A District Energy Management Based on Thermal Comfort Satisfaction and Real-Time Power Balancing

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09 April 2024

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Abstract— This paper presents a district energy management strategy devoted to monitor and control the district power consumption in a twofold human centered perspective: respecting the user's comfort preferences and minimizing the power consumption and costs. The presented District Energy Management System forwards the power profile determined the day-ahead to each Building Energy Management System that in turn minimizes its power consumption and costs (based on rewards and penalties) of the next day by respecting the comfort preferences. Successively, the power is redistributed among the district buildings in order to minimize the penalties and by applying two approaches: a centralized approach for public buildings and a distributed methodology for private buildings. Such optimization problems are formalized by defining some Linear Programming problems: two case studies are solved to show the applicability of the proposed management strategies.

Note to Practitioners— This paper is motivated by the necessity of optimizing the energy distribution in districts of smart buildings in order to guarantee the user comfort and, on the same time, to limit wastes and costs. For this purpose, both municipal managers and private administrators aim at optimizing the building consumptions on the basis of the weather forecast. This paper presents a hierarchical management strategy that can be applied by the energy district managers on the basis of the day-ahead energy market. The main modules of the proposed management system are based on Linear Programming models that are used in centralized (for public buildings) and distributed (for residential buildings) approaches.

Future research aims at considering the impact of alternative and distributed energy sources and at taking into account the visual and air-quality comfort.

Index Terms—Building Management Systems, Energy Management, Optimization, Day-Ahead Energy Market.

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I. INTRODUCTION

In recent years, smart and green building management has become one of the main challenges for automation and building construction.

Besides the utilization of renewable energy resources, the necessity to guarantee both high level comfort and power efficiency can be satisfied by adopting new suitable control and management systems. In a smart district context, each building of the district requires high-energy efficiency to reduce energy consumption but, on the other hand, the satisfaction of the indoor environment comfort needs more energy usage [1], [2].

The comfort of the building environment depends generally on three factors: thermal comfort, visual comfort and air-quality comfort. Since the major building energy consumption comes from the heating/cooling systems, it is relevant to optimize the Heating Ventilation and Air-Conditioning (HVAC) system utilization [1]. On the other side, the need to reduce the demand peaks of the utility grid and the energy cost for the customers led to the necessity of saving buildings energy consumption [3]. To reach the objectives of comfort maximization, cost and consumption minimization, the district (building network) has to be managed for purchasing energy into the Day-Ahead Energy Market and for optimal balancing the real-time energy consumptions [4]-[7]. The Day-Ahead Energy Market is a short-term market in which energy prices are computed for the next 24 hours on the basis of energy generations and storages, demand bidding and scheduled bilateral transactions [8]-[15]. In this context, the power offers are the result of a two-side auction where both producers and consumers submit their energy bids (curves of energy price and quantity), by generating significant energy data flows to be appropriately treated [16], [17]. The producers submit supply bids while the consumers submit demand bids by means of a load aggregator. The load aggregator purchases energy for consumers network at more competitive prices than a customer can obtain by work individually [4], [5], [16]. On the basis of the submitted curves, the Independent System Operator (ISO) determines a Market Clearing Price that is the equilibrium price obtained by the intersection of the offer and demand curves and that fixes the day-ahead price of energy. Moreover, once the day-ahead market is closed, the load aggregator operates in real-time to balance the misplacement between the forecasted bids and the actual ones [4], [7], [11], [12]. For these reasons, it is relevant to coordinate the

consumers, both public and private, that belong to the energy district by means of a district manager. In particular, the district manager, like a load aggregator, the day-ahead forecasts the power to be assigned to the buildings. On the basis of the forecasted profiles, the district manager aims at minimizing the energy consumptions in real-time by guaranteeing the comfort and minimizing the costs due to possible misplacement between day-ahead and real-time markets.

This paper focuses on the district energy manager operations that are performed in real-time on the basis of the day-ahead negotiations and the thermal comfort satisfaction.

The district energy management problem is approached in a twofold human centered perspective. First, the power assigned to each building for the HVAC system is optimized in order to guarantee the user's thermal comfort and satisfaction. Second, energy wastes and costs are minimized for public and private users. To this aim, once the day-ahead negotiation establishes the energy costs and profiles of the district, we optimally balance the power consumption by considering both penalties and rewards in real-time.

In order to deal with such a district management problem, we consider the hierarchical architecture of the district energy management that is proposed in [18] and composed of three levels: the District Energy Management System (DEMS), the Building Energy Management Systems (BEMSs) and the home/office level.

The DEMS operates as a load aggregator and energy manager for the district, collects the data about the energy that is consumed by each building and forwards the power profile for the next day to each BEMS, on the basis of the day-ahead negotiation. At the beginning of the next day, each BEMS of the district optimizes its power consumption and cost on the basis of the received DEMS power profile and by respecting the comfort preferences.

Two different cases are considered: i) a centralized approach for public buildings that are centrally managed by a single public authority; ii) a distributed approach for private residential buildings that have to minimize the own energy consumption and costs by pairwise negotiations. Hence, two different approaches for public and private buildings are presented to satisfy the different management objectives: public buildings are managed by a public authority in a centralized way; private buildings are autonomously managed by private users.

Hence, the considered optimization problems are formalized by defining three Linear Programming (LP) problems: the LP problem solved by the BEMS to optimize the power profiles on the basis of the comfort satisfaction and the outdoor temperatures; the LP problem solved by the DEMS to balance the power among the public buildings; the LP problem solved by the BEMS of the private buildings that pairwise minimize the total power costs.

We note that the proposed approach exploits the possibilities of the building automation in order to satisfy the user requirements and satisfaction: the temperature can be remotely monitored in real time and the energy consumption can be adapted to obtain the desired performances.

In order to show the applicability of the proposed approach two case studies are solved in the two different cases: the centralized management for public buildings and the distributed management for residential buildings.

The paper is organized as follows. Section II provides the literature review. Section III presents the district energy management architecture and Section IV specifies the BEMS optimization problems. Moreover, Section V presents the centralized and distributed approaches for the costs redistribution. Sections VI and VII discuss the case studies for the public and private buildings, respectively. Finally, Section VIII summarizes the conclusions and the future works.

II. LITERATURE REVIEW

In the related literature a large number of contributions deals with the optimization of the HVAC energy usage to guarantee the comfort. In particular, some authors address the problem of controlling the heating ventilating and air conditioning system with the purpose of achieving the desired thermal comfort and minimizing the energy spent to comply with it. In this context, Ferreira *et al.* [19] present a predictive control implemented by radial basis function. Moreover, a neural network identifies such a function by a multi-objective genetic algorithm and a branch and bound optimization method to save energy for an HVAC system. Ari *et al.* [20] propose an intelligent modeling approach to individual thermal comfort and energy optimization problem, which aims at minimizing energy consumption and improving thermal environmental conditions for human occupancy, based on fuzzy logic control. Moreover, Du *et al.* [21] present an appliance commitment algorithm that schedules thermostatically controlled household loads based on consumption forecasts. Users' comfort settings are considered to meet optimization objectives such as minimum payment or maximum comfort from a single user point of view.

In addition, in Yang *et al.* [22] a control strategy is proposed to control the HVAC system for maintaining building's indoor environment. The control strategy is based on swarm intelligence technique and it determines the amount of energy dispatched to each equipment in the HVAC system. Nguyen *et al.* [23] develop a home strategy management solution that minimizes the electricity cost and guarantees the user comfort in terms of preferred home temperature. Moreover, Guo *et al.* [24] review thermal comfort based control strategies for commercial buildings with HVAC system. They present the advantages of using better system operations, technologies and control algorithms to HVAC systems that can be operated in an energy saving mode as well as provide a favorable environment to occupants. In the same context, Sun *et al.* [25] present a novel formulation capturing key interactions of the heating, cooling, lighting, shading and ventilation systems to minimize the total daily energy cost. To obtain effective integrated strategies in a timely manner, the authors develop a methodology that combines stochastic dynamic programming and rollout technique within the price-based coordination framework.

