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# Smart District Energy Management With Cooperative Microgrids

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**ABSTRACT** This paper faces the energy management problem of cooperative microgrids in a smart energy district. In particular, the aim of the research work is to propose an innovative optimization model to solve the problem of energy management in a district composed of several microgrids, taking into account uncertainties of key parameters. In this context, the objective of the paper is threefold: i) maximize the use of energy purchased at the day-ahead market; ii) minimize the need of additional and expensive energy in real-time iii) optimize the integration of renewable energy sources (RES), energy storage systems (ESS) and electric vehicle (EV) batteries in the microgrid. To these goals, the District Energy Management System (DEMS), i.e. the central controller of the district, must balance the microgrids energy demand with the optimal integration of RES, ESS and the batteries of EVs that are seen as movable storage devices shared among buildings. Moreover, the energy surplus can be sold back to the main power grid. The DEMS problem is solved by two approaches. In the first approach, the energy demand, the RES production and the costs are known and a linear programming problem is formalized and solved by the DEMS. In addition, a second approach is proposed in order to address the parameters uncertainty and is formalized as a stochastic linear programming problem. The optimization problems solutions provide the optimal strategy to schedule the charging and discharging operations of the storage systems and the electric vehicle batteries. A simulated case study demonstrates the benefits of the proposed approaches for the smart district.

**INDEX TERMS** Electric vehicle, energy storage, microgrid, optimization, renewable energy, smart district, stochastic programming.

## NOMENCLATURE

### ACRONYMS

DAEM	Day-Ahead Energy Market.
DEMS	District Energy Management System.
ESS	Energy Storage System.
EV	Electric Vehicle.
LP	Linear Programming.
SLP	Stochastic Linear Programming.
HVAC	Heating Cooling and Ventilation System.
MM	Microgrid Management.
PV	Photovoltaic.
PG	Power Grid.
RES	Renewable Energy Sources.
V2G	Vehicle to Grid.

### SETS

$B$	set of $N$ buildings (microgrids).
$\mathcal{T}$	set of $T$ time units.
$S^i$	set of $K^i$ ESSs of building $i \in B$ .
$V$	set of $J$ EVs.
$\mathcal{H}$	set of $H$ scenarios.

### VARIABLES

$s^i(t)$	day-ahead purchased energy for building $i \in B$ at $t \in \mathcal{T}$ .
$u^i(t)$	real time energy required by building $i \in B$ from the power grid at time $t \in \mathcal{T}$ . (to be optimized).
$y^i(t)$	real time additional energy for building $i \in B$ at time $t \in \mathcal{T}$ .
$a(t)$	real time cost for purchasing energy from the power grid at time $t \in \mathcal{T}$ .
$b(t)$	real time cost for selling energy to the power grid at time $t \in \mathcal{T}$ .

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$z^i(t)$	energy sold back to the power grid by building $i \in B$ .
$r_{tot}^i(t)$	total energy produced by the RESs of building $i \in B$ at time $t \in \mathcal{T}$ .
$r^i(t)$	used RES energy for satisfying the demand of building $i \in B$ .
$e_{s,k}^i(t)$	energy stored at time $t \in \mathcal{T}$ in ESS $k \in S^i$ of building $i \in B$ .
$c_{s,k}^i(t)$	energy stored in ESS $k \in S^i$ .
$e_{v,j}(t)$	energy stored in vehicle $j \in V$ at time $t \in \mathcal{T}$ .
$c_{v,j}^{i-}(t)$	energy required by vehicle $j \in V$ to building $i \in B$ at time $t \in \mathcal{T}$ .
$c_{v,j}^{i+}(t)$	energy transferred by building $i \in B$ to vehicle $j \in V$ at time $t \in \mathcal{T}$ .
$d_{v,j}^i(t)$	energy transferred by vehicle $j \in V$ to building $i \in B$ at time $t \in \mathcal{T}$ .
$e_{v,j,min}(t)$	lower energy to be stored in vehicle $j \in V$ at time $t \in \mathcal{T}$ .
$q_j^i(t)$	EV travel variable with $q_j^i(t) = 1$ ( $q_j^i(t) = 0$ ) if $j \in V$ is (is not) plugged-in to building $i \in B$ at time $t \in \mathcal{T}$ .
$m_j^{i,p}(t)$	energy consumed by EV $j \in V$ to travel from $i \in B$ to $p \in B$ with $i \neq p$ at time $t \in \mathcal{T}$ .
$l(t)$	energy demand of building $i \in B$ at time $t \in \mathcal{T}$ .
$n^i(t)$	energy transferred by ESS of building $i$ at time $t \in \mathcal{T}$ .
$v^i(t)$	energy transferred by EVs plugged-in to building $i$ at time $t \in \mathcal{T}$ .
$l_h(t)$	energy demand of building $i \in B$ at time $t \in \mathcal{T}$ in scenario $w_h$ .
$r_{tot}^i(t)$	total energy produced by the RESs of building $i \in B$ at time $t \in \mathcal{T}$ in scenario $w_h$ .
$a_h(t)$	real time cost for purchasing energy from the power grid at time $t \in \mathcal{T}$ in scenario $w_h$ .
$b_h(t)$	real time cost for selling energy to the power grid at time $t \in \mathcal{T}$ in scenario $w_h$ .
$y_h^i(t)$	real time additional energy for building $i \in B$ at time $t \in \mathcal{T}$ in scenario $w_h$ .
$z_h^i(t)$	energy sold back to the power grid by building $i \in B$ in scenario $w_h$ .

**PARAMETERS**

$e_{s,k,max}^i$	upper bound of the energy stored in ESS $k \in S^i$ of building $i \in B$ .
$e_{s,k,0}^i$	initial value of the energy stored in ESS $k \in S^i$ of building $i \in B$ .
$\gamma_{c,s,k}^i$	efficiency coefficient for energy stored in ESS $k \in S^i$ of building $i \in B$ .
$\gamma_{d,s,k}^i$	efficiency coefficient for energy discharged from ESS $k \in S^i$ of building $i \in B$ .
$e_{v,j,max}$	maximum energy that can be stored in vehicle $j \in V$ at time $t \in \mathcal{T}$ .

$e_{v,j,0}$	energy stored in vehicle $j \in V$ at time $t = 0$ .
$\gamma_{c,v,j}$	efficiency coefficient modeling the energy loss during EV $j \in V$ charging.
$\gamma_{d,v,j}$	efficiency coefficient modeling the energy loss during EV $j \in V$ discharging.
$b_{ip}$	energy consumed by an EV to travel from $i \in B$ to $p \in B$ with $i \neq p$ .
$w_h$	scenario $h$ .
$p_h$	probability of occurrence of scenario $h$ .

**UNKNOWN VARIABLES (TO BE OPTIMIZED)**

$u^i(t), y^i(t), z^i(t), r^i(t), e_{s,k}^i(t), c_{s,k}^i(t), c_{s,k}^i(t), e_{v,j}(t), c_{v,j}^{i-}(t), c_{v,j}^{i+}(t), d_{v,j}^i(t), n^i(t), v^i(t), y_h^i(t), z_h^i(t).$
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**INDICES**

$i, p$	Building index.
$j$	Vehicle index.
$k$	ESS index.
$h$	Scenario index.

**I. INTRODUCTION**

In recent years, the smart grid is becoming the key technology to enable the optimal integration of the Renewable Energy Sources (RESs) and Energy Storage Systems (ESSs) into the microgrid energy management systems [1]. Typically the microgrid is composed of energy demanding devices, RESs and ESSs that have been introduced to decrease the harmful emissions caused by fossil fuel power plants and to reduce the need of energy to be purchased from the main electric grid [2]. Therefore, the microgrids allow at minimizing the energy consumption and costs and at enhancing power system reliability in smart districts, providing cheaper and green energy to users [3].

In particular, the Microgrid energy Management (MM) is typically treated as an optimization problem in smart grids interconnecting energy generation systems with energy consumption systems and storage devices [4]. In this framework, the aim is typically to balance the energy flows from supply and demand side, minimizing the cost of energy for final users and/or utilities [5]. In the MM, the importance of using energy storage devices mainly stands in the possibility to conserve energy provided by the RES, whether possible, to be used to satisfy consumption in period of peak of demand, avoiding to stress the distribution systems.

The concept of Day-ahead market is introduced to consider day-ahead energy profiles that normally are purchased at lower cost for the microgrid with respect to real time energy market prices [6]. Respecting the day-ahead profile can guarantee the reduction of the cost for final users and the preservation of the grid. In the MM framework, it is also necessary to take into account the stochasticity of some key variables like the production of RESs, the energy consumption and costs. Therefore, the deterministic approaches [7], based on a perfect knowledge of such parameters are overcome by stochastic and robust approaches to deal with

parameters uncertainties. In addition, electric vehicles can be used in the microgrid mix both as static and dynamic storage systems, moving energy among microgrids [8], [9]. In this framework, the energy management problem can not only be solved for the single microgrid, but several approaches are proposed to deal with network of cooperative multi-microgrids.

