AN ENERGY MANAGEMENT FRAMEWORK FOR OPTIMAL DEMAND RESPONSE IN A SMART CAMPUS

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Abstract: A framework for the power management in a smart campus environment is proposed, which enables the integration of renewable local energy sources, storage banks and controllable loads, and supports Demand Response with the electricity grid operators. We describe the system components, including an Energy Management System for the optimal scheduling of power usage, a telecommunication infrastructure for data exchange, and power production/consumption forecast algorithms. We also analyzes relevant use cases and propose quality metrics for the performance validation of the framework.

1 INTRODUCTION

The incorporation of Smart technologies in buildings is considered as the key factor for the achievement of the objectives of energy efficiency, integration of Renewable Energy Sources (RESes), and reduction in the emissions of pollutants. Nowadays, the prevalent amount of energy usage is due to building conditioning and management in urban centres, rather than to transportation and industrial plants (Yamamoto and Graham, 2009). Therefore, in order to ensure environmental sustainability and to adhere to the concept of Nearly Zero Energy Buildings (NZEB) (Kurnitski et al., 2011), novel infrastructures combining Smart Grids and Information and Communication Technologies (ICT) must be designed.

Though several studies on methodologies for optimal energy management of smart buildings and microgrids have appeared and demonstrators for specific use cases have recently been proposed (Noritake et al., 2013; Lu et al., 2010; Koss et al., 2012), the design of a general framework for the energy management of a smart campus still needs to be addressed. Such framework must take into account the multiple entities interacting in the Smart Grid ecosystem (e.g. Distribution and Transmission System Operators, utilities, users, and third party services). Moreover, it must provide effective management tools for

the local schedule of the energy usage at the users' side, supporting the integration of distributed energy sources (e.g. photovoltaic and wind power plants), energy storage banks, and various categories of controllable loads (including water/heat pumps; Heating, Ventilating and Air Conditioning (HVAC) plants; trigeneration plants; and electric vehicles). Such local Energy Management System (EMS) must ensure to the users quality of service guarantees while enabling Automatic Demand Response (ADR) with variable energy tariffs and interactions between users and utilities/grid operators in case of emergencies. To these aims, the framework must also include prediction models for energy production/consumption patterns and building thermal inertia based on weather forecasts and expectations about building occupation, and a system to collect human feedbacks about the perceived thermal comfort, as well as all the data on energy consumption and thermal conditions of the controlled spaces. A suitable ICT infrastructure is needed to support data storage/retrieval and the communications required by the EMS to coordinate generators, loads and field sensors/actuators.

In this paper, we propose an energy management framework for a smart campus that addresses all the above mentioned issues. However, the proposed solution can be easily generalized for application in residential buildings. The framework has been designed

to be implemented in a set of demonstrators, including a group of buildings in Politecnico di Milano and a private house. After providing an overall view of the related work in Section 2, in Section 4 we first introduce the general framework concepts, then we describe the optimization approach implemented by the Energy Management System and the ICT infrastructure for data transmission and management. We analyze some relevant use cases in Section 3. Finally, Section 6 concludes the paper.

2 RELATED WORK

The research community has recently investigated several optimization methodologies for the energy management of residential, industrial and commercial scenarios, with real-time or day-ahead approaches. They are often based on the users' behavior profiling with the purpose of inferring the main habits and automatically act on them to reduce energy dissipation, e.g. by switching off stand-by devices (Nesse et al., 2014; Nguyen and Aiello, 2013). The main drawback of the analyzed proposals w.r.t. the collected knowledge, is that data are stored with ad-hoc solutions that usually do not support data sharing and access by multiple entities. In the context of "Smart Office" scenarios, in (Zarkadis et al., 2014) data from multiple sensors and actuators has been recorded for 6 years in a building of the EPFL campus. The collected data include room temperature, presence, lighting level, windows opening, blinds position, electric lights and heating power; weather data have been collected as well, and includes ambient temperature, solar radiation on a horizontal surface (direct and diffuse components), wind speed and direction and rain alarm. The main goal of the proposal is to validate control algorithms for the actuation of solar shadings, electric lighting and heating equipment. It was shown that such control algorithms were able to significantly reduce the energy consumption while maintaining the same comfort level or even improving it. In (Counsell et al., 2009) the authors describe a case study about the refurbishment of a 1960's student accommodation. The refurbishment was predicted to possibly achieve a standard called Code for Sustainable; building information modeling and visualization are used for analyzing and comparing different design solutions. (Bull et al., 2012) presents a proposal to evaluate the role of Apps as an enabler of behavioral changes with specific aim of reducing energy consumption in buildings.

