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Introducing user preferences for peer-to-peer electricity trading through stochastic multi-objective optimization ☆

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ABSTRACT

Peer-to-peer electricity markets are dedicated markets that enable the direct participation of small electricity end-users in energy trading activities. They are seen as a promising alternative that can empower end-users and accelerate the energy transition, by researchers, business developers, and legislators. Moreover, they can include environmental, social, or altruistic preferences that are relevant to end-users, in addition to the economic perspective. Such preferences are sometimes included in the modeling of P2P markets in the existing literature, but the assumptions behind them are rarely validated in practice. To investigate the desired attributes and preferences of end-users to participate in P2P markets, an online survey including a discrete choice experiment was conducted in The Netherlands The results of the survey are used to design a P2P electricity market with product differentiation. The participants in the market are residential end-users that are equipped with a home energy management system that can control some of the household appliances and automate the decision-making process for participation in the market. To facilitate this, a multi-objective stochastic optimization model is presented that incorporates results from the discrete choice experiment and real smart-meter measurements. The case study results demonstrate user preferences' influence on market outcomes.

1. Introduction

1.1. Background and motivation

User-centric energy markets are dedicated markets that enable the direct participation of (small) end users, who otherwise would not have direct access to existing energy markets. Such markets include local and community energy markets (LEM & CEM) as well as peer-to-peer (P2P) energy markets [1,2]. There is a significant and continuously growing body of literature that studies different aspects of the design and implementation of such markets. Also, a number of pilot projects have been established around the world to evaluate the practical feasibility and implementation of user-centric markets [2]. Moreover, their development is supported by national and international legislation, such as the European Directive on the internal electricity market which aims for active inclusion and involvement of the electricity end-users in the energy transition [3].

From the perspective of small residential end-users, the electrification of heating and mobility increases their reliance on electricity and its importance as an energy carrier. Furthermore, the interest in the installation of distributed energy resources (DERs), such as PV and battery systems continues to rise, whereas the subsidies that support these activities are being phased out. Considering these developments, P2P electricity markets, which are the focus of this paper, represent a viable alternative that empowers end-users and supports the energy transition. The deployment of smart meters that enable granular tracking of electricity prosumption and the existence of commercial home energy management systems (HEMS) that can control household appliances can facilitate the development of P2P markets from a technological point of view.

The development of P2P markets has therefore been an active area of research in recent years, with the initial works in [4,5], highlighting the benefits of such electricity markets for end users and for the electrical system in general. A vast area of research focuses on the design and modeling of P2P markets. Methods from mathematical optimization, especially decomposition techniques that are suitable for the distributed nature of P2P markets are vastly used, mostly for convex problem formulations [6,7]. Methods from bilateral negotiation [8,9] and auction theory [10,11] have also been used as well as game

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theory [12,13] that accounts for the possible strategic behavior of participants. A majority of the earlier studies demonstrate proof of concept and use deterministic models as identified in the recent review paper [14]. Even in the presence of sophisticated forecasting algorithms, the consumption and production of individual users are very stochastic and to a great degree uncontrollable. Therefore, a properly designed P2P market should also consider the inherent uncertainty of commitments that are made before the time of delivery and possible deviations and recourse actions concerning this uncertainty. More recent studies focus on incorporating uncertainty in the models [15–19]. Moreover, little attention is paid to the interaction of new P2P market models and the existing retail market, which is relevant for their large-scale deployment [2].

Large body of literature dedicated to P2P electricity markets, focuses on the economic aspects of these markets and maximizing the financial benefits for the participants or related stakeholders. However, by placing the focus solely on the financial benefits [10,20,21], which may be relatively small and thus not sufficient motivation for participation, other reasons for the establishment and participation in these markets are being neglected. In addition to financial benefits, P2P energy markets can offer product and service differentiation that currently cannot be found through traditional channels [22]. This may include preferences for the type of electricity traded [7], its location of origin [23], or the choice of a specific trading partner [24]. Moreover, these markets offer a unique possibility to consider the social dimension and enable altruistic behaviors, such as providing electricity for free [7,24]. Thus, it is important to evaluate which attributes are desirable to end-users in the first place. At the same time, it is relevant to determine the end-user preferences and willingness-to-pay (WTP) for these attributes. Afterward, these attributes can be incorporated as different products in P2P energy markets.

From an implementation point of view, the design of the participation and communication structure that will enable end-users to get involved in P2P markets is another important factor that can significantly influence the success of their implementation and the level of consumer engagement [25]. Decision support systems that can incorporate feedback from end-users, but do not require input on a regular basis can overcome the challenges of active user participation [11]. Decision support systems should also be able to incorporate user preferences and automate the control actions, which can be done if they are combined with a Home Energy Management System (HEMS) [26].

The objective of this paper is to address the following two questions regarding the integration of end-users in P2P electricity markets. First, the question of eliciting user preferences is addressed and designing a P2P market that supports product differentiation. Second, the question of modeling an automated decision support tool for participation in such a market on behalf of end users is analyzed. The goal is that model should be able to incorporate user preferences and deal with multiple and somewhat conflicting objectives, as well as consider the underlying uncertainty of the load and consumption in a household and the P2P market prices.

1.2. Related work

In this section, a review of the relevant studies related to the relevant aspects of this paper, namely modeling and elicitation of user preferences for P2P electricity trading, as well as considering uncertainty and multiple objectives in the HEMS modeling is presented.

In the existing literature, the modeling of user preferences in P2P electricity markets and market clearing has been addressed in different ways. An additional utility that is expressed in monetary terms is used in [7] to model preference for purchasing renewable, i.e. green energy, and for supplying low-income households with subsidized, and consequently cheaper electricity. Trading preferences have also been modeled through bilateral coefficients that can serve for product differentiation in the P2P market models [27] or develop different bilateral trading strategies [20]. Price-based prosumer preference coefficients are used to model the quadratic objective functions of prosumers in intra-day transactive markets [18]. Preferences that are determined by the distribution system operator (DSO) based on the electrical distance between the market participants in the distribution network are used in [28]. However, these preferences actually reflect the potential benefits for the DSO and do not necessarily reflect the wishes of participating peers. Thus, studies that include user preferences in their models, focus solely on the modeling and they do not elicit preferences nor do they validate the assumptions behind them.

In order to derive user preferences, preference elicitation methods can be used. User preference elicitation is an important field that is overlapping the fields of economics, market research, and multiple attribute decision-making (MADM) [29]. For products or services that are not yet present, such as P2P electricity markets, the revealed preferences (RP) of consumers that are determined through their actual choices cannot be evaluated. Hence, the analysis of stated preference (SP) is the most common method to collect and analyze user preference data in these cases [30].

There are several preference elicitation methods and Discrete choice experiments (DCE), also called choice-based conjoint analysis (CBC), is one of the prominent methods to derive and analyze user preferences. In recent years, CBC has also been applied as a method to evaluate how users may engage with new products and services in the energy domain. The willingness to pay for electricity supplied by cooperatives [31] or the willingness to pay for renewable or locally produced energy [32] has been evaluated by applying DCE. Moreover, it has also been applied to evaluate preferences in local or P2P electricity markets. In [23], an Adaptive Choice-Based Conjoint (ACBC) analysis is performed to analyze the acceptability and interest of German residential customers to participate in local energy markets (LEM). In [33], the preferences for economic, environmental, social, and technological aspects of P2P energy markets were evaluated for Dutch prosumers. The results of these studies provide insights into the preferences of users, potential clusters, and market segments. However, the focus of these papers is to assess the wider techno-economical-policy ecosystem of prosumer-centric electricity markets. Therefore, some of the attributes that are considered cannot be directly related to the market or the product itself, nor it will necessarily result in a direct correlation. Hence, these studies usually conclude with recommendations on policy and regulatory matters that correspond to study findings. None of the existing studies that use DCE attempted to incorporate the preferences in a model and investigated how they would affect the outcomes in a P2P market.

Other methods for deriving user preferences in the form of preference weights have been used in the existing literature to extract information from homeowners for different energy applications, including P2P markets. The SMARTER method for determining priority and acceptable levels for the decisions of a HEMS is presented in [34], whereas an analytical hierarchy process (AHP) is used to determine priorities for HEMS for demand response in [35]. Preferences for selling surplus electricity in P2P markets related to the state of charge of the owned battery system and the offered electricity price are studied in [36]. Lastly, pricing preferences toward different possible trading partners were evaluated in a survey in UK and Germany in [24]. This study provides insights into the differences in preferences across two different countries. This highlights the necessity to investigate the attitudes and preferences of prosumer-centric markets per country, as cultural and societal differences contribute to variations in their acceptance or their structure.

Different sources of uncertainty can influence the outcomes of P2P markets. This includes stochastic consumption and production, as well as stochastic market clearing prices. When it comes to the consideration of uncertainty in P2P markets, most of the implemented pilot projects perform the calculation of the price and traded energy after the time of realization, using measurements of the actual consumption and production [2]. Even though the majority of papers propose deterministic

Table 1
Classification of relevant literature.

Reference	Preference elicitation	Preference modeling	Uncertainty modeling	Recourse actions	Product differentiation	Multi-objective optimization
[7,20,27,28]	×	✓	×	×	✓	×
[23,24,31–33]	✓	×	×	×	✓	×
[18,38]	×	✓	✓	×	×	×
[15–17,39]	×	×	✓	×	×	×
This work	✓	✓	✓	✓	✓	✓

P2P trading models as a concept, the question of uncertainty in the commitments in the P2P markets has also been addressed more recently in the existing literature. This has been done in different ways and it is dependent on the adopted modeling framework of the P2P market.

Stochastic optimization has been applied in the scheduling stage of the household appliances [18], in P2P matching with cooperative game theory, [16] and day-ahead stochastic decentralized community market with the option to adjust the commitments in real-time [17]. Instead of adjustments, penalties for not fulfilling the bids can also be foreseen [37]. Call options that are traded after closing the forward P2P market and before real-time operation have also been considered [9] and incorporating risk preferences through conditional value-at-risk is used in [38]. Lastly, considering the DSO perspective of the impacts of P2P trading on the electrical network, distributional locational marginal pricing considering uncertainty is used to send signals to the P2P market [15,39].

1.3. Research gaps and contributions

Several challenging questions need to be addressed to enable the successful practical implementation of prosumer-centric electricity markets. The design of prosumer-centric markets should provide opportunities to include product differentiation and consider different user preferences in the matching mechanism. These preferences or the assumptions behind them should be validated or based on experimental results, which is not done in the existing literature. Moreover, the interaction with other existing market stakeholders, such as the existing retail market is rarely addressed. In addition, Finally, the underlying uncertainty in the market commitments and the P2P market-clearing prices should be addressed. Whereas methods for addressing the uncertainty in the market commitments have been proposed, recourse actions are often not considered nor the uncertainty in the P2P market-clearing prices has been covered.

As summarized in Table 1, existing studies focus on different aspects of the design and modeling of P2P markets. Studies that focus on eliciting preferences do not include modeling and vice versa. Moreover, studies that consider uncertainty, do not account for recourse actions nor do they support product differentiation. Finally, none of the studies provides a multi-objective model formulation. Thus, none of the existing studies proposes an encompassing approach that includes all necessary aspects to bring forward these markets to reality.

Therefore, to address the aforementioned challenges, we propose a forward P2P market design in which product differentiation is possible and user preferences can be expressed toward different products and goals. To derive user preferences and investigate desirable products in the P2P market, a DCE is conducted in the Netherlands through an online survey. The specific product classes that are included in the market are derived based on the DCE results to be relevant for the studied context. Moreover, the results of the survey are used as inputs in a HEMS that automates the decision-making of households participating in the P2P market. By aptly accounting for the user preferences, the HEMS will be able to make decisions following those preferences without requiring constant input from the user. The operation of the HEMS is cast as a two-stage stochastic multi-objective optimization model. Hence, the stochasticity in the load and generation of each market participant as well as the uncertainty concerning the P2P clearing prices are considered.

The contributions of this paper are twofold:

1. A method for elicitation of user preferences for electricity products based on desired attributes in a P2P market is proposed. The method is based on a discrete choice experiment and real data gathered from a sample of residential users in the Netherlands was used to design a P2P market with product differentiation.
2. A multi-objective stochastic optimization model with recourse actions is proposed. Its purpose is to automate the decision-making process of home energy management systems for households participating in P2P electricity trading.

The remainder of the paper is organized as follows: The general context and methodology proposed in this paper are outlined in Section 2. The methodology behind the discrete choice experiment, as well as the design and the results of the survey are presented in Section 3. The methodology and the exact formulation for the stochastic multi-objective optimization model used for modeling user preferences in a HEMS for P2P markets as well as the results of a case study are shown in Section 4. Finally, conclusions are drawn in Section 5.

