Two-Stage Stochastic Model for the Price-based Domestic Energy Management Problem

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Abstract

Residential buildings have become an active market participant in future power grid transactions due to the development of smart grid technologies, particularly smart meters. Keeping this in mind, this paper proposes a two-stage stochastic model including day-ahead and real-time local energy markets with the aim of domestic equipment scheduling, which reflects the uncertain mobility pattern of Electric Vehicle (EV) as well as the variability of micro wind turbine generation. The contribution of EV and battery in providing additional flexibility through bi-directional energy trading has been investigated considering deterministic and stochastic EV mobility patterns. Moreover, the smart home is modeled as a price-taker agent in the local market. Hence, different price-based Demand Response (DR) programs can affect its decisions. On this basis, a comprehensive analysis on the participation of a smart home in various price-based DR strategies is carried out with the aim of determining the most effective DR program from smart home owner point of view. The obtained results reveal that the participation of the smart home in Time-of-Use (ToU) pricing scheme not only reduces the operation cost, but also leads to smart home profitability.

Keywords: Demand response program; domestic energy management system; energy flexibility; stochastic programming; smart home.

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Nomenclature

Indices

t	Index of time periods.
ω	Index of scenarios.
ξ	Index of EV mobility scenarios.

Variables

EP	Expected profit.
$P_t^{net,da}$	Day-ahead transacted energy
$P_{t\omega\xi}^{sold,rt}$	Real-time energy sold from home to the local market.
$P_{t\omega\xi}^{pur,rt}$	Real-time energy purchased from home by the local market.
$S_{t\omega\xi}$	Spilled power of wind micro-turbine.
$L_{t\omega\xi}^{shed,sh}$	Load shedding of the space heater.
$L_{t\omega\xi}^{shed,swh}$	Load shedding of the storage water heater.
$P_t^{wind,da}$	Day-ahead wind power generation.
$P_t^{b,dis,da}$	Day-ahead discharged power of the battery.
$P_t^{ev,dis,da}$	Day-ahead discharged power of the EV.
$P_t^{b,ch,da}$	Day-ahead charged power of the battery.
$P_t^{ev,ch,da}$	Day-ahead charged power of the EV.
Dis_t^{da}	Driving distance in the day-ahead stage.
$C_t^{b,da}$	Day-ahead stored energy in the battery.
$u_t^{b,da}$	Day-ahead discharging commitment binary variable for the battery.
$C_t^{ev,da}$	Day-ahead stored energy in the EV.
Mob_t^{da}	Day-ahead mobility discharging variable of the EV.
$u_t^{ev,da}$	Day-ahead discharging commitment binary variable for the EV.
$P_{t\omega\xi}^{wind,rt}$	Real-time wind power generation.
$P_{t\omega\xi}^{b,dis,rt}$	Real-time discharged power of the battery.
$P_{t\omega\xi}^{ev,dis,rt}$	Real-time discharged power of the EV.
$L_{t\omega\xi}^{sh,rt}$	Real-time load of the space heater.
$L_{t\omega\xi}^{swh,rt}$	Real-time load of the storage water heater.
$L_{t\omega\xi}^{mrs,rt}$	Real-time load of the must-run services.
$C_{t\omega\xi}^{b,rt}$	Real-time stored energy in the battery.
$u_{t\omega\xi}^{b,rt}$	Real-time discharging commitment binary variable for the battery.

$Dis_{t\omega\xi}^{rt}$	Driving distance in the real-time stage.
$C_{t\omega\xi}^{ev,rt}$	Real-time stored energy in the EV.
$Mob_{t\omega\xi}^{rt}$	Real-time mobility discharging variable of the EV.
$u_{t\omega\xi}^{ev,rt}$	Real-time discharging commitment binary variable for the EV.
$\theta_{t+1,\omega\xi}^{in}$	Indoor temperature.

Parameters

λ_t^{da}	Day-ahead electricity price.
$\lambda_t^{sold,rt}$	Electricity price of the sold energy to the real-time local market.
$\lambda_t^{pur,rt}$	Electricity price of the purchase energy from the real-time local market.
π_ω	Probability of scenarios.
π_ξ	Probability of scenarios for EV's mobility.
V^S	Spillage cost.
$VOLL^{sh}$	Value Of Lost Load of the space heater.
$VOLL^{swh}$	Value Of Lost Load of the storage water heater.
γ_b	Flexibility coefficient of the battery.
γ_{ev}	Flexibility coefficient of the EV.
$L_t^{sh,pred,da}$	Day-ahead load prediction of the space heater.
$L_t^{swh,pred,da}$	Day-ahead load prediction of the storage water heater.
$L_t^{mrs,pred,da}$	Day-ahead load prediction of the must-run services.
f_{max}	Maximum capacity of the end-user distributed line.
$P_t^{wind,pred}$	Predicted wind power generation.
η_{H2B}	Charging efficiency of the battery.
η_{B2H}	Discharging efficiency of the battery.
C_i^b	The initial available energy in the battery.
P_b^{max}	Maximum storage level of the battery.
P_b^{min}	Minimum storage level of the battery.
ω_b^{max}	Maximum ramping rate of the battery's state of charge.
η_{H2V}	Charging efficiency for the EV.
η_{V2H}	Discharging efficiency for the EV.
C_i^{ev}	The initial state of the charge of the EV.
P_{ev}^{max}	Maximum storage level of the EV.
P_{ev}^{min}	Minimum storage level of the EV.
ω_{ev}^{max}	Maximum ramping rate of the EV's state of charge.
$P_{t\omega\xi}^{wind,scen}$	Scenarios of wind power generation.

R	Thermal resistance of the building shell.
$\theta_{t\omega\xi}^{out,pred}$	Predicted outdoor temperature.
θ_{i}^{in}	Initial indoor temperature.
θ_{des}^{in}	Desired indoor temperature.
L_{sh}^{max}	Maximum electrical consumption for the space heater.
L_{swh}^{max}	Minimum electrical consumption of the storage water heater.
U_{swh}^{max}	Daily energy consumption for the storage water heater.
$L_{t\omega\xi}^{mrs,pred}$	Predicted electrical consumption for the must-run services.
ϑ^{ev}	Consumption of EV for one mile driving

Abbreviations

ARMA	Auto Regressive Moving Average
CPP	Critical Peak Pricing
DEMS	Domestic Energy Management System
DR	Demand response
EP	Expected Profit
ES	Energy Storage
EV	Electric vehicle
LM	Local Market
MILP	Mixed Integer Linear Programming
PV	Photovoltaic
RTP	Real-Time Pricing
SOC	State-of-Charge
TOU	Time-of-Use
VOLL	Value of Lost Load

1. Introduction

The residential sector comprises a large part of the total energy demand of most countries. Therefore, it is essential to utilize a proper Domestic Energy Management System (DEMS) in order to guarantee active participation of residential consumers with the aim of achieving either economic or technical targets from both the user and utilities point of views. The emerging smart grid technologies such as smart meters can create a new window of opportunity for residential consumers to share their operational flexibility with the utilities. This may lead to not only a lower operation cost, higher efficiency and less wear-and-tear from utilities perspective, but also a lower energy bill for customers without affecting their satisfaction level. Thus, it is necessary to precisely study on the concept of Dems taking into account more details and realistic assumptions.

The literature in the area of DEMS can be categorized from different aspects including the domestic electrical equipment, scheduling objectives and considered uncertainties. Domestic electrical equipment consists of smart home electrical appliances, small-scale generation units, as well as Electric Vehicles (EVs) and Energy Storages (ESs). Note that the customers' electrical appliances are associated with the characteristics of the house, the lifestyle, the economic level, and the possessions of customers [1].It is noteworthy that, small-scale generation units, EVs and ESs have been gradually integrated into residential community due to the development of smart meters. These resources can contribute to the efficient operation of DEMS through offering their potential flexibility. According to the literature, the DEMS is employed for the purpose of reducing energy bills, maintaining a level of comfort, reaching the desired consumption pattern, and decreasing the emissions [1]. From the uncertainty point of view, the main uncertainty sources of a DEMS include renewable generation, inhabitants' manners, weather, as well as possessions [2].

The state of the art includes many studies that have investigated the problems described above and have developed several models to provide answers to them from the perspective of the household. For instance, in [3], computational intelligence is employed to solve the problem of DEMS. In [4], various multi agent-based energy management systems are reviewed and compared in terms of technical and economic features. In [5], a domestic Demand Response (DR) scheme is proposed for scheduling and controlling electrical appliances. With the aim of saving energy, a decision-support system is presented to predict the electricity demand at home and to find an optimal time running schedule for the appliances regarding the Time-of-Use (ToU) tariffs. However, the comfort level of the inhabitants is not considered.

The authors of [6-8] presented deterministic models for optimal residential scheduling under DR implementation taking into account different load categories in order to minimize the electricity bill of the consumer while maintaining an optimal comfort level. The authors of [9] go a step further by proposing a model for the DEMS where the cost is minimized while the residents' comfort is guaranteed considering a response fatigue index. The model simulates different DR programs in a smart house including renewable energy resources, EV and battery. However, the mobility pattern of EV has been not considered. Also, the contribution of EV and ES in providing flexibility has been not evaluated.

In [10], a model of the DEMS is presented considering a more accurate electro-thermal model of the building that includes HVAC system and plastering mortars. In the model, the minimization of the electricity cost in different DR programs and inhabitants' comfort are simultaneously considered. An algorithm based on the nonlinear programming model for optimal energy consumption in a smart home has been proposed in [11] which considers a trade-off between the energy saving and the comfort level. In [12], electrical appliances are scheduled to minimize the total energy cost and decrease the load factor (i.e., peak-to-average) of a smart home while the users' comfort is also taken into account. However, in the last of these references, the impact of the EV on the operation of the DEMS is not addressed.