Our proposal includes an integrated data repository collecting all the relevant information gathered by different sources and available to be accessed by different actors.

A mixed integer linear model for the joint optimization of gas and electricity bills of a university campus building has been presented by Guan *et al.* (Guan et al., 2010). The building is equipped with a controllable combined heat-power system, battery storage and a photovoltaic plant. The optimizer can run either under assumption of "a priori" knowledge about future events, or assuming a "scenario tree",in which multiple possible future production/consumption patterns are considered, each one weighted with its probability of occurrence. This way, uncertainty about future energy usage is taken into account. Our approach also uses a linear program, but our EMS relies on energy production/consumption forecast models. Moreover, the optimization procedure is repeated multiple times during the scheduling horizon, and decisions are dynamically updated. Other recent works addressing Smart Office environments include studies on energy saving strategies for lightening management based on room occupancy (by Stojanovic *et al.* (Stojanovic et al., 2011)) and some demonstrators deployed in office buildings aimed at the development of self-sustained distributed energy systems (Noritake et al., 2013; Lu et al., 2010; Koss et al., 2012).

For what concerns residential environments, Bozchalui *et al.* (Bozchalui et al., 2012) and Kriett *et al.* (Kriett and Salani, 2012) provide optimization models for the usage of individual electrical appliances and combine multiple objectives such as the minimization of energy consumption, energy costs, carbon emissions, and peak load. Our proposed EMS also optimizes different objective functions, including energy costs, the comfort of the buildings' occupants, and the fulfillment of ADR requests from the Distribution System Operator (DSO).

3 USAGE SCENARIOS

The interaction between the smart campus and the grid comprises three major usage scenarios: the market-driven, the demand response, and the emergency scenarios. In the market driven scenario, the EMS can decide to buy (or sell) any amount of power subject only to the contractual limits. Depending on the contract, the campus can either have predetermined flat or time-varying tariffs. These, in turn, can be known in advance for the whole optimization horizon, either because specified in the contract or because they depend on the day-ahead market. Alternatively, the tariffs can be only partly known because

they depend on the real-time energy market.

In the demand response scenario, the DSO periodically issues Demand Response Events (DRE). Each DRE is targeted towards one or more Point of Delivery (POD), i.e. an electricity subscriber, and is characterized by a manifest specifying: an upper limit to the active power that the subscriber can drain from the grid, an upper limit to the active power that the subscriber can inject into the grid, an amount of reactive power that the customer should inject into the grid. The DRE is also associated to an initial time, a final time, and an economic incentive. The DRE is issued 1.5 hours to one day in advance with respect to the start time, and the EMS is not required to explicitly accept or refuse the DRE offer, but is expected to take the offer into account when optimizing the campus behavior. At the end of the DRE, the DSO checks what PODs complied to the manifest and subtracts the incentive from the subscriber's bill.

In the emergency scenario, the DSO takes full control of the subscriber's load. The DSO can either detach the subscriber, limit the power generation, or change the amount of reactive power.

It is worth noting that the EMS has a much finer control of the campus behavior than the DSO during the emergency scenario, thus DREs should be seen as a way to avoid emergency situations while sacrificing energy efficiency as little as possible.

4 THE ENERGY MANAGEMENT FRAMEWORK

4.1 System Overview

The energy management framework involves Distribution and Transmission System Operators (DSO/TSO), which are responsible for the electricity dispatchment; the retail users (equipped with local generation and storage capabilities); the energy utility, which sells electricity to the retail users; the energy market (both on real-time or day-ahead basis); and third party services (e.g. a weather forecast provider).

With reference to Figure 1, the framework includes the following domains:

- *Demand Side Management Domain*: it consists of the energy dispatchment and management infrastructure of the DSO and its interfaces with the TSO.