2. Methodology

In this paper, a P2P electricity trading market is considered to be complementary to the existing retail market. Hence, users have the option to buy electricity from other peers, in addition to the option to buy from a conventional retailer. Moreover, they can also sell the excess electricity they produce (for example, through PV panels) to other peers instead of selling it back to their retailer at the contracted feed-in-tariff (FiT) rate. Moreover, the participating users can decide on acceptable buying and selling prices for electricity. The term end users or users is used in this paper to refer to both users that produce as well as for users that only consume electricity.

An overview of the methodology followed in this paper is presented in Fig. 1. To determine the preferences and objectives of participants to participate in P2P electricity markets, a descriptive analysis is performed. This is done through conducting an online survey that includes a DCE through which the preferences for different attributes of electricity are evaluated. DCE is chosen as an adequate method for deriving user preferences for several reasons. It is an implicit method for deriving preferences, so the incentive to provide potentially untrue but socially acceptable answers is disabled [32]. Other methods require that the respondents rank and explicitly state their preferences which strongly relies on the following assumptions: (1) that they know their true preferences for a new product, and (2) that they are able to evaluate the trade-offs and express the preferences explicitly. Finally, DCE simulates a setting in which respondents are faced with choices very similar to real implementation, making it a state-of-the-art method for deriving user preferences [40]. The list of relevant attributes for the DCE is formulated based on a literature review and discussion with experts. It is taken into consideration that the selected attributes can be represented as market commodities or market parameters in the proposed P2P market.

Based on the analysis of the desired attribute levels, several products can be defined for the market. Moreover, the utility that different attributes bring to the end-user is used to express the objectives for participation in P2P electricity markets. This results in a multi-attribute decision-making problem. This can be formulated as a multi-objective

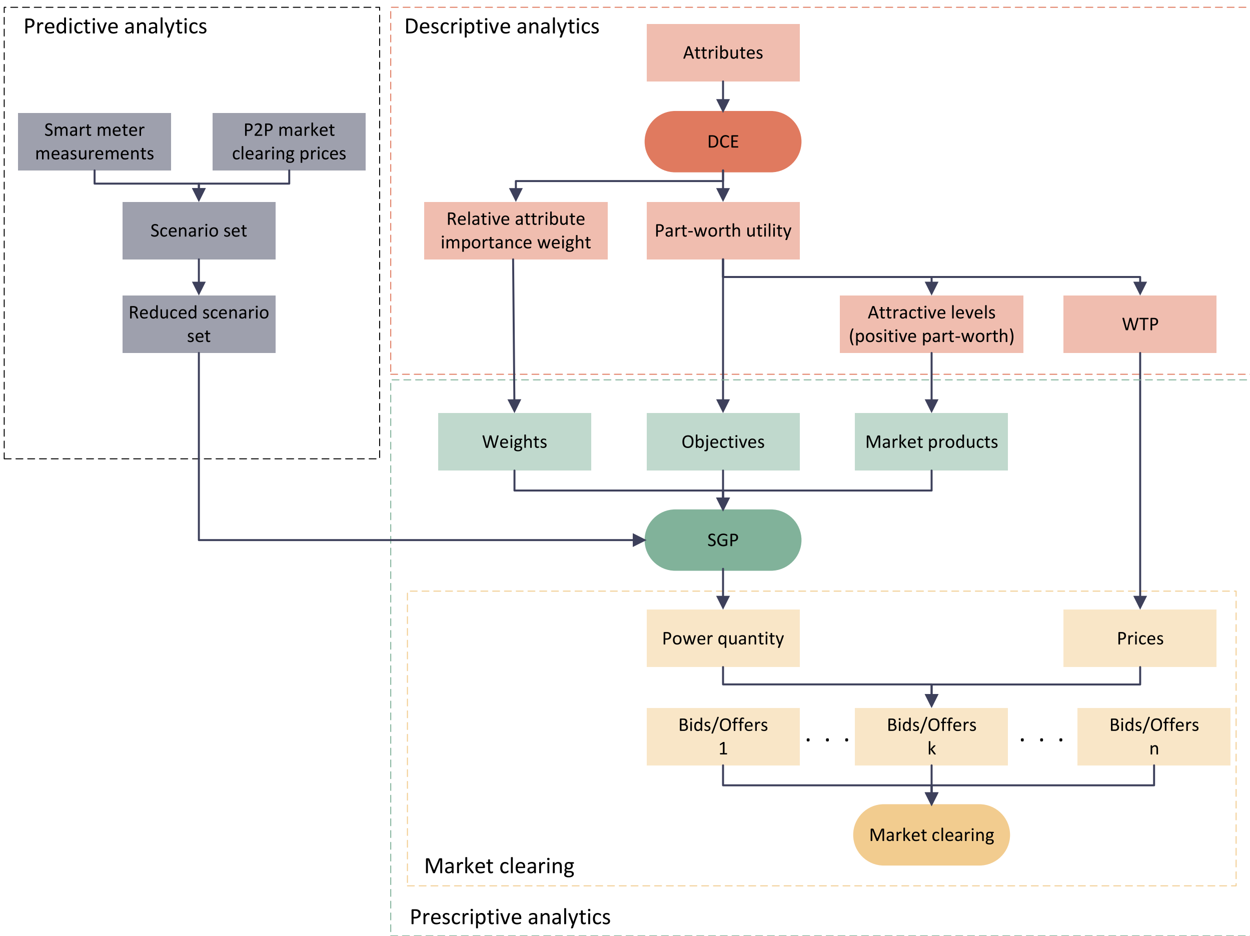


Fig. 1. Overview of the proposed methodology.

optimization problem which is part of the prescriptive analytics performed in this study. As a method to solve the resulting MOO, stochastic goal programming (SGP) is used. Goal programming (GP) as a method supports non-convex multi-objective optimization, which has not been applied to the problem of P2P electricity trading, to the best of the authors' knowledge. Since the preference weights are discovered in the previous stage of the descriptive analytics, a decision for each HEMS can be made by incorporating the weights in the SGP, instead of first generating a Pareto front and then selecting a solution based on the user preferences, a process that may take longer computation time. In addition to the objectives, and the defined market products, the relative attribute importance weights of the DCE are used to weigh the importance of the different objectives in the SGP. The different objectives are directly related to the attributes of electricity and are determined for each prosumer. They do not depend on the availability of electricity in the market [20], the related cost function [18], or the (electrical) distance between the trading partners [20,28,41].

To consider the uncertainty in both production and generation as well as the P2P market clearing prices, stochastic programming is used in combination with goal programming. Recourse actions that follow the realization of the two sources of uncertainty can be included in the model. Therefore, there is no need to formulate probabilistic constraints and adequate response to uncertainty can be modeled by using only stochastic programming. Moreover, stochastic programming is a better-suited method than robust optimization since it is less conservative. Very conservative estimates may lead to a lower market activity which will reduce the attractiveness of P2P markets. For the purposes of the SGP, as part of the predictive analytics, a joint scenario set based on actual smart meter measurements and simulated P2P market clearing prices is created and used as input in the SGP model.

The HEMS should decide if and how much power the household needs to buy or sell to participate in the P2P market which is a forward market. The time between the market clearing and the realization depends on the technological and regulatory requirements. The clearing can be done day-ahead or at a shorter time frame before realization. In this paper, a day-ahead market clearing is considered. The quantity that is bid or offered in the P2P market or scheduled for exchange with the retailer is a result of solving the SGP. The willingness-to-pay for different products in the survey is used to determine the prices for the bids and offers for the market product.

The resulting tuples of quantity and price for each bid and offer can be submitted to several market-clearing mechanisms, either directly or with minor adjustments. Such mechanisms include bilateral matching-based methods [8,21,28] and (continuous) double auction-based methods [10–12]. In this paper, we opt for a double-sided auction-based method that is cleared for every time interval and each market product. It is further assumed that the participants are non-strategic and therefore they are bidding truthfully. Further research into strategic behavior and the design of suitable incentive-compatible market-clearing mechanisms is beyond the scope of the paper.

3. Descriptive analytics with discrete choice experiments

3.1. Discrete choice experiments and data analysis

A Discrete choice experiment or Choice-based Conjoint is a methodology to mathematically model user preferences and predict the choice behavior of users, based on random utility theory. The utility of a given alternative consists of a deterministic observable part of the

Table 2
List of attributes and corresponding levels.

Attribute	Levels
Supplier	Conventional supplier | P2P market
Energy type	Green | Mixed | Gray
Selling price [€ct/kWh]	10 |6|3| Donate
Monthly costs [€]	30 |40|50|60| 70

utility that is the sum of part-worth utilities of the different attributes and a random, error component [42]. It is assumed that users aim to maximize their utility. In a DCE, respondents are provided with menus consisting of several alternatives with different attribute levels of the specific product or service to choose from. Through repeated choices of alternatives from these menus, the stated preferences of the respondents can be estimated.

Due to the combinatorial nature of the different attributes and levels, the total number of possible alternatives is too large for the complete set to be presented to individual respondents. Therefore, each respondent receives a subset of alternatives for a predetermined number of choice tasks in any DCE method. Several methods can be used to analyze the data from a DCE, such as the multinomial logit model or latent class analysis [43] that can calculate the preferences or part-worth utilities on an aggregate level or cluster level, respectively. One of the most advanced methods that consider heterogeneity among respondents' preferences and is able to calculate individual part-worth utilities is the Hierarchical Bayes (HB) method. To deal with the lack of complete information at the individual level, the HB method consists of two levels. At the higher level of the group, it assumes a multivariate normal distribution, with a vector of means and covariance matrix that both need to be estimated. At the lower, individual level, it assumes that the heterogeneous part-worth utilities follow a multinomial logit model. The evaluation of the parameters of both levels is done in an iterative way using Markov Chain Monte Carlo until convergence is reached [44].

3.2. Choice of attributes and levels

The design of the survey investigating desirable product or service attributes should be relatable and easily understandable by respondents [42]. On the one hand, they should understand the meaning of the proposed attributes and the impact of their choices to derive meaningful conclusions. On the other hand, it may be difficult to present a new concept with limited explanation and rely on the ability of the respondent to understand the context. A preliminary set of attributes identified in the relevant literature was tested in an initial survey with experts, which resulted in the final set of four attributes. The criteria for the choice of relevant attributes for this study was to have attributes that can be directly translated into features of electricity as a product in prosumer-centric markets. The attributes and their corresponding levels are presented in Table 2.

The outcomes in markets, including P2P electricity markets, depend on the actions of all participants, the market-clearing mechanism in place, as well as the availability of energy to be traded. Thus, it is not possible to estimate the costs of participating in such a market through the individual choices of a single agent. Therefore, the total cost for a choice option is not directly correlated to the attribute levels, as in the summed-pricing approach used in [23]. This is done to avoid the respondents assuming that individual attributes such as P2P trading always lead to lower or higher costs, but instead allow for both possibilities to be offered to the respondents.

Since DCE creates a semi-random combination of all levels of the attributes, there may be some illogical combinations. For this reason, a limitation of combinations can be imposed. This should be done with consideration so as not to limit some potential combinations that although not possible currently, may still be desired. In this study the following two limitations are imposed: (1) The level *Donating electricity* of *Selling price* is only possible for the P2P market as a supplier, and (2) it is assumed that electricity offered in the P2P market will not be generated solely by conventional energy sources, therefore the level *Gray energy* was excluded for the P2P market level of the *Supplier* attribute.

3.2.1. Supplier

For the choice of trading partner, two options are given, the conventional supplier, i.e. a retailer, or the possibility to trade with a peer from the local P2P market. Additional specifications about the type of peers, such as neighbors or friends are not considered. This is a design choice to keep the market frameworks as general as possible. Not considering geographically close users explicitly, provides for a market framework that can be extended for participation to a larger geographical area, on a national or even international level. Nevertheless, to make the choice relatable and comprehensible to the respondents, it was indicated that the P2P market is local, whereas local was not defined in further detail. The reason for this is the residents in the Netherlands are familiar with local activities related to energy through the postcode-based reduced rate scheme [45] and energy cooperatives which are usually established on a local level. Moreover, due to the way of implementation or regulations limitations, it may not be possible to choose a specific trading partner. Finally, such specific choices in P2P networks can lead to undesired effects such as discrimination and limit the access for the participation of some social categories [46]. Since electricity is a public good, the markets that are designed for it should be inclusive and not discriminatory.

