., 2014).

From this review, it is seen that there are major gaps in the state of the art in regard to MVEMS, such as a lack of descriptions of real MGs, since most of the works are based on theoretical scenarios. This also means that the MVEMSs proposed in the literature have not been tested using real data, and have not been implemented in actual installations. In addition, the scheduling of HVAC systems is not included in a multi-vector scenario, and hydrogen electrolysers and EV charging stations have also not been considered as controllable assets in most cases. Another important drawback is that technical constraints arising from human behaviour, such as work schedules, are not considered in these schemes.

Finally, the majority of the works reviewed here do not take into account the computational time required to perform the optimisation calculations. These schemes employ methods that cannot be used in real time due to their high computational requirements, such as their latency and calculation time.

With the aim of overcoming the limitations described above, the authors present a MVEMS in which the overall objective is to provide an optimal solution for a 24-hour day-ahead schedule for the existing controllable assets in an energy system. The proposal includes a detailed, low-level description of the MG, and is based on real data and installations.

The proposed MVEMS, and the OS inside it, are used to find an optimal schedule for the following assets: HVAC, EV charging station, electrolyser and hydrogen refuelling station. The OS operates the HVAC system based on energy efficiency and economic incentives, shifting its electricity consumption to off-peak hours and thus reducing electricity bills. Load shifting is also applied to the EV charging stations and hydrogen refuelling stations, promoting the use of green mobility and reducing CO_2 emissions while increasing the use of local generation sources. Regarding the electrolyser, the proposed solution provides an optimal scheduling for hydrogen production and storage, which also increases the use of local generation resources together with the scheduling of hydrogen refuelling stations. As a global objective of the MVEMS, all these actions increase the self-consumption and degree of autonomy of the MG.

In order to calculate an optimal schedule for the existing controllable assets in a hybrid MG, a range of tools are needed. First, forecasts of the local renewable generation and the non-controllable consumption must be calculated. Next, the controllable assets must be modelled in order to simulate their energy consumption in the optimal schedule. Following this, the authors used an optimising algorithm that provides a solution to the problem with an objective defined based on a mix of mathematical functions, models and black box forecasting. Finally, the inclusion of existing operational constraints and requirements of the assets must be taken into account in the definition of the optimisation problem.

This work presents a real case of the optimisation of an hybrid MG, with distinct energy sources and multiple controllable assets. The hybrid MG is a technology park with local photovoltaic and wind generation (100 kW and 635 kW, respectively) and four types of controllable assets: the HVAC system in one of the buildings of the park, the EV charging station, an electrolyser, and the electric/fuel cell vehicles charging station. The technology park has seven buildings and its peak power consumption is 360 kW. Present work describes how forecasts of the generation and consumption are created, how the distinct assets are modelled, and how the cost function is constructed and solved using an optimisation algorithm.

This work is structured as follows. Next section presents a general overview of the OS and their elements. Section three describes how the OS is implemented in the specific MG of the technology park. In section four, the OS is tested during two weeks and results are shown and discussed. The fifth section provides a discussion of the findings of this work. Finally, the last section includes acknowledgements of the research projects that have funded this work and other people who have contributed in specific parts of it.

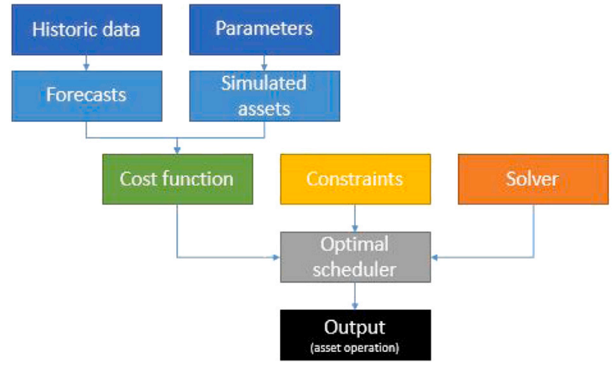

Fig. 1. Block diagram of the inputs and outputs of the OS.

2. General methodology

In this chapter, the general methodology and blocks are depicted and generically described. In the next section, the authors describe the exact methodology to be applied in the presented case.

Based on the overall definition of the MVEMS explained above, the OS is described in this section. The OS is a module that forms part of the MVEMS and calculates a hourly day-ahead schedule for the controlled assets in the energy system according to a pre-set objective.

Fig. 1 shows a general overview of the OS module. This module is composed of the following elements: state variables, control variables, constraints, cost function and solver.

2.1. State variables

The state variables are the inputs that contribute to the mathematical definition of the objective (cost function) to be optimised. These variables are predicted or simulated energy values (for generation and consumption), depending on whether they are controllable or non-controllable assets, respectively. These energy values may include the electrical or thermal demand of buildings, renewable energy production, and EV/FCEV consumption, for example.

Calculation of the energy demand is approached differently for non-controlled and controlled demand. In the first case, the energy consumption forecast is calculated by the energy forecaster (EF), based on data-driven models of the demand which include weather forecasting and contextual information such as the hour of the day and its type (that is, working/non-working periods). In the second case, energy consumption is simulated using the OS module, since it depends on the operational state of some controllable asset. Different types of methods, such as data-based models, first principles models, etc. may be used to simulate the controllable loads.

2.2. Control variables and constraints

The control variables are the parameters of the controllable assets to be optimised. They represent the output of the OS module, and depending on the nature of the control variable, they may be binary, discrete or continuous. Examples of control variables include the ON/OFF control of the chiller and its set-point temperature, and whether or not an electrical vehicle charger is enabled for charging.

The constraints are defined as certain limitations on the control variables, such as a maximum value permitted or a range of discrete values. These limitations may also correspond to limitations on the assets, such as the capacities of electric batteries or hydrogen storage tanks, or limitations introduced by use, such as the daily time-frame in which an EV can be charged.