This paper starts from the energy management model of the smart district presented in [2] and improves it by considering more realistic situations, introducing an enhanced optimization objective and taking into account uncertainties of costs for purchasing and selling energy. In particular, the smart district is composed of a network of interconnected buildings and at each building is associated a microgrid equipped with RES, ESS and EVs that are shareable storage systems. An EV fleet is shared among the microgrids of the district acting as movable storage devices. The smart district is managed by the District Energy Management System (DEMS) aiming at minimizing the cost of real time energy, maximizing the energy stored in batteries and sold back to grid. Moreover, differently from [2], in this paper surplus energy can be sold back to grid generating revenues for the microgrids. The optimization objective is also modified with respect to [2] in which time-consuming double objective functions were used to first minimize the overall costs and then maximize the stored energy in a lexicographic order. In this study, one objective function is evaluated in which vehicle to grid (V2G) economic revenues are taken into account. Furthermore, in this paper, the uncertainties of energy (purchasing and selling) costs are considered and investigated together with uncertainties of RES production and demand loads of the buildings by using a multi-scenario based stochastic optimization method. In addition, while in [2] a Monte Carlo simulation is adopted to generate the stochastic scenarios, this paper presents a larger simulation campaign in which the multi-scenario approach is based on real energy data records taken from the database of the Italian research project RES NOVAE.

Therefore, the paper solves the MM management problem first in a deterministic framework and then a stochastic model is formulated to take into account uncertainties of the energy costs, RES production and demand load. In the first approach a Linear Programming (LP) problem is formalized, solved by the DEMS and the optimal solution is used by the DEMS to determine timing, quantities and devices in which the energy must be stored, sold and distributed in the microgrids. In the second approach the LP problem is reformulated as a Stochastic Linear Programming (SLP) problem. In the SLP problem a multi-scenario approach allows to take into account the parameters uncertainty. A simulated case study compares the two approaches, demonstrating the benefits of taking into account the parameters uncertainties by the stochastic approach in the smart district.

The rest of the paper is structured as follows. Section II reviews the state of the art of the MM approaches. Moreover,

Section III presents the energy management architecture and the strategy of the smart district for solving the MM problem. Moreover, the models of microgrid components are specified in detail. Section IV presents the LP and SLP optimization problems solved by the DEMS and Section V compares the deterministic and stochastic approach in a case study showing the benefits of including uncertainties. Section VI discusses the benefits and limitations of the proposed optimization model. Section VII provides the conclusions and future works.

## II. RELATED WORKS

The problem of managing MM is studied and analyzed by many researchers and practitioners over the last years, proposing different microgrid model configurations and objectives [4], [5]. In this section we review the state of the art of MM approaches starting from the following classification of the analyzed works:

- day-ahead based approaches: [1]–[3], [7], [8], [10]–[14], [16], [19], [21], [22], [25], [27]–[30], [33], [40]–[42], [48], [50], [53];
- deterministic approaches: [7]–[10], [15]–[20], [23]–[25], [28], [33]–[35], [38], [39], [41], [43]–[45], [47]–[55];
- uncertainties management/stochastic approaches: [1], [3], [10]–[12], [16], [20]–[34], [36], [37], [39], [40], [43], [47], [48], [50], [51], [53], [54], [58];
- EV and V2G based approaches: [2], [7]–[9], [14], [15], [17], [26]–[28], [30], [35], [40], [46], [47], [49];
- RES and/or ESS based approaches: [1]–[3], [7]–[45], [47]–[55], [58];
- Multi-Microgrid based approaches: [2], [7], [12]–[14], [17]–[25], [33], [35]–[39], [45], [50], [52]–[55], [58];
- reviews: [4], [5].

There are contributions where the MM management problem is addressed on the basis of on the Day-Ahead Energy (DAEM) Market concept [10]. In the DAEM energy prices are defined the day-ahead and a group of users can benefit of purchasing energy at lower tariff with respect to real-time ones. The day-ahead energy profiles are usually defined on the basis of prediction of consumption for the next 24 hours [2]. In this context, [1] proposes a hierarchical strategy for the optimal energy management of a hybrid energy storage system to balance the energy and mitigate the power fluctuations impact on the grid.

In this paper the authors include in their model the stochastic renewable energy and loads. Moreover, in [11] the authors propose a microgrid composed by a photovoltaic, battery storage system and wind turbine generator with the aim of enhancing the system reliability and reducing the cost of energy and the total annual cost. The stochastic characteristics of the Renewable energies are introduced in the energy balance model. In [12] interconnected microgrids are managed through a hierarchical stochastic energy management system. In [1], [11], [12] the

presence of electric vehicles in the mix is not taken into account.

In [8] electric vehicles are integrated into the microgrid network for which the use of different home appliances is optimized with a holistic method based on the preferences of prosumers and predefined schedules. In this framework, the charging/discharging of energy storage devices and EVs is controlled and through the proposed energy management system and the mixed integral linear programming and the energy procurement of a single smart home is optimized, to guarantee the minimum cost and to increase consumer comfort. In [5] electric vehicles are also part of the microgrid management system and smart charging and V2G technology are applied. The microgrid is composed of a 31 kWp photovoltaic (PV) system, internet servers, three households, an office and two EVs. Three control algorithms are applied to manage the charging operations of several EVs within the microgrid.

Furthermore, the MM problem is solved by using deterministic and/or stochastic approaches. The deterministic approach is applied when a perfect knowledge of RES production, energy demand and costs is assumed in the microgrid like in [13]. In particular, [13] proposes a smart grid model in which, through a day-ahead Demand Side Management strategy, two optimization approaches are treated: i) a non cooperative approach and a ii) cooperative approach. In the first optimization problem, users are seen as players of a noncooperative game aiming at reducing their own monetary cost using storage devices and finding a Nash equilibrium. In the second approach, a standard nonlinear optimization problem is solved by a coordinator which minimizes the overall cost for the demand side. In the proposed model no EVs and no uncertainties of key variables such as RES generation, energy demand and costs are taken into account.

The authors in [14] deal with the energy management of buildings and microgrids considering renewable energy, storage devices, electric vehicles, load management and dynamic pricing. The MM problem is solved as a mixed-integer, nonlinear, constrained optimization problem not including a stochastic approach to deal with parameter uncertainties. Additionally, in [15] the use of EVs as active agents in the microgrid energy balance is investigated in a microgrid with a rule-based controller managing the power flows among the main grid and the batteries of photovoltaic and EVs. In [16], the same authors replace the rule-based controller with an optimal control model to manage the power flows. An optimal strategy for the charging and discharging of EVs in the microgrid energy management is proposed in [17]. A cooperative planning of RES generation for interconnected microgrids is proposed in [18] based on real meteorological data in Hong Kong. It is demonstrated how interconnected microgrids jointly decide how the RES generations must be deployed, and how to manage the associated investment cost, showing that the cooperative framework minimizes the overall system cost. In this work no EVs and ESSs

are integrated in the microgrid framework as well as no day-ahead dynamics are considered. The same authors in work [19] propose a holistic model to jointly optimize power scheduling within individual microgrids and energy trading among interconnected microgrids including ESS and day-ahead market analysis. However, EVs and uncertainties of key parameters are not taken into account.

On the other hand, stochastic and robust approaches are introduced to take into account the variability of key parameters [20]. In [21] a stochastic framework of cooperative microgrids is proposed for optimal power scheduling, maximizing the expected profit and minimizing the losses, but EVs are not taken into account. In [22]–[24] stochastic and multi-agent approaches are applied to deal with the uncertainty of renewable energy generation and energy loads while economically balancing energy supply and demand in multiple microgrids where no EVs are considered. In detail, [22] deals with the daily optimal scheduling problem of networked microgrids considering uncertainty in generation and load. Two demand response programs based on time of use and real time pricing are integrated into the optimal energy scheduling model that is solved using a metaheuristic algorithm. Numerical simulations are performed to demonstrate the effectiveness of the proposed model through comparison with other stochastic optimization solution.

Furthermore, in [23] a new predictive control scheme for the stochastic energy management of multi-microgrids is studied to maintain uncertain supply and demand balanced in an economical manner. The results of a case study with 10 microgrids indicate that the proposed scheme successfully reduces the system operating cost. The authors in [24] present an ontology-driven multi-agent approach for the energy management of an integrated microgrid system with renewable energy and controllable loads. Different cooperative agents are implemented to reach an optimal operating strategy for the integrated energy system. To verify the effectiveness and applicability of the proposed architecture different case studies are carried out.

On the contrary, in [25] no uncertainties of the energy demand is taken into account. The authors propose a two-stage adaptive robust optimization for a residential microgrid to derive the energy scheduling minimizing the operation cost under stochastic PV output. The proposed collaborative model allows at reducing the cost and the energy interactions between the microgrid and the main grid. In [26], EVs and responsive loads are integrated in the microgrid management model to peak shaving and compensate the uncertainty of renewable energies. A novel demand response program integrating plug-in electric vehicles, ESSs, RESs is presented in [27] where uncertainties regards only EVs batteries and travels.

In [28] a modified harmony search algorithm is presented to tackle the uncertainty of plug-in hybrid electric vehicles, loads, prices and renewable energies. The authors address the microgrid energy management problem proposing smart

charging methods and focusing on a single microgrid. In several papers the MM management problem is addressed in which distributed and robust approaches are applied without taking into account EVs. In [3] an online algorithm is presented for the real-time energy management of a microgrid by combining the off-line optimal solution with the sliding-window based sequential optimization. Simulations are conducted using the real wind generation data of the Ireland power system to evaluate the performance of the algorithm, compared with other heuristics, and dynamic programming based solution.

Moreover, [29] proposes a distributed energy management system taking into account the power flow, load uncertainty and the system operational constraints in a distribution network. With the proposed simulations they show that the algorithm is efficient in both grid-connected and isolated mode. In [30] a power scheduling approach is introduced including renewable energies to balance the supply and demand. The optimal scheduling strategy minimizes the microgrid cost, including generation and storage costs, dispatchable loads, and the uncertainty of RES. In [31], a multiagent-based model is introduced to study distributed energy management in a microgrid.

