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A Stochastic Home Energy Management System considering Satisfaction Cost and Response Fatigue

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***Abstract*—Home Energy Management (HEM) systems enable residential consumers to participate in Demand Response Programs (DRPs) more actively. However, HEM systems confront some practical difficulties due to the uncertainty related to renewable energies as well as the uncertainty of consumers' behavior. Moreover, the consumers aim for the highest level of comfort and satisfaction in operating their electrical appliances. In addition, technical limits of the appliances must be considered. Furthermore, DR providers aim at keeping the participation of consumers in DRPs and minimize the "response fatigue" phenomenon in the long-term period. In this paper, a stochastic model of an HEM system is proposed by considering uncertainties of EV's availability and small-scale renewable energy generation. The model optimizes the customer's cost in different DRPs, while guarantees the inhabitants' satisfaction by introducing a response fatigue index. Different case studies indicate that the implementation of the proposed stochastic HEM system can considerably decrease both the customers' cost and response fatigue.**

***Index Terms*—Demand response programs, electric vehicle, inhabitants satisfaction, home energy management, response fatigue, renewable energy generation, stochastic programming.**

NOMENCLATURE

A. Superscripts

Acc	Acceptable by inhabitants.
App	Appliance.
B	Battery.
$B2G$	Battery to grid.
$B2H$	Battery to household.
ch	Charge.
$Cntrl$	Controllable appliance.
$Crit$	Critical demand.
$Degr$	Battery degradation.
dis	Discharge.
$dissat$	Dissatisfaction.
En	Energy.
EV	Electric vehicle.
$G2H$	Grid to household.
H	Household.
$H2G$	Household to grid.
$H2B$	Household to batteries.
$H2V$	Household to vehicle.
in	Inside/room.
ini	Initial value (without participating in DRPs).
Nom	Nominated power of appliances.
out	Outside/ambient.
PV	Photovoltaic.
Req	Required power of appliances.
$V2G$	Vehicle to the grid.
$V2H$	Vehicle to the household.

B. Index (Set)

i	Controllable appliances.
t (T)	Time.
$\omega\,(\Omega)$	Scenarios.

C. Parameters and Variables

B	Benefit function of customer.
Cap	Battery capacity.
$Cost^{cap}$	Capital cost of battery.
C^d	Cost of battery degradation.
Inc	Rate of incentive for load reduction.
L^{ET}	Batteries' lifetime.
P	Power.
Pen	Rate of penalty for not decreasing the load.
r	Charging/discharging rates of battery.
RFI	Response fatigue index.
SOC	State of the charge.
s	Binary variable of the appliance's statement.
U	Customer's utility function.
v	Inelasticity parameter of load.
V	Customer's dissatisfaction function.
WP	Working period of appliances.
θ	Temperature.
η	Charge/discharge efficiency.
π	Scenario probability.
λ	Price or tariff.
χ,γ	Binary variables of direction of transferring energy.

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I. INTRODUCTION

A. Aims and Motivation

THE residential sector constitutes a major portion of overall electricity consumption around the world. On this basis, optimization of the home energy management (HEM) has received many attention from the researchers' perspective. The key idea beyond the mind of the researchers is related to changing the role of the end user in the chain of electric energy system from a passive consumer to an active market player. To this end, the end users must participate more actively in energy exchange mechanisms by adjusting their consumption patterns and even decision making on their own available generation devices that transform the end users into *prosumers*.

However, according to some strong evidence, some reasons such as a sudden need to make frequent active consumption decisions may cause a phenomenon so-called "response fatigue"

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that means the consumers grow tired of keeping track of tariffs and usage, and of having to reprogram appliances accordingly [1]. As a result of response fatigue that occurs in long-term, some consumers may be expected to return to a default flat rate plan. To avoid the response fatigue, the HEM system should fulfill the need of active consumers through communication with both household appliances and the utility. The HEM system can receive external information signals to modify not only the energy consumption pattern of the households but also their energy generation schedule considering the customer's comfort.

B. Literature Review and Background

There are numerous studies that have addressed the problem of HEM from different aspects considering the role of DR strategies that can be summarized as follows.

- *Residential electric devices*: Residential electric devices consist of household appliances and also household generation technologies. The diversity in the devices may be influenced by several factors such as dwelling characteristics, lifestyle, affluence, and occupancy [2]. Typical examples for household appliances are air conditioners, washing machines, space heaters, water heaters, and refrigerators. In addition to usual household appliances, renewable energy generation (PV/Wind), Electric Vehicles (EVs), and Energy Storages (ESs) have recently received much attention in the smart household context.
- *Residential scheduling objectives*: The objectives for HEM system in the literature can be classified into four main categories including cost reduction, maintaining well-being level, achieving a desirable consumption pattern, and emission reduction as stated in [2].
- *Uncertainty characteristics of household*: The main uncertainties related to the households include PV/wind generation, energy consumption behavior, weather conditions, and occupancy [3].

In [4], an incentive-based energy consumption scheduling is presented with the aim of minimizing the total energy costs as well as reducing peak-to-average ratio of a household considering user comfort. However, the main drawback with the mentioned work is the assumption that all appliances have the same properties (Homogeneous assumption). In [5] and [6], a smart house has been operated using an optimization method that considers dynamic prices. In [7] and [8], the HEM limits the house's load peak for the smart households containing EVs. Pipattanasomporn et al. [7] added the priority of an appliance for the customers in the face of DR programs implementation and their reported algorithm can keep the total household power consumption below a predetermined level. It is notable that the mentioned work does not include the price-based DRPs. An optimal scheduling of electrical appliances to minimize the monthly electricity bill of a household through a price-based DRP is presented in [9]. Although the comfort level of the customers is considered in [9], other types of DRPs such as incentive-based strategies are not addressed. In [10], the customer's participation in DR is inspired through a priority-based incentive mechanism. In these reports, renewable energy resources, EVs and household batteries are not considered. Ref. [11] shows that DR has significant impacts on the overloading of distribution transformers resulted from EVs' charging. Moreover, Ref. [12] investigates the consumers' response for different DRPs powered by an estimation approach. In [13], a game theoretic model is presented to schedule the consumption plan of residential customers by managing their appliances.

