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A New Risk-Based Decentralized Model for Peer-to-Peer Energy Trading Among Smart Homes

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ABSTRACT

Smart homes could have a significant impact on supplying the demand of both household consumers and the smart grid. Household consumers can trade energy via peer-to-peer (P2P) energy trading to reduce their costs. In other words, each of them can participate in the smart grid as a prosumer that can both produce and consume energy. On the other hand, more participation of smart homes in the demand-side management (DSM) program could help electricity decentralization. Also, energy storage systems (ESSs) and distributed energy resources (DERs) can lead to further decentralization of a smart microgrid. The production of renewable energy resources, such as photovoltaic (PV) systems, is associated with uncertainty. ESSs could be used as a reserve for PV systems. This paper presents a new risk-based model for P2P energy management of smart homes that consists of a PV system and EES and participates in the DSM program. The risk associated with the uncertainties of PVs' production and market prices has been modeled by conditional value-at-risk (CVaR). The mixed integer non-linear programming (MINLP) model of the problem has been solved by COUENNE in GAMS software. Numerical results show that the expected cost of all resources and the related risk is reduced by the proposed decision-making model for smart homes.

I. Introduction

In smart homes, a home energy management system (HEM) shifts and curtails the electricity demand of consumers to improve energy costs, global warming, load profiles, and consumer comfort [1]. Load changing is considered a delay and reduces power for the operation of household devices. It causes consumer discomfort, which can be expressed by the disutility function [2]. This function estimates disutility by applying a penalty cost when an appliance operation is delayed or operated at reduced power [3]. With the advancement of smart homes, consumers can both produce and consume energy, so they are called prosumers [4]. When prosumers have extra energy, they can save it with energy storage systems (ESSs), give it back to the main grid, or sell it to other consumers or prosumers. This connection among prosumers is called the peer-to-peer (P2P) mechanism [5]. P2P energy trading decentralizes system management by strengthening local ownership. In [6], new frameworks have been presented for HEM considering DSM and a self-scheduling framework has been proposed to minimize the electricity bill and discomfort of end users.

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TABLE 1
TAXONOMY OF REFERENCES IN LITERATURE REVIEW

Reference	Smart home	P2P	DSM	ESS/EV	DER	Risk
[1]-[5]	×		×			
[6]	×		×	×	×	
[7], [8]	×	×				
[9], [10]	×	×	×			
[11], [12]			×	×	×	
[13], [14]	×			×	×	
[15], [16]				×	×	×
[17]-[19]				×	×	
This paper	×	×	×	×	×	×

A. Literature review

Many studies have discussed P2P energy trading in smart grids. For instance, a new model to classify the main technologies in P2P energy trading has been proposed in [7]. This reference has considered the energy consumption flexibility of prosumers. An approach has been presented in [8] for P2P electricity markets (EMs) with product differentiation, such as user preferences, based on an appropriate economic dispatch. A model has been presented in [9] to exchange energy along with a demand response program (DRP) for a microgrid containing P2P prosumers. This reference has designed a P2P energy trading mechanism and considered a game-based framework in its simulation. A transactive market based on energy value signals has been modeled in [10]. This reference has presented a distributed strategy based on P2P energy trading to schedule the transactions among prosumers.

Using DERs and storage devices on the demand side reduces the amount of electric energy received from the grid, so it can reduce greenhouse gas emissions. DERs, ESSs, and the main grid must be allowed to meet the limits of emissions determined by the standardization agency of each country [11], [12].

The scheduling of residential houses is an interesting subject because of the importance of cost savings. The importance of energy scheduling for residential houses along with the presence of electric vehicles (EVs) to have a flat load has been investigated in [13]. Smart homes could consist of ESS and photovoltaic (PV) systems [14].

Risk management has been investigated in some research [15], [16]. A risk-based bidding strategy for generation companies in a smart grid has been proposed in [15]. A risk-based framework in presence of DERs and ESSs has been presented in [16]. In this reference, the uncertainties of EM price and DER have been taken into account.

The energy scheduling for smart microgrids has been investigated in some studies [17]–[19]. An energy scheduling based on renewable energy resources has been proposed in [17] to obtain the optimal scheduling for the microgrid. The impacts of EVs on microgrid scheduling have been investigated in [18]. An appropriate framework for maximizing all microgrids' profits has been proposed in [19]. According to this reference, energy trading could be done among microgrids.

The taxonomy of references in the literature review has been shown in Table 1.

B. Research gap

The following limitations can be found in previous research.

- Many papers have investigated smart homes, but they have not considered them as a tool to increase self-organization for supplying the demand of the smart grid.
- Previous works have not adequately addressed the effects of advanced metering infrastructure (AMI) signals in communication and there is not a comprehensive model for decentralized energy management.

To bridge these research gaps, the P2P energy trading optimization and demand-side management optimization for smart homes are presented in this paper, where the major contributions are listed as follows:

C. Contributions

The main contributions of this paper are as follows:

- Solving the problem in three different modules. In the first module, the demand-side management problem is solved for smart homes in the smart grids in the scenarios with and without of DERs. In the second module, P2P energy trading is solved in the scenario forecasting microgrid energy and the scenario forecasting microgrid energy and price. In the third module, both DSM and P2P problems are solved simultaneously. The proposed P2P energy trading model is presented in the third module.
- A new risk-based model is presented for P2P energy trading among smart homes.