To deal with uncertainties a reinforcement learning algorithm is developed to allow customers to develop optimal strategies for energy management and load scheduling without a priori information about the microgrid. Case studies are provided to show that the overall performance of all agents converges to the Nash equilibrium. In [32], a microgrid is considered which includes distributed generation, environmental factors and demand response with the goal of optimizing the system operation cost and respecting user comfort.

On the other hand, [33] deals with the energy scheduling of multi-microgrids applying a deterministic and a robust optimization-based scheduling considering uncertainties in renewable energy sources and electric loads with the objective of minimizing costs.

Moreover, in [34] a two-stage stochastic programming model is adopted for the optimal design of distributed energy systems. A two-stage decomposition based strategy is used to solve the optimization problem with genetic algorithm at the first stage and a Monte Carlo method to deal with uncertainty in the second stage. The model is applied for planning of a distributed energy system in a hotel. The authors in [35] propose a distributed model predictive control strategy to operate interconnected microgrids with the aim of increasing the infeed of RES. Moreover, in [36] a robust distributed control strategy based on partially nested information among interconnected microgrids is studied. The objective is to optimize power flows and energy storage and to react to uncertainties.

Similarly, [37] propose a framework for interconnected multi-microgrids power dispatch at smart grid level. Uncertainties are modeled with Weibull probability distribution functions and a heuristic algorithm is applied for solving the

problem. Moreover, in [38] a hierarchical energy scheduling method is studied to optimize the management of power, trading, distribution and storage considering cooperative microgrids and a macrogrid. The problem is formalized as a convex optimization problem and then decomposed in two-tier problems. In the first problem, users, transmission cost and grid load variance are jointly considered and an online algorithm is used to solve it. The second problem is solved with a distributed algorithm minimizing the transmission cost and power generation, exploiting the storage, without EVs implication.

A similar problem is solved by [39] in a centralized way. In particular, a linear quadratic gaussian problem is defined for the optimal control of power flows not including V2G. In [40] a finite-horizon mixed integer linear programming problem is iteratively formulated and solved to analyze the optimal control actions of a residential microgrid under a model predictive control framework. Here, a simplified model is used for forecasting of PV generation, electricity cost and load in a single microgrid. Another model predictive control strategy is presented in [41] to control the energy flows in a distribution network node composed of an ESS and serving a part of the grid with the penetration of renewable energies. The control strategy goal is to make sure that the power flow follows the established day-ahead profile. In [42], [43] the focus is on the use of HVAC and battery storage system for the efficient energy management in smart buildings.

From the performed analysis of the state of the art it emerges that there is the lack of a contribution in which day-ahead market dynamics are considered to reduce the real-time expensive energy purchasing and electric vehicles are integrated together with RES and ESS and can be exploited as movable batteries among smart buildings to support the energy balance and cost minimization with a deterministic and stochastic optimization approach in a network of interconnected microgrids, dealing with uncertainties of energy demand, cost and RES generation at the same time.

Therefore, to address the above research gap, this paper includes in the proposed smart district energy management architecture the following systems and features: 1) a day-ahead approach to consider a forecasted demand profile of each building microgrid for the next 24 hours, purchased at lower cost, to be respected in order to minimize the request of additional expensive real time energy; 2) a network of microgrids composed by RES, ESS and shareable EV batteries; 3) the EVs are considered storage systems shared among buildings in different day times; 3) a deterministic approach and a stochastic multi-scenario based approach are introduced to solve the energy balance problem for the district optimizing the charging/discharging of ESS and EVs, while minimizing the energy costs; 4) uncertainties of RES, energy costs (purchasing/selling) and demand loads are considered; 5) surplus energy is appropriately sold back to the grid generating revenues for the microgrids in the energy balance.

TABLE 1. At-a-glance overview of the last 4 years literature.

Ref.	Day-ahead approach	Deterministic approach	Stochastic approach/ uncertain managem.	EVs (movable storage)	V2G with monetary revenues	RES	ESS	Multi-Microgrids
[1]	✓	x	✓	x	x	✓	✓	✓
[2]	✓	✓	✓	✓	x	✓	✓	✓
[7]	✓	✓	x	✓	x	✓	✓	✓
[8]	✓	✓	x	✓	✓	✓	✓	x
[10]	✓	✓	✓	x	x	✓	✓	x
[15]	x	✓	x	✓	✓	✓	✓	x
[19]	x	✓	x	x	x	✓	✓	✓
[21]	✓	x	✓	x	x	✓	✓	✓
[25]	✓	✓	✓	x	x	✓	✓	✓
[27]	✓	x	✓	✓	x	x	✓	x
[28]	✓	✓	✓	✓	x	✓	✓	x
[29]	✓	x	✓	x	x	✓	✓	x
[31]	x	x	✓	x	x	✓	✓	x
[32]	x	x	✓	x	x	✓	✓	x
[35]	x	✓	x	✓	x	✓	✓	✓
[43]	x	✓	✓	x	x	✓	✓	x
[47]	x	✓	✓	✓	✓	✓	x	x
[48]	✓	✓	✓	x	x	x	✓	x
[49]	x	✓	x	x	x	✓	✓	x
[50]	✓	✓	✓	x	x	✓	✓	✓
[51]	x	✓	✓	x	x	✓	✓	x
[52]	x	✓	x	x	x	✓	✓	✓
[53]	✓	✓	✓	x	x	✓	✓	✓
[54]	x	✓	✓	✓	x	✓	✓	✓
[55]	x	✓	x	x	x	✓	x	✓
this paper	✓	✓	✓	✓	✓	✓	✓	✓

Table 1 points out how our approach manages to deal with all the aspects considered in the district energy management by the related literature during the last four years.

### III. THE ENERGY MANAGEMENT ARCHITECTURE OF THE SMART DISTRICT

This section presents the architecture for the energy management of the smart district. Fig. 1 shows the proposed energy management framework consisting of a DEMS connected to the building microgrids network, where each microgrid is also connected to the main Power Grid (PG). Each day, the DEMS receives the energy consumption data from each microgrid through a local controller in order to manage both day-ahead and real time energy demand. In addition, the DEMS establishes a day-ahead travel plan for the EVs fleet based on information from building managers. Based on the above information, the DEMS works as load aggregator of the district, forecasting and purchasing the energy profiles at the day-ahead market to satisfy the demand of the next day. Moreover, the DEMS acts in real-time to define the optimal strategy for the district energy balance and communicates the optimization results to the microgrids. Each microgrid controller, in turn, elaborates the DEMS information and performs the necessary actions to apply the optimal strategy by properly exchanging energy with the PG. Therefore, in the proposed architecture, the DEMS is the energy manager aiming at satisfying the energy demand of the district with three goals: i) minimizing the real time energy needs of the district, with the integration of RESs, ESSs and EVs; ii) maximizing the use of the day-ahead energy by storing the

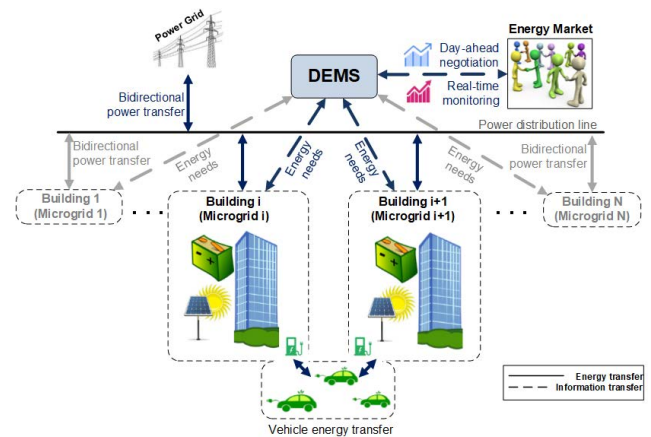


FIGURE 1. The architecture for the energy management of the smart district.

coverage in the ESSs and EV batteries iii) selling the residual energy back to the PG.

#### A. PROBLEM STATEMENT

The smart district is assumed to be composed by a set  $B = \{i \mid i = 1, \dots, N\}$  of buildings, where each building is seen as a microgrid. In this context, a set  $\mathcal{T} = \{t \mid t = 0, \dots, T - 1\}$  of  $T$  time units is introduced and  $s^i(t)$  for  $t \in \mathcal{T}$  is used to denote the energy purchased by the DEMS to cover the forecasted energy consumption at time  $t$  of each building  $i \in B$ . Moreover,  $u^i(t)$  is introduced to denote the energy that building  $i \in B$  requires to the PG in real time at time  $t \in \mathcal{T}$ . In this framework, the variables  $y^i(t)$  denote the real-time

additional energy to be purchased for building  $i \in B$  at time  $t \in \mathcal{T}$ :

$$\begin{cases} y^i(t) = u^i(t) - s^i(t) & \text{if } u^i(t) \geq s^i(t) \\ y^i(t) = 0 & \text{otherwise.} \end{cases} \quad (1)$$

Considering the real-time energy cost at time  $t \in \mathcal{T}$  denoted by  $a(t)$ , the DEMS minimizes the sum of the energy costs  $a(t)y^i(t)$  for each building  $i \in B$  and time  $t \in \mathcal{T}$ . The proposed strategy is based on the assumption that buildings are connected with ESSs, RESs and EVs which significantly contribute to the minimization of the additional energy  $y^i(t)$  requests. Firstly, renewable energy is used to satisfy the building consumption. Afterwards, if renewable energy is still available, it can be stored in the ESSs or EVs batteries for future necessities. Hence, in this scenario, RESs, ESSs and EVs energy are used to balance the building consumption avoiding to exceed the purchased day-ahead profile  $s^i(t)$ . In particular, the EV batteries are mobile energy storages shared by the buildings. Indeed, the EV batteries are seen like moveable storage to transfer energy among buildings, thanks to the vehicle-to-grid (V2G) technology ([17]). After minimizing the expensive additional real-time requests by the proposed strategy, the DEMS aims also at selling back the residual energy to the grid. Therefore, the variable  $z^i(t) \in \mathbb{R}$  is defined to take into account the energy that building  $i \in B$  sells back to the grid at the cost  $b(t)$  with  $b(t) < a(t), \forall t \in \mathcal{T}$ .

