Peer-to-Peer Energy Trading for Residential Prosumers with Photovoltaic and Battery Storage Systems

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***Abstract*—The popularization of solar generation enables residential households to supply their loads and trade the surplus energy through residential peer-to-peer (P2P) energy trading market. Facing the increasing complexity of the market structure and decision-making strategies, this paper proposes a P2P energy trading model for residential households, and the objective is to help the centralized market coordinator optimize the benefit of participants under such a P2P market. To this end, a new mathematical model, including the rules for buying and selling energy, is presented. In this model, a supply function bidding mechanism is formulated to match the power supply imbalance and calculate the market-clearing price. An optimization problem is formulated to identify the optimal strategies for energy buying and selling, which consists of two parts: the first part is to maximize the social welfare; the second part is to minimize the unfair benefit distribution that participants can gain through P2P energy trading. The case study based on the real data for four different household categories has revealed that households can achieve 26.38% net cost reduction, and the proposed fair benefit distribution function also can fairly allocate the benefit by enforcing households' benefit variance indexes at a low level.**

***Index Terms*—Peer-to-Peer energy trading, residential, battery energy storage system, supply function bidding, smart grid.**

NOMENCLATURE

Variables

$\hat{Q}_h^*$	Minimum net energy cost when not attending the proposed P2P market
$\hat{S}$	Overall net cost when households are not trading in the P2P market
$\hat{x}_h^G(t)$	Energy exchange between the P2P market and household h when households are not trading in the P2P market
$\tilde{Q}_h$	Cost saving of household h when trading in the P2P market
$\tilde{Q}_{avg}$	Average cost saving of all households when trading in the P2P market
f_{σ,H_k}^N	Category variance for households in Category H_k
$f_{\sigma,h}^N$	Individual variance for household h
f_σ^N	Normalized overall population variance
f_S^N	Normalized social welfare function
f_σ	Overall population variance
f_S	Social welfare function
H^B	Number of buyers in P2P market
H^S	Number of sellers in P2P market
p^{MCP}	Clearing price in P2P market
Q_h	Net cost of household h when trading in the P2P market
x_h^B	Charging/discharging energy for the household h's BESS
x_h^G	Energy exchange between the retailer and household h
x_h^{P2P}	Energy exchange between the P2P market and household h
x_{total}^{P2P}	Total energy demand from the P2P market

Parameters

$\boldsymbol{H}$	Household categories
η_h^{ch}	Charging efficiency
η_h^{dis}	Discharging efficiency
$\hat{C}_h$	Cost on buying energy when not attending the proposed P2P market
$\hat{P}_h$	Benefit on selling energy when not attending the proposed P2P market
μ_1	Weighting factor on social welfare function
μ_2	Weighting factor on population variance function
E_h^c	BESS capacity for household h
$f_{\sigma,max}$	Maximum value of f_σ
$f_{\sigma,min}$	Minimum value of f_σ
$f_{S,max}$	Maximum value of f_S
$f_{S,min}$	Minimum value of f_S
H	Total number of P2P market participants
h	Index for household
p	Electricity trading price with the utility company
p^{FIT}	Feed-in-Tariff price
p^U	Electricity retailing price
t	Index for time interval
$x_{h,max}^{B,ch}$	Maximum charging rate
$x_{h,max}^{B,dis}$	Maximum discharging rate
x_h^L	Predicted energy consumption
x_h^{PV}	Predicted PV generation

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I. INTRODUCTION

IN recent years, the feed-in-tariff (FIT) program has been introduced around the world to promote the ongoing decarbonization of electricity systems through the installation of a range of small-scale renewable generation units for residential households [1]. However, the tariff rate has continued to reduce due to the decreased installation costs and limited government incentive budget for a large number of new installations [2] [3]. Consequently, residential photovoltaic (PV) owners are facing profit reduction on selling electricity in the traditional manner. Given this context, an efficient solution to increase the residential gain could be achieved by encouraging the use of excess energy within neighborhoods. This can be realized by introducing a peer-to-peer (P2P) energy trading market. Upon the background mentioned above, this paper aims to study how residential PV owners decide their P2P energy trading strategies to reach the optimal social welfare, where a fair benefit distribution problem is also integrated into the optimal trading strategy to evaluate whether the benefit by introducing energy trading is fairly distributed to every household.

In the traditional retail market structure, residential PV owners are only able to individually buy and sell energy with electricity retailers [4]. In this way, PV owners cannot maximize the full potentials of the solar system since the extra generated energy is only tradable with electricity retailers, who are profit seeker and offers low FIT price [5]. To improve the financial benefit of residential prosumers, the P2P trading platform is introduced as a new market paradigm, where this novel market allows the direct energy exchange among residential households and thus to provides more resilience to power systems [6]. Through the P2P energy trading market, residential households are able to reduce energy costs by sharing distributed energy resources (DERs) with each other. On the other hand, due to the price advantage, the energy generated from local DERs is more attractive than the energy supplied from electricity retailers [7]. The combination of renewable energy and P2P trading market not only helps to relieve the pressure of energy supply for energy retailers during the peak period but also improves the efficiency of the renewable usage, making energy supply more eco-friendly [8].

In the current research community, the existing P2P trading approaches can be generally adopted to two scenarios: decentralized P2P market and centralized P2P market. In the decentralized P2P market, the energy trading is processed directly by market participants, where a centralized market coordinator is not required since the energy trading price and quantity are determined based on bilateral negotiations [9]. The advantages of adopting the decentralized P2P market have been explored by many studies. A prominent feature of the decentralized P2P market is the privacy protection, which has been tested in micro power systems [10] and zonal power systems [11]. Moreover, a study in [12] validates that with the limited shared information, an optimization of the energy utilization efficiency and the operational cost reduction for each integrated energy system can still be effectively solved using an decentralized alternating direction multiplier method. Regarding the decentralized P2P market design, a decentralized energy trading mechanism is proposed for industrial users to reduce operational costs and CO_2 emission in [13], where the underlying problem is solved using a novel multi-agent twin delayed deep deterministic policy gradient approach. However, since most of the information in the decentralized market is not transparent, it is hard to evaluate the community social welfare. Due to the same limitation, service providers also find it is challenging to maintain and upgrade the decentralized power system [14]. On the other hand, the centralized P2P market, such as pool-based market and whole-sale electricity market, manages the market coordination and information exchange through a centralized market coordinator, who is able to propose the trading strategies for market participants to realize the optimal social welfare by solving a global optimization problem [15]. As a cutting-edge trading concept, the centralized P2P trading method can be adopted to either residential scenario [16] or industrial scenario [17]. Although such centralized market architecture requires the complete disclosure of the private information to the market coordinator, which may raise privacy concerns, a novel transaction model proposed in [18] can effectively cover this issue by integrating blockchain technology and Ciphertext-Policy Attribute-Based Encryption algorithm.