Furthermore, some contributions deal with the problem of maintaining HVAC systems in good conditions through early fault detection [26], [27]. In particular, Sun *et al.* [27] present a model-based and data driven method for robust system level fault detection with potential for large-scale implementation.

However, the control strategies and the fault detection methods focus on the home or building energy management and do not consider the complex energy management of sets of buildings connected in a district.

In addition, in the related literature some authors face the problem of the energy management in the day-ahead energy market context [28]-[31]. For instance, Moradzadeh *et al.* [28] present a decentralized optimization of residential energy demand to reduce the cost both for utility and customers by satisfying the customer preferences. A two-stage pricing is proposed to manage the uncertainty of the residential demand. Moreover, Kumaraguruparan *et al.* [29] consider dynamic residential pricing to promote a more efficient use of energy for residential customers. They introduce the multiple knapsack problem to ensure optimal scheduling of appliances. Furthermore, Karami *et al.* [30] adopt a scheduling algorithm for the optimal day-ahead management of distributed energy resources. In particular, combined heat and power plant and energy storage systems are considered in a smart home for the minimization of electricity fee. In Atzeni *et al.* [31] the home energy managers can interact each other to minimize the electricity costs by using cooperative and distributed strategies.

Other contributions face the problem of the building management in the real-time context. Several existing works have studied neighborhoodwise collaborative energy management, though different models and optimization goals are considered [6], [32]. In [33] a heuristic algorithm is proposed for scheduling the load of customers in a neighborhood and in [34] and [35], distributed energy scheduling algorithms, based on game-theoretic approaches, were proposed. In particular, the papers of Chang *et al.* [6], [7] propose a coordinated home energy management architecture composed by home energy units that communicate each other in order to balance the neighborhood demand and supply. Moreover, the authors propose a novel model to represent interruptible appliances such as Plug-in Hybrid Electric Vehicle (PHEV) and adopt a decentralized approach to allow optimal real-time appliances scheduling for each unit. Furthermore, Alizadeh *et al.* [36] propose a methodology to allow the ISO to use time-deferrable loads as a resource to minimize costs, shave the peaks of demand and control the electricity prices.

Summing up, the analyzed literature proposes different techniques, models and methodologies to solve the home energy management problem, mainly referring to deferrable loads such as PHEV and Energy Storage System.

The new contribution of this paper is presenting a novel strategy devoted to the real time management of the power assignment and consumption. We enlighten that the proposed strategy is placed at an intermediate decision level with respect to the main contributions presented in the related literature: after the day-ahead energy market that provides the inputs of the proposed management strategy; before the HVAC system control that uses the parameters in output of the proposed procedure to maintain the indoor comfort.

Furthermore, with respect to the contributions about the energy management real-time coordination, the proposed strategy exhibits three advantages: i) considering both public and private building networks; ii) solving in real time efficient optimization problems (LP problems) both in centralized and distributed approaches; iii) simultaneously satisfying the requirements of thermal comforts by minimizing the power consumption and costs.

III. DISTRICT ENERGY MANAGEMENT ARCHITECTURE

In this section we present the three levels hierarchical architecture for the management of the district energy network. In particular, the levels of the management structure are shown in Fig. 1: the district, the building, and the office/home levels.

The District Energy Management System (DEMS) monitors the buildings energy consumption and interacts with every Building Energy Management System (BEMS) to optimize the use of energy and maximize the user's comfort. To this aim, the DEMS receives the building power consumption from the BEMSs and stores it in the database module. Then, the DEMS negotiates the power costs at the day-ahead market and sends the power profile of the next day to each BEMS that has to respect the received energy target.

A smart metering system allows the two-way communication between the BEMS and the measurement and actuation system. The last level of the management architecture is constituted of sensors and actuator devices that receive commands from the BEMS in order to control the electric loads.

In the following we describe in detail the district control strategy performed thank to the interaction among the BEMSs, the DEMS and the external environment.
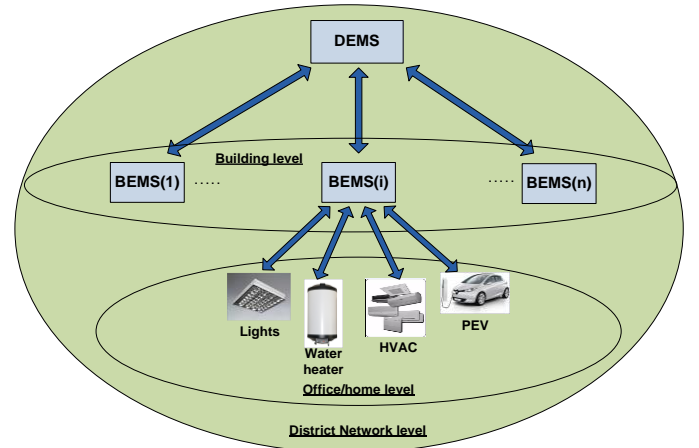

Figure 1. The district energy management architecture.

A. District Management Strategy

In this section we describe the conceptual structure of the district control strategy and the connections among DEMS, BEMS and home measurement and actuation systems both in public and in residential buildings.

Typically, the DEMS is composed of three modules: a data base module, an energy module and an optimization module (see Fig. 2).
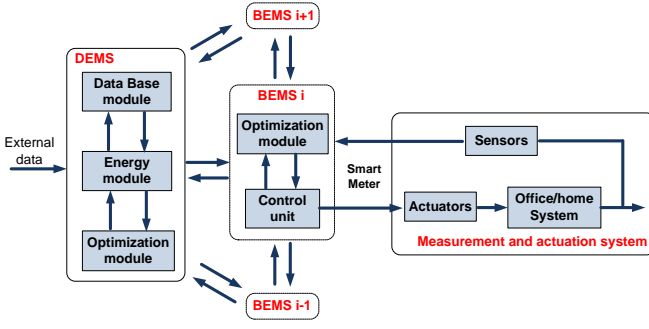
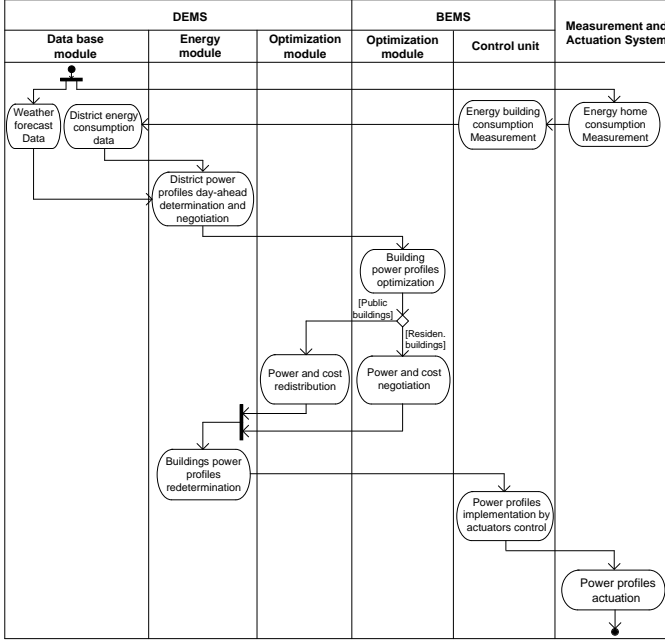Figure 2.   The district management structure.

Figure 3.   The UML activities diagram of the district management system.