There are several reports that address price-based DR programs in smart home models. For example, in [13], a decentralized framework is proposed to deal with time-varying prices in which consumers minimize the costs, while some additional incentives may be paid to them. References [14] and [15] optimize the operation of the smart home by using a price signal. The presented models in [16-18] are almost similar to each other. The mentioned papers are assigned to optimal day-ahead scheduling of household appliance considering dynamic pricing and peak-limiting based on DR strategies in the presence of EVs and Energy Storage Systems(ESS).The papers presented a deterministic model without paying attention to stochastic mobility pattern of EVs as well as variability of renewable generation resources. Moreover, only one price-based DR scheme is considered.

Due to the growth of EV developments, the presence of this new technology in the future smart home is vital. Hence, there are many reports that included EVs in their developed models. In [19] and [20], a DEMS is proposed which employs dynamic tariffs for EVs to restrict the demand peak. In [21], a heuristic framework is conducted to manage the charging of EV based on dynamic tariffs. In an effort to improve the management of EVs in smart homes and smart grids, Ref. [22] presents an EV charger prototype, detailing the strategies used in the system. In this report, the experimental results are shown for diverse operation modes of EV considering the concept of the smart home. In [23], a game-based demand response is developed where the charging needs of the EV are satisfied at home and the retailer's profits are also maximized. In [24], a multi-level strategy is presented which encompasses two representations of a medium voltage chain for the optimization of the charging of the EV with the objective of minimizing the cost, through a modeling day-ahead market with losses prediction. In [25], a DEMS is developed consisting of EV, PV, and ES systems. However, the vehicle to grid mode of the EV is not addressed. In [26], a price-based DEMS is presented considering the priority in the operation of electrical appliances. Although the model in[26] includes EVs, uncertainty and renewable energies are not considered. Other papers such as [27-29] mainly concentrate on modeling the stochastic behavior of EV owners in order to evaluate the possible helps of EVs in power system operation including load-generation balance as well as smooth out load fluctuations [27], peak shaving and valley filling [28], and PV integration [29].

An uncertain environment can cause deviations in electricity prices and loads, so a probabilistic study of the performance of DEMS is important and has been addressed in the literature. Hence, in [30], an improved particle swarm optimization and a two-point estimated method are employed to obtain the optimal chance constrained solution in a home energy management system. In [31], stochastic programming is presented for the purpose of scheduling the appliances of a smart home considering the uncertainties of their operation time and the renewable resources. It is notable that the EV has been neglected in the aforementioned paper and only one DR strategy has been considered. In [32], a DEMS approach is proposed which considers stochastic models of plug-in and wireless EVs, considering the past events and the drivers' charging requirements. With regard to uncertainty modeling, Ref. [33] goes a step further and defines a strategy where the probability distributions of house consumption, EV, and photovoltaic production (PV) have been combined.

It is noticeable that there are a set of studies that investigated a similar problem in the context of microgrid. For instance, a generic framework for optimal design and operational scheduling of microgrids has been developed in [34] which includes both the renewable-based and fuel-based energy resources. An energy management system has been presented in [35] for a grid-connected microgrid in order to control the power flow between the main grid and microgrid with application to maximize the economic benefits of either customers or utility operator. In addition, a robust bi-level energy sharing model is formulated in [36] for a prosumer microgrid with renewable energy generation, multiple storage units and load shifting. Unlike the previous works, the authors in [37] presented a stochastic market clearing model incorporating the uncertainty of wind power as well as EVs using a scenario-based approach in transmission grid level.

As seen in the literature review, there are several relevant works in the scope of the DEMS domain. Although the interaction between the electricity market on the local level and the distribution network joining DR programs has also been explored, it is meaningful and necessary to assess the DEMS in terms of price-based DR programs and flexible behavior of the ESS, e.g., the battery and the EV, in smart residential systems.

Consequently, this paper proposes:

- A two-stage stochastic model including day-ahead and real-time local energy markets with the aim of domestic equipment scheduling which reflects the uncertain pattern of EV mobility as well as variability of micro wind turbine generation.
- A flexibility oriented approach in order to evaluate the flexibility offering by EV and ES through bi-directional energy transaction in the residential energy management problem.
- A comprehensive analysis on participation of a smart residential building in different price-based DR strategies to opt the most effective DR program from building owner point of view.

The rest of this paper is organized as follows. Section 2 introduces the proposed stochastic method for domestic energy management problems. Section 3 describes the simulation results. Finally, Section 4 concludes the paper.

2. Proposed Stochastic Domestic Energy Management Model

In this paper, a two-stage stochastic model is defined for the domestic energy management problem. It is noteworthy that the two-stage stochastic programming is a well-known approach to model the problems with uncertainty. The structuring of the stochastic programming problem into two stages is justified by the fact that electricity markets must be cleared well in advance that the uncertainty associated to wind power as well as EV mobility are realized. According to the proposed model, the DEMS is able to make its optimum decisions independently. In this problem, a smart home, as a prosumer in a smart grid, can transact energy with its upstream system. This upstream system can be a local market, distribution system, retailer, among others. The proposed DEMS includes the wind micro-turbine, battery, EV, space heater, storage water, and must-run services.

In the first stage, the day-ahead trading problem between the DEMS and upstream system (from now on, called the Local Market (LM) in this paper) is defined without considering the uncertainty of wind power generation and EV mobility. However, their uncertainty is considered on the basis of stochastic scenarios in the second stage. Also, the real-time energy transaction problem with the DEMS and the LM is modeled in the second stage.

It should be noted that, in the proposed model, local markets are considered distributed trading environments, e.g., local energy communities. In this way, trading and communications only involve a limited number of players, which are in nearby geographical areas. In this way, building/residential energy resource management models will be used by the individual players to manage their own energy and optimize the bids to place in the market.

It is noticeable that the uncertainty of electricity price, outdoor temperature, and must-run services is ignored only to simplify the problem. Thus, Figure 1 shows a physical schematic of our proposed stochastic domestic energy management system. As seen in Figure 1, domestic data provider unit is in charge of providing point forecasting and stochastic scenarios related to uncertain parameters of the system. Furthermore, the domestic energy management system receives electricity price data from the local electricity market. According to data that the domestic energy management system receives from the data provider unit and the local electricity market, it makes optimum decisions regarding load consumption and energy generation of each residential appliance. However, this paper does not deal with how each individual appliance is operating within the DEMS framework. Besides, it transacts energy with the local electricity market according to its optimum decision-maker system.

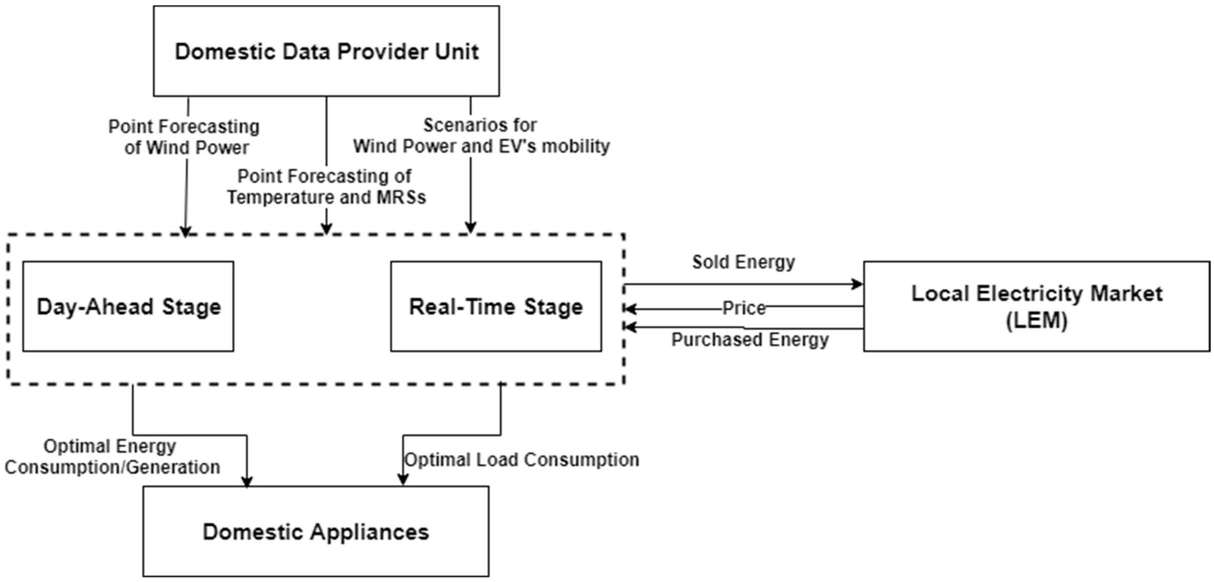

Figure 1. The physical features of our domestic energy management system.

2.1. Objective Function

Here, the objective function is defined as the total Expected Profit (EP) of the domestic energy management problem in the day-ahead and real-time stages. In this paper, the wind micro-turbine, battery, and EV play as distributed energy resources in the home. Moreover, the space heater, storage water heater, and must-run services are defined as electrical loads. In this case, the space heater, the storage water heater, and the must-run services are defined as controllable, shiftable, and non-dispatchable loads, respectively. The objective of the DEMS is to maximize its EP as a result of selling/purchasing energy to/from the day-ahead and real-time LMs. Hence, the objective function is represented by Eq. (1). As it is seen in Eq. (1), EP consists of two parts. The first part represents the expected profit from trading energy with the day-ahead LM. However, the second part includes five terms that express the profit gained from transacting energy in real-time LM. These terms state energy revenue, energy cost, spillage cost of the wind system, and load shedding costs of the space heater and the storage water heater, respectively. It is noticeable that the cost of the battery system and the EV equals zero in this problem because it is a domestic energy management problem in the operating time horizon. However, the operation costs can be seen as a limitation in this study. This can affect the utilization of the EV and the battery. It can be observed in Eq. (1) that the uncertainty of wind power generation and mobility of the EV is only considered in the second part of the EP that is related to the real-time stage of the domestic energy management problem. The decision variables achieve from solving the problem are the sold/purchased power to/from the local market at day-ahead and real-time stages, spilled power of micro wind turbine, load shedding of space heater and storage water heater, day-ahead/real-time charging/discharging power of the EV and ES and also the scheduled wind power generation at day-ahead and real-time stages.

$$\text{Maximize: } EP = \sum_t \lambda_t^{da} P_t^{net,da} + \sum_\omega \pi_\omega \sum_\xi \pi_\xi \sum_t \left[\lambda_t^{sold,rt} P_{t\omega\xi}^{sold,rt} - \lambda_t^{pur,rt} P_{t\omega\xi}^{pur,rt} - V^S S_{t\omega\xi} - VOLL^{sh} L_{t\omega\xi}^{shed,sh} - VOLL^{swh} L_{t\omega\xi}^{shed,swh}\right] \quad (1)$$

The following express the corresponding constraints of the day-ahead and real-time stages.

