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Published in:
2022 IEEE International Conference in Power Engineering Application

DOI (link to publication from Publisher):
10.1109/ICPEA53519.2022.9744666

Publication date:
2022

Document Version
Accepted author manuscript, peer reviewed version

Link to publication from Aalborg University

Citation for published version (APA):
Akbari-Dibavar, A., Zare, K., Mohammadi-Ivatloo, B., Anvari-Moghaddam, A., & Abdul-Malek, Z. (2022). CVaR-based Stochastic Energy Management of a Smart Home. In *2022 IEEE International Conference in Power Engineering Application: ICPEA* IEEE (Institute of Electrical and Electronics Engineers). https://doi.org/10.1109/ICPEA53519.2022.9744666

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CVaR-based Stochastic Energy Management of a Smart Home

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***Abstract*— Considering recent developments in photovoltaic (PV) systems, storage, and electrical vehicles, not unexpected that one day smart homes will also take part in energy markets directly. In this regard, the presented paper proposes a stochastic programming approach to manage the consumption of a smart home according to intermittent PV system production and uncertain energy prices to make the smart home available for taking part in the local day-ahead (DA) energy market. A battery storage system is integrated to make flexibility against price fluctuations. Furthermore, modeling of plug-in electric vehicles (PEV) is also provided, where the traveling pattern is modeled through scenarios. The goal is to maximize the daily profit of the smart home while the welfare of the inhabitants is satisfied by considering comfort constraints. In addition, the conditional value at risk (CVaR) risk index is considered to manage associated risk with gained profit. The obtained results show the effectiveness of the optimization framework, in which the expected daily profit of the homeowner can reach $ 1.72 per day in the risk-neutral condition.**

Keywords*— *Smart home, energy management, stochastic programming, energy market, conditional value at risk (CVaR).

I. INTRODUCTION

The term *smart home* refers to houses that contain various types of smart meters, communication and controlling infrastructures, power generation resources (e.g. PV systems), storage units (e.g. battery) and can participate in demand-side management programs to achieve extra financial benefits. Furthermore, the extra power generated by the PV systems can be sold to the local electrical network (by aggregators or directly). An efficient energy management system (EMS) considers existing uncertainties (e.g., PV generation or market prices), as well as consumer's comfort, which is not practicable by consumers themselves. The EMS's task is energy and time management of controllable and uncontrollable appliances according to a control signal derived from energy price or consumer's comfort index. Both criteria can be considered in a single optimization framework [1]. For example, an optimization model utilized by [2] optimally holds the indoor temperature in a predefined margin as a comfort index while assuring the minimum cost of energy. In [3], a holistic optimization model is presented for optimal scheduling of energy consumptions within a home in the presence of renewable generation according to consumer preference. The charging/discharging states of energy storage and PEV are also controlled considering their capital cost and total economic benefits. For an autonomous off-grid smart building, the authors of [4] proposed a mixed-integer linear programming problem, which tries to minimize the fuel consumption of the diesel generator of the building. However, in nature, the cost minimization and consumers comfort satisfaction are conflicting objectives. With this respect, the authors of [5] proposed an energy management scheme for smart homes that balances the energy cost minimization and dissatisfaction of the user under two pricing mechanisms.

Smart homes are prosumers that can provide energy flexibility services in terms of demand-side management and power market participation [6]. Reference [7] evaluated the flexibility capacity of smart homes for active power control in distribution and transmission levels and found that flexibility services from smart homes can make a profit. For successful service provision, the EMS should coordinate the available energy generation resources and load consumption. In this regard, based on the daily behaviors of consumer, the optimal scheduling of energy resources and home appliances are addressed in [8]. Their proposed method can schedule the PV and battery operation for minimum cost using single and multi-objective optimizations. Similarly, a multi-objective optimization problem is proposed in [9], that automatically decides on a real-time demand response strategy in the presence of a dynamic pricing scheme, assuring the minimum operational cost and proper user satisfaction level. While the previous works do not consider the uncertainty of operation, the authors of

[10] prescribed an uncertainty-based smart home scheduling problem. Their proposed framework considers the stochastic characteristics of PV generation, and PEV's state-of-charge and arrival/departure times.