The proposed MM strategy leads to the following benefits: i) the real-time energy cost is minimized (real time energy cost is typically higher than the day-ahead cost); ii) the surplus energy can be sold back in order to further reduce the final costs for the customers iii) the reliability of the main grid is strengthened ([2]).

### B. RENEWABLE ENERGY SOURCE MODEL

The variable  $r_{tot}^i(t)$  is introduced to denote the total energy production of the RESs at time  $t \in \mathcal{T}$ . In addition,  $r^i(t)$  is the part of renewable energy used by the DEMS to balance the demand of building  $i \in B$  at time  $t \in \mathcal{T}$ . Therefore, the following conditions must be verified:

$$0 \leq r^i(t) \leq r_{tot}^i(t) \quad \forall i \in B \quad \forall t \in \mathcal{T}. \quad (2)$$

If no RESs is available at building  $i \in B$ , then  $r_{tot}^i(t) = 0, \quad \forall t \in \mathcal{T}$ .

### C. ENERGY STORAGE SYSTEM MODEL

The set of  $K^i$  ESSs of building  $i \in B$  is denoted as  $S^i = \{k \mid k = 1, \dots, K^i\}$ . In addition, the variables  $e_{s,k}^i(t)$ ,  $e_{s,k,max}^i$  and  $e_{s,k,0}^i$  are introduced to respectively denote the energy stored at time  $t \in \mathcal{T}$ , the upper bound and the initial value of the energy stored in the ESS  $k \in S^i$  of  $i \in B$ .

Therefore, the following conditions must be verified:

$$0 \leq e_{s,k}^i(t) \leq e_{s,k,max}^i \quad \forall i \in B, \quad \forall k \in S^i, \quad \forall t \in \mathcal{T} \quad (3)$$

$$e_{s,k}^i(0) = e_{s,k,0}^i \quad \forall i \in B, \quad \forall k \in S^i. \quad (4)$$

Considering ESS  $k \in S^i$  two cases can arise at time  $t$ : 1) energy  $c_{s,k}^i(t)$  is stored in the ESS with efficiency  $0 < \gamma_{c,s,k}^i < 1$ ; 2) energy  $d_{s,k}^i(t)$  is used by the microgrid. the energy stored in the ESSs is described by the following equation:

$$e_{s,k}^i(t) = e_{s,k}^i(t-1) + \gamma_{c,s,k}^i c_{s,k}^i(t) - d_{s,k}^i(t) \quad \forall i \in B, \quad \forall k \in S^i \quad \forall t \in \mathcal{T}. \quad (5)$$

### D. ELECTRIC VEHICLE BATTERY MODEL

The fleet of EVs is represented by the set  $V = \{j \mid j = 1, \dots, J\}$ . The EVs need to be charged by the PG but their batteries can also be used as energy sources for the buildings that require additional energy in real time. To this goal, the EVs can move among buildings to transfer energy. The following variables are introduced to represent the energy stored in EV  $j \in V$ :

- $e_{v,j}(t)$ , energy stored in  $j \in V$  at time  $t \in \mathcal{T}$ ;
- $c_{v,j}^i(t)$ , energy required by  $j \in V$  to building  $i \in B$  at time  $t \in \mathcal{T}$ ;
- $c_{v,j}^i(t)$ , energy transferred by building  $i \in B$  to EV  $j \in V$  at time  $t \in \mathcal{T}$ ;
- $d_{v,j}^i(t)$ , energy transferred by EV  $j \in V$  to building  $i \in B$  at time  $t \in \mathcal{T}$ .

In addition, the following parameters are defined:

- $e_{v,j,min}(t)$ , lower value of energy that must be stored in EV  $j \in V$  at time  $t \in \mathcal{T}$ ;
- $e_{v,j,max}$ , higher value of energy that can be stored in EV  $j \in V$ ;
- $e_{v,j,0}$ , energy stored in EV  $j \in V$  at time  $t = 0$ ;
- $q_j^i(t) \in \{0, 1\}$ , with  $q_j^i(t) = 1$  if  $j \in V$  is plugged-in to building  $i \in B$  at time  $t \in \mathcal{T}$ , else  $q_j^i(t) = 0$ ;
- $0 < \gamma_{c,v,j} < 1$ , efficiency coefficient representing the energy loss during the charging of EV  $j \in V$ ;
- $0 < \gamma_{d,v,j} < 1$ , efficiency coefficient representing the energy loss during the discharging of  $j \in V$ ;
- $b_{ip}$ , energy consumed by an EV to travel from  $i \in B$  to  $p \in B$  with  $i \neq p$ .

At each time  $t \in \mathcal{T}$  the following conditions must be satisfied:

$$e_{v,j,min}(t) \leq e_{v,j}(t) \leq e_{v,j,max} \quad \forall j \in V \quad \forall t \in \mathcal{T} \quad (6)$$

$$e_{v,j}(0) = e_{v,j,0} \quad \forall j \in V. \quad (7)$$

It is assumed that 1 time unit is necessary for an EV to travel from building  $i \in B$  to building  $p \in B$  and the EV trips are scheduled the day ahead. The energy consumed for a trip from  $i$  to  $p$  starting at time  $t - 1$  can be denoted as follows:

$$m_j^{i,p}(t) = [q_j^i(t) - q_j^i(t-1)] b_{ip} \quad \forall i, p \in B. \quad (8)$$

Considering that  $q_j^i(t) = 0$  and  $q_j^i(t-1) = 1$ , it holds  $m_j^{i,p}(t) = -b_{ip}$ .

Thus, the energy stored in  $j \in V$  at time  $t \in \mathcal{T}$  is defined as follows:

$$\begin{aligned}
 e_{v,j}(t) &= e_{v,j}(t-1) \\
 &+ \sum_{i \in B} [q_j^i(t) \gamma_{c,v,j} [c_{v,j}^{i+}(t) + c_{v,j}^{i-}(t)] - d_{v,j}^i(t)] \\
 &+ \sum_{i \in B} \sum_{p \in B, p \neq i} q_j^i(t-1) m_j^{i,p}(t) \quad \forall j \in V, \forall t \in \mathcal{T}.
 \end{aligned} \tag{9}$$

According to equation (9), vehicle  $j$  leaving building  $i$  at time  $t-1$  to arrive at  $p$  at time  $t$  implies that, at time  $t$ , the energy stored in EV  $j$  is  $e_{v,j}(t-1)$  with the addition of the energy traded with building  $p$  at time  $t$  (i.e.,  $\gamma_{c,v,j} [c_{v,j}^{i+}(t) + c_{v,j}^{i-}(t)] - d_{v,j}^i(t)$ ) and the subtraction of the energy consumed for travelling (i.e.,  $m_j^{i,p}(t) = -b_{ip}$ ).

### E. MICROGRID ENERGY BALANCING

In the microgrid, the energy required by the building and by the EVs is balanced with energy available from the grid and the storages. Before introducing the energy balance equations, it is necessary to define the following variables:

- $n^i(t) = \sum_{k \in S^i} \gamma_{d,s,k}^i d_{s,k}^i(t)$ , energy transferred by ESSs of building  $i$  at time  $t$  lowered by the efficiency coefficient  $\gamma_{d,s,k}^i$ ;
- $v^i(t) = \sum_{j \in V} \gamma_{d,v,j} q_j^i(t) d_{v,j}^i(t)$ , energy transferred by EVs plugged-in to building  $i$  at time  $t$  lowered by the efficiency coefficient  $\gamma_{d,v,j}$ ;
- $l^i(t)$ , energy consumption of building  $i$  at time  $t$ .
- $z^i(t)$ , energy sold back to the grid by building  $i$  at time  $t$ .

Therefore, the building energy balancing is formulated as follows:

$$\begin{aligned}
 u^i(t) + r^i(t) + n^i(t) + v^i(t) &= z^i(t) + l^i(t) + \dots \\
 &\dots + \sum_{j \in V} \frac{1}{\gamma_{c,v,j}} c_{v,j}^{i-}(t) \\
 \forall i \in B \quad \text{and} \quad \forall t \in \mathcal{T}, \tag{10}
 \end{aligned}$$

where the term on the right of (10) denotes the energy demand of building  $i$ , summing the aggregated building energy consumption, the energy  $c_{v,j}^{i-}(t)$  for recharging  $j \in V$  and the energy sold to the PG.

### IV. THE DISTRICT ENERGY MANAGEMENT STRATEGY

This section presents the DEMS strategy for minimizing the costs of the real time additional energy, optimizing the energy storing and selling. More specifically, the DEMS strategy aims at i) storing energy in the ESS and EV batteries, when  $s^i(t)$  can satisfy the building demand; ii) selling energy surplus back to the PG if it is not possible to store it (e.g. the ESSs and batteries are fully charged); iii) taking energy from RES, ESS and EV batteries when  $s^i(t)$  can not fulfill the building demand.