Moreover, in order to give a description of the district management system activities and actions and in particular how the DEMS modules interact with the BEMS and the office/home devices, we use the Unified Modeling Language (UML) activity diagram shown in Fig. 3. Indeed, the UML activity diagram is a graphic and textual modeling language intended to understand and describe systems from behavioral viewpoints [37]. In particular, the use of the swim lanes in the activity diagrams allows easily showing, which part of the system is responsible in each phase of the activities. Fig. 3 shows that the district management system activities start when the data base of the DEMS receives information about the weather forecasts, the power consumption and production (the renewable energy, the energy storage, etc.) from each building. Hence, the DEMS collects the data about the energy consumed by each building and determines an historical database to foresee the future consumption and production. Moreover, the DEMS energy module communicates with the data base module, determines for each building the necessary power profile and negotiates it within the energy market.

This paper specifies the optimization modules of the BEMS and the DEMS devoted to determine the power profile of each building. More precisely, referring to Fig. 3 we solve the three problems relative to the three activities appearing in the lanes labeled "Optimization module" in the UML activity diagram:

"Building power profiles optimization", "Power and cost redistribution" and "Power and cost negotiation".

In particular, the "Building power profiles optimization" module receives from the DEMS the power profile and optimizes its power consumption in order to minimize the costs on the basis of the specific building comfort necessities. Moreover, if a building saves energy with respect to the power amount forecasted by the DEMS, then it receives some rewards. On the contrary, penalties are assigned to the buildings that consume more energy. In addition, different electricity prices at different daily time slots are considered.

At this point, we present two different procedures for public and residential buildings, respectively.

The public buildings send the power consumptions to the DEMS that re-calculates the buildings power profiles by minimizing the total district costs. To this aim the DEMS includes also the "Power and cost redistribution" module that updates the values of the building energy powers in order to balance the provided energy with the different buildings requests. Fig. 2 shows the scheme of the district control strategy for public buildings and the information exchanged among them.

Moreover, we consider the possibility of applying a distributed management strategy to the residential buildings that could prefer to decide and bargain autonomously the power costs. To this aim, we present a distributed "Power and cost negotiation" module: pairs of buildings may negotiate power and costs in order to reach a common decision. We enlighten that in this case the energy cost optimization is performed by the BEMS only.

Finally, the BEMS control unit applies the appropriate commands to the home/office actuators.

IV. BEMS Optimization Module Specification

This section specifies the optimization problem that is solved by the buildings belonging to a district described by the set $B = \{b_1, ..., b_K\}$ of K buildings. In this paper we deal with the heating demand by pointing out that the cooling problem can be solved with few changes in a similar way.

Since the public buildings have the common interest of reducing their overall energy costs, they can use a centralized energy management. On the contrary, the residential building manager needs to optimize the power consumption of each building in a decentralized approach.

We assume that the day is divided in N time slots. The DEMS provides the district power profile $P(t)$ (for $t = 1, ..., N$) that is forecasted to satisfy the heating demand of the next day, and distribute it to the BEMSs. At this point two cases are considered:

1) *public buildings*: the DEMS initially assigns the same power profile $P_D(t)$ for $t = 1, ..., N$ to each public building.

2) *residential buildings*: the DEMS initially assigns to each building a suitable power profile $P_D(t)$ on the basis of the historical data about its consumptions.

Note that the initial assignment could be the same for all the public buildings since the public manager will reduce the overall costs by the successive DEMS centralized

optimization. On the contrary, the DEMS has to assign to each residential building its own power profile so that the BEMS will autonomously negotiate the energy for the cost reduction.

Hence, in the next subsections we consider the following three optimization problems.

First, the DEMS optimizes the power profiles of the buildings (public and residential) in order to minimize the costs on the basis of the specific building comfort necessities. To this aim rewards and penalties are assigned to the BEMS that respectively saves power or consumes more energy with respect to the power amount forecasted by the DEMS.

Second, considering the public buildings, the DEMS solves a second optimization problem and modifies the power profiles by minimizing the penalties obtained by the BEMSs and reducing the rewards received by other buildings.

On the other hand, the BEMSs of the residential buildings solve local optimization problems with neighbor buildings in order to autonomously negotiate powers and costs and reach a common decision.

A. BEMS optimization problem

Each day the BEMSs of the district (public and residential) buildings receive from the DEMS N values of the forecasted outdoor temperature $T_{out}(t)$ (for $t = 1, ..., N$) and the thermal power $P_D(t)$ (for $t = 1, ..., N$).

Each BEMS knows the value of the initial indoor temperature $T_{in}(0) = T_{start}$ and determines for each time slot the indoor temperature $T_{in}(t)$ (for $t = 1, ..., N$) that guarantees the thermal comfort. Moreover, the BEMS has to calculate the power $P_B(t)$ (for $t = 1, ..., N$) necessary to obtain the requested temperature $T_{in}(t) \geq T_{set}$ (for $t = 1, ..., N$). Note that the temperature T_{set} is the set point chosen by the building manager on the basis of the standard thermal comfort indices, according to the ASHRAE standard thermal sensation scale [38], [39]. Moreover, $T_{in}(t)$ can be major than T_{set} in order to compensate the time slots in which the power $P_D(t)$ is not sufficient to satisfy the condition $T_{in}(t) \geq T_{set}$, by exploiting the thermal gradient. This approach guarantees the thermal comfort at each time slot.

In this paper we refer to the Predicted Mean Vote (PMV) index and the Predicted Percentage of Dissatisfied (PPD) index that can be obtained from the PMV. In particular, the PMV predicts the thermal sensation for the human body on the basis of in-door temperature, mean radiant temperature, air velocity and air humidity, while the PPD provides information on the thermal discomfort or dissatisfaction [39].

Typical values of PMV and PPD are $-0.5 \leq PMV \leq +0.5$ and $PPD \leq 10\%$ [40], respectively.

The main objective of the BEMS optimization module is minimizing the cost of the power that will be consumed by the building during the next day, guaranteeing the customer comfort.

The following formula determines the evolution of the indoor temperature $T_{in}(t)$ at each time t on the basis of the outdoor temperature $T_{out}(t)$ and the thermal power $P_B(t)$ [41]:

$$T_{in}(t) = T_{in}(t-1) + \alpha\big(T_{out}(t) - T_{in}(t-1)\big) + \beta P_B(t), \text{ for } t = 1, ..., N. \tag{1}$$

where α and β are parameters that specify the thermal characteristic and the environment: $\beta > 0$ refers to the heating mode, $\beta < 0$ refers to the cooling mode. Moreover, the term $\alpha(T_{out}(t) - T_{in}(t-1))$ of (1) models the heat transfer and $\beta P_B(t)$ models the thermal efficiency of the system.

The decision variables of the BEMS optimization module are the powers $P_B(t)$ for $t = 1, ..., N$.

In order to formulize the optimization problem, we introduce vector $\boldsymbol{\theta} \in \mathbb{R}^N$ that is defined as follows:

$$\theta(t) = P_B(t) - P_D(t), \text{for } t = 1, ..., N. \tag{2}$$

Furthermore, recalling that the electricity supply has different prices at different daily time slots, we introduce the following vectors $\boldsymbol{a} \in \mathbb{R}^N$, $\boldsymbol{b} \in \mathbb{R}^N$ and $\boldsymbol{c} \in \mathbb{R}^N$, whose corresponding elements are defined as follows: $a(t)$ for $t = 1, ..., N$ is the power cost factor (in €/kWh) and represents the $P_B(t)$ price; $b(t)$ for $t = 1, ..., N$ is the penalty cost factor (in €/kWh) that penalizes the building for exceeding $P_D(t)$ at time t ($\theta(t) > 0$); $c(t)$ for $t = 1, ..., N$ is the reward cost factor (in €/kWh) that rewards the building that saves energy by respecting the comfort ($\theta(t) < 0$) at time t.

Let us assume $b(t) \geq c(t)$ for $t = 1, ..., N$: i.e., the penalty factors $b(t)$ are equal or greater than the reward factors $c(t)$ at each time step t.