3.2.2. Energy type

The electricity sold in P2P electricity markets usually is generated by renewable energy resources. As such it can expand the offer of renewable (green) electricity at the level of the retail market. It is relevant to assess how much and at what price the users are interested in purchasing green electricity as opposed to conventionally generated electricity (gray), or a combination of it (mixed) and what is the role of P2P markets in this.

3.2.3. Selling price

P2P electricity markets can offer the unique possibility for prosumers to indicate and influence the price at which they would like to sell their electricity. Three levels were defined, that range between the low and high FiT prices on the retail market in the Netherlands [47]. Due to the phasing out of the current net-metering scheme [48], it is planned that after 2023 the FiT prices will be reduced, which can lead to increased interest in alternative user-centric markets for selling electricity. In addition to the regular options for indicating the selling price, a special price category was introduced for the P2P market, i.e. the option to donate electricity to economically disadvantaged participants in the P2P market. The reason for this option is to evaluate the altruistic behavior of people.

3.2.4. Monthly costs

To make the estimate of the resulting costs easily understandable to respondents, the total costs for trading electricity on monthly basis are translated into a monthly bill. The value of 50 € is chosen as a reference point for average expenses for electricity in the Netherlands. Variations of 40% below or above this value are the boundary levels of this attribute.

3.3. Design of survey and method of data collection

In this survey, a balanced profile design was used for the DCE. Each respondent was shown 10 choice tasks to avoid respondent fatigue. Each choice task consisted of three product alternatives. A description was provided to the respondents at the beginning of the survey explaining to them briefly the context and the meaning of the different attributes and levels. This was followed by the DCE section. Then the respondents were asked several socio-demographical questions and other general questions regarding their attitudes toward smart grid technologies and initiatives.

The target population for the survey was residential electricity customers that live in the Netherlands. The survey was distributed to a user panel maintained by the Product Evaluation Lab (PEL) at Delft University of Technology (TUD) [49]. The initial analysis of the survey design was conducted using Sawtooth Software [50]. The final survey was created and conducted through an online surveying platform, Qualtrics [51]. Therefore, the limitation for participation in the survey is that the panel members have an email, which amounts to 1600 potential respondents. For the design of the survey with ten choice tasks, a minimum of 170 responses was required. The survey was opened by 408 people and was completed by 397, resulting in a response rate of 25%. From the completed survey, 68 were removed due to the incompleteness of the CBC, leaving a total of 329 responses who were included in the analysis. The survey was available from May 20 to June 17 2021 and was conducted in Dutch. Supplementary data about the survey can be found at [52].

3.4. Results from the discrete choice experiment

3.4.1. General characteristics of the sample

The social-demographic characteristics of the respondents and a general analysis of the sample are presented in this section. Based on the part-worth utility values presented in Section 3.4.2, Qualtrics identified two clusters of prosumers, with 171 respondents in the first cluster and 158 respondents in the second cluster. The analysis is done per cluster as well as for the total sample. The socio-demographical characteristics are given in Table 3. Since few of the respondents did not complete the full questionnaire after the DCE, the number of responses per question is indicated in parentheses in the table. In terms of gender, there are more male than female respondents in the total sample, however, their representation in Cluster 1 is relatively balanced. Regarding age, the majority of the people that filled in the survey are over the age of 40. In Cluster 2, the percentage of the elderly population over 70 years is higher than in the other cluster, whereas, in Cluster 1, the percentages of people of age groups 40–54 and 55–69 are higher. The age distribution corresponds to the results of the employment status. The percentage of working people, either full-time or part-time amounts to 54.01%, i.e. half of the respondents for the total sample, as well as 57% in Cluster 1 and 42.08% in Cluster 2. Moreover, 44.81% of the respondents in Cluster 2 are retired, compared to the total sample percentage of 37.35%. The largest percentage in each group has obtained a university education, followed by education at universities of applied sciences and vocational education. A majority of the respondents in the total sample (70%), but also in the two clusters live in a house compared to a smaller percentage that lives in an apartment (25% for the total sample). The other types of properties are significantly less present. Moreover, the majority of respondents own their households (80.19%) as compared to 19.5% that are renting. This difference is higher for Cluster 1, in favor of ownership, and smaller for Cluster 2, where the percentage of renting is higher (22.22%). The fact that the majority of respondents own their houses indicates that the respondents will likely not be biased against taking energy-related actions in their homes, which may not always be so in the case of renting [53]. Lastly, the majority of households are composed of 1–2 members across the sample and two clusters, followed by 3–4 members households. Larger household sizes are less frequent.

Table 3
Socio-demographic characteristics of the final sample in % (the number of responses is given in parentheses).

	Sample [%] (329)	Cluster 1 [%] (171)	Cluster 2 [%] (158)
Gender	(324)	(170)	(154)
Female	45.99	49.41	42.21
Male	54.01	50.59	57.79
Other	0	0	0
Age	(324)	(170)	(154)
<25	0.31	0.59	0
25–39	6.5	7.07	5.85
40–54	19.13	21.76	16.25
55–69	47.54	52.34	42.24
>70	26.57	18.23	35.73
Employment status	(324)	(170)	(154)
Student	0.62	0.59	0.65
Unemployed/Searching	2.78	4.12	1.3
Part-time	21.6	26.47	16.23
Full-time	32.41	31.18	33.77
Retired	37.35	30.59	44.81
Other	5.25	7.06	3.25
Education	(324)	(170)	(154)
Elementary school	3.09	1.77	4.55
Secondary school	9.57	7.06	12.34
High school	6.17	8.82	3.25
Vocational education	10.8	5.88	16.23
Univ. of applied sciences	32.1	35.29	28.57
University	37.65	41.18	33.77
Other	0.62	0	1.3
House type	(323)	(170)	(153)
House	70.59	73.53	67.32
Apartment	25.39	23.53	27.45
Studio	0	0	0
Room	0.93	1.18	0.65
Care facility	0.62	0	1.31
Boat/Trailer	0.31	0	0.65
Other	2.17	1.76	2.61
Household ownership	(323)	(170)	(153)
Own	80.19	82.94	77.12
Rent	19.5	17.06	22.22
Other	0.31	0	0.65
Household size	(323)	(170)	(153)
1–2	72.14	72.35	71.89
3–4	22.29	22.94	21.57
5–6	4.03	3.53	4.57
>7	1.55	1.18	1.96

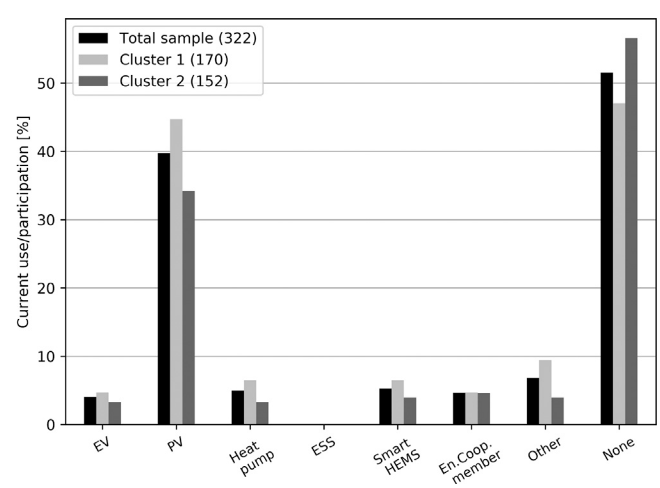
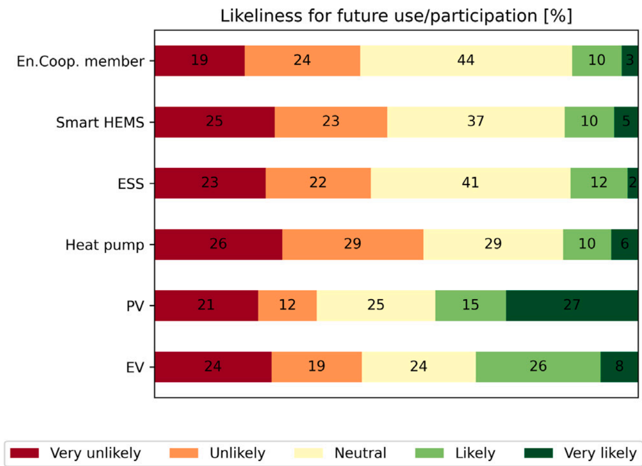
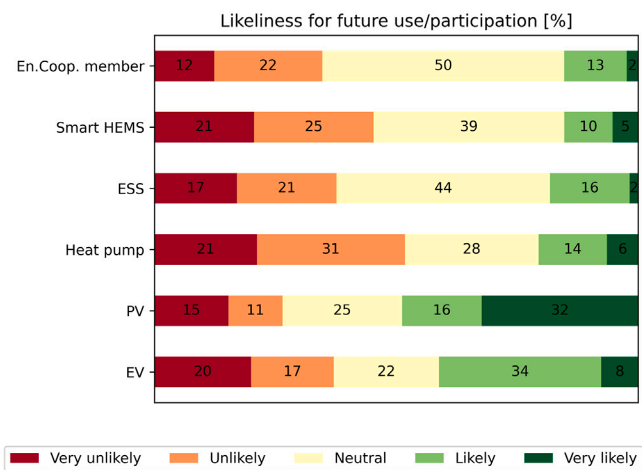


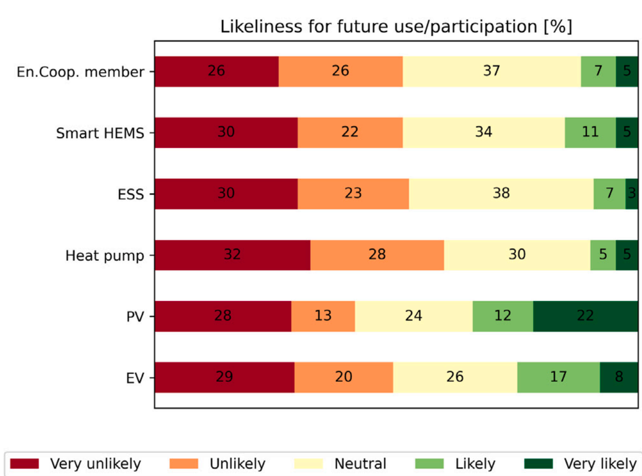
Fig. 2. Percentage of current usage of DER and participation in energy-related activities.



(a) Total sample (322)



(b) Cluster 1 (170)



(c) Cluster 2 (152)

Fig. 3. Likeliness for future use/participation for the respondents [%].

In order to gain insight into the energy-related behaviors of the respondents, they were asked about the types of devices that they are already using in their homes (such as PV or EV) and initiatives in which they are taking part (such as membership in an energy cooperative). Moreover, they were asked to express their willingness to use them or participate in the next 5 years. The results of these two inquiries are shown in Fig. 2 for the present and Fig. 3 for the future. Around half of the respondents are standard consumers. They do not have any DER installed in their home nor do they use smart HEMS or are members of a cooperative. The percentage is higher for members of Cluster 2 compared to Cluster 1. The most represented DER is PV systems, which are installed in the household of 44.71% of respondents from Cluster 1 and 34.21% of Cluster 2. In terms of other activities that the respondents are involved in, 9 respondents indicated that they own a hybrid or hydrogen-powered vehicle. Other responses included among other: green energy, solar thermal heater, or shared installation for PV.

Regarding the 5-year outlook, a large portion of the respondents is neutral regarding the purchase of DER or participation in energy cooperatives. The percentage of responses in the category 'Very unlikely' or 'Unlikely' is higher for members of Cluster 2, whereas the members of Cluster 1, are more likely to have a positive outlook or neutral. From the listed options, a PV system is likely to be installed for respondents of Cluster 1 and to a lower degree for Cluster 2. A similar trend is observed for EVs for Cluster 1; however, members of Cluster 2 are not likely to purchase an EV. It is interesting to observe that the interest in electrification of the heating with heat pumps is very low and unlikely to happen, considering the plans and legislation in the Netherlands to phase out gas boilers and replace them with hybrid heat pumps [54]. The majority of respondents are mostly neutral toward purchasing ESS, Smart HEMS, or participating in an energy cooperative, with the balance weighing toward unlikely to do it. Nevertheless, the considerable percentage of neutral responses, indicates that with the proper incentives and mechanisms in place these options can have a higher uptake in the future.

3.4.2. Part-worth utilities

The analysis of the DCE data was conducted using Hierarchical Bayes (HB) estimation of the part-worth utility values that comprise the utility function of the respondents at the individual level. The results are zero-centered on the level of an attribute and they are normalized, so a comparison between the different groups can be performed. The results of the part-worth utilities of the total sample and the two identified clusters are presented in Table 4.