For centralized P2P market, an appropriate trading model is essential as it determines energy trading prices and regulates the bidding and offering rules, which will finally impact the optimal energy trading strategies of the market participants [19]. A two-level P2P energy trading model is presented for a prosumer-based community in [20] to optimize social welfare, where the price competition among sellers is modeled as a non-cooperative game, and the sellers' decision making is modeled as an evolutionary game. A supply function equilibrium is formulated to clear the pool-based P2P energy trading in [21], where the critical improvement in power balance is discussed in the case study by using the proposed clearing mechanism. Moreover, a supply function bidding method is proposed in [22], which is able to dynamically calculate the market-clearing price (MCP), where the effectiveness of the supply function bidding method is further validated in [23].

Previous works have adopted different centralized P2P trading mechanisms to optimize the social welfare. However, the social welfare optimization results have no guarantee on fair benefit allocation for market participants. Within a scenario of multiple community microgrids, energy users with BESSs are able to take more advantages of electricity cost reduction than those people who do not have such equipment, which may lead to the P2P market being less attractive [24]. To motivate more energy users to participate into the P2P market, a benefit distribution problem should also be considered when optimizing social welfare. Prior research on fair benefit distribution for P2P market participants is limited but emerging. For instance, a cost distribution problem is proposed in [25], where the Pareto optimality is adopted and solved by an ECO-Trade algorithm. Although enforcing Pareto optimality to the proposed model can ensure that no residential prosumers will be worse off to improve the cost of others, the analysis regarding the fair benefit distribution is not further discussed in the case study. A sharing contribution rate is implemented in [26] to quantify the contribution to the energy sharing and peak shaving for energy users, where the fair benefit distribution problem is further formulated with a Nash bargaining model. However, the flexibility of the proposed P2P energy trading market is impacted by the assumption that P2P trading prices are assured to be constants.

Based on the literature review above, further study on a fair trading price mechanism and the evaluation of benefit allocation are necessary. To this end, this paper studies how a centralized market coordinator determines the strategies of the market participants to solve the designed social welfare optimization problem. In addition, a fair benefit distribution function is applied in the proposed P2P market model to evaluate if the benefit is fairly allocated to every residential client. Based on the designed objective, the case study shows that through the proposed P2P energy trading model and optimization problem, the centralized market coordinator can achieve different goals with respect to cost reduction and fair benefit distribution based on the practical requirement of the market.

The main contributions of this paper can be summarised as follows:

- A centralized residential P2P energy trading market is proposed using the supply function method, where the MCP is co-decided by all market participants, ensuring the fairness and transparency of the residential P2P market.
- Based on the proposed P2P trading model, the residential energy trading and BESS management problem is formulated considering social welfare and fair benefit distribution.
- The case study based on the real household data reveals that on the premise of ensuring fair benefit distribution, a 26.38% net cost reduction is still observed when households are trading in the proposed P2P market. Moreover, the market flexibility is further explored to help the centralized market coordinator realize different targets on social welfare and fair benefit distribution by adjusting different weighting factors.

The remaining part of this paper is organized as follows.

The proposed P2P trading model for residential households, including objective functions and related constraints, is explained in Section II. Detailed simulation results are discussed in Section III. Finally, Section IV concludes this paper.

II. Design of the Residential P2P Trading System

With the transit position from energy price takers to price makers, households within the smart grid are allowed to fairly trade energy through a platform provided by P2P market. In this paper, a PV and BESS featured smart grid is used as an example to explain the proposed bidding strategy. The schematic of the proposed system is illustrated in Fig. 1. Since the data of PV generation and energy consumption in the case study are recorded hourly, the sampling time interval in this paper is set as 1 hour. Therefore, there are 24 time intervals a day (*T = 24*) for the P2P energy trading. Forward sampling is taken here in this paper, e.g., the first time period within the 24-hour is from 0:00 am to 1:00, the second time period is from 1:00 to 2:00, etc. Notation *t (t=1,2,3...,T)* is used to represent these time periods.

A. System Description

In the proposed market, residential households perform the roles of market participants. During each trading period,

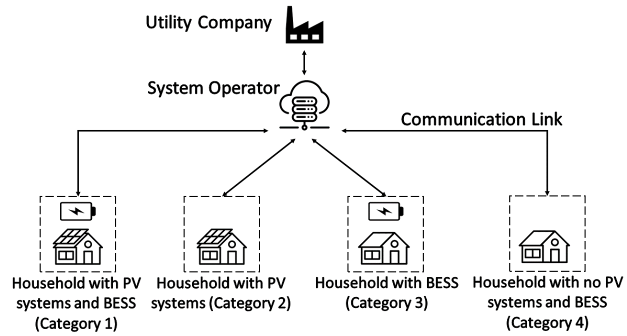

Fig. 1: Basic structure of the considered P2P market

TABLE I: Categories of Households

Category	Facility DER	Facility BESS
H_1	Yes	Yes
H_2	Yes	No
H_3	No	Yes
H_4	No	No

transactions are performed either between households and the utility company, or between households. It is assumed that the considered community is geographically small and thus power transmission losses are ignored. In addition, they are assumed to own various combinations of BESS and DERs. In our proposed system, four categories of households ($\boldsymbol{H} \in H_1, H_2, H_3, H_4$) with different types of facilities are considered, where the details are illustrated in Table I.

In the proposed scenario, a smart meter is installed in every residential house to record the energy generation and consumption. Residential households are also able to make P2P trading decisions and send to the centralized market coordinator through the communication between the smart meter and the centralized market coordinator. The centralized market coordinator is liable to calculate the MCP by collecting the bidding strategies of the market participants. Then the centralized market coordinator announces the successful bids/offers and sends the information back to the participants. During the transaction, the centralized market coordinator acts as an information exchanger and does not intervene in the transactions within the market. Thus, the fairness of this market can be realized at all times.