One of the most important opportunities for smart homes is in deregulated local energy markets. In particular, the energy arbitrage capability of battery systems and PEV brings this opportunity to buy energy at off-peak times and sell it at peak times for monetary benefits due to price changes [11]. To reach the best performance in the market, the EMS should derive optimal bids/offers according to the level of energy consumption of the home, energy price, capacity limitations, and forecasting of renewable generation. Hence, most of the works in this field, attempted to use various uncertainty management techniques. For instance, in [12], a stochastic-interval optimization is proposed for energy management of a smart home for deriving optimal bids/offers to take part in day-ahead and real-time energy markets. A robust optimization approach is used by [13] to make the aggregators of smart homes able to participate in DA energy markets. An interval-based optimization is presented in [14] to investigate the transacted power between a smart building and a local electrical grid. A hybrid robust-stochastic optimization framework is developed by [15] to schedule the energy consumption of a smart home where the uncertainty of market price and PV generation is tackled by the proposed hybrid methodology.

It can be deduced that the scheduling of smart homes in the energy markets has attracted enormous attention in recent years. However, investigating the associated uncertainties will give sight and lead to efficient and risk-averse energy management. This paper also aims to provide a stochastic optimization for a privately owned smart home to participate in the DA energy market and make revenue by selling power to the local grid. Different kinds of loads are investigated, i.e., a space heater, a pool pump, and a storage water heater which are referred to as shiftable loads, and a prediction of fixed and must-run loads for all hours are added to the optimization to model the non-curtailable loads (e.g., lightning, vital consumptions, etc.). In addition, straightforward modeling of a PEV with stochastic behavior is considered to make the EMS more applicable. Finally, the CVaR risk measure controls the uncertainty effects, where it is added to the objective function of the optimization problem. CVaR is an adjustable risk measure that takes into account the risk of operating scenarios and provides different scheduling plans according to the level of risk acceptance. Inclusion of CVaR does not complicate the solution process due to its convex formulation. It should be noted that the closest works to this paper are [16], [17], where the authors have used a CVaR-based energy management scheme for optimal scheduling of a smart home, while they use the CVaR method to reduce the risk of loss of load, and solar generation, respectively. In comparison with these recent works, this paper provides the following contributions:

1. Providing more comprehensive modeling in terms of different controllable, must-run, and PEV loads.
2. Investigation of uncertainty effects of energy price, PEV behavior, and PV generation.
3. Deriving optimal bidding strategy for the smart home to take part in the DA energy market, for risk-neutral and risk-averse strategies.

II. Problem Formulation

The objective function is to maximize the gained profit, which is from the difference between the sold and purchased power to/from the local network considering the losses due to curtailment of PV generation and load consumption. The battery, PEV, and load constraints would be described next.

A. Objective Function

The expected profit of the energy management problem for the smart home is written as (1). Where t and s are time and scenario indexes, ρ_s is scenarios' probability; $\lambda_{t,s}$ is hourly energy price scenarios; $P_{t,s}^{Grid}$ and $P_{t,s}^{Sold}$ are bought and sold energy to the local market; S^{PV} is the spilled PV generation and V_S^{PV} is the value of it; $LS_{t,s}^{Total}$ and $Voll$ are the amount and value of the curtailed load, respectively. The objective function (1) tries to maximize the expected revenue of exchanged power while minimizing the expected amount of PV spillage and load curtailment.

$$\begin{aligned} OF_1 = \sum_t \sum_s \rho_s \times (\lambda_{t,s} \times (P_{t,s}^{Sold} - P_{t,s}^{Grid})) \\ -V_S^{PV} \times S_{t,s}^{PV} - Voll \times LS_{t,s} \end{aligned} \qquad (1)$$

B. PV and Battery Constraints

The following constraint (2) shows that whether the home purchases or sells energy, its net exchanged power amount should be within a limit that is determined based on the distribution line's capacity connected between the home and local network, $S_{\max}$.