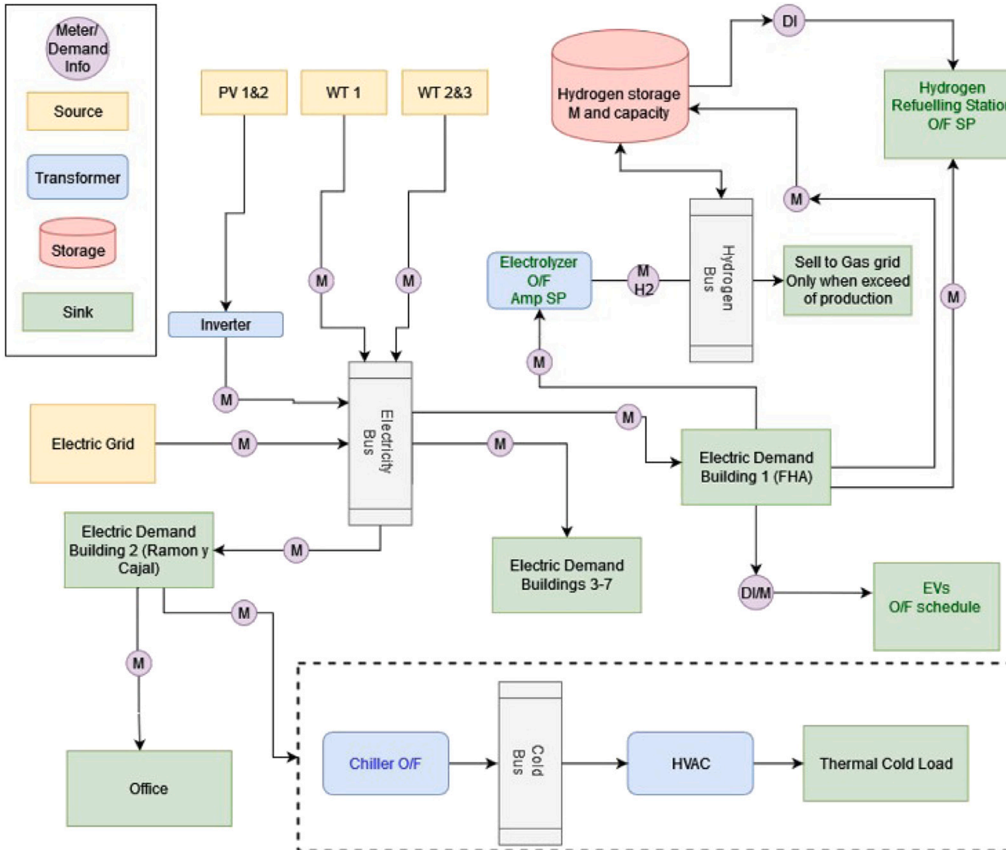

Fig. 2. Installations and assets at Walqa technology park.

2.3. Cost function and solver

The objective that the OS must pursue when calculating a schedule for the controllable assets is described as a cost function. This function typically includes the amount or the price of the energy that is supplied by a utility grid (such as a distribution electricity company), and is implemented based on the state variables, controlled variables and constraints. The solver is the algorithm that finds the minimum of the cost function.

This methodology is used in real scenarios and needs to deal with as many as possible types of cost functions. So, computing time needs to be controllable, and having a sub-optimal solution is much more desirable than having no solution for a given time. The author's purpose is to use metaheuristic techniques as they usually adapt better with these requirements. Finally, genetic algorithm (GA) (Volta et al., 1995) was selected for the particular case presented in next section as it was the one performing better in results and time by the present case.

3. Description of the case study

The proposed optimisation for the MVEMS was implemented and tested in Walqa technology park, located in the northeast of Spain close to the Pyrenees. The technology park is a pilot associated with the E-LAND European project. It is an initiative promoted by the Aragon General Government, and includes four buildings that are rented out and several others that are owned by private companies. Electrical energy, electricity-to-hydrogen and electricity-to-cold are included in this scenario. These three types of energy usage are marked in Fig. 2 as the electricity bus, the hydrogen bus and the thermal bus. The figure also shows the existing assets in the MG. These assets are divided into four types: power supply (source), consumption (sink), conversion of electrical energy to hydrogen and cold (transformer), and storage.

Electrical energy is supplied by the electric grid and the local energy generation units, which consist of two PV plants (100 kW) and three WTs (635 kW).

Electrical energy is consumed in seven buildings located in the park (360 kW peak). These buildings are divided into three sets based on the assets included in each of them. The first includes the building Fundacion de Hidrógeno Aragón (FHA), in which electrical energy is used for the offices and to charge electrical vehicles and produce hydrogen. The second includes the Ramon *y* Cajal building, in which the HVAC system is modelled to include the conversion of electricity to cold in the energy management system (EMS). The third set includes the rest of the buildings, for which the consumption is not optimised by the EMS.

The storage asset in the MG is a hydrogen storage tank, which is connected to an FCEV refuelling station.

In order to improve the operation of the MG, optimise the use of local renewable resources and minimise operational costs, some of the previous consumption assets are controlled by the EMS based on the forecasting of local production and non-scheduled consumption assets. In this case study, the controlled assets are the electrolyser, which generates hydrogen from electricity; the chiller, which generates cold in the HVAC system; the chargers of the EV charging station; and the hydrogen refuelling station, which provides hydrogen to the FCEV.

3.1. Implementation of the case study

The OS for the Walqa MG was implemented by defining the necessary inputs (state variables), outputs (control variables) and technical/operational constraints, together with the cost function that describes the objective of the optimisation and the solver that calculates the optimal scheduling of assets. Fig. 3 provides a general overview of the implementation, and the information presented in the figure is described in more detail below.