- *Back-End Domain*: it comprises the EMS for the energy usage schedule, a *data repository* for information storage/retrieval, and multiple interfaces for the collection of input data provided by external entities. Such data include weather forecasts, historical data about the usage patterns of electric vehicles, historical/current energy tariffs, predictions about the future energy production of local energy sources and about the energy consumption due to uncontrollable loads.

- *Front-end Domain*: it includes field sensors/actuators and communication gateways which convert the scheduling outputs provided by the EMS into commands to control the field devices.

- *Application Domain*: it comprises all the software applications that support interactions between users and the energy management system, including interfaces for the setting of users' preferences about the management of their electrical appliances, for the collection of users' feedbacks about their perceived comfort level, and for data monitoring.

4.2 The ICT Infrastructure

The ICT infrastructure has been designed by prioritizing the following goals:

1. The field devices must work even if there is no input from the EMS.

2. The infrastructure must provide sufficient flexibility to accommodate multiple adapters for a wide variety of field devices.

3. The frequency data is collected from the field devices depends on the specific field device and is independent from the EMS decisions.

4. The EMS makes its decisions on the basis of snapshots of the state at a given time and of the available forecasts of the future energy production/consumption due to generators/loads.

5. The EMS provides a schedule of all the power consumption set points of the various field devices over a given time horizon. The field actuators map these set points into commands to be issued to the devices.

6. The running frequency of the EMS and the optimization horizon can change over time.

On the basis of the stated goals, the ICT infrastructure leverages the two main functional elements in the back-end: the data repository and the EMS. The data repository collects data from the field gateways, which read the field sensors, from the forecast models, and from the EMS, which logs its decisions. Such data is read by the forecast models, by the EMS, and
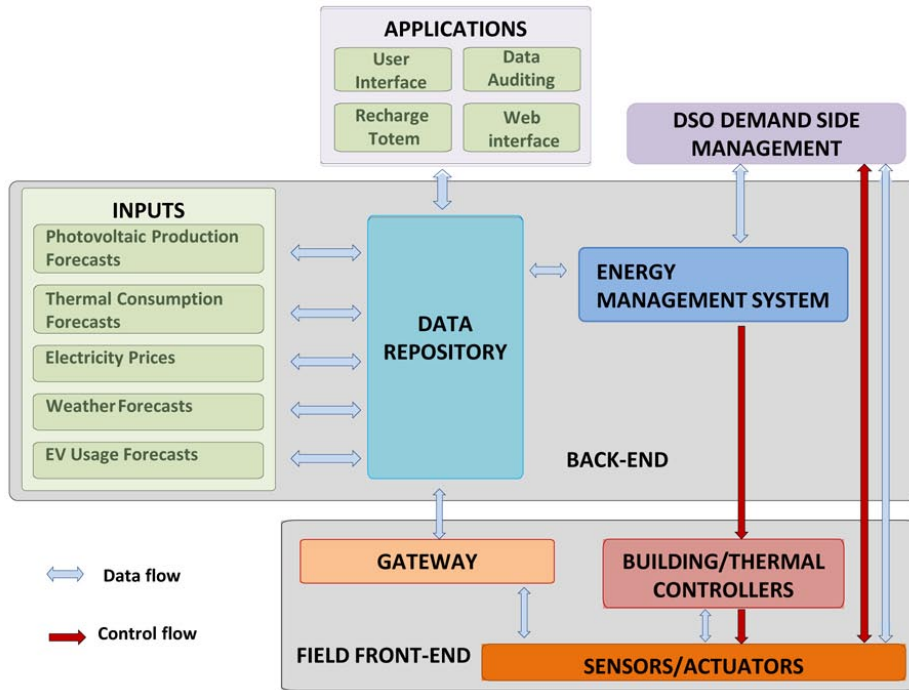
Figure 1: The framework architecture

by the various Business Intelligence and data presentation applications.

The Energy Management System is expected to run at every time slot, but it can be configured to run less frequently. The EMS collects data from the data repository and DRE manifests from the DSO and executes an optimization algorithm, which schedules the power demand by passive loads, such as HVACs and EVs, and the storage of the power generated by RESes.

In general, the EMS's decisions are based on predictions and the field devices cannot always comply to the EMS decisions. For example, the production from PV units or the demand by EVs can be less than expected. Therefore, the EMS pushes the schedule for each field device to a controller that transforms the chosen set points into constraints to the maximum power that the device can drain or inject into the system.