Constraints (11) decide that the energy saved in comparison with the day-ahead profile  $s^i(t)$  at time  $t$ , i.e.  $s^i(t) - u^i(t)$  with  $u^i(t) < s^i(t)$ , can be stored in the ESS and EV batteries:

$$\begin{aligned}
 &\sum_{k \in S^i} c_{s,k}^i(t) + \sum_{j \in V} q_j^i(t) c_{v,j}^{i+}(t) \\
 &\leq -u^i(t) + s^i(t) + y^i(t) + r_{tot}^i(t) - r^i(t) \quad \forall i \in B, \forall t \in \mathcal{T}.
 \end{aligned} \tag{11}$$

Specifically, at time  $t$ ,  $-u^i(t) + s^i(t) + y^i(t)$  is the part of day-ahead energy that building  $i \in B$  has saved. It is verified that  $-u^i(t) + s^i(t) + y^i(t) = -u^i(t) + s^i(t)$  if  $u^i(t) < s^i(t)$  since  $y^i(t) = 0$ . On the contrary, it holds  $-u^i(t) + s^i(t) + y^i(t) = 0$  if  $u^i(t) \geq s^i(t)$  since  $y^i(t) = u^i(t) - s^i(t)$ . Regarding the RES, the energy amount  $r_{tot}^i(t) - r^i(t)$  can be accumulated in the ESS and EV batteries.

The district energy management problem is solved by two approaches. The first approach, is based on the a priori knowledge of the loads energy consumption  $l^i(t)$ , the energy production of RESs  $r_{tot}^i(t)$  and the energy costs  $a(t)$  and  $b(t)$  for  $t \in \mathcal{T}$ . In this case, a LP problem is formulated for minimizing the real time energy costs for the district. In the second approach, the variables  $l^i(t)$ ,  $r_{tot}^i(t)$ ,  $a(t)$  and  $b(t)$  for  $t \in \mathcal{T}$  are uncertain and a multi scenario-based SLP problem is formalized and solved.

Solving the DEMS problem by the two approaches, the optimal strategies are obtained for charging/discharging operations and for the energy usage of ESSs and EVs, given by  $c_{s,k}^i$ ,  $c_{v,j}^{i+}$ ,  $c_{v,j}^{i-}$ ,  $d_{s,k}^i$ ,  $d_{v,j}^i$  and  $r^i$ . Those variables are communicated to each microgrid controller to actuate the energy balance strategy.

### A. SINGLE SCENARIO APPROACH

In this section, the LP problem is presented for minimizing the additional energy costs with the a priori knowledge of the energy consumption and costs. The following objective function is defined to optimize the district energy costs:

$$\begin{aligned}
 F &= \min \sum_{i \in B} \sum_{t \in \mathcal{T}} a(t) y^i(t) - b(t) z^i(t). \tag{12}
 \end{aligned}$$

$$\begin{aligned}
 &\left\{ \begin{array}{l} \text{Equations (2) - (11)} \\ y^i(t) \geq u^i(t) - s^i(t) \quad \forall i \in B \tag{13a} \\ y^i(t) \geq 0 \quad \forall i \in B \tag{13b} \\ r^i(t), u^i(t), e_{s,k}^i(t), e_{v,j}(t), c_{s,k}^i(t), z^i(t) \\ c_{v,j}^{i-}(t), c_{v,j}^{i+}(t), d_{s,k}^i(t), d_{v,j}^i(t) \geq 0 \quad \forall i, k, j, t \end{array} \right. \tag{13}
 \end{aligned}$$

Constraints (13a) and (13b) are defined for satisfying (1): it is due to the objective function (12) which minimizes the decision variable  $y^i(t)$  and maximizes  $z^i(t)$ . The number of the non-negative variables and constraints are respectively,

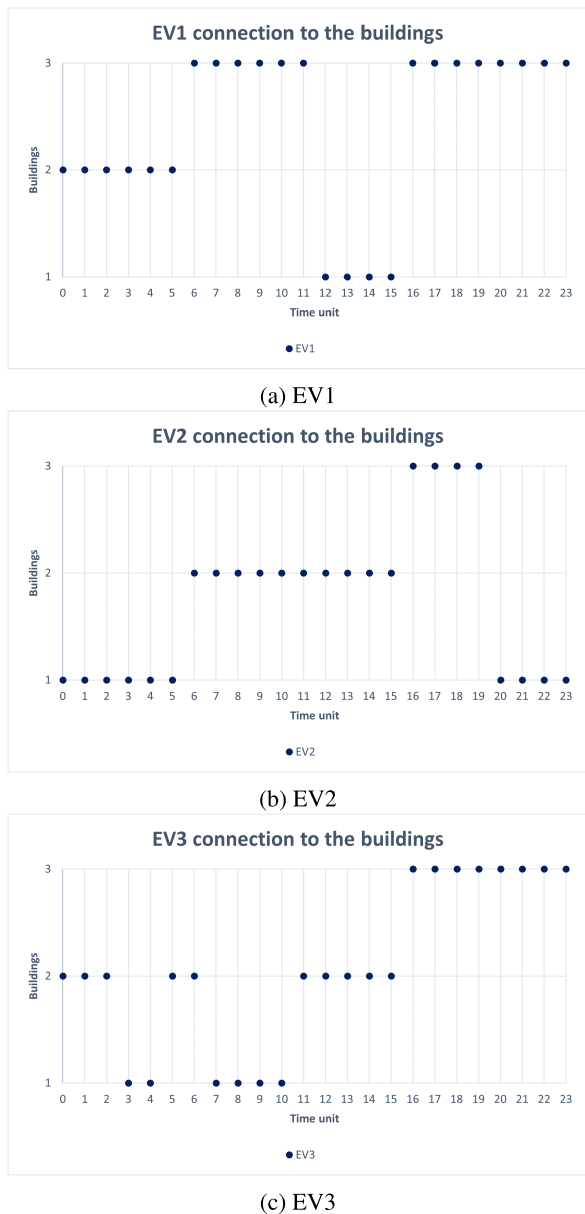


FIGURE 2. EVs travels across the three buildings.

$$T \cdot [4N + 3 \sum_{i=1}^N K^i + J + 3NJ] \text{ and } T \cdot [4N + 3J + 3 \sum_{i=1}^N K^i] + J + \sum_{i=1}^N K^i.$$

Fig. 3 depicts the consumption, day-ahead and renewable energy profiles of building 1, 2 and 3, respectively in the most probable scenario ( $w_1$ ). Moreover, Fig. 4 shows respectively the energy stored and used by ESS and EV of building 1, 2 and 3 in scenario  $w_1$ .

**B. MULTI-SCENARIO STOCHASTIC APPROACH**

In the real life, key variables like  $l^i(t)$ ,  $r_{tot}^i(t)$ ,  $a(t)$  and  $b(t)$  are affected by uncertainties. Therefore, the LP problem (13) is reformulated as a SLP problem minimizing the expected value  $\mathbb{E}[F]$  of the total energy cost for the district. The SLP problem is here formulated as a single scenario

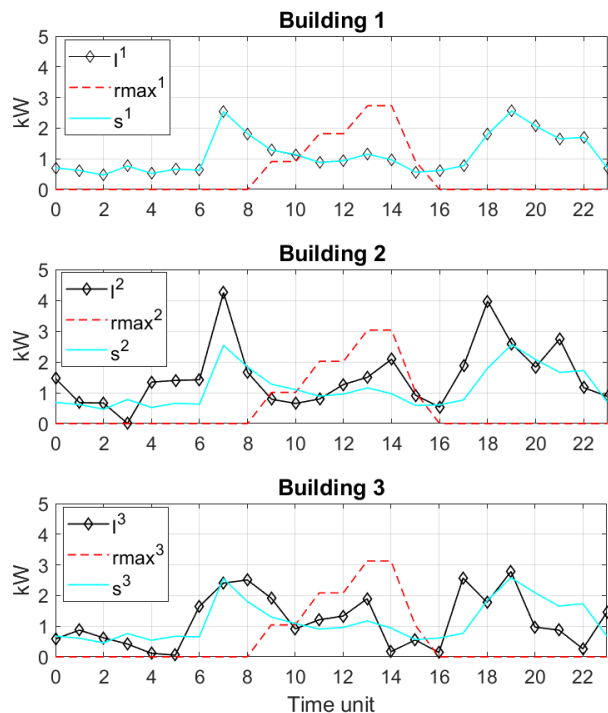


FIGURE 3. The profiles of energy demand, day-ahead and renewable energy of building 1, 2 and 3 in scenario  $w_1$ .