Another set of literature has gone a step further by considering small-scale renewable generations in the HEM problem [14]. For instance, a demand side energy management for a household with a locally generated PV is reported in [15]. In [16], the energy scheduling of a smart house equipped with a solar assisted heating is studied in the real-time pricing. An HEM system is also utilized for a house containing HVAC, PV and ESs in [17]. However, the stochastic nature of renewable generation is not addressed. In addition, the overall household demand is investigated without considering different household's appliance characteristics as well as consumer's preferences. Moreover, DR strategies are not addressed. Chen et al. [18] reported a stochastic scheduling algorithm in order to handle the uncertainty in household appliance operation time as well as the energy generated from renewable resources using a dynamic pricing scheme.

EVs also constitute an essential part of the smart homes due to the fact that these vehicles can be charged and discharged and consequently affect both the power generation and consumption pattern of households. Therefore, it is necessary to incorporate the EVs in the HEM design. In [19], a price-based HEM framework is designed for scheduling different appliances considering the priority of household's appliance operation. The study incorporates EVs in the scheduling framework, although other renewable technologies are not taken into account and uncertainty is not addressed. Integrated scheduling of DRPs, EV, PV generation, and ES systems for a smart household is investigated in [20]. However, the mentioned report does not take into account the grid to vehicle operation mode of EV, and the uncertainty of EV availability is not addressed.

C. Contributions

According to the technical literature, a considerable share of the studies have provided impressive models for the smart HEM. However, a combined scheduling of different types of household appliances, renewable energy resources, bi-directional operation of EV, and ESs under different price-based and incentive-based DR strategies have not been addressed. The contributions of this paper can be summarized as follows:

- Incorporating uncertainties of the distributed renewable resources and the EV availability for charging/discharging into the scheduling of smart houses, and modeling the HEM system using a stochastic formulation
- Developing a more complete model of customers' satisfaction by optimizing the set point of HVAC systems
- Modeling the response fatigue in the HEM system as well as introducing a response fatigue index and utilizing it in the customers' satisfaction-based HEM system

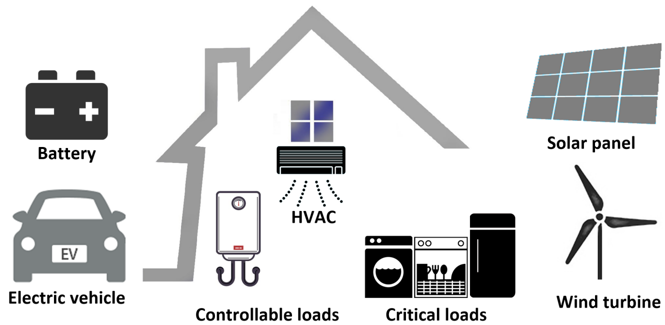

Fig. 1. Schematic diagram of the smart home.

D. Paper Organization

The mathematical formulation of the proposed method is presented in Section II. The problem uncertainties are modeled in Section III. Section IV contains the numerical studies and discussion. Section V presents the conclusions of the paper.

II. The proposed model of responsive smart household

A. Objective Function

If the electricity tariff (in price-based DRPs) or the penalty/payment (in incentive-based ones) changes at hour *t*, it can be assumed that the customer's demand is modified from d_t^{ini}, the initial demand, to d_t, the new demand.

Eq. (1) formulates the customer's total benefit for the time interval T by participating in both incentive- and price-based DRPs [21].

$$B_{tot} = \sum_{t=1}^{T} \left(U_t - d_t\,\lambda_t + Inc_t\,\Delta d_t - Pen_t\,\left(d_t^{Cont} - \Delta d_t\right)\right) \tag{1}$$

where U_t is the customer's utility at hour *t* that is a function of demand, d_t. d_t^{Cont} denotes the contract level for hour t. Δd_t represents the amount of the load change resulted from the DRP.

Particularly, the customer's utility indicates the production income for industrial customers, while it is the productivity for commercial demands. $d_t\,\lambda_t$ denotes the cost of buying the electricity. The third term represents the amount of incentive, and the fourth term denotes the amount of penalty.

According to (1), a typical customer's benefit B_{tot} from both price- and incentive-based strategies is formulated that denotes the major variable to make a decision about responding to DR signals. The general formulation is specifically employed for the smart household, as following.

A schematic diagram of the smart household is illustrated in Fig. 1. The HEM system controls the the smart home appliances considering signals from Load Serving Entity (LSE), DRPs, SOC of EVs and batteries, generation of renewable units, consumption of critical/controllable loads, etc.

Modifying the load pattern of consumers is the aim of DR providers. Thus, DR providers motivate their customers (such as residential consumers) for adjusting their load profile. If a fixed rate tariff implements, these consumers tend to operate their electrical appliances in a way to have the highest comfort level that is linked to their personal preferences. As a result, they use HVAC systems in warm hours, thus a load peak can occur.

In this paper, the penalties/incentives that the DR providers offer can encourage the consumers to adjust their consumption. The objective of each customer is that of maximizing the net payoff [22].

Therefore, the presented model maximizes the customer's profit as formulated in (2). The customer's incomes are derived from selling energy and DRPs' incentive. The costs are derived from purchasing energy, DRPs' penalty, batteries' degradations and inhabitants' dissatisfaction.