2.2. Day-ahead Stage

Eq. (2) represents the power balance equation due to the power output of the wind micro-turbine, $P_t^{wind,da}$, discharged power of the battery, $P_t^{b,dis,da}$, discharged power of the EV, $P_t^{ev,dis,da}$, charged power of the battery, $\mathrm{P_t^{b,ch,da}}$, charged power of the EV, $P_t^{ev,ch,da}$, and the energy traded with the LM, $P_t^{net,da}$. Thus, if $P_t^{net,da}$ is positive, the home sells energy to the LM. However, the home buys energy from the LM when $P_t^{net,da}$ is negative. Besides, in the day-ahead only point forecasting of the loads is considered ($L_t^{sh,pred,da}$, $L_t^{swh,pred,da}$, and $L_t^{mrs,pred,da}$).

As seen in Eq. (2), γ_b and γ_{ev} are flexibility coefficients that have been defined for the first time in [38] to represent the flexibility of the energy storage systems in the distributed energy management problem, especially residential energy management problems. These coefficients can take values between 0 and 1 that denote the flexibility of the home energy management system on using the battery and EV in the day-ahead and real-time stages. If the flexibility coefficient is equal to zero, the battery or EV is only utilized for the real-time stage; while, home energy management system can utilize the full capacity of the batteries in the day-ahead stage, if the flexibility coefficients equal one.

$$P_t^{wind,da} + \gamma_b P_t^{b,dis,da} + \gamma_{ev} P_t^{ev,dis,da} = L_t^{sh,pred,da} + L_t^{swh,pred,da} + L_t^{mrs,pred,da} + \\ + \gamma_b P_t^{b,ch,da} + \gamma_{ev} P_t^{ev,ch,da} + P_t^{net,da}, \qquad \forall t \quad (2)$$

Eq. (3) represents the constraint regarding the end-user's power flow limitation. Here, f_{max} represents the maximum power capacity of the distribution line. Moreover, there are some limitations that apply to all appliances.

$$-f_{max} \le P_t^{net,da} \le f_{max}, \qquad \forall t \quad (3)$$

The power generation of the wind system is stated in Eq. (4) that equals wind point forecasting in the day-ahead stage.

$$P_t^{wind,da} = P_t^{wind,pred}, \qquad \forall t \quad (4)$$

The constraints related to the battery system are represented by Eqs. (5)-(9). Eq. (5) represents the stored energy in the battery in the day-ahead stage, where C_i^b is the initial available energy in the battery.

$$C_t^{b,da} = C_{t-1}^{b,da} + P_t^{b,ch,da}\eta_{H2B} - \frac{P_t^{b,dis,da}}{\eta_{B2H}}, \qquad \forall t \geq 2$$
$$C_{t=1}^{b,da} = C_i^{b} + P_{t=1}^{b,ch,da}\eta_{H2B} - \frac{P_t^{b,dis,da}}{\eta_{B2H}}, \qquad \forall t = 1 \tag{5}$$

Eq. (6) represents the maximum and minimum limitations of the stored energy in battery.

$$P_b^{min} \leq C_t^{b,da} \leq P_b^{max}, \qquad \forall t \tag{6}$$

The maximum charging and discharging power of battery are expressed in Eq. (7) and Eq. (8), respectively. Note that $\omega_b^{max}$is the maximum charging/discharging rate of the battery. Also, $u_t^{b,da}$ is a binary variable that represents the charging status of the battery. If $u_t^{b,da}$ is equal to 1, thebattery enters into a discharging mode and vice versa, if $u_t^{b,da}$ is equal to 0, the battery is in charging mode.

$$0 \leq \mathrm{P_t^{b,ch,da}} \leq \omega_\mathrm{b}^{\mathrm{max}}(1 - \mathrm{u_t^{b,da}}), \qquad \forall \mathrm{t} \tag{7}$$

$$0 \leq \mathrm{P_t^{b,dis,da}} \leq \omega_\mathrm{b}^{\mathrm{max}}\mathrm{u_t^{b,da}}, \qquad \forall \mathrm{t} \tag{8}$$

The EV's constraints in the day-ahead stage are stated in Eqs. (9)-(13). Specifically, Eq. (9) expresses the stored energy in the EV, and C_i^{ev} is the initial available energy in the EV.

$$C_t^{ev,da} = C_{t-1}^{ev,da} + P_t^{ev,ch,da}\eta_{H2V} - \frac{P_t^{ev,dis,da}}{\eta_{V2H}} - Mob_t^{da}, \qquad \forall t \geq 2$$
$$C_{t=1}^{ev,da} = C_i^{ev} + P_{t=1}^{ev,ch,da}\eta_{H2V} - \frac{P_t^{ev,dis,da}}{\eta_{V2H}} - Mob_{t=1}^{da}, \qquad \forall t = 1 \tag{9}$$

where Mob_t^{da}denotes the discharge of the EV due to driving. Mob_t^{da} is zero when the EV is parked at home, and it is bigger than zero when it is not available at home. It is a function of the consumption of the EV in each mile and the travel distance as presented in Eq. (10).

$$Mob_t^{da} = Dis_t^{da}.\vartheta^{ev} \qquad \forall t \tag{10}$$

where$Dis_t^{da}$is the driving distance in the day-ahead stage and discussed in Section 3.3. Eq. (11) represents the maximum and minimum limitations of the stored energy in the EV. Moreover, Eq. (12) and (13) express the maximum charging and discharging rates of the EV, respectively.

$$P_{ev}^{min} \leq C_t^{ev,da} \leq P_{ev}^{max}, \qquad \forall t \tag{11}$$

$$0 \leq \mathrm{P_t^{ev,ch,da}} \leq \omega_\mathrm{ev}^{\mathrm{max}}(1 - \mathrm{u_t^{ev,da}}), \qquad \forall \mathrm{t} \tag{12}$$

$$0 \leq \mathrm{P_t^{ev,dis,da}} \leq \omega_\mathrm{ev}^{\mathrm{max}}\mathrm{u_t^{ev,da}}), \qquad \forall \mathrm{t} \tag{13}$$

2.3. Real-time Stage

In the real-time stage, the smart home can trade energy with the real-time LM. In this case, the real-time electricity price could be different with the electricity price in the day-ahead. In addition, the price of sold/purchased energy to/from the LM could be different in the real-time stage. The following equations represent the constraints related to the real-time domestic energy management problem.

The power balance equation in the real-time is stated in Eq. (14), representing the purchased/sold energy from/to the real-time LM. Moreover, load shedding terms of the space heater and storage water heater are considered in the real-time balancing equation, and load shedding of the must-run services is not modeled because must-run services are considered as non-dispatchable loads and should not be interrupted. Eq. (15) represents the power flow limitation in a distribution line that leads to the smart home. It is noticeable that both, Eqs. (14) and (15), are coupling constraints that cause the day-ahead and real-time problems to be solved simultaneously.

Furthermore, while in the day-ahead stage, only one variable, $P_t^{net,da}$, has been defined to represent the energy traded between the DEMS and the LM, two variables, $P_{t\omega\xi}^{pur,rt}$ and $P_{t\omega\xi}^{sold,rt}$are defined in the real-time stage to express the purchased and sold energy, respectively, because the real-time purchasing and selling prices can vary in our proposed model. It must be noted that the prices in DA and RT markets are different. Therefore, it is obvious that the decisions for commitment of various energy resources in DA and RT markets are not similar. In fact, the commitment status of resources in DA market directly affect the decision variable$P_t^{net,da}$. This variable also directly affects the real-time balance equation, i.e. Eq. (14). It should be mentioned that the actual amounts of wind power generation and EV are realized in real-time stage. On this basis, the load-generation balance is met in real-time stage according to either the DA decisions or RT realization of uncertain resources such as wind generation and EV.

$$\begin{aligned}P_{t\omega\xi}^{wind,rt} &+ P_{t\omega\xi}^{b,dis,rt} + P_{t\omega\xi}^{ev,dis,rt} + P_{t\omega\xi}^{pur,rt} \\ &= L_{t\omega\xi}^{sh,rt} + L_{t\omega\xi}^{swh,rt} + L_{t\omega\xi}^{mrs,rt} - \left(L_{t\omega\xi}^{sh,shed,rt} + L_{t\omega\xi}^{swh,shed,rt}\right) + P_{t\omega\xi}^{b,ch,rt} + P_{t\omega\xi}^{ev,ch,rt} \\ &\quad + P_t^{net,da} + P_{t\omega\xi}^{sold,rt}, \qquad \forall t, \forall\omega, \forall\xi\end{aligned} \tag{14}$$

$$-f_{max} \leq P_t^{net,da} + P_{t\omega\xi}^{sold,rt} - P_{t\omega\xi}^{pur,rt} \leq f_{max}, \qquad \forall t, \forall\omega, \forall\xi \tag{15}$$