The utility of the total sample and the first cluster for the attribute *Supplier* is higher for the Local P2P market. However, the second cluster receives a higher utility from exchanging electricity with a Conventional supplier. Both clusters have the highest utility for green electricity from the attribute *Energy type*. The utility decreases for the other levels of the attribute, with the least steep decline being the one from the second cluster, which indicates the smallest reduction in utility if the type of electricity is not renewable. The results for the attribute *Selling price* are quite straightforward, as all respondents get the highest utility from the highest level. A very interesting observation is that all respondents get a negative utility for the level Donate, which is drastically different from the positive utilities obtained for the other levels. This finding contradicts the findings in [33], where prosumers indicated a high willingness to share electricity for indirect financial or no return at all to households that cannot afford electricity. However, it is in line with the findings from an actual implementation of a P2P electricity market in which participants can adjust their selling prices, and in which, none of the participants was willing to offer their electricity at a price lower than the FiT [55]. Lastly, the utility for the attribute *Monthly cost* is the highest for the lowest level and decreases as the costs per level increase. The decline is higher for respondents of Cluster 2.

Table 4
Average part-worth utility values for the total sample and the two clusters.

Attribute	Levels	Sample	Cluster 1	Cluster 2
Supplier	Conventional supplier	−4.47	−4.29	4.75
	Local P2P market	4.47	4.29	−4.75
Energy type	Green	19.29	25.12	9.42
	Mixed	0.64	−1.74	5.77
	Gray	−19.93	−23.38	−15.19
Selling price [€ct/kWh]	10	5.51	4.93	6.30
	6	2.74	1.25	5.21
	3	2.20	0.86	4.43
	Donate	−10.44	−7.04	−15.94
Monthly cost [€]	30	15.77	13.48	19.37
	40	10.19	8.79	12.39
	50	1.75	1.72	1.80
	60	−7.60	−6.53	−9.28
	70	−20.12	−17.46	−24.29

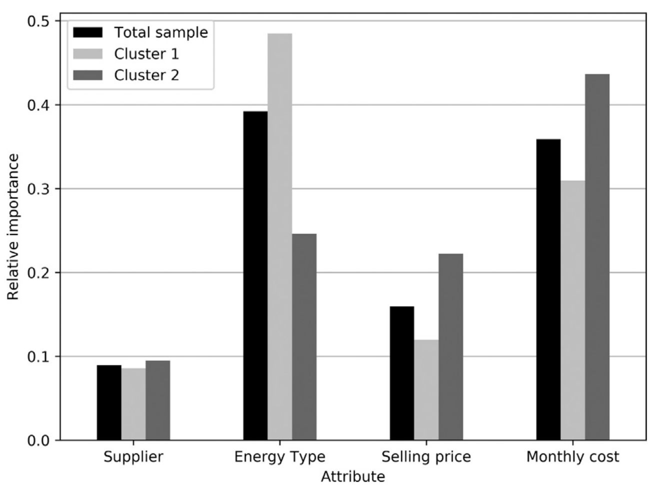


Fig. 4. Relative attribute importance weights.

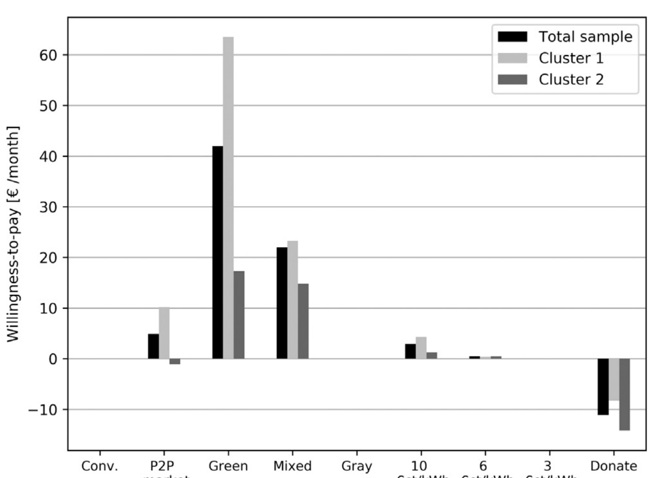


Fig. 5. Willingness-to-pay for different levels of the attributes (one level is the base).

3.4.3. Attribute importance and attributes ranking

The importance of each attribute for making the final decision can be calculated using the part-worth utilities. The importance is calculated as the range of the maximum and minimum value for all levels of a single attribute and divided by the sum of the ranges of all attributes. Thus, the total sum of the attributes' importance weights is

Table 5
Results of explicit ranking of the attributes (1-most important, 4 - least important).

Attribute	Total sample Mean (SD)	Cluster 1 Mean (SD)	Cluster 2 Mean (SD)
Energy type	1.71 (0.9)	1.37 (0.69)	2.08 (0.96)
Supplier	3.05 (1.0)	3.06 (0.92)	3.03 (1.08)
Selling price	3.06 (0.87)	3.3 (0.71)	2.81 (0.96)
Monthly cost	2.18 (1.03)	2.26 (0.94)	2.08 (1.12)

equal to 1, the weight of each attribute is relative to the other attributes and cannot be analyzed independently. The relative importance of the attributes is presented in Fig. 4. These weighting factors are used in the multi-objective optimization problem formulation in Section 4.

The two most important attributes are the *Energy type* and the *Monthly cost*, in that order for the total sample and the first cluster. Respondents from the second cluster are more influenced by the *Monthly cost*. They also give larger importance to the attribute *Selling price*, indicating that their decisions are motivated by economic reasons. The fact that respondents do not attribute high importance to the *Selling price* can be due to a preference for using automated prices and not having to set prices by themselves, at least on a regular basis [25]. The importance for *Supplier* received the lowest weight across the respondents. This may indicate that the respondents do not necessarily find participation in a P2P market to be of great importance. However, it may mean that they are not opposed to participating in such a market if it offers them benefits or is on par with the option of a conventional supplier. This finding can be related to the finding that consumers value the type of energy produced by the P2P market, i.e. how renewable it is, the most, compared to other attributes, based on the willingness-to-pay [31].

In the survey, after completing the DCE, the respondents were asked to rank the attributes in order of importance to their decisions. The objective is to compare the implicitly derived attribute importance weights from the actual choices with the self-declared explicit importance rankings which are shown in Table 5. The analysis aims to discover whether the respondents can truthfully and explicitly state their preferences or if there is a discrepancy. By doing this after the DCE, the respondents could reflect on their choices and assess their attitude toward the importance of attributes. The explicit responses for the total sample are in line with the implicit weights derived from the DCE analysis. For the total sample, the mean of the ranking results corresponds to the implicit weights for relative attribute importance. However, the ranks for *Supplier* and *Selling price* are close to each other, due to the high percentage of respondents ranking them as the least important - 4 (44.44% - *Supplier* and 37.35 % - *Selling price*. The ranking for Cluster 1 is more definitive. However, in the explicit ranking, the *Selling price* is ranked lower than *Supplier*, which is the opposite of the derived attribute weights. The rankings of Cluster 2 for the top two attributes *Monthly cost* and *Energy type* have the same mean value, which is contradictory to the derived attribute importance weights. According to the latter, the attribute *Monthly cost* significantly outweighs the *Energy type*. The rankings for the other two attributes are more spaced out and in line with the results of the implicitly derived weights. This discrepancy may be due to the so-called "warm glow" effect which explains that people will select an option because it makes them feel better about themselves or in the eyes of others [56]. Consuming renewable energy is generally considered to be desired behavior, according to social norms [56]. Therefore, respondents may over-estimate the importance they give to this attribute than what they actually do when faced with simulated choices or actual behavior in reality, an example of the intention-behavior gap [11,33].

3.4.4. Willingness to participate

The respondents were asked to express their willingness to participate in a P2P market as described in the study if that was possible. A considerable part of the respondents (41.97%) are likely or very likely to participate in such a market. A significant percentage are neutral (36.73%) regarding their participation. This can be related to the relatively low importance of the attribute *Supplier* that can be interpreted that participation in P2P markets is not a goal per se for some users, but it may be an attractive option if it provides additional benefits to its participants. Lastly, a smaller portion of the respondents (21.29%) declared that they would not want to participate in such a market. In terms of practical implementation and successful deployment of P2P electricity markets, such attitudes have to be considered in the design of the markets and related products and services.

3.4.5. Willingness-to-pay

The willingness-to-pay (WTP) is another indicator of how the respondents value different attributes of electricity as a product, in monetary terms. The WTP is calculated using the monthly cost attribute for the three other attributes. For each attribute, one level is taken as a base related to which the WTP is calculated. The results for WTP are shown in Fig. 5. The highest WTP is regarding the type of electricity, specifically green energy. This indicates that the respondents are willing to pay more for renewable electricity, in line with [31]. The level P2P market from *Supplier* attribute received positive WTP for members of Cluster 1 and negative for Cluster 2. This represents a clear distinction between these two clusters. For the attribute *Selling price*, it is observed that the higher prices have a higher WTP. Moreover, it is evident that the option of donating electricity is not attractive to a varying level to none of the respondents.

3.4.6. Generalization of the results

The generalization of the results can be to some extent limited since the majority of the respondents are over 55 years old. The study contained a relatively balanced ratio between prosumers and consumers which is important for the viability of user-centric markets, as their design should accommodate the needs of both. Even though the results of the study are quite plausible and in line with some pilot experiments [25], the possibility of a gap between the stated preferences and the actual behavior still exists. This should be evaluated further, preferably with real-life pilot and sandbox projects.

4. Prescriptive analytics with mathematical optimization

4.1. Stochastic goal programming

The methods available in the field of multi-objective optimization can be divided into no-preference methods for which the preferences of the decision-maker are not considered, a priori and a posteriori methods, in both of which the preferences of the decision-maker are considered. The difference between the a priori and a posteriori methods lies in which stage are the preferences considered in the MOO. Whereas in the a posteriori methods, the Pareto front is calculated first, and then preference weights are used to find a satisfactory solution, in a priori methods the preferences are incorporated in the MOO method in the initial stage.

Goal programming is a method within the field of multi-objective optimization methods that belongs to the subgroup of a priori methods. It can be applied to solving optimization problems in which multiple and possibly conflicting objective functions exist [57]. This is the case in this study where there are three objective functions $f_i(x)$, $i \in I$ derived from the attributes assessed in the survey. For each of these objectives, a target or aspiration level for the goal $g_i, \forall i \in I$ is determined. The deviation or distance to these target levels is subject to minimization in goal programming. The deviations can be both positive (δ_i^-) and negative (δ_i^+), or only of one type, depending on the problem formulation. One method of solving GP problems is the weighted approach, in which the weighted deviations from the targets for each objective are minimized [57,58]. In a priori MOO methods, the preferences of the decision-maker are known beforehand and are used as weights in the weighted GP model. In this study, the attribute importance weights from the DCE analysis are used as preference weights in the weighted GP model, providing a natural connection between the descriptive DCE model and the prescriptive mathematical optimization model.

Due to the forward market-clearing adopted in this study, there is inherent uncertainty regarding the actual production of renewable energy as the main source of electricity offered in the P2P market as well as uncertainty regarding the actual uncontrollable demand. Moreover, due to the auction-based market clearing, there is uncertainty regarding the market-clearing prices, and their realization is not known during the decision-making process. To address this uncertainty a stochastic optimization approach is adopted. To combine stochastic programming and goal programming, a combined stochastic goal programming model is proposed and a deterministic reformulation that minimizes the distance from the expected target values is used [59].

$$\min \sum_{i \in I} w_i(\delta_i^- - \delta_i^+) \tag{1a}$$

$$\text{s.t. } \mathbb{E}(f_i(x,\cdot)) + \delta_i^- - \delta_i^+ = \mathbb{E}(g_i), \qquad \forall i \in I \tag{1b}$$

$$\delta_i^+, \delta_i^-, \geq 0, \qquad \forall i \in I \tag{1c}$$

The general SGP formulation is given in (1). In this formulation, the deviations of the expected value of the objective functions $\mathbb{E}(f_i(x,\cdot))$ from the expected value of the target levels of the goals $\mathbb{E}(g_i)$ are minimized.