B. Basic Trading Processes

In the market structure, households can be either a buyer or a seller. As an energy buyer, this household can buy the needed energy from the utility company and through the P2P market from the sellers who have intention to sell the energy. For those buyers who own BESS, they are also allowed to consider discharging BESS for full or partial power supply to the energy demand. Therefore, the demand for an energy buyer can be from the local DERs, the P2P market, the utility company and the discharge from the BESS. Due to the economic issue, we assume that buyers are not allowed to sell any energy to the proposed P2P market and the grid. On the other hand, as an

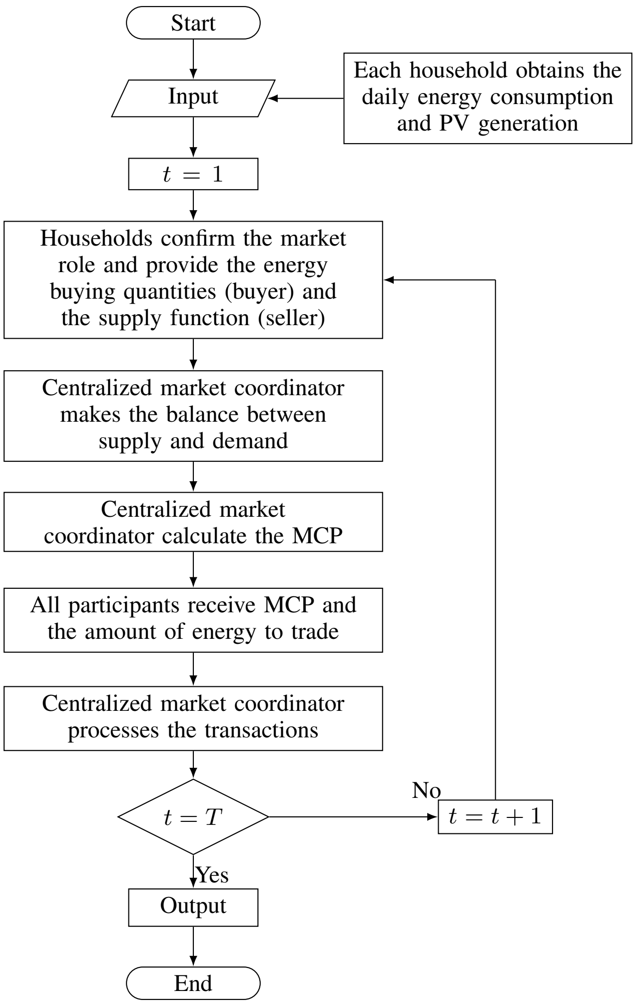

Fig. 2: Flowchart of the P2P energy trading strategy

energy seller, this household can sell the energy to either the P2P market or the utility company to earn the benefit. If this seller owns a BESS, he can also choose to store the extra energy in the BESS. In the proposed model, it is assumed that energy sellers who own the BESS are allowed to sell the energy by discharging their BESSs. To protect the benefit of buyers and keep the market electricity price stable, sellers are also forbidden to buy electricity from the P2P market and the grid.

C. Modeling of the Residential P2P Trading Market

In this section, we present the structure and the model with objective functions and related constraints of the proposed residential P2P trading system. An example of the energy flow diagram for a household with PV systems and BESS is illustrated in Fig. 3. The parameter definition regarding $x_h^{P2P}(t)$, $x_h^G(t)$, $x_h^B(t)$ and $p(t)$ is presented as follows.

$$\begin{cases} x_h^{P2P}(t) \geq 0, & \text{Buying energy from the P2P market} \\ x_h^{P2P}(t) < 0, & \text{Selling energy to the P2P market} \end{cases}$$

$$\begin{cases} x_h^{B}(t) \geq 0, & \text{Battery is charging} \\ x_h^{B}(t) < 0, & \text{Battery is discharging} \end{cases}$$

$$\begin{cases} x_h^{G}(t)) \geq 0, & \text{Buying energy from the retailer} \\ x_h^{G}(t)) < 0, & \text{Selling energy to the retailer} \end{cases}$$

$$p(t) = \begin{cases} p^U(t), & \text{if } x_h^G(t) \geq 0 \\ p^{FIT}(t), & \text{if } x_h^G(t) < 0 \end{cases}$$

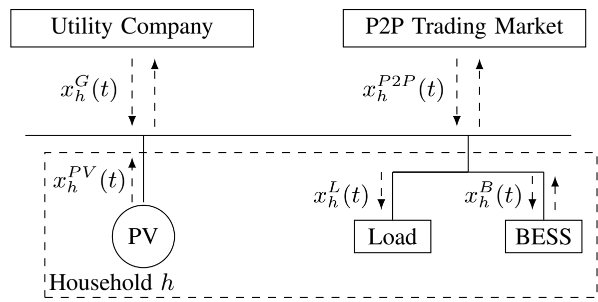

Fig. 3: Household h ($h \in H_1$) with energy trading conditions

1) Objective Function: An objective function f_o in (1) is proposed to evaluate the households' energy trading strategies in terms of social welfare f_S and market fairness index on benefit distribution f_σ.

$$f_o = \mu_1 f_S + \mu_2 f_\sigma \tag{1}$$

where weighting factors μ_1 and μ_2 are non-negative, and satisfy

$$\mu_1 + \mu_2 = 1 \tag{2}$$

Since there is a significant difference in the range of numerical values between social welfare and population variance, we normalize them to the range [0, 1] to improve the objective sensitivity, where the normalized objective is expressed as

$$f_o^N = \mu_1 f_S^N + \mu_2 f_\sigma^N \tag{3}$$

with

$$\begin{cases} f_S^N = \frac{f_S - f_{S,min}}{f_{S,max} - f_{S,min}} \\ f_\sigma^N = \frac{f_\sigma - f_{\sigma,min}}{f_{\sigma,max} - f_{\sigma,min}} \end{cases} \tag{4}$$