- A decentralized management system is modeled in the smart microgrid.
- Optimal energy management for household customers owning a PV system and ESS is discussed.
- Considering the conditional value at risk (CVaR) of the uncertainties in PV generation and EM price.

The mixed integer non-linear programming (MINLP) model of the optimal energy management problem is solved by COUENNE in GAMS software.

D. Paper organization

The outline of the paper is as follows. The problem formulation is introduced in Section 2. The studied systems and results are presented in Section 3. Finally, conclusions are made in Section 4.

II. Problem Formulation

The P2P energy trading scheduling problem is formulated in three modules.

The first module calculates microgrid energy. The microgrid energy calculated in the first module is used as a constant vector for the second module.

The second module calculates microgrid energy prices. The microgrid energy prices are used as a constant vector for the third module.

The third module calculates energy traded through P2P in the microgrid. Fig. 1 shows the relationship between all modules and the problem-solving steps.

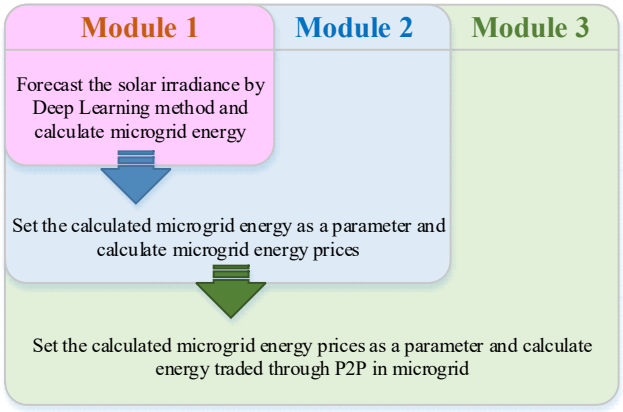


Fig. 1. The relationship between problem-solving modules.

2.1. Module 1: Initial demand and supply module

The energy cost of each smart home has been optimized in module 1 while none of them participate in the smart grid P2P energy trading. This module calculates the initial values for both demand and supply. Module 2 uses them as constants in the first iteration of the proposed optimization algorithm.

2.1.1. Modeling of objective function for module 1

The goal of smart homes' prosumers is to minimize their expected cost taking into account the risk. The objective function integrated with CVaR can be defined as (1).

$$min\cdot\left\{\sum_{r,s}\left((1-\beta)\cdot\xi_s\cdot\xi_r\cdot C_{k,s,r}^{NoTrade}\right)-\beta\cdot\mathrm{CVaR}\right\} \quad (1)$$

The energy cost of a smart home without participating in the P2P energy trading can be calculated by (2) [21].

$$C_{k,s,r}^{NoTrade}=\sum_{h\in H}\left[\begin{matrix}GP_{h,s}\cdot GE_{k,h,s,r}\\+\sum_{i\in I}d_{k,i}\cdot\left(\tau_{k,i}-\left(\begin{matrix}rt_{k,i,h}\cdot h\\+t_{k,i}-1\end{matrix}\right)\right)\end{matrix}\right] \quad (2)$$

where $C_{k,s,r}^{NoTrade}$ is the total cost of the *k*-th smart home when it does not participate in smart grid energy trading, $GP_{h,s}$ is the smart grid energy price, $GE_{k,h,s,r}$ is the value of energy purchased from the smart grid, $d_{k,i}$ is the disutility factor of a home appliance, and $rt_{k,i,h}$ is the reservation time of an appliance.

2.1.2. Risk constraints

The CVaR linear function is modeled as (3). It is based on the scenario-dependent cost for measuring relevant risk.

In (4), $C_{k,s,r}^{NoTrade}$ represents the energy cost in the scenarios *k*, *s*, and *r*, and $\eta_{s,r}$ is an auxiliary variable, which is the difference between the corresponding expected cost and VaR with respect to (5). β represents the balance between risk and expected costs.

$$\mathrm{CVaR}=\mathrm{VaR}-\frac{1}{1-\alpha}\sum_{s,r}\xi_s\cdot\xi_r\cdot\eta_{s,r} \quad (3)$$

$$\mathrm{VaR}-EC_{k,s,r}^{NoTrade}\le\eta_{s,r} \quad (4)$$

$$\eta_{s,r}\ge 0 \quad (5)$$

2.1.3. Energy balance constraints

The balance between energy consumption and production for all smart homes has been ensured by (6). The energy consumption of home appliances and the charge of ESS have been considered loads and the energy purchased from the smart grid, the energy generated by renewable energies, and the discharge of ESS are considered energy resources or generation.

$$\sum_{i\in I}AOT_{k,i,h}\cdot P_{k,i}+CH_{k,h,s,r}^{ESS}= GE_{k,h,s,r}+RE_{k,h,r}+DCH_{k,h,s,r}^{ESS} \quad (6)$$

$$(k\in K,h\in H,s\in S,r\in R)$$

where $AOT_{k,i,h}$ represents the appliance operating time, $P_{k,i}$ is the power consumption of the appliance, $CH_{k,h,s,r}^{ESS}$ is the charge of ESS, $DCH_{k,h,s,r}^{ESS}$ is the discharge of ESS, and $RE_{k,h,r}$ is the energy used from the renewable energy resource.