4.2. Stochastic goal programming model of HEMS for P2P markets

This section details the decision-making problem of a HEMS that can control some household appliances and make decisions on participation in the P2P electricity market based on user preferences. A multi-period model is considered, in which decisions can be made for each time interval. Based on the DCE analysis, there are two types of products that can be traded in the P2P market: green electricity (or $P2P, g$) which is directly sold electricity produced by renewable resources, and regular electricity (or $P2P, r$) which is electricity that comes either from non-renewable sources or comes from storage devices. Even though electricity that is stored and sold at a later stage can come from renewable sources, the proposed division encourages real-time consumption of renewable energy and diminishes the possibility of influencing the market through arbitrage. Since donating electricity had negative utility across the two clusters, indicating that the analyzed sample did not consider this to be a desirable product in a P2P electricity market, it was not included in the market design. However, the market model can be extended to include this type of product as well as other attributes that can be potentially considered to be desirable.

In this study, it is considered that the electricity consumption and PV production of the households are stochastic and each household has its own set of possible realizations. Moreover, the P2P market-clearing prices are also uncertain, and the same set of price scenarios is used for all households participating in the P2P electricity market. The uncertainty is accounted for in the model by using stochastic optimization. The SGP model is a two-stage stochastic multi-objective optimization model. In the first stage, the power that will be bought or sold to the P2P market or the retailer is scheduled. The first stage variables related to the P2P market are then sent as bids or offers. Adjustments to the first stage variables with regards to possible realizations of uncertainty considered in the scenario sets are possible in the second stage. Recourse actions are possible by adjusting the local flexible loads or buying or selling more energy from the conventional retailer. In this manner, the retailer acts as a balancing party for the market participants and provides certainty about fulfilling the market-clearing commitments. The objective functions and the constraints of the model are presented

Table 6
Nomenclature.

Sets and indices	
$h(H)$	Index (set) of households.
$t(T)$	Index (set) of time intervals.
$s(S)$	Index (set) of scenarios.
$T^{EV,av}$	Set of time intervals when EV is available.
$T^{EV,nav}$	Set of time intervals when EV is not available.
Parameters	
$c_{t,s}^{b,P2P,g}$	Price for buying green electricity from P2P market in time t in scenario s €/kWh].
$c_{t,s}^{b,P2P,r}$	Price for buying regular electricity from P2P market in time t in scenario s €/kWh].
$c_{t,s}^{s,P2P,g}$	Price for selling green electricity to P2P market in time t in scenario s €/kWh].
$c_{t,s}^{s,P2P,r}$	Price for selling regular electricity to P2P market in time t in scenario s €/kWh].
$c_t^{b,R,g}$	Price for buying green electricity from retailer in time t €/kWh].
$c_t^{b,R,r}$	Price for buying regular electricity from retailer in time t €/kWh].
$c_t^{s,R,r}$	Price for selling regular electricity to retailer in time t €/kWh].
$E^{EV,eom}$	SOE of EV at end-of-morning [kWh].
$E^{EV,eod}$	SOE of EV at end-of-day [kWh].
$P_{t,s}^{L}$	Inflexible demand in period t in scenario s [kW].
$P_{t,s}^{PV}$	PV production in period t in scenario s [kW].
$\overline{P}^{EV}$	Charging rate of EV [kW].
$\overline{P}^{h}$	Power limit of the household h [kW].
$SOE^{EV,m}$	Initial morning SOE of EV for [kWh].
$SOE^{EV,a}$	Initial afternoon SOE of EV [kWh].
$\overline{SOE}^{EV}$	Maximum SOE of EV [kWh].
$\underline{SOE}^{EV}$	Minimum SOE of EV [kWh].
T^{a}	Arrival time of EV [h].
T^{d}	Departure time of EV [h].
Δt	Time interval duration [h].
$\eta^{EV,ch}$	EV charging efficiency.
$\eta^{EV,dc}$	EV discharging efficiency.
w^{c}, w^{p}, w^{cp}	Preference weights for cost, profit, and cost-profit.
w^{s}, w^{e}	Preference weights for supplier and energy type.
π_s	Probability of scenario s.
Decision variables	
$\hat{P}_t^{b}$	Scheduled power to buy in time t [kWh].
$P_{t,s}^{b}$	Power to buy in time t in scenario s [kW].
$\hat{P}_t^{b,P2P,g}$	Scheduled green power to buy from P2P market in time t [kW].
$\hat{P}_t^{b,P2P,r}$	Scheduled regular power to buy from P2P market in time t [kW].
$\hat{P}_t^{b,R,g}$	Scheduled green power to buy from retailer in time t [kW].
$\hat{P}_t^{b,R,r}$	Scheduled regular power to buy from retailer in time t [kW].
$\hat{P}_t^{d}$	Scheduled demand in time t [kWh].
$\hat{P}_t^{s}$	Scheduled power to sell in time t [kWh].
$P_{t,s}^{s}$	Power to sell in time t in scenario s [kW].
$\hat{P}_t^{s,P2P,g}$	Scheduled green power to sell to P2P market in time t [kW].
$\hat{P}_t^{s,P2P,r}$	Scheduled regular power to sell to P2P market in time t [kW].
$\hat{P}_t^{s,R,r}$	Scheduled regular power to sell to retailer in time t [kW]
$\hat{P}_t^{EV,ch}$	Scheduled EV charging power in time t [kW].
$\hat{P}_t^{EV,dc}$	Scheduled EV discharging power in time t [kW].
$\hat{P}_t^{EV,s}$	Scheduled EV power to sell in time t [kW].
$\hat{P}_t^{EV,u}$	Scheduled EV power to use in time t [kW].
$P_{t,s}^{EV,ch}$	EV charging power in time t in scenario s [kW].
$P_{t,s}^{EV,dc}$	EV discharging power in time t in scenario s [kW].
$P_{t,s}^{EV,s}$	EV power to sell in time t in scenario s [kW].
$P_{t,s}^{EV,u}$	EV power to use in time t in scenario s [kW].
$\hat{P}_t^{L}$	Scheduled inflexible load in time t [kW].
$\hat{P}_t^{PV,s,g}$	Scheduled green PV power to sell in time t [kW].
$\hat{P}_t^{PV,s,r}$	Scheduled regular PV power to sell in time t [kW].
$\hat{P}_t^{PV}$	Scheduled PV power in time t [kW].
$\hat{P}_t^{PV,u}$	Scheduled PV power to use in time t [kW].
$P_{t,s}^{PV,s}$	PV power to sell in time t in scenario s [kW].
$P_{t,s}^{PV,u}$	PV power to use in time t in scenario s [kW].
$\hat{P}_t^{u}$	Scheduled power for household use in time t [kWh].
$\hat{SOE}_t^{EV}$	Scheduled SOE of EV in time t [kWh].
$SOE_{t,s}^{EV}$	SOE of EV in time t in scenario s [kWh].
$\hat{u}_t^{EV}$	Binary variable: 1 if EV is scheduled to charge in time t , 0 otherwise.
$u_{t,s}^{EV}$	Binary variable: 1 if EV is charging in time t in scenario s , 0 otherwise.
$u_{t,s}^{EV,ch,+}$	Binary variable: 1 if EV is charging more in time t in scenario s , 0 otherwise.
$u_{t,s}^{EV,ch,-}$	Binary variable: 1 if EV is charging less in time t in scenario s , 0 otherwise.
$u_{t,s}^{EV,dc,+}$	Binary variable: 1 if EV is discharging more in time t in scenario s , 0 otherwise.
$u_{t,s}^{EV,dc,-}$	Binary variable: 1 if EV is discharging less in time t in scenario s , 0 otherwise.
$\hat{u}_t^{h}$	Binary variable: 1 if household is scheduled to buy in time t , 0 otherwise.
$u_{t,s}^{h}$	Binary variable: 1 if household is buying in time t in scenario s, 0 otherwise.
$(\hat{\delta}^{cp})\ \delta^{cp}$	(Normalized) Distance to goal for cost-profit.
$(\hat{\delta}^{e})\ \delta^{e}$	(Normalized) Distance to goal for energy type.
$(\hat{\delta}^{s})\ \delta^{s}$	(Normalized) Distance to goal for supplier.
$\Delta P_{t,s}^{b,+}$	Plus power to be bought in time t in scenario s [kW].
$\Delta P_{t,s}^{b,-}$	Minus power to be bought in time t in scenario s [kW].
$\Delta P_{t,s}^{s,+}$	Plus power to be sold in time t in scenario s [kW].
$\Delta P_{t,s}^{s,-}$	Minus power to be sold in time t in scenario s [kW].
$\Delta P_{t,s}^{EV,ch,+}$	Plus power to charge EV in time t in scenario s [kW].
$\Delta P_{t,s}^{EV,ch,-}$	Minus power to charge EV in time t in scenario s [kW].
$\Delta P_{t,s}^{EV,dc,+}$	Plus power to discharge EV in time t in scenario s [kW].
$\Delta P_{t,s}^{EV,dc,-}$	Minus power to discharge EV in time t in scenario s [kW].

in the remainder of this Section. Each household that participates in the P2P electricity market solves individually a SGP model using its own parameters, objectives, and preferences. The majority of the symbols are defined in Table 6, whereas the remaining are defined where they are first introduced.

4.2.1. *Objective functions and target distance constraints*

Objective functions for the optimization problem are introduced for the four attributes that are evaluated in Section 3. The two attributes related to financial aspects, i.e. costs and selling price are combined in a single objective. The objectives for the remaining two attributes: the type of energy bought and the energy bought from different suppliers are considered separately.

Based on the average part-worth utility values for the two clusters, users receive a higher utility for lower monthly costs and for higher accepted selling prices. This can be translated into two separate objectives: minimization of the costs and maximization of the profits. By reversing the sign of the expression for the expected value for profits, this objective function should be minimized and can be combined with the minimization of costs, in a single objective f^{cp} as given in (2). The components from (2): energy bought ($E^{b,P2P}$) and sold ($E^{s,P2P}$) in the P2P market, as well as the energy bought ($E^{b,R}$) and sold ($E^{s,R}$) by the retailer are decomposed in (3)–(6) The combination of these two objectives allows for simultaneous optimization of the household's expenses for electricity. Moreover, it prevents a situation in which the aspiration value for the profit objective equals 0, which happens for users that only consume electricity and do not have own generation. Since the resulting objective function is minimized, only the positive deviation from its target value is considered in (10).

The expected value of the second objective function f^{e} is to maximize the purchase of green electricity, either from the P2P market or from a retailer that sells green electricity. Both clusters receive higher utility when they purchase green electricity as seen in Section 3 albeit to a different extent. Due to the maximization of this objective function, the negative deviation from its target is minimized in (11).

For the third objective, regarding maximizing the electricity purchased from different suppliers f^s, there is a difference in the desired utility for the two clusters. Hence, participants belonging to Cluster 1 maximize their utility when purchasing electricity from the P2P market, whereas participants from Cluster 2 prefer to purchase regular electricity from the retailer. This is reflected in (8) and (9). In both cases, the negative deviation to the target is minimized in (12). All distance variables are positive or equal to 0, as in (13).

$$\mathbb{E}(f^{cp}(x,\cdot)) = \frac{w^c}{w^{cp}}(E^{b,P2P} + E^{b,R}) - \frac{w^p}{w^{cp}}(E^{s,P2P} + E^{s,R}) \tag{2}$$

$$E^{b,P2P} = \sum_{s\in S}\pi_s\Big(\sum_{t\in T}(c_{t,s}^{b,P2P,g}P_t^{b,P2P,g} + c_{t,s}^{b,P2P,r}\hat{P}_t^{b,P2P,r})\Big) \tag{3}$$

$$E^{b,R} = \sum_{s\in S}\pi_s\Big(\sum_{t\in T}(c_t^{b,R,g}\hat{P}_t^{b,R,g} + c_t^{b,R,r}(\hat{P}_t^{b,R,r} + \Delta P_{t,s}^{b,+} + \Delta P_{t,s}^{s,-}))\Big) \tag{4}$$

$$E^{s,P2P} = \sum_{s\in S}\pi_s\Big(\sum_{t\in T}(c_{t,s}^{s,P2P,g}\hat{P}_t^{s,P2P,g} + c_{t,s}^{s,P2P,r}\hat{P}_t^{s,P2P,r})\Big) \tag{5}$$

$$E^{s,R} = \sum_{s\in S}\pi_s\Big(\sum_{t\in T}(c_t^{s,R,g}\hat{P}_t^{s,R,g} + c_t^{s,R,r}(\hat{P}_t^{s,R,r} + \Delta P_{t,s}^{s,+} + \Delta P_{t,s}^{b,-}))\Big) \tag{6}$$

$$\mathbb{E}(f^e(x,\cdot)) = \sum_{t\in T}\Big(\hat{P}_t^{b,R,g} + \hat{P}_t^{b,P2P,g}\Big) \tag{7}$$

$$\mathbb{E}(f^s(x,\cdot)) = \sum_{t\in T}\Big(\hat{P}_t^{b,P2P,r} + \hat{P}_t^{b,P2P,g}\Big),\ \text{for C1} \tag{8}$$

$$\mathbb{E}(f^s(x,\cdot)) = \sum_{t\in T}\Big(\hat{P}_t^{b,R,r} + \hat{P}_t^{b,R,g}\Big),\ \text{for C2} \tag{9}$$

$$\mathbb{E}(f^{cp}(x,\cdot)) - \delta^{cp} = \mathbb{E}(g^{cp}) \tag{10}$$

$$\mathbb{E}(f^e(x,\cdot)) + \delta^e = \mathbb{E}(g^e) \tag{11}$$

$$\mathbb{E}(f^s(x,\cdot)) + \delta^s = \mathbb{E}(g^s) \tag{12}$$

$$\delta^{cp}, \delta^e, \delta^s \geq 0 \tag{13}$$

where $x = \{\hat{P}_t^{b,R,r}, \hat{P}_t^{b,R,g}, \hat{P}_t^{b,P2P,r}, \hat{P}_t^{b,P2P,g}, \hat{P}_t^{s,R,r}, \hat{P}_t^{s,P2P,r}, \hat{P}_t^{s,P2P,g}, \forall t\in T\}$

4.2.2. Household appliance constraints

Each household can schedule how much power to buy or sell for all time intervals, based on their expected production and consumption. Some households have PV generation and all households have an electric vehicle (EV) that is a controllable load and can operate in vehicle-to-grid and vehicle-to-home modes. The model can be extended and other controllable appliances can be added. In this subsection, the first stage constraints related to decisions made for scheduling the commitments to the markets are presented. Moreover, the second stage constraints related to the recourse actions as well as the linking constraints that connect the first and second stage decisions are detailed.