It is also important to ensure that the net energy cost of a random participant through the trading in the proposed P2P market is always lower than the optimal cost when this participant is not trading in the proposed P2P market, and the corresponding mathematical constraint can be found in (5)

$$\sum_{t=1}^{T} (\hat{Q}_h^*(t) - Q_h(t)) \geq 0 \tag{5}$$

where

$$\hat{Q}_h^*(t) = \arg\min \hat{S} \tag{6}$$

$$\hat{S} = \sum_{h=1}^{H} \sum_{t=1}^{T} \hat{Q}_h(t) \tag{7}$$

$$\hat{Q}_h(t) = p(t) \hat{x}_h^G(t) \tag{8}$$

$$Q_h(t) = p^{MCP}(t) x_h^{P2P}(t) + p(t) x_h^G(t) \tag{9}$$

In (9), the first term represents the cost/benefit when buying/selling energy in the P2P market; the second term represents the cost/benefit when buying/selling energy with the utility company. In the proposed model, the value of MCP must be between the FIT price and grid price to attract customer participation, that is

$$p^{FIT}(t) < p^{MCP}(t) < p^{U}(t) \tag{10}$$

Meanwhile, it should be noted, household h could never buy and sell electricity at the same time interval. The following constraint is presented that ensures the buying behavior and selling behavior cannot be processed at the same time.

$$x_h^{P2P}(t) \times x_h^{G}(t) \geq 0 \tag{11}$$

The optimization problem is to find the best trading strategies for households to minimize the proposed normalized function f_o^N, which is defined in (12)

$$\min\ f_o^N \tag{12}$$

2) Social Welfare Modelling: In the modelling, the social welfare is evaluated by the summation of all participants' net electricity cost, where the mathematical expression is

$$f_S = \sum_{h=1}^{H}\sum_{t=1}^{T} Q_h(t) \tag{13}$$

3) Benefit Distribution Modelling: In the P2P energy trading market, it is essential that the earning for participants through the P2P energy trading ought to be fairly distributed. To quantify the extent of the fairness of the market, the benefit distribution function is designed to measure the variance between the overall saved cost and the individual saved cost, and the definition is

$$f_\sigma = \sum_{h=1}^{H} \frac{f_{\sigma,h}}{H} \tag{14}$$

where

$$f_{\sigma,h} = (\tilde{Q}_h - \tilde{Q}_{avg})^2 \tag{15}$$

$$\tilde{Q}_h = \sum_{t=1}^{T} (Q_h(t) - \hat{Q}_h^*(t)) \tag{16}$$

$$\tilde{Q}_{avg} = \frac{1}{H}\sum_{h=1}^{H} \tilde{Q}_h \tag{17}$$

Based on individual variance defined in (15), we further propose the category variance that is used to evaluate the variance index for each household category, which is expressed as

$$f_{\sigma,H_k} = \sum_{h=1}^{H_k} \frac{f_{\sigma,h}}{H_k} \quad (k \in [1,2,3,4]) \tag{18}$$

4) Distributed Energy Resources: In the proposed model, solar energy is considered as the DERs where the surplus energy can be either sold to other households through the P2P market or to the energy retailer. According to the conservation law of energy flow (in our model, the line losses are ignored, since the residential households considered in our model are geographically close), the following energy constraint would be satisfied.

$$x_h^{PV}(t) + x_h^{G}(t) + x_h^{P2P}(t) = x_h^{L}(t) + x_h^{B}(t) \tag{19}$$

where

$$\begin{cases} x_h^B(t) = 0, & \text{if } h \in H_2, H_4 \\ x_h^{PV}(t) = 0, & \text{if } h \in H_3, H_4 \end{cases} \tag{20}$$

In (19), $x_h^{PV}(t)$ and $x_h^L(t)$ are predicted values based on the historical data, which are non-negative.

5) State-of-Charge Constraints: In the proposed model, the state-of-charge (SOC) of BESS in household h ($h \in H_1, H_3$) can be modeled as

$$SOC_h(t) = \frac{SOC_h(t-1) \times E_h^C + X_h^B(t)}{E_h^C} \tag{21}$$

where

$$X_h^B = \begin{cases} x_h^B \times \eta_h^{ch} & \text{if } x_h^B \geq 0 \\ \frac{x_h^B}{\eta_h^{dis}} & \text{if } x_h^B < 0 \end{cases} \tag{22}$$

$$x_{h,max}^{B,dis} \leq x_h^B(t) \leq x_{h,max}^{B,ch} \tag{23}$$

$$SOC_h^{min} \leq\ SOC_h(t) \leq SOC_h^{max} \tag{24}$$

In (21), $SOC_h(0)$ represents the initial SOC for household h's BESS. For the designed BESS model, charging/discharging at the same time is prohibited since this behavior would cause unnecessary energy loss.

6) Market Clearing Price Computation: To make the P2P market fair and efficient, MCP is used as the final electricity trading price. In this model, we use supply function method to derive the MCP: for a seller h at time t, the electricity could be sold to the grid and P2P market. In this article, it is assumed that each seller defines the selling strategy by the supply function $x_h^{P2P}(t)$ ($x_h^{P2P}(t) < 0$), then we would apply supply function mechanism to compute the market-clearing price. It is assumed that $x_h^{P2P}(t)$ is decided by the P2P market electricity price $p(t)$, a variable parameter $b_h(t)$ and a constant c as follows [27]:

$$x_h^{P2P}(t) = -b_h(t)\,p(t) + c \tag{25}$$

If the maintenance cost and operation cost of PV systems are ignored, the above supply function can be further simplified as follows,

$$x_h^{P2P}(t) = -b_h(t)\,p(t) \tag{26}$$

At each time interval, buyers would submit their energy demand from the P2P market to the centralized market coordinator and sellers would submit their supply functions (proposed in (26)) as a bid to the centralized market coordinator. Centralized market coordinator then clears the market according to the decisions of participants. For all household buyers at time t, the total amount of electricity bought from the P2P market is expressed as

$$x_{total}^{P2P}(t) = -\sum_{i=1}^{H_B(t)} x_i^{P2P}(t) \tag{27}$$

In the bidding market, MCP is determined when the supply equals the demand. Hence, Eq. (27) is re-written as:

$$p^{MCP}(t) = \frac{x_{total}^{P2P}(t)}{\sum_{j=1}^{H_S(t)} b_j(t)} \tag{28}$$

Eq. (28) shows that the MCP is proportional to the total demand in the P2P trading market. Moreover, according to (26) and (28), the supply function for household h can be updated as

$$x_h^{P2P}(t) = -\frac{b_h(t) x_{total}^{P2P}}{\sum_{j=1}^{H_S(t)} b_j(t)} \tag{29}$$

Eq. (29) shows that the energy supply of household h to P2P market is not only proportional to x_{total}^{P2P} and inversely proportional to the overall bidding strategies $\sum_{j=1}^{H_S(t)} b_i(t)$, but also relevant to this prosumer's biding option $b_h(t)$. Thus, both buyers and sellers are positively to be engaged in the MCP decision.