2.1.4. Energy storage system constraints

The charge and discharge rate of storage energy should be

limited to an ascertained value. Charging and discharging constraints of ESS are given by (7) and (8), respectively.

$$0 \le CH^{ESS}_{k,h,s,r} \le CH^{max} \tag{7}$$

$$0 \le DCH^{ESS}_{k,h,s,r} \le DCH^{max} \tag{8}$$

In the first time slot, the energy stored in ESS is a function of primary storage energy and charging and discharge efficiency. The state of charge (SOC) in the first hour is calculated as follows:

$$SOC^{ESS}_{k,h,s,r} = SOC^{ESS}_{k,h-1,s,r} + \left(\frac{CH^{ESS}_{k,h,s,r} \cdot \eta^{ESS}_{CH}}{E^{max}_{ESS}} - \frac{DCH^{ESS}_{k,h,s,r}}{E^{max}_{ESS} \cdot \eta^{ESS}_{DCH}} \right) \tag{9}$$

where $SOC_{k,1,s,r}$ represents the energy level of ESS at the first timeslot and $\eta_{CH}{}^{ESS}$ and $\eta_{DCH}{}^{ESS}$ is the charge and discharge efficiency of ESS, respectively.

2.1.5. Task duration constraints

For all appliances, Eq. (10) holds the entire length of the service. The appliances of the residential houses are classified into the interruptible and non-interruptible categories. For instance, if an interruptible appliance takes one hour to complete a task and should end by 12 am, it is not important what one hour the interruptible appliance has been operated.

$$\sum_{h \in H} AOT_{k,i,h} = t_{k,i} \quad (k \in K, i \in I, h \in H) \tag{10}$$

where $t_{k,i}$ is the duration of an appliance's running time.

2.1.6. Renewable energy availability constraints

Eq. (11) specifies the energy used from renewable energies ($RE_{k,h,r}$) cannot be more than the available energy ($RQ_{k,h,r}$).

$$RE_{k,h,r} \le RQ_{k,h,r} \quad (k \in K, h \in H, r \in R) \tag{11}$$

2.1.7. Reservation time constraints

Eq. (12) ensures the appliances' operation cannot start before the reservation time. $\sum_{h \in H} rt_{k,i,h} \cdot h$ represents the reservation time slot. Appliances are reserved only once within 24 hours of schedule.

$$\sum_{h \in H} AOT_{k,i,h} = \sum_{h=\sum_{h \in H} rt_{k,i,h} \cdot h}^{N} AOT_{k,i,h} \tag{12}$$

$$(k \in K, i \in I, h \in H)$$

If multiple requests are made for an appliance within the same time horizon, the operation of the appliance will be scheduled as if it has several identical appliances.

2.1.8. Relationship between the scheduling vector and the end time constraints

Eq. (13) binds $\tau_{k,i}$ with $AOT_{k,i,h}$. The end time of each appliance has to be the last execution time.

$$AOT_{k,i,h} \cdot h = \tau_{k,i} \quad (k \in K, i \in I, h \in H) \tag{13}$$

2.1.9. Maximum allowable delay constraints

Eq. (14) ensures each appliance operation should not end after the maximum allowable time limit ($\beta_{k,i}$). It should be defined by the user.

$$\tau_{k,i} \le \beta_{k,i} \quad (k \in K, i \in I) \tag{14}$$

2.1.10. Non-interruptible appliances constraints

Eq. (15) and (16) define that non-interruptible appliances keep running without no interruption until they end their schedule.

$$\sum_{d=0}^{t_{k,i}-1} AOT_{k,i,h+d} - t_{k,i} \ge -t_{k,i}(1 - US_{k,i,h}) \tag{15}$$

$$(k \in K, i \in U, h = [1, N - t_{k,i} + 1])$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1 \tag{16}$$

$$(k \in K, i \in U)$$

where $US_{k,i,h}$ is the start time of non-interruptible appliances.

2.1.11. Utility grid max power limit constraints

The energy that could be purchased from the grid is limited by Eq. (17).

$$GE_{k,h,s,r} \le L^{max}_{k} \quad (k \in K, h \in H, s \in S, r \in R) \tag{17}$$

where L^{max}_{k} is the maximum grid power limit.

2.1.12. Demand and supply constraints

Eq. (18) calculates the demand or supply of energy from external energy sources. If the value of $DS_{k,h,s,r}$ is positive, the smart home has energy shortage. If it is negative, the smart home has an energy surplus or supply.

$$DS_{k,h,s,r} = \sum_{i \in I} \left(\begin{matrix} AOT_{k,i,h} \cdot p_{k,i} + CH^{ESS}_{k,h,s,r} \\ -DCH^{ESS}_{k,h,s,r} - RQ_{k,h,r} \end{matrix} \right) \tag{18}$$

$$(k \in K, h \in H, s \in S, r \in R)$$

2.2. Module 2: price calculation module

Module 2 calculates the microgrid energy price. In this module, microgrid energy ($ME_{k,h}$) is a constant and microgrid energy price ($MP_{h,s}$) is variable.