Prediction errors are dealt with in two ways. Small errors are managed by running the EMS frequently and by using up-to-date data at each iteration. This way, the EMS can continuously update its decisions to cope with changed conditions and avoid accumulating large errors, thus limiting inefficiencies. Large errors, such as a completely wrong weather forecast, are dealt by each controller, which can lift the EMS constraints if the controlled field device cannot provide a minimum service. This happens, for example, with the HVACs. In case the allocated power would result in a too low (or too high) temperature and, consequently, in a too high discomfort, the controller can remove the constraint and make the system work freely.

The back-end domain includes the data repository, the EMS, and all the forecast models. The data repository can be either in the campus data center or at any IaaS or Paas provider. All the components of the back-end communicate with external data sources, such as the DSO or the weather forecast service, with the data presentation applications via the Internet and with the field front-end by means of the campus LAN.

The gateways and the controllers are physical devices equipped with the networking interfaces required to communicate with the sensors and actuators and with the back-end. In addition, they are equipped with sufficient computational capabilities to perform some predefined automated control operations, such as lifting power constraints if some target values of the sensors are not met. Generally, controllers also behave as gateways.

4.3 The data repository

As discussed, the proposed framework includes a *data repository* collecting all the relevant information exploited by the different actors, i.e., the EMS, the other controllers (thermal, EV charger totems) and data an-
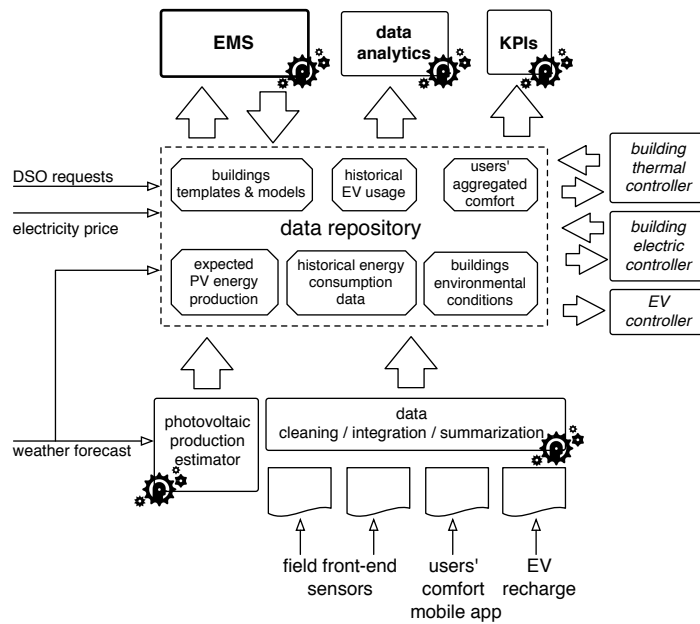
Figure 2: The data repository

alytics/KPI evaluators. The data stored in the repository, depicted in Figure 2, consist of the following pieces of information:

- electricity market prices;

- data collected from sensors monitoring the building thermal conditions, energy consumption (within the buildings and from the EV chargers) and the users' feedback on their thermal comfort; the data are processed to be cleaned, integrated and summarized, in order to be exploited by the EMS and the other controller. Such data constitute the actual status of the *system*, and incrementally contributes to the definition of the historical data, used by the EMS to make forecasts on future energy requests/thermal conditions;

- weather forecasts to enable the estimation of energy production from photovoltaic sources;

- buildings models and templates, actuators and sensors technical features and space occupancy patterns.

In line with the definition of a flexible framework, which should fit various application environments possibly characterized by different peculiarities that might affect the overall EMS strategy, the architecture of the data repository has been organized in two layers.