Hence, both variables that represent sold and purchased energies in the real-time stage should be positive variables as stated in Eq. (16).

$$P_{t\omega\xi}^{sold,rt}, P_{t\omega\xi}^{pur,rt} \geq 0, \qquad \forall t, \forall\omega, \forall\xi \tag{16}$$

Eq. (17) represents the power output equation of the wind micro-turbine in the real-time stage. According to Eq. (17), $P_{t\omega\xi}^{wind,scen}$ represents the scenario-based potential wind power generation, and $S_{t\omega}$ is the spilled wind power.

$$P_{t\omega\xi}^{wind,rt} = P_{t\omega\xi}^{wind,scen} - S_{t\omega\xi}, \qquad \forall t, \forall\omega, \forall\xi \tag{17}$$

The wind power can be spilled based on economic and technical constraints of the system. The maximum and minimum limitations of spilled wind power are represented by Eq. (18).

$$0 \leq S_{t\omega\xi} \leq P_{t\omega\xi}^{wind,scen}, \qquad \forall t, \forall\omega, \forall\xi \tag{18}$$

The real-time constraints related to the battery system are represented in Eqs. (19)-(23). Hence, stored energy in the battery in real-time by Eq. (19).

$$C^{b,rt}_{t\omega\xi} = C^{b,rt}_{t-1,\omega\xi} + P^{b,ch,rt}_{t\omega\xi}\eta_{H2B} - \frac{P^{b,dis,rt}_{t\omega\xi}}{\eta_{B2H}}, \qquad \forall t \geq 2, \forall\omega, \forall\xi$$
$$C^{b,rt}_{(t=1)\omega\xi} = C^{b}_{i} + P^{b,ch,rt}_{(t=1)\omega\xi}\eta_{H2B} - \frac{P^{b,dis,rt}_{t\omega\xi}}{\eta_{B2H}}, \qquad \forall t = 1, \forall\omega, \forall\xi \tag{19}$$

The battery's real-time max and min stored energy constraints are stated in Eq. (20).

$$P^{min}_{b} \leq C^{b,rt}_{t\omega\xi} \leq P^{max}_{b}, \qquad \forall t, \forall\omega, \forall\xi \tag{20}$$

Finally, Eqs. (21) and (22) present constraints of the battery's real-time maximum discharged and charged power, respectively.

$$0 \leq \mathrm{P}^{\mathrm{b,dis,rt}}_{\mathrm{t}\omega\xi} \leq \omega^{\max}_{\mathrm{b}}\mathrm{u}^{\mathrm{b,rt}}_{\mathrm{t}\omega\xi}, \qquad \forall \mathrm{t}, \forall\omega, \forall\xi \tag{21}$$

$$0 \leq \mathrm{P}^{\mathrm{b,ch,rt}}_{\mathrm{t}\omega\xi} \leq \omega^{\max}_{\mathrm{b}}(1 - \mathrm{u}^{\mathrm{b,da}}_{\mathrm{t}\omega\xi}), \qquad \forall \mathrm{t}, \forall\omega, \forall\xi \tag{22}$$

In addition, the constraints related to the EV in the real-time stage are stated in Eqs. (23)-(27). This way, the real-time stored energy in the EV is represented by Eq. (23).

$$C^{ev,rt}_{t\omega\xi} = C^{ev,rt}_{t-1,\omega\xi} + P^{ev,ch,rt}_{t\omega\xi}\eta_{H2V} - \frac{P^{ev,dis,rt}_{t\omega}}{\eta_{V2H}} - Mob^{rt}_{t\omega\xi}, \qquad \forall t \geq 2, \forall\omega, \forall\xi$$
$$C^{ev,rt}_{(t=1)\omega\xi} = C^{ev}_{i} + P^{ev,ch,rt}_{(t=1)\omega\xi}\eta_{H2V} - \frac{P^{ev,dis,rt}_{t\omega}}{\eta_{V2H}} - Mob^{rt}_{(t=1)\omega\xi}, \qquad \forall t = 1, \forall\omega, \forall\xi \tag{23}$$

Note that, $Mob^{rt}_{t\omega\xi}$ can be calculated through Eq. (24). Also, $Dis^{rt}_{t\omega\xi}$ is the driving distance in the real-time stage as presented in Section 3.3.

$$Mob^{rt}_{t\omega\xi} = Dis^{rt}_{t\omega\xi}\vartheta^{ev} \qquad \forall t \tag{24}$$

Maximum and minimum limitations of the available energy in EV in the real-time stage are expressed in Eq. (25).

$$P^{min}_{ev} \leq C^{ev,rt}_{t\omega\xi} \leq P^{max}_{ev}, \qquad \forall t, \forall\omega, \forall\xi \tag{25}$$

Eqs. (26) and (27) state maximum bounds of the discharged and charged power of the EV in real-time, respectively.

$$0 \leq \mathrm{P}^{\mathrm{ev,dis,rt}}_{\mathrm{t}\omega\xi} \leq \omega^{\max}_{\mathrm{ev}}\mathrm{u}^{\mathrm{ev,rt}}_{\mathrm{t}\omega}, \qquad \forall \mathrm{t}, \forall\omega, \forall\xi \tag{26}$$

$$0 \leq \mathrm{P}^{\mathrm{ev,ch,rt}}_{\mathrm{t}\omega\xi} \leq \omega^{\max}_{\mathrm{ev}}(1 - \mathrm{u}^{\mathrm{ev,rt}}_{\mathrm{t}\omega\xi}), \qquad \forall \mathrm{t}, \forall\omega, \forall\xi \tag{27}$$

As mentioned before, three types of electrical loads are considered in this paper, specifically, the space heater as a controllable load, the storage water heater as a shiftable load, and the must-run services as non-dispatchable loads. The space heater provides the indoor temperature at the desired temperature band.

Eq. (28) represents the equation between the indoor temperature and the electrical consumption of the space heater. Here, θ^{in}_{i} is the initial indoor temperature which is assumed to be equal to the desired temperature, θ^{in}_{des}.

$$\theta^{in}_{t+1,\omega\xi} = e^{\frac{-1}{RC}}\theta^{in}_{t\omega\xi} + R\left(1 - e^{\frac{-1}{RC}}\right)L^{sh,rt}_{t\omega\xi} + \left(1 - e^{\frac{-1}{RC}}\right)\theta^{out,pred}_{t\omega\xi}, \qquad \forall t \geq 2, \forall\omega, \forall\xi$$
$$\theta^{in}_{t\omega\xi} = \theta^{in}_{i} = \theta^{in}_{des}, \qquad \forall t = 1, \forall\omega, \forall\xi \tag{28}$$

Eq. (29) expresses that indoor temperature is limited to 1 more and less than the desired temperature.

$$-1 \le \theta_{t\omega\xi}^{in} - \theta_{des}^{in} \le 1, \qquad \forall t, \forall \omega, \forall \xi \tag{29}$$

Besides, the corresponding maximum and minimum bands of the space heater's load consumption and load shedding are stated in Eqs. (30) and (31), respectively.

$$0 \le L_{t\omega\xi}^{sh,rt} \le L_{sh}^{max}, \qquad \forall t, \forall \omega, \forall \xi \tag{30}$$

$$0 \le L_{t\omega\xi}^{sh,shed,rt} \le L_{t\omega\xi}^{sh,rt}, \qquad \forall t, \forall \omega, \forall \xi \tag{31}$$

The storage water heater is an appliance that stores the heat in the water tank. The load and energy limitations of the storage water heater are represented by Eqs. (32) and (33), respectively. It is noticeable that the heat loss of the tank is not considered in this work.

$$0 \le L_{t\omega\xi}^{swh,rt} \le L_{swh}^{max}, \qquad \forall t, \forall \omega, \forall \xi \tag{32}$$

$$\sum_{\omega} \pi_{\omega} \sum_{\xi} \pi_{\xi} \sum_{t} L_{t\omega\xi}^{swh,rt} = U_{swh}^{max}, \qquad \forall t, \forall \omega, \forall \xi \tag{33}$$

The load shedding constraint related to the storage water heater is represented by Eq. (34).

$$0 \le L_{t\omega\xi}^{swh,shed,rt} \le L_{t\omega\xi}^{swh,rt}, \qquad \forall t, \forall \omega, \forall \xi \tag{34}$$

Must-run services include the loads that should be provided quickly, and they should not be interrupted. In this paper, for simplicity, the uncertainty of must-run services is not considered. Note that the DA and RT stages are linked to each other through linking constraints and consequently, there is just one optimization problem including both the DA and RT stages which is solved simultaneously.

$$L_{t\omega\xi}^{mrs,rt} = L_{t\omega\xi}^{mrs,pred}, \qquad \forall t, \forall \omega, \forall \xi \tag{35}$$

3. Simulation Results

3.1. Case Study

The test system that is used to assess the proposed stochastic DEMS has been used before in [39-41]. However, the PV system and pool pump are omitted in the test system of this paper, and one wind micro-turbine is added as shown in Figure 2. This way, the power production capacity of the wind micro-turbine is 2kW. The battery can store between 0.48 and 2.4kWh. Also, its maximum charging and discharging rate is 400W. Besides, the charging and discharging efficiency of the battery is 90%. Moreover, the EV can store energy between 1.77 and 5.9kWh, and the EV's maximum charging and discharging rate is 3kW. Furthermore, its charging and discharging efficiency is 90%.