2.2.1. Objective function

In module 2, an optimization problem is solved as (19).

$$min \cdot \left(\begin{matrix} \sum_{r,s} \left((1-\beta) \cdot \xi_s \cdot \xi_r \cdot C_{T_{k,s,r}} \right) - \beta \cdot \mathrm{CVaR}, \\ \sum_{r,s} \left((1-\beta) \cdot \xi_s \cdot \xi_r \cdot C_{k,s,r} \right) - \beta \cdot \mathrm{CVaR} \end{matrix} \right) \tag{19}$$

where $C_{T_{k,s,r}}$ is the total cost of all households and $C_{k,s,r}$ is the total cost of the *k*-th household, which are defined as Eq. (20) and (21), respectively.

$$C_{T_{k,s,r}} = \sum_{k \in K} \sum_{h \in H} \left[\begin{matrix} GP_{h,s} \cdot GE_{k,h,s,r} \\ + \sum_{i \in I} d_{k,i} \cdot \left(\tau_{k,i} - \left(\begin{matrix} rt_{k,i,h} \cdot h \\ + t_{k,i} - 1 \end{matrix} \right) \right) \end{matrix} \right] \tag{20}$$

$$C_{k,s,r} = \sum_{h \in H} \begin{bmatrix} GP_{h,s} \cdot GE_{k,h,s,r} \\ +MP_{h,s} \cdot ME_{k,h} \\ +\sum_{i \in I} d_{k,i} \cdot \left(\tau_{k,i} - \begin{pmatrix} rt_{k,i,h} \cdot h \\ +t_{k,i} - 1 \end{pmatrix} \right) \end{bmatrix} \quad (21)$$

The total energy purchased from the microgrid is the same as the total energy sold to the microgrid. Therefore, the microgrid energy cost is not required in Eq. (20). The optimization problem is solved by minimizing $C_{T_{k,s,r}}$ as the sole objective function and the remaining objective functions ($C_{k,s,r}$) as inequality constraints. Therefore, the objective function of module 2 is expressed as (22).

$$min \cdot \left\{ \sum_{r,s} \left((1-\beta) \cdot \xi_s \cdot \xi_r \cdot C_{T_{k,s,r}} \right) - \beta \cdot \mathrm{CVaR} \right\} \quad (22)$$

The constraints (6)–(17), as well as the following constraints, should be satisfied.

2.2.2. Energy balance constraints

As specified in Eq. (23), in a specific smart home, total energy consumption should not be more than the total available energy.

$$\begin{pmatrix} \sum_{i \in I} AOT_{k,i,h} \cdot P_{k,i} \\ +CH^{ESS}_{k,h,s,r} \end{pmatrix} \leq \begin{pmatrix} GE_{k,h,s,r} + RE_{k,h,r} \\ +DCH^{ESS}_{k,h,s,r} + ME_{k,h} \end{pmatrix} \quad (23)$$

$(k \in K, h \in H, s \in S, r \in R)$

2.2.3. Microgrid energy price constraints

The up and down limits of microgrid prices are defined by Eq. (24) and (25), respectively.

$$MP_{h,s} \geq 0 \quad (h \in H, s \in S) \quad (24)$$

$$MP_{h,s} \leq GP_{h,s} \quad (h \in H, s \in S) \quad (25)$$

2.2.4. Pareto optimality constraints

Eq. (26) implements Pareto optimality. It ensures the cost of a household participating in microgrid energy trading should not be more than the cost when it does not participate.

$$C_{k,s,r} \leq C^{NoTrade}_{k,s,r} \quad (k \in K, s \in S, r \in R) \quad (26)$$

2.3. Module 3: energy computation module

The third module calculates the microgrid energy ($ME_{k,h}$) using the constant microgrid prices ($MP_{h,s}$) provided by module 2.

2.3.1. Energy balance constraints in module 3

Eq. (27) indicates that the total demand should be the same as the total available energy for a smart home.

$$\begin{pmatrix} \sum_{i \in I} AOT_{k,i,h} \cdot P_{k,i} \\ +CH^{ESS}_{k,h,s,r} \end{pmatrix} = \begin{pmatrix} GE_{k,h,s,r} + RE_{k,h,r} \\ +DCH^{ESS}_{k,h,s,r} + ME_{k,h} \end{pmatrix} \quad (27)$$

$(k \in K, h \in H, s \in S, r \in R)$

The positive value of $ME_{k,h}$ represents the smart home is an energy buyer at that specific time slot. A negative value represents that the smart home is a seller.

2.3.2. Energy balance constraints for microgrid

Eq. (28) specifies that the total energy sold in the microgrid by all smart homes should be equal to the total energy purchased from the smart homes.

$$\sum_{k \in K} ME_{k,h} = 0 \quad (h \in H) \quad (28)$$

2.3.3. Energy constraints while trading in microgrid

Eq. (29) determines the amount of available energy ($MQ_{k,h,s,r}$) in the microgrid.

$$MQ_{k,h,s,r} = \begin{pmatrix} \sum_{i \in I} AOT_{k,i,h} \cdot P_{k,i} + CH^{ESS}_{k,h,s,r} \\ -GE_{k,h,s,r} - RQ_{k,h,r} - DCH^{ESS}_{k,h,s,r} \end{pmatrix} \quad (29)$$