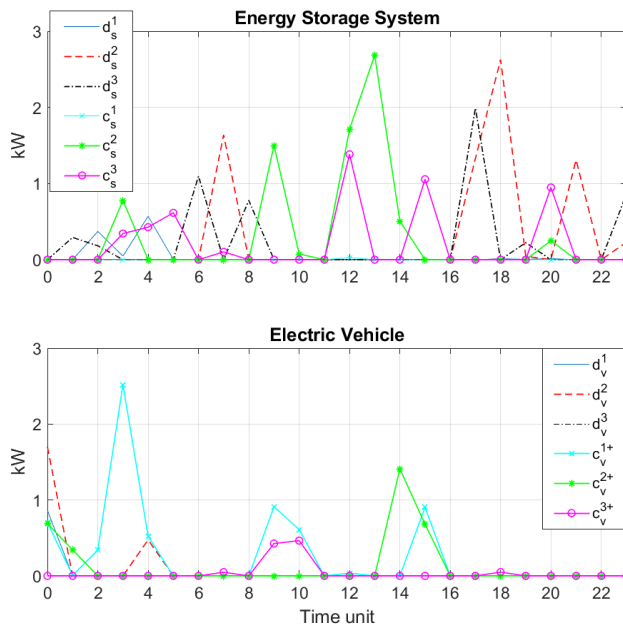


FIGURE 4. Energy stored and used by ESS and EV of building 1  $w_1$ .

optimization problem in which multiple scenarios representing the uncertainty are taken into account. More precisely, a set  $\mathcal{H}$  of  $H$  scenarios  $w_1, \dots, w_H$  is introduced and for each scenario different values of the variables  $l_h^i(t)$ ,  $r_{tot}^i(t)$ ,  $a_h(t)$  and  $b_h(t)$  are considered with probabilities  $p_1, \dots, p_H$ . Let us denote by  $F_h$  the objective function of scenario  $w_h$ . Hence,

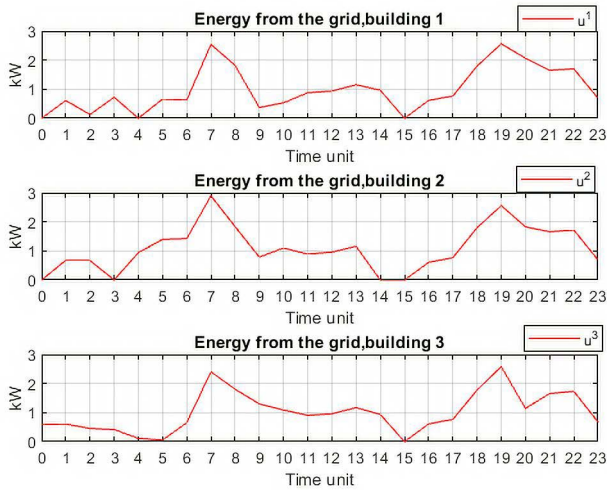


FIGURE 5. Real time Energy from the grid for the 3 buildings in scenario  $w_1$ .

the expected value  $\mathbb{E}[F]$  can be formulated as follows:

$$\mathbb{E}[F] = \sum_{h=1}^H p_h F_h. \tag{14}$$

Consequently, the SLP problem is defined as follows:

$$\begin{aligned} \min \mathbb{E}[F] &= \sum_{h=1}^H \sum_{i \in B} \sum_{t \in \mathcal{T}} p_h (a_h(t) y_h^i(t) - b_h(t) z_h^i(t)). \\ \text{subject to} & (15.1) - (15.13). \end{aligned} \tag{15}$$

with  $y_h^i(t)$ ,  $z_h^i(t)$  respectively denoting the additional real-time energy and the energy to be sold at time  $t$  in scenario  $h$  for  $h = 1, \dots, H$ . It is noted that the SLP problem (15) – (15.13), as shown at the bottom of the next page, can be decomposed into  $H$  different LP problems (12) – (13). The optimal solution of the SLP problem provides the stochastic strategy to manage and schedule the charging and discharging operations of the ESSs and EV batteries and the energy use. Note that the computational complexity of the LP/SLP problem is polynomial and it holds that the optimal solution can be obtained in a reasonable time even for large size problem.

## V. CASE STUDY

The efficacy and benefits of the proposed approaches are demonstrated with a simulated case study in this section. The optimization problems have been solved by the GNU Linear Programming Kit ([56]) solver running on a Personal Computer with an 11th Gen Intel(R) Core(TM) i7-1165G7, 2.80 GHz, with 16GB RAM. All the simulations are completed in few seconds.

### A. THE BUILDING MICROGRIDS

The district is made of 3 buildings included in set  $B = \{1, 2, 3\}$  connected to the PG and managed by the DEMS.

More in detail, the 3 considered buildings are located in different sites belonging to the Polytechnic University of Bari, each one equipped with one electric charging station, solar panels and one storage device. Moreover, the 3 buildings microgrids share a fleet of 3 EVs. Therefore, it holds  $S^1 = S^2 = S^3 = \{1\}$  and  $V = \{j \mid j = 1, 2, 3\}$ . A time horizon of  $T = 24$  time units (1 t.u. = 1 hour) is considered by defining the set  $\mathcal{T} = \{t \mid t = 0, \dots, T - 1\}$ . Furthermore, the fleet of 3 EVs  $q_j^i$  for  $i, j = 1, 2, 3$  accomplish the trips depicted in Figs. 2a, 2b, 2c according to the day-ahead schedules. For instance, as depicted in Fig. 2a, EV1 is initially plugged-in to building 2. At time  $t = 5$  it moves towards building 1 remaining connected until  $t = 11$ . At  $t = 11$ , it leaves building 1 moving to building 3. Finally, at  $t = 15$  it makes the last trip of the day towards building 1.

In addition, the following parameters, based on technical data sheets, are considered :

- $\gamma_{c,s,1}^1 = 0.92$ ;  $\gamma_{c,s,1}^2 = 0.84$ ;  $\gamma_{c,s,1}^3 = 0.90$ .
- $\gamma_{d,s,1}^1 = 0.91$ ;  $\gamma_{d,s,1}^2 = 0.83$ ;  $\gamma_{d,s,1}^3 = 0.90$ .
- $e_{s,1,max}^1 = e_{s,1,max}^2 = e_{s,1,max}^3 = 60kWh$ .
- $\gamma_{c,v,1} = 0.80$ ;  $\gamma_{c,v,2} = 0.84$ ;  $\gamma_{c,v,3} = 0.86$ .
- $\gamma_{d,v,1} = 0.86$ ;  $\gamma_{d,v,2} = 0.81$ ;  $\gamma_{d,v,3} = 0.87$ .
- $e_{v,1,max} = e_{v,2,max} = e_{v,3,max} = 15kWh$ .
- $b_{12} = b_{21} = 0.13kWh$ ;  $b_{13} = b_{31} = 0.31kWh$ ;  $b_{23} = b_{32} = 0.71kWh$ .

A set of initial scenarios were collected during the national project RES NOVAE [57]. The needed energy data records, i.e., the variables and parameters described in Section III, including the uncertain variables, are taken from the project database in order to generate the considered initial set of daily scenarios. In particular, the project database records datasets of the daily energy flows/exchanges in the 3 considered microgrids over 3 years. In this context, the proposed case study focuses on the observation of the time period January-May of three consecutive years generating an initial set of 400 scenarios. Hence, in order to reduce the computational effort, it is necessary to apply a method to reduce the number of the initial scenarios. The applied strategy consists in cutting off the scenarios with low probability and aggregating the remaining scenarios on the basis of a probability metric [58]. In particular, we adopt the GAMS/SCENRED [59] software to reduce the set of scenarios: SCENRED algorithm determines a scenario subset (of predefined cardinality) and assigns high probabilities to the preserved scenarios (probability zero is assigned to the deleted scenarios). In the considered case study, a reduction to  $H = 12$  scenarios  $w_1, w_2, \dots, w_H$  is obtained and each scenario is respectively characterized by the following occurrence probability:  $p_1 = 0.35$ ,  $p_2 = 0.09$ ,  $p_3 = p_4 = 0.08$ ,  $p_5 = p_6 = 0.04$ ,  $p_7 = p_8 = p_9 = p_{10} = 0.03$ ,  $p_{11} = p_{12} = 0.02$ .

The optimal solution for the charging / discharging operations of ESSs and EVs batteries results from the application of the single scenario approach and solving the LP problem (12)-(13) in scenario  $w_1$ . The resulting total energy cost for the district is  $F = -0.75 \text{ €}$ . The negative cost means

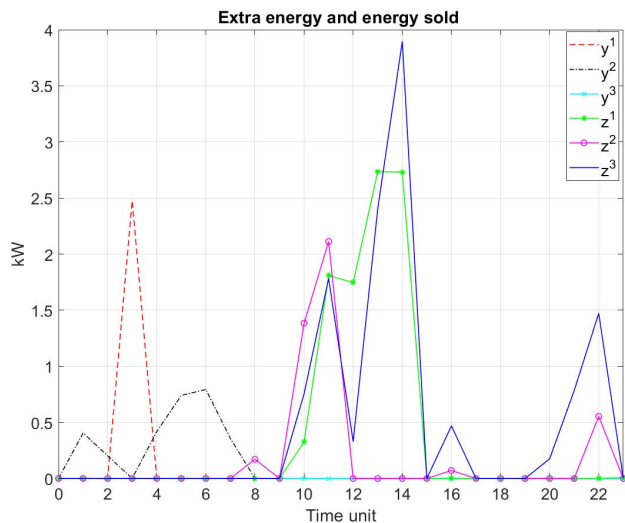


FIGURE 6. Extra energy and sold energy of building 1, 2 and 3 in  $w_1$ .

that the day-ahead prediction of energy consumption of the district is accurate allowing to minimize the extra-energy need and to sell back the energy surplus to the PG. Fig. 5 depicts the real time energy from the grid for the 3 buildings in scenario  $w_1$ . In addition, Fig. 6 shows respectively the extra energy and sold energy of building 1, 2 and 3 in scenario  $w_1$ . The total cost of each studied scenario is reported in Table 2.