The optimization objective aims at minimizing the sum of three costs: $a(t)P_B(t)$ (€) that represents the cost of the thermal power at time t, $b(t)\theta(t)$ (€) (when $\theta(t) > 0$) that is the penalty cost for exceeding the DEMS power threshold, and $c(t)\theta(t)$ (€) (when $\theta(t) \leq 0$ – a negative cost) that quantifies the reward cost for the power savings.

Now, the following Linear Programming (LP) problem is defined as:
LP1

$$\min \sum_{t=1}^{N} [a(t)P_B(t) + c(t)\theta(t) + y(t)(b(t) - c(t))] \tag{3a}$$

s.t.

$$\begin{cases} T_{in}(0) = T_{start} & (3b) \\ T_{in}(t) - (1-\alpha)T_{in}(t-1) - \beta P_B(t) \geq \alpha T_{out}(t), t = 1, .., N & (3c) \\ T_{in}(t) \geq T_{set} \text{ for } t = 1, ..., N & (3d) \\ y(t) \geq \theta(t), y(t) \geq 0, \text{for } t = 1, ..., N & (3e) \\ P_B(t) \geq 0, T_{in}(t) \geq 0, \text{for } t = 1, ..., N & (3f) \end{cases}$$

where the non negative vector $\boldsymbol{y} \in \mathbb{R}^N$ is an auxiliary variable. Since $b(t) \geq c(t)$ and the objective function (3a) has to be minimized, constraints (3e) imply at optimality the following conditions:

$$y(t) = \theta(t) \text{ if } \theta(t) > 0, \text{for } t = 1, ..., N,$$

$$y(t) = 0 \quad \text{ if } \theta(t) \leq 0, \text{for } t = 1, ..., N.$$

Moreover, constraint (3b) assigns the initial temperature value and constraints (3c) determine the indoor temperatures according to (1). The set-point T_{set} is imposed as the lower bound for $T_{in}(t)$ for $t = 1, ..., N$ by constraint (3d).

Hence, when $\theta(t) > 0$ (i.e. the building power exceeds $P_D(t)$ at time t the objective function is

$\min \sum_{t=1}^{N}[a(t)P_B(t) + b(t)\theta(t)]$ and the objective is minimizing the sum of power and penalty costs. On the contrary, at time t, when $\theta(t) \leq 0$, the objective function is $\min \sum_{t=1}^{N}[a(t)P_B(t) + c(t)\theta(t)]$ and the objective is minimizing the difference of power and reward costs.

Finally, we remark that the assumption $b(t) \geq c(t)$ for $t = 1, ..., N$ is not really restrictive: the case $b(t) < c(t)$ can be managed as well with obvious modifications of the optimization problem formulation. Hence, for the sake of the simplicity, we assume in the sequel of the paper $b(t) \geq c(t)$.

V. BALANCING OF PENALTIES AND REWARDS

A. Centralized Optimization Problem for Public Buildings

The DEMS receives from the K district BEMSs the solutions of the K LP1 problems (3 a-f): the optimum values of the powers $P_B^i(t)$ for $t = 1, ..., N$ and the vectors $\boldsymbol{\theta^i} \in \mathbb{R}^N$ (with $\theta^i(t) = P_B^i(t) - P_D^i(t)$ for $t = 1, ..., N$) associated with each building $b_i \in B$.

At this point, the DEMS aims at minimizing the penalties obtained by the BEMSs by possibly reducing the rewards received by some buildings. To this aim, the DEMS can reduce or increase the power $P_D^i(t) = P_D(t)$, that it has initially assigned to $b_i \in B$, on the basis of the values $P_B^i(t)$ optimized by the BEMS of b_i. Hence, the DEMS determines a common value $\theta_n(t) = P_B^i(t) - P_{D\_opt}^i(t)$ for all the public buildings $b_i \in B$ for each time $t = 1, ..., N$, where $P_{D\_opt}^i(t)$ is the new power that the DEMS has to assign to the BEMS at time t.

The following LP problem minimizes the total cost of the district power by balancing the penalties with the rewards assigned to the buildings.

LP2

$$\min \sum_{t=1}^{N}[c(t)\theta_n(t) + y(t)(b(t) - c(t))] \quad (4a)$$

s.t.

$$\begin{cases} K\theta_n(t) = \sum_{i=1}^{K}\theta^i(t) \ , \forall t = 1, ..., N & (4b) \\ \\ y(t) \geq \theta_n(t) \ , \text{for } t = 1, ..., N & (4c) \\ y(t) \geq 0 \ , \text{for } t = 1, ..., N & (4d) \end{cases}$$

The objective function $(4a)$ minimizes the total penalties and maximizes the total rewards of the K BEMSs in the N time slots.

The constraints $(4b)$ impose that the sum of the total power penalties and rewards remains constant for each $t = 1, ..., N$. Hence, constraint $(4b)$ guarantees that the penalties and rewards are equal for all the buildings in the district.

The non-negative vector $\boldsymbol{y} \in \mathbb{R}^N$ is an auxiliary variable that by constraints $(4c$-$d)$ implies at the optimality the following conditions:

$y(t) = \theta_n(t)$ if $\theta_n(t) > 0$,
$y(t) = 0$ if $\theta_n(t) \leq 0$.

Note that the LP2 problem can be decomposed in N independent LP problems.

Then, on the basis of the LP2 solution, the energy module of the DEMS modifies the values of the powers $P_D^i(t)$ assigned to the BEMSs and determines the new power $P_{D\_opt}^i(t)$ according to the following relation:

$$P_{D_{opt}}^i(t) = P_D^i(t) + \theta^i(t) - \theta_n^*(t), \text{for } i = 1, ..., K, t = 1, ..., N, \quad (5)$$

where $\theta_n^*(t)$ is the optimal solution of LP2.

The DEMS adjusts the values of the power assigned to each building $b_i \in B$, by adding the gap between $\theta^i(t)$ and $\theta_n^*(t)$ for $t = 1, ..., N$.

B. Distributed Optimization Problem for Residential Buildings

In this section we consider a district composed by a set $B = \{b_1, ..., b_K\}$ of K residential buildings. After the power optimization and the determination of penalties and/or rewards, each residential building can bargain with the other buildings the cost reduction.

To this purpose, each BEMS selects a subset of buildings with which it intends to perform the energy negotiation. Then the communication among the BEMS is described by an indirect and connected graph $G_c = (B, E)$ where B indicates the set of nodes (the buildings) and E is the set of edges. If edge $e_{ij} \in E$ then building $b_i \in B$ can communicate with building $b_j \in B$.

We denote by $CB_i \subseteq B$ the set of buildings with which b_i can communicate, i.e., $CB_i = \{b_j \in B : e_{ij} \in E\}$. We denote by $\theta^i(t) = P_B^i(t) - P_D^i(t)$ for $t = 1, ..., N$ the elements of vector $\boldsymbol{\theta^i} \in \mathbb{R}^N$ associated with $b_i \in B$ and by $\boldsymbol{\theta_n^i} \in \mathbb{R}^N$, the new vector of elements $\theta_n^i(t)$ for $t = 1, ..., N$ obtained after the negotiation.

In order to distinguish between the powers that enjoy rewards and the powers that have penalties, the following variables are defined for $t = 1, ..., N$:

$x^i(t) = \theta^i(t)$ if $\theta^i(t) > 0$ else $x^i(t) = 0$
$z^i(t) = -\theta^i(t)$ if $\theta^i(t) \leq 0$ else $z^i(t) = 0$
$x_n^i(t) = \theta_n^i(t)$ if $\theta_n^i(t) > 0$ else $x_n^i(t) = 0$
$z_n^i(t) = -\theta_n^i(t)$ if $\theta_n^i(t) \leq 0$ else $z_n^i(t) = 0$.