$(k \in K, h \in H, s \in S, r \in R)$

Eq. (30) expresses that the energy that could be traded among smart homes should be equal to or less than microgrid energy.

$$ME_{k,h} \geq MQ_{k,h,s,r} \quad (k \in K, h \in H, s \in S, r \in R) \quad (30)$$

III. Results

3.1. Case Study

The studied system is a microgrid composed of two smart homes. Each home can exchange energy with the main grid and another home. Home appliances have been divided into two categories: interruptible and uninterruptible. Interruptible appliances could operate at each time among eight timeslots and also interrupt during timeslot operation, but uninterruptible appliances must operate at a certain timeslot without any interruption. The appliances' characteristics have been shown in Table 2. All the household appliances of smart homes have a different operational duration and power. The presented model structure of the system has been indicated in Fig. 2.

TABLE 2
APPLIANCE CHARACTERISTICS [19]

Smart home	Appliance	Duration [timeslot]	Power [kW]	Disutility factor	Reservation timeslot	Max delay
Smart home 1	App 1 (interruptible)	5	1	0.01	1	8
	App 2 (uninterruptible)	2	4	0.01	1	8
Smart home 2	App 1 (interruptible)	3	3	0.01	1	8
	App 2 (uninterruptible)	4	2	0.01	1	8

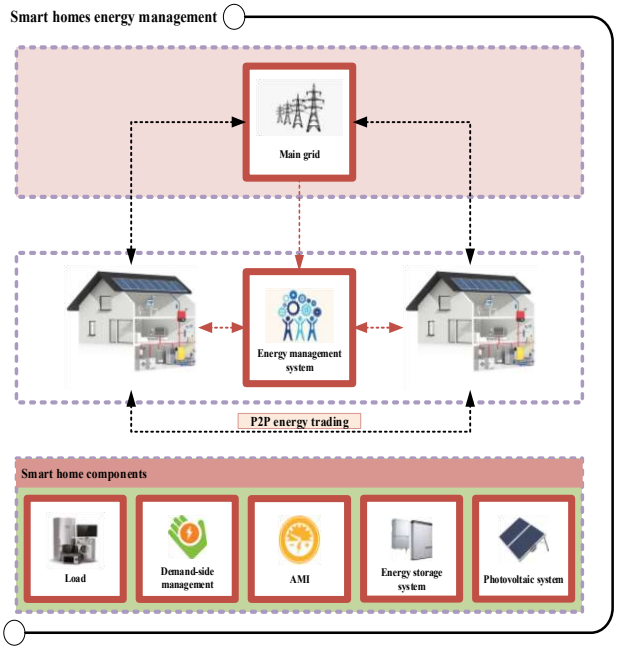


Fig. 2. The structure of the proposed model of the system.

Each smart home has a solar panel and an electrical storage system. The capacity of each storage is limited to 5 kW and should never be less than 3 kW. The characteristics of the storage devices are shown in Table 3. The solar panels are capped to 2 kW. The maximum power that each home could receive from the main grid is 20 kW.

The output power of the solar panel and the energy price of the main grid are associated with uncertainty. The CVAR is used to consider these uncertainties. We consider the risk of each module in accordance with the following scenarios:

- Without any risk ($\beta = 1$)
- With maximum risk ($\beta = 0$)

The risk aversion has been specified by $\beta \in (0,1)$

TABLE 3
STORAGE CHARACTERISTICS [19]

Characteristics	Smart home 1	Smart home 2
Initial energy [kWh]	3	5
Charging and discharging rate [kW]	1	2
Max capacity [kWh]	5	5
Min capacity [kWh]	3	3
Charging efficiency	80%	90%
Discharging efficiency	80%	90%
Self-discharging rate (per timeslot)	1%	1%

3.2. Numerical Results

In this section, the results are presented for each module and then the total cost of the microgrid is compared in each

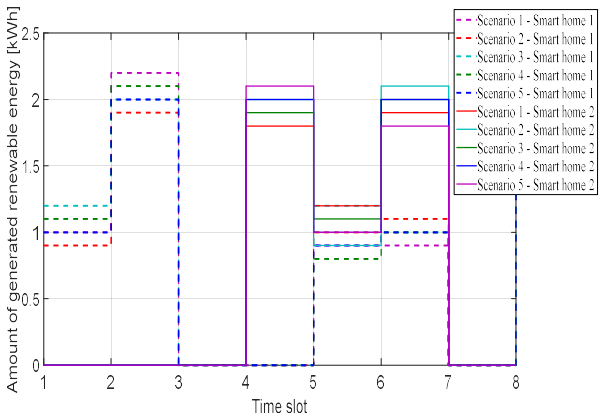


Fig. 2. The amounts of generated energy by the renewable resource for each smart home at each timeslot and scenario

