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P2P Electricity Trading Considering User Preferences for Renewable Energy and Demand-Side Shifts

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Abstract: In the global trend towards decarbonization, peer-to-peer (P2P) energy trading is garnering increasing attention. Furthermore, energy management on the demand side plays a crucial role in decarbonization efforts. The authors have previously developed an automated bidding agent that considers user preferences for renewable energy (RE), assuming users own electric vehicles (EVs). In this study, we expand upon this work by considering users who own not only EVs but also heat pump water heaters, and we develop an automated bidding agent that takes into account their preferences for RE. We propose a method to control the start time and presence of daytime operation shifts for heat pump water heaters, leveraging their daytime operation shift function. Demonstration experiments were conducted to effectively control devices such as EVs and heat pumps using the agent. The results of the experiments revealed that by controlling the daytime operation of heat pumps with our method, the RE utilization rate can be improved compared to scenarios without daytime operation shifts. Furthermore, we developed a simulator to verify the outcomes under different scenarios of demand-side resource ownership rates, demonstrating that higher ownership rates of EVs and heat pumps enable more effective utilization of renewable energy, and that this effect is further enhanced through P2P trading. Based on these findings, we recommend promoting the adoption of demand-side resources such as EVs and heat pumps and encouraging P2P energy trading to maximize the utilization of renewable energy in future energy systems.

Keywords: P2P energy trading; electric vehicle; heat pump water heater; optimization

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1. Introduction

1.1. Background

Renewable energy (RE) plays a crucial role in the global decarbonization trend, contributing to the large-scale deployment of clean energy sources. In the transition towards decarbonized energy systems, it is important to focus not only on diversifying power generation, including RE, but also on demand-side energy management, such as energy storage and energy efficiency improvements [1]. Consequently, this study emphasizes demand-side controls that utilize energy storage systems and heat pumps on the demand side.

Peer-to-peer (P2P) energy trading has emerged as a promising solution for enabling dynamic demand-side energy management and coordinating a multitude of distributed energy resources. Various studies have examined different aspects of P2P energy trading, including optimizing trading strategies and market design [2,3], harnessing blockchain technology for efficiency, transparency, and security [4–8], and demonstrating the effectiveness of these systems through real-world case studies [9–13]. For instance, Liu et al. [2] and AlSkaif et al. [3] proposed innovative P2P energy trading platforms to optimize demand response schemes and trading preferences, respectively. These platforms aim to improve the overall efficiency of energy management in residential systems. Blockchain technology has been extensively explored to facilitate secure and transparent P2P energy trading, as evidenced by the work of Dang et al. [6] for big industrial energy users and Shukla et al. [8] for smart grid applications. Real-world case studies further substantiate the potential of P2P energy trading systems. For example, the Brooklyn Microgrid project, discussed by Mengelkamp et al. [10], illustrates how blockchain technology can be effectively implemented to create a decentralized microgrid energy market.

Not only the technical aspects but also the social acceptability and institutional aspects of energy management and decentralization are studied. Studies [14,15] focus on the role of blockchain technology in the energy sector and institutional development for distributed energy systems. Study [16] examines business models and policy interactions for microgrids, finding natural gas technologies as the most robust option. Study [17] evaluates peer-to-peer energy sharing mechanisms, with supply and demand ratio mechanisms outperforming others. Lastly, study [18] proposes a multi-stage incentive model for micro-grid project development involving multiple stakeholders.

Furthermore, research on demand-side demand timing adjustment and energy management using energy storage systems has demonstrated the effectiveness of demand-side energy management [19–22].

This study proposes a trading algorithm for electricity trading agents in a P2P electricity trading market for households with electric vehicles (EVs) and heat pump water heaters, considering the subject's preference for RE on the consumer side. The authors proposed a trading algorithm for electricity trading agents in the P2P electricity trading market in 2021 for households with EVs [23], but the mechanism to adjust the operating timing of the heat pump water heater was not considered in that algorithm. In this study, we propose a mechanism to optimize not only the charging and discharging of EVs, but also the operating timing of heat pump water heaters according to user preferences.

1.2. Related Work

Energy management on the demand side includes the use of storage batteries and changes in demand timing. Various studies have been conducted on the use of storage batteries, and consumers who own EVs can be expected to enjoy cost advantages by optimizing the recharge and discharge of their EVs, procuring more electricity from the market when electricity prices are low, storing it in batteries, and discharging it from the batteries when market electricity prices are high. This is expected to be a cost advantage. Optimizing EV recharge/discharge is also important not only from a cost perspective, but also in terms of satisfying individual users' RE preferences by inexpensively increasing the RE ratio by charging EVs when surplus cheap RE is generated. If users do not own EVs or storage batteries, their own electricity demand will be a constraint on electricity transactions, but if they own EVs or storage batteries, they can reduce costs and improve their RE ratios by recharging and discharging them at appropriate times.

Wu et al. [19] formulated a stochastic optimization problem to optimize EV charging and discharging plans with the goal of minimizing the cost of paying electricity bills while meeting household electricity demand and PEV charging requirements. Vivekananthan et al. [20] proposed an algorithm to control home appliances with the goal of reducing the total cost of residential energy consumption through real-time monitoring, stochastic scheduling, and real-time control while application combinations were considered. Langer [22] minimized costs and discomfort for market participants by mixed integer linear programming, assuming a home with a home energy management system, adjustable heat pump, and photovoltaic power generation, combined with electrical and thermal storage systems.

In addition to the energy storage facility, another example of energy management by changing demand timing would be to adjust the operating timing of the heat pump water heater. For example, excess solar power generation during the daytime can be used to operate the heat pump water heater, making effective use of surplus electricity. Studies on adjusting the operation timing of heat pump water heaters include those by Clift et al. [24] and the aforementioned Langer [22].

Studies from a preference perspective include [25–27], whereby all of them take into account the preferences of individual users while ultimately maximizing overall utility, which is a framework in which users cooperate. Our study differs significantly in that individual users move independently toward satisfying their own preferences. Reis et al. [28] assess how prosumers and consumers pursuing different goals can influence the energy self-sufficiency of a local energy community. The preferences are considered in the modeling to represent a smart community. Yet it does not take into account the orientation toward RE. Pena-Bello et al. [29] assessed P2P trading decisions of German homeowners on the basis of an online experimental study and showed that P2P energy trading based on human decision-making may lead to financial benefits for prosumers and traditional consumers, plus reduced stress for the grid. When prosumers have not only RE generation facilities but also demand-shifting facilities such as EVs and heat pumps, it is possible to reduce the load on the grid even more. Therefore, in this study, we will conduct simulations assuming that many entities own demand-shifting facilities such as EVs and heat pumps, and we will confirm the effect of such facilities.

In summary, various studies have explored energy management on the demand side, including the use of storage batteries, EVs, and adjusting the operation timing of heat pump water heaters. These studies have achieved some success in optimizing energy consumption and costs. However, there is still room for improvement in fully considering individual users' preferences and ensuring that renewable energy orientation and other user-specific priorities are adequately addressed. Further research is needed to develop more tailored energy management solutions that effectively meet the diverse preferences of users.

Therefore, the goal is to develop an operational planning model for EVs and heat pumps that takes into account the orientation toward RE in P2P transactions. It is also important to establish an actual controllable mechanism in a manner that is compatible with the standards that drive existing heat pump water heaters. In this study, the optimization of bidding contents, charging/discharging timing, and daytime shift timing is designed by keeping in mind the Application Programming Interface (API) for control and information acquisition provided by the ECHONET Lite [30] standard used by heat pump water heaters that enjoy widespread popularity in Japan.

1.3. Contribution of This Paper

In this study, we envision an electricity P2P trading market and develop an agent system that automatically performs electricity transactions on behalf of users in the market. The objective is to enable power trading based on individual user circumstances by not only bidding based on user assets such as heat pump water heaters, EVs, and solar power generation and user electricity demand, but also bidding based on user preferences for RE. The main novelty of this study is that it proposes a mechanism for energy management that takes into account individual preferences for RE, including the operation of heat pumps as well as EVs, thus achieving both economic efficiency and satisfying individual preferences for RE. In particular, this study examined how optimizing the operation of heat pumps could benefit heat pump users.

1.4. Organization of This Paper

This paper is structured as follows. First, in Section 2, we provide an overview of the P2P energy trading platform. Subsequently, in Section 3, we describe the functionalities of user agents. Then, in Section 4, we elaborate on the crucial aspects of bidding and facility operation optimization within the user agent functionalities. In Section 5, we discuss the demonstration experiments involving actual EVs and heat pumps. Since there are limitations to feasible settings in the demonstration experiments, we develop a P2P energy trading simulation in Section 6 and conduct the simulation. Finally, we present our conclusions in Section 7.

2. P2P Energy Trading Platform

Figure 1 shows an overview of the P2P power trading platform for the demonstration experiment in this study. The role of the user agent in this P2P electricity trading platform is to acquire the electricity usage and generation status of each consumer and prosumer, forecast demand and generation based on this information, plan energy procurement and usage in consideration of the facilities owned by each consumer and prosumer, such as EVs and heat pumps, and bid on the blockchain market. The system then submits bids to the blockchain market. It also has the role of issuing commands for the recharge and discharge of EVs and the daytime shift time of heat pumps based on the optimization and execution results. In this experiment, a total of five entities (HOME1 to HOME4 as demand entities and one PV as power generation entity) conduct transactions, with only HOME1 having EVs and heat pumps, and HOME2 to HOME4 having none of them. The bidding agents communicate with the Internet gateway and the Blockchain energy market to obtain information on the demand and generation of these bidding entities and to send control signals. HOME1 owns the EV and heat pump, but HOME1, EV, and heat pump have different smart meters. In the experiment, they are treated as one entity in a virtual sense. Each entity may purchase electricity from the market or from retailers. They can also sell the electricity they generate to the market or retailers. Each entity can choose whether to deal with the market or the retailer, whichever has better terms, but cannot purchase RE from the retailer. If they have EVs or storage batteries, they can purchase electricity from the market or retailers when it is cheap, store it in their batteries, and use it when the price rises.