$$-S_{\max} \le P_{t,s}^{Grid} - P_{t,s}^{Sold} \le S_{\max}, \forall t, \forall s \qquad (2)$$

In constraints (3)-(4), the binary variable ($v_{t,s}$) indicates that the smart home acts as a buyer or seller (i.e., $v_{t,s} = 1$ or 0).

$$P_{t,s}^{Grid} \le S_{\max} \times v_{t,s} \qquad , \forall t, \forall s \qquad (3)$$

$$P_{t,s}^{Sold} \le S_{\max} \times (1 - v_{t,s}) \qquad , \forall t, \forall s \qquad (4)$$

As it was denoted before, a smart home is equipped with a PV system and battery storage to be able to actively operate. In (5), it is defined that the produced power by the PV system (P^{PV}) is divided into two parts. The first item ($P_{t,s}^{PV-in}$), will be injected into the indoor, feed the loads, and charge the battery. The second item, ($P_{t,s}^{PV\_out}$), will be exported to the local network and makes income for the smart home. However, the excess energy should be spilled, which is determined and limited by (6) and (7), respectively. $P_{t,s}^{PV,pred}$ is the hourly forecasted PV scenarios.

$$P_{t,s}^{PV} = P_{t,s}^{PV\_in} + P_{t,s}^{PV\_out}, \forall t, \forall s \tag{5}$$

$$P_{t,s}^{PV} = P_{t,s}^{PV,pred} - S_{t,s}^{PV}, \forall t, \forall s \tag{6}$$

$$0 \le S_{t,s}^{PV} \le P_{t,s}^{PV,pred}, \forall t, \forall s \tag{7}$$

The below equations are technical constraints of the battery storage (8)-(14). $SOC_{t,s}^{B}$ is the stored energy in the battery at each time and scenario; SOC_{B}^{init} is the initial stored energy; $P_{t,s}^{Ch,B}$ and $P_{t,s}^{Dis,B}$ are charged and discharged powers by the battery. The charging and discharging efficiencies are denoted by $\eta^{Ch,\mathrm{B}}$ and $\eta^{Dis,B}$. $SOC_{B}^{\min}$ and $SOC_{B}^{\max}$ are the minimum and maximum amounts of stored energy in the battery, and $R_{B}^{\max}$ is the maximum amount of charged and discharged power. $u_{t,s}^{Ch,B}$ and $u_{t,s}^{Dis,B}$ are binary variables indicating charging and discharging states.

$$SOC_{t,s}^{B} = SOC_{B}^{init} + P_{t,s}^{Ch,B} \times \eta^{Ch,B} - P_{t,s}^{Dis,B} / \eta^{Dis,B}, \forall t = 1, \forall s \tag{8}$$

$$SOC_{t,s}^{B} = SOC_{t-1,s}^{B} + P_{t,s}^{Ch,B} \times \eta^{Ch,B} - P_{t,s}^{Dis,B} / \eta^{Dis,B}, \forall t > 1, \forall s \tag{9}$$

$$SOC_{B}^{\min} \le SOC_{t,s}^{B} \le SOC_{B}^{\max}, \forall t, \forall s \tag{10}$$

$$0 \le P_{t,s}^{Ch,B} \le R_{B}^{\max} \times u_{t,s}^{Ch,B}, \forall t, \forall s \tag{11}$$

$$0 \le P_{t,s}^{Dis,B} \le R_{B}^{\max} \times u_{t,s}^{Dis,B}, \forall t, \forall s \tag{12}$$

$$u_{t,s}^{Ch,B} + u_{t,s}^{Dis,B} \le 1, \forall t, \forall s \tag{13}$$

$$P_{t,s}^{Dis,B} = P_{t,s}^{Dis\_in,B} + P_{t,s}^{Dis\_out,B}, \forall t, \forall s \tag{14}$$

Equation (8) initializes the SOC (i.e., stored energy) of the battery at time *t*=1, and (9) calculates the SOC of the battery storage at the other times. Equation (10) defines the upper and lower bounds of the SOC. While (11) and (12) limit the amount of charged/discharged powers of the battery at each time and scenario. Simultaneous charging and discharging are prohibited by (13). As for the PV-generated power, discharged power by the battery can also be injected to the home ($P_{t,s}^{Dis\_in,B}$) or be sent out to the grid ($P_{t,s}^{Dis\_out,B}$) in (14).