1. First stage constraints. The power balance for the electricity that is scheduled for use and purchase by the household is given in (14). The decomposition of the household demand is given in (15), whereas the decomposition of the power bought and the power used within the household are given in (16) and (17), respectively. A household can sell power in the form of different products, as in (18). The power that can be sold as green to the P2P market comes solely from PV (19), whereas the remainder of the PV power that is sold as well as power from the EV can be sold as regular electricity, either to the P2P market or to the retailer as in (20). The household is limited to only buying or selling power at a given time interval, and up to the allowed limit by (21) and (22). The power produced by the PV can be either sold or used to cover some of the load of the household, as per (23). The power that can be scheduled from the PV and the load is limited by the maximum values observed in the scenario set for the given time interval as detailed in (24) and (25).

$$\hat{P}_t^d = \hat{P}_t^b + \hat{P}_t^u,\ \forall t\in T \tag{14}$$

$$\hat{P}_t^d = \hat{P}_t^L + \hat{P}_t^{EV,ch},\ \forall t\in T \tag{15}$$

$$\hat{P}_t^b = \hat{P}_t^{b,P2P,g} + \hat{P}_t^{b,P2P,r} + \hat{P}_t^{b,R,g} + \hat{P}_t^{b,R,r},\ \forall t\in T \tag{16}$$

$$\hat{P}_t^u = \hat{P}_t^{PV,u} + \hat{P}_t^{EV,u},\ \forall t\in T \tag{17}$$

$$\hat{P}_t^s = \hat{P}_t^{s,P2P,g} + \hat{P}_t^{s,P2P,r} + \hat{P}_t^{s,R,r},\ \forall t\in T \tag{18}$$

$$\hat{P}_t^{s,P2P,g} = \hat{P}_t^{PV,s,g},\ \forall t\in T \tag{19}$$

$$\hat{P}_t^{s,P2P,r} + \hat{P}_t^{s,R,r} = \hat{P}_t^{PV,s,r} + \hat{P}_t^{EV,s},\ \forall t\in T \tag{20}$$

$$\hat{P}_t^b \leq \hat{u}_t^h\overline{P}^h,\ \forall t\in T \tag{21}$$

$$\hat{P}_t^s \leq (1-\hat{u}_t^h)\overline{P}^h,\ \forall t\in T \tag{22}$$

$$\hat{P}_t^{PV} = \hat{P}_t^{PV,u} + \hat{P}_t^{PV,s,g} + \hat{P}_t^{PV,s,r},\ \forall t\in T \tag{23}$$

$$\hat{P}_t^{PV} \leq max_{s\in S}P_{t,s}^{PV},\ \forall t\in T \tag{24}$$

$$\hat{P}_t^L \leq max_{s\in S}P_{t,s}^L,\ \forall t\in T \tag{25}$$

The (dis)charging of the EV vehicle is divided into two cycles during the day, before the time of departure in the morning T^d and after arrival in the evening T^a, which define two intervals: when the EV is available $T^{EV,av} = [0,T^d)\cup[T^a,T]$ and when the EV is not available $T^{EV,nav} = T\setminus T^{EV,av}$. Based on these intervals the limits for the non-negative charging and discharging variables of the EV (26) are enforced by (27)–(30). The end use of the power discharged by the EV is scheduled in (31). The state of energy of the battery is defined in (32)–(34), depending on the time interval. Its allowable operational limits are imposed in (35), whereas the desired charging levels at departure time or end of the day is imposed in (36) and (37)

$$\hat{P}_t^{EV,ch}, \hat{P}_t^{EV,dc} \geq 0, \forall t\in T \tag{26}$$

$$\hat{P}_t^{EV,ch} \leq \hat{u}_t^{EV}\overline{P}^{EV}, \forall t\in T^{EV,av} \tag{27}$$

$$\hat{P}_t^{EV,ch} = 0,\ \forall t\in T^{EV,nav} \tag{28}$$

$$\hat{P}_t^{EV,dc} \leq (1-\hat{u}_t^{EV})\overline{P}^{EV}, \forall t\in T^{EV,av} \tag{29}$$

$$\hat{P}_t^{EV,dc} = 0,\ \forall t\in T^{EV,nav} \tag{30}$$

$$\hat{P}_t^{EV,u} + \hat{P}_t^{EV,s} = \hat{P}_t^{EV,dc}\eta^{EV,dc},\ \forall t\in T^{EV,av} \tag{31}$$

$$S\hat{O}E_t^{EV} = SOE^{EV,m} + (\eta^{EV,ch}\hat{P}_t^{EV,ch} - \hat{P}_t^{EV,dc})\Delta t, t=0 \tag{32}$$

$$S\hat{O}E_t^{EV} = SOE^{EV,a} + (\eta^{EV,ch}\hat{P}_t^{EV,ch} - \hat{P}_t^{EV,dc})\Delta t, t=T^a \tag{33}$$

$$S\hat{O}E_t^{EV} = S\hat{O}E_{t-1}^{EV} + (\eta^{EV,ch}\hat{P}_t^{EV,ch} - \hat{P}_t^{EV,dc})\Delta t, \forall t\in T^{EV,av} \tag{34}$$

$$\underline{SOE}^{EV} \leq S\hat{O}E_t^{EV} \leq \overline{SOE}^{EV},\ \forall t\in T^{EV,av} \tag{35}$$

$$S\hat{O}E_t^{EV} \geq E^{EV,eom},\ t=T^d \vee t\in T^{EV,nav} \tag{36}$$

$$S\hat{O}E_t^{EV} \geq E^{EV,eod}, t=T \tag{37}$$

2. Second stage constraints. The balance for the power that is bought or sold has to be maintained for each scenario as in (38) and (39). The power that can be bought or sold by a household is limited by the allowed limit and these actions cannot be performed simultaneously as in (40) and (41). The decomposition of the power produced by the PV per scenario is given in (42).

$$P_{t,s}^L + P_{t,s}^{EV,ch} = P_{t,s}^b + P_{t,s}^{PV,u} + P_{t,s}^{EV,u},\ \forall t\in T, \forall s\in S \tag{38}$$

$$P_{t,s}^s = P_{t,s}^{PV,s} + P_{t,s}^{EV,s},\ \forall t\in T, \forall s\in S \tag{39}$$

$$P_{t,s}^b \leq u_{t,s}^h\overline{P}^h,\ \forall t\in T, \forall s\in S \tag{40}$$

$$P_{t,s}^s \leq (1-u_{t,s}^h)\overline{P}^h,\ \forall t\in T, \forall s\in S \tag{41}$$

$$P_{t,s}^{PV} = P_{t,s}^{PV,u} + P_{t,s}^{PV,s}, \ \forall t \in T, \forall s \in S \tag{42}$$

The scheduling of the EV in each scenario is done in the same manner as in the first stage. Hence, the desired charging levels at departure time and end of optimization are always maintained. Constraints (26)–(37) are also implemented for the second stage variables as stated in (43).

Variables: $\{\hat{P}_t^{EV,ch}, \hat{P}_t^{EV,dc}, u_{t,s}^{EV}, \hat{P}_t^{EV,u}, \hat{P}_t^{EV,s}, S\hat{O}E_t^{EV}, \ \forall t \in T\}$
from (26)–(37) are replaced with

$$\{P_{t,s}^{EV,ch}, P_{t,s}^{EV,dc}, u_{t,s}^{EV}, P_{t,s}^{EV,u}, P_{t,s}^{EV,s}, SOE_{t,s}^{EV}, \ \forall t \in T, \forall s \in S\} \tag{43}$$

3. Linking constraints. Constraints (44) and (45) relate the scheduled quantities with the actual power that is bought or sold per scenario. Plus adjustments of power are considered those that result in increased selling of power or increased consumption, whereas minus adjustments of power result in the opposite, i.e. decreased selling of power or decreased consumption. The minus adjustments for the bought power ($\Delta P_{t,s}^{b,-}$) and the minus adjustment for the sold power ($\Delta P_{t,s}^{s,-}$) are limited by the scheduled quantities in (46) and (48). The plus adjustment for bought power and ($\Delta P_{t,s}^{b,+}$) and the plus adjustment for the sold power ($\Delta P_{t,s}^{s,+}$) are then limited by the remaining capacity between the household limit and the scheduled quantities in (47) and (49), respectively.

$$P_{t,s}^{b} = \hat{P}_t^{b} + \Delta P_{t,s}^{b,+} - \Delta P_{t,s}^{b,-}, \ \forall t \in T, \forall s \in S \tag{44}$$

$$P_{t,s}^{s} = \hat{P}_t^{s} + \Delta P_{t,s}^{s,+} - \Delta P_{t,s}^{s,-}, \ \forall t \in T, \forall s \in S \tag{45}$$

$$\Delta P_{t,s}^{b,-} \leq \hat{P}_t^{b}, \ \forall t \in T, \forall s \in S \tag{46}$$

$$\Delta P_{t,s}^{b,+} \leq \overline{P}^{h} - \hat{P}_t^{b}, \ \forall t \in T, \forall s \in S \tag{47}$$

$$\Delta P_{t,s}^{s,-} \leq \hat{P}_t^{s}, \ \forall t \in T, \forall s \in S \tag{48}$$

$$\Delta P_{t,s}^{s,+} \leq \overline{P}^{h} - \hat{P}_t^{s}, \ \forall t \in T, \forall s \in S \tag{49}$$

The relation between the scheduled power and the possible realizations per scenario is enabled through the adjustments for power in (50) for charging and (51) for discharging. The minus charging adjustment ($\Delta P_{t,s}^{EV,ch,-}$) and the minus discharging adjustment ($\Delta P_{t,s}^{EV,dc,-}$) are limited by the scheduled power in (53) and (56). Then, the plus charging adjustment ($\Delta P_{t,s}^{EV,ch,+}$) and the plus discharging adjustment ($\Delta P_{t,s}^{EV,dc,+}$) are limited by the remaining available capacity as in (52) and (55). It is not possible to simultaneously adjust the power upwards and downwards, as stated in (54) for charging and (57) for discharging.