III. Case Study

In this part, a community microgrid with 40 prosumers is investigated as a case study to validate the proposed model. The community microgrid is connected to a single utility grid, which sells energy at the market prices and buys the energy at the FIT prices. The specific number of participants are given in Table II.

TABLE II: Number of Participants in Each Category

Categories	Number	Categories	Number
H_1	10	H_2	10
H_3	10	H_4	10

A. Simulation Setup

In the case study, the predicted hourly PV energy demand profiles and the PV generation are based on the Ausgrid data-set [28]. The capacity of BESS is set to be 4.8 kWh, and the battery SOC is restricted to lie between 10% and 90%. The charging and discharging efficiency are considered to be both 90% [29]. The maximum charging/discharging rate of the battery is 1 kW. The initial SOC for every SOC owner is set to be 0.1. The real grid price and FIT price from an Australian electricity retailer, Red Energy, are applied; see Table III. Since we only consider a one-day scenario, the battery degradation cost is not included in this case study. Matlab built-in function FMINCON is used in solving the optimization model, and YALMIP, a MATLAB toolbox, is also used to translate the model constraints to MATLAB language [30].

TABLE III: Energy Unit Price (AU$/kWh)

	Grid Price	FIT Price
0:00-7:00	0.1430	0.0840
7:00-14:00	0.2420	0.0840
14:00-20:00	0.5225	0.0840
20:00-22:00	0.2420	0.0840
22:00-24:00	0.1430	0.0840

B. Evaluation of the Net Cost and Variance ($\mu_1 = \mu_2 = 0.5$)

Fig. 4 reveals market participants' net cost and variance level defined in (15). Compared with the case without any P2P energy trading market, the overall net cost can be saved by 26.38% when households trade in the proposed P2P market. On the other hand, such a significant cost reduction is based on the low level of individual variance values, which indicates that the saved cost is fairly allocated to each household. Regarding the performance of the households in each category, the households in Category H_3 and H_4 generally have higher net energy costs than other category households who own PV systems, where the result demonstrates the significant role of DERs in reducing electricity costs. On the other hand, BESS also plays an essential role in reducing energy costs. It is observed that households in Category H_2 and H_4 have lower variance values than households in Category H_1 and H_3, which means that under the scenario of $\mu_1 = \mu_2 = 0.5$, the centralized market coordinator allows more cost reduction for households with BESS to balance the social welfare and variance.

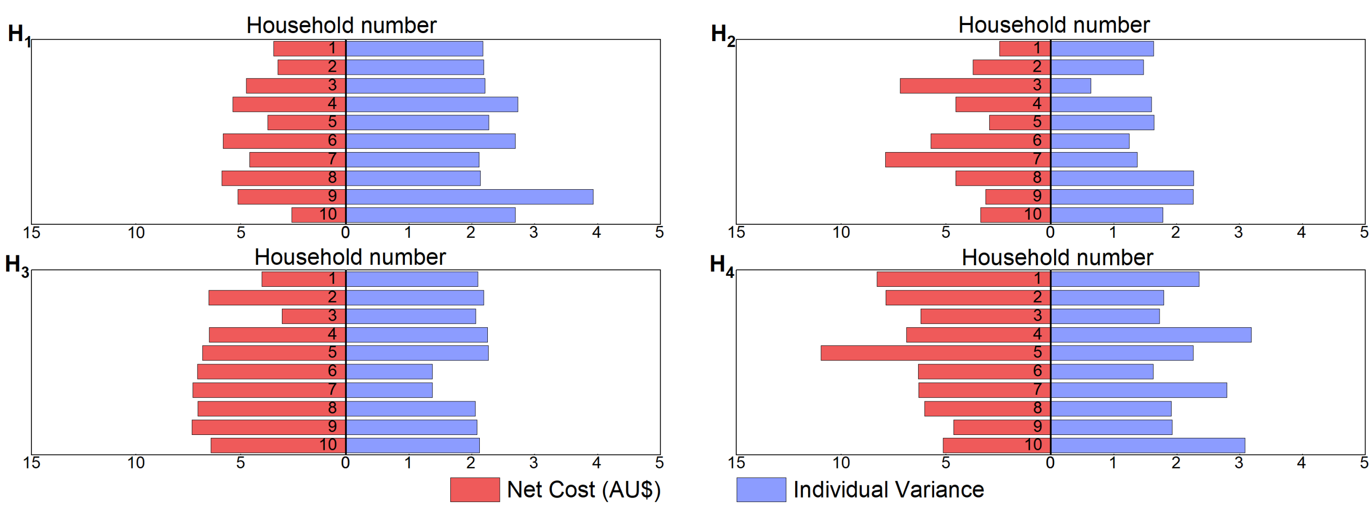

Fig. 4: Net Cost and Variance Level for every household in each category ($\mu_1 = \mu_2 = 0.5$)

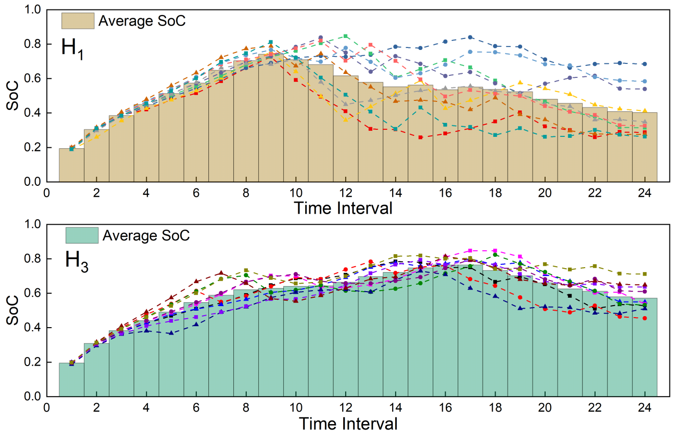

Fig. 5: SOC for Each Household in Category H_1 and H_3

The role of BESSs can be further explored in Fig. 5, which reveals the SOC level and the average SOC for households in Category H_1 and H_3. At the first 9 time intervals, the households in Category H_1 and H_3 charge the BESSs, where households in Category H_1 emerge a faster charging speed than households in Category H_3 in the morning time due to the extra generated power from PV systems of households in Category H_1. After 10 am, while the average SOC of Category H_1 decreases and then keeps around constant from 2pm to 6pm before decreasing till midnight, the average SOC of Category H_3 keeps increasing before the night peak time. On the other hand, by comparing the SOC level in the last few time intervals for Category H_1 and H_3, households in Category H_3 maintain higher average SOC. Although the centralized market coordinator suggests such optimal energy management strategy of SOC to mitigate the excessive gap of the benefit distribution variance, the households with higher SOC levels are able to reduce net energy costs further when the market tends to emphasize more on social welfare (e.g., μ_1 increases and μ_2 decreases), where such impact will be analyzed at the end of the case study.