C. *Load constraints*

In this section, the controllable loads' mathematical characteristics and formulation would be expressed, according to Ref. [12]. It is assumed that the smart home contains three types of controllable loads as follows: space heater, storage water heater, and pool pump, where, $L_{t,s}^{SH}$, $L_{t,s}^{SWH}$, $L_{t,s}^{PP}$, $P_{t,s}^{SH}$, $P_{t,s}^{SWH}$, and $P_{t,s}^{PP}$ are the electricity and energy consumption of the SH, SWH, and PP, respectively. And $LS_{t,s}^{SH}$, $LS_{t,s}^{SWH}$ and $LS_{t,s}^{PP}$ are the curtailed SH, SWH, and PP loads, respectively. The task of the space heater (SH) is to adjust the indoor temperature and provides thermal comfort to inhabitants. This load is modeled through (15)-(20). $\theta_{t,s}^{in}$ is the indoor temperature; R and C are the thermal resistance and capacity of the building. $\theta_{t,s}^{pred,out}$ is forecasted ambient temperature. θ_0 and $\theta_{Desired}$ are the initial and desired temperatures, respectively.

$$\theta_{t+1,s}^{in} = \exp[-1/R \times C] \times \theta_{t,s}^{in} + R \times (1 - \exp[-1/R \times C]) \times L_{t,s}^{SH} + (1 - \exp[-1/R \times C]) \times \theta_{t,s}^{pred,out}, \forall t > 1, \forall s \tag{15}$$

$$\theta_{t,s}^{in} = \theta_0 = \theta_{Desired}, \forall t = 1, \forall s \tag{16}$$

$$-1 \le \theta_{t,s}^{in} - \theta_{Desired} \le 1, \forall t, \forall s \tag{17}$$

$$P_{t,s}^{SH} = \tfrac{1}{2}(L_{t,s}^{SH} - L_{t-1,s}^{SH}), \forall t > 1, \forall s \tag{18}$$

$$P_{t,s}^{SH} = \tfrac{1}{2}(L_{t,s}^{SH} - L^{SH,init}), \forall t = 1, \forall s \tag{19}$$

$$0 \le LS_{t,s}^{SH} \le P_{t,s}^{SH}, \forall t, \forall s \tag{20}$$

Equation (15) models the indoor temperature. From (16), the initial indoor temperature is set to the desired temperature. In (17), a restricted margin is defined for the indoor temperature (i.e., 1°C). Equations (18) and (19) calculate the electricity consumption of the SH. In (20), the curtailed energy is limited. The storage water heater (SWH) charges energy to heat a water tank.

$$\sum_t L_{t,s}^{SWH} = U_{SWH}^{\max}, \forall s \tag{21}$$

$$P_{t,s}^{SWH} = \frac{1}{2}(L_{t,s}^{SWH} - L_{t-1,s}^{SWH}), \forall t > 1, \forall s \tag{22}$$

$$P_{t,s}^{SWH} = \frac{1}{2}(L_{t,s}^{SWH}(t,s) - L^{SWH,init}), \forall t = 1, \forall s \tag{23}$$

$$0 \le LS_{t,s}^{SWH} \le P_{t,s}^{SWH}, \forall t, \forall s \tag{24}$$

$$0 \le LS_{t,s}^{SWH} \le L_{SWH}^{\max}, \forall t, \forall s \tag{25}$$

Equation (21) shows the maximum required electricity used ($U_{SWH}^{\max}$) to supply the SWH. Equations (22)-(24) model the energy consumption of the SWH. The curtailed energy of the SWH is limited by (25). The total pool pump (PP) operation time ($z_{t,s}$) should not be more than a predefined amount i.e., T_{on}, for a day; $L^{PP,init}$ and $L_{PP}^{\max}$ show the initial and maximum electrical consumptions of the PP, respectively.