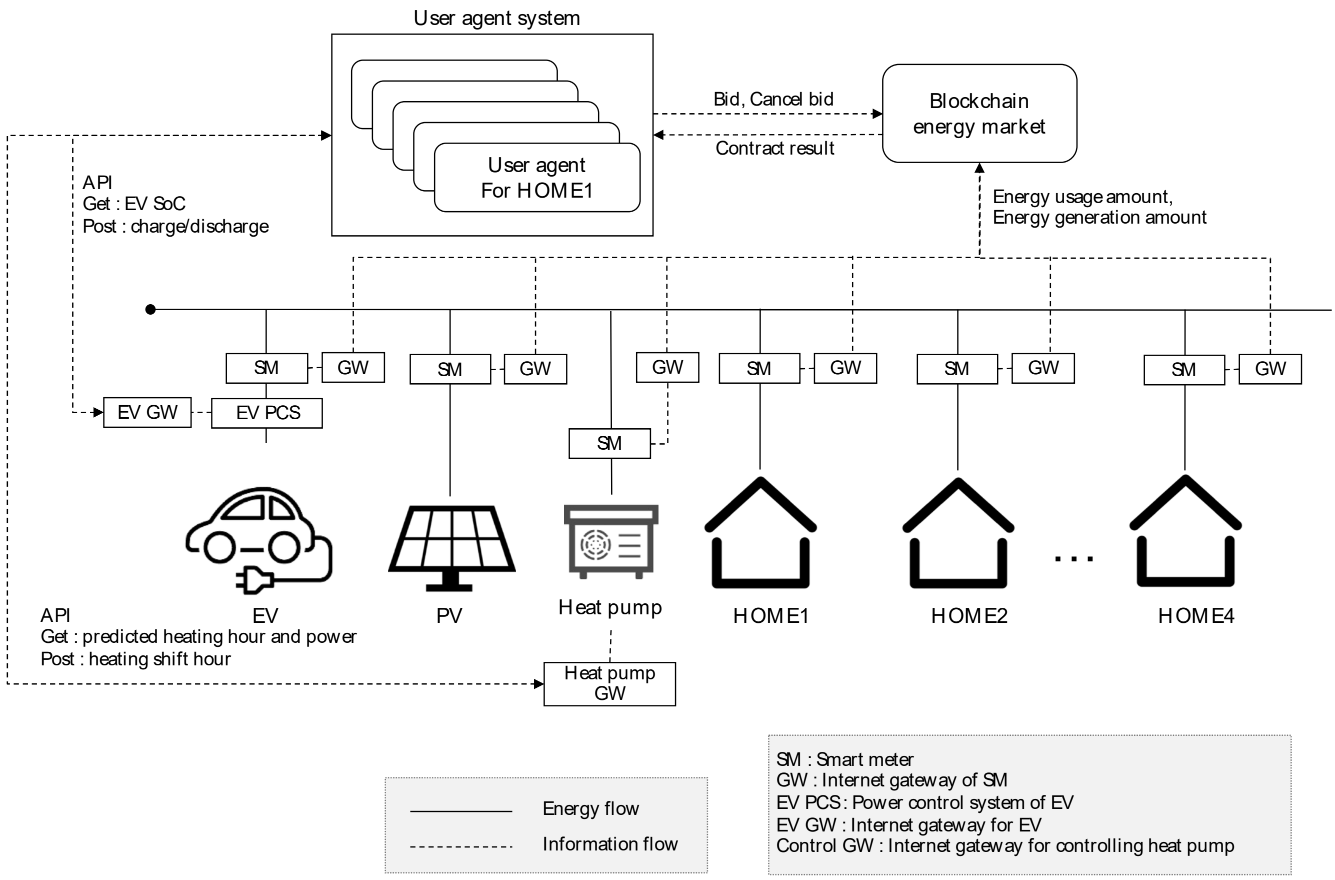

Figure 1. Diagram of demonstration experiment.

3. Functions of User Agents

Figure 2 shows the processing flow of the bidding agent. In the electricity demand forecasting function, electricity demand is forecasted based on customer demand data and weather data, and in the PV power generation function, PV power generation is forecasted based on historical power generation data and weather data. Here, the Meteorological Engineering Center's solar radiation forecasting API [31] is used to create a machine learning model using a random forest [32] to learn the relationship between actual PV power generation and forecasted solar radiation values. The inputs of this model are forecasted solar radiation, plus hour and month. In heat pump electricity demand forecasting, past electricity consumption data and schedule information on hot water demand patterns are used to forecast heat pump electricity consumption on the target day. The hot water demand patterns are determined in advance and are supposed to repeat itself on a two-week cycle. The heat pump itself has a heat demand pattern learning function and operates by predicting heat demand. The ECHONET Lite API [30] used in this project does not have a function to acquire the heat pump operation schedule, so the average value of operation during the same heat demand pattern in the past was used as a forecast. In the bid creation function, the system optimizes the power usage plan based on the transaction mode (green mode or economy mode) set by the user, demand and power generation forecast results, EV SoC, and heat pump operation forecasts, and creates a bid specifying the contents, time frame, amount of power, and price to be bid on the P2P market. In the bid execution function, the created bids are submitted to the energy market. The function for acquiring contract results gets a record of bids that have been contracted in the energy market and re-submits the results to the function for creating bids and recalculating new bids. The energy market trades power in 30-min increments, and bids can be submitted from 24 h prior to the actual power meltdown to one hour prior to the meltdown, and bidding agents change their bids for the same market every 30 min. At that time, the bid cancellation function is a function to submit a command to the market to cancel old bids made in the past. The series of processes from forecasting to bidding is repeated for each agent at 30-min intervals from the auction deadline of the previous day to the upcoming deadline (one hour before the electricity supply date and time).

The device control function is used to set charging/discharging commands to EVs and daytime boil-up shift times to heat pumps; charging/discharging commands to EVs are performed via the EV Power Control System (PCS) API based on the calculated EV charging/discharging plan once the target market is closed. The EV PCS API was developed as a mechanism that enables continuous charging and discharging at a user-defined output level for a specified duration, utilizing a REST API over HTTP. The optimal daytime shift start time for heat pumps is calculated at 9:00 p.m. on the previous day for the following day, and the results are then used to set the shift time via the ECHONET Lite API [30]. The optimal daytime shift start time is obtained by optimizing the daytime shift start time k in Bid Creation. After 21:00 on the previous day, k is fixed to the value obtained by optimization at 21:00 during the day subject to optimization.

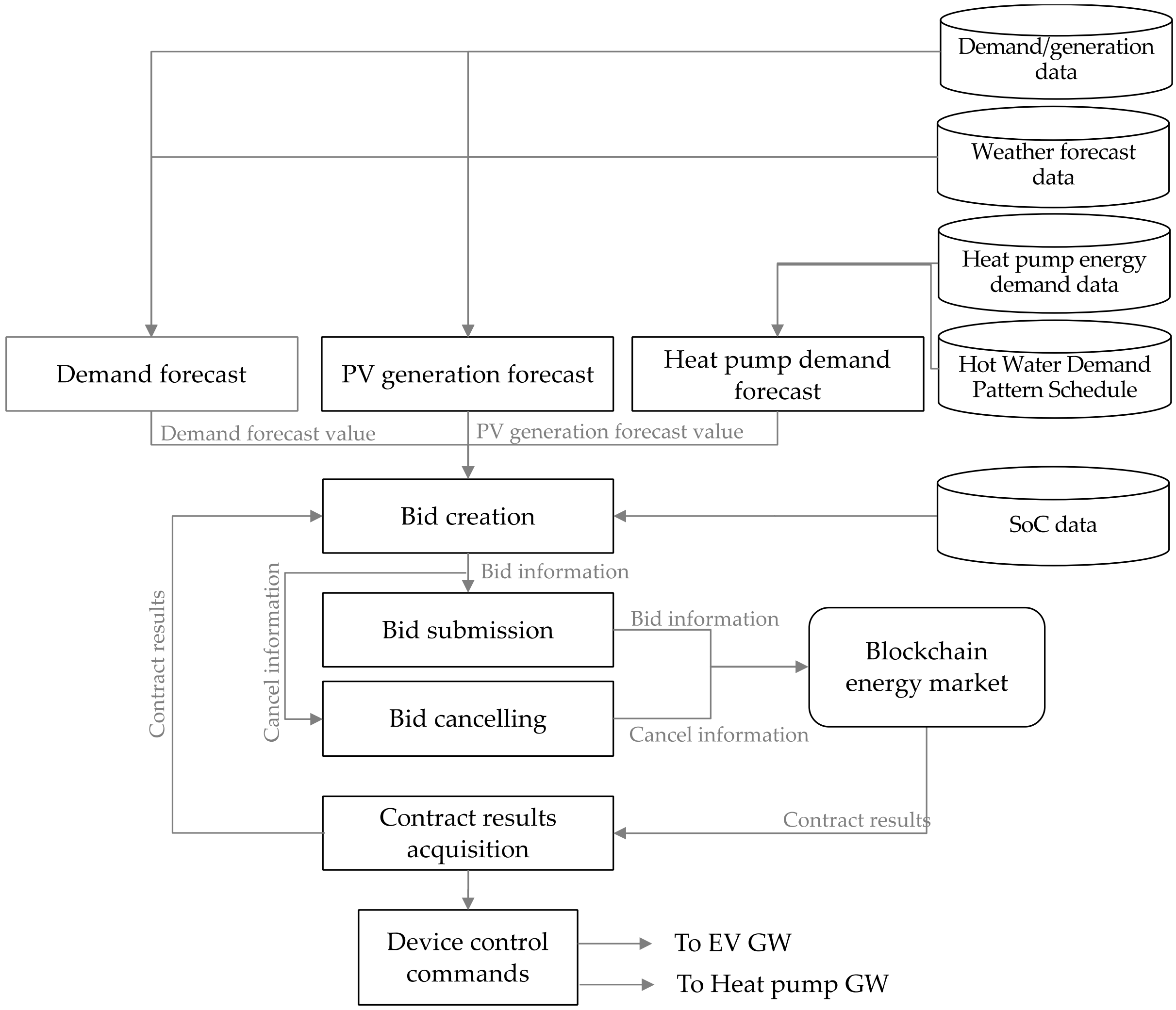

Figure 2. Calculation flow of bidding agent.

4. Bidding and Facility Operation Optimization

The bid creation function (bid creation) optimizes market bids and EV recharge/discharge based on forecasted demand, forecasted generation, SoC value, expected market contract price, and retail electricity price. The bid creation function has two modes: economy mode and green mode. In the economy mode, the optimization process aims to minimize costs by taking into account the revenues generated from electricity sales. It aims to maximize profits (minimize costs) by adjusting the timing and quantity of procurement from the market and the grid, and by controlling the shift times of its own EVs' recharge/discharge and its own heat pumps. In the green mode, the optimization process aims to minimize costs, including the revenue from electricity sales, while satisfying the target RE ratio set by the user as a constraint.