At the bottom layer, which collects data from the field, sensors organized in wired/wireless sensor networks have been deployed to continuously monitor the smart campus spaces, the EV recharge stations and the energy production sensors. Different technologies have been adopted (e.g. Zigbee and Z-Wave), exploiting existing solutions and deploying new ones, thus integrating an ecosystem of monitoring solutions. Gateways gather data from field sensors and transmit them to the central data repository; a polling-based acquisition approach has been adopted to efficiently manage the data acquisition given the high number of sensors. Moreover, the users' thermal comfort is collected by means of a mobile app to have a feedback on the perceived conditions of the spaces being controlled by the EMS optimization strategies. All this data needs to be be cleaned and summarized before being stored into a relational database, for further exploitation. Therefore, a NoSQL datastore solution has been adopted, suitable for storing wide data sources constituted by semi-structured heterogeneous data. We opted for the NoSQL-based Cassandra (Lakshman and Malik, 2010) distributed database management system, which is designed to handle large amounts of data providing high availability and fault tolerance. Within the framework, we define a set of distributed algorithms to perform data cleaning and summarization. Moreover, the system supplies online data analysis using an sql-like query language and supports batch processing over its distributed file system. The Cassandra File System also enables the usage of powerful Big Data frameworks, useful to carry

out *data analytics* and *KPI* evaluations to improve the EMS mission.

Once the data have been summarized, they are pushed into a Postgresql database, where they remain available to be used by the controllers and the EMS. This relational database is the second layer of the data repository architecture and stores all the i) structured static data, including buildings templates and models, actuators and sensors technical features and occupancy patterns, ii) structured data related to weather forecasts, electricity prices, DSO requests, and iii) semi-structured real-time data, coming from the lower layer.

Altogether, the main purpose of the data repository is to collect data coming from the whole demonstrator and to supply each controller with the summarized information it needs, offering a comprehensive view of the overall system. The two-layer architecture allows for gathering both raw data (to be processed in parallel) and summarized data (that should be more reliable) thus optimizing the data analytics and KPI extraction processes, to better support the EMS.

4.4 The EMS Optimization Model

The EMS optimization algorithm must allocate the power demand of users over a scheduling horizon (e.g. 24 hours) divided into a set $\mathcal{K}$ of time slots of fixed duration (e.g. 15 minutes). Users have two different kinds of loads: fixed and adjustable. Fixed loads are non-manageable appliances (e.g. lighting) and are characterized, in each time slot $k \in \mathcal{K}$, by their overall power consumption p_k^F. Adjustable loads are manageable appliances whose consumption can be modified by the EMS. In our framework, we consider two different sets of adjustable loads: electric vehicles and thermal units. In the first case, the EMS must decide the charging schedule of a set $\mathcal{V}$ of electric vehicles. Each vehicle v, powered with a battery of capacity C_v^{EV}, arrives at the charging station at time A_v^{EV} and departs at time D_v^{EV}. The State Of Charge (SOC) of its battery at the arrival time is S_v^{EV} and its charge target is $S_v^{EV,target}$. Moreover, each vehicle is characterized by its maximum and minimum charge rates, respectively $\tau_v^{EV,max}$ and $\tau_v^{EV,min}$, and by its charge efficiency η_v^{EV}. In case of the thermal units, which are used to heat and cool buildings and are represented by the set $\mathcal{U}$, the EMS must decide their operating plan. In this case, each unit u is characterized by a set of possible operating plans $\mathcal{T}$, each one characterized, in each time slot $k \in \mathcal{K}$, by a known power consumption p_{utk}^T and thermal comfort q_{utk}^T.

In our framework, local PhotoVoltaic (PV) plants are used to generate electric energy that can be either used locally or injected into the grid. PV sources are characterized by their total amount of power which is predicted to be generated in each time slot $k \in \mathcal{K}$ p_k^{PV}. In order to optimize the usage of PV plants (e.g. minimize the power exchange with the grid, increase the percentage of energy used from PV generation) a storage bank is used. This bank is characterized by a set of parameters: its capacity C^{PV}, its state of charge at the beginning of the time horizon $\mathcal{K}$ S^{PV}, its maximum/minimum charge/discharge rates, respectively $\tau^{PV,max}$, $\tau^{PV,min}$, $\vartheta^{PV,max}$ and $\vartheta^{PV,min}$ and, finally, its charge/discharge efficiency η^{PV}.

