Organization-based Multi-Agent Structure of the Smart Home Electricity System

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***Abstract*—This paper proposes a Building Energy Management System (BEMS) as part of an organization-based Multi-Agent system that models the Smart Home Electricity System (MASHES). The proposed BEMS consists of an Energy Management System (EMS) and a Prediction Engine (PE). The considered Smart Home Electricity System (SHES) consists of different agents, each with different tasks in the system. In this context, smart homes are able to connect to the power grid to sell/buy electrical energy to/from the Local Electricity Market (LEM), and manage electrical energy inside of the smart home. Moreover, a Modified Stochastic Predicted Bands (MSPB) interval optimization method is used to model the uncertainty in the Building Energy Management (BEM) problem. A demand response program (DRP) based on time of use (TOU) rate is also used. The performance of the proposed BEMS is evaluated using a JADE implementation of the proposed organization-based MASHES.**

***Index Terms*—Building energy management system, multi-agent system, local electricity market, interval optimization, decision-making under uncertainty.**

NOMENCLATURE

A. Indices

t	Index of time periods.
i	Index of Distributed Energy Resources (DERs).
j	Index of electrical loads.
k	Index of energy storage systems.

B. Variables

OF	Objective function.
P_{i_t}	Total power generation for DER i in period t.
P_{net_t}	Power generation that is bought from local electricity market in period t.
P_{k_t}	Total power generation for energy storage system k in period t.
C_t^k	State of charge for energy storage system k in period t.
L_{j_t}	Electrical load j in period t.
$L_{j_t}^{shed}$	Load shedding for load j in period t.
S_{i_t}	Spillage amount for DER i in period t.
D_{i_t}	Difference between the scheduled day-ahead and predicted power generation for DER i in time period t.

C. Parameters

$\lambda_{i_t}/\lambda_{net_t}$	Electricity price for DER i/network in period t.
f_{max}	Maximum power capacity for the line.
$P_{i_t}^{pred}$	Predicted power generation for DER i in period t.
α_i	Optimistic coefficient related to the power generation for DER i.
σ_i	Prediction variance related to the power generation for DER i.
U_j^{max}	Maximum energy consumption for load j.

I. INTRODUCTION

The power and energy system has been experiencing a complete change in paradigm due to the worldwide increase of renewable energy sources. The distributed and unpredictable nature of these energy sources is bringing new challenges to the traditionally centrally operated sector [1]. Moreover, the world is increasing its energy consumption and in particular, the consumption of electricity. European reports from 2010 mention an increase in global consumption in EU-27, where the domestic consumers represent about 29.70% of the total electricity usage [2].

This paradigm shift requires new visions and approaches in order to deal with new challenges. One of the most consensual solutions is the so-called Smart Grid (SG) [3], its success, however, depends on active participation from the consumer side. In this scope, the consumer is no longer a static load to be assumed by the system, rather an active player, who can both purchase and sell the generated energy locally [4]. Thereby, BEM are becoming crucial, and should include new characteristics and advanced functions, namely the management of Electric Vehicles (EVs), the interface with external operators, among others. In this sense, these management systems are defined as a smart home system. The smart home represents a house with network communication between all devices allowing the control, monitoring and remote access of the management system [5]. Several works deal with the smart home as a house management system to effectively manage consumption, storage, distributed generation and the participation in Demand Response (DR) programs [6]. Smart

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homes will function as prosumers in the SGs. A smart home electricity system includes the electrical loads that consume electricity, Distributed Energy Resources (DERs) that produce electrical energy, and Energy Storage Systems (ESSs) that can store electrical energy. Besides, there is an Energy Scheduler (ES) in the SHES that schedules production/consumption of energy in all of the system's agents. Additionally, smart homes should be able to connect the power grid. Hence, they will be able to sell/buy electrical energy to/from the Local Electricity Market (LEM).