The decision variables are the transferred power from the grid, $P_{\omega,t}^{G2H}$, the transferred power from the house to the grid, $P_{\omega,t}^{H2G}$, the charging and discharging powers of the EV, $P_{\omega,t}^{H2V}$ and $P_{\omega,t}^{V2H}$, the charging and discharging power of the house battery, $P_{\omega,t}^{H2B}$ and $P_{\omega,t}^{B2H}$, the On/Off state of controllable appliances, $s_{i,\omega,t}^{App}$, and the set point temperature of HVAC, $\theta_{\omega,t}^{Set-point}$.

$$\begin{aligned}
&\text{Maximize}\left\{profit^{Household}\right\} = \\
&\sum_{\omega}\pi_\omega \sum_{t=1}^{T}\{P_{\omega,t}^{H2G}\,\lambda_t - P_{\omega,t}^{G2H}\,\lambda_t \\
&-Cost_{\omega,t}^{Degr} + Inc_t\,\left(\Delta P_{\omega,t}^{G2H} + P_{\omega,t}^{H2G}\right) \\
&-Pen_t\,\left(P_t^{G2H,Cont} - \Delta P_{\omega,t}^{G2H}\right) - V_{\omega,t}\}
\end{aligned} \tag{2}$$

The first two terms are respectively the selling income and purchasing cost of the household due to trade the energy with the grid. The third term considers the batteries degradation cost due to be operated in discharging modes. The degradation cost is calculated by (3).

$$\begin{aligned}
Cost_{\omega,t}^{Degr} &= \left(P_{\omega,t}^{B2H} + P_{\omega,t}^{B2G}\right)\,C^{d,B} \\
&+ \left(P_{\omega,t}^{V2H} + P_{\omega,t}^{V2G}\right)\,C^{d,EV} \qquad \forall t, \forall \omega
\end{aligned} \tag{3}$$

where $Cost_{\omega,t}^{Degr}$ is the degradation cost arisen from being operated in B2G, B2H, V2G and V2H modes. $C^{d,B}$ and $C^{d,EV}$ are the battery and EV battery costs that are considered as wear for the mentioned modes because of extra cycling of the batteries and are calculated by (4).

$$C^{d,X} = Cost^{cap,X}/L^{ET,X} \qquad {\scriptstyle X\in\{B,EV\}} \tag{4}$$

$Inc_t\,(\Delta P_{\omega,t}^{G2H} + P_{\omega,t}^{H2G})$ represents the incentive income for participation in an incentive-based DRP. While, $Pen_t\,(P_{\omega,t}^{G2H} - P_t^{G2H,Cont})$ is the penalty cost resulted from taking part in the DRP. $\Delta P_{\omega,t}^{G2H}$ shows the transfered energy to the house when a fixed-rate tariff is implemented minus the one when an incentive-based DRP is applied. It should be mentioned that the term $Inc_t\,P_{\omega,t}^{H2G}$ models the incentive-based income of customer from injecting the power back to the grid. Lastly, $V_{\omega,t}$ shows a function that models the dissatisfaction of consumers due to variation from the initial consumption and is given by (5).

$$\begin{aligned}
V_{\omega,t} &= \sum_{i} v_i^{App}\,\left(P_{i,\omega,t}^{App} - P_{i,\omega,t}^{App,ini}\right) \\
&+v^{EV}\left[\left(P_{\omega,t}^{G2V} - P_{\omega,t}^{ini,G2V}\right) + \left(P_{\omega,t}^{ini,V2G} - P_{\omega,t}^{V2G}\right)\right]
\end{aligned} \tag{5}$$

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where $v_i^{App} \geq 0$ is defined as the load's inelasticity parameter [22]. The higer amounts of v_i^{App} indicate that operation of the appliance i at the initial time (i.e., the most convenient time) is the more important for the consumer.

The first line of (5) denotes the amount of controllable appliance i with participating in DRPs minus the one without participating in DRPs. As the dissatisfaction of inhabitants increases proportionally to the distance from the controllable loads when the fixed-rate is implemented, $V_{\omega,t}$ can be assumed as a convex function of controllable loads [22]. Both price- and incentive-based programs financially encourage the customer to modify its load pattern.

Note that modeling the impact of batteries' degradation cost not only maintains the batteries' lifetime but also provokes that the HEM does not consider the discharging the batteries as the first reaction to the electricity tariff. This means that, the HEM adjusts the controllable parts of demand in advance of discharging a battery, if this adjustment does not create higher cost due to the dissatisfaction of the customer.

B. Response Fatigue Index

Eq. (6) introduces the response fatigue index (RFI) for the consumer. Based on [1], there are two important factors that highly influence the response fatigue of consumers, namely, the frequency of DR signals/calls and duration of each DR event, and the importance appliances that their operation are affected by the DRP. These two factors are included in the proposed RFI.

$$RFI = \sum_{\omega} \pi_{\omega} \left(\frac{\sum_i v_i^{App} \, \tau_{i,\omega}^{dissat}}{T \sum_i v_i^{App}} \right) \times 100\% \tag{6}$$

where $\tau_{i,\omega}^{dissat}$ represents the duration that the customer is dissatisfied because of changing the operation time of appliance i from the most convenient time, T_i^{ini}, in a DRP.

In order to keep the customer taking part in DRPs, RFI should keep low. RFI tends to zero when the customer does not experience any uncomfortable situation arisen from the implementation of DRPs. In the most dissatisfaction state, the proposed index tends to 100%.

The following constraints are considered in the proposed model.

$$RFI \leq RF^{max} \tag{7}$$

Constraint (7) limits RFI to the given amount that can be set by the DR provider, RF^{max}. By setting an appropriate RF^{max} the DR provider ensures that the customer keeps participating in the DRP. RF^{max} can be obtained from a long-term study on consumers, and can be set based on the education and economic class of consumers.