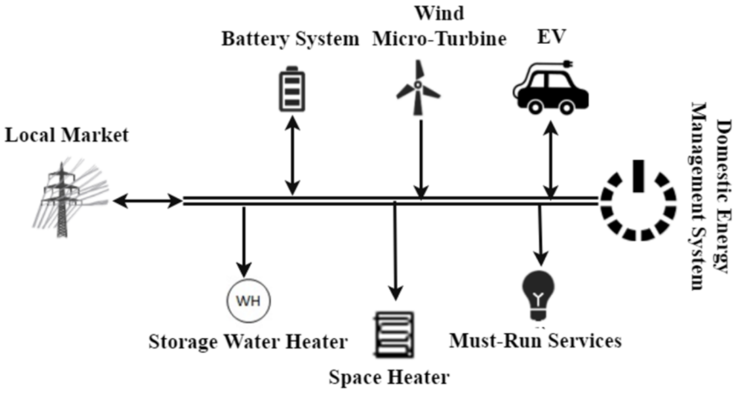

Figure 2. The residential energy system modified in [39-41].

Regarding the electrical loads, the maximum load capacity of the space heater in each period is equal to 5.525kW. However, the daily energy capacity of the storage water heater is 10.46kWh (180lt), which has a 2kW heating element. The desired temperature of the building is assumed to equal 23℃. Furthermore, the thermal resistance of the building shell and C are equal to 18℃/kW and 0.525kWh/℃, respectively.

The proposed Mixed Integer Linear Programming (MILP) is solved in GAMS 24.2.3 [42]. Table 1 presents the Value of Lost Load (VOLL) and spillage cost of wind power generation. The VOLL is considered due to the fact that electricity supply interruptions, i.e. lost load, have financial and social impacts on customers. In other words, the VOLL can be defined as the amount the customers wish to be compensated in the event of an electricity interruption. Also, the price data for the four cases under study are shown in Table 2. Table 2 shows that the flat rate tariffs are considered the average of the Real-Time pricing (RTP). In Time of Use (ToU), the tariff in peak period is 50% higher than the flat rate tariff, while in the valley the tariff is half the flat rate one. The tariff in off-peak period is also equal to the flat rate tariff. In Critical Peak Pricing (CPP), the tariff in critical peak hours is three times higher than the flat rate tariff, but there is no difference between the tariffs in peak, off-peak and valley periods.

Table 1. VOLL and spillage cost

Time (h)	VOLL ($/kWh)		Spillage Cost ($/kWh)
	SH	SWH	Wind
1-24	0.5	0.2	1

Table 2. Price data

Time (h)	Price ($/kWh)			
	Flat rate	ToU	CPP	RTP
1	0.2384	0.1192	0.2384	0.1615
2	0.2384	0.1192	0.2384	0.1765
3	0.2384	0.1192	0.2384	0.1967
4	0.2384	0.2384	0.2384	0.2200
5	0.2384	0.2384	0.2384	0.2294
6	0.2384	0.2384	0.2384	0.2414
7	0.2384	0.2384	0.2384	0.2354
8	0.2384	0.2384	0.2384	0.2320
9	0.2384	0.3576	0.7152	0.3110
10	0.2384	0.3576	0.7152	0.2795
11	0.2384	0.3576	0.2384	0.2662
12	0.2384	0.3576	0.2384	0.2622
13	0.2384	0.2384	0.2384	0.2391
14	0.2384	0.2384	0.2384	0.2289
15	0.2384	0.2384	0.2384	0.2464
16	0.2384	0.2384	0.2384	0.2467
17	0.2384	0.3576	0.2384	0.2600
18	0.2384	0.3576	0.7152	0.3142
19	0.2384	0.3576	0.7152	0.2698
20	0.2384	0.3576	0.2384	0.2573
21	0.2384	0.2384	0.2384	0.2253
22	0.2384	0.1192	0.2384	0.2088
23	0.2384	0.1192	0.2384	0.2103
24	0.2384	0.1192	0.2384	0.1987

Table 3 gives point forecasting and scenarios of the wind power generation, respectively. An Autoregressive Moving Average (ARMA) model is used to generate wind speed scenarios based on the wind speed data in the state of South Australia [43].

The wind speed scenarios are reduced to ten scenarios for each wind farm using the K-means clustering technique [44] and then transformed into power scenarios considering the GREEF 2kW micro turbine model [45]. It should be noted that the relationship between the power output of wind turbine and wind speed is according to Eq. (38). In (38), $P_W$is the generated power corresponding to a specific wind speed, WS. Moreover, A, B and C are constants that can be computed as discussed in [46]. Also,V_{ci},V_{co}, and $V_r$represent cut in, cut out and rated speeds of wind turbine, respectively.

$$P_W = \begin{cases} 0 & 0 \leq WS \leq V_{ci} or WS \geq V_{co} \\ P_r(A + B \times WS + C \times WS^2) & V_{ci} \leq WS \leq V_r \\ P_r & V_r \leq WS \leq V_{co} \end{cases} \quad (38)$$

To evaluate the proposed DEMS, four price-based cases are assumed according to Table 2. These cases are described in the following:

- Case 1: CPP is considered as price data for the day-ahead LM price, and RTP is considered as the real-time LM price.
- Case 2: Flat rate is considered as price data for the day-ahead LM price, and RTP is considered as the real-time LM price.

- Case 3: ToU is considered as price data for the day-ahead LM price, and RTP is considered as the real-time LM price.
- Case 4: RTP is considered as price data for the day-ahead LM price. In the real-time LM, the purchasing energy price equals 120% of the RTP in the day-ahead LM, and selling energy price equals 80% of the RTP in the day-ahead LM.

It should be highlighted that both selling and purchasing real-time energy prices are equal to RTP in cases 1, 2 and 3.

Table 3. Point forecasting and scenarios for wind power generation

Time (h)	Scenarios (kW)										Point Forecast (kW)
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	
1	0.097	0.234	0	0.123	0.079	0	0.030	0.082	0.560	0.385	0.139
2	0.411	0.312	0.191	0.718	0.237	0.256	0.295	0.394	1.221	1.339	0.486
3	1.012	0.750	0.569	1.802	0.671	0.774	0.585	0.536	1.418	1.339	0.826
4	1.957	1.102	1.319	1.546	0.973	0.827	1.251	0.914	1.949	1.059	1.290
5	1.900	0.890	0.695	1.978	1.517	0.941	0.737	0.770	1.731	1.751	1.491
6	1.792	0.837	0.995	1.949	1.575	1.389	0.783	0.909	1.771	1.649	1.385
7	1.187	1.553	1.300	1.888	1.292	0.783	0.722	1.552	1.687	1.649	1.564
8	1.614	1.229	1.214	1.924	1.535	0.607	0.610	0.877	1.810	1.185	1.261
9	1.060	0.708	1.201	1.765	1.577	0.501	0.473	0.802	1.810	1.185	1.275
10	0.547	0.550	1.526	1.461	1.543	0.748	0.356	0.495	1.086	1.249	0.956
11	0.925	0.737	0.703	1.011	0.887	1.040	0.697	0.519	1.043	1.229	0.979
12	0.849	0.677	0.421	0.905	0.621	1.375	0.846	0.906	0.921	0.957	0.848
13	0.529	0.748	0.224	0.806	0.508	0.829	0.714	0.613	1.004	0.850	0.644
14	0.187	0.287	0.305	0.237	0.338	0.770	1.215	1.048	0.424	0.378	0.439
15	0.196	0.215	0.750	0.325	0.294	0.898	0.700	0.909	0.444	0.067	0.600
16	0.250	0.308	0.522	0.075	0.441	0.412	0.679	0.991	0.176	0.202	0.398
17	0.143	0.092	0.217	0.088	0.028	0.303	0.984	0.645	0.173	0.033	0.271
18	0.217	0	0.260	0	0	0.197	0.717	0.481	0.094	0.075	0.204
19	0.510	0	0.339	0	0	0.158	0.454	0.095	0.091	0	0.165
20	0.411	0	0.145	0	0	0.254	0.387	0.197	0.031	0	0.142
21	0.575	0	0.046	0	0.010	0.583	0.497	0.055	0.023	0	0.179
22	0.729	0	0.075	0	0	0.043	0.360	0.057	0	0	0.086
23	0.401	0	0	0	0.340	0	0.172	0.013	0	0	0
24	0.795	0	0	0	0.051	0	0.165	0	0	0	0

3.2. Deterministic Study

In this section, EV's mobility is not considered in our proposed domestic energy management problem. Hence, it is assumed that the EV leaves home at 7:00AM and returns home at 17:00PM. This scenario defines that the EV should be full of charge when it leaves home and it will be out-of-charge when it returns home.

3.2.1. Price-based Analysis

In this section, the performance of the proposed model is evaluated in four price-based cases. In this regard, each case study is solved separately. Also, the flexibility coefficient of the battery and the EV are considered to equal 0 in this section. As shown in Figure 3, the day-ahead energy traded with the LM is the same in all cases. Moreover, $P_t^{net,da}$ is negative at all times. This means that the smart home buys the energy from the day-ahead local market. In Figure 4, the sold and purchased real-time energies are demonstrated in cases 1, 2, and 3. Figure 4 expresses that there is no difference between traded energies in cases 1, 2 and 3 that sold and bought electricity price are the same, and both are equal to the RTP.

Moreover, Figure 4 represents that the smart home cannot play as a producer and a consumer simultaneously. In other words, according to the proposed model, the DEMS provides all its electrical demand first. Then, if it can generate extra power, it sells it to the LM. According to Figure 4, the home sells power to the real-time LM in all time periods instead of $t = 2$. At $t = 2$, the home plays as both a producer and a consumer. First, it seems that it is not reasonable for the DEMS to sell/buy energy to/from the real-time LM. However, Figure 4 (b) states that the home plays only as a producer or a consumer in different scenarios. The real-time traded energies in case 4 are shown in Figure 5. According to Figure 5, the smart home changes its behaviour in all time periods, especially for $t = 2$, in case 4. It is for this reason that the purchased electricity price is higher than the price sold in the real-time LM, so the DEMS does not decide to buy energy from the real-time LM as seen in Figure 5. In Figure 6, charged and discharged energies of the battery and the EV are shown. It should be noticed that Figure 6 (a) represents the discharged and charged energy of the EV that is transacted with the DEMS and not the quantity of energy discharged due to the mobility of the EV. Hence, as seen in Figure 6 (a), the EV is only in charging mode in time steps 5 and 6, because it should be fully charged at $t = 7$ when it leaves the home. Besides, the EV cannot help the DEMS when it returns to the home because the EV is out-of-charge, and the power produced by the wind turbine is not enough for the system in those time periods.