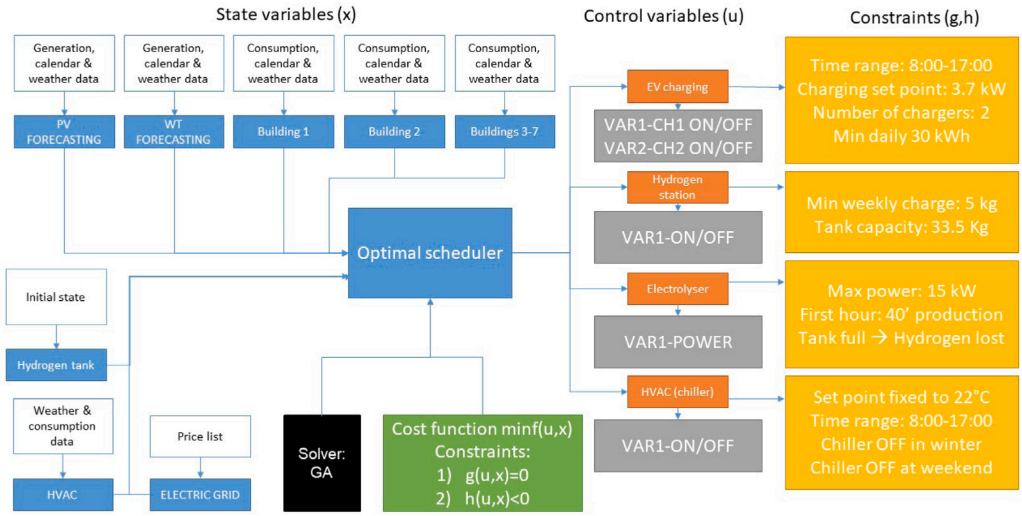

Fig. 3. Walqa pilot block diagram of the OS.

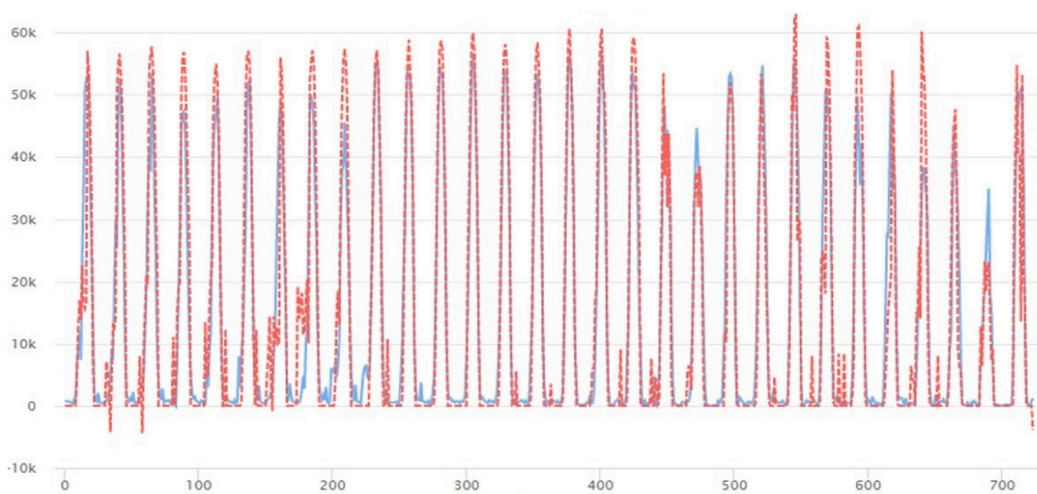

Fig. 4. PV generation forecasting. On vertical axis there is the PV generation (blue) and the PV generation prediction (red) in Watts. In horizontal axis there is the time in hours.

3.1.1. State variables

The state variables are the inputs of the OS, and are used to define the cost function. Two types of state variables can be distinguished: forecast and simulated variables. The difference between them is that forecast values are calculated by the EF models, whereas simulated values are calculated in the OS depending on the equations used. In the following, an overview of these state variables is given.

- **PV generation:** The daily electric energy (D_{GEN}) produced by the two PV plants was forecast by means of a random forest model (Breiman, 2001), which was parameterised as follows: trees = 100 and maximal depth = 15. The preprocessing methodology included windowing, missing average substitution, normalisation, feature selection, etc. The model was created using historical data on PV energy generation and weather. As an example, Fig. 4 shows the real PV generation vs the predicted PV generation, between 15th January 2022 and 14th February 2022. The correlation coefficient between them is 0.943.
- **WT generation:** The daily electric energy produced (D_{GEN}) by the three WTs was forecast by means of a random forest model (Breiman, 2001), which was parameterised as follows: trees = 25 and maximal depth = 15. The preprocessing methodology included missing average substitution, normalisation, feature selection, etc. The model was created using historical data on WT energy generation and weather. As an example, Fig. 5 shows the real WT generation vs the predicted WT generation, between 29th December 2021 and 4th March 2022, note that the forecasting includes the required energy by wind turbines to operate. The correlation coefficient among the two is 0.88.
- **Non-controllable consumption:** The daily electrical consumption (D_{CON}) of those assets that were not optimised by the OS was forecast using a RF model (Breiman, 2001), which was parameterised as follows: trees = 120 and maximal depth = 15. The preprocessing methodology included windowing, missing average substitution, normalisation, feature selection, etc. The model was created using historical data on electricity consumption, and weather and calendar data. As an example, Fig. 6 shows the real consumption vs the predicted consumption for the test data, between 15th January 2022 and 14th February 2022. The correlation coefficient between them is 0.915.
- **HVAC consumption:** To simulate the daily HVAC consumption (D_{HVAC}), the authors needed to also model the thermal behaviour of the Ramon *y* Cajal building depending on the ON/OFF operation. This thermal simulation was carried out in order to check that the users' comfort range requirements were met and to capture the system dynamics that affected electrical consumption. The HVAC consumption simulation model consisted of two distinct models.