Equations (1)–(9) show the optimization equation for the economy mode. The basic equation is similar to that of Sagawa et al. [23], with the difference that a new heat pump electricity demand value $A^{h}_{t,k}$ is added. This is based on the value of the heat pump electricity demand forecast for no daytime shift, and the time of daytime operation shift is set to k.

Here, we provide an overview of each equation used in our model. Equation (1) represents the objective function, which aims to minimize the sum of power procurement costs and penalty amounts. The penalty term is introduced to prevent wasteful transactions that offset each other through buying and selling. For example, it serves to prevent scenarios where 100 kWh are purchased and 90 kWh are sold to procure 10 kWh.

Equations (2) and (3) impose constraints to ensure that the amount of energy traded in the market does not become negative. Equations (4) and (5) are constraints to ensure that the charging and discharging of electric vehicles (EVs) do not exceed their output limits. Equation (6) represents an energy balance constraint, ensuring that the balance between consumption, generation, selling, and purchasing is maintained. Equations (7) and (8) impose upper and lower limits on the SoC for EVs. Lastly, Equation (9) is a constraint used to determine the SoC for the next time step based on the previous time step's SoC and the charging/discharging amounts.

The expected operating hours and expected power consumption during daytime shift operation obtained from the heat pump API are taken into account to calculate the electricity consumption of the heat pump at each hour of the daytime shift operation. The following table shows the calculation of the power consumption of the heat pumps at different times of the day. The amount of electricity shifted during the daytime is newly added, and at the same time, the same amount of electricity shifted during the daytime is subtracted from the amount of electricity used during the nighttime, so that the daily electricity consumption of the heat pumps is the same with and without the daytime shift. This optimization is performed for each daytime shift time k of the heat pump, and the daytime shift time k at which the objective function is minimized and the value of the variable to be optimized at that time are adopted. This equation assumes prosumers, but mere consumers or generators can also be expressed as special cases of this equation. For example, to express consumers, it should always be $A_t^p = 0$ since they do not have PV. For example, to represent a generator, it should always be $A_t^d = 0$ since it has no demand. The penalty term C in (1) was introduced to prevent excessive transactions that would offset each other in buying and selling activities.

$$Minimize. \sum_{t=n}^{n+48\times 2} \left[P_t^m (B_t^m - S_t^m) + P_t^g B_t^g + C(B_t^m + S_t^m) \right] \tag{1}$$

$$\begin{gathered} Subject\ to. \\ B_t^m \geq 0 \end{gathered} \tag{2}$$

$$S_t^m \geq 0 \tag{3}$$

$$\frac{C_{max}}{2} \geq C_t \geq 0 \tag{4}$$

$$\frac{D_{max}}{2} \geq D_t \geq 0 \tag{5}$$

$$A_t^d + A_{t,k}^h - B_t^m - \left(A_t^p - S_t^m \right) + C_t - D_t - B_t^g = 0 \tag{6}$$

$$E_t \geq E_l \tag{7}$$

$$E_t \leq E_u \tag{8}$$

$$E_{t+1} = \begin{cases} \frac{E_t E_{cap} + C_t R_c - D_t R_{dis}}{E_{cap}} \ (if\ V_t = False) \\ E_t - F_t \ (if\ V_t = True) \end{cases} \tag{9}$$

Each variable is defined as follows.

B_t^m Amount of electricity to be purchased in the market at time t [kWh] (Optimization target)

S_t^m Amount of electricity to be sold in the market at time t [kWh] (Optimization target)

B_t^g Amount of electricity to be purchased from electricity retailers at time t [yen/kWh] (Optimization target)

C_t Amount of charge to the battery at time t [kWh] (Optimization target)

D_t Amount of discharge from the battery at time t [kWh] (Optimization target)

P_t^m Expected price at time t [yen/kWh] (estimated by each agent based on expected power generation)

P_t^g Retail price of electricity at time t [yen/kWh] (defined in advance)

A_t^d Expected electricity demand except heat pump at time t [kWh] (calculated by demand forecast)

$A_{t,k}^h$ Expected heat pump electricity demand with daytime shift start time k at time t [kWh] (calculated by heat pump demand forecast)

A_t^p Expected power generation at time t [kWh] (calculated by power generation forecast)

E_t Percentage of remaining charge of the battery at time t [%]

C_{max} Maximum charging output of the battery [kW] (6.7 [kW])

D_{max} Maximum discharge output of the battery [kW] (6.0 [kW])

E_l Lower limit of SoC [%] (set to 20 percent)

E_u Upper limit of SoC [%] (set to 90%)

E_{cap} Rated capacity of battery [kWh] (40 [kWh] was set.)

R_c Battery charging efficiency [%] (set to 86.6%, so that CHARGE_RATE × DISCHARGE_RATE = 75%)

R_{dis} Discharge efficiency of the battery [%] (set to 86.6%, the same as CHARGE_RATE)

F_t Expected energy consumption by driving at time t [kWh]. This is always set to 0 because the EV is not running in this demonstration experiment.

V_t The bool value indicating whether or not the EV is running at time t. It is always set to "false" because it is not run in this verification experiment.

m A subscript indicating that it is related to the market.

g A subscript indicating that it is related to the electricity retailers.

d A subscript indicating that it is related to the electricity demand.

p A subscript indicating that it is related to the power generation.

u A subscript indicating upper limit.

l A subscript indicating lower limit.

c A subscript indicating charge.

dis A subscript indicating discharge.

cap A subscript indicating battery capacity.

C Penalty term [yen/kWh]

P_t^m is the expected market price at time t. Similar to Sagawa et al. [23], this expected price is calculated based on each agent's forecast of all the PV generation in the market on the target day based on weather information, and the expected PV generation rate p_t which is the predicted PV power generation divided by the rated maximum output. In the experiment, parameters are set to A = 3, B = 5, C = 23 and D = 5.

$$P_t^m = C * exp\left(-A * {p_t}^B\right) + D \tag{10}$$

P_t^g gives the price list for each time. We used "Hapi-e-time R" of Kansai Electric Power Co., [33] as used in Sagawa et al. [23]. This price list is shown in Table 1.

Table 1. Table of Retail price of electricity.

Hour	Price [Yen/kWh]
7:00–10:00	22.89
10:00–17:00	26.33
17:00–23:00	22.89
23:00–7:00	15.20

(Equations (11)–(20)) show the optimization equation for green mode. Again, the basic equation is the same as in Sagawa et al. [23], but a new heat pump electricity demand value, $A^h_{t,k}$, is added. If a solution does not exist, the target RE ratio will be temporarily lowered by 5% in stages until a solution is found.

In this paper, we have built upon our previous work [23] to enhance the modeling and analysis of the home energy management system with RE, EVs, and heat pump water heaters. Although the optimization problems formulated in this paper may bear some resemblance to those in [23], we have introduced a notable modification by integrating a water heater into the model. This integration affects the constraints (6) and (17) by adding a constant and, more importantly, influences the overall energy consumption patterns and optimization results. By incorporating this refinement, we contend that our current paper presents a more comprehensive contribution to the field compared to [23], addressing the intricate interplay between various components of home energy management systems and their implications for energy trading strategies.

$$Minimize. \sum_{t=n}^{n+48*2}\left[P^m_t(B^m_t - S^m_t) + P^g_t B^g_t + C(B^m_t + S^m_t)\right] \tag{11}$$

$$Subject\ to.$$

$$\sum_t\left(A^p_t - S^m_t + B^m_t\right) \geq R_{re}\sum_t\left[A^d_t + F_t + C_t(1-R_c) + D_t(1-R_d)\right] \tag{12}$$

$$B^m_t \geq 0 \tag{13}$$

$$S^m_t \geq 0 \tag{14}$$

$$\frac{C_{max}}{2} \geq C_t \geq 0 \tag{15}$$

$$\frac{D_{max}}{2} \geq D_t \geq 0 \tag{16}$$

$$A^d_t + A^h_{t,k} - B^m_t - \left(A^p_t - S^m_t\right) + C_t - D_t - B^g_t = 0 \tag{17}$$

$$E_t \geq E_{ll} \tag{18}$$

$$E_t \leq E_{hl} \tag{19}$$

$$E_{t+1} = \begin{cases} \frac{E_t E_{cap} + C_t R_c - D_t R_d}{E_{cap}}\ (if\ V_t = False) \\ E_t - F_t\ (if\ V_t = True) \end{cases} \tag{20}$$

Each variable is defined as follows.
R_{re} Target RE ratio (set by user between 0~100%)
The other items are the same as in (1–9).

5. Demonstration Experiment

5.1. Configuration of the Demonstration Experiment

Table 2 lists the entities that will conduct transactions in the demonstration experiment. The demand side consists of four entities (HOME1~HOME4) and the supply side consists of one entity (PV1). All data used in this study are based on the actual power demand and generation amounts originating from these respective facilities.

Table 2. Composition of Consumers and Generators in the Demonstration Experiment.

Entities	Description
HOME1	Laboratory A with EV and Heat pump
HOME2	Laboratory B
HOME3	Laboratory C
HOME4	Laboratory D
PV1	Solar power generation

Table 3 describes the settings for each experimental period. The period is divided into phases 1~4, each of which has a different setting. By comparing the results of these phases, we aim to show that owning both EVs and heat pumps can increase the RE ratio by having EVs absorb excess electricity generation during the daytime and by having heat pumps shift their operation to the daytime, and to confirm how this approach affects costs. The goal of the project is to determine the impact on costs.

Table 3. Experimental phase and set values.

Experimental Phase	Period	Setting
Phase 1	2022/1/26–2022/2/1	Set only HOME1 to green mode and all others to economy mode.
Phase 2	2022/2/2–2022/2/8	All users are set to economy mode.
Phase 3	2022/2/9–2022/2/15	The daytime shift of the heat pump of HOME1 is not performed and set all users to economy mode.
Phase 4	2022/2/16–2022/2/22	The daytime shift of the heat pump of HOME1 is not performed, and only HOME1 is set to Green Mode, while all other users are set to Economy Mode.