However, the battery helps the DEMS in time periods, $t = 9$, $t = 10$, and $t = 19$, which are peak times of the system. Table 4 represents the total, day-ahead, and real-time EPs of the proposed stochastic domestic energy management problem in all price-based cases. As seen in Table 4, the day-ahead EP is negative in all cases, because the home plays only as a consumer and buys electricity for the day-ahead LM as demonstrated in Figure 3. However, the real-time EP is positive in all cases, because the home acts more as a producer in the real-time LM. Moreover, the real-time EP in case 4 is the lowest in comparison with other cases. For this reason, the real-time selling price in case 4 is 80% of the RTP. Also, Table 4 states that the total expected cost of the DEMS in case 3 is lower than in the other cases. In other words, the ToU is the most appropriate electricity tariff for the DEMS according to the considered case study.

Table 4. Expected profit of the domestic energy management problem in cases 1, 2, 3, and 4

	Case 1	Case 2	Case 3	Case 4
EP ($)	-4.668	-1.553	-0.325	-4.069
Day-ahead EP ($)	-14.826	-11.711	-10.484	-10.973
Real-time EP ($)	10.159	10.159	10.154	6.905

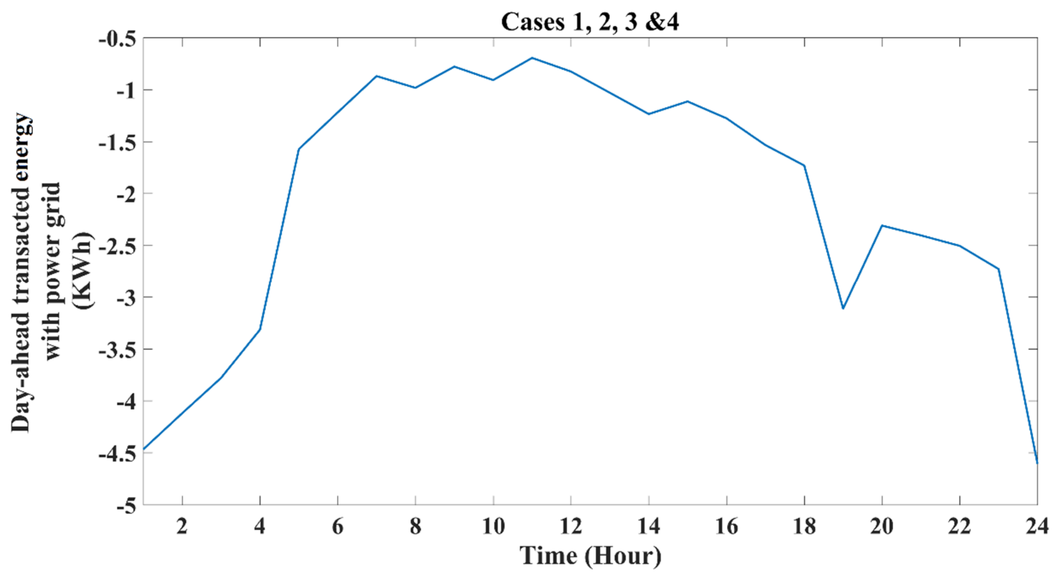

Figure 3. Day-ahead energy transacted with the local market in cases 1, 2, 3 and 4.

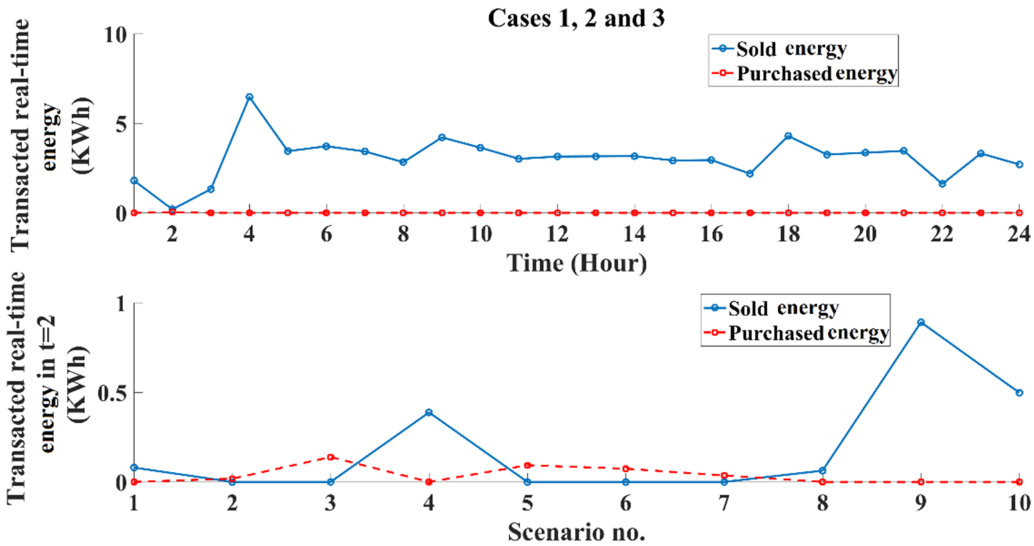

Figure 4. (a) Real-time expected energy transacted in cases 1, 2, and 3 in all time periods; (b) Real-time energy transacted in cases 1, 2, and 3 in $t = 2$.

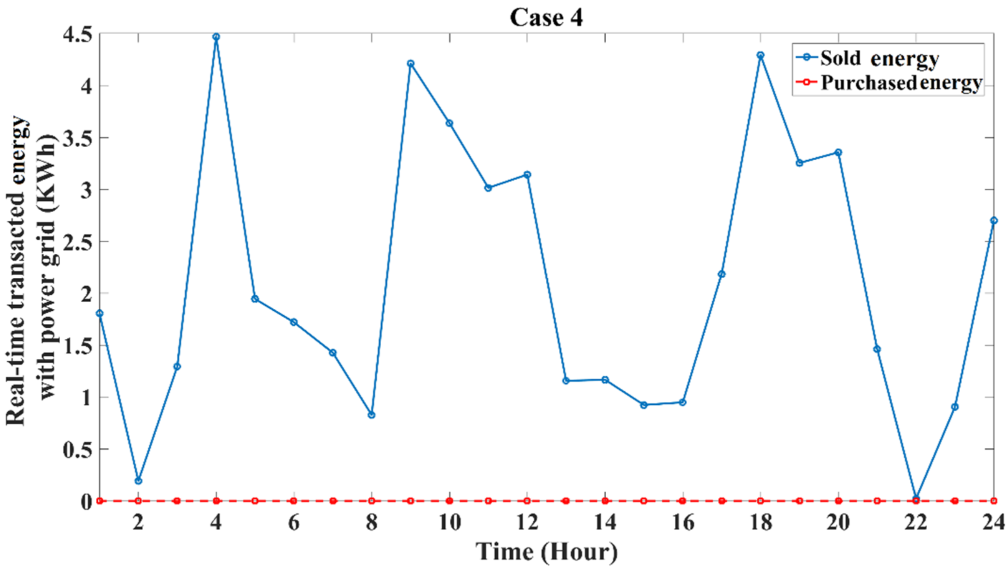

Figure 5. Real-time expected energy transacted in case 4.

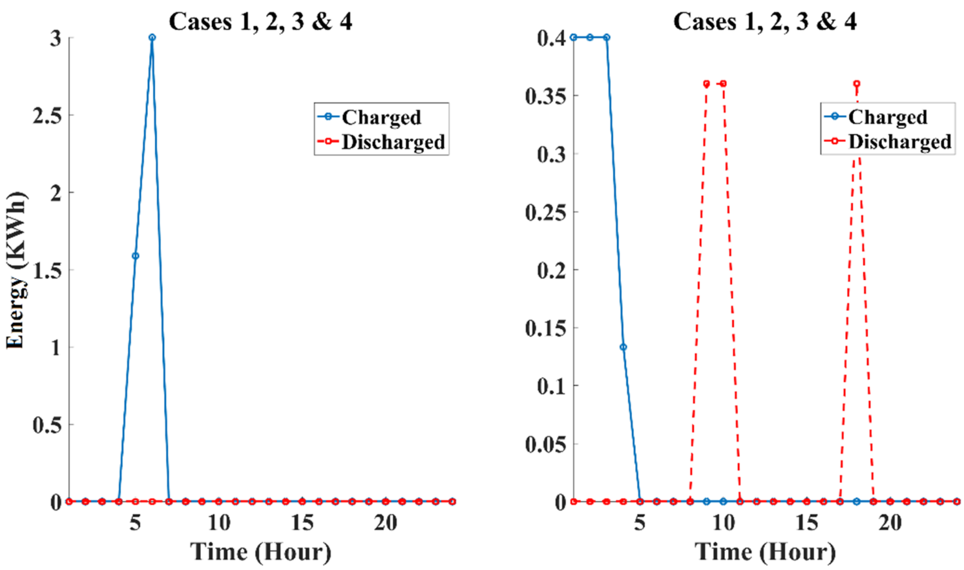

Figure 6. Expected charged and discharged energy of the EV that is transacted with the home (a) and the battery (b) in cases 1, 2, 3 and 4 in real-time.

3.2.2. Flexibility-based Analysis

In this section, the impact of the battery and the EV's flexibility coefficients on the expected profit of the system is assessed in all price-based cases. As shown in Figure 7, there is a linear pattern between an increase in the flexibility coefficients of the battery and the EV, and the expected profit of the problem. However, this impact can be positive or negative, and it depends on the considered price-based case.