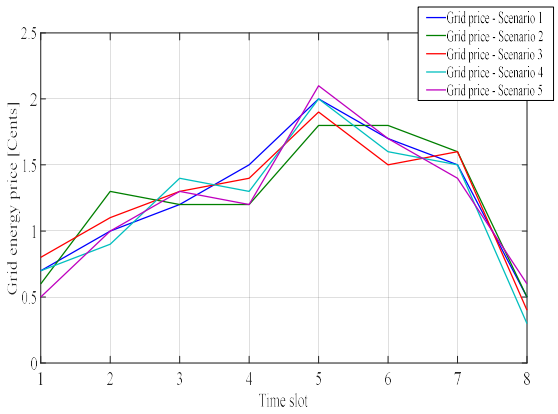


Fig. 3. The main grid energy prices at each timeslot and scenario

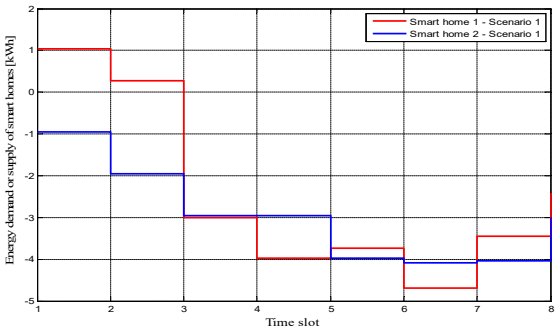


Fig. 4. The energy demand/supply of each smart home at scenario 1. Positive value represents the energy demand and negative value represents the energy surplus

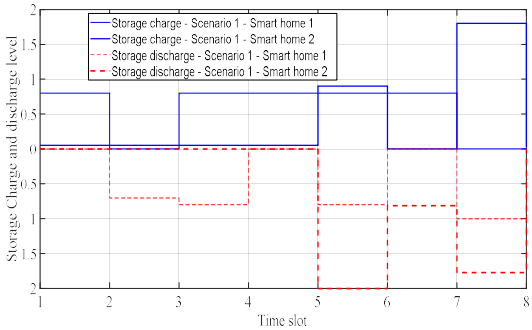


Fig. 5. The charge and discharge levels of the energy storage system for each smart home at each timeslot and scenario in module 1

scenario. The energy used from the renewable resource

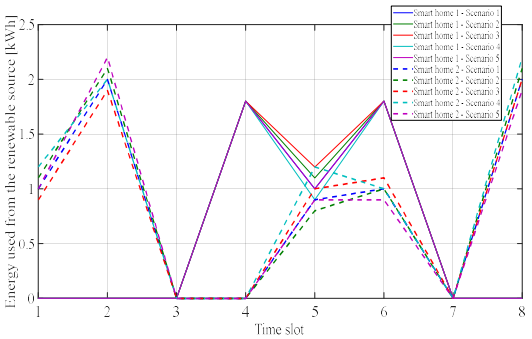


Fig. 6. The energy used from the renewable source of each smart home at each timeslot and scenario in module 1

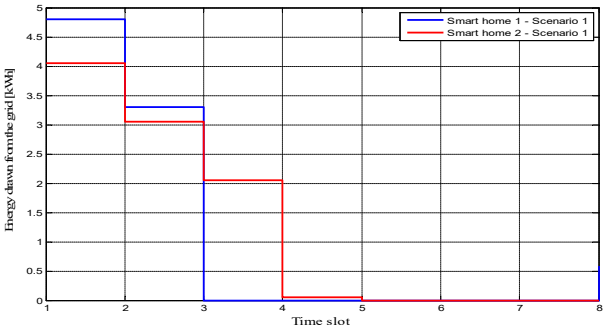


Fig. 7. The energy drawn from main grid for each smart home at scenario 1 in module 1

cannot be higher than the energy generated by that resource. Fig. 2 shows the amounts of energy generated by the PV system, as a renewable resource, for each smart home at each timeslot and scenario. The main grid energy prices at each timeslot and scenario are shown in Fig. 3.

The energy demand or supply of each smart home at scenario 1 is shown in Fig. 4. The energy demand or supply of each smart home is a variable in module 1 and a parameter in modules 2 and 3.

According to Fig. 4, the peak demand for smart home 1 occurred at timeslots 1 and 2; also, the peak demand for smart home 2 occurred at timeslots 7 and 8.

The levels of charge and discharge of ESS for each smart home at each timeslot and scenario in module 1 are shown in Fig. 5.

The energy used from the PV system, as a renewable source, of each smart home at each timeslot and scenario in module 1 is specified in Fig. 6. It cannot be higher than the energy generated by the PV system.

The energy drawn from the main grid for each smart home in scenario 1 in module 1 is presented in Fig. 7. The lower the energy drawn from the main grid, the lower the total cost of the microgrid.

The charge and discharge levels of ESS for each smart home at each timeslot and scenario in module 2 are shown in Fig. 8.

The energy drawn from the main grid for each smart home in scenario 1 in module 2 is presented in Fig. 9. In the case the demand and supply are balanced, the lower the energy drawn from the main grid, the lower the total cost of the microgrid. The microgrid energy prices at each timeslot and scenario are presented in Fig. 10. A smart home could exchange energy with others at these prices.

The charge and discharge levels of ESS for each smart home at each timeslot and scenario in module 3 are shown in Fig. 11.

The energy drawn from the main grid for each smart home in scenario 1 in module 3 is presented in Fig. 12. In the case the demand and supply are balanced, the lower the energy drawn from the main grid, the lower the total cost of the microgrid.

The energy traded in the microgrid through the P2P platform is presented in Fig. 13. A positive value represents the purchased energy and a negative value represents the sold energy. According to Fig. 13, the amount of energy purchased by a smart home through P2P energy trading is equal to the amount of energy sold by another smart home via P2P energy trading.