The previous works can be evaluated based on their scales, goals, strategies, utilized technologies, and software. For instance, in [7], the scale has been considered to be the power grid. The goal was to minimize the operation costs. Besides, a hierarchical and decentralized strategy has been presented based on the Multi-Agent System (MAS). Moreover, JADE [8] have been used to implement the problem in the real system. In [9], the authors reviewed how to model the SGs as MASs. Also, [10] has reviewed the agent-based technologies of large-scale energy systems and SG projects. A hierarchical central approach of Micro-Grids (MGs) has been presented in [11]. In [12], a new method has been presented to solve AC-optimal power flow problem in the multi-agent decision-making framework. In [13], the multi-objective problem has been defined, and a bottom-up estimation state approach has been applied to minimize energy costs. In [14], the economic dispatch problem has been solved by decentralized and self-organizing strategies. The proposed strategy of [14] was non-hierarchical, and the operation costs have been minimized locally and then applied to the system globally. In [15], an energy management system has been presented based on the integration of smart meters. The hierarchical method for the management of the energy has been proposed in [15]. In [16], an intelligent method has been demonstrated to manage energy dynamically in the MG. The proposed method of [16] has been defined as either optimal or sub-optimal. Besides, providing the critical loads continuously is the purpose of [16]. In [17], the agent-based approach to optimize the operation costs of SG and BEMS has been presented. Also, the Partical Swarm Optimization (PSO) method has been used to maximize welfare and energy efficiency in the proposed model of [17]. In [18], BEM has been defined as an intelligent MAS. In [19], an adaptive and integrated method has been presented for DRP and BEMS based on real-life conditions. In [20], a method is proposed to apply the local energy resources optimally through minimizing the loss of energy. In [21], the scheduling problem of BEM has been solved considering DRP. The objective function of [21] was the trade-off between the purchasing cost of electricity and dissatisfaction of the consumers.

In this paper, SHES is defined as a class of organization-based multi-agent system. Hence, MASHES includes different agents each of whom have different tasks in the system. It will also talk about of the ES to manage electrical energy as well as smart home ability to trade electrical energy in the LEM. In addition, information provider is defined as an agent to provide all the required information for the system agents. For this purpose, JADE is utilized to implement the proposed organization-based MASHES. Furthermore, modified stochastic predicted bands method that has been introduced in [22] is utilized in the proposed building energy management system in this work, in order to model the uncertainty of stochastic variables.

The rest of this paper is organized as follows. Section II introduces the proposed organization-based agents of the SHES. Then, the proposed building energy management problem formulation is described in Section III and the MAS structure is described in Section IV. Besides, the simulation results of the case study are illustrated in Section V. Finally, the findings of the paper are summarized in Section VI.

II. Organization-Based Agents of the SHES

SHES consists of different organization-based agents that each of them has different tasks in the system. In this section, all agents of the SHES will be introduced and their task will be described. Moreover, the physical system of the organization-based MASHES is seen in Fig. 1. MASHES includes two layers. First layer is the electricity system which is displayed by black lines. However, second layer is the communication system that is shown by blue lines.

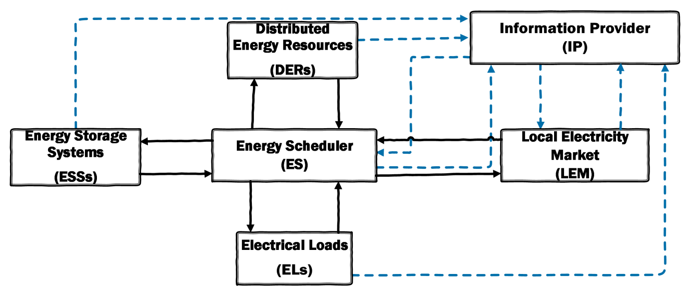

Fig. 1. MASHES physical system.

A. Electrical Loads (ELs)

Electrical Loads (ELs) are a group of agents that consume electrical energy in the SHES. Generally, ELs are classified into different types of loads such as shiftable, controllable, Must-Run Services (MRS), etc. Therefore, ELs can be considered as an organization basis for different agent types in the MASHES.

B. Distributed Energy Resources (DERs)

DERs are a set of agents that are responsible for the generation of electrical energy in a smart home. DERs are intermittent energy resources, so they inject uncertainty in the system. However, increasing the prediction accuracy of these stochastic variables can decrease the corresponding uncertainty in the system.

C. Energy Storage Systems (ESSs)

ESSs are the agents in the MASHES that can store electrical energy such as EVs and batteries. Batteries can help to smooth the electrical demand profile. On the other hand, even though the main purpose of EVs is to provide clean transportation, they can assist the MASHES as ESSs too.

D. Information Provider (IP)

IP is an agent in the SHES that is in charge of providing real-time and historical data information. It senses and records information from all the agents as well as environmental conditions.

E. Local Electricity Market (LEM)

LEM is defined as a set of external agents of a building. In this work, external agents consist of a retailer (the energy supplier) and a DR aggregator. Smart homes should be able to connect to the LEM to trade electricity. Hence, electricity price and power are two variables that are exchanged between smart homes and the LEM.