$$L_{t,s}^{PP} \le L_{PP}^{\max} \times z_{t,s}, \forall t, \forall s \tag{26}$$

$$\sum_t z_{t,s} \le T_{on}, \forall s \tag{27}$$

$$P_{t,s}^{PP} = \tfrac{1}{2}(L_{t,s}^{PP} - L_{t-1,s}^{PP}), \forall t > 1, \forall s \tag{28}$$

$$P_{t,s}^{PP} = \tfrac{1}{2}(L_{t,s}^{PP} - L^{PP,init}), \forall t = 1, \forall s \tag{29}$$

$$0 \le LS_{t,s}^{PP} \le P_{t,s}^{PP}, \forall t, \forall s \tag{30}$$

Equation (26) determines the electricity consumption of the PP as a function of its operation time. The operation time is limited in (27). Equations

(28) and (29) calculate the consumed energy of the PP. The amount of curtailed energy related to the PP is restricted by (30).

The total consumed energy ($P_{t,s}^{Total}$) and curtailed load ($LS_{t,s}^{Total}$) are written in (31) and (32), respectively. With this description, the balance constraint of the proposed optimization can be written as (33).

$$P_{t,s}^{Total} = P_{t,s}^{SH} + P_{t,s}^{SWH} + P_{t,s}^{PP} + P_{t}^{pred}, \forall t, \forall s \quad (31)$$

$$LS_{t,s}^{Total} = LS_{t,s}^{SH} + LS_{t,s}^{SWH} + LS_{t,s}^{PP}, \forall t, \forall s \quad (32)$$

$$\begin{aligned} &P_{t,s}^{PV\_in} + P_{t,s}^{Dis,B} + P_{t,s}^{Dis,EV} + P_{t,s}^{Grid} = \\ &P_{t,s}^{Total} - LS_{t,s}^{Total} + P_{t,s}^{Ch,B} + P_{t,s}^{Ch,EV} + P_{t,s}^{Sold}, \forall t, \forall s \end{aligned} \quad (33)$$

D. PEV constraints

The PEV is modeled using (34)-(41).

$$SOC_{t,s}^{EV} = SOC_{EV}^{init} + P_{t,s}^{Ch,EV}\eta^{Ch,EV} - \frac{P_{t,s}^{Dis,EV}}{\eta^{Dis,EV}} - P_{t,s}^{tra}, \forall t = 1, \forall s \quad (34)$$

$$SOC_{t,s}^{EV} = SOC_{t-1,s}^{EV} + P_{t,s}^{Ch,EV}\eta^{Ch,EV} - \frac{P_{t,s}^{Dis,EV}}{\eta^{Dis,EV}} - P_{t,s}^{tra}, \forall t > 1, \forall s \quad (35)$$

$$SOC_{EV}^{\min} \le SOC_{t,s}^{EV} \le SOC_{EV}^{\max}, \forall t, \forall s \quad (36)$$

$$0 \le P_{t,s}^{Ch,EV} \le R_{EV}^{\max} \times u_{t,s}^{Ch,EV}, \forall t, \forall s \quad (37)$$

$$0 \le P_{t,s}^{Dis,EV} \le R_{EV}^{\max} \times u_{t,s}^{Dis,EV}, \forall t, \forall s \quad (38)$$

$$u_{t,s}^{Ch,EV} + u_{t,s}^{Dis,EV} \le 1, \forall t, \forall s \quad (39)$$

$$P_{t,s}^{Dis,EV} = P_{t,s}^{Dis\_in,EV} + P_{t,s}^{Dis\_out,EV}, \forall t, \forall s \quad (40)$$