Hence, $b(t)x^i(t)$ are the penalty costs and $c(t)z^i(t)$ are the reward costs.

Now, each building $b_i \in B$ performs a negotiation with a building $b_j \in CB_i$ chosen at random. The objective of the negotiation is minimizing the total costs of the two buildings $b_i, b_j \in B$ involved in the optimization. However, since the two residential buildings want to keep their earning, each BEMS agrees to divest a reward at one time slot if it can receive the same value of the reward at a different time slot.

The new elements $\theta_n^i(t)$ and $\theta_n^j(t)$ for $t = 1, ..., N$ are obtained by b_i and b_j by solving the following LP problem:

LP3

$$\min \sum_{t=1}^{N} [b(t)(x_n^i(t) + x_n^j(t)) - c(t)(z_n^i(t) + z_n^j(t))] \quad (6a)$$

s.t.

$$\begin{cases} x_n^j(t) - z_n^i(t) = x^j(t) - z^i(t), \text{ for } t = 1, \dots, N & (6b) \\ x_n^i(t) - z_n^j(t) = x^i(t) - z^j(t), \text{ for } t = 1, \dots, N & (6c) \\ \sum_{t=1}^{N} b(t)(x_n^j(t) - x^j(t)) - c(t)(z_n^j(t) - z^j(t)) = \\ = \sum_{t=1}^{N} b(t)(x_n^i(t) - x^i(t)) - c(t)(z_n^i(t) - z^i(t)) & (6d) \\ x_n^i(t) \le x^i(t), \text{ for } t = 1, \dots, N & (6e) \\ x_n^j(t) \le x^j(t), \text{ for } t = 1, \dots, N & (6f) \\ z_n^i(t) \le z^i(t), \text{ for } t = 1, \dots, N & (6g) \\ z_n^j(t) \le z^j(t), \text{ for } t = 1, \dots, N & (6h) \\ x_n^i(t), z_n^i(t), x_n^j(t), z_n^j \ge 0, \text{ for } t = 1, \dots, N & (6i) \end{cases}$$

The objective function (6a) minimizes the total costs of buildings $b_i, b_j \in B$ involved in the optimization.

The constraints (6b) impose that the gap between the total penalties of b_j and the total rewards of b_i does not change for $t = 1, \dots, N$ after the optimization. Analogously, (6c) imposes that the gap between the total penalties of b_i and the total rewards of b_j remains the same for $t = 1, \dots, N$. Moreover, the constraint (6d) imposes that the gap between the total costs of b_i and b_j does not change after the optimization. The constraints (6e-6f) and (6g-6h) impose that penalties and rewards, respectively, of b_i and b_j do not increase after the negotiation. Hence, constraints (6b-6h) guarantee the fairness of penalties and rewards. Note that constraint (6d) imposes that the reduction of power cost between two private users is always the same during the negotiation. Obviously, such a constraint is not necessary for public buildings where the common objective is the minimization of the total power cost of the buildings in the district.

The following result proves that each building would not improve the power costs if negotiating a second time with the same building.

Proposition 1: Let us consider a set $B = \{b_1, \dots, b_K\}$ of K residential buildings. If a pair of buildings negotiates the power rewards and penalties by solving a LP3 problem, then a second negotiation among them does not modify their rewards and penalties.

Proof: Let us assume that the buildings $b_i, b_j \in B$ optimize their power costs by solving the LP3 problem. After the execution of the LP3 problem, one of the two buildings cannot exchange further rewards with the other one. Then one of the two buildings (say b_i) is in one of the following conditions: i) $z_n^i(t) = 0$ for $t = 1, \dots, N$, i.e., all the rewards of b_i are equal to zero; ii) there exists at least a time instant $\bar{t}$ such that $z_n^i(\bar{t}) > 0$, and the penalty at the same time of building b_j is equal to zero, i.e. $x_n^j(\bar{t}) = 0$.

Now, let us assume that the two buildings b_i and b_j are chosen at random a second time and optimize again their costs

by solving LP3. The rewards $z_n^i(t)$ cannot be increased because the constraints (6g-6h) impose that rewards of b_i and b_j do not increase after the negotiation. On the other hand, the penalties $x_n^j(\bar{t})$ cannot increase because of constraints (6e-6f). This proves that the second negotiation between b_i and b_j does not modify their rewards and penalties. ∎

The following procedure is applied for the distributed optimization: the idea is that each building has to negotiate the power costs with all its neighbors one and only one time.

Algorithm 1:
Step 1. Set $AB = B$, $ACB_i = CB_i$ for $i = 1, \dots, K$
Step 2. **Select at random** $b_i \in AB$
Step 3. **Select at random** $b_j \in ACB_i$.
Step 4. *Negotiation between pairs of buildings*
  Solve LP3.
Step 5. *Updating of the sets AB, ACB_i and ACB_j*
  Set $ACB_i = ACB_i - \{j\}$, $ACB_j = ACB_j - \{i\}$
  if $ACB_j = \emptyset$ then set $AB = AB - \{j\}$
Step 6. If $ACB_i \ne \emptyset$ **then go to Step 3**
  else set $AB = AB - \{i\}$
Step 7. If $AB \ne \emptyset$ **then go to Step 2.**
Step 8. End

A random building $b_i \in B$ begins the negotiation with a neighbor building $b_j \in CB_i$ chosen at random. At step 5 the auxiliary sets AB, ACB_i and ACB_j are updated: b_j is deleted from ACB_i and b_i is deleted from ACB_j because only one negotiation between b_i and b_j is allowed. Moreover, b_i selects at random a neighbor building till the set ACB_i is empty. If ACB_i is empty then b_i can not negotiate with any other building and it is cancelled from the set AB.

The procedure goes to an end when each building has negotiated with all the neighbors for only one time (i.e., the set AB is empty). Hence, a number of $\frac{K(K-1)}{2}$ LP3 problem solutions between pairs of neighbor buildings are necessary.

Finally, each building sends the new profiles of penalties and rewards to the DEMS that determines the new power $P_{D\_opt}^i(t)$ according to equation (5).

VI. CASE STUDY FOR PUBLIC BUILDINGS

In this section a real case study is presented to show the effectiveness of the DEMS and BEMS optimization modules for public buildings. To this purpose, we consider a district composed by $K = 10$ public buildings of Bari, a town of the South of Italy.

In order to collect data for the parameters identification, two temperature sensors are installed for inside and outside measurements, respectively. Moreover, we measure the HVAC heating power consumptions. The experiment to determine α and β parameters of equation (1) is performed according to the following procedure:

  1. we collect a set of H indoor and outdoor temperatures and power measures;

2. on the basis of the collected measures, we identify the parameters α and β by minimizing the following function according to the least squares method:

$$\sum_{t=1}^{H} \left[T_{in}(t) - \left(T_{in}(t-1) + \alpha\left(T_{out}(t) - T_{in}(t-1) \right) + \beta P_B(t) \right) \right]^2$$

The experiment results are summarized in Table I.

TABLE I.

PARAMETERS α, β AND INITIAL TEMPERATURE OF THE BUILDINGS

Building	α	β	$T_{in}(0)[°C]$
1	0.120	1×10^{-3}	17.0
2	0.125	9×10^{-4}	17.5
3	0.110	9.5×10^{-4}	16.5
4	0.134	1.2×10^{-3}	17.0
5	0.120	8.5×10^{-4}	18.0
6	0.130	8.8×10^{-4}	17.5
7	0.100	9.8×10^{-4}	18.0
8	0.117	7×10^{-4}	17.0
9	0.128	7.5×10^{-4}	18.0
10	0.122	1.2×10^{-3}	17.0

*A. Power optimization performed by the BEMSs*

The heating mode of the HVAC system is considered. We choose $T_{set} = 20°C$ as comfort set-point that corresponds to $PMV = -0.5$ and $PPD = 10\%$. In addition, the vectors $\boldsymbol{a}$, $\boldsymbol{b}$ and $\boldsymbol{c}$ are set as follows: $a(t) = 8 \times 10^{-3}$, $b(t) = 7 \times 10^{-3}$ and $c(t) = 1 \times 10^{-3}$ for $t = 1, \dots, N$.