F. Energy Scheduler (ES)

ES is a virtual organization of agents who plays as a system operator in the MASHES. The proposed energy scheduling method is based on day-ahead energy management approach. The ES consists of two agents in the MASHES, one is the Prediction Engine (PE) and the other is the Energy Management System (EMS). The tasks of both are described below:

1) Prediction Engine (PE): PE provides accurate prediction of all stochastic variables of the system (e.g. wind speed, solar radiation, weather temperature, electricity price and electrical unshiftable loads) for EMS. Hence, the outputs of this agent will be the inputs of the EMS. As the DERS utilized in the SHES are non-dispatchable resources, the forecasting of its power output will be very important for the EMS. Hence, accurate forecasting of PE can assist the EMS to make optimum decisions.

2) Energy Management System (EMS): The task of the EMS is to make optimum decisions in the MASHES. An optimum decision depends on the objective(s) of the smart home owner. Maximizing the profit of the SHES is the proposed objective function (OF) of this paper. Therefore, after the OF is defined in the system, this agent should make an optimum decision. In this case, EMS faces a discrete optimization problem under uncertainty of the PE's outputs. This uncertainty causes some problems for the EMS, such as increasing the operating costs of the MASHES and computational overload. There are different methods to model the uncertainty in the optimization problems such as stochastic programming [23], interval optimization [24], robust optimization [25], etc. In our case, MSPB is used as an interval method to model the uncertainty in the BEM problem.

III. Building Energy Management Problem

We propose that each smart home can participate in two different types of LEM. These LEMs are called Day-Ahead Local Electricity Market (DALEM) and Balancing Local Electricity Market (BLEM). The building energy management problem is modeled as a two-stage problem. The first stage is called day-ahead stage, and the second stage is called the balancing stage. Here, the OF is to maximize the revenue of energy services. The OF is defined in the EMS, and the decision-maker determines the optimum amount of the objective function. As stressed on our approach, we consider the uncertainty in the problem. The modeling of uncertainty is done by bands based on the prediction of the stochastic variables. Besides, *Optimistic Coefficient* (OC) is defined as an auxiliary parameter to allow the decision-maker decides between optimistic or pessimistic strategies.

A. Day-Ahead Stage

The objective function of the MASHES in DALEM is defined in the Day-Ahead (DA) stage. The purpose of the energy management system is to make the best decisions for all the agents of the MASHES in each of the decision periods during the day d. However, the DA stage obtains optimum decisions for the system in day d-1. Hence, the objective function for the DA stage is represented as (1):

$$OF^{da} = \sum_{t=1}^{N_t} \Big(\sum_{i \epsilon DERs} \lambda_{i_t} P^{da}_{i,out_t} - \lambda_{net_t} P^{da}_{net_t} \Big) \tag{1}$$

OF^{da} consists of two parts. While the first part represents the revenue of selling the electrical energy produced by DERs to the DALEM, the second part states the costs of buying the electrical energy from the DALEM. The constraints of the DA stage are:

$$P^{da}_{net_t} + \sum_{i \epsilon DERs} P^{da}_{i,in_t} = \sum_{j \epsilon ELs} L^{da}_{j_t} \tag{2}$$

$$-f_{max} \le P^{da}_{net_t} - \sum_{i \epsilon DERs} P^{da}_{i,out_t} \le f_{max} \tag{3}$$

(2) establishes the power balance equation due to the power output of DERs that is injected into the home, P^{da}_{i,in_t}, grid power input, $P^{da}_{net_t}$, and electrical loads, $L^{da}_{j_t}$. In this paper, power loss is not considered for simplicity. (3) represents the power flow limitation through the distribution line which ends at the building. f_{max} expresses the maximum power capacity of the distribution line that links the smart home with the distribution power network. Besides, there are some limitations corresponding to all appliances. Only the maximum and minimum limitations of the energy produced/consumed are defined in each device at this stage because the uncertainty is not considered in the DA stage.

$$P^{da}_{i_t} = P^{da}_{i,in_t} + P^{da}_{i,out_t} \tag{4}$$

$$P^{min}_{i_t} \le P^{da}_{i_t} \le P^{max}_{i_t} \tag{5}$$

$$L^{min}_{j_t} \le L^{da}_{j_t} \le L^{max}_{j_t} \tag{6}$$

The total power generation of the DERs is stated in (4). (5) states the power output limitations of DERs agents. Besides, (6) represents the electrical power consumed by ELs agents.