C. Evaluation of P2P Energy Trading ($\mu_1 = \mu_2 = 0.5$)

Fig. 6 investigates the trading prices and quantities in different time intervals over the proposed P2P market. As shown in this figure, there are some transactions recorded from the morning to the afternoon, and the trading quantity has the rising trend until $t = 14$. This is because households start to generate lots of energy through PV panels, which exceeds their energy demand. Despite the option to charge the extra energy into the BESS for households equipped with BESS, the households also choose to sell some energy through the proposed P2P energy trading market, expecting more benefits than selling them to the grid at a low FIT price. For those households who buy energy in the proposed P2P market, this transaction is also helpful to decrease their energy cost as the P2P electricity price is lower than the traditional utility price. Moreover, the P2P trading quantity starts the declining trend from $t = 14$ due to the tense of DERs. There is no P2P energy transaction between $t = 1$ and $t = 7$ since there is no PV generation. However, P2P transactions are still recorded in low amounts after $t = 20$, which is contributed by BESS discharging. To realize the cost reduction of households in Category H_2 and H_4, the centralized market coordinator proposes households with BESSs to sell the stored energy to avoid high utility prices. However, by comparing the average cost reduction rate of each household category presented in Table IV, it is observed that households with BESSs are still able to reduce more energy costs than others, demonstrating the key effect of BESSs on achieving more energy cost reduction with a wise charging/discharging strategy.

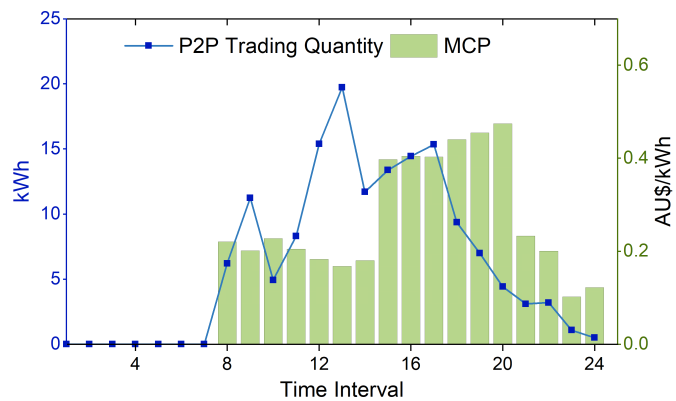

Fig. 6: Hourly MCP and Total Trading Quantity over the Proposed P2P Market

TABLE IV: Average Cost Reduction in Each Household Category

Category	H_1	H_2	H_3	H_4
Average Cost Reduction (AU$)	**2.54**	**1.32**	**2.42**	**1.04**

Regarding the MCPs in a day, it can be observed that MCPs are heavily impacted by the utility selling price. From the morning to $t = 14$, MCPs have a decline trend caused by the abundant PV generation. MCP sharply rises at $t = 15$ when the utility price increases from AU$ 0.2420 /kWh to AU$ 0.5225/kWh, and it keeps increasing during the peak time due to the high energy demand and low manageable DERs.

D. Evaluation of the Energy Trading with the Utility Company ($\mu_1 = \mu_2 = 0.5$)

Fig. 7 shows the energy trading quantity with the local utility company for each household category. Households in Category H_1 take the least energy from the local utility company. This is because the PV generation can support the energy demand, and BESSs provide sufficient flexibility on demand side management and arbitrage opportunity. The highest total power needed from the utility company is recorded at $t = 19$ during the peak time. Apart from this, another peak of the total power needed from the utility company is also recorded in $t = 7$, where households in Category H_1 and H_3 take the lead due to the BESS charging purpose. By contrast, compared with the morning and evening time, households need less energy from the local utility company in the afternoon, where the total energy trading quantity in the proposed P2P market is the highest in a day. Through the proposed P2P energy trading market, market participants have a win-win solution, where energy sellers can sell the energy with MCPs that are significantly higher than the flat FIT price, and energy buyers can obtain energy with a price lower than the utility price. On the other hand, according to Fig. 6 and Fig. 7, the local utility company covers the majority of the total energy demand in a day, demonstrating that the local utility company is still the main contributor to the local energy demand since the generation of the PV system is not stable and significantly impacted by external factors, such as weather, time, and location.

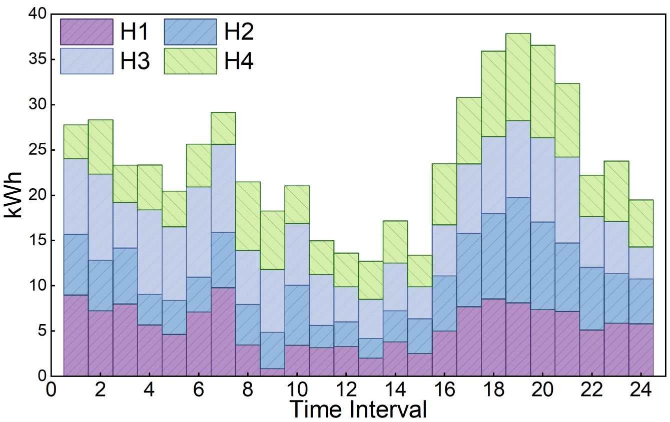

Fig. 7: Total Trading Quantity with the Utility Company for Each Household Category

E. Evaluation of Weighting Factors

Prior case studies have revealed the performance of the social welfare and variance index for the residential market participants. In this section, further investigation will be conducted to analyze how the optimal social welfare and variance index will change when adopting different weighting factors.