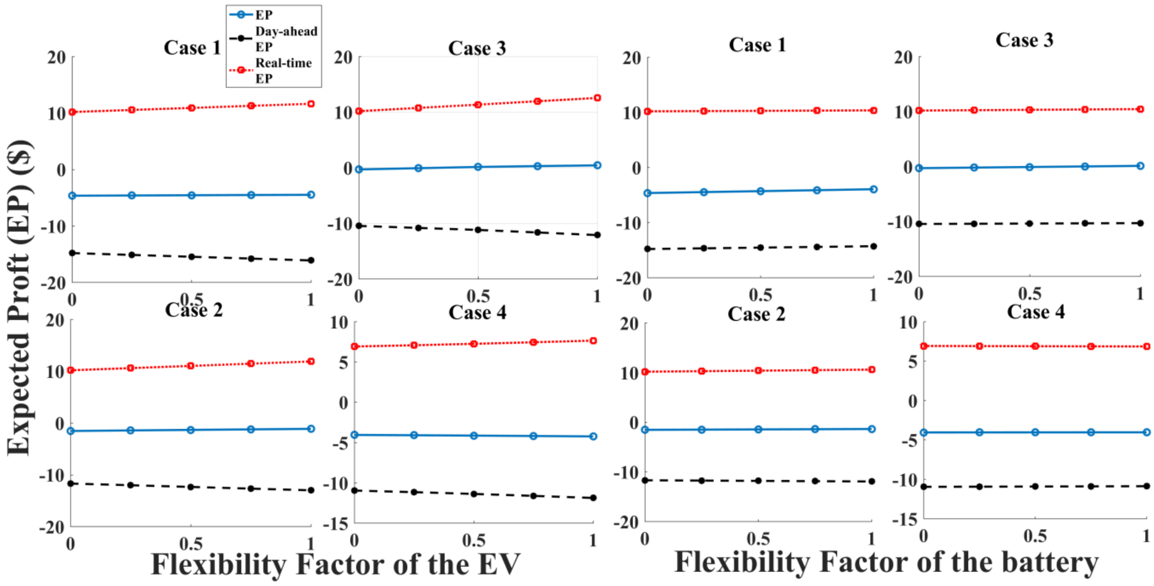

Figure 7. Impact of the flexibility coefficients on the expected profit of the domestic energy management problem without uncertainty of EV mobility.

In cases 1, 2, and 3, increasing the amount of both flexibility coefficients increases the total expected profit. However, in case 4, increasing the EV's flexibility coefficients has a negative effect on the total expected profit of the system, and it decreases the total expected profit. It is noticeable that increasing the battery's flexibility coefficients has a positive influence on the amount of total expected profit in case 4 too. Moreover, the highest impact of the flexibility coefficients on the expected profit is in case 3 that the expected profit gets positive amounts based on an increment of the battery and the EV's flexibility coefficients.

3.3. Stochastic Study

This section describes the conducted EV case study in which its mobility uncertainty is considered. Figures 8 to10 illustrate the probability distribution of the EV's departure time, arrival time and driving distance, respectively. The data of the probability distributions have been extracted from [47]. The arrival time is considered based on the last trip home. Figure 8 indicates a peak at 7:00, and the distribution profile matches with the common commuting periods. The mean value of departure time is about 10:30, and the standard deviation is equal to 3.26 hours. According to [47], chi-square distribution is considered for the departure time distribution. Based on Figure 9, the probability distribution of arrival time illustrates a distribution similar to Gaussian with two small peaks around 17:00-18:00 and 20:00-21:00. According to the trend in Figure 9, the customer arrives home haphazardly and can drive for another trip after work. The mean value of arrival time is 19:10, and the standard deviation is 3.62 hours. It is noteworthy that the standard deviations of the departure and the arrival distributions are quite close, while the distribution shapes are not similar. In order to model the probability of the driving distance, the data are split into different segments with the same probability on the cumulative distribution function. Each segment can denote a particular travel patterns in terms of driving distances. Every single driving cycle is created by the Markov chain, and the driving cycle that attains the dominant statistical measure is considered the representative cycle. The representative cycles in each segment are selected as the average cumulative distribution in that segment. The probability distribution of the travel distance can be regressed by the form of chi-square distribution.

$$P_{DIST}(x_{i,n}) = \frac{x_{i,n}^{(\nu-2)/2} EXP(-0.5x_{i,n})}{2^{\nu/2}\Gamma(\nu/2)} \tag{39}$$

where ν is determined to minimize the root-mean-square error by applying sequential quadratic programming. $\Gamma(.)$denotes the Gamma function. $x_{i,n}$ represents the normalized travel distance calculated as follows:

$$x_{i,n} = \frac{x_i}{\Delta d} \tag{40}$$

where x_i is the average travel distance in ith travel distance segment, and $\Delta d$is the segment size.

According to Figure10, the probability distribution of the driving distance ranges up to 22.8 mi. The mean value is about 5.83 mi, and the standard deviation equals to 3.26 mi.

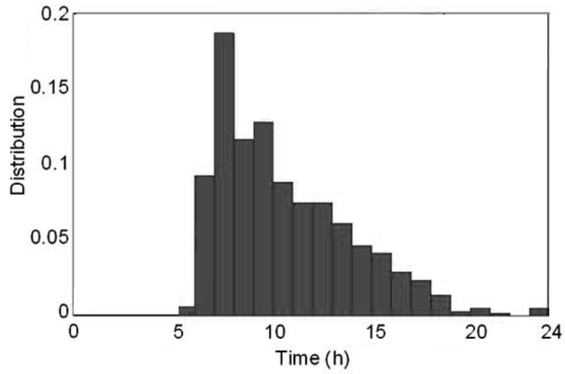

Figure 8. Probability distribution of departure time.

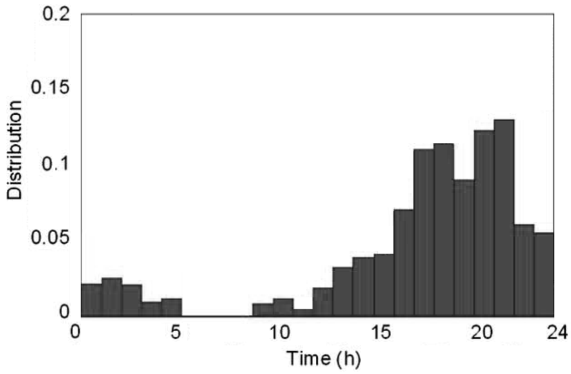

Figure 9. Probability distribution of arrival time.

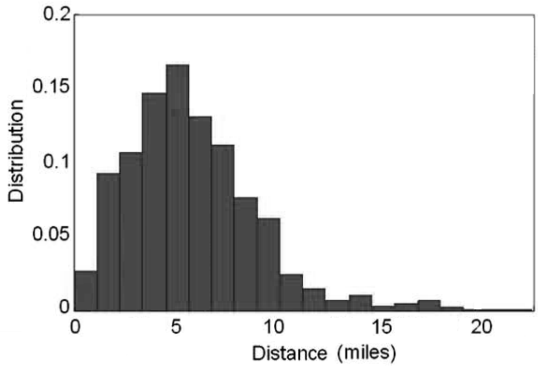

Figure 10. Probability distribution of driving distance.

It should be noted that Ref. [47] had demonstrated that the driving distance could be considered as an independent variable with respect to the departure time and the arrival time. On this basis, several realizations of the EV's behavior are taken into account by employing the scenario generation process. To this end, due to the above-mentioned probability distributions, RWM is utilized to generate scenarios [48].

Finally, since a large number of scenarios yield a complex optimization problem, K-means clustering technique [49] is utilized to reduce the number of scenarios as presented in Table 5.

Table 5 gives scenarios of the departure time, arrival time, driving distance, state of charge of the EV, and the corresponding probability of scenarios after scenario reduction, respectively. In addition, it is assumed that the EV should be fully charged when it leaves home. Also, the flexibility coefficient of the battery is assumed to equal 0 in this section.

Table 5. Scenarios for EV's mobility

	Scenarios (kW)									
	Scn1	Scn2	Scn3	Scn4	Scn5	Scn6	Scn7	Scn8	Scn9	Scn10
Departure time (h)	8	11	10	8	17	11	13	13	14	10
Arrival time (h)	20	21	16	20	24	15	19	18	23	22
Driving distance (mile)	3.328	3.880	6.172	4.90	1.263	5.022	2.966	1.347	2.561	11.8
SOC at arrival time	0.8	0.77	0.63	0.71	0.93	0.7	0.82	0.92	0.85	0.3

3.3.1. Price-based Analysis

In this section, the impact of EV's mobility uncertainty on the stochastic DEMS is assessed in four price-based cases. Also, the flexibility coefficient of the battery and the EV are assumed to equal 0 and 1 in this section. As seen in Table 6, the expected profit of the system reaches the maximum amount in Case 3 with/without mobility uncertainty. On the other hand, mobility uncertainty has a positive effect on the EP in all Cases apart from Case 4. Thus, Figures 8-10 show the comparison between the results of the stochastic and deterministic models of the EV's mobility in Case 3.

As shown in Figure 11, the day-ahead and real-time energy traded with the power grid are different in stochastic and deterministic models. These differences are in departure and arrival times. Hence, while the mobility uncertainty decreases the expected real-time energy sold to the LM, it increases the quantity of transacted energy in the day-ahead LM. Figure 12 shows the impact of mobility uncertainty on charged and discharged energies of the EV which is transacted with the building in Case 3. As seen in Figure 12, the pattern of charged and discharged energy curves of the EV is more dynamic in the stochastic case due to the uncertainty of EV mobility. According to Figure 12, it seems that the EV is charged and discharged simultaneously in some time steps. However, Figure 12 shows expected charged and discharged energies. Furthermore, Figure 13 displays charged and discharged energies of the EV which are transacted with the home at t=1 and t=8. As seen in Figure 13, the EV is only charged or discharged in each scenario in both of these time steps.