C. Modeling the Controllable Appliances

Eq. (8) shows that the demand containing the residential load (i.e., $P_{\omega,t}^{Cntrl}$ and P_t^{Crit}) and the charging requirements of both the batteries of household and EV (i.e., $P_{\omega,t}^{H2B}$ and $P_{\omega,t}^{H2V}$) is either supplied through the grid ($P_{\omega,t}^{G2H}$) or by the internal generation of wind and PV, or by the energy from the battery or the EV.

$$\begin{aligned} & P_{\omega,t}^{G2H} + P_{\omega,t}^{wind2H} + P_{\omega,t}^{PV2H} \\ & + \chi_{\omega,t}^{B} \, P_{\omega,t}^{B2H} + \chi_{\omega,t}^{EV} \, P_{\omega,t}^{V2H} = \\ & P_{\omega,t}^{Cntrl} + P_t^{Crit} + \gamma_{\omega,t}^{B} \, P_{\omega,t}^{H2B} + \gamma_{\omega,t}^{EV} \, P_{\omega,t}^{H2V} \end{aligned} \tag{8}$$

where P_t^{Crit}, the critical load, represents the critical part of the load that is unadjustable and subsequently it does not depend on the implemented DR strategies. where $P_{\omega,t}^{Cntrl}$ denotes the amount of controllable load with participating in DRPs. χ_t^B and γ_t^B show binary variables to guarantee that a household battery cannot be charged and discharged simultaneously. Similarly, binary variables χ_t^{EV} and γ_t^{EV} guarantee that each EV battery cannot be charged and discharged concurrently as presented in (9).

$$\chi_{\omega,t}^{X} + \gamma_{\omega,t}^{X} = 1 \qquad \forall t, \forall \omega, {\scriptstyle X \in \{B,EV\}} \tag{9}$$

Total consumption of controllable appliances gives the controllable part of household demand as presented in (10). The consumption of each of the controllable appliances is considered equal to its nominal power. Hence, the HEM controls each single appliance by determining its ON/OFF states, $s_{i,\omega,t}^{App}$. It should be mentioned that the operation of appliances is also considered as a function of scenarios. In other words, the uncertainty of renewable energies can be covered by controlling the appliances, as well as operating the household battery and the EV.

$$P_{\omega,t}^{Cntrl} = \sum_i \{ s_{i,\omega,t}^{App} \, P_i^{Nom} \} \qquad \forall t, \forall \omega \tag{10}$$

Inequality (11) limits the daily consumption of each controllable appliance to the required consumption. It is noteworthy that this constraint can be extended to one week, since some electrical appliances (e.g., washing machine) can be operated some times per week. In addition to the considered dissatisfaction function, V_t, to model the consumers' tendency to preserve the initial consumption pattern, an operation time is considered to guarantee each controllable appliance to be used in a given period that is appropriate for the inhabitants.

$$P_i^{Req} \leq \sum_t \{ P_{i,\omega,t}^{App} \} \quad t \in T_i^{Acc}, \forall i, \forall \omega \tag{11}$$

The HEM must not switch off some types of appliances when they are working. This means that, the HEM system respects the operation period of each appliance. On this basis, (12) to (14) are considered to assure that all controllable appliances are ceaselessly used in their operation period.

$$\alpha_{i,\omega,t} + \sum_{j=1}^{WP_i - 1} \beta_{i,\omega,t+j} \leq 1 \qquad \forall t, \forall i, \forall \omega \tag{12}$$

$$\alpha_{i,\omega,t} - \beta_{i,\omega,t} = s_{i,\omega,t}^{App} - s_{i,\omega,t-1}^{App} \qquad \forall t, \forall i, \forall \omega \tag{13}$$

$$\alpha_{i,\omega,t} + \beta_{i,\omega,t} \leq 1 \qquad \forall t, \forall i, \forall \omega \tag{14}$$

where $\alpha_{i,\omega,t}$ and $\beta_{i,\omega,t}$ are auxiliary binary variables. Moreover, WP_i denotes the working period of the controllable electrical appliance i.

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D. Modeling the HVAC System

The HVAC system can be operated in order to decrease its consumption cost, however, this can negatively affect the inhabitants' comfort level. To overcome this issue, the inside temperature of the smart house is observed and the set point temperature of the HVAC is adjusted, as a variable, to reflect the dissatisfaction cost on the HVAC performance. Based on this, both $s_{i,\omega,t}^{App}$ and $\theta_{\omega,t}^{Set-point}$ are variables to control the HVAC consumption. The inside temperature is a function of weather condition and building characteristics. This paper employs a linearized model of thermal inertia of buildings [23], [24] as formulated in (15)-(16).

$$\theta_{\omega,t}^{in} = \left(1 - \frac{1}{M^{air}\,Cp^{air}\,R}\right)\theta_{\omega,t-1}^{in} + \frac{\theta_{t-1}^{out}}{M^{air}Cp^{air}R} - s_{i,\omega,t-1}^{App}\frac{Q^{HVAC}}{M^{air}\,Cp^{air}} \qquad \forall t,\forall\omega, i = {\scriptstyle HVAC} \tag{15}$$

$$\theta_{\omega,t}^{Set-point} - \theta^{db} \le \theta_{\omega,t}^{in} \le \theta_{\omega,t}^{Set-point} + \theta^{db} \tag{16}$$

where R is the equivalent thermal resistance of the building. M^{air} and Cp^{air} denote the mass and the heat capacity of air, respectively. Q^{HVAC} is the heating/cooling energy delivered by the HVAC. $\theta_t^{Set-point}$ and θ^{db} represent the set point temperature and the dead-band of HVAC, respectively.

E. Modeling the SOC of Household and EV Batteries

Eq. (17) describes the model considered to evaluate the SOC variations for the house and EV batteries.

$$SOC_{\omega,t}^{X} = SOC_{\omega,t-1}^{X} + \gamma_{\omega,t}^{X}\,\eta^{ch,X}\left(\frac{P_{\omega,t}^{H2X}}{Cap^{X}}\right) - \chi_{\omega,t}^{X}\left(\frac{P_{\omega,t}^{X2H} + P_{\omega,t}^{X2G}}{\eta^{dis,X}\,Cap^{X}}\right) \qquad {\scriptstyle X\in\{B,EV\}} \tag{17}$$

$$SOC^{min,X} \le SOC_{\omega,t}^{X} \le SOC^{max,X} \qquad {\scriptstyle X\in\{B,EV\}} \tag{18}$$

$$r_{\omega,t}^{ch,X} = \frac{SOC_{\omega,t}^{X} - SOC_{\omega,t-1}^{X}}{\eta^{ch,X}} \qquad \forall t,\forall\omega,{\scriptstyle X\in\{B,EV\}} \tag{19}$$

$$r_{\omega,t}^{dis,X} = \left(SOC_{\omega,t-1}^{X} - SOC_{\omega,t}^{X}\right)\eta^{dis,X} \qquad {\scriptstyle X\in\{B,EV\}} \tag{20}$$

$$0 \le r_{\omega,t}^{ch,X} \le r^{ch,max,X} \qquad \forall t,\forall\omega,{\scriptstyle X\in\{B,EV\}} \tag{21}$$

$$0 \le r_{\omega,t}^{dis,X} \le r^{dis,max,X} \qquad \forall t,\forall\omega,{\scriptstyle X\in\{B,EV\}} \tag{22}$$