The expected total cost of microgrid, the expected cost of each smart home, and the CVaR value are presented in Table.4 for different amounts of the risk coefficient and in different cases. According to Table 4, the expected total cost of the microgrid and the expected cost of both smart homes

increase with increasing the risk coefficient. In other words, as the risk coefficient of smart homes decreases, they tend to be risk-takers and the cost is expected to decrease. Similarly, as the risk coefficient of smart homes increases, they tend to be risk-averse and the cost is expected to increase.

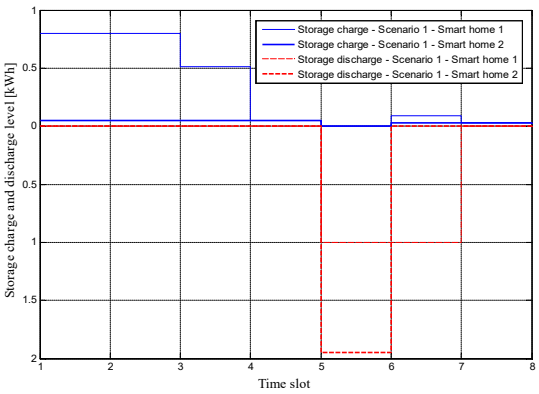


Fig. 8. The charge and discharge levels of the ESS for each smart home at each scenario in module 2

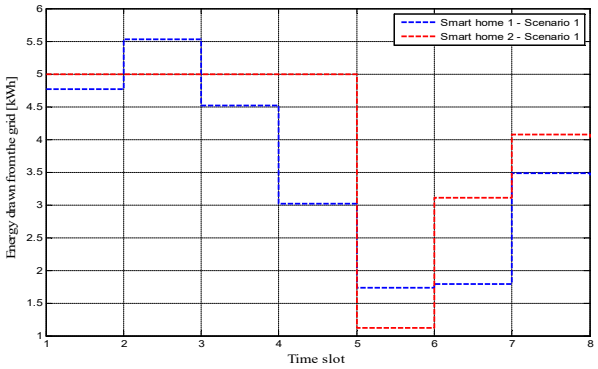


Fig. 9. The energy drawn from the main grid for each smart home at scenario 1 in module 2

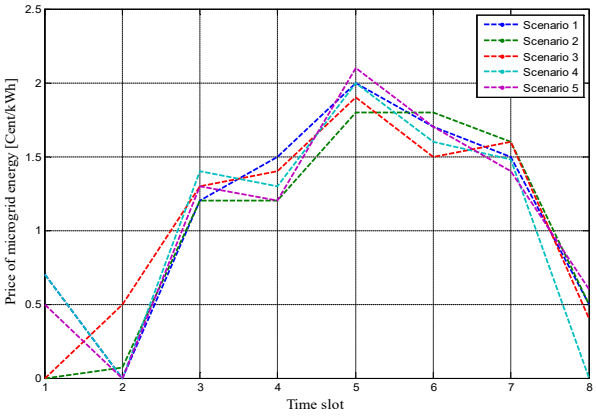


Fig. 10. The microgrid energy prices in each scenario

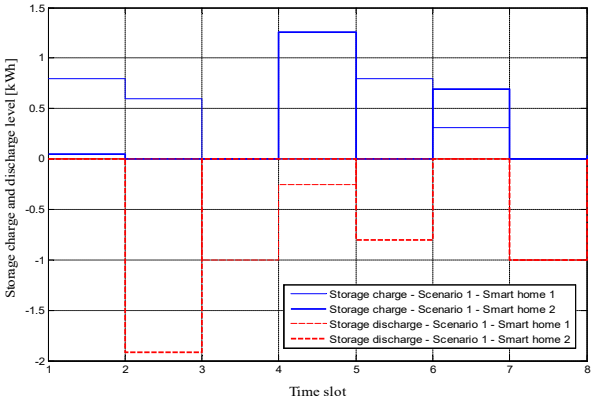


Fig. 11. The charge and discharge levels of ESS for each smart home in each scenario in module 3

TABLE 4
THE EXPECTED TOTAL COST OF THE MICROGRID, THE EXPECTED COST OF EACH SMART HOME, AND THE CVAR VALUE FOR DIFFERENT AMOUNTS OF THE RISK COEFFICIENT

Case	Risk coefficient (β)	Expected total cost of microgrid	Expected cost of smart home 1	Expected cost of smart home 2	CVaR
Without P2P energy trading	0	15.450	6.980	8.470	15.208
	0.5	22.603	11.679	10.924	22.316
	1	54.966	25.485	29.480	54.564
With P2P energy trading	0	12.324	11.997	0.207	12.130
	0.5	16.846	15.865	0.981	16.468
	1	39.079	31.855	7.224	38.697

IV. Conclusions

The smart grid participants that can both produce and consume energy are known as prosumers. They can exchange energy between themselves through the P2P mechanism. The presence of DERs and ESSs along with DSM in residential houses makes the smart grids more efficient. In this paper, a new risk-based model is presented for P2P energy trading among residential houses consisting of the PV system and ESS. The uncertainties of solar irradiance and EM price have been taken into account. CVaR models the risk associated with PVs' generation and EM price uncertainties. The results show that as the risk coefficient of smart homes decreases, the cost is expected to decrease. Moreover, this paper shows that P2P energy trading can reduce the total cost of the smart grid. The research has some limitations, e.g., considering the game between smart homes. The authors intend to consider the game theory in the P2P mechanism in their future studies.