B. Balancing Stage

In this stage, the objective function of the smart home due to participating in the BLEM is defined. In addition, the uncertainties of decision-making variables are considered. These variables are determined based on the outputs of the first stage and the prediction engine. The objective function of the balancing stage, OF^b, is represented as:

$$OF^b = \sum_{t=1}^{N_t} \Big(\sum_{i \epsilon DERs} \lambda_{net_t} (P^b_{i,out_t} - P^{da}_{i,out_t}) \tag{7}$$

$$+ \sum_{k \epsilon ESSs} \lambda_{net_t} P_{k,out_t} - \sum_{j \epsilon ELs} VOLL_j L^{shed}_{jt} - \sum_{i \epsilon DERs} V_i^s S_{i_t} \Big)$$

$$OF = OF^{da} + OF^b \tag{8}$$

OF^b consisting of five parts. The first part represents the revenue for selling energy produced by DERs to the BLEM. The total cost of electrical energy that is bought from the BLEM is represented in the second part. The third part expresses the profit due to selling the stored electrical energy of ESSs to the BLEM. The Value of Loss Load (VOLL), $VOLL_j$, is stated in the fourth part. Finally, the spillage costs of DERs are represented in the last part. As seen in (7), it is proposed that if the DERS's power generation in the balancing stage, P^b_{i,out_t}, is more than the DER's power generation in DA stage, the smart home can only sell its extra power at the net price, λ_{net}, that is less than the price that is established for the purchase of the power generated by the DERs on the DALEM, λ_i. Hence, the smart home can increase its revenue if it has better day-ahead prediction accuracy of its DERs' power generation. Besides, the total objective function of the system, OF, is defined in (8) as the sum of OF^{da} and OF^b.

$$P^b_{net_t} + \sum_{i \epsilon DERs} P^b_{i,in_t} + \sum_{k \epsilon ESSs} P^b_{k,in_t} = \sum_{j \epsilon ELs} (L^b_{jt} - L^{shed}_{jt}) \tag{9}$$

$$-f_{max} \leq P^b_{net_t} - \sum_{i:DERs} P^b_{i,out_t} - \sum_{k:ESSs} P^b_{k,out_t} \leq f_{max} \tag{10}$$

In the balancing stage, (9) is the power balance equation, and (10) shows power flow limitation in a distribution line. Besides, there are specific definitions for all appliances in the building energy system whose uncertainties are considered in the balancing stage.

1) DERs: The power output of DERs in the balancing stage, $P^b_{i_t}$, is obtained based on (11).

$$P^b_{i_t} = P^b_{i,p_t} - S_{i_t} \tag{11}$$

$$P^{min}_{i_t} \leq P^b_{i,p_t} \leq P^{max}_{i_t} \tag{12}$$

$$P^b_{i_t} = P^b_{i,in_t} + P^b_{i,out_t} \tag{13}$$

$$0 \leq S_{i_t} \leq P^b_{i,p_t} \tag{14}$$

Where as (11), P^b_{i,p_t} is the potential power generation of DER in the balancing, and S_{i_t} is the spillage power of the DER. (12) states the maximum and minimum power limitations of the DER. (13) represents that the total power output of the DER equals its power output consumed in the home, P^b_{i,in_t}, and the amount of power generation that is sold to the BLEM, P^b_{i,out_t}. The spillage amount of DER is the amount of power that is spilled in period t. This amount is positive or equal to zero, and is limited to the actual power generation of DER as presented in (14).

In this model, the MSPB method is used to model the uncertainty of variables in the BEM problem. As highlighted, the proposed interval method to model the uncertainty of DERs has been defined for the first time in [22]. This is why the performance of MSPB is explained briefly in this section. Knowing the probability distribution function of decision-making variables is one of the requirements in stochastic scenario-based methods [25]. Hence, in this approach, the uncertainty of stochastic variables is modeled based on their predicted amounts. Therefore, the prediction amounts of DERs' power generation that come from the PE are used in the formulations of MSPB. Also, σ_i^{up} and σ_i^{down} are parameters that state the amounts of upper and lower variances of the predicted variables with respect to their actual amounts, respectively. Then, the difference between the day-ahead DERs' power generation, $P^{da}_{i_t}$, and their predicted amount for each time, $P^{pred}_{i_t}$, is determined as (15):

$$D_{i_t} = P^{da}_{i_t} - P^{pred}_{i_t} \tag{15}$$

According to the state of D_{i_t}, the balancing DERs' power generation, $P^b_{i_t}$, is limited to the max and min bands. If D_{i_t} is positive/negative, it means that the DA power generation of DER is more/less than the predicted amount. Hence, the balancing power generation of DER should be upper/downer than the predicted amount to converge to the amount of DA variable.