5.2. Results of the Demonstration Experiment

Table 4 shows the electricity transaction volume and price for each user for each experimental phase. For Phase 1 of the experiment, HOME1 is the only user in green mode, so HOME1 actively purchases RE even if the price is high, with 107.3 kWh of PV1's 111.6 kWh purchased by HOME1. This indicates that HOME1 purchased approximately 96% of the total contracted amount. In addition, in Phase 2 of the experiment, all users were in economy mode, and in particular, the average contract price for HOME1, which owns an EV, was lower than that of other HOME2~4. By utilizing the charging and discharging of EVs, the trading entity can purchase power on the market when prices are low and charge EVs and discharge the power from the EVs when prices are high. Experimental phase 3 is the case where all users are set to economy mode without the heat pump daytime shift in HOME 1. This phase was prepared to understand the effect of the heat pump daytime shift. It can be seen from Tables 4 and 5 that Phase 2 and Phase 3 do not differ significantly in their results. Phase 4 is the case where the daytime shift of the heat pump in HOME1 is not performed, and only HOME1 is set to green mode and the rest are set to economy mode. The average contract price of HOME1 is about 4 yen/kWh lower in Phase 4 than in Phase 1. This can be attributed to the fact that the amount of PV generation during Phase 4 was higher than in Phase 1, and more PV generation flowed into the market. In fact, total PV generation in Phase 4 was 91.11 kWh compared to 75.19 kWh in Phase 1. Since bidding prices are determined by the amount of electricity generated, it is reasonable to assume that the price difference is due to the difference in total generation rather than to the effect of the daytime shift of the heat pump.

Table 4. Amount and price of electricity traded by each user per experimental phase.

Phase	Entities	Contract Amount [kWh]	Average Contract Price [Yen/kWh]
1	PV1	111.6	30.46
	HOME1	107.3	30.68
	HOME2	2.1	24.74
	HOME3	1.3	25.78
	HOME4	0.9	24.28
2	PV1	85.4	22.10
	HOME1	22.7	16.85
	HOME2	19.6	24.01
	HOME3	14.2	24.03
	HOME4	28.9	23.97
3	PV1	94.5	22.32
	HOME1	23.7	16.31
	HOME2	22.0	24.15
	HOME3	15.9	24.48
	HOME4	32.9	24.38
4	PV1	139.9	25.52
	HOME1	100.9	26.13
	HOME2	12.1	23.97
	HOME3	9.3	24.03
	HOME4	17.6	23.91

Table 5 shows the total demand, market purchases, RE ratio, etc. for each demand-side user for each experimental phase. This study focuses on an individual's preference for RE. Therefore, we focused on the RE ratio as an indicator for individuals, rather than for the community as a whole. In Phase 1, only HOME1 is in green mode, so it can be seen that its RE ratio is higher than the others at 37.68%. In Phase 2, all users are in economy mode, but only HOME1, which owns an EV, has a smaller RE ratio. This is due to the fact that the users only execute contracts when PV, which is even cheaper than the cheap electricity purchased from nighttime retailers, is available in the market during the daytime. Phase 3 did not differ significantly from Phase 2, and it was confirmed that in the case of the economy mode, there was not much change depending on whether the customer owned a heat pump or not. In Phase 4, it can be seen that the RE ratio of HOME 2~4 has increased compared to Phase 1. As mentioned earlier, this can be attributed to the fact that PV generation was higher during Phase 4 than in Phase 1. On the other hand, the RE ratio of HOME1 has decreased. This can be attributed to the fact that the demand for the daytime operation of the heat pump in Phase 1 was no longer met by RE due to the turning off of the daytime shift of the heat pump.

Table 5. RE ratio of each demand-side user per experimental phase.

Phase	Entities	Demand	Contract Amount in the Market [kWh]	Amount Purchased from the Grid [kWh]	RE Ratio [%]
1	HOME1	177.0	107.3	110.3	37.68
	HOME2	30.4	2.1	29.0	4.61
	HOME3	33.7	1.3	32.5	3.56
	HOME4	86.6	0.9	85.8	0.92
2	HOME1	201.5	22.7	186.7	7.34
	HOME2	35.6	19.6	25.9	27.25
	HOME3	34.5	14.2	24.9	27.83
	HOME4	86.6	28.9	66.8	22.86
3	HOME1	199.0	23.7	183.8	7.64
	HOME2	32.9	22.0	20.7	37.08
	HOME3	34.1	15.9	22.2	34.90
	HOME4	86.5	32.9	61.8	28.55
4	HOME1	200.8	100.9	140.8	29.88
	HOME2	33.4	12.1	26.3	21.26
	HOME3	35.2	9.3	28.7	18.47
	HOME4	87.2	17.6	75.3	13.65

5.3. Experimental Results of Phase 1

Figure 3 shows the execution price trends for all users in Phase 1 of the experiment. The dotted line shows the retail price (Table 1). Many contracts are due to HOME1 in green mode. HOME2~4 in economy mode are always executed at or below the retail price. This is because the economy mode procures electricity from the more economically advantageous side of the market and retail.

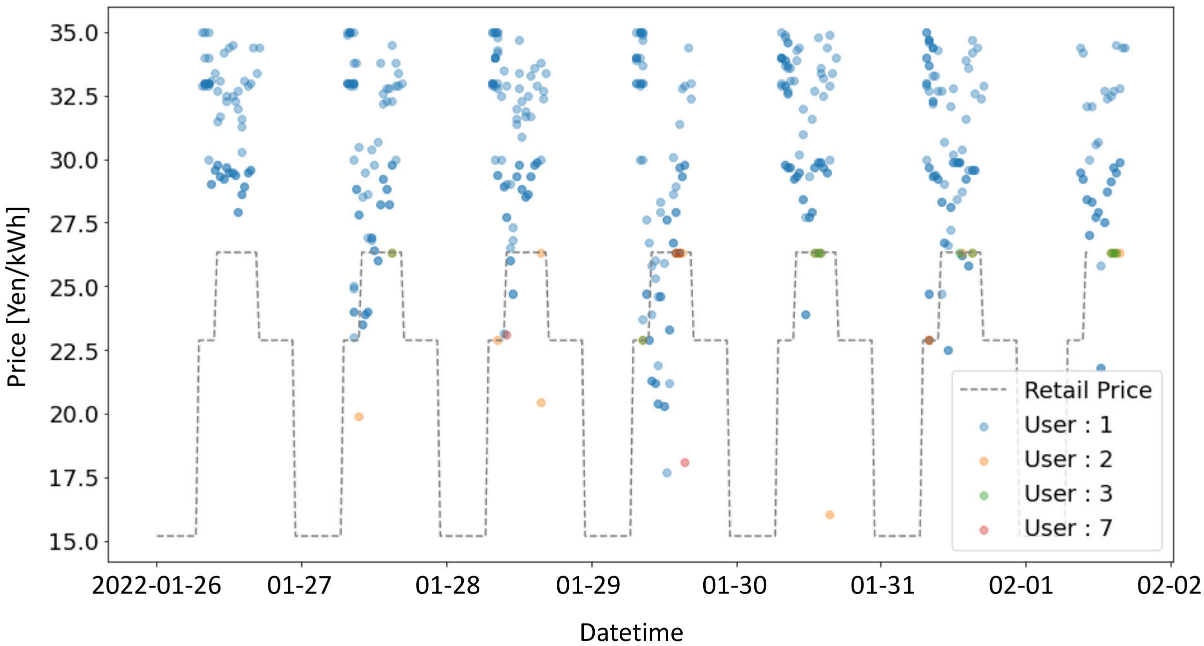

Figure 3. Trends in contract prices for all users in Phase 1 of the experiment.

Figure 4 shows the transition of electricity use by HOME1 on 28 January 2022. The blue line represents the electricity demand excluding the heat pump, the orange line shows the actual electricity demand of the heat pump, the green line indicates the predicted electricity demand of the heat pump, the red line displays the contracted amount in the market, the purple dashed line illustrates the charging amount, the brown dashed line denotes the discharging amount, and the light blue shaded area represents the SoC. HOME1 is in green mode, so it actively purchases electricity generated during the day to charge its batteries and uses the charged electricity from evening to night (increase/decrease in the light blue area). It can also be seen how the heat pump is operated during the day to provide its power with RE (rise in the orange line during the day).

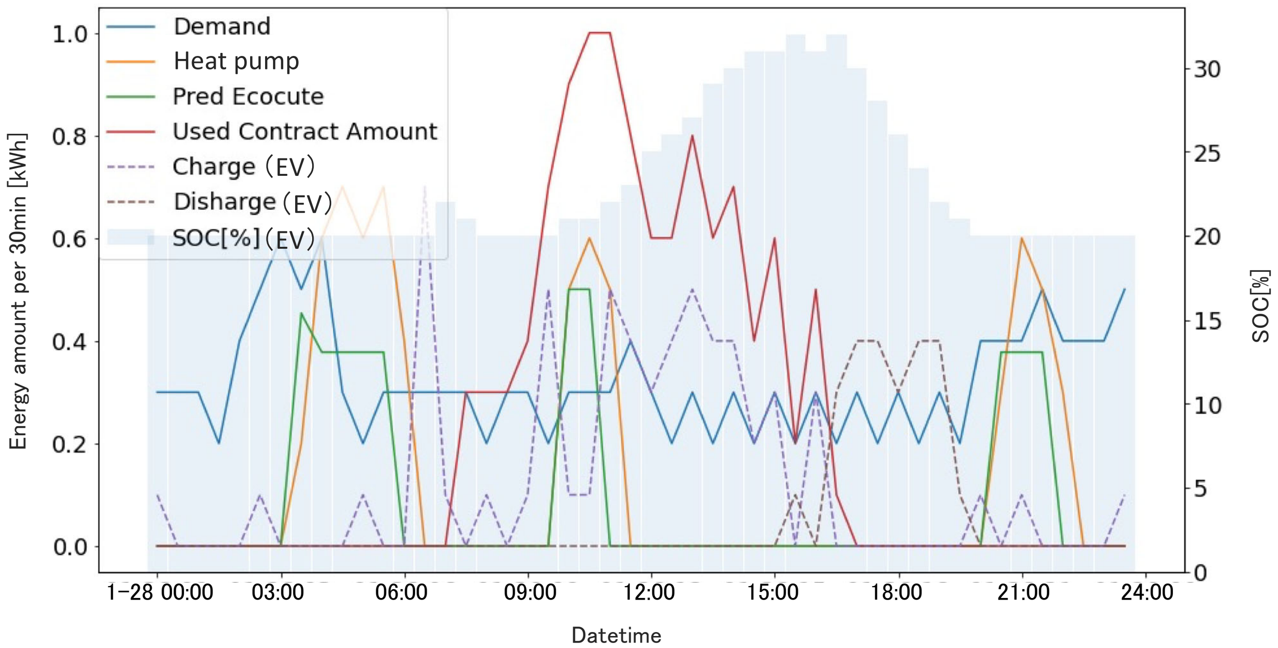

Figure 4. Electricity usage of HOME1 on one day during Phase 1 of the experiment.