The SLP problem (15)-(15.13) is solved for the  $H = 12$  selected scenarios (12)-(13) that provide  $\mathbb{E}[F] = -0.42 \text{ €}$ . It can be observed that the cost of energy increases

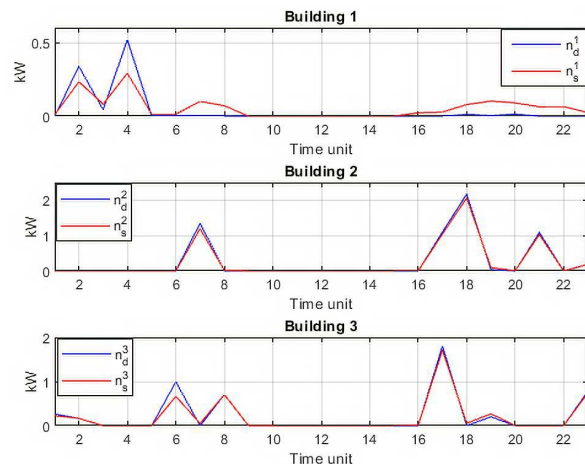


FIGURE 7. Energy from the ESS to the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

with respect to the cost obtained in Scenario  $w_1$  solving LP problem (12)-(13), if the uncertainties are considered. Moreover, in Figs. 7-12 we provide a comparison of the main variables trend obtained solving the LP problem in scenario  $w_1$  and the SLP problem.

Afterwards, to demonstrate the advantages of using the stochastic multi-scenario approach with respect to the single scenario approach, 10 different instances are extracted by the initial set of 400 scenarios and are used as term of comparison between the two approaches. In particular, for each instance, the energy balancing and distribution solutions obtained by the two approaches are applied, i.e. i) the optimal distribution strategy resulting from the LP problem

$$\begin{cases}
 0 \leq r_h^i(t) \leq r_{tot,h}^i(t), \quad \forall i \in B, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.1) \\
 0 \leq e_{s,k,h}^i(t) \leq e_{s,k,max}^i, \quad \forall i \in B, \forall k \in S^i, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.2) \\
 e_{s,k,h}^i(0) = e_{s,k,0}^i, \quad \forall i \in B, \forall k \in S^i, h \in \mathcal{H} & (15.3) \\
 e_{s,k,h}^i(t) = e_{s,k,h}^i(t-1) + \gamma_{c,s,k}^i c_{s,k,h}^i(t) - d_{s,k,h}^i(t), \quad \forall i \in B, \forall k \in S^i, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.4) \\
 e_{v,j,min}(t) \leq e_{v,j,h}(t) \leq e_{v,j,max}, \quad \forall j \in V, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.5) \\
 e_{v,j,h}(0) = e_{v,j,0}, \quad \forall j \in V, h \in \mathcal{H} & (15.6) \\
 m_j^{i,p}(t) = [q_j^i(t) - q_j^i(t-1)] b_{ip}, \quad \forall i, p \in B & (15.7) \\
 e_{v,j,h}(t) = e_{v,j,h}(t-1) + \sum_{i \in B} [q_j^i(t)(\gamma_{c,v,j} [c_{v,j,h}^{i+}(t) + c_{v,j,h}^{i-}(t)] - d_{v,j,h}^i(t))] + \sum_{i \in B} \sum_{p \in B, p \neq i} q_j^i(t-1) m_j^{i,p}(t) & (15.8) \\
 \forall j \in V, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} \\
 u_h^i(t) + r_h^i(t) + n_h^i(t) + v_h^i(t) = z_h^i(t) + l_h^i(t) + \sum_{j \in V} \frac{1}{\gamma_{c,v,j,h}} c_{v,j,h}^{i-}(t), \quad \forall i \in B, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.9) \\
 \sum_{k \in S^i} c_{s,k,h}^i(t) + \sum_{j \in V} q_j^i(t) c_{v,j,h}^{i+}(t) \leq -u_h^i(t) + s^i(t) + y_h^i(t) + r_{tot,h}^i(t) - r_h^i(t), \quad \forall i \in B, \forall t \in \mathcal{T}, \forall h \in \mathcal{H} & (15.10) \\
 y_h^i(t) \geq u_h^i(t) - s_h^i(t), \quad \forall i \in B, \quad \forall h \in \mathcal{H} & (15.11) \\
 y_h^i(t) \geq 0 \quad \forall i \in B \quad h \in \mathcal{H} & (15.12) \\
 r_h^i(t), u_h^i(t), e_{s,k,h}^i(t), e_{v,j,h}(t), c_{s,k,h}^i(t), z_h^i(t), c_{v,j,h}^{i-}(t), c_{v,j,h}^{i+}(t), d_{s,k,h}^i(t), d_{v,j,h}^i(t) \geq 0, \quad \forall i, k, j, t; h \in \mathcal{H} & (15.13)
 \end{cases}$$

TABLE 2. Total costs for the 12 scenarios.

	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$	$w_9$	$w_{10}$	$w_{11}$	$w_{12}$
F [€]	-0,75	-0,83	-0,56	-0,12	-0,33	0,09	1,80	0,47	1,11	-1,25	-1,41	-1,06

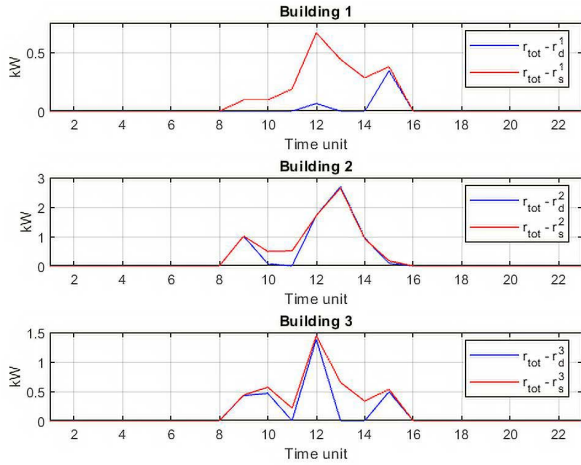


FIGURE 8. Renewable energy stored in the ESS for the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

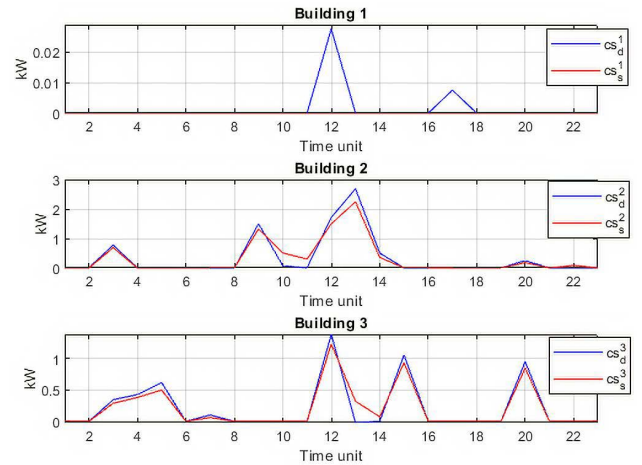


FIGURE 10. Energy stored in the ESS for the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

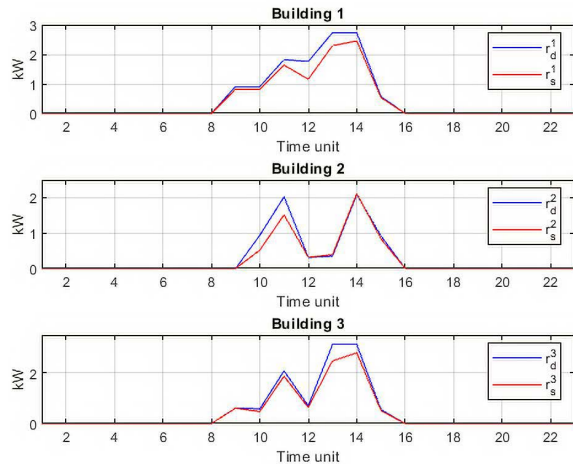


FIGURE 9. Energy from the RES to the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

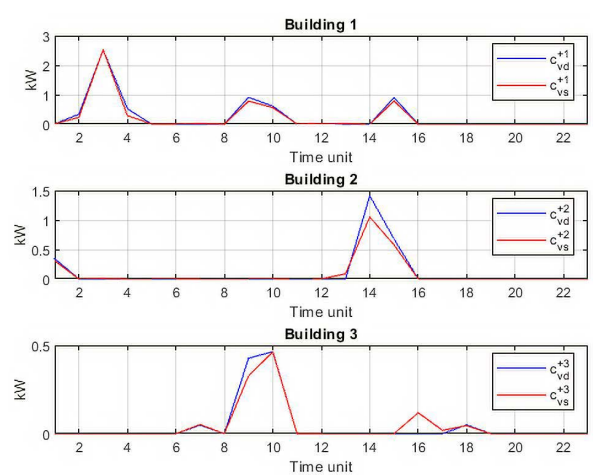


FIGURE 11. Energy stored in EV batteries for the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

solution for the most probable scenario  $w_1$ ; ii) the optimal distribution strategy resulting from the multi-scenario based SLP problem solution. For the comparison of the two approaches over the 10 instances, the following cost indices are calculated:

- building total costs of energy  $y$  from the PG:  $C_y^i = \sum_{t \in \mathcal{T}} a(t)y^i(t)$  for  $i = 1, 2, 3$ ;
- district total costs of energy  $y$  from the PG:  $C_y = \sum_{i \in B} C_y^i$ .
- building total costs of energy  $z$  to the PG:  $C_z^i = \sum_{t \in \mathcal{T}} b(t)y^i(t)$  for  $i = 1, 2, 3$ ;

- district total costs of energy  $z$  to the PG:  $C_z = \sum_{i \in B} C_z^i$ .