Based on (17), the SOC of the battery at time t is a function of the SOC at time $t-1$, the injected energy to the battery, and the injected energy back to the grid and house at time t. Inequality (18) limits the depth of discharge and guarantees that the battery is not overcharged. The charging and discharging rates of household and EV batteries are limited as presented in (19) to (22).

F. Modeling the Transferred Power with the Grid

The transferred power to the grid equals to the surplus of wind and PV generations and injection of batteries, as presented in (23).

$$P_{\omega,t}^{H2G} = P_{\omega,t}^{wind} - P_{\omega,t}^{wind2H} + P_{\omega,t}^{PV} - P_{\omega,t}^{PV2H} + P_{\omega,t}^{B2G} + P_{\omega,t}^{V2G} \qquad \forall t,\forall\omega \tag{23}$$

Constraints (24) and (25) limit the transferred power with the grid to the line/grid capacity,$P_{\omega,t}^{G,max}$.

$$\chi_{\omega,t}^{H}\,P_{\omega,t}^{G2H} + \gamma_{\omega,t}^{H}\,P_{\omega,t}^{H2G} \le P^{G,max} \qquad \forall t,\forall\omega \tag{24}$$

$$\chi_{\omega,t}^{H} + \gamma_{\omega,t}^{H} = 1 \qquad \forall t,\forall\omega \tag{25}$$

where binary variables $\chi_{\omega,t}^{H}$ and $\gamma_{\omega,t}^{H}$ ensure the house not to be fed and to inject back concurrently. In other words, drawing the power from the grid and injecting it back do not occur simultaneously.

III. Modeling the problem uncertainties

In this paper, three types of uncertainty are considered to generate appropriate input scenarios. These uncertainties are EV availability, wind power, and PV generation. Various realizations of the uncertain variables are modeled through Roulette Wheel Mechanism (RWM) as a scenario generation method. To this end, the probability distribution function of each uncertain variable is split into several class intervals associated with a probability. Then, RWM is employed for scenario generation based on the intervals and the probabilities. Each of the mentioned uncertainties can be modeled by a specific probability distribution function. On this basis, the wind speed distribution is generally characterized by Weibull distribution [25], [26]. A common function to model the behavior of solar irradiance is Beta distribution [27].

In order to model the uncertainty of EV availability in the house parking, truncated Gaussian distribution is utilized. This distribution is widely used for arrival time, departure time and initial SOC (i.e., SOC at arrival time) of EVs [28] and [29]. Details of the distribution are given in Section IV.

IV. Numerical results

A household in Italy is considered to investigate the proposed model. According to [30], the dynamic tariffs of a typical day of January 2016 are presented in Table I. Several price- and incentive-based programs are taken into account.

As illustrated in Table I, the base case presents a fixed rate tariff for the electricity. The tariff equals to the average of the

TABLE I
STUDIED CASES FOR DRPS

Case	Off-peak	Peak (8-11AM)	Critical peak (6-8PM)
Base case	tariff: 0.06 €/kWh		
TOU	0.045 €/kWh	0.06 €/kWh	0.09 €/kWh
CPP	tariff: 0.06 €/kWh		0.120 €/kWh
RTP	0.047 0.044 0.042 0.042 0.043 0.045 0.053 0.065 0.081 0.080 0.070 0.060 0.053 0.052 0.054 0.059 0.067 0.093 0.091 0.083 0.060 0.054 0.053 0.050 €/kWh		
EDRP	-	-	Inc: 0.018 €/kWh
I/C service	-	20 % curtailment for one hour	

TABLE II
DETAILS OF HOUSEHOLD AND EV BATTERIES

$r^{ch/dis,max}$ (pu/h)	$Cost_B$ (€/kWh)	$\eta^{ch/dis}$
0.2	300	0.95
L_{ET} (MWh)	SOC^{min}	SOC^{max}
43840*	0.3	0.95

* Based on the depth of discharge.

TABLE III
CONSIDERED DATA FOR THE AVAILABILITY OF EV

	Mean	Standard deviation	Min	Max
Arrival SOC of EV (%)	50	25	30	95
Departure time (h)	8	3	5	10
Arrival time (h)	16	3	14	19

TABLE IV
DATA OF CONTROLLABLE LOADS

Appliance	No.	WP (min)	P_i^{Nom} (kW)	T_i^{ini} (h)	T_i^{Acc} (h)	v^{App} (€/kWh)
Water heating	1	60	4.5	8, 19	7-9, 18-22	0.03
HVAC system	1	20	2.2	-	-	0.02
Lamp	6	60	0.8	17-23	17-23	0.01

TABLE V
STRUCTURAL DATA OF THE HOUSE

Length (m)	Width (m)	Height (m)	Wall thermal coefficient $(J/hm°C)$	Wall thickness (m)
12	10	3	132	0.20

hourly prices given in RTP. Hence, the base case reflects the operation of the HEM system without considering any DRP. A TOU case is also studied in which the tariff of the off-peak period is 50% lower than the peak one, while the critical peak tariff 50% higher than the peak tariff. A CPP case is also considered in which a large amount of electricity rate (i.e., 120 €/MWh) is applied for consumption during the critical peak hours.

To analyze the EDRP case, 30% of base case tariff (i.e., 0.018 €/kWh) is assumed as an incentive, if the customer reduces its electricity load during critical peak hours. To study I/C service case, a signal is considered to be sent to the HEM system to decrease the load at an hour. The load curtailment is considered 20% in the peak and critical peak periods.