In the considered case study we compute $N = 15$ time slots, i.e, we study a period of 15 hours (from 6 a.m. till 9 p.m. of a winter day).

For the sake of brevity, we discuss and depict the responses of three buildings that represent three different conditions with diverse values of α and β: b_1, b_4 and b_8. Fig. 4 shows the profile proposed by the DEMS and the profiles obtained by the LP1 problem solution of b_1, b_4 and b_8. Note that the power profile of b_4 does not exceed the DEMS threshold: the b_4 power is sufficient to satisfy the thermal comfort thanks to the thermal efficiency of its HVAC system and the good initial temperature value. Moreover, Fig. 5 shows the cumulative increase of penalties and rewards during the day. Then no penalty is applied during the day to b_4 that receives only rewards as Fig. 5 shows. On the contrary, b_1 receives both rewards and penalties while b_8 suffers penalties for most of the day. Thus, the HVAC system of b_8 results to be inefficient: the initial condition does not allow satisfying the thermal comfort and suffers high penalties.

Fig. 5 points out that b_8 is the most penalized building (74.73 €/day) and receives very few rewards (0.43 €/day). On the contrary, b_1 receives a reward of 3.24 €/day and a penalty of 13.73 €/day and b_4 receives the highest amount of rewards (6.89 €/day) and no penalty.
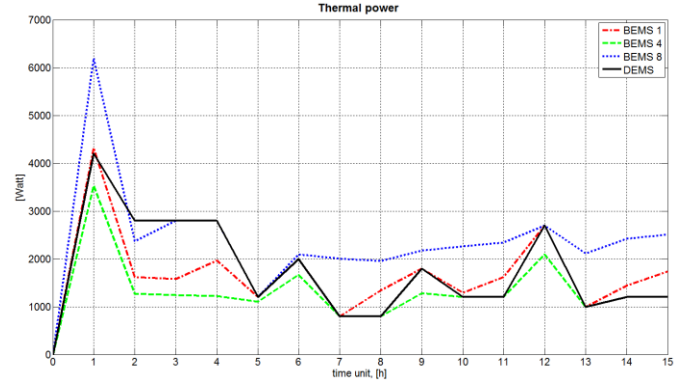
Figure 4. The optimized thermal power profiles of buildings b_1, b_4 and b_8.
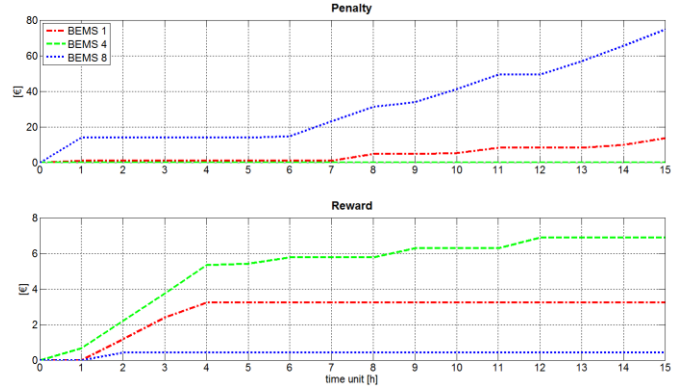
Figure 5. Cumulative reward and penalty profiles of buildings b_1, b_4 and b_8.

In addition, Fig. 6 shows the effectiveness of comfort satisfaction of b_1 by comparing the indoor temperature, the PMV and the PPD that are obtained by the optimization with the considered set points. We point out that in some situations in which the DEMS power is not sufficient to satisfy the comfort, the optimization module tends to slightly increase the indoor temperature over the set point in order to increase the PMV and decrease the PPD to satisfy the set-points at each time slot.
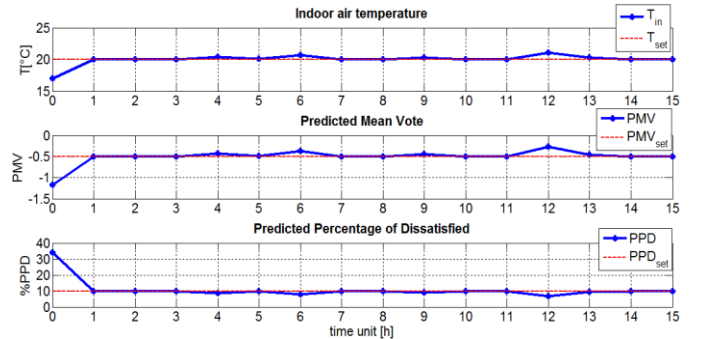
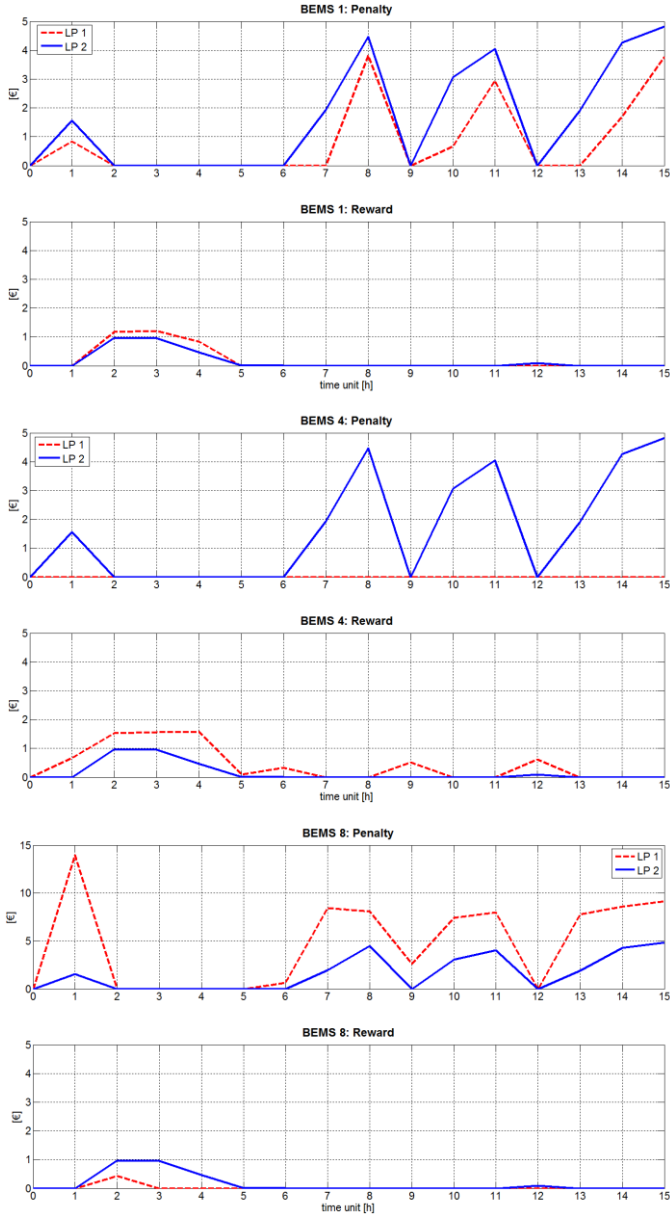Figure 6. T_{in}, PMV and PPD of b_1 obtained by the optimization.

Figure 7.　Rewards and penalties comparison after BEMS and DEMS optimization.

Figure 8.　Comparison of the initial DEMS power profile, the new DEMS profile, and the BEMS profile.