Firstly, Fig. 8 illustrates the optimal result of the normalized social welfare, the objective function and the benefit distribution function based on different weighting factors. As illustrated in this figure, when μ_1 is close to one, the community can achieve its minimum overall net cost; when μ_1 is close to zero, the community can achieve its minimum fair benefit distribution index. On the other hand, when μ_1 increases from $\mu_1 = 0.1$, the trend of f_σ^N is increasing but the trend of f_S^N is decreasing. However, the value of f_σ^N is always lower than f_S^N before $\mu_1 = 0.55$, indicating the fair benefit allocation is more important than the participants' cost savings in this power system. Moreover, a turning point exists at $\mu_1 = 0.55$, or equivalently, $\mu_2 = 0.45$. When μ_1 keeps increasing, f_σ^N becomes bigger than f_S^N. Under this scenario, the centralized market coordinator will propose the optimal energy trading and management strategies that emphasize more on a proper management of cost reduction for market participants.

More details with respect to net cost and variance for households in different categories when weighting factors are changing can be found in Fig. 9. In terms of the net cost, households in H_1 and H_3 show a stronger ability to reduce more cost than other households when μ_1 increases. By contrast, although

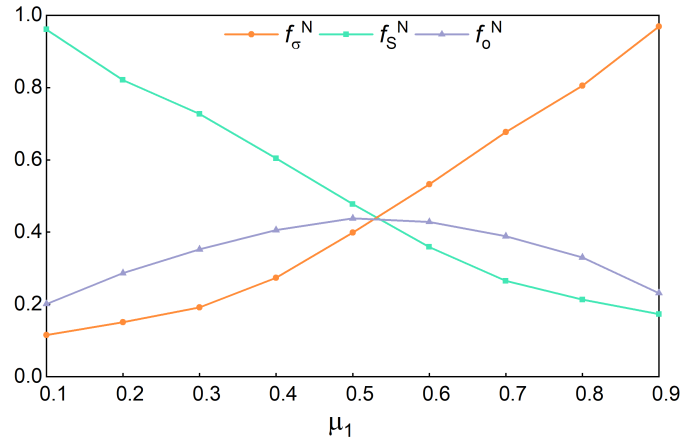

Fig. 8: Optimization result for population variance function, social welfare and objective function

households without BESSs have a significant cost reduction, these households find it harder to further reduce the energy cost when μ_1 increases. This is because households in H_2 and H_4 are more likely to buy energy from the utility company with high electricity prices due to the limitation of the energy sources during the night peak time. Regarding the category variance index which is defined in (18), each household category shares the similar variance when μ_1 is lower than 0.5. However, with the increasing of μ_1, the optimal results reveal higher category variance for households in H_3 and H_4. When $\mu_1 = 0.9$, the category variances for H_3 and H_4 are at the same level, which are 6.49 and 6.09, respectively. However, similar variance levels result in different performances of cost-saving. When $\mu_1 = 0.9$, households in H_3 can save AU\$ 4.01 in average, while this number for households in H_4 is AU\$ 2.21 (obtained by $\sum_{h=1}^{H_k} \tilde{Q}_h / H_k$). Such discrepancy illustrates the importance of BESSs in achieving more energy cost reduction for residential households through an appropriate BESS management strategy.

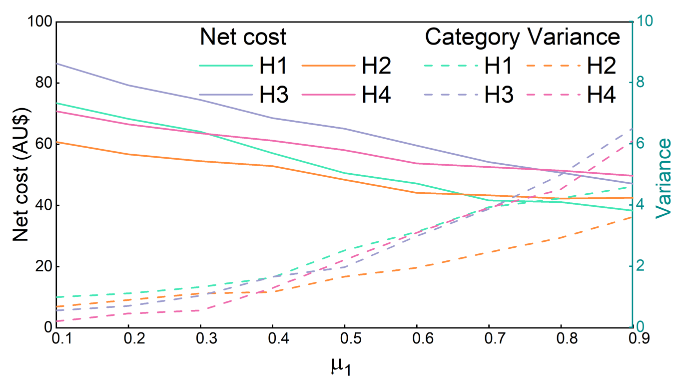

Fig. 9: Optimization results for Net Cost and Variance for Each Category

The reasons causing the cost reduction when μ_1 increases vary, but one of the important factors is induced by more trading activity in the proposed P2P energy trading market. Table V presents the overall energy trading quantity under the scenarios of different weighting factors. It is observed that when μ_1 goes bigger, households are suggested to trade more energy in the proposed P2P energy market to achieve lower overall net cost.

TABLE V: Total Trading Quantity over the P2P Market with different weighting factors

μ_1	0.1	0.3	0.5	0.7	0.9
Trading Quantity (kWh)	**79.3**	**116.2**	**156.3**	**205.9**	**254.3**

IV. Conclusion

In this paper, a residential P2P energy trading system and relevant rules are proposed for residential households. In the P2P trading market, the proposed model considers four categories of participants: households with RESs and BESS, households with RESs only, households with BESS only and households with none of the RES or BESS. In the proposed market, participants decide the energy procurement to enable them from traditional passive energy receivers to active market participants, and the energy sellers decide the amount of energy sold through P2P market by a supply function mechanism. The market clearing prices are codetermined by buyers and sellers to ensure the fairness and transparency of the proposed P2P market. Based on the proposed model, this paper formulates the objective function that considers both social welfare and fair benefit distribution. Simulation results show that the proposed trading mechanism can efficiently reduce the electricity bills for households and ensure the fairness of the revenue distribution. For example, when $\mu_1 = 0.5$, 26.38% of the total cost saving can be achieved during keeping the fair benefit distribution at a low level. Essentially, the centralized market coordinator can realize different targets on social welfare and fair benefit distribution by adjusting different weighting factors, reflecting the strong flexibility of the proposed model.

In future work, the proposed market will be investigated by considering communication delays. Besides, the uncertainty of the energy demand and PV outputs would be considered to enhance the accuracy of the results.

References

[1] D. N.-y. Mah, D. M.-w. Cheung, M. K. Leung, M. Y. Wang, M. W.-m. Wong, K. Lo, and A. T. Cheung, "Policy mixes and the policy learning process of energy transitions: Insights from the feed-in tariff policy and urban community solar in hong kong," *Energy Policy*, vol. 157, p. 112214, 2021.