A 22 kWh Renault Zoe with a 3 kW charging/discharging power limitation (single-phase) is considered, while the household battery has 2 kWh capacity and the impact of different capacities is analyzed. The considered data of the household batteries and the availability of the EV are given in Tables II and III, respectively.

Table IV shows the characterization of electric appliances. According to Table IV, it is assumed that the consumer operates the water heating at hours 8:00 and 19:00 without considering any DRP, otherwise, the mentioned times can be changed between 7:00-9:00 and 18:00-22:00 (the acceptable time by the consumer) counting a dissatisfaction factor equals to 3 cent/kWh. According to Table IV, the inhabitants turn on six lamps (besides the critical lighting load) if no DR program exists. It should be noted that dishwashers and washing machines are considered as critical load, because it is hard to impossible to incentivize load shifting with these two appliances due to their high impact on the users' comfort.

It is assumed that, in the highest satisfaction level, the inhabitants tend to charge the EV at the arrival time (uncertain parameter) and stop charging once the battery is full, without operating the battery in V2H and V2G modes. Moreover, the details of the critical load consumption are derived from a typical 120 meter-square house in January as shown in Fig. 3a. The structural data of the house is shown in Table V.

It is assumed that the household contains a small-scale PV system of 1 kWp and a small-scale wind turbine of 1 kWp, while the impact of different sizes of these renewable energy sources is also analyzed. The generation of the mentioned PV system and wind turbine are based on the measured daily profiles of solar and wind farm productions, respectively. The measured data have been employed to generate scenarios by RWM as mentioned in Section III.

The inside temperatures without incorporation of DR and by employing TOU program are compared in Fig. 2. This

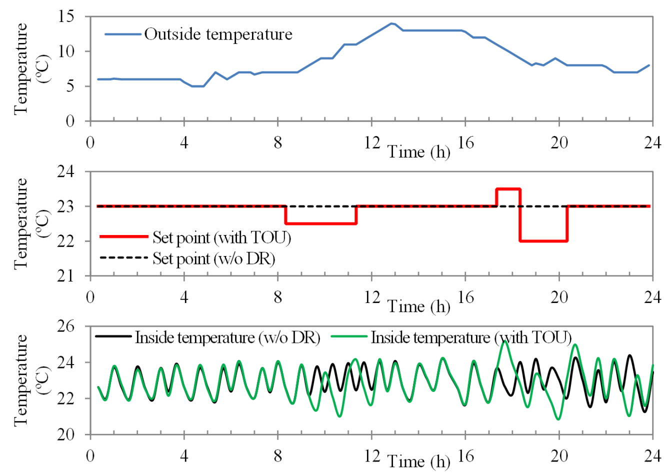

Fig. 2. Temperature set point with and without DR.

figure also represents the temperature set point in different hours in these two cases. The initial set point is considered equal to $23°C$ in winter, while the dead-band of the HVAC is $0.5°C$. The proposed satisfaction-based model determines a reduction of the consumed energy of the HVAC system from 20.53 kWh per day in w/o DR case to 19.8 kWh in the TOU. Moreover, the billing cost is more affected, because the consumption reduction mostly happens in peak and critical peak periods, due to the reduction of the set point in these two periods. It should be noted that in the TOU case, although the HEM system decreases the set point of the HVAC system at the critical peak hours, it increases the set point from $23°C$ to $23.5°C$ 40 minutes before the mentioned period. This helps the system to keep the room temperature comfortable during the critical peak period and to retain the comfort level of the customer.

The impact of the proposed model considering the TOU program on the consumption of electrical appliances is shown in Fig. 3. By comparing the consumption in Figs. 3a and 3b it can be observed that employing the TOU program curtails

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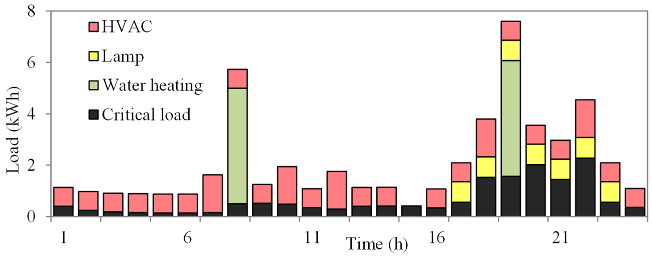
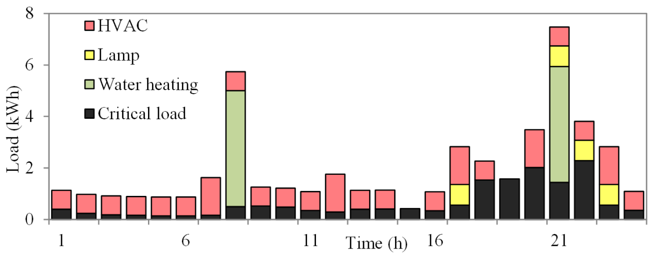
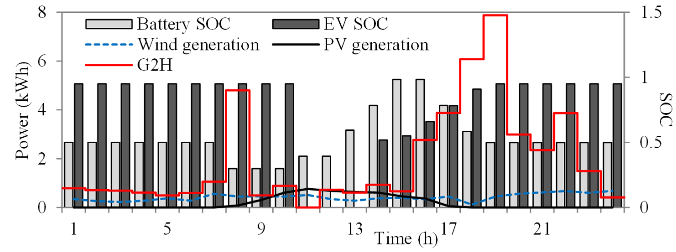


(a) Initial load (w/o DR, w/o the proposed HEM system)

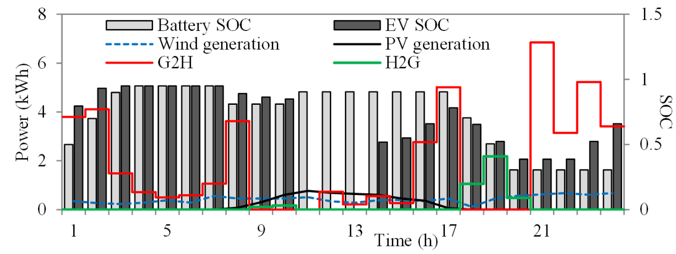


(b) With the proposed HEM system through the TOU program

Fig. 3. Appliances consumption.