Moreover, α_i is defined as a slack variable for the EMS to apply its knowledge regarding the stochastic behavior of the DER power generation. Therefore, α_i is called an *optimistic coefficient* with values between 0 and 1. In this paper, outdoor temperature and must-run services are considered as deterministic variables for simplicity. However, the uncertainty of DERs is considered based on (16).

$$\begin{cases} P^{pred}_{i_t}\alpha_i + (P^{pred}_{i_t} - \sigma_i^{up})(1-\alpha_i) \leq P^b_{i_t} & \\ \leq (P^{pred}_{i_t} + \sigma_i^{down})\alpha_i + P^{pred}_{i_t}(1-\alpha_i) & D_{i_t} \geq 0 \\ (P^{pred}_{i_t} - \sigma_i^{up})\alpha_i + P^{pred}_{i_t}(1-\alpha_i) \leq P^b_{i_t} & \\ \leq P^{pred}_{i_t}\alpha_i + (P^{pred}_{i_t} + \sigma_i^{down})(1-\alpha_i) & D_{i_t} \leq 0 \end{cases} \tag{16}$$

2) ESSs: ESSs can be utilized economically based on the charge and discharge strategies in the BEM problem. There are different factors that should be considered to model the effect of the use of ESSs in the BEM problem. These factors are mobility patterns and battery characteristics of the ESSs. It should be mentioned that the mobility pattern is only related to the EVs.

$$P_{k_t}^b = -P_{k,b_t}^b - \omega_t^c + \omega_t^d + \omega_t^m \tag{17}$$

$$C_t^k = C_{t-1}^k + \omega_t^c \eta_{G2V} - \omega_t^d / \eta_{V2G} - \omega_t^m / \eta_{V2T}, t \geq 2 \tag{18}$$

$$C_t^k = C_i^k, t = 1$$

$$P_{k,d_t}^{min} \eta_k (1 - u_t^k) \leq \omega_t^d \leq P_{k,d_t}^{max} \eta_k (1 - u_t^k) \tag{19}$$

$$P_{k,c_t}^{min} \eta_k u_t^k \leq \omega_t^c \leq P_{k,c_t}^{max} \eta_k u_t^k \tag{20}$$

$$0 \leq \omega_t^d \leq (C_t^k - P_{k,d_t}^{min}) \eta_k \tag{21}$$

$$0 \leq \omega_t^c \leq (P_{k,c_t}^{max} - C_t^k) \eta_k \tag{22}$$

$$P_{k,d_t}^{max} - C_{t-1}^k \leq P_{ev,b_t}^b \leq P_{k,c_t}^{max} - C_{t-1}^k, t \geq 2 \tag{23}$$

$$P_{k_t}^b = P_{k,in_t}^b + P_{k,out_t}^b \tag{24}$$

The power generation of ESSs, $P_{k_t}^b$, is expressed in (17) and (24). (18) represents the state of charge balance equation in an ESS, where C_i^k is the initial state of charge in the ESS. Maximum and minimum limitations of discharge current of the ESS are presented in (19) and (21). Moreover, (20) and (22) express constraints of ESS in the charge state. Finally, (23) enforces power limitations of the ESS.

3) ELs: ELs include loads that can be controllable and/or shiftable. (25) and (26) represent ELs' power and energy consumed maximum and minimum limitations. Moreover, (27) expresses the electrical load shedding, $L_{j_t}^{shed}$, constraint of ELs, while (28) and (29) express equal and unequal constraints of ELs. The interested readers are referred to [22] to know more information about the modeling of different loads.

$$L_{j_t}^{min} \leq L_{j_t}^b \leq L_{j_t}^{max} \tag{25}$$

$$U_j^{min} \leq \sum_{t=1}^{N_t} L_{j_t}^b \leq U_j^{max} \tag{26}$$

$$0 \leq L_{j_t}^{shed} \leq L_{j_t}^b \tag{27}$$

$$f_a(M_t^b) = 0; a = 1, ..., N_a.M \in \{L_j, \theta_{out}, \theta_{in}\} \tag{28}$$

$$g_b(M_t^b) \leq 0; b = 1, ..., N_b. \tag{29}$$

IV. MAS Design

The MAS for BEMS allows to model different devices in a house through autonomous agents as discussed in Section II. In addition to the representation of the different devices through software agents, the modeling of possible existing generation sources that can be connected to the house are also considered. Through this multi-agent modeling, it is possible to simulate different scenarios taking into account the optimization of the costs related to energy consumption. To this end, this MAS includes negotiation methods that allow various devices to reach consensus when it is necessary to reduce the overall energy consumption of a house in order to respond to the changes in energy prices, e.g. times of the day when the tariff is the highest, and to variations in generation due to their variable nature because of climatic conditions.