The proposed framework supports demand response services. Specifically, in case of system emergencies or in response to supply conditions, the grid operator may request to reduce/increase the power demand and supply of users, providing an economic incentive in case users meet such requests. In order to enable demand response services, the operator must specify:

- the set of time slots where it sets an upper bound on the power demand $\mathcal{K}^{y,U} \subseteq \mathcal{K}$, the upper limit of the power demand $\pi_k^{y,U}$ and the reward paid to incentivize users to meet its request $r_k^{y,U}$;

- the set of time slots where it sets a lower bound on the power demand $\mathcal{K}^{y,L} \subseteq \mathcal{K}$, the lower limit of the power demand $\pi_k^{y,L}$ and the reward paid to incentivize users to meet its request $r_k^{y,L}$;

- the set of time slots where it sets an upper bound on the power supplied to the grid $\mathcal{K}^{z,U} \subseteq \mathcal{K}$, the upper limit of the power supply $\pi_k^{z,U}$ and the reward paid to incentivize users to meet its request $r_k^{z,U}$;

- the set of time slots where it sets a lower bound on the power supplied to the grid $\mathcal{K}^{z,L} \subseteq \mathcal{K}$, the lower limit of the power supply $\pi_k^{z,L}$ and the reward paid to incentivize users to meet its request $r_k^{z,L}$.

Whenever a new time slot starts, the EMS receives the energy production/consumption forecasts computed by the prediction modules of the framework, the amounts of energy generated and consumed in the previous slot, the current state of charge of the storage bank and of the batteries of the electric vehicles plugged for recharge. The EMS then runs a Mixed Integer Linear Programming (MILP) model to schedule the energy usage plan over the horizon $\mathcal{K}$. The optimization model is defined as follows.

Constraints description

Thermal units In our system, the model has to decide the optimal operating plan of the thermal units. To this end, a set of binary variables, β_{ut}, is defined for each unit $u \in \mathcal{U}$ and each possible plan $t \in \mathcal{T}$: β_{ut} is equal to 1 if plan t is chosen for the thermal unit u and 0 otherwise. Such variables are subject to the following constraints:

$$\sum_{t \in \mathcal{T}} \beta_{ut} = 1 \quad \forall u \in \mathcal{U} \tag{1}$$

which guarantee that only one operating plan is chosen.

EV charging station In order to model the charging station of electric vehicles, three sets of variables are introduced. Firstly, a set of binary variables, ω_{vk}^{EV}, is defined for each time slot $k \in \mathcal{K}$: ω_{vk}^{EV} is equal to 1 if the station is charging the storage system of the EV v at time k and 0 otherwise. The charge rates must be decided by the model as well. They are represented by the continuous non-negative variables c_{vk}^{EV} which are bounded, for each $k \in \mathcal{K}$, according to the following constraints:

$$\tau_v^{EV,min} \omega_{vk}^{EV} \leq c_{vk}^{EV} \quad \forall v \in \mathcal{V}, k : A_v^{EV} \leq k \leq D_v^{EV}$$

$$c_{vk}^{EV} \leq \tau_v^{EV,max} \omega_{vk}^{EV} \quad \forall v \in \mathcal{V}, k : A_v^{EV} \leq k \leq D_v^{EV} \tag{2}$$

$$c_{vk}^{EV} = 0 \quad \forall v \in \mathcal{V}, k : k < A_v^{EV} \mid k > D_v^{EV}$$

The state of charge of vehicles is represented by the continuous non-negative variables s_{vk}^{EV} which are defined for each EV v and each time slot k. The SOC of an EV in a time slot depends on the SOC of the same EV in the previous time slot and on the charge rates, according to the following constraints:

$$s_{vk}^{EV} = S_v^{EV} + \eta_v^{EV} c_{vk}^{EV} \quad \forall v \in \mathcal{V}, k = A_v^{EV}$$

$$s_{vk}^{EV} = s_{v(k-1)}^{EV} + \eta_v^{EV} c_{vk}^{EV} \quad \forall v \in \mathcal{V}, k : k > A_v^{EV} \tag{3}$$

The state of charge of the battery of each EV is bounded according to the following constraints:

$$s_{vk}^{EV} \leq C_v^{EV} \quad \forall v \in \mathcal{V}, k \in \mathcal{K} \tag{4}$$

Finally, the SOC of the battery of each EV must be greater than or equal to the SOC target by the end of the charging window:

$$s_{vk}^{EV} \geq S_v^{EV,target} \quad \forall v \in \mathcal{V}, k = D_v^{EV} \tag{5}$$

Photovoltaic panels and storage bank Two set of binary variables, ω_k^{PV} and σ_k^{PV}, are introduced to model the storage bank of the PV: ω_k^{PV} is equal to 1 if the battery is charging at time k and 0 otherwise, while σ_k^{PV} is equal to 1 if the battery is discharging at time k and 0 otherwise. Such variables are subject to the following constraints:

$$\omega_k^{PV} + \sigma_k^{PV} \leq 1 \quad \forall k \in \mathcal{K} \tag{6}$$

which guarantee that in every time slot, the storage bank can be in only one of three possible modes: charge, discharge and off.