$$P_{t,s}^{tra} = D_{t,s} \times \xi, \forall t, \forall s \quad (41)$$

The stored energy of the battery of the PEV ($SOC_{t,s}^{EV}$) is calculated by (34) and (35) that depends on the charging ($P_{t,s}^{Ch,EV}$), discharging ($P_{t,s}^{Dis,EV}$) powers of the battery, and the traveling state ($P_{t,s}^{tra}$). The stored energy has minimum and maximum limits (i.e., $SOC_{EV}^{\min}$ and $SOC_{EV}^{\max}$), which is formed by (36). Also, (37) and (38) introduce limits on the maximum charging and discharging powers ($R_{EV}^{\max}$) of the battery of the PEV. The simultaneous charging and discharging is prohibited by (39) by defining binary variables $u_{t,s}^{Ch,EV}$ and $u_{t,s}^{Dis,EV}$. The discharged power of the PEV can be injected into the smart home ($P_{t,s}^{Dis\_in,EV}$), or can be sold ($P_{t,s}^{Dis\_out,EV}$) to the local market through (40). According to (41), the traveling state is a function of distance ($D_{t,s}$) and efficiency of the PEV (ξ) [18].

E. Conditional value at risk (CVaR) implementation

The objective function (1) is a risk-neutral formulation where stochastic programming tries to find the expected profit. However, due to uncertainties, the expected profit found by the optimization problem might not be reached in real operation. The CVaR risk index measures the expected profit for the $(1-\alpha)\times 100\%$ worst cases to control the risk of encountering undesired profits [19]. The CVaR method makes the homeowner be able to select a risk-taker or risk-averse decision by changing weighting parameter β , ranging from zero (i.e., risk-neutral condition) to one (i.e., risk-averse condition) by 0.1 steps. In this paper, α is set to 0.75.

The method is included in the objective function of the optimization; however, some additional constraints should also be met. The generic form of the CVaR or average value-at-risk method is introduced in (42).

$$CVaR(\alpha, x) = \max\left\{\eta - \frac{1}{1-\alpha}\varepsilon_s\left\{\max(\eta - f(x,s), 0)\right\}\right\} \quad (42)$$

After integrating the CVaR with the EMS, the objective function of the risk-averse problem will be changed to (43), which consists of two parts and is linked using an adjustable parameter, beta. The first part indicates the risk-neutral objective function and the second part indicates the risk-based objective function. By increasing the parameter, beta, the importance of risk is increased and the optimization problem puts more attention on the effects of worst scenarios and tries to maximize the profit over them.

$$OF_2 = (1-\beta)\cdot OF_1 + \beta\cdot(\eta - \frac{1}{1-\alpha}\sum_s \rho_s SW_s) \quad (43)$$

Where $\beta = 0$ leads to pervious risk-neutral objective function. The additional constraints are (44) and (45).

$$\eta - (\sum_t \lambda_{t,s} \times (P_{t,s}^{Sold} - P_{t,s}^{Grid}) - V_S^{PV} \times S_{t,s}^{PV} - Voll \times LS)) \le SW_s \quad (44)$$

$$SW_s \ge 0 \quad (45)$$

Where, η and SW_s are decision variables.

III. Numerical Evaluation

The information related to load consumption, PV generation, energy price scenarios, and their probabilities are available in [12]. The hourly traveling patterns of ten PEVs are provided by [18] that are used as ten traveling pattern scenarios of one PEV in this paper. Any other required information about the PEV can also be found in [18]. The results are obtained by solving the proposed MILP problem with the GAMS optimization package using the Cplex solver. Due to the linearity of the model, it takes less than 1 sec and the solutions are confidently optimal. It should be noted that the results are depicted for the risk-neutral condition; however, Figure 1 shows the deviation of the profit versus a risk-measuring parameter β . The expected profit decreased by beta, which confirms the validity of the risk-averse problem. In fact, by increasing beta, the profit is calculated based on the worst scenarios. By increasing beta from zero to one, the expected profit reduced by 10% from \$1.72 to \$1.56. The amount of curtailed load and PV spillage are zero for all times and scenarios.