5.4. Experimental Results of Phase 2

Since all users are in economy mode, they appear to be contracting at a price lower than the retail price. Figure 5 shows contract prices for all users in phase 2. In particular, since HOME1 owns an EV, it can take the strategy of storing inexpensive late-night power and using it during the daytime, so the contract price is not only lower than the retail price at the same time but is optimized so that the contract is only executed at a price that is economically advantageous, including charging and discharging inexpensive late-night power, so the contract price is particularly low. This is especially true for low contract prices.

In Figure 6, HOME1 is in economy mode, which means that the strategy is to store inexpensive electricity at night in the battery and use it during the day, and the optimization does not appear to result in a daytime shift of the heat pump.

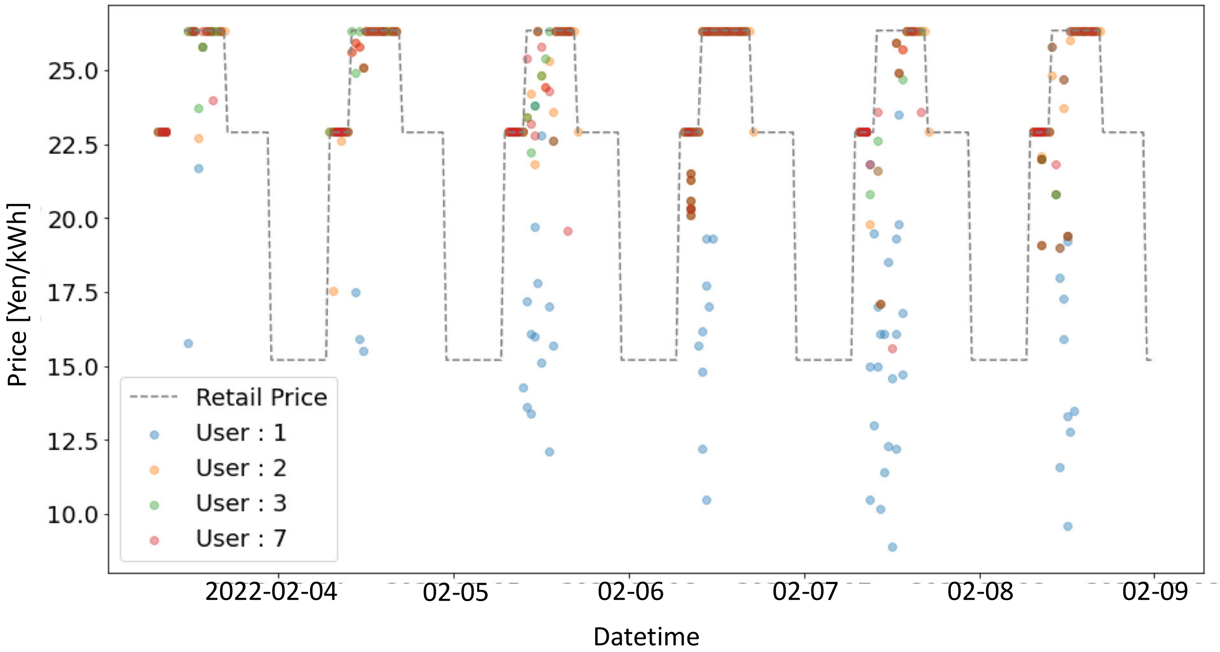

Figure 5. Trends in contract prices for all users in Phase 2 of the experiment.

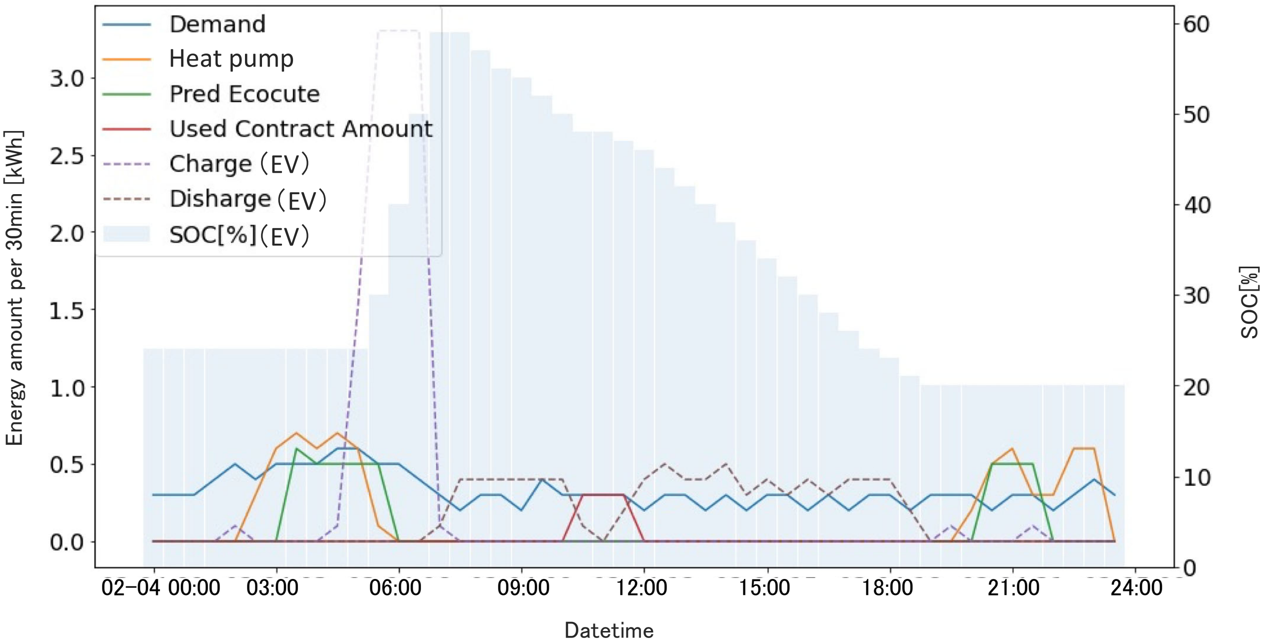

Figure 6. Electricity usage of HOME1 on one day during Phase 2 of the experiment.

5.5. Experimental Results of Phase 3

Figure 7 shows the price transition. Since all entities are in economy mode, it can be seen that they are moving in a similar manner to Phase 2.

In this phase, all entities are in economy mode, so inexpensive power at night is stored in batteries and used during the day. Therefore, it can be seen from Figure 8 that the situation is basically the same as in Phase 2. In addition, since there was a lot of PV generation on this day and inexpensive electricity was available in the market during the day, it can be confirmed that the electricity is stored in batteries during the day as well. In Phase 3, the heat pump is set to not shift during the daytime, but in Phase 2, the heat pump did not shift during the daytime, so the timing of the heat pump operation is also unchanged.

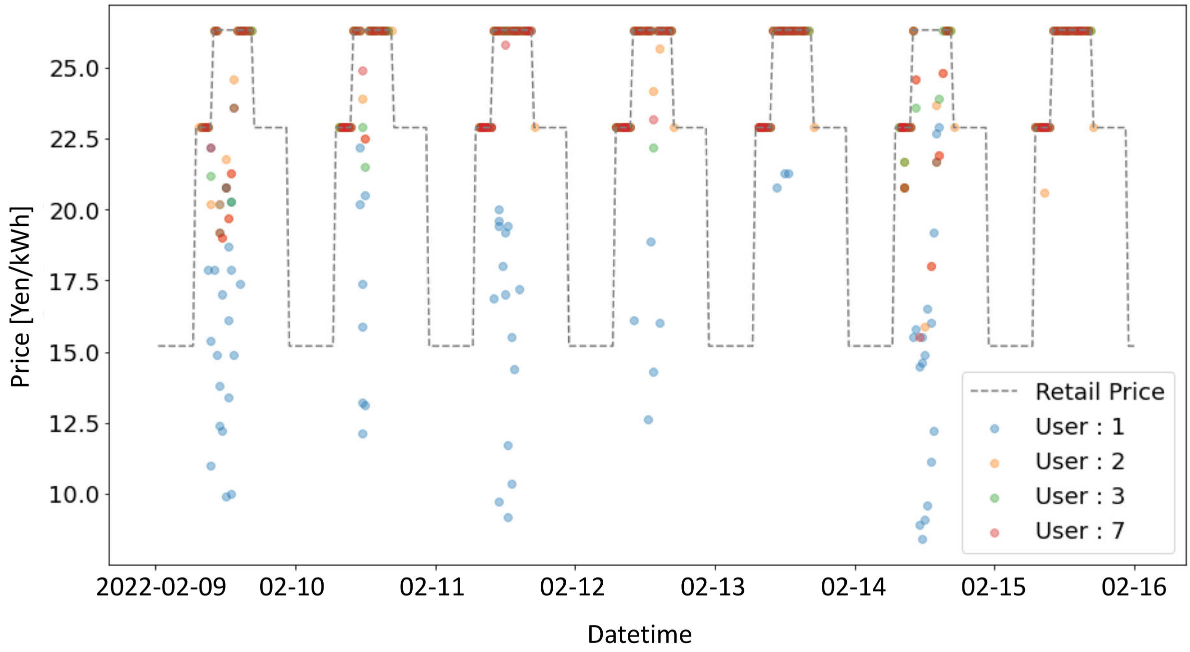

Figure 7. Trends in contract prices for all users in Phase 3 of the experiment.