The charge and discharge rates must be decided by the model as well. They are represented by the continuous non-negative variables c_k^{PV} and d_k^{PV}. Such variables are bounded according to the following constraints:

$$\tau^{PV,min} \cdot \omega_k^{PV} \leq c_k^{PV} \leq \tau^{PV,max} \cdot \omega_k^{PV} \quad \forall k \in \mathcal{K}$$

$$\vartheta^{PV,min} \cdot \sigma_k^{PV} \leq d_k^{PV} \leq \vartheta^{PV,max} \cdot \sigma_k^{PV} \quad \forall k \in \mathcal{K} \tag{7}$$

A continuous non-negative variable s_k^{PV} is defined for each time slot k, which represents the state of charge of the storage bank at time k. The SOC of a storage system in a time slot depends on the SOC of the same storage bank in the previous time slot and on the charge and discharge rates, according to the following constraints:

$$s_k^{PV} = S^{PV} + \eta^{PV} c_k^{PV} - \frac{1}{\eta^{PV}} d_k^{PV} \quad \forall v \in \mathcal{V}, k = 1$$

$$s_k^{PV} = s_{k-1}^{PV} + \eta^{PV} c_k^{PV} - \frac{1}{\eta^{PV}} d_k^{PV} \quad \forall k \in \mathcal{K} : k > 1 \tag{8}$$

The state of charge of the battery is bounded according to the following constraints:

$$s_k^{PV} \leq C^{PV} \quad \forall k \in \mathcal{K} \tag{9}$$

Finally, the following balancing constraints have to be verified:

$$p_k^{PV} + d_k^{PV} = c_k^{PV} + o_k^{PV} \tag{10}$$

where o_k^{PV} is the overall net output power of the system composed of the photovoltaic panel and the storage bank.

Energy Balancing The following constraints force the balance between the input and output electric power of the system in each time slot:

$$y_k + o_k^{PV} = z_k + \sum_{u \in \mathcal{U}} \sum_{t \in \mathcal{T}} \beta_{ut} p_{utk}^T + p_k^F + \sum_{v \in \mathcal{V}} c_{vk}^{EV} \quad \forall k \tag{11}$$

where y_k and z_k are, respectively, the power demand and supply of users at time k. The left hand side of constraints (11) represents the input power (power demand of users and overall net output power of the PV and storage bank system), while the right hand side is the sum of the output power (power injected into the grid and power consumed by thermal units, fixed loads and electric vehicles).

The grid operator may send emergency signals to the EMS to request to increase/decrease its power demand/supply. To this end, we define the binary variables $\xi_k^{y,U}$ ($\xi_k^{y,L}$) which are equal to 1 if the power demand reduction (increase) request at time k is met and 0 otherwise. Similarly, in reference to the power injected into the grid, we introduce the binary variables $\xi_k^{z,U}$ ($\xi_k^{z,L}$) which are equal to 1 if the power supply reduction (increase) request at time k is met and 0 otherwise. The following constraints guarantee that if the power demand at time k is less (greater) than $\pi_k^{y,U}$ ($\pi_k^{y,L}$), then the energy reduction (increase) requirement is met and the corresponding variable $\xi_k^{y,U}$ ($\xi_k^{y,L}$) is set to 1. Similar constraints are also defined in reference to the energy injected into the grid.

$$y_k \leq \pi_k^{y,U}\xi_k^{y,U} + \pi^{CPP}(1-\xi_k^{y,U}) \quad \forall k \in \mathcal{K}^{y,U} \qquad (12)$$

$$y_k \geq \pi_k^{y,L}\xi_k^{y,L} \quad \forall k \in \mathcal{K}^{y,L} \qquad (13)$$

$$z_k \leq \pi_k^{z,U}\xi_k^{z,U} + o_k^{PV}(1-\xi_k^{z,U}) \quad \forall k \in \mathcal{K}^{z,U} \qquad (14)$$

$$z_k \geq \pi_k^{z,L}\xi_k^{z,L} \quad \forall k \in \mathcal{K}^{z,L} \qquad (15)$$

where π^{CPP} is the mandatory power limit which must be always fulfilled.