This MAS is implemented in JADE, which is compliant with FIPA [26] guidelines. The architecture of the agent society can be seen in Fig. 2. The organization-based MAS is composed by:

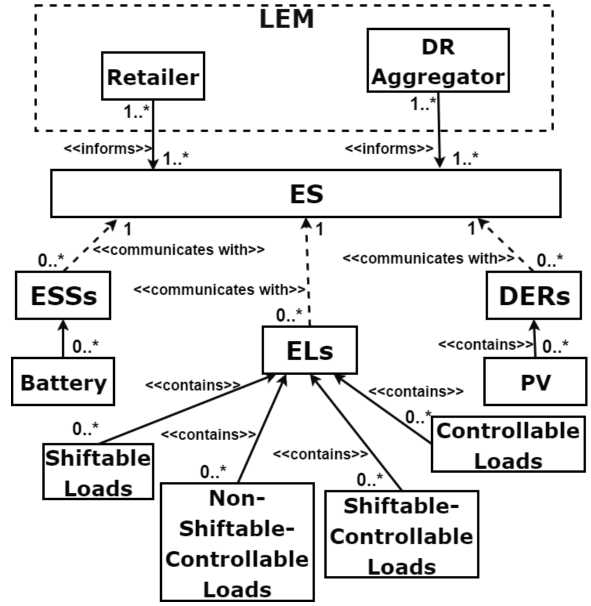

Fig. 2. MAS architecture.

1) LEM: Two external agent sets the retailer-the energy supplier- and the DR aggregator.

2) IP: In our structure, the Main Agent is created initially when the simulation is performed. It is responsible for creating the remainder agents. Another agent in the IP is called Management Information Base (MIB) that is responsible to interconnect agents.

3) ES: The ES-agent is included in this group of agents because it is responsible for connecting all the agents in a house. In addition, it analyses and predicts data. Also, the energy management is done by the ES.

4) DERs: This agent is responsible for renewable energy resources, e.g. as wind micro-turbines and PV panels.

5) ESSs: ESSs is a set of agents, that represent the energy storage units, e.g. battery, EVs.

6) ELs: ELs is an organization-based agent of different agents that only consume the electrical energy but whose type is different:

- Shiftable Loads are responsible for all units that may have changeable consumption.
- Shiftable-Controllable Loads are another type of agents that are responsible for all units which can be controlled and changed in their turn.
- Controllable Loads are the type of agents that are responsible for all units in which only consumption amount can very each time, but not to change their consumption in another time.
- Non-Shiftable-Controllable are responsible for all units that have not been included in any of the previously defined agents, i.e. all units that can neither control nor vary their power consumption in time.

In the agents representing the smart home, only the Manager agent is unique for each smart home and is responsible for the energy management of the respective house.

This proposed organization-based MAS structure is also capable of interacting with the Multi-Agent Smart Grid Simulation Platform (MASGriP) [27], which is a simulation platform that simulates, manages and controls the most relevant players acting in a smart grid and microgrid environment. Moreover, the Multi-Agent Simulator of Competitive Electricity Markets (MASCEM) is yet another MAS that enables the simulation of electricity markets [28]. Interaction with this system allows for the simulation of the participation of different players, even small players like houses, in distinct types of electricity market negotiations. The interaction between these different MAS is achieved through the use of specifically conceived ontologies, which are used to set a communication language between agents of the different systems, thus allowing them to understand each other and communicate effectively [29].

V. Simulation Results

A. Case Study

To assess the performance of the proposed BEMS, the physical system from [30] is applied. However, some modifications of the system parameters are made. The maximum energy produced by the PV system is 2-kW. The battery can store between 0.48 and 2.4 kWh, and maximum charging/ discharging rates are 400 W. Besides, charging and discharging efficiencies are 90%. Hence, the round trip efficiency (charging and discharging) reduces down to 81%. Maximum heating power of the Space Heater (SH) equals 2 kW to maintain the temperature of the house within ± 1 of desired temperature (23°C). The thermal resistance of the building shell is equal to 18°C/kW, and C equals 0.525 kWh/°C . The energy capacity of the Storage Water Heater (SWH) is 10.46 kWh (180 L) which has 2 kW heating element. The rated power of the Pool Pump (PP) is 1.1 kW, and it can run for a maximum of 6 hours during the day. The performance of the proposed BEM model is assessed in three cases. The program implemented is solved in GAMS 23.7 [31]. Table I displays the predicted data of stochastic variables [32]. Table II gives the price data of the system. Moreover, VOLL, and spillage costs of PV-battery power generation are shown in Table III. Generally, the PV system is an agent in the DERs, the battery system is an agent in the ESSs, the SH is a controllable load, the SWH and PP are shiftable electrical loads, and the must-run services are non-shiftable-controllable loads.