B. Power and cost redistribution for public buildings

The BEMSs send the resulting values of rewards and penalties to the DEMS optimization module that solves the LP2 problem. Fig. 7 shows the LP2 solutions by considering again b_1, b_4 and b_8. In particular, the penalties of b_1 and b_4 increase and the rewards decrease in order to reduce the district total cost. On the contrary, the b_8 penalties decrease.

Fig. 8 compares the new DEMS power profile $P_{D\_opt}^i$ with P_D^i and P_B^i of b_1, b_4 and b_8. We remark that at time $t = 1$ the value of P_D^4 is reduced by the DEMS because it loses the reward.

TABLE II.

BEMS OPTIMIZATION RESULTS

Building	Penalty [€/day]	Reward -[€/day]	Cost [€/day]
1	13,73	3,24	10,49
2	20,81	2,38	18,43
3	27,18	2,14	25,04
4	0,00	6,89	-6,89
5	29,90	1,98	27,92
6	21,31	2,43	18,88
7	22,35	2,63	19,72
8	74,73	0,43	74,3
9	71,63	0,18	71,45
10	0,00	5,73	-5,73
Total[€]	**281,65**	**28,02**	**253,63**

TABLE III.

DEMS OPTIMIZATION RESULTS

Building	Penalty [€/day]	Reward -[€/day]	Cost [€/day]
1	26,07	2,50	23,57
2	26,07	2,50	23,57
3	26,07	2,50	23,57
4	26,07	2,50	23,57
5	26,07	2,50	23,57
6	26,07	2,50	23,57
7	26,07	2,50	23,57
8	26,07	2,50	23,57
9	26,07	2,50	23,57
10	26,07	2,50	23,57
Total [€]	**260,65**	**25,02**	**235,63**

On the contrary, at time $t = 1$ the value of $P_{D\_opt}^8$ of b_8 is greater than the corresponding value of P_D^8, because it takes advantage from the reduction of the rewards of other BEMSs.

Tables II and III summarize for each building the power costs that BEMSs and DEMS forecast for the next day, before and after the DEMS optimization, respectively. More precisely, the first and second columns of Tables III and IV report the sum of the penalty costs ($\sum_{t=0}^{15} b(t)\theta^i(t), \theta^i > 0$) and the reward costs ($\sum_{t=0}^{15} c(t)\theta^i(t)$) of b_i, for $i = 1 \dots K$. Moreover, the last columns of Tables III and IV reports the costs (difference between penalties and rewards) after BEMS and DEMS optimization, respectively. The final result is that the total cost is reduced of 10% thanks to penalties and rewards compensation.

We solve the LP1 and LP2 problems by a standard solver, i.e., GNU Linear Programming Kit [42] by using an Intel-Core i7-4770 CPU at 3.40 GHz, with 16GB RAM. The performed tests are solved in few seconds.

VII. CASE STUDY FOR RESIDENTIAL BUILDINGS

In this section a real case study is presented to show the effectiveness of the BEMS optimization module applied to a district B composed by $K = 5$ residential buildings of Bari (Italy).

We repeat the experiments described in Section IV to identify the parameters α, β and the initial temperature. The results are summarized in Table IV.

TABLE IV.

PARAMETERS α, β AND INITIAL TEMPERATURE OF THE BEMSs

Building	α	β	$T_{in}(0)[°C]$
1	0.270	1×10^{-3}	17.5
2	0.250	1.2×10^{-3}	18.0
3	0.275	1×10^{-3}	18.5
4	0.258	1.3×10^{-3}	18.5
5	0.264	1×10^{-3}	18.0

A. Power optimization performed by the BEMSs

The heating mode of the HVAC system is considered. The temperature set-point T_{set}, and the vectors a, b and c are set as in Section V.A, for each building. Moreover, we consider $N = 15$ time slots, i.e, we study a period of 15 hours (from 6 a.m. till 9 p.m. of a winter day).
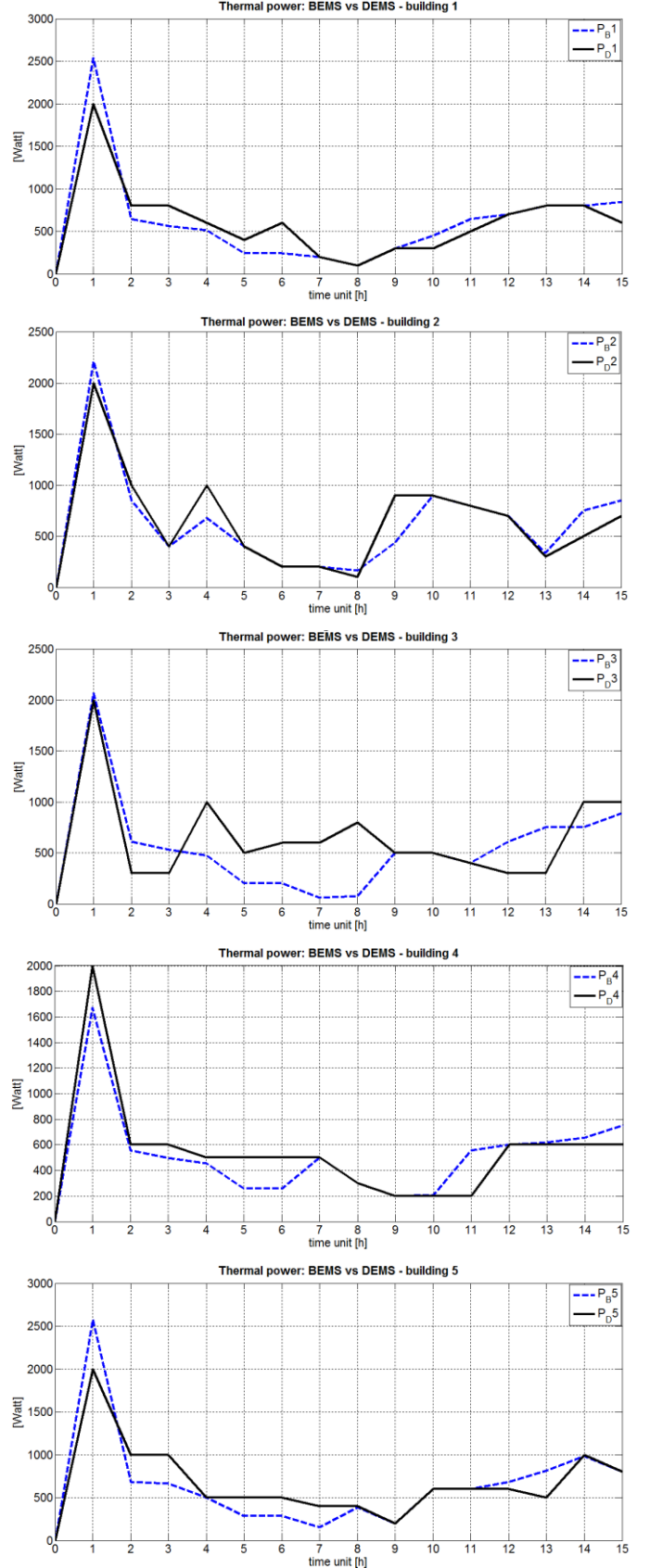

Figure 9.   The optimized thermal power profiles of each building $b_i \in B$.
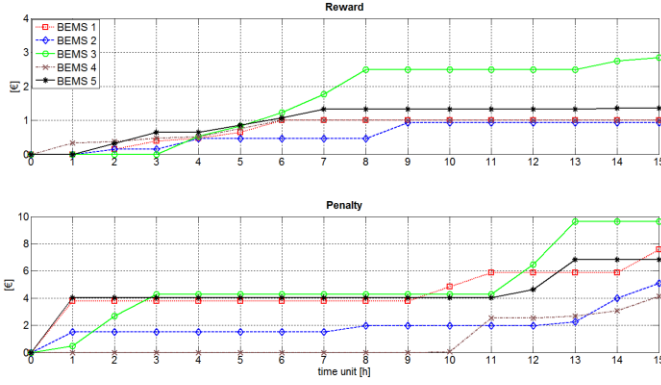
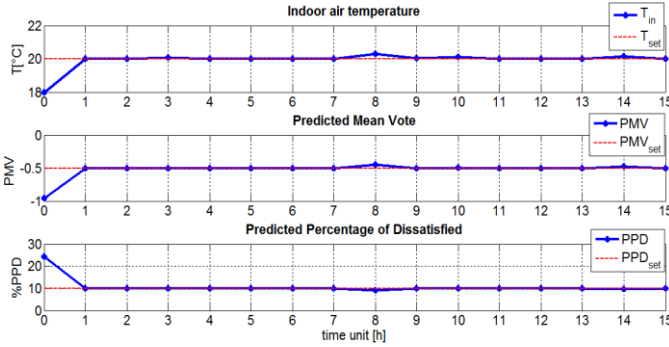Figure 10. Cumulative reward and penalty profiles for the five BEMSs.