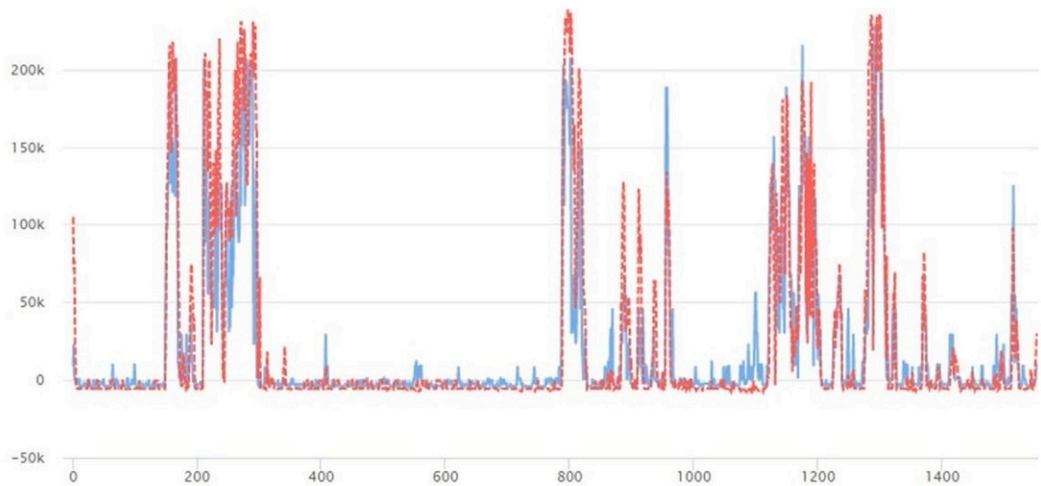

Fig. 5. WT generation forecasting. On vertical axis there is the WT generation (blue) and the WT generation prediction (red) in Watts. In horizontal axis there is the time in hours.

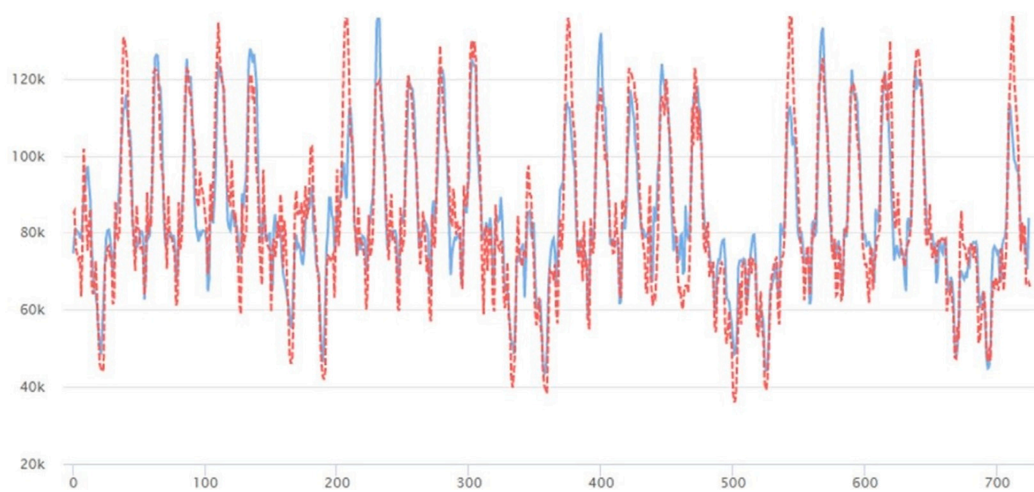

Fig. 6. Non-controllable consumption forecasting. On vertical axis there is the non-controllable consumption (blue) and the non-controllable consumption prediction (red) in Watts. In horizontal axis there is the time in hours.

First model is used to forecast the indoor building temperature depending on the outdoor temperature, relative humidity, the temperature setpoint and ON/OFF operation. Different existing methodologies in the literature were tested, being multiple linear regression (MLR) the one that provides the most accurate results. The correlation coefficient between them is 0.963.
Second, a model to forecast the consumption of the HVAC system is also created. This model is based on outdoor temperature, the forecasted indoor temperature of the first model, the operational status of the HVAC system ON/OFF and the hour of the day. The HVAC consumption simulation model consisted of an RF (Breiman, 2001) model, and the most accurate results were obtained with the following parameters: trees = 120 and maximal depth = 15. The preprocessing methodology included windowing, missing average substitution, normalisation, feature selection, etc. The model was created using historical data on HVAC consumption and operation, and weather and calendar data. As an example, Fig. 7 shows the real HVAC consumption vs. the simulated consumption for the test data, between 2th and 8th October 2021. The correlation coefficient between them is 0.925.

- **Electric vehicle charging station:** The energy consumed by the EV charging station (D_{EC}), which allows two vehicles to be recharged at the same time, is simulated in the OS based on the charging power set point of each charger (3.7 kW) and the hours that they are active, as shown in Eq. (1).

$$D_{EC} = \sum_{i=1}^{24} [m1(i) \cdot Power\ ch1(i) \cdot \Delta t + m2(i) \cdot Power\ ch2(i) \cdot \Delta t] \quad (1)$$

where:
D_{EC} = daily energy consumed by EV charging station (kWh)
$m1,\ m2$ = one if the charger is active; zero otherwise
$Power\ ch1,\ ch2$ = charging power set-point (3.7 kW)
Δt = time increment (one hour)

- **Hydrogen storage tank:** The state of the tank (kg of stored hydrogen) is calculated in the OS to simulate how much hydrogen is produced by the electrolyser from its energy consumption and stored in the tank using Eq. (2). The authors then subtract the amount of hydrogen delivered by the hydrogen refuelling station in Eq. (3). Finally, the consumption of the electrolyser is calculated using Eq. (4).

$$D_{HP} = \sum_{i=1}^{24} [m(i) \cdot Power(i) \cdot \Delta t \cdot Conversion\ Factor(i)] \quad (2)$$

where:

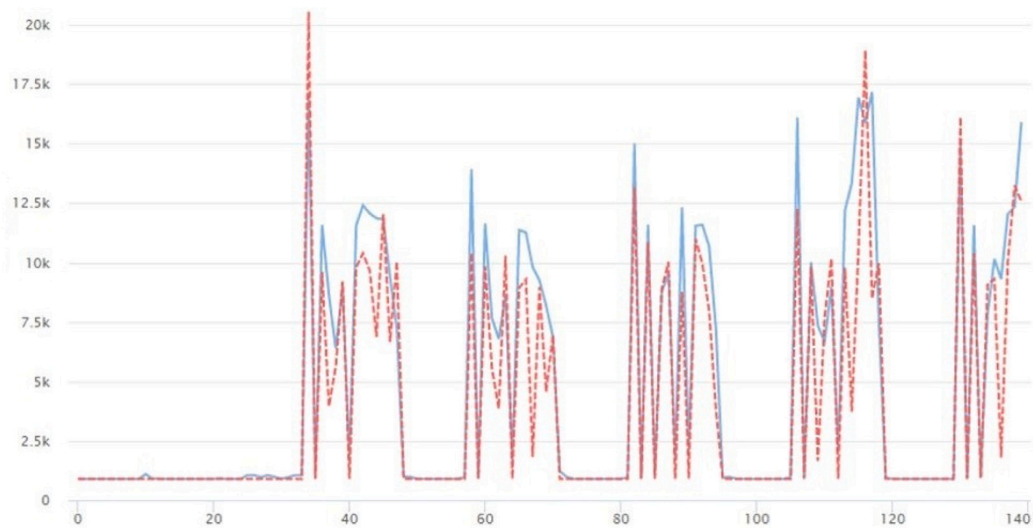

Fig. 7. HVAC consumption forecasting. On vertical axis there is the HVAC consumption (blue) and the HVAC consumption prediction (red) in Watts. In horizontal axis there is the time in hours.

D_{HP} = daily hydrogen production (kg)
m = one if the electrolyser is active; zero otherwise
$Power$ = power consumption (kW)
$Conversion\ Factor$ = energy consumption for hydrogen production (kg/kWh)
Δt = time increment (one hour)

$$TS(i) = Initial\ tank\ state + \sum_{j=1}^{i}[Hydrogen\ production(j) - Hydrogen\ consumption(j)] \quad (3)$$

where:
$TS(i)$ = state of the tank at hour i (kg)
$Hydrogen\ production(j)$ = amount of hydrogen produced during hour j (kg)
$Hydrogen\ consumption(j)$ = amount of hydrogen delivered by hydrogen refuelling during hour j (kg)

$$D_{EL} = \sum_{i=1}^{24}[Power(i) \cdot \Delta t] \quad (4)$$

where:
D_{EL} = daily energy consumed by the electrolyser (kWh)
$Power$ = power consumption (kW)
Δt = time increment (one hour)

- **Electricity price:** The hourly day-ahead electricity prices are provided to the OS by external service providers (Central Collection, 2022; Precio Horario del Mercado Diario, 2022).
- **Hydrogen price:** The buying and selling prices for hydrogen are fixed. In the case of the hydrogen used to fuel the FCEV, the price is 3.6 euros/kg (Collins, 2020), whereas the price of the hydrogen injected into the utility grid is 1.6 euros/kg.

3.1.2. Control variables and constraints

As can be seen from Fig. 1, there are four controllable assets: the electrolyser, the hydrogen refuelling station, the EV charging station and the HVAC system. The OS provides the hourly day-ahead schedule for one or more parameters of a controllable asset. In the following, the schedule created for each asset and their technical/operational specifications are explained.

Electrolyser: The OS produces a schedule for when to produce hydrogen from electricity and how much hydrogen to produce, fixing the energy consumption. The electrolyser can work at six levels of power (from 0%–100% of the nominal power), and the OS will fix the optimal value if the electrolyser is scheduled to be active. The OS also has to comply with the following technical requirements and specifications:

- 15 kW maximum power.
- Once turned on, the electrolyser does not produce hydrogen for the first 20 min and has a fixed cost.
- Any hydrogen produced when the tank is full is lost, as it is liberated to the atmosphere.

Hydrogen refuelling station: The OS schedules the activation or deactivation of the refuelling station. A user can only refuel a car if the station is active. Moreover, the OS has to comply with the following technical requirements and specifications:

- A weekly recharge of 5 kg must be guaranteed.
- The maximum capacity of the hydrogen storage system is 33.5 kg.

EV charging station: In the same way as the hydrogen refuelling station, the OS schedules the activation or deactivation of each of the two chargers in the EV charging station. A user can only refuel a car if one of these chargers is active. The OS must comply with the following technical requirements and specifications:

- The set point for the charging power is equal to 3.7 kW.
- There are two chargers.
- A minimum daily global charge of 30 kWh must be guaranteed between the two chargers (availability).
- A user can recharge a car between 8:00 and 17:00 h.

HVAC system: This is located in the Ramon *y* Cajal building. It is composed of a chiller and fan coils, and is the major source of consumption due to the chiller. The OS schedules the turning ON and OFF of the chiller, ensuring that the indoor temperature is maintained at the fixed set point temperature during summer time. The OS also has to comply with the following technical requirements and specifications:

- The set-point temperature of the building is fixed at 22 °C.
- The HVAC system can work between 8:00 and 17:00 h.
- The chiller is not operated in winter.
- The chiller is not operated at weekends.
- Valid rang of indoor temperatures is 22 to 25 Celsius.

3.1.3. Cost function

The cost function, or the objective function that the OS must minimise, is defined in this subsection. Based on the cost function, the OS finds the best combination of the control variables in order to minimise the day-ahead operational cost of the MG, and to integrate as much local generation as possible in the system. Depending on when and how the controllable assets are used, how the demand is covered and how the prices vary, it is possible to find an hourly day-ahead schedule for these assets that minimises the cost function.