TABLE I
PREDICTED DATA OF UNCERTAIN VARIABLES [32]

t	$P_{pv_t}^{pred}$	σ_{pv}^{down}	σ_{pv}^{up}	$\theta_{out_t}^{pred}$	$L_{mrs_t}^{pred}$
1	0	0.00	0.00	5.5	0.005
2	0	0.00	0.00	5.5	0.005
3	0	0.00	0.00	5.2	0.005
4	0	0.00	0.00	5.2	0.005
5	0	0.00	0.00	4.8	0.005
6	0	0.00	0.00	5.5	0.005
7	0.10	0.01	0.02	6.5	0.005
8	0.20	0.02	0.04	7.5	0.005
9	0.42	0.03	0.07	9.8	0.005
10	0.76	0.08	0.26	10	0.005
11	1.1	0.12	0.23	11	0.005
12	1.32	0.13	0.26	12	0.005
13	1.91	0.10	0.19	12	0.005
14	0.85	0.02	0.04	12	0.005
15	0.29	0.02	0.04	11	0.005
16	0.31	0.02	0.03	10	0.005
17	0.06	0.01	0.01	9	0.005
18	0	0.00	0.00	8.5	0.005
19	0	0.00	0.00	8	0.005
20	0	0.00	0.00	7.5	1.218
21	0	0.00	0.00	7	0.262
22	0	0.00	0.00	6.5	0.14
23	0	0.00	0.00	6.2	0.127
24	0	0.00	0.00	6	0.005

TABLE II
PRICE DATA OF THE SYSTEM

	Price ($/MW)	
Time (hour)	λ_i	λ_{net}
23-7	2.2	0.0814
8-14	2.2	0.1408
15-20	2.2	0.3564
21-22	2.2	0.1408

TABLE III
VOLL AND SPILLAGE COSTS

	VOLL ($/MW)				Spillage Cost ($/MW)
Time (hour)	SH	SWH	PP	MRS	PV
22-7	1	1	-0.5	2.2	4
8-21	1	1	0.25	2.2	4

B. Impact of Energy Management Model

In this section, the energy management optimization problem is modeled in two cases. First, the objective functions of the day-ahead and balancing stages are optimized simultaneously. However, the objective functions of the day-ahead and balancing stages are optimized sequentially in the second one. In other words, in the second one, the objective function of the day-ahead stage is optimized first, then the balancing stage is optimized based on the decisions of the day-ahead one. Fig. 3 illustrates the amounts of OF^{da}, OF^{b}, and total OF in both of these cases. As seen in Fig. 3, the objective functions when energy management problem is optimized simultaneously is more sensitive to the amounts of α. Because of this, the day-ahead stage does not depend on the α when the energy management problem is optimized sequentially. Hence, the amounts of OF^{da} will be the same in all amounts of α in this case. Moreover, the increment of OF^{b} goes in line with α. Meaning that the highest and lowest amounts of OF occur when α equals 1 and 0, respectively. However, the lowest OF of the simultaneous building energy management problem

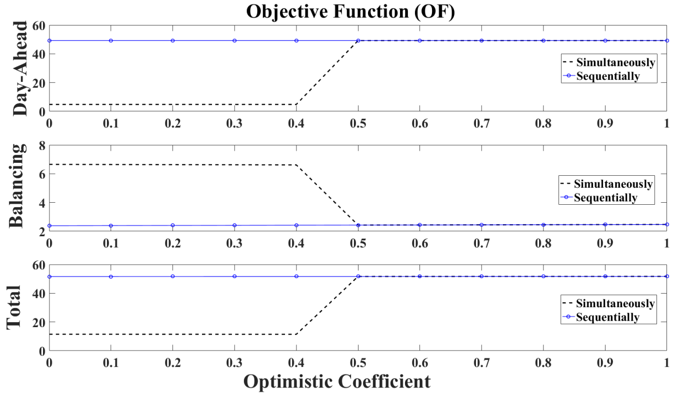

Fig. 3. Impact of optimistic coefficient on the DA, balancing and total OFs in simultaneous and sequential BEM problems.

TABLE IV
IMPACT OF PV POWER GENERATION UNCERTAINTY, BATTERY, AND DEMAND RESPONSE PROGRAM ON DAY-AHEAD, BALANCING, AND TOTAL OBJECTIVE FUNCTIONS

	α=0.4			α=1		
Scenarios	OF^{da}	OF^{b}	OF	OF^{da}	OF^{b}	OF
with uncertainty	4.836	6.613	11.449	49.232	2.475	51.707
without uncertainty	49.232	2.386	51.618	49.232	2.386	51.618
with battery	4.836	6.613	11.449	49.232	2.475	51.707
without battery	4.232	5.553	10.389	49.232	1.416	50.647
with DRP	4.836	6.613	11.449	49.232	2.475	51.707
without DRP	6.063	0.723	6.786	50.459	-2.087	48.372

happens when α equals 0.4.