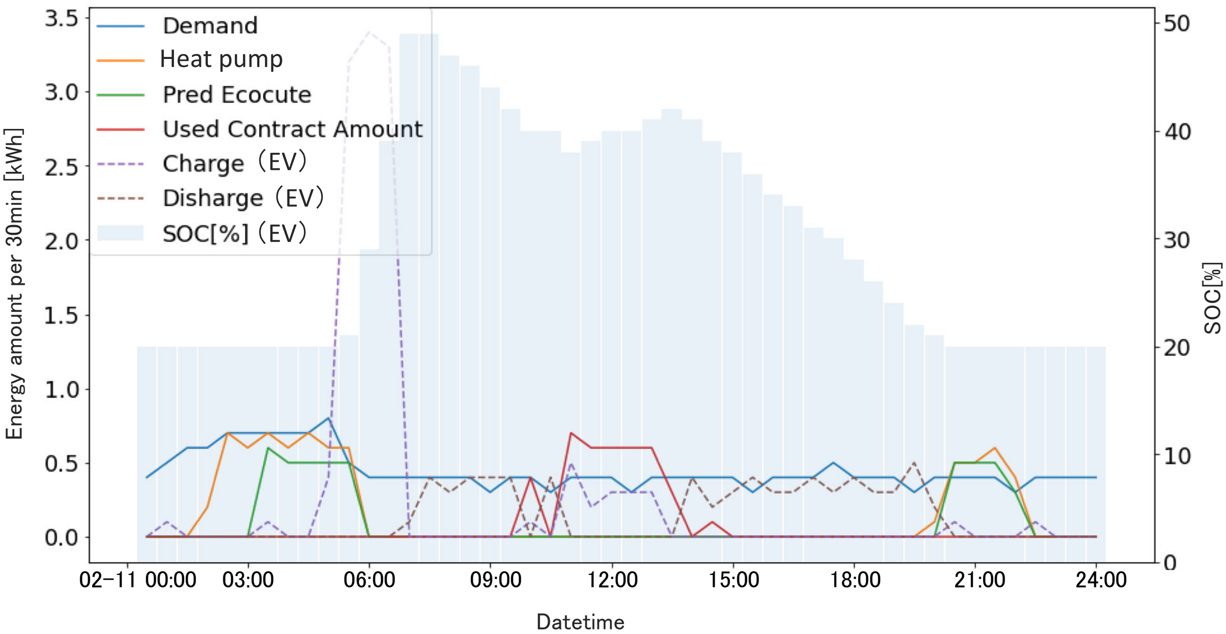

Figure 8. Electricity usage of HOME1 on one day during Phase 3 of the experiment.

5.6. Experimental Results of Phase 4

It is similar to Phase 1 in that the heat pump is set to not shift during the day and is in green mode, so it actively purchases RE during the day. The movement of contract price is also similar in Figures 3 and 9 of Phase 1. The difference between Phase 4 and Phase 1 is that the heat pump is not shifted during the daytime in Phase 4.

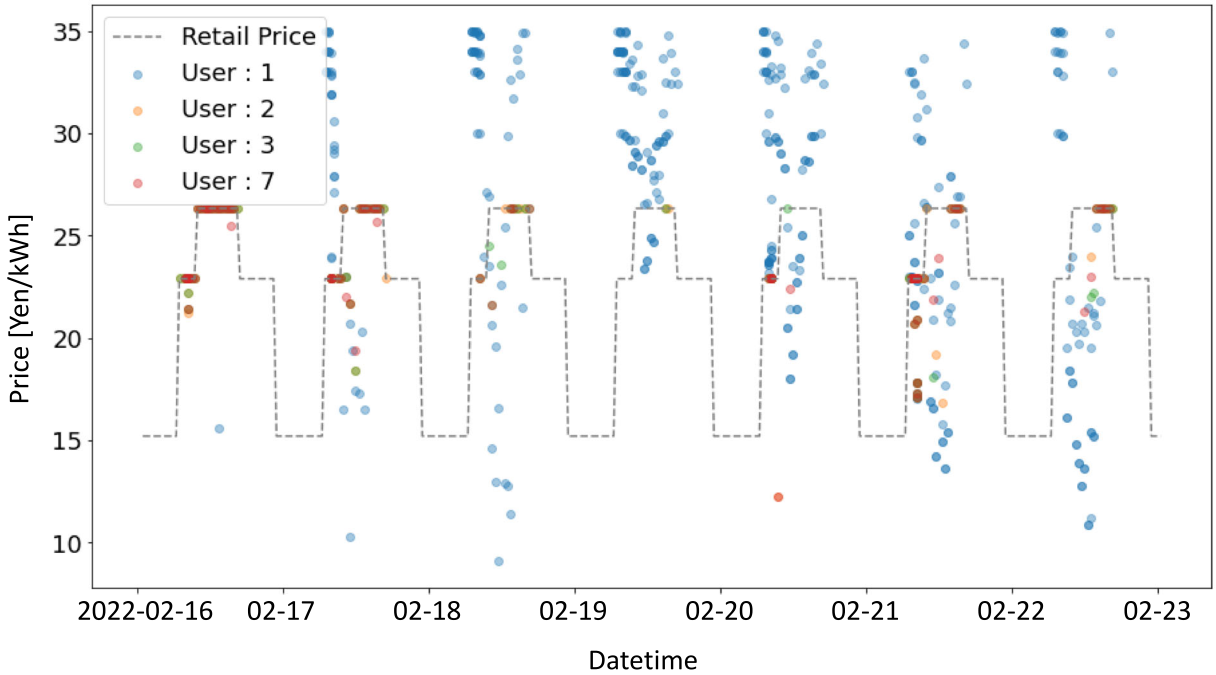

Figure 9. Trends in contract prices for all users in Phase 4 of the experiment.

Figure 10 shows the electricity usage of HOME1, and it can be seen that the heat pump is not running during the daytime. This is thought to have caused the RE ratio to be lower than in Phase 1. It can be said that in Phase 1, the RE ratio could be improved by shifting the heat pump operation to daytime compared to Phase 3.

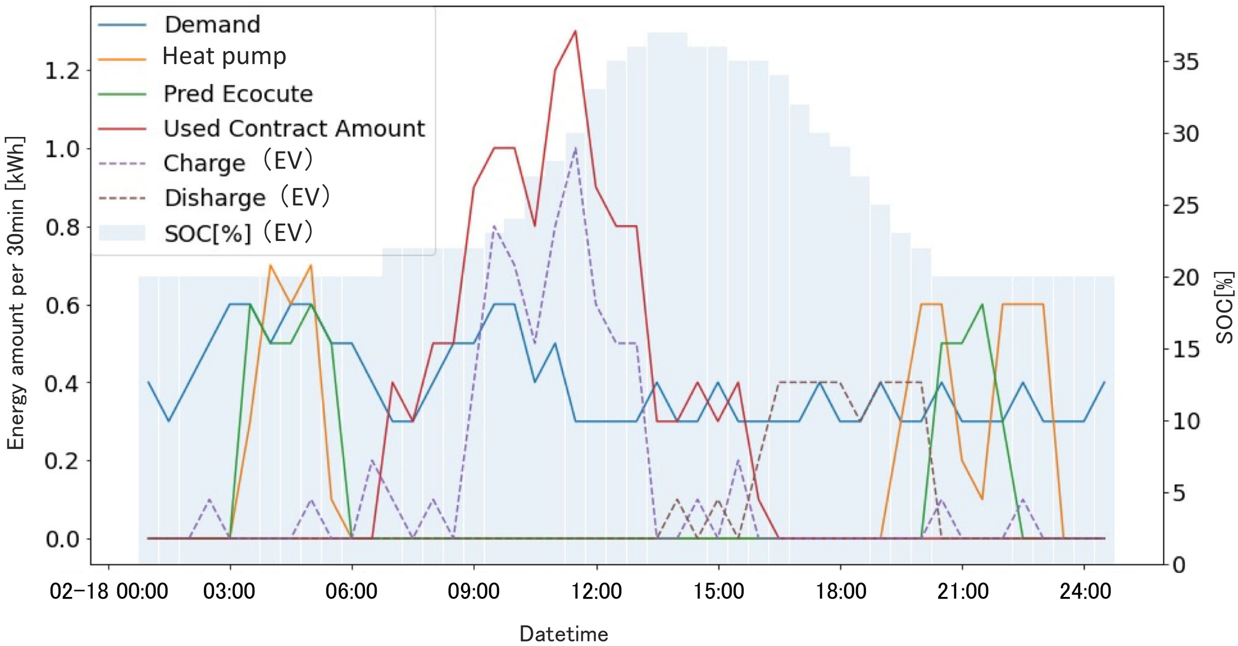

Figure 10. Electricity usage of HOME1 on one day during Phase 4 of the experiment.

5.7. Discussions

P2P trading allows consumers to make better use of surplus energy by proactively controlling their equipment while taking into account their own RE orientation. This study aimed to enable participants to automatically and optimally control their own devices in P2P transactions to reflect their own preferences.

In this experimental setup, the comparison of Phase 1 and Phase 4 showed that the RE ratio can be increased during green mode by optimizing the operating timing of the heat pumps. In the economy mode of Phase 2 and Phase 3, the benefit of optimizing the heat pump operation timing was not confirmed, but this was due to the low amount of PV generation in Phase 2 (the contract amount of PV in Phase 2 in Table 4 is small.) This may be because the amount of PV generation in Phase 2 was small (the contract amount of PV in Phase 2 in Table 4 is small), and there were not many times when the market price was low during the day, so the heat pumps could not be operated at those times. It should be added that in a demonstration experiment such as this, there is a limit to the comparison between phases because the weather conditions cannot be matched between phases. The emphasis of this experiment was on proof of concept, including the actual operation of the equipment.

6. P2P Energy Trading Simulation

Since it was practically difficult to conduct the demonstration experiment with various configurations in terms of the number and attributes of participants and distributed resources owned by each participant due to constraints such as the number of participants and procurement of resource equipment, a simulator was developed to verify various scenarios. In addition, the heat pump operation strategy in Demonstration Experiment 2 was limited to selecting from a limited number of options concerning what time to start heating during the daytime according to the operation plan created by the heat pump equipment based on its own internal logic. Therefore, it was not a truly efficient operation strategy. To solve this problem, we constructed a simulator as a mechanism to create operation plans on a zero-based basis according to the demand for hot water, and to evaluate potentials that are not affected by manufacturers' proprietary algorithms. Using such a simulator, we conducted experiments with various participant and resource configurations to simulate P2P electricity trading assuming a virtual community and evaluated differences in results depending on the configuration of participants' preferences and differences in the resources they possess. The agent and market system constructed in the demonstration experiment was reconstructed as a simulator. The bid creation function was developed based on Equations (21)–(34).