[2] L. Poruschi, C. L. Ambrey, and J. C. Smart, "Revisiting feed-in tariffs in australia: A review," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 260–270, 2018.

[3] N. Martin and J. Rice, "The solar photovoltaic feed-in tariff scheme in new south wales, australia," *Energy Policy*, vol. 61, pp. 697–706, 2013.

[4] S. Jiang, C. Wan, C. Chen, E. Cao, and Y. Song, "Distributed photovoltaic generation in the electricity market: status, mode and strategy," *CSEE Journal of Power and Energy Systems*, vol. 4, no. 3, pp. 263–272, 2018.

[5] J. Koskela, A. Rautiainen, and P. Järventausta, "Using electrical energy storage in residential buildings–sizing of battery and photovoltaic panels based on electricity cost optimization," *Applied energy*, vol. 239, pp. 1175–1189, 2019.

[6] K. Moslehi and A. B. R. Kumar, "Autonomous resilient grids in an iot landscape vision for a nested transactive grid," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4089–4096, 2018.

[7] G. Sæther, P. C. del Granado, and S. Zaferanlouei, "Peer-to-peer electricity trading in an industrial site: Value of buildings flexibility on peak load reduction," *Energy and Buildings*, vol. 236, p. 110737, 2021.

[8] H. Kim, H. Choi, H. Kang, J. An, S. Yeom, and T. Hong, "A systematic review of the smart energy conservation system: From smart homes to sustainable smart cities," *Renewable and Sustainable Energy Reviews*, vol. 140, p. 110755, 2021.

[9] M. Khorasany, Y. Mishra, and G. Ledwich, "A decentralized bilateral energy trading system for peer-to-peer electricity markets," *IEEE Transactions on industrial Electronics*, vol. 67, no. 6, pp. 4646–4657, 2019.

[10] M. Qu, T. Ding, W. Jia, S. Zhu, Y. Yang, and F. Blaabjerg, "Distributed optimal control of energy hubs for micro-integrated energy systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 4, pp. 2145–2158, 2020.

[11] T. Ding, Q. Yang, Y. Wen, Y. Ning, Y. Yang, and F. Blaabjerg, "Zonally robust decentralized optimization for global energy interconnection: Case study on northeast asian countries," *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 4, pp. 2120–2129, 2020.

[12] C. Mu, T. Ding, M. Qu, Q. Zhou, F. Li, and M. Shahidehpour, "Decentralized optimization operation for the multiple integrated energy systems with energy cascade utilization," *Applied Energy*, vol. 280, p. 115989, 2020.

[13] T. Chen, S. Bu, X. Liu, J. Kang, F. R. Yu, and Z. Han, "Peer-to-peer energy trading and energy conversion in interconnected multi-energy microgrids using multi-agent deep reinforcement learning," *IEEE Transactions on Smart Grid*, 2021.

[14] H. Wu, J. Cao, Y. Yang, C. L. Tung, S. Jiang, B. Tang, Y. Liu, X. Wang, and Y. Deng, "Data management in supply chain using blockchain: Challenges and a case study," in *2019 28th International Conference on Computer Communication and Networks (ICCCN)*. IEEE, 2019, pp. 1–8.

[15] A. Esmat, M. de Vos, Y. Ghiassi-Farrokhfal, P. Palensky, and D. Epema, "A novel decentralized platform for peer-to-peer energy trading market with blockchain technology," *Applied Energy*, vol. 282, p. 116123, 2021.

[16] T. Morstyn and M. McCulloch, "Multi-class energy management for peer-to-peer energy trading driven by prosumer preferences," *IEEE Transactions on Power Systems*, 2018.

[17] C. Dang, J. Zhang, C.-P. Kwong, and L. Li, "Demand side load management for big industrial energy users under blockchain-based peer-to-peer electricity market," *IEEE Transactions on Smart Grid*, 2019.

[18] Z. Guan, X. Lu, W. Yang, L. Wu, N. Wang, and Z. Zhang, "Achieving efficient and privacy-preserving energy trading based on blockchain and abe in smart grid," *Journal of Parallel and Distributed Computing*, vol. 147, pp. 34–45, 2021.

[19] O. Abrishambaf, F. Lezama, P. Faria, and Z. Vale, "Towards transactive energy systems: An analysis on current trends," *Energy Strategy Reviews*, vol. 26, p. 100418, 2019.

[20] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 8, pp. 6087–6097, 2018.

[21] M. Zhang, F. Eliassen, A. Taherkordi, H.-A. Jacobsen, H.-M. Chung, and Y. Zhang, "Energy trading with demand response in a community-based p2p energy market," in *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. IEEE, 2019, pp. 1–6.

[22] M. M. Jalali and A. Kazemi, "Demand side management in a smart grid with multiple electricity suppliers," *Energy*, vol. 81, pp. 766–776, 2015.

[23] N. Li, L. Chen, and M. A. Dahleh, "Demand response using linear supply function bidding," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1827–1838, 2015.

[24] N. K. Meena, J. Yang, and E. Zacharis, "Optimisation framework for the design and operation of open-market urban and remote community microgrids," *Applied Energy*, vol. 252, p. 113399, 2019.

[25] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," *Applied energy*, vol. 238, pp. 1434–1443, 2019.

[26] J. Wang, H. Zhong, C. Wu, E. Du, Q. Xia, and C. Kang, "Incentivizing distributed energy resource aggregation in energy and capacity markets: An energy sharing scheme and mechanism design," *Applied Energy*, vol. 252, p. 113471, 2019.

[27] S. Clò, A. Cataldi, and P. Zoppoli, "The merit-order effect in the italian power market: The impact of solar and wind generation on national wholesale electricity prices," *Energy Policy*, vol. 77, pp. 79–88, 2015.

[28] Ausgrid. Solar home electricity data - Ausgrid. [Online]. Available: https://www.ausgrid.com.au/Industry/Innovation-and-research/Data-to-share/Solar-home-electricity-data

[29] I. Dusparic, A. Taylor, A. Marinescu, F. Golpayegani, and S. Clarke, “Residential demand response: Experimental evaluation and comparison of self-organizing techniques,” *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 1528–1536, 2017.

[30] J. Lofberg, “Yalmip: A toolbox for modeling and optimization in matlab,” in *2004 IEEE international conference on robotics and automation (IEEE Cat. No. 04CH37508)*. IEEE, 2004, pp. 284–289.