The cost function takes into account the four controllable assets and the cost of energy (both electrical and hydrogen). It includes:

- The price of electricity provided by the utility. This energy is the difference between the energy consumption (buildings, electrolyser, HVAC system, and EV charging station) and the local generation (PV and WT).
- The price of the hydrogen that is produced. The hydrogen is considered at the lowest selling price. This means that hydrogen is considered as it has to be sold to the grid.

The resulting cost function is expressed in Eq. (5):

$$f(control_v) = P_e \cdot [D_{CON} + D_{EL} + D_{HVAC} + D_{EC} - D_{GEN}] - D_{HP} \cdot P_h \quad (5)$$

where:

$control_v$ = controlled variables

D_{CON} = daily electrical energy consumed by non-controllable assets (kWh)

D_{GEN} = daily electrical energy generated by local generation resources (kWh)

D_{EL} = daily electrical energy consumed by the electrolyser (kWh)

D_{HVAC} = daily electrical energy consumed by the HVAC system, mainly the chiller (kWh)

D_{EC} = daily electrical energy consumed by the EV chargers (kWh)

D_{HP} = daily hydrogen production (kg)

P_e = the price of selling energy to the grid, which is set to 0.068 euros/kWh, and a dynamic price for buying

P_h = the price of selling hydrogen to the grid, which is set to 1.6 euros/kg

3.1.4. Solver

As stated in the previous subsection, the cost function defines the objective to be minimised in the MG. The control variables are calculated to reach this objective, while complying with the technical specifications and requirements for each asset. From the range of existing solvers, the genetic algorithm (GA) (Volta et al., 1995) was selected since it is capable of performing well with a wide range of optimisation functions, and can handle discrete attributes. GA is a search algorithm for optimisation problems inspired by the process of biological evolution.

The configuration used in the GA algorithm is the following one: the number of particles to be used is 51, one particle for each hour of each controllable variable, the population size is 100, the mutation probability used is 0.1, the elite ratio for ensure not losing the best solution is set to 0.01 and the crossover probability is 0.5, using an uniform crossover method.

4. Example of application

This section describes an example of applying the proposed OS (Section 2) to the MG described in Section 3. This example involves optimisation of the MG over 14 days. The example data relate to the period from 4th to 17th May 2022. At the end of each day at 23:50 h the actual data were collected from the MG via different web services in order to obtain the schedule for the next day to apply directly to the grid the results on the optimisation. First, the state variables (input variables) are defined based on real data gathered from Walqa technology park and the optimisation results are then presented and discussed. Existing technical specifications and requirements are described in Section 3.

4.1. State variables

In this section, the inputs to the OS are described. Each day, the state variables were collected from the MG. Day-ahead consumption and generation data were provided by the EF described in Section 3, using data-driven models based on historical data gathered at Walqa technology park over a period of four months, while weather forecasting data were provided by external services, seen in Dark Sky (2022), Openweather (2022) and solcast (2022). Electricity buying prices were obtained from Central Collection (2022) and Precio Horario del Mercado Diario (2022), and the rest of prices were fixed by contract. Finally, the initial status of the hydrogen storage tank was obtained from a measurement device in the tank. These input data are summarised in Fig. 8, with the aim of simplifying all the days are shown together but OS uses a day-ahead horizon.

4.2. Results

Once the forecasts are available to the OS, together with the predefined technical specifications and requirements of the assets, the cost function in Eq. (5) is solved by means of a GA. The solver provides the hourly day-ahead schedule for the four controllable assets in Walqa technology park.

The hourly day-ahead schedule of the control variables calculated by the OS is used to simulate the consumption of the corresponding controllable assets. These simulations of the consumption, together with the forecasts for local generation and non-controllable consumption, allow us to assess the optimisation results calculated by the OS for the day. In order to interpret the results in Fig. 9, some simulations can be seen on the best case found during the optimisation process for each day. It should be noted that the scheduling is done for the day ahead, and this is the reason why the tank profile changes at 00:00 h. Updating is done when scheduling is started with real values from the tank for the next day's operation, and not at the real hour at which the car was charged.

Finally, Fig. 10 shows the operation for each of the controllable assets. Again, the results for each of the 14 days are shown.

In general terms, the assets are operated based on the requirements, the energy prices and the availability of renewable energy. In the following paragraphs these assets are explained in more detail:

- **Electrolyser:** It can be seen from Fig. 10(a) that the electrolyser tends to be used at minimum power, since there is usually no excess electricity. That is true, except the days that the requirements of having a minimum of 5 kg in the tank are not met. As an example of exploiting energy surpluses, it seen that on 15th May there are some hours with excess energy, in which the electrolyser generates hydrogen at full power.
- **HVAC:** From Fig. 10(b), it is seen that the OS calculated that the HVAC system (that is, the chiller) should be active and operate from 8:00 to 17:00 h in order to maintain the fixed indoor conditions. The operation of the HVAC was similar for all the days for which the summer mode was active. This was because the testing days were particularly hot and the HVAC power was limited. Summer mode is the period in which there is the option to operate the HVAC.
- **EV chargers:** The OS calculates that the chargers for the station should be active during the working hours of the day, when more local renewable generation is available, as can be seen from Fig. 10(c). The operation of the EV charger changes from one day to the next, due to varying electricity prices and the amount of available generation sources. It is worth pointing out that due to technical specifications, the station must remain inactive before 17:00 h. Electricity from the grid is used to charge the cars to the minimum capacity required. On 12th of May, since there was a small surplus, both EV chargers were allowed to charge at once.