C. Impact of PV power Generation Uncertainty

The uncertainty due to the PV power generation and its influence on the objective functions is analyzed in this section. It is noticeable that the uncertainty of outdoor temperature of the home and must-run services are not considered in this section in order to simplify the model. As mentioned before, the simultaneous BEM problem is more realistic than the sequential one since this is more sensitive to the amounts of α. Therefore, the uncertainty of PV power generation is analyzed in the worst/best case that α equals 0.4/1. As shown in Table IV, the amounts of objective functions do not depend on the α when uncertainty does not consider in the problem. In other words, the forecasting error equals zero when there is no uncertainty in the system, and α cannot impact on the results of the system when the up and down forecasting errors are equal to zero. Hence, the objective functions are the same in all amounts of α, and the worst and best cases do not have any meaning in the scenario which there is no uncertainty. On the other hand, while the uncertainty has not been considered in the day-ahead stage, it does not mean that the amount of OF^{da} does not dependent on uncertainty of the system. OF^{da} dependents on uncertainty and α because of the day-ahead and balancing problems have been optimized simultaneously. However, OF^{da} does not dependents on uncertainty and α when the problems are optimized sequentially.

TABLE V
IMPACT OF BATTERY SYSTEM AND DEMAND RESPONSE PROGRAM ON THE AMOUNT OF SOLD/ BOUGHT ELECTRICAL ENERGY TO/FROM ELECTRICITY MARKET

	$\alpha = 1$			
	with battery	without battery	with DRP	without DRP
E_{sold}	12.68	7.88	12.68	12.68
E_{bought}	32.23	37.497	32.23	41.918

In addition, the uncertainty of PV power generation has a positive effect on the OFs, an OF is the profit of the building energy management system, when α equals 1 because the energy management system has an optimistic view of the system in this case. However, PV's power generation impacts negatively on objective functions when α equals 0.4 which is more rational. Hence, this evidences that the simulation results of the proposed BEMS are more realistic in the worst case.

D. Impact of ESS

To make this work simpler, only one battery system is considered as an ESS in the BEMS. The impact of a battery system on the OFs is shown in Table IV. From this table it is clear that the battery system can increase the amounts of all objective functions in both cases. In other words, the positive influence of the battery system on the BEMS's OF does not depend on the α. Also, Table V expresses that considering the battery in the BEMS causes to increase the amount of smart home's electrical energy that is sold to the local electricity market, and it decreases the amount of smart home's electrical energy that is bought from the local electricity market.

E. Impact of Demand Response Program (DRP)

In this section, the effect of the DRP on the OFs and the smart home's electrical energy that is sold/bought to/from locale electricity market is assessed. Here, TOU program is used. As seen in Table IV, DRP causes the positive effect on the amount of total objective function on the BEMS. In other words, while OF^{da} is increased when DRP is not considered in the system, OF^{b} is decreased dramatically because electrical loads are not flexible when DRP is not considered in the BEMS. Furthermore, considering DRP decreases the amount of electrical energy that a smart home buys from the LEM, because the main purpose of applying DRP is to eliminate the need of electrical energy by shifting the electrical load in the energy management time-period, and to reduce the electrical loads in some situations.

VI. CONCLUSION

In this paper, the organization-based multi-agent system of the smart home electricity system has been introduced. Besides, a new building energy management system has been implemented in the MASHES. It consists of an energy management system and a prediction engine. MSPB has been used as a novel interval method to model the uncertainty of decision-making variables in the BEM problem. The bands of the MSPB method come from the prediction engine to model the uncertainty of these variables. In this model, the smart home connects to the power grid to sell/buy electrical energy to/from the local electricity market.

The performance of the proposed BEM model has been assessed based on the impacts of energy management model, the uncertainty of PV power generation, energy storage system, and demand response program. From the simulation, it is noticed that:

- Simultaneous BEM problem is more sensitive to the amounts of the *optimistic coefficient*.
- Simulation results of the proposed BEMS are more realistic in the worst case.
- Considering the battery system can increase the amounts of all objective functions in BEMS.
- DRP has a positive effect on the amount of BEMS's total objective function. Also, DRP decreases the required electrical energy generation of a smart home.

Finally, it should be mentioned that the proposed building energy management system has been modeled to present its optimum action in the local energy market. Future work will consist of modeling a home energy management system able to manage electrical energy in the real-time operation. This will requires further research.

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