$$P_{t,s}^{EV,ch} = \hat{P}_t^{EV,ch} + \Delta P_{t,s}^{EV,ch,+} - \Delta P_{t,s}^{EV,ch,-}, \ \forall t \in T, \forall s \in S \tag{50}$$

$$P_{t,s}^{EV,dc} = \hat{P}_t^{EV,dc} + \Delta P_{t,s}^{EV,dc,+} - \Delta P_{t,s}^{EV,dc,-}, \forall t \in T, \forall s \in S \tag{51}$$

$$0 \leq \Delta P_{t,s}^{EV,ch,+} \leq (\overline{P}^{EV} - \hat{P}_t^{EV,ch}) u_{t,s}^{EV,ch,+}, \ \forall t \in T, \forall s \in S \tag{52}$$

$$0 \leq \Delta P_{t,s}^{EV,ch,-} \leq \hat{P}_t^{EV,ch} u_{t,s}^{EV,ch,-}, \ \forall t \in T, \forall s \in S \tag{53}$$

$$u_{t,s}^{EV,ch,-} + u_{t,s}^{EV,ch,+} \leq 1, \forall t \in T, \forall s \in S \tag{54}$$

$$0 \leq \Delta P_{t,s}^{EV,dc,+} \leq (\overline{P}^{EV} - \hat{P}_t^{EV,dc}) u_{t,s}^{EV,dc,+}, \ \forall t \in T, \forall s \in S \tag{55}$$

$$0 \leq \Delta P_{t,s}^{EV,dc,-} \leq \hat{P}_t^{EV,dc} u_{t,s}^{EV,dc,-}, \forall t \in T, \forall s \in S \tag{56}$$

$$u_{t,s}^{EV,dc,-} + u_{t,s}^{EV,dc,+} \leq 1, \forall t \in T, \forall s \in S \tag{57}$$

4.2.3. Goal targets

An aspiration target value is set for each objective. It is set to a minimum value for minimization objectives and a maximum obtainable value for maximization objectives. Therefore, the distance from the goal targets can only be one-directional. The target for the cost-profit objective is determined by individually optimizing the cost-profit objective in (2), as in (58).

$$\mathbb{E}(g^{cp}) = \min_x \mathbb{E}(f^{cp}(x,\cdot)) \quad \text{s.t.}(14)\text{–}(57) \tag{58}$$

The targets for the goals for energy type and supplier are determined using the results of solving problem (58). The total expected electricity that the household schedules to buy can be determined from the optimization of the cost-profit objective in (59). This value is adopted both as the expected target value for the energy type objective f^e green energy as well as for the supplier objective in (60) with the following meaning. When optimizing the objective for the energy type f^e, the household aims to maximize electricity purchased from the desired type, which in this case is green electricity for both clusters. Similarly, when optimizing the objective for desired supplier f^s, the household aims to buy as much electricity as possible from the desired supplier, which differs per cluster. Moreover, since the individual objective functions differ in their units, the calculated targets also serve to normalize the distances in the objective functions as in (61).

$$\mathbb{E}(\hat{E}^b) = \sum_{t \in T} \hat{P}_t^b \tag{59}$$

$$\mathbb{E}(g^e) = \mathbb{E}(\hat{E}^b), \ \mathbb{E}(g^s) = \mathbb{E}(\hat{E}^b) \tag{60}$$

$$\hat{\delta}^{cp} = \frac{\delta^{cp}}{\mathbb{E}(g^{cp})}, \hat{\delta}^{e} = \frac{\delta^{e}}{\mathbb{E}(g^{e})}, \hat{\delta}^{s} = \frac{\delta^{s}}{\mathbb{E}(g^{s})} \tag{61}$$

4.2.4. Final SGP HEMS model

The final SGP model for the HEMS is outlined here. The main objective function is to minimize the normalized and weighted distances or the deviations to the target levels set for each objective as given in (62). The weights that are used in the SGP model are based on the attribute importance weights implicitly derived from the DCE analysis in Section 3.4.3 and shown on Fig. 4. The weights for supplier w^s and energy type w^e are equal to the corresponding importance weights, whereas the weights for monthly cost and selling price are combined in a single weight for cost and profit $w^{cp} = w^c + w^p$.

$$\min_x \ w^{cp}\hat{\delta}^{cp} + w^e\hat{\delta}^e + w^s\hat{\delta}^s \quad \text{s.t.}(2)\text{–}(61) \tag{62}$$

4.3. P2P market-clearing model with double auction

The market-clearing mechanism that is adopted in this study is a double-sided auction, which is cleared for every time interval. It is a forward market that for the purpose of this study is cleared day-ahead. However, the model can be adjusted and the market can be cleared in near-real time in a rolling-horizon manner. The participating peers submit bids and offers consisting of quantity and price $(\overline{q}_t^b, \overline{p}_t^b)$ for bids, and $(\overline{q}_t^o, \overline{p}_t^o)$ for offers, for each time interval, for each of the products that are traded in the market. The quantity of the products is determined by the SGP optimization for the HEMS. The price for the products is determined using the WTP for each type of product as determined by the DCE analysis. This price serves as the maximum price a participant is willing to pay for a specific product in the P2P market. To introduce variability in the submitted prices per customer and per time interval, it is assumed that the submitted prices are sampled from a normal distribution with a mean equal to the WTP. The objective of the market-clearing mechanism is to minimize the costs for the energy exchange while maintaining a balance between the exchange and respecting the limits imposed by the submitted prices, as outlined in (63). The clearing mechanism is pay-as-clear, so there is a single clearing price per time interval and product. The clearing price is calculated as the average price of the last accepted bid in descending order and the last accepted offer in ascending order.

$$\min_{\mathbf{q^o},\mathbf{q^b}} \sum_{t \in T} \Big(\sum_{o \in O} q_t^o p_t^o - \sum_{b \in B} q_t^b p_t^b \Big) \tag{63a}$$

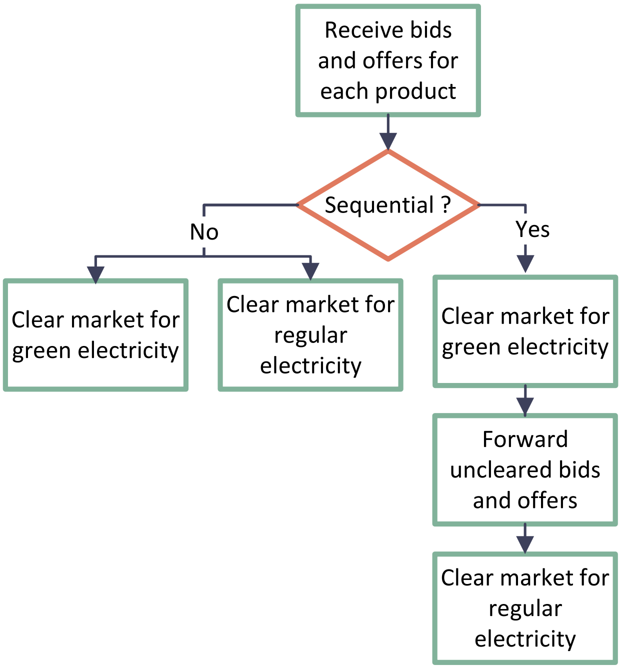


Fig. 6. Flowchart for separate and sequential market clearing.

$$\text{s.t.} \sum_{o \in O} q_t^o = \sum_{b \in B} q_t^b, \ \forall t \in T \tag{63b}$$

$$0 \leq q^o \leq \overline{q}^o, \ \forall o \in O, \forall t \in T \tag{63c}$$

$$0 \leq q_t^b \leq \overline{q}_t^b, \ \forall b \in B, \forall t \in T \tag{63d}$$

Since bids and offers are submitted for each product present in the market, they can be cleared separately. However, some products that have differentiating properties can also be considered to be part of a more general product. For example, green electricity is a subset of regular electricity, with the origin of production being its differentiating property. If some of the offers or bids for the specialized products are not (completely) cleared in their dedicated market, they can be added, with updated prices, to the bids and offers of the more general product. This represents a sequential clearing of the products in the market, starting from the more specific products and going to the general product categories. In this study, the sequence goes from clearing first green electricity and then regular electricity, as shown in Fig. 6.

4.4. Case study

4.4.1. Description of case study and input data

Several sources from the Netherlands are used to source the input data used for the case study, including the data from the conducted survey. Based on the survey results, 48% of the respondents, belong to Cluster 2, whereas the remaining 52% are from Cluster 1. These percentages are used to determine the number of participants from each cluster, according to the total number of market participants for different simulations.

For the electricity consumption and production of the households, smart meter measurements from August provided by a Dutch distribution system operator are used. The range between the minimum and maximum values and the mean value for the considered smart meters, over a single day, are shown in Fig. 8. The input data for the inflexible demand and PV generation and the scenario sets related to these two variables are created from this data. To generate load and PV scenarios, noise that follows a normal probability density function with standard deviation $\sigma = 0.2$ is added to the actual measurements to generate 100 scenarios for load and PV per household.

Moreover, it is assumed that all the EVs have similar specifications to a Tesla Model 3, as this is the model with the highest share in the Dutch market [60]. The energy required for charging on daily basis is set at 8.2 kWh, based on data about 75% of the charging events in private stations from ElaadNL [61]. The estimated arrival and departure times for the EVs are also derived using data from ElaanNL. The parameters for the EV are given in Table 7.

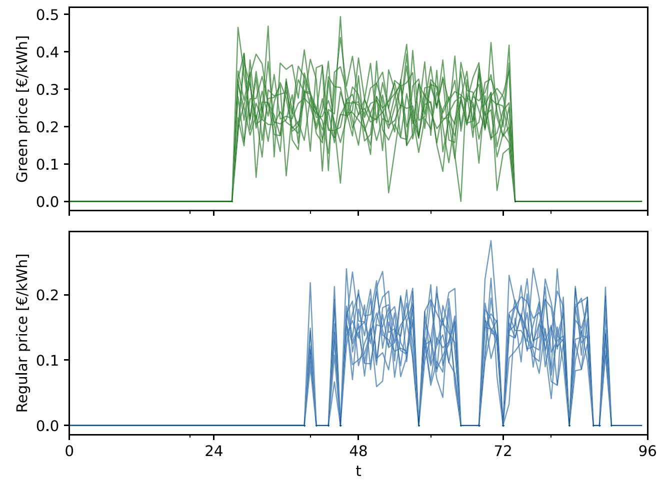
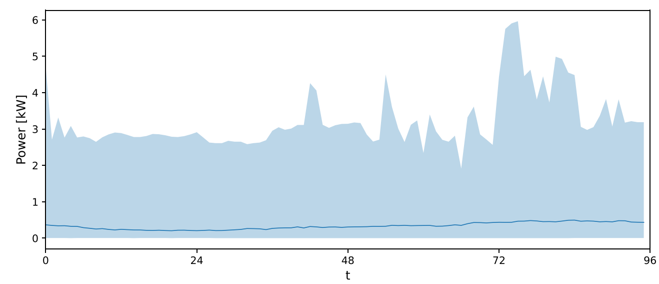
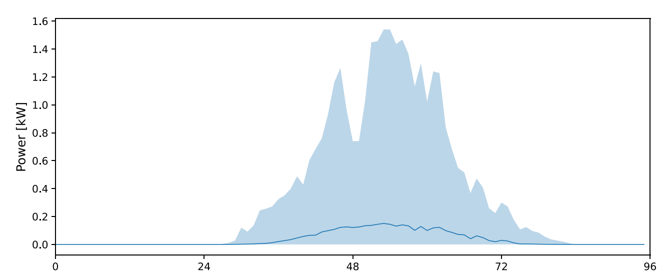


Fig. 7. Price scenarios for the P2P market.



(a) Load



(b) PV production

Fig. 8. Range and mean values for input data.

Table 7
EV parameter values.

Parameter	Parameter
$\overline{E}^{EV} = 57$ kWh	$\underline{SOE}^{EV} = 0.2\overline{E}^{EV}$
$\overline{P}^{EV} = 3.7$ kW	$\overline{SOE}^{EV} = 0.95\overline{E}^{EV}$
$\eta^{EV,ch} = 95\%$	$T^d \sim \text{Beta}(23.6, 62.36) \cdot T$
$\eta^{EV,dc} = 95\%$	$T^a \sim \text{Beta}(76.42, 33.40) \cdot T$

Table 8
Electricity price data [€/kWh].

Tariff	Regular	Low	Max. price	Cluster 1	Cluster 2
$c^{b,G}$	0.46	0.38	$c^{b,P2Pg}$	0.47	0.31
$c^{b,R}$	0.34	0.28	$c^{b,P2Pr}$	0.28	0.25
$c^{s,R}$	0.08	/	$c^{s,P2Pg/P2Pr}$	0.10	0.09

The average values for electricity prices for regular and renewable electricity from energy providers in the Netherlands are used as inputs [47]. The values are given in Table 8. The low tariff period is active from 21:00 until 7:00. The WTP for different attributes of electricity as provided by the survey analysis has been converted to a price per kWh of electricity, using the average consumption of electricity in the Netherlands of 3500 kWh/year for the provided monthly cost in the survey [62,63]. A reference value of 0.25 [€/kWh] is added to form the maximum price for buying electricity in the P2P market. This value is based on the low tariffs of the retailers. The resulting prices per product ($c^{b,P2P,g}$ or $c^{b,P2P,r}$) for the two clusters serve to generate electricity bid prices. Since the highest utility is derived from selling at the highest price, according to Table 4, the WTP for selling electricity at 10 €/kWh is used to calculate the maximum price for selling either green or regular electricity. This value is added to the average feed-in tariff price, resulting in the price for selling electricity ($c^{s,P2P,g}$ / $c^{s,P2P,r}$) in Table 8.