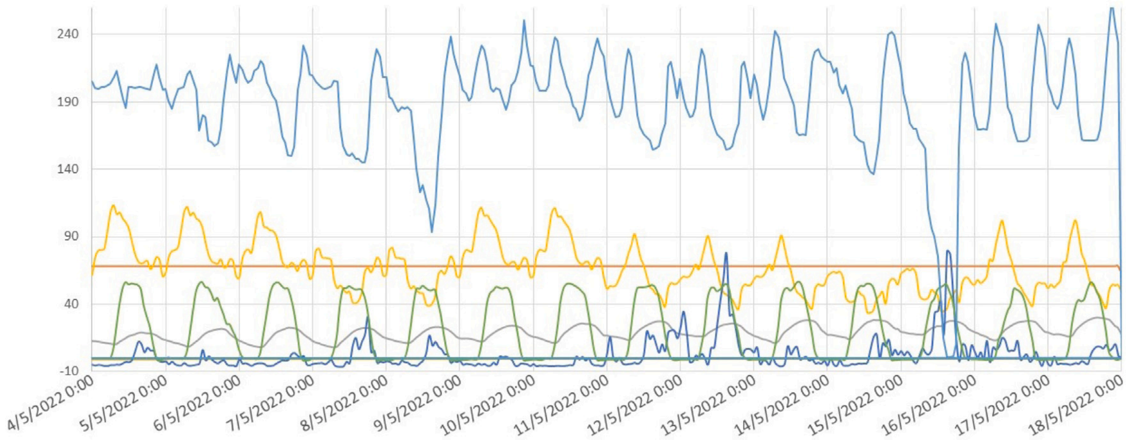

Fig. 8. OS inputs for each of the 14 days. In vertical axis there is the electricity selling price in euros/MWh (orange), the building consumption in kW (yellow), the solar production in kW (green), the outdoor forecasted temperature in Celsius (grey), the wind production in kW (dark blue) and the electricity buying price in euros/MWh (blue). In the horizontal axis there is the time in hours.

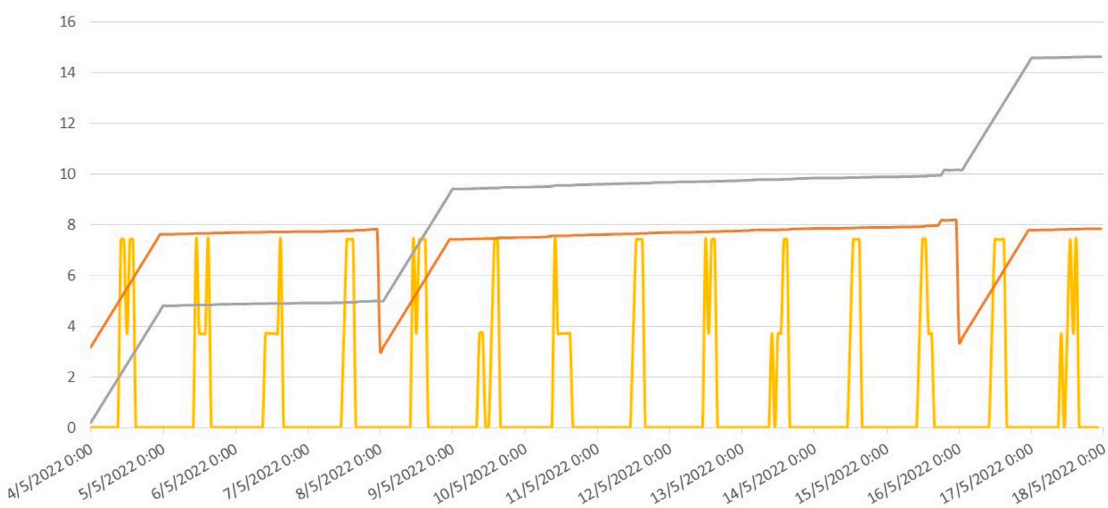

Fig. 9. Simulation of assets over the experimentation period. In vertical axis there is the tank profile in kg (orange), EV chargers consumption in kW (yellow) and hydrogen generated in kg (grey). In the horizontal axis there is the time in hours.

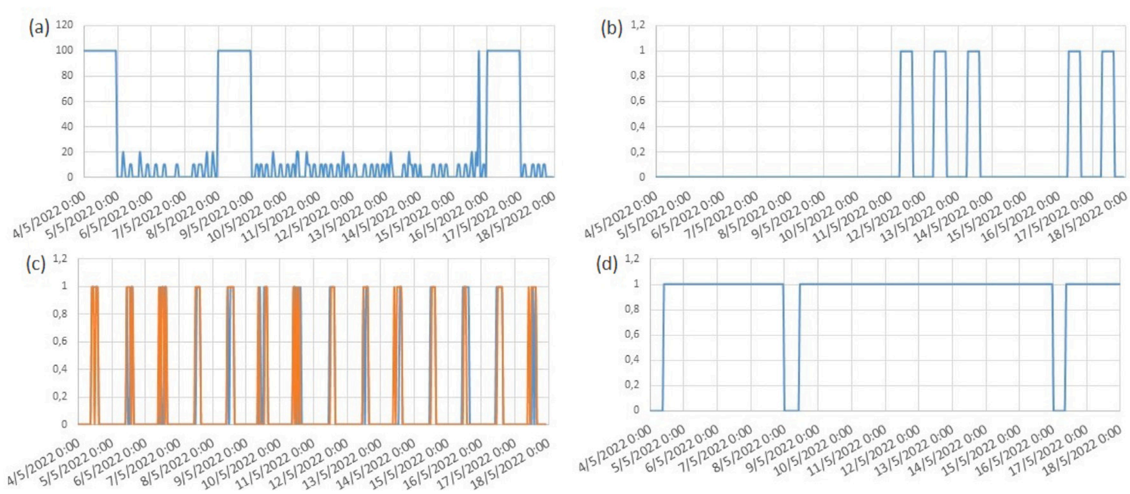

Fig. 10. Optimal operation of assets on each day of the experiment. (a) Is the electrolyser operation. Vertical axis is the percentage of utilisation. Horizontal axis is the time in hours. (b) Is the HVAC operation. Vertical axis is 1 or 0, being 1 for turned on and 0 for turned off. Horizontal axis is the time in hours. (c) Is the EV Cargers operation. Vertical axis is 1 or 0, being 1 for turned on and 0 for turned off. Horizontal axis is the time in hours. EV charger 1 operation (blue) and EV charger 2 operation (orange) (d) Is the refuelling station operation. Vertical axis is 1 or 0, being 1 for turned on and 0 for turned off. Horizontal axis is the time in hours.