(a) Initial load (w/o DR, w/o the proposed HEM system)



(b) With the proposed HEM system through the TOU program

Fig. 4. Performance of batteries and renewable generators.

a part of the load during the critical peak by turning off the lamps. Moreover, in spite of a large value of the dissatisfaction factor of the water heating, it is shifted from the critical peak (i.e., 19:00) to 21:00. However, the high dissatisfaction cost of the water heating causes that the HEM system does not shift the water heating from the peak hour (i.e., 8:00). Instead, a part of the water heating load is supplied by the batteries of the household and EV. The details of the expected operation of the batteries are indicated in Fig. 4.

According to Fig. 4a in which the proposed HEM system is not employed, when the EV arrives at home (that is a stochastic variable) it is plugged-in and starts being charged. The charging time of the EV quite coincides with the critical peak period. However, the household battery aims at reducing the demand peak and it limits the power drawn from the grid (i.e., G2H) to a value lower than 8 kW. To this end, the household battery is charged between 11:00-15:00 (when the residential demand is the lowest and the PV generation is the highest), and it is discharged when the demand is high due to the charging of uncontrolled EV. In this case, the household battery is charged and discharged once, while the EV is not enabled for operation on the V2G mode.

According to Fig. 4b, by employing the proposed HEM system and considering a TOU program, the operation of the batteries essentially changes. On this basis, both the household battery and the EV are discharged during the critical peak period, not only to supply the demand but also to inject the power back to the grid. To this end, the EV is charged once it arrives at home (that is a stochastic variable) and it keeps being charged until 18:00 in order to have sufficient stored energy to use during the critical peak period. From 23:00 to 3:00 of the next day when the demand is low and there is the off-peak tariff, the batteries are charged.

The household battery supplies a part of demand at hour 8:00 when there is the peak tariff and the demand is high due to the water heating consumption. During the peak period, the contribution of the EV in supplying the demand is not high because the availability of the EV (i.e., the probability that the EV is plugged-in at home) is low. Despite the mentioned unavailability of the EV, the power drawn from the grid is reduced at hour 8:00 and it is zero during the period 9:00-11:00. Even the house can inject the power to the grid during the period 9:00 and 10:00 thanks to the energy produced by the renewable generators. Note that the household battery is charged by the renewable generators at 11:00 when the total power generated by the PV and wind systems is higher than the consumption of the electrical appliances. The HEM system prefers to store the extra energy in the household battery (instead of selling to the grid at the peak tariff) so that it can supply the household demand by using the stored energy during the critical peak hours when the tariff is 50% bigger than the peak tariff.

The cost terms of different cases are shown in Table VI. The total cost denotes the electric bill in a typical day. A comparison of the different DRPs and different HEM systems indicates that employing a deterministic HEM system (i.e., considering the expected values of PV, the wind, and EV availability as certain parameters) can reduce the electric bill from 16% up to 21% depending on the DRP. Whereas, considering the proposed stochastic method, the HEM system can significantly decrease the electric bill from 31% up to 42%. If the deterministic HEM system is used, the EDRP is the most economic option for the customer since an incentive is applied for reducing the demand without any penalty. But, if the proposed stochastic HEM system is employed, TOU is the most economic DRP for the customer.

The highest difference between the deterministic and the stochastic HEM can be noted when considering TOU, CPP and I/C services in which the application of the stochastic model reduces the total cost respectively by 31%, 27% and 29% if compared to the deterministic model. The TOU and CPP use

TABLE VI
COST TERMS OF THE HOUSEHOLD IN DIFFERENT CASES

-	HEM system	G2H cost	H2G income	Inc.	Pen.	Total cost
Base case	-	2.751	0	0	0	2.751
TOU	-	2.920	0	0	0	2.920
	deterministic	2.692	0.249	0	0	2.443
	stochastic	2.039	0.351	0	0	1.687
RTP	-	3.220	0	0	0	3.220
	deterministic	2.904	0.371	0	0	2.533
	stochastic	2.420	0.370	0	0	2.050
CPP	-	3.770	0	0	0	3.770
	deterministic	3.351	0.356	0	0	2.995
	stochastic	2.646	0.465	0	0	2.181
EDRP	-	2.751	0	0.086	0	2.665
	deterministic	2.604	0.208	0.239	0	2.157
	stochastic	2.312	0.336	0.148	0	1.828
I/C services	-	2.751	0	0.164	0.720	3.307
	deterministic	2.538	0.134	0.241	0.591	2.754
	stochastic	2.392	0.184	0.277	0.012	1.943

step changes in hourly tariffs, hence the uncertainty of EV availability can have a more significant impact on the schedule of the household demand. In the case of the deterministic HEM system, the uncertainty of EV availability is also the main reason determining that the penalty cost is considerably high in I/C services.

The impact of different DRPs on the expected load shifting and load curtailment is illustrated in Fig. 5. As it can be seen, in the TOU program, about 6.7 kWh of load is shifted where 2.2 kWh is related to the shifting of the operation time of the HVAC system and 4.5 kWh is related to the shifting of the water heating operation time. Moreover, in this DR program, about 3.1 kWh of energy is curtailed, where about 2.4 kWh is the curtailment of lamps and about 0.7 kWh is related to the HVAC system. As it can be seen from Fig. 5, in all the DRPs the water heating is shifted. Moreover, there is no load curtailment for the HVAC system in RTP and CPP, while the operation of the HVAC is not shifted in EDRP. Therefore, TOU and I/C services are the most effective DRPs on managing the HVAC system. Furthermore, the curtailment of lamps is the same in all the DRPs except CPP that curtails more lamps due to the very high tariff during the peak period.