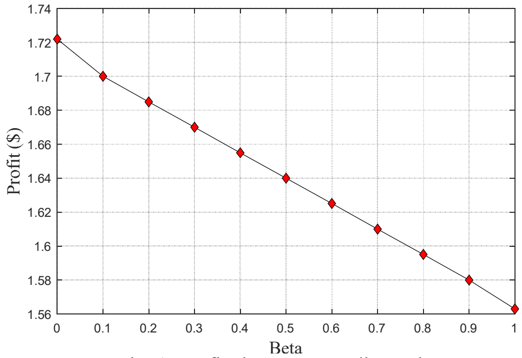

Fig. 1. Profit changes according to beta

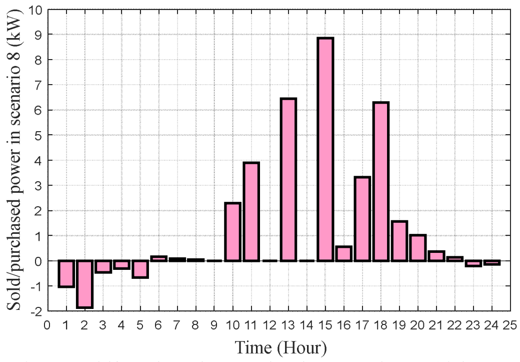

Fig. 2. Sold/purchased power by the smart home (risk-neutral)

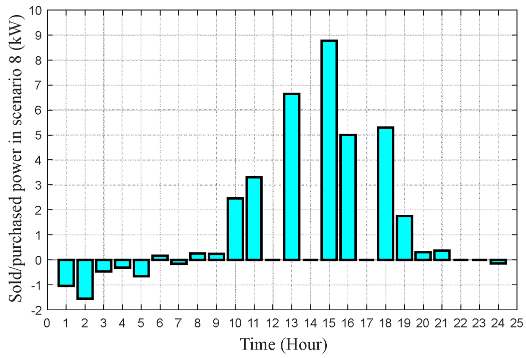

Fig. 3. Sold/purchased power by the smart home (risk-averse)

In Figs. 2 and 3, the amounts of bought and sold electrical powers are shown for a risk-neutral and risk-averse decision-maker. The positive numbers show the sold power and vice versa. In the early hours, when the PV generation is zero, the home buys energy from the grid, while in other times, it acts as a producer and sells power. The differences between risk-neutral and risk-averse traders are remarkable leading to different expected profits. It should be noted that scheduling of other resources under risk-neutral and risk-averse strategies are more or less the same with minor differences. The main reason for different expected profits under two strategies return to the scenarios of energy price and PV and PEV behaviours that change the trades in DA market. Thus, the results for battery and PEV are shown for risk-neutral case. As mentioned, the battery's discharged power could be injected into the home and sold to the market. Figure 4 illustrates the exported powers by the battery in scenario #8 that are sold to the grid.