To provide some variability in the submitted bids in different time intervals and by different households, prices for the bids and offers are sampled from a normal distribution. The mean of the probability density function is equal to the prices from Table 8, whereas the standard deviation is assumed to be $\sigma = 0.005$. With this approach, it is possible to have a situation in which the price that the households bid for electricity bought in the P2P market is sometimes higher than the retailer's prices. From Table 8, it is evident that participants belonging to Cluster 2 are more price-sensitive and are not willing to pay high prices specifically for green electricity or electricity coming from the P2P market.

The SGP model requires market-clearing prices from the P2P market ($c_t^{P2P,g}, c_t^{P2P,r}$) as input. Since such data is not available, the following procedure is done to generate scenarios for the prices. An initial set of 10 price scenarios, which is shown in Fig. 7, is used in combination with 100 *(load, PV)* scenarios to create a set of 1000 equiprobable scenarios with the tuple *(load, PV,* $c_t^{P2P,g}, c_t^{P2P,r}$*)* per household. It is considered that 100 households participate in the market. The SGP HEMS model is solved for each household and then the bids and offers from the 100 households are sequentially cleared in the market. This procedure is repeated for 100 different instances from the initial scenario set. The mean and the standard deviation over the 100 market-clearing prices are used to generate a new set of price scenarios for green and regular electricity that correspond to the actual market results.

The new set of price scenarios is combined with the scenarios for *(load, PV)* of each household. To reduce the scenario set to a smaller set with representative scenarios, k-medoid clustering is performed for each household. A final set of 10 non-equiprobable scenarios of the tuple *(load, PV,* $c_t^{P2P,g}, c_t^{P2P,r}$*)* are determined for each household. For different simulation cases, depending on the required number of participants, households are selected from the available dataset. Moreover, for each case, 10 independent runs are performed and a summary of the results is presented. The simulations are performed using Python 3.8 environment, whereas the optimization models are modeled with Pyomo [64] and are solved using Gurobi [65] as the solver.

4.4.2. Simulation results

SGP HEMS results. A case of a market with 100 participants, 52% belonging to Cluster 1 and 48% to Cluster 2 is simulated for a single day. The first stage variables are shown in Fig. 9 for two households, each from a different cluster. The influence of the preferences is visible in the scheduled commitments for buying electricity from different sources. The HEMS for a household from Cluster 1, attempts to schedule and purchase green electricity for the majority of time intervals. When it is possible, i.e. during the daytime, this energy is scheduled to be bought from the P2P market. Otherwise, green energy is bought from the conventional retailer. In the early hours of the day, the electric

Fig. 9. First stage variables for households from the two clusters.

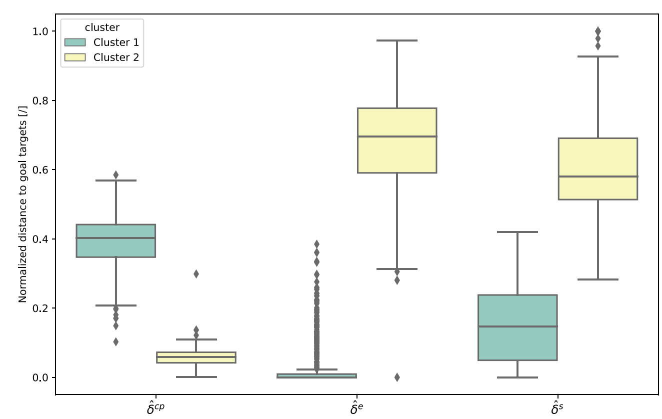


Fig. 10. Normalized distance to goal targets.

Table 9
Expected costs for households per cluster over the simulated period [€].

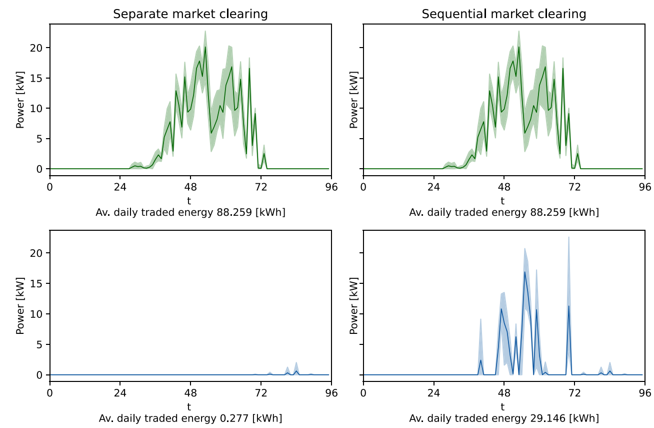
Cluster	min	mean	max	SD
Cluster 1	1.84	3.44	7.68	1.21
Cluster 2	1.28	2.54	5.06 1	0.87

vehicle is scheduled to charge, taking advantage of the lower tariff period for green electricity. The household from Cluster 2 demonstrates different behavior. It schedules to buy regular electricity, which is cheaper, and its purchase of green electricity is on a lower scale than the household from Cluster 1. When it comes to selling electricity, both households try to sell the electricity produced by the PV, as green electricity in the P2P market, since its clearing price is the highest. Consequently, they would get higher utility than selling it as regular electricity. Moreover, it is evidently not attractive to sell some of the electricity stored by the EV as regular electricity.

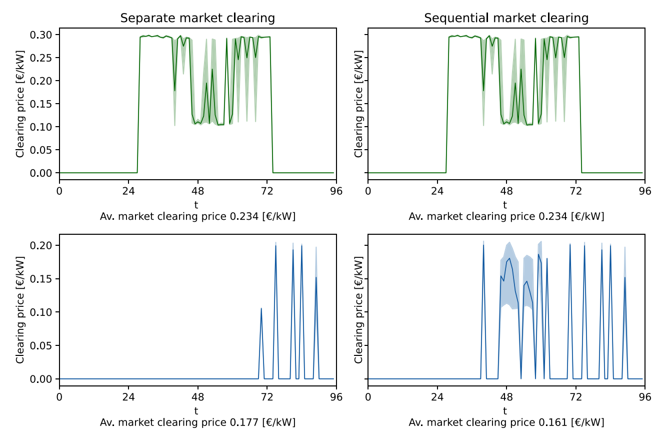
Distance to goal targets. A summary of the normalized distance to the goal targets for 100 households over 10 simulation runs is presented in Fig. 10. Since the source of electricity is the most important goal for participants from Cluster 1, the optimization results in the smallest distances to that aspiration level. This is followed by the distance to the desired supplier, which for Cluster 1 is the P2P market. Finally, the cost and profit goals do not carry a lot of weight resulting in the largest distance to the target. The situation for the households from Cluster 2 is the opposite. Since the weights for cost and profit are relatively high, their distance to this target is very low. The distance to the desired, green type of electricity is relatively large because this type of electricity is more expensive. However, the prices for green electricity from the P2P market can be lower than the retailer's prices allowing these households to simultaneously satisfy the two goals. The distance to the target for the supplier is more widely spread because even though these participants prefer trading with a traditional retailer, it is sometimes economically more profitable for them to buy and sell energy from the P2P market. This happens because the clearing prices in the P2P market can be lower than the retailer's prices and higher than the FiT tariff and the importance of cost-profit outweighs the importance for the supplier. These results indicate that P2P markets can be an alternative for both participants who explicitly want to join such initiatives and for participants who are looking to achieve cost savings. The analysis of the expectation of the daily costs for the households from different clusters presented in Table 9 corresponds to these results. In general, participants from Cluster 1 expect higher costs, since they prefer buying renewable energy which is priced higher than regular, regardless if it comes from the retailer or the P2P market.

Order of market clearing. The impact of the separate or sequential market-clearing on the quantity of electricity cleared is presented in Fig. 11(a). Green electricity is traded during the daytime since the only renewable source of production are PV systems. Since green electricity is the first product that is cleared, the outcome is not affected by the clearing order. However, for the regular type of electricity, the impact is significant. The average energy that is cleared in a day changes from 0.277 kWh in the separate market-clearing to 29.146 kWh in the sequential market clearing. This consequently influences the total volume of energy traded in the P2P market. Nevertheless, the volume of green electricity that is cleared is always higher than regular electricity. This is because purchasing green electricity is a goal that is favored by all market participants. In this regard, the P2P market may represent an incentive for end-users to install renewable generation systems, as the income from selling the electricity in these markets can reduce the return on investment period, especially when there are no other subsidies in place.

The average price in the market for green electricity is also not influenced by the order of clearing as seen in Fig. 11(b). It is noticeable that for some time periods the range between the maximum and minimum prices achieved is wider, whereas it is relatively constant in other periods. Moreover, in the sequential market clearing for regular electricity, the average price is lower than in the separate market clearing, from 0.161 €/kWh to 0.177 €/kWh. This is a result of the availability of bids and offers and is a matter of matching supply and demand. The higher volume that is matched can lead to slightly lower market-clearing prices. It can be noted that even though some market



(a) Average and min-max range of energy cleared



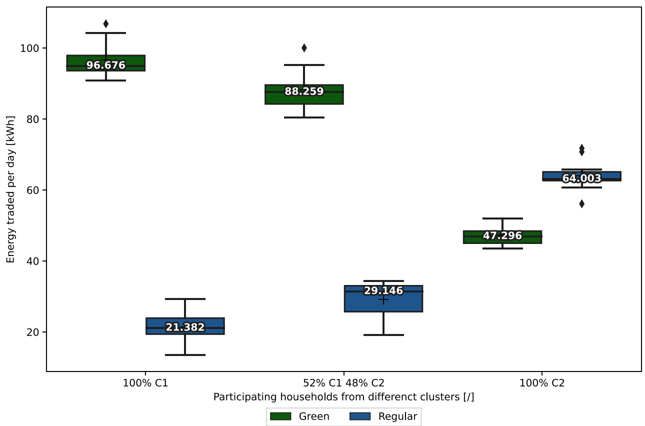
(b) Average and min-max range of market-clearing price

Fig. 11. Separate and sequential market-clearing results.

participants may have higher WTP and submit bids that are higher than the retailers' prices for buying, the market-clearing prices for both products are lower than the retailers' prices and higher than the FiT price for selling. To summarize, since trading higher volumes brings benefits to the participants, and there are no major drawbacks, the sequential market-clearing represents an efficient method to operate such markets with multiple products with partially overlapping characteristics.

Cluster representation. The effect of the preferences of the market participants reflected in the two clusters on the market is shown in Fig. 12. To demonstrate this, in addition to the base case with 52% participants belonging to C1 and 48% to C2 as in the survey, two other cases in which 100% of the participants come from the each of the two clusters are performed. This is done for a market comprised of 100 households. A box plot of the energy traded in a single day and the average values are shown in Fig. 12(a). The highest amount of green energy is traded when all participants belong to Cluster 1, who have strong preferences for buying green energy and higher WTP. The least green energy is traded when all participants belong to Cluster 2. The opposite is true for regular electricity. Although the ratio of the energy traded for the two products changes according to the preferences, the total energy that is cleared in the market remains relatively the same.

Concerning the prices shown in Fig. 12(b), the highest prices for the two products are achieved when all participants belong to Cluster 1, because they have a higher willingness to pay and as a result submit higher bids to the market. Therefore, although the user preferences do not influence significantly the total energy that is traded, they do influence the quantity of the different products that are traded, as well



(a) Energy cleared per day including average value [kWh]

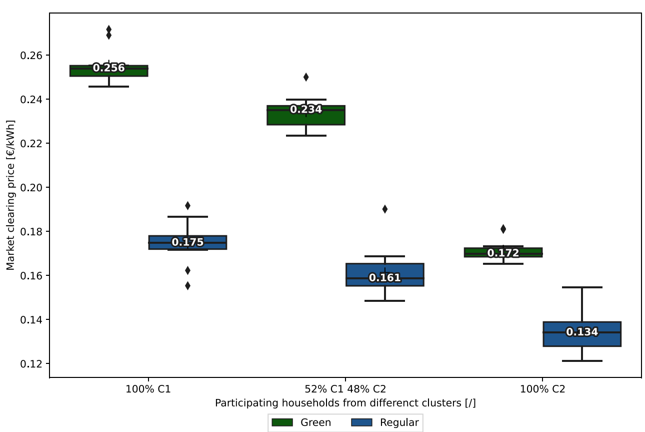