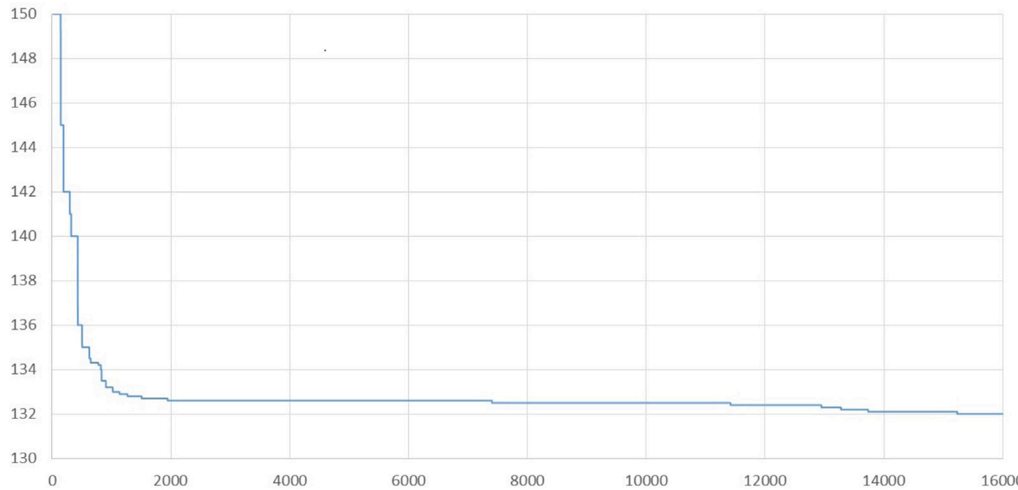

Fig. 11. Cost function evolution for one specific day. Vertical axis is the cost of the best solution in the actual population expressed in euros. Horizontal axis are the iterations.

- **Hydrogen refuelling station:** The OS calculated when the hydrogen charge should be available to users. As shown in Fig. 10(d), the station was available during hours where at least a charge of 5 kg is allowed.

Fig. 11 shows an evaluation of the cost function during the calculation of the OS by means of GA for one day. The horizontal axis shows the number of iterations of the GA, starting from random solutions and evolving to the best solutions once the algorithm is executed and the maximum number of iterations reached, that is 16,000 iterations.

The vertical axis shows the evaluation of the cost function in Eq. (5) for the best solution calculated at each iteration. Although the cost function is defined in terms of euros, the value of the function may differ from the exploitation cost of implementing the schedule provided by the OS, as this cost is computed from the simulations and some assets are computed at its maximum operation cost as for example EV chargers. It can be seen that the cost is mainly reduced during the first 2000 iterations, and minor reductions are then made indicating that the algorithm converged to a solution. As the authors use GA, the solutions are not always easy to interpret as can depend on many factors, but also as GA is not an exact methodology, the provided solution can be a local minimum or a sub-optimal solution. In any case GA allows stabling a maximum number of iterations and ensure a response inside the time restrictions. The authors remind the reader that this is a real application example, that means time is critical as the solution must be found and sent to the pilot before 00:00 h in order to correctly apply it. In the present case a maximum time of ten minutes for data gathering, preprocessing, forecasting, optimisation and sending results is required. These ten minutes correspond to: five minutes for GA computation, one minute for preprocessing and forecasting the data and four minutes for data transfer and delays.

5. Conclusions

This work proposes an OS that provides a 24-hour optimal scheduling plan to operate the controllable assets in a MG. The proposed tool is implemented in a technology park, where the proposed MVEMS, and the OS inside it, are used to find an optimal schedule for four different assets: HVAC, EV charging station, electrolyser and hydrogen refuelling station.

The complexity of solving the optimisation problem implies a balance between the accuracy of the solution and the time and resources required to obtain it. In order to find the optimal schedule for the controlled variables, the day ahead forecast of three variables have been trained using real measurements and applied on-line. In the same way three different variables have been simulated. RF has been used for forecasting as well as for simulating one variable. Two of the simulations have been carried out based on simple first principles models. Finally, the cost function to be minimised takes into account the four controllable assets and the price of energy, and it is solved using a genetic algorithm (GA) that can handle the variety of attributes. The combination of the proposed forecasting and simulation tools, the cost functions and the proposed solver offers in this case a good performance in terms of accuracy of results and ensures a response in a fixed computing time.

Based on the solution price that results from the tests, it is seen that the OS helps to improve the performance of the energy system operation by reducing the old daily consumption bill (an average cost of 548 euros in 2021), achieving a minimum cost of 131 euros for the best day, and an average cost of around 360 euros per day in the tested period. Thus, local energy generation is better used in the energy system, increasing its efficiency. This benefit, together with the computational time required by the OS to perform the calculation of day-ahead optimal schedule plan, allows its potential exploitation integrated in a new or existing MVEMS.

Finally, authors will continue this work adding other energy vectors and assets, such as solar thermal collectors and thermal storage, aiming the objective of provide tools that optimises an energy system co-managing different energy vector types.

CRediT authorship contribution statement

Joaquim Massana: Conceptualization, Writing, Experiments. **Llorenç Burgas:** Conceptualization, Writing, Experiments. **Sergio Herraiz:** Writing. **Joan Colomer:** Writing. **Carles Pous:** Forecasting models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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