Equation (21) represents the objective function, which, similar to the one previously introduced, aims to minimize the energy procurement cost and penalty amount. Equation (22) is a constraint related to the energy balance of consumption, generation, purchase, and sale. Equation (23) is a constraint regarding the amount of available renewable energy for sale. Equation (24) is a constraint that represents the amount of energy that can be purchased when all the power in the market is derived from solar energy, preventing plans to purchase solar-generated power during non-generation periods. Equation (25) is a constraint related to the trading of grid-derived power. Equation (26) is a constraint used to calculate the next time step's state of charge (SoC) based on the previous time step's SoC and charging/discharging amounts. Equation (27) is a constraint used to determine the next time step's hot water storage amount based on the previous time step's hot water storage amount, additional hot water amount, and used hot water amount. Equations (28) and (29) are constraints related to the trading amount in the market. Equation (30) sets the upper and lower limits for the charging/discharging amount per 30 min. Equations (31) and (32) set the upper and lower limits for the SoC. Equation (33) sets the lower limit for hot water storage amount. Equation (34) is valid only during the RE mode and serves as a constraint to ensure that the RE ratio exceeds the desired value.

$$Minimize. \sum_{t=n}^{n+48*2} \left[\begin{array}{c} P_t^{mr}(B_t^{mr} - S_t^{mr} + C_t^{mr}) + P_t^{mb}\left(B_t^{mb} - S_t^{mb} + C_t^{mb}\right) + \\ P_{buy,t}^{g} B_t^{g} - P_{sell,t}^{g} S_t^{g} + C\left(B_t^{mr} + S_t^{mr} + B_t^{mb} + S_t^{mb}\right) \end{array} \right] \tag{21}$$

$$Subject\ to.$$

$$A_t^d + A_t^h - B_t^{mr} - B_t^{mb} - A_t^p + S_t^{mr} + S_t^{mb} + C_t - C_t^{mr} - C_t^{mb} - B_t^g + S_t^g = 0 \tag{22}$$

$$S_t^{mr} - C_t^{mr} \leq A_t^p \tag{23}$$

$$B_t^{mr} \leq kR_t \tag{24}$$

$$S_t^{mb} - C_t^{mb} - B_t^{mb} \leq E_{cap}(E_t - E_{ll}) \tag{25}$$

$$E_{t+1} = \begin{cases} \frac{E_t E_{cap} + C_t}{E_{cap}} (if\ V_t = False) \\ \frac{E_t E_{cap} - F_t}{E_{cap}} (if\ V_t = True) \end{cases} \tag{26}$$

$$W_{t+1}^h = W_t^h + \frac{A_t^h * K_{COP} * K_{kWhtoJ}}{K_s * (T^h - T^g)} - \frac{W_t^d \left(T^d - T^g\right)}{T^h - T^g} \tag{27}$$

$$B_t^m \geq 0 \tag{28}$$

$$S_t^m \geq 0 \tag{29}$$

$$\frac{C_{max}}{2} \geq C_t \geq -\frac{C_{max}}{2} \tag{30}$$

$$E_t \geq E_{ll} \tag{31}$$

$$E_t \leq E_{hl} \tag{32}$$

$$W_t^h \geq W_{ll} \tag{33}$$

$$\begin{gathered} if\ RE\ mode \\ \sum_{t=n}^{n+48*2} \left(A_t^p - S_t^{mr} + B_t^{mr} + C_t^{mr} - S_t^{mb}\right) \geq R_{re} \sum_{t=n}^{n+48*2} \left(A_t^d + A_t^h\right) \end{gathered} \tag{34}$$

B_t^{mr} Amount of electricity of RE origin purchased in the market at time t [kWh] (Optimization target).

B_t^{mb} Grid-derived electricity purchased in the market at time t [kWh] (Optimization target).

S_t^{mr} Electricity of RE origin sold in the market at time t [kWh] (Optimization target).

S_t^{mb} Amount of grid-derived electricity sold in the market at time t [kWh] (Optimization target).

B_t^g Amount of electricity purchased from electricity retailers at time t [yen/kWh] (Optimization target).

S_t^g Amount of electricity sold to electricity retailers at time t [yen/kWh] (Optimization target).

C_t Amount of charge/discharge to battery at time t [kWh] +: charge −: discharge (Optimization target).

A_t^h Electricity consumption of heat pump at time t [kWh] (Optimization target).

A_t^d Estimated demand at time t [kWh] (calculated by demand forecast).

A_t^p Estimated electricity generation at time t [kWh] (calculated by electricity generation forecast).

C_t^{mr} Amount of electricity of RE origin purchased and sold in the market at time t that has already been contracted through past bids [kWh] +: amount purchased, −: amount sold.

C_t^{mb} Amount of grid-derived electricity purchased and sold in the market at time t that has already been contracted through past tenders [kWh] +: Purchased, −: Sold.

R_t Predicted solar radiation [MJ/m^2].

k Constant that allows the purchase of electricity derived from RE from the market only when solar radiation is available.

E_{cap} Rated capacity of batteries [kWh].

E_{ll} Lower limit of SoC [%].

E_{hl} Upper limit of SoC [%].

E_t Remaining charge of the battery at time t (SoC).

F_t Expected energy consumption by driving at time t [kWh]. In this simulation, the value is always set to 0 because the EV is not driving.

V_t The bool value indicating whether or not the EV is running at time t. In this demonstration experiment, the value is always set to "false" because the EV is not driving.

W_t^h Volume of hot water stored in the heat pump thermal storage tank at T^h °C at time t [L].

T^h Temperature of stored hot water in the heat pump storage tank [°C].

W_t^d Hot water demand at time t [L].

T^d Hot water temperature when using hot water supply [°C].

T^g Temperature of tap water [°C].

K_s Specific heat of water [J/L-K] 4186.

K_{COP} COP of heat pump (=heat quantity [J]/energy consumption [J]).

K_{kWhtoJ} Constant for converting kWh to J. 3.6×10^6.

P_t^{mr} Expected price of RE-derived electricity in the market at time t [yen/kWh] (estimated by each agent based on expected solar radiation).

P_t^{mb} Expected market price of grid-derived electricity at time t [yen/kWh].

P_t^g Retail price of electricity at time t [yen/kWh].

C_{max} Maximum battery charge/discharge output [kW].

C Penalty term [yen/kWh].

In this study, we have formulated two optimization problems to model the automatic bidding strategy for home energy management systems with RE, EVs, and heat pump water heaters. It is important to note that both of these optimization problems are linear programs. Linear programming is a mathematical optimization technique that is widely used to find the best possible solution to problems that can be represented by linear relationships. Linear programs are relatively easier to solve and have efficient algorithms, such as the simplex method, available for finding optimal solutions. We have employed the PuLP library, a Python-based linear programming library, to solve the linear programs formulated for the automatic bidding strategy. For our analysis, we used the default PuLP solver, which is the open-source COIN-OR Linear Programming (CLP) solver. The CLP solver is a robust and high-performance linear programming solver, making it suitable for tackling the optimization problems in our proposed approach.

Bid Creation of the Simulator

We assume a case in which a large number of houses have photovoltaic power generation facilities. This is in consideration of the fact that the Tokyo Metropolitan Government will require new buildings with a total floor area of less than 2000 m^2 to be equipped with RE facilities such as solar power generation starting in April 2025, targeting house builders and other businesses with a certain annual total floor area of supply in Tokyo. The purpose of this study is to confirm the effectiveness of these distributed resources in utilizing RE in the community under P2P transactions by varying the ownership rates of EVs and heat pump water heaters of individual entities. Table 6 shows the resource retention scenarios for which the resource retention rates of the entities were set. In all scenarios, the ownership rate is set to 75%, assuming a situation where PV is widely deployed. Resource Ownership Scenario One assumes a 20% EV/heat pump ownership rate. The current ownership rate of EVs is 1.51%, heat pumps 19% (owner-occupied in Tokyo) and 2% (renters in Tokyo), so a 20% ownership rate is a large value, but it is the closest to the future assumed in this scenario. Resource Ownership Scenario Two assumes a future in which the EV/heat pump ownership rate is further increased to 50%. Resource Ownership Scenario Three is a future scenario in which the EV/heat pump ownership rate is increased to 80%. These resource ownership scenarios are applied to a community of 20 households. The demand data utilized in this study was obtained from actual household consumption.

Table 6. Equipment ownership scenario.

Equipment Ownership Scenario	Percentage of PV Owned	Percentage of EV Owned	Percentage of HP Owned
1	75%	20%	20%
2	75%	50%	50%
3	75%	80%	80%

The agent system, which represents the individual entities, will be able to make decisions on resource operation, taking into account the overall situation. This is expected to enable the effective use of RE generated by the community as a whole. In this section, we evaluate the difference in energy use by the community as a whole depending on the presence or absence of the coordination mechanism.

Figure 11 shows the difference in the degree of load on the grid for the entire community depending on the resource ownership scenario with and without P2P trading. The two indicators of the community's overall load on the grid are the rate of inflow of RE generation into the grid and the percentage of grid-derived electricity consumed, which are plotted on the vertical and horizontal axes, respectively. The inflow rate of renewable electricity into the grid is defined as the amount of PV electricity sold to the grid/the total amount of PV electricity generated, and the consumption rate of grid-derived electricity is defined as the amount of electricity purchased from the grid/the total amount of electricity consumed. In other words, the inflow rate of RE into the grid is the proportion of RE generated by the community as a whole that is not fully consumed by the community and is taken back by the power grid. Currently, the handling of RE surpluses is an issue, as RE output is curtailed to stabilize the power system, and a small value is desirable from the perspective of stabilizing the power system. The consumption ratio of grid-derived electricity is also a desirable indicator from the perspective of effectively using RE in the community. In the figure, $\bullet$ represents the case with a cooperative mechanism and $\times$ represents the case without a cooperative mechanism, and the color indicates the resource ownership scenario. In both resource ownership scenarios, the introduction of the cooperative mechanism reduces two indicators: the inflow rate of RE into the grid and grid-derived electricity. In other words, the cooperative mechanism allows the community to consume more of the RE generated within the community and to reduce the amount of electricity procured from external sources. In addition, the two indices are smaller in the scenarios with higher resource ownership, indicating that the proportion of resources owned by the community has a significant impact on the differences among the ownership scenarios. The difference between the scenarios with and without a cooperative mechanism within the ownership scenarios shows that the difference between the scenarios with and without a cooperative mechanism is smaller in the scenarios with higher ownership ratios. This indicates that the higher ownership of demand-shifting resources such as storage batteries, EVs, and heat pumps enables the individual entities to consume RE to some extent even without a cooperative mechanism, but the introduction of a cooperative mechanism still reduces the two indicators more. In addition, especially in Resource Ownership Scenario Three, both the EV ownership rate and the heat pump ownership rate are extremely high at 80%, and it is considered that it will take a considerable period of time to reach this point. In addition to the installation of solar power generation facilities, the introduction of demand-shifting equipment such as storage batteries, EVs, and heat pumps and their appropriate control systems is required.