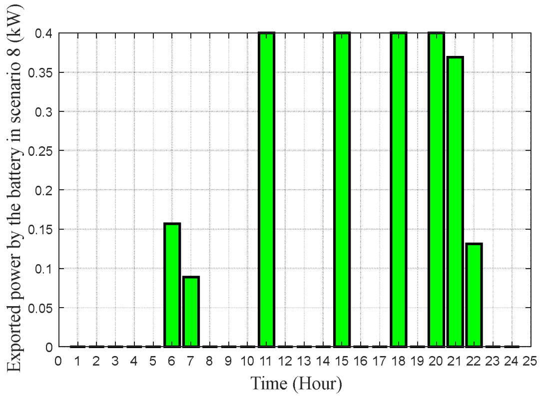

Fig. 4. Sold power by the battery to the local energy market

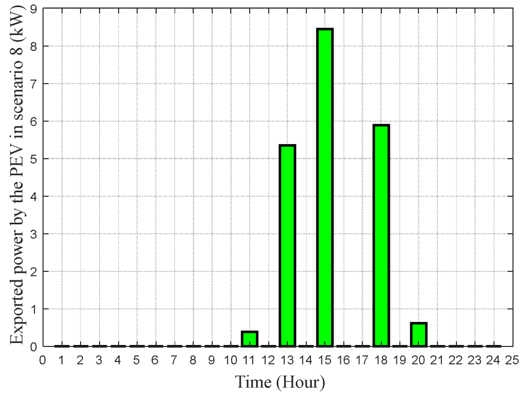

Fig. 5. Sold power by the PEV to the local energy market

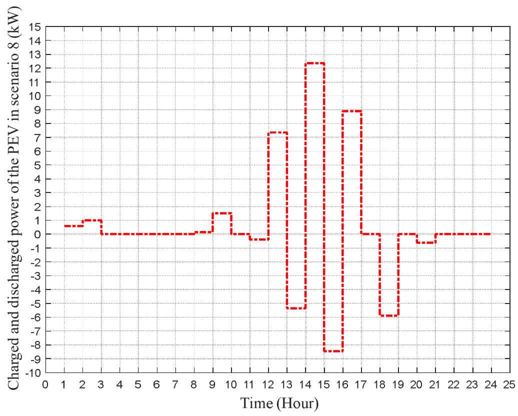

Fig. 6. Charged and discharged power by the PEV

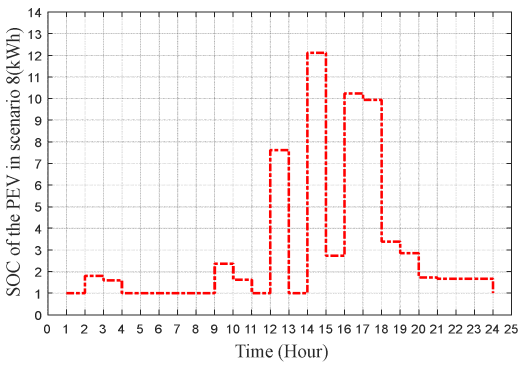

Fig. 7. The stored energy in the battery of the PEV

Similarly, Fig 5 shows the exported powers of the PEV during its discharging (power to grid mode), where injected power into the home is zero. From Figs.

5 and 6, the battery and PEV have the critical roles in market participation and the powers sold to the grid are mainly procured by them at the middle of day. Figure 6 illustrates the charging (positive amounts) and discharging (negative amounts) powers of the PEV. The charging and discharging of the PEV should consider the traveling pattern. The stored energy in the battery of the PEV is shown in Fig. 7, according to the charged and discharged powers and traveling patterns. From Fig. 7, the state-of-charge of the PEV is sharply decreased when the PEV has travelled and when the PEV have sold the power to the market. However, the results confirm that the limitations on the charged/discharged powers for the battery and PEV are all seen in the proposed EMS to prevent damages.

IV. Conclusion

This paper offered stochastic energy management for a smart home, which makes it be able to participate in the DA energy market. The energy management was done considering a smart home with different kinds of controllable and fixed loads. The home is connected to a PV system and local network to feed loads. The battery storage is integrated to add more flexibility to the energy management process. Furthermore, a PEV is considered with a stochastic traveling pattern, which can be used in power to grid mode. Ten scenarios model the PV generation and energy prices uncertainties. The well-known CVaR risk index is also included to reduce the risk of gained profits. In the risk-neutral case, the expected daily profit of $ 1.72 per day is achieved through the energy transactions, while in the risk-averse case, the profit was reduced to $ 1.56 per day indeed with lesser risk. The proposed energy management method can be adopted in realistic practices for experimental verification because all physical requirements do exist in most smart homes. In this regard, detailed load modeling is required. Moreover, to reduce the operational risk, the proposed method can be updated for a residential complex. In this context, a peer-to-peer strategy will be propounded that not only increases the resilience but also enhances the flexibility of operation by optimal sharing of resources between buildings. Moreover, also the proposed CVaR technique manages the risk of operation for a smart home, it might be intractable for large-scale cases with numerous operational scenarios and high fluctuations, in which more powerful techniques to investigate the risk and uncertainty management mission. The mentioned issues are left for probable future works.

Acknowledgement

Authors wish to thank Universiti Teknologi Malaysia (Vote numbers: 00P17, 05G88, 05G89 and 4B482).

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