The response fatigue of the consumer in different cases are compared in Fig. 6. According to Fig. 6, RTP and I/C services impose the highest response fatigue on the customer due to the high frequency of DR signals. CPP and EDRP have the lowest DR signals and consequently the lowest RFI. It can be observed that by employing the proposed stochastic HEM model, the response fatigue of the customer can be reduced up to about 50% in all DRPs, that is a considerable value. This is due to the fact that in the deterministic HEM model, the time and energy of charging/discharging of the EV's battery is calculated based on the expected arrival/departure time and the expected SOC of the EV. However, because of the uncertainty of EV owner's behavior, the EV may be unavailable for charging/discharging at the determined time, and this can significantly increase the response fatigue. In addition, the proposed stochastic model considers the uncertainty of EV and consequently the HEM system can more accurately take

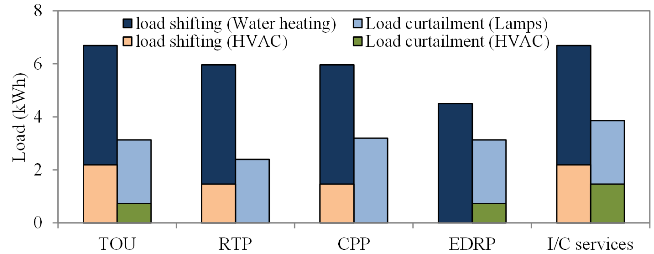


Fig. 5. Expected load shifting and load curtailment in different DRPs.

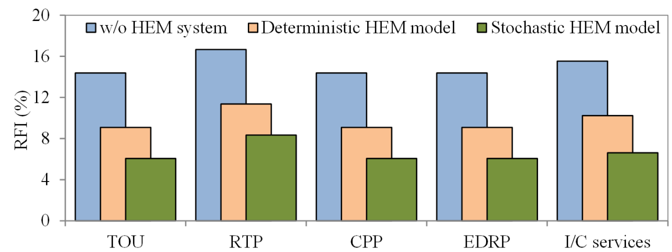


Fig. 6. Response fatigue of the consumer in different cases.

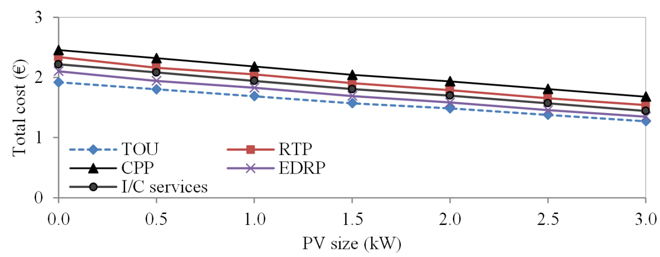


Fig. 7. Expected total cost for different PV sizes.

benefit from the capacity of the EV's battery to manage the other loads.

In order to analyze the impact of household equipment and resources on the effectiveness of the proposed model, different capacities of household batteries and different sizes of the renewable energy resources are individually investigated. Figs. 7 and 8 illustrate the expected total cost for different sizes of PV and wind turbine, respectively. As it can be seen, increasing the size of the renewable energy resources can decrease the expected cost. However, the wind turbine has a higher impact on the cost reduction compared to the PV. Furthermore, it can be observed from Fig. 8 that by increasing the size of the wind turbine, the implementation of different DRPs has a lower impact on the customers cost. This is due to the fact that, in the studied case, the customers demand is high during the price peak hours and the wind speed is also high during these hours.

Fig. 9 indicates the effect of the battery capacity on the total cost in different DRPs. It can be observed that adding even a battery of small size (e.g., 0.5 kWh) can significantly reduce the daily cost. This cost reduction in CPP and I/C services is more considerable. However, by increasing the battery capacity, the implementation of different DRPs led to similar costs. In other words, households with greater battery capacities are less affected by the DR strategies.

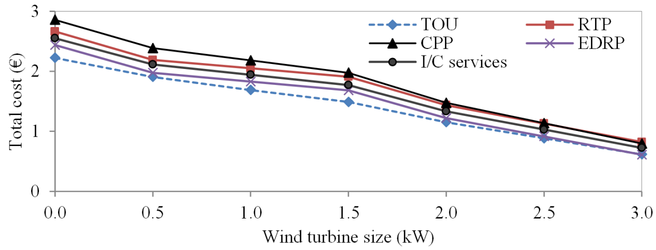


Fig. 8. Expected total cost for different wind turbine sizes.

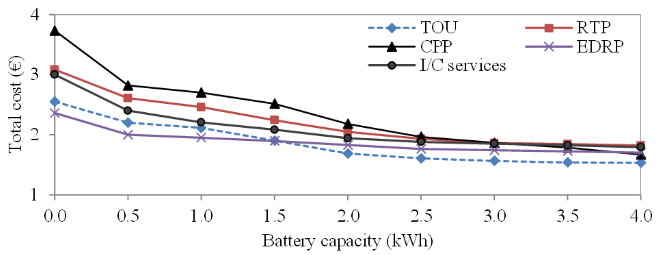


Fig. 9. Expected total cost for different battery capacities.

V. CONCLUSIONS

This paper proposed a stochastic model of HEM system by considering uncertainties of EV availability and small-scale renewable energy generation. Simulation results confirmed that the model is able to minimize the customer's cost considering different DRPs while guaranteeing the inhabitants satisfaction considering the technical limits of EV and household batteries, and electrical appliances. **The proposed stochastic HEM system could dramatically decrease the electric bill up to 42%. By using the proposed stochastic model, the customers cost was up to 31% lower than the one obtained by using a deterministic model.** The highest difference between the deterministic and the stochastic HEM can be evidenced in TOU, CPP, and I/C services. Due to the uncertainty of EV availability, the high steps in tariffs of TOU and CPP, and the penalizing system of I/C services significantly a ffect the schedule of household demand. Moreover, in the considered case study, the size of wind turbine had a higher impact on the customers cost compared to the size of PV. Furthermore, the greater battery capacity could meaningfully mitigate the effect of various DRPs on the customers cost. It should be mentioned that the results are case-sensitive and different results may be obtained by changing the data related to the building and to the customer.

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