Figure 11. T_{in}, PMV and PPD of b_5.

Fig. 9 shows the power profile proposed by the DEMS and the profiles obtained by the LP1 problem solution of each building $b_i \in B$.

Fig. 10 shows the cumulative increase of penalties and rewards obtained from the LP1 problem solutions performed by each $b_i \in B$. In this situation all the BEMSS receive both rewards and penalties during the day: b_3 is the most penalized building (9.63 €/day) and receives the highest reward (2.85 €/day); b_1 obtains 7.57 €/day of penalty and 1 €/day of reward; b_2 receives 5.08 €/day of penalty and 0.93 €/day of reward; b_4 obtains 4.14 €/day of penalty and 1 €/day of reward and b_5 receives 6.83 €/day of penalty and 1.35 €/day of reward.

In addition, Fig. 11 shows the effectiveness of the comfort satisfaction of b_5 by comparing the indoor temperature, the PMV and the PPD that are obtained by the optimization with the considered set points.

B. Power and cost redistribution by the distributed approach

In this section we show the effectiveness of the application of the distributed approach for the cost redistribution performed by the set $B = \{b_1, ..., b_5\}$ of residential buildings.

Each BEMS selects a subset of buildings with which it intends to perform the cost negotiation. In the presented scenario, the communication among the BEMSs is described by the indirect and connected graph $G_c = (B, E)$ shown in Fig. 12. According to G_c, the following subsets are

defined: $CB_1 = \{2,3,5\}$, $CB_2 = \{1,3\}$, $CB_3 = \{1,2,4\}$, $CB_4 = \{3,5\}$, $CB_5 = \{1,4\}$.
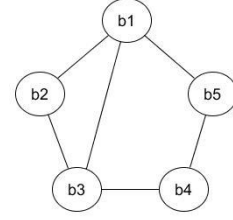
Figure 12. The indirect and connected graph G_c

In the following we describe the main steps of Algorithm 1 performed during the first negotiation.

At **Step 2** b_3 is selected at random and at **Step 3** $b_1 \in CB_3$ is selected at random. Then LP3 is solved by b_3 and b_1. The results are shown in Table VI.

TABLE V.

BEMS OPTIMIZATION RESULTS FOR b_3 AND b_1

| Time [h] | Power optimization | | | |
| | b_3 | | b_1 | |
	Penalties [W/h]	Rewards [W/h]	Penalties [W/h]	Rewards [W/h]
1	70	0	540	0
2	313	0	0	155
3	230	0	0	236
4	0	525	0	90
5	0	300	0	160
6	0	400	0	360
7	0	537	0	0
8	0	725	0	0
9	0	0	0	0
10	0	0	152	0
11	0	0	145	0
12	313	0	0	0
13	450	0	0	0
14	0	250	0	0
15	0	113	244	0
Total W/h	1375	2850	1081	1001

Table V shows the LP1 problem results performed by the BEMS optimization modules of b_3 and b_1. Table VI shows the results of LP3 problem performed by b_3 and b_1. In particular, the first column indicates the times (starting from $t = 1$), the second and third columns report penalties and rewards of b_3 respectively, and the last columns report penalties and rewards of b_1. Comparing Table V and VI, we remark that two power exchanges of 113 W occur at $t = 2$ and $t = 15$. Let us remark that no other equal power exchanges are possible between the considered pair at other time instants t. The total savings after the negotiation is 0,68 € both for b_3 and b_1 and are computed as follows:

$$b\big(x_n^1(2) - x^1(2)\big) - c\big(z_n^1(2) - z^1(2)\big) =$$
$$= b\big(x_n^3(15) - x^3(15)\big) - c\big(z_n^3(15) - z^3(15)\big) = 0,68 \, €.$$

TABLE VI.

NEGOTIATION RESULTS OF b_3 AND b_1

Power negotiation results at the first step				
	b_3		b_1	
Time [h]	Penalties [W/h]	Rewards [W/h]	Penalties [W/h]	Rewards [W/h]
1	70	0	540	0
2	**200**	0	0	**42**
3	230	0	0	236
4	0	525	0	90
5	0	300	0	160
6	0	400	0	360
7	0	537	0	0
8	0	725	0	0
9	0	0	0	0
10	0	0	152	0
11	0	0	145	0
12	313	0	0	0
13	450	0	0	0
14	0	250	0	0
15	0	**0**	**131**	0
Total W/h	1262	2737	968	888

TABLE VII.

RESULTS OF THE DISTRICT NEGOTIATION

Cost negotiation results					
	b_1	b_2	b_3	b_4	b_5
Penalties [€/day]	7,57	5,08	9,63	4,14	8,82
Rewards -[€/day]	1,00	0,93	2,74	1,00	2,51
Cost [€/day]	**6,57**	**4,15**	**6,89**	**3,14**	**6,31**
Savings: [€/day]	**0,99**	**0,88**	**1,50**	**0,12**	**0,31**
%Saving [%/day]	**15%**	**21%**	**27%**	**12%**	**6%**

Applying Algorithm 1, building b_3 solves LP3 with the remaining neighbors b_2 and b_4. When b_3 finishes the negotiation, building b_4 is selected at random and executes the negotiation with b_5. Successively, building b_2 negotiates with the b_1. Finally, b_1 is selected and negotiates with b_5. Then, all the possible pairs of buildings are considered and the negotiation goes to an end. Table VII shows the final results: rows 1 and 2 report the total penalties (sum of penalty for $t = 1 \dots N$) and the total rewards of the day (sum of reward for $t = 1 \dots N$), respectively. The difference between total penalties and total rewards are reported in row 3. Moreover, rows 4 and 5 indicate the total savings of the day in € and in percentage (%) for each BEMS, respectively. The results show that the residential buildings are able to bargain autonomously the costs and the penalties obtained in the first optimization and each building can save the energy cost with advantages for all of them.

VIII. CONCLUSION

This paper deals with the building network management problem on the basis of the Day-Ahead Market concept and a hierarchical architecture of the district energy management. In particular, the district energy management optimizes the district power distribution by taking into account two human objectives: guaranteeing the human thermal comfort and minimizing wastes and costs. To this aim, a day-ahead negotiation establishes the energy cost and profile of the district by adopting both power penalties and rewards.

More precisely, the District Energy Management System (DEMS) provides the power profile to each Building Energy Management System (BEMS) on the basis of the day-ahead energy market negotiation. Each BEMS of the district solves a Linear Programming (LP) problem and determines its power consumption and cost for the next day. Successively, the power profiles are optimized by proposing two different strategies: a centralized approach is applied to public buildings and a distributed and autonomous negotiation is applied to residential buildings. Two case studies show the efficiency of the presented strategies in the two different scenarios.

In the future research the district energy management system will consider also the impact of the alternative energy sources. Moreover, other factors of the building environment comfort will be studied, such as the visual and air-quality comfort.

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