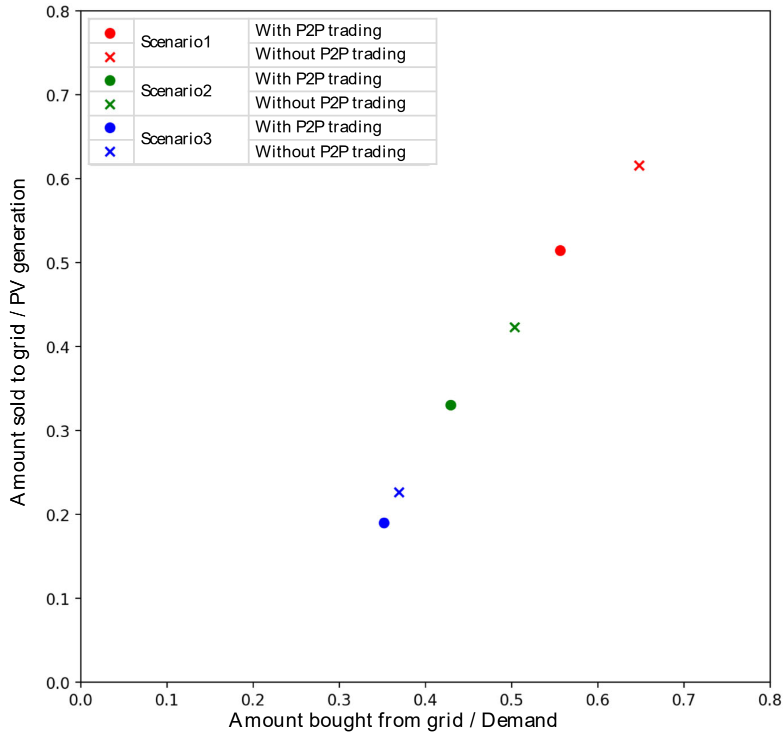

Figure 11. Differences in the degree of load on the electricity system for the entire community with and without P2P trading based on resource ownership scenarios.

Table 7 shows the community-wide demand and supply for the six patterns in Figure 11. In particular, in Scenario 3 with P2P, it can be seen that only 480 kWh of the 2517 kWh of electricity generated by the PV goes to the grid, and the rest can be consumed within the community. It can also be seen that the amount of electricity purchased from the grid is thereby reduced.

Table 7. The supply and demand of electricity throughout the community.

Scenario	with or without P2P	PV Generation [kWh]	Demand [kWh]	Amount Sold to Grid [kWh]	Amount Bought from Grid [kWh]	Amount Sold to Grid ÷ PV Generation [%]	Amount Bought from Grid ÷ Demand [%]
Scenario1	With	2517	2755	1295	1533	51.5%	55.6%
	Without	2517	2743	1551	1777	61.6%	64.8%
Scenario2	With	2517	2954	832	1269	33.0%	42.9%
	Without	2517	2924	1065	1472	42.3%	50.3%
Scenario3	With	2517	3143	480	1105	19.1%	35.2%
	Without	2517	3086	571	1140	22.7%	36.9%

The fact that the consumption rate of RE is increased and the amount of electricity procured from the power grid can be reduced through this cooperative mechanism is due to the fact that consumers without RE generation equipment can use RE through the flexibility of surplus generation, and that the community as a whole can coordinate their use of RE. This effect is due to the fact that when surpluses occur, consumers actively utilize demand-shifting equipment to absorb the excess power. Figures 12 and 13 show the results of electricity use by the entire community without the coordination mechanism and with the coordination mechanism, respectively. The green line indicates PV power generation, the yellow area indicates power consumption by heat pumps, the light blue area indicates power consumption by non-heat pumps, the brown area indicates discharge from EVs, and the purple area indicates charge to EVs. The timing of the heat pump operation and the EV recharge/discharge timing change depending on the presence or absence of the coordination mechanism. In Figure 12, the individual entities are planning the operation of their resources in a closed manner, so the heat pumps are often operating and the EVs are storing electricity even when there is no surplus electricity in the community, while in Figure 13, the individual entities are planning to procure surplus electricity through the market. In Figure 13, we can see that the demand shift reflects the whole community situation, such as running heat pumps and charging EVs when there is a surplus of electricity in the community, because the individual entities plan the operation of resources considering the procurement of surplus electricity through the market. The system is flexible in its charging plan according to the situation.

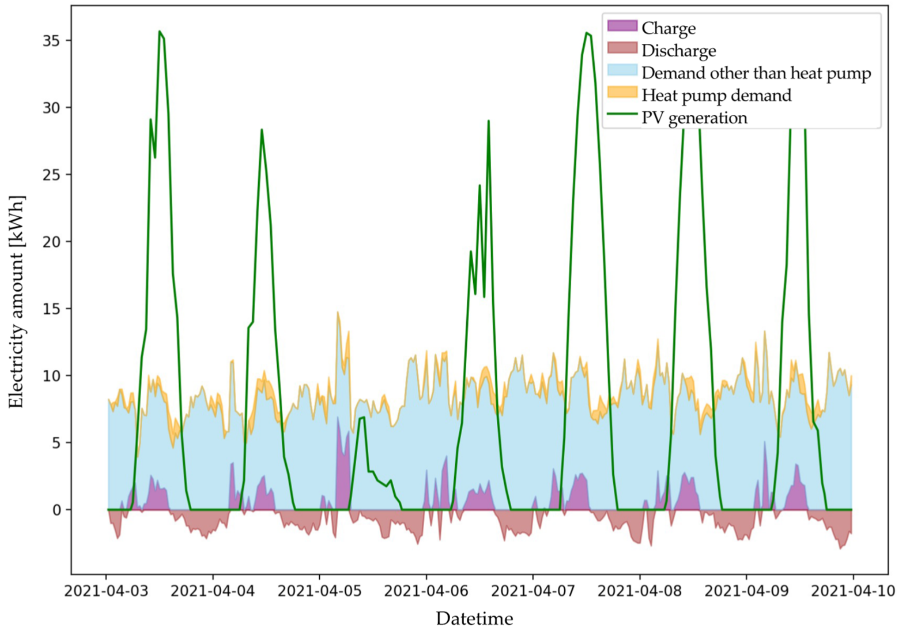

Figure 12. Demand changes for one week without P2P transactions (Scenario 1).

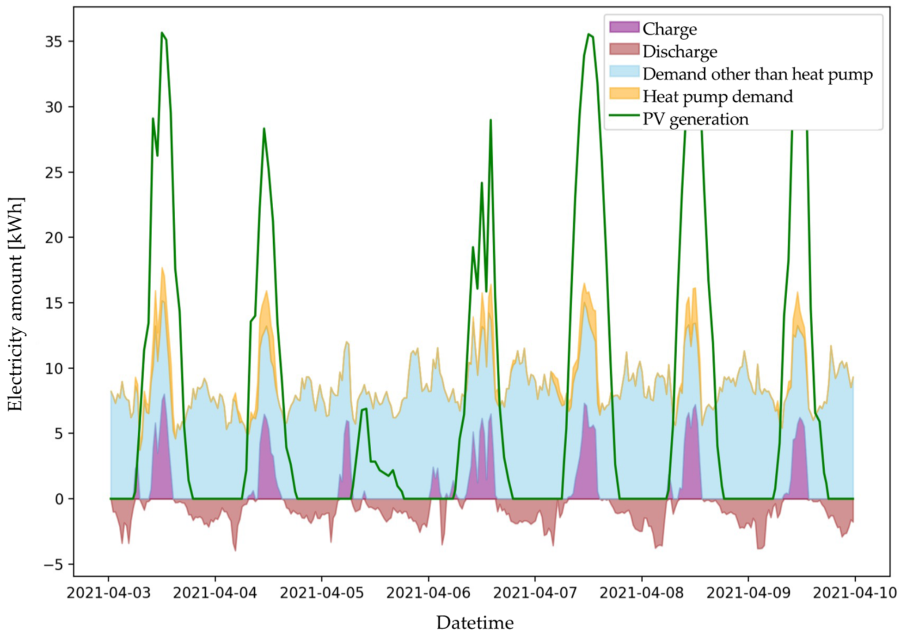

Figure 13. Demand changes for one week with P2P transactions (Scenario 1).

7. Conclusions and Future Work

7.1. Conclutions

In this study, we developed an agent system that automatically performs electricity transactions on behalf of users, assuming an electricity P2P trading market. We developed a bidding agent system that not only performs bidding based on the user's assets such as heat pump water heaters, EVs, and solar power generation plus the user's electricity demand, but also performs bidding based on the user's preferences for RE, enabling power transactions tailored to individual users. The main novelty of this study is that, in contrast to the automatic bidding agent system proposed in the existing study [23] that takes into account the charging and discharging of EVs and users' preferences for RE, we proposed a mechanism to optimize the system by including the operating timing of heat pumps as part of controlling demand itself.

We also conducted a demonstration experiment using the proposed model. The following results were obtained in the demonstration experiment.

- The demonstration experiment confirmed that users in economy mode who own an EV can lower the average contract price.
- In the case of economy mode, there was no significant difference depending on whether the user owned a heat pump or not. This is thought to be because the economic benefits of the daytime shift did not arise due to the low power generation in Phase 2.
- In the case of green mode, it was confirmed that optimizing the daytime shift of a heat pump can improve the RE ratio while reducing the unit cost of electricity compared to the case where a heat pump is not shifted during the daytime.

Finally, we constructed a P2P trading simulator based on the agent algorithm developed in the demonstration experiment, and conducted a P2P transaction simulation assuming a future in which photovoltaic power generation facilities are widely used and showed that a cooperative mechanism of P2P transactions can improve the utilization ratio of RE for the entire community. The results show that the P2P trading cooperative mechanism can improve the ratio of RE use in the community as a whole. In particular, we showed that it is important to increase the share of demand-shiftable resources such as EVs and heat pumps in order to improve the utilization ratio of RE.

7.2. Future Work

One of the potential areas for future research is to address the uncertainty in RE generation, which is not explicitly considered in our current model. Incorporating stochastic optimization techniques could be an effective way to handle such uncertainties. By formulating the problem as a stochastic optimization, we could account for the variability and unpredictability of RE generation, leading to more robust and adaptive bidding strategies. Additionally, investigating the impact of various forecasting methods on the proposed approach would provide valuable insights into the performance and reliability of the automatic bidding strategy under uncertain conditions. We believe that addressing these aspects would significantly enhance the applicability of our work in real-world settings with uncertain RE generation.

Although the present study demonstrates the effectiveness of our proposed algorithm in the context of peer-to-peer energy trading with heat pumps, we have not yet assessed its scalability. In future work, we plan to investigate the performance of our algorithm when applied to larger-scale energy systems, involving a greater number of participants and more diverse energy sources. This analysis will help us understand how our approach performs in more complex energy networks and identify any potential challenges or limitations. By addressing scalability, we aim to contribute further to the development of efficient and sustainable energy management solutions that can be widely adopted in various energy market scenarios.

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Conflicts of Interest: The authors declare no conflict of interest.

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