The resulting costs are reported in Table 3. It is demonstrated that the district total cost obtained by applying the multi-scenario stochastic strategy is lower than the same cost obtained by applying single-scenario strategy. Therefore, the performance indices show the benefits of considering the uncertainty in the MM problems in order to reduce the costs. In particular, the maximum (minimum) cost saving of stochastic approach with respect deterministic one is achieved by stochastic approach in instance 6 (instance 7) by 0.51 (0.15) €/day. The results over the 10 analyzed instances demonstrate that the stochastic approach allows to reduce the

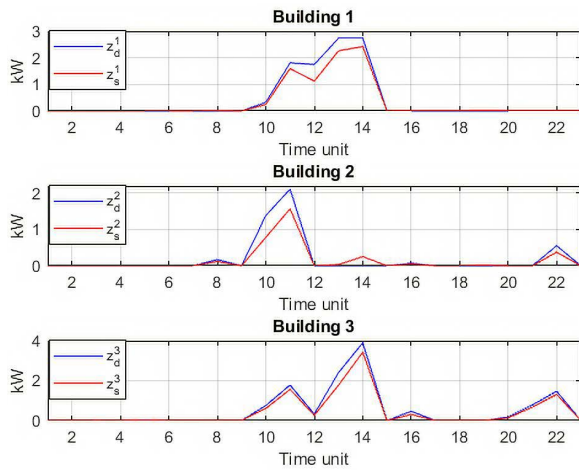


FIGURE 12. Energy sold to the PG by the 3 buildings applying the LP to  $w_1$  (blue line) and SLP (red line) approaches.

total cost for the district of 1.45 €/day corresponding to a reduction of 25%.

VI. BENEFITS AND LIMITATIONS

The optimal solution obtained by LP and SLP are important in order to determine timing, quantities and devices in which the energy must be stored, sold and distributed in the microgrids, taking into account uncertainties, within a day. The proposed optimization method can be integrated in the district control unit, i.e. the DEMS, and can be used to manage the operations of energy storing and distribution using ESS and EV batteries.

More in detail, a classic internet connection between DEMS and DAEM Market is needed to establish the day-ahead power profiles and costs for the district. However, this information is not sufficient to perform the optimization method. Indeed, the microgrids must be connected with DEMS and transmit data about local RES, ESS, EVs. This connection can be realized through a LAN (Local Area Network) and/or a PLC (Power Line Communication) for small size districts, like a university campus, and by using WAN (Wide Area Network) for large size districts. In order to perform the optimization method, the DEMS must be equipped by a linear programming problem solver like CPLEX, Matlab (e.g. function linprog.m) and Gurobi. The DEMS derives the necessary information from the optimal solution to be transmitted to the local microgrid controllers in order to actuate the optimal electric flows strategy. The optimal solution is obtained in polynomial time which well fits with real time applications.

In the proposed architecture particularly important are the electric vehicles that are seen as movable energy storages among the buildings in the district. Therefore, we can conclude that the proposed method can be a valid tool to be used from energy managers of municipalities and district areas in order to minimize the energy cost and consumption, exploiting the use of green energy and storage devices. The

TABLE 3. Total costs in € by the single scenario and multiscenario approaches applied to the 10 instances.

Instance	Deterministic approach				Stochastic approach			
	B 1	B 2	B 3	Total	B 1	B 2	B 3	Total
1	0,32	0,40	0,07	0,78	0,25	0,41	0,08	0,73
2	0,24	0,28	0,00	0,52	0,24	0,31	0,04	0,58
3	0,87	1,12	0,60	2,59	0,63	0,95	0,42	2,00
4	0,36	0,46	0,11	0,93	0,26	0,45	0,10	0,80
5	1,11	1,43	0,83	3,37	0,82	1,21	0,59	2,63
6	1,25	1,61	0,96	3,81	0,93	1,37	0,71	3,01
7	0,58	0,75	0,36	1,69	0,41	0,64	0,25	1,31
8	0,76	0,98	0,50	2,24	0,54	0,83	0,35	1,72
9	0,44	0,56	0,19	1,20	0,31	0,52	0,14	0,98
10	0,99	1,27	0,71	2,97	0,72	1,08	0,50	2,30
<b>Total</b>	<b>6,93</b>	<b>8,84</b>	<b>4,33</b>	<b>20,10</b>	<b>5,12</b>	<b>7,77</b>	<b>3,17</b>	<b>16,06</b>
	$C_y^1$	$C_y^2$	$C_y^3$	$C_y$	$C_y^1$	$C_y^2$	$C_y^3$	$C_y$
1	0,47	0,22	0,61	1,30	0,39	0,16	0,52	1,07
2	0,47	0,22	0,60	1,29	0,39	0,16	0,51	1,06
3	0,55	0,26	0,72	1,53	0,46	0,19	0,60	1,25
4	0,49	0,23	0,63	1,34	0,41	0,17	0,53	1,10
5	0,59	0,27	0,76	1,63	0,49	0,20	0,64	1,34
6	0,62	0,28	0,79	1,70	0,51	0,21	0,67	1,39
7	0,46	0,21	0,59	1,27	0,38	0,16	0,50	1,04
8	0,54	0,25	0,69	1,47	0,45	0,18	0,58	1,21
9	0,50	0,23	0,64	1,37	0,41	0,17	0,54	1,12
10	0,57	0,27	0,74	1,58	0,48	0,20	0,62	1,30
<b>Total</b>	<b>5,26</b>	<b>2,43</b>	<b>6,79</b>	<b>14,48</b>	<b>4,37</b>	<b>1,81</b>	<b>5,70</b>	<b>11,89</b>
	$C_z^1$	$C_z^2$	$C_z^3$	$C_z$	$C_z^1$	$C_z^2$	$C_z^3$	$C_z$
1	-0,16	0,18	-0,54	-0,52	-0,15	0,24	-0,43	-0,34
2	-0,23	0,06	-0,61	-0,77	-0,15	0,15	-0,47	-0,48
3	0,32	0,86	-0,11	1,07	0,17	0,76	-0,18	0,75
4	-0,13	0,23	-0,52	-0,41	-0,15	0,28	-0,43	-0,30
5	0,52	1,15	0,06	1,74	0,33	1,01	-0,05	1,29
6	0,63	1,32	0,16	2,12	0,42	1,16	0,04	1,61
7	0,12	0,53	-0,24	0,42	0,03	0,49	-0,25	0,27
8	0,23	0,73	-0,19	0,76	0,10	0,65	-0,23	0,51
9	-0,05	0,33	-0,45	-0,17	-0,10	0,35	-0,40	-0,15
10	0,42	1,00	-0,03	1,39	0,25	0,88	-0,13	1,00
<b>Total</b>	<b>1,67</b>	<b>6,41</b>	<b>-2,46</b>	<b>5,62</b>	<b>0,75</b>	<b>5,96</b>	<b>-2,53</b>	<b>4,17</b>
	$C^1$	$C^2$	$C^3$	$C$	$C^1$	$C^2$	$C^3$	$C$

minimization of the costs also impacts the final users whose energy bill will be reduced. In addition, the minimization of consumption of non-green energy has positive effects on the reduction of dangerous emissions for the environment.

One of the practical limitation of the proposed method is that, in some countries, district energy management is not performed due to the lack of automation and optimization systems.

Moreover, several municipalities still use obsolete systems for the energy management of buildings facilities that do not support the proposed architecture implementation. To overcome this limitation, the proposed optimization tool can be useful to show to energy managers the potential of implementing such an architecture in reducing costs. The optimal solution can suffer for small deviations in real cases in which other constraints related to the particular configuration of transmission and distribution systems need to be taken into account. Finally, our approach is assuming that the EVs move among buildings according to a predefined schedule. In real cases there can be misalignment with the scheduled travels that should be taken into account.

## VII. CONCLUSION

This paper proposes an energy management system for a smart district composed of a network of smart buildings. In this framework, each smart building is a microgrid with Renewable Energy Sources (RESs), Energy Storage Systems (ESSs) which can manage the charging/discharging operation of EVs. Acting in a scenario where the energy consumption profiles for the next 24 hours are purchased in the Day-Ahead Market (DAEM), the District Energy Management System (DEMS) operates a strategy to minimize the need of additional energy to be purchased in the expensive real-time market, as well as maximizing the energy storage. Moreover, the surplus energy can be sold back to main grid generating revenues for the microgrids.

The proposed strategy is formulated by two approaches: 1) a deterministic or single-scenario approach where the microgrid management problem is modelled as a Linear Programming (LP) problem; 2) the LP problem is reformulated as a Stochastic Linear Programming (SLP) problem that minimizes the expected value of the district total energy cost to deal with uncertainties of RES production, building loads, and energy costs.

The case study results demonstrate that the proposed method is effective for the district energy management dealing with electric vehicles that can travel among buildings as movable energy storages. Moreover, the proposed method has polynomial complexity, thus requiring limited computational effort. Considering the multi-scenario stochastic formulation, it is shown that the total district cost is decreased by 25% with respect to the deterministic approach. In particular, the stochastic approach performs better than the deterministic one especially in cases where the real time consumption overcomes the predicted day-ahead consumption. On the contrary, in cases where the day-ahead profiles are over estimated, the deterministic approach can be slightly more convenient. The proposed method can be a valid tool for energy managers of smart districts in order to effectively manage a network of building microgrids, aggregated in the

energy market, minimizing the costs and maximizing the use of green and stored energy.

In future works, a more accurate model of the EV batteries will be integrated in the architecture. In addition, the uncertainty of EVs travels among buildings will be studied in the stochastic approach. Furthermore, distributed and decentralized approaches will be investigated.

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