REFERENCES

[1] Slama, Sami Ben. "Design and implementation of home energy management system using vehicle to home (H2V) approach." Journal of Cleaner Production 312 (2021): 127792.

[2] Alıç, Oğuzkağan, and Ümmühan Başaran Filik. "A multi-objective home energy management system for explicit cost-comfort analysis considering appliance category-based discomfort models and demand response programs." Energy and Buildings 240 (2021): 110868.

[3] Ashrafi, Reza, Soodabeh Soleymani, and Mehdi Ehsan. "An Energy Management System based on Economic and Environmental aspects for Microgrids Incorporating Active and Reactive Power Sources and Demand Response Programs." International Journal of Industrial Electronics Control and Optimization, 3, no. 3 (2020): 259-273.

[4] Luo, Yuan, Satoko Itaya, Shin Nakamura, and Peter Davis. "Autonomous cooperative energy trading between prosumers for microgrid systems." In 39th annual IEEE conference on local computer networks workshops, pp. 693-696. IEEE, 2014.

[5] Hamari, Juho, Mimmi Sjöklint, and Antti Ukkonen. "The sharing economy: Why people participate in collaborative consumption." Journal of the association for information science and technology, 67, no. 9 (2016): 2047-2059.

[6] Tushar, Wayes, Tapan Kumar Saha, Chau Yuen, Thomas Morstyn, Malcolm D. McCulloch, H. Vincent Poor, and Kristin L. Wood. "A motivational game-theoretic approach for peer-to-peer energy trading in the smart grid." Applied Energy, 243 (2019): 10-20.

[7] Sorin, Etienne, Lucien Bobo, and Pierre Pinson. "Consensus-based approach to peer-to-peer electricity markets with product differentiation." IEEE Transactions on Power Systems, 34, no. 2 (2018): 994-1004.

[8] Zhang, Chenghua, Jianzhong Wu, Yue Zhou, Meng Cheng, and Chao Long. "Peer-to-Peer energy trading in a Microgrid." Applied Energy, 220 (2018): 1-12.

[9] Lotfi, M., Monteiro, C., Javadi, M.S., Shafie-khah, M. and Catalão, J.P. "Optimal prosumer scheduling in transactive energy networks based on energy value signals." International Conference on Smart Energy Systems and Technologies (SEST), IEEE, 2019, pp. 1-6.

[10] Kostakis, Vasilis, Andreas Roos, and Michel Bauwens. "Towards a political ecology of the digital economy: Socio-environmental implications of two competing value models." Environmental Innovation and Societal Transitions, 18 (2016): 82-100.

[11] Emami, Iman Taheri, Mojgan MollahassaniPour, Masoumeh Rostam Niakan Kalhori, and Mohammadhassan Saboori Deilami. "Short-run economic–environmental impacts of carbon tax on bulk electric systems." Sustainable Energy, Grids and Networks, 26 (2021): 100480.

[12] Khemakhem, Siwar, Mouna Rekik, and Lotfi Krichen. "A collaborative energy management among plug-in electric vehicle, smart homes and neighbors' interaction for residential power load profile smoothing." Journal of Building Engineering, 27 (2020): 100976.

[13] Jung, Seunghoon, Hyuna Kang, Minhyun Lee, and Taehoon Hong. "An optimal scheduling model of an energy storage system with a photovoltaic system in residential buildings considering the economic and environmental aspects." Energy and Buildings, 209 (2020): 109701.

[14] Ansari, Bananeh, and Ashkan Rahimi-Kian. "A dynamic risk-constrained bidding strategy for generation companies based on linear supply function model." IEEE Systems Journal, 9, no. 4 (2015): 1463-1474.

[15] Thatte, Anupam A., Le Xie, Daniel E. Viassolo, and Sunita Singh. "Risk measure based robust bidding strategy for arbitrage using a wind farm and energy storage." IEEE Transactions on Smart Grid, 4, no. 4 (2013): 2191-2199.

[16] Khan, Muhammad Waseem, Jie Wang, Meiling Ma, Linyun Xiong, Penghan Li, and Fei Wu. "Optimal energy management and control aspects of distributed microgrid using multi-agent systems." Sustainable Cities and Society, 44 (2019): 855-870.

[17] Bahramara, Salah, and Hêriş Golpîra. "Robust optimization of micro-grids operation problem in the presence of electric vehicles." Sustainable cities and society, 37 (2018): 388-395.

[18] Marvasti, Amin Kargarian, Yong Fu, Saber DorMohammadi, and Masoud Rais-Rohani. "Optimal operation of active distribution grids: A system of systems framework." IEEE Transactions on Smart Grid, 5, no. 3 (2014): 1228-1237.

[19] Alam, Muhammad Raisul, Marc St-Hilaire, and Thomas Kunz. "Peer-to-peer energy trading among smart homes." Applied Energy, 238 (2019): 1434-1443.



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