3.3.2. Flexibility-based Analysis

In this section, the influence of the EV's flexibility coefficient on the EPs of the proposed DEMS with/without mobility uncertainty is assessed in all price-based cases. As seen in Figure 14, increment of the EV's flexibility coefficient increases the amount of the EP in Cases 1, 2, and 3.

Table 6. Expected profit of the domestic energy management problem in deterministic and stochastic studies.

	Deterministic mobility			**Stochastic mobility**		
	Day-ahead EP ($)	**Real-time EP ($)**	**EP ($)**	**Day-ahead EP ($)**	**Real-time EP ($)**	**EP ($)**
Case 1	-16.128	11.618	-4.51	-14.155	10.481	-3.674
Case2	-13.013	11.870	-1.14	-11.823	10.583	-1.239
Case 3	-12.134	12.541	0.407	-10.777	11.339	0.562
Case 4	-11.889	7.637	-4.252	-10.669	6.646	-4.023

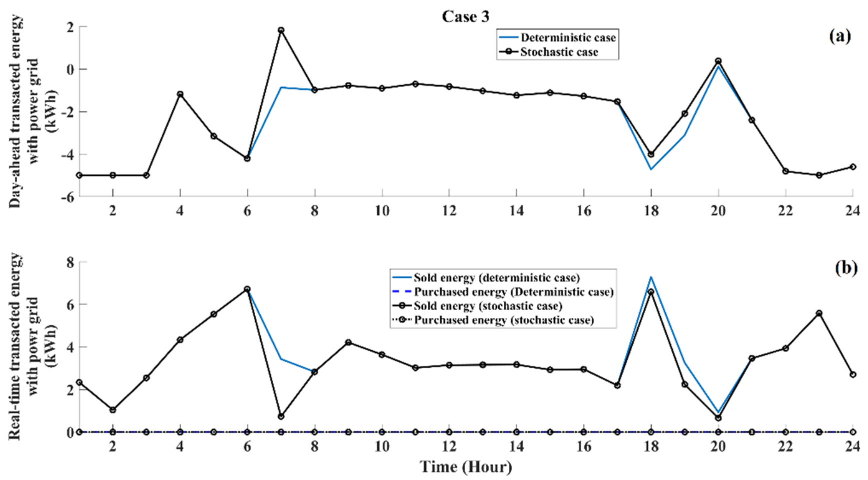

Figure 11. Impact of uncertainty of the EV's mobility on the day-ahead transacted energy (a) and real-time expected transacted energy (b).

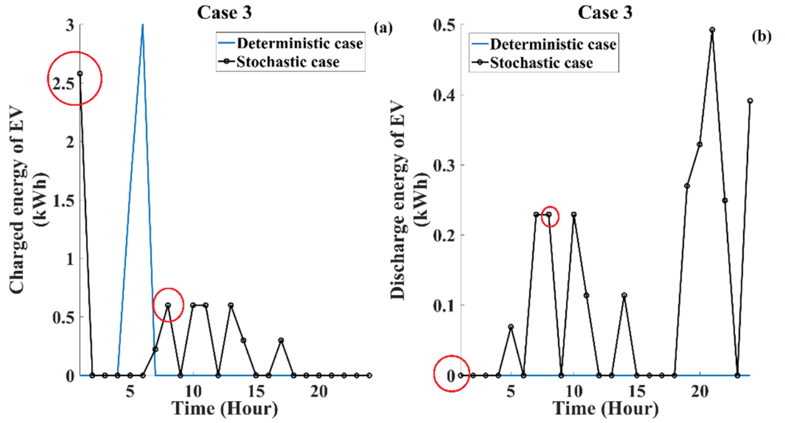

Figure 12. Impact of mobility uncertainty on expected charge (a) and discharged energies (b) of the EV that are transacted with the home.

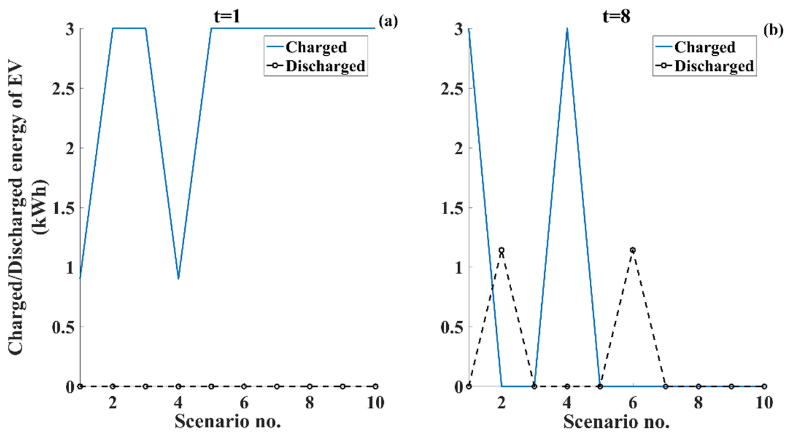

Figure 13. Real-time charged and discharged energies of the EV that are transacted with the home at t=1 (a) and t=8 (b).

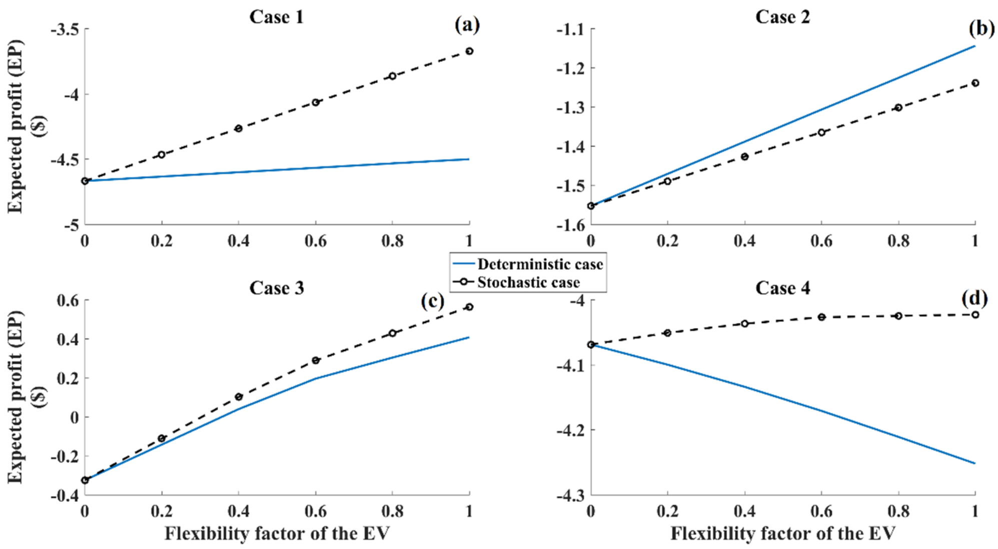

Figure 14. Impact of the flexibility coefficients on the expected profit of the domestic energy management problem in comparison with stochastic and deterministic models that consider the uncertainty of EV mobility in Case 1 (a), Case 2 (b), Case 3 (C), and Case 4 (d).

While in Cases 1 and 3, the EP of the stochastic model is higher than the deterministic one, the EP of the deterministic model is higher than the stochastic one in Case 2. Also, the increment of the EV's flexibility coefficient decreases the amount of the EP in Case 4. Moreover, while the amount of the EPs of the stochastic and deterministic models is different in all Cases where the EV's flexibility coefficient equals 1, the uncertainty of EV mobility does not affect the EP of the DEMS where the EV's flexibility coefficient equals 0.

The MILP problem was solved by CPLEX 12.0 and the implementation was performed on a laptop with 8 GB RAM, Intel Core i7 2.6 GHz. The computation cost of the problem is presented in Table 7.

Table 7. Optimization statistics of the proposed stochastic model

Number of equations	Number of variables	Number of discrete variables	Number of iterations	Execution time (sec)
72,710	44,499	4,848	19,578	0.25

4. Conclusions

In this paper, a price-based stochastic DEMS has been presented. A two-stage stochastic programming model employed to model the uncertainty of wind power generation and EV mobility. It was assumed that the home was able to transact energy with the local electricity market. However, in the proposed domestic energy management problem, homes were considered as price-taker agents in the local market.

In the first stage, the day-ahead home energy management problem was modeled disregarding the uncertainty of wind power generation and EV mobility in this stage. In addition, the performance of the proposed DEMS was evaluated based on the impacts of the price-based programs and flexibility coefficients of the battery and the EV. It is noticeable that multiple charging and discharging of EV and ES may have negative effects on the battery lifetime and deal the smart home owner with some difficulties that need further researches in future. The simulation results reveal that the smart home played only as a consumer and bought electricity for the day-ahead local market in all price-based cases; hence, the day-ahead expected profit in all cases was negative. Furthermore, the real-time expected profit was lower in RTP in comparison with other DR programs, because the real-time selling price was equal to 80% of the RTP. Moreover, the increment rate of the expected profit due to the EV storage level at its return time was maximum in ToU program. However, the increment rate of the expected profit in flat rate program was negative, which makes the flat rate an inefficient rating price in the day-ahead LM.

Although the results are case sensitive, the most important results of the work are summarized below:

- There was a linear pattern between increasing the flexibility coefficients of the battery and the EV, and the expected profit of the problem.
- Increasing the energy flexibility increased the total expected profit.
- The highest impact of the flexibility coefficients on the expected profit was when ToU was considered. The expected profit gained positive amounts thanks to an increment of the battery and EV's flexibility coefficients.
- ToU was the most appropriate electricity tariff for the DEMS.

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