The grid operator may incentivize users to meet its requests via economic rewards earned in the case they fulfill its bounds on the power demand and supply. The overall reward, r, is defined as follows:

$$r = \sum_{k \in \mathcal{K}^{y,U}} r_k^{y,U}\xi_k^{y,U} + \sum_{k \in \mathcal{K}^{y,L}} r_k^{y,L}\xi_k^{y,L} + \\ + \sum_{k \in \mathcal{K}^{z,U}} r_k^{z,U}\xi_k^{z,U} + \sum_{k \in \mathcal{K}^{z,L}} r_k^{z,L}\xi_k^{z,L} \qquad (16)$$

where $r_k^{y,U}$, $r_k^{y,L}$, $r_k^{z,U}$ and $r_k^{z,L}$ represent the rewards paid by the retailer to incentivize users to meet its requests on the power demand and supply profiles.

Objective function

The objective of the EMS is to decide the schedule of electric resources over the horizon $\mathcal{K}$ with the goal of minimizing the difference between the total cost of users and their (thermal) comfort. To this end, the objective function is modelled as follows:

$$min \ \alpha\left(\sum_{k \in \mathcal{K}} (e_k^{EB}y_k - e_k^{EI}z_k) - r\right) - \sum_{u \in \mathcal{U}}\sum_{t \in \mathcal{T}}\sum_{k \in \mathcal{K}} \beta_{ut}q_{utk}^T \qquad (17)$$

where e^{EB} and e^{EI} are, respectively, the cost of the energy absorbed from and injected into the grid at time k, and α is a weight used to control the trade-off between costs and comfort. The first objective of (17) represents the total cost incurred by the system which is obtained as the difference between the daily bill and the incentives, while the second one represents the thermal comfort of users.

5 FRAMEWORK VALIDATION

The proposed framework will make it possible to gain insight into several open problems in the context of Demand Response.

In the market-driven and in the demand response scenario, the optimizer tries to strike a balance among heterogeneous needs such as the thermal comfort level, the availability rate of electric vehicles, and the availability of power from renewable sources. Thus, one of the goals of the proposed framework is cut the Smart Campus energy costs without penalizing the comfort of the various campus users. The actual trade-off depends on empirical constants that try to model the cost of a decrease in user comfort, the most important of which is parameter α in (17). A too high cost of discomfort results in a limited freedom of choice and in limited savings. On the other hand a too low cost, results in unsatisfied users. We plan to make an extensive measurement campaign to assess the impact of the cost of discomfort on the resulting savings.

In the Demand-Response scenario, the optimizer takes into account the availability of the DSO incentive and modify its behavior accordingly. Since the framework makes it possible to schedule a large number of devices and also to exploit various ways to accumulate thermal and electrical energy, we expect that in many situations the EMS will be able to comply to the DSO requests without jeopardizing the user satisfaction. In this way, the DSO obtains a change in

electric usage with no need of emergency actions. On the other hand, if the incentive is too low, the campus will not change its consumption pattern, possibly resulting in thecnical problems and in emergency actions by the DSO. If the incentive is too high, the EMS might lower the campus user comfort level in order to obtain the incentive. This case could be undesirable for the campus users, who may be more willing to take a risk of an unlikely emergency action rather than experiment a low discomfort for a long time. We plan to study the impact of different incentives on the discomfort and on the willingness to experiment discomfort in exchange for a lower probability of emergency actions. The goal is to provide data to the DSO regarding the effectiveness of a DSO-driven incentive-based policy to increase system availability.

6 CONCLUSIONS

This paper proposes an energy management framework for a smart campus including local renewable energy sources, a storage bank, and several controllable loads. The framework incorporates an optimizer which schedules the usage of electrical loads, of various predictors for the energy production/consumption patterns, and of a repository and an ICT infrastructure for data collection. The paper discusses relevant use cases and proposes quality metrics for the performance evaluation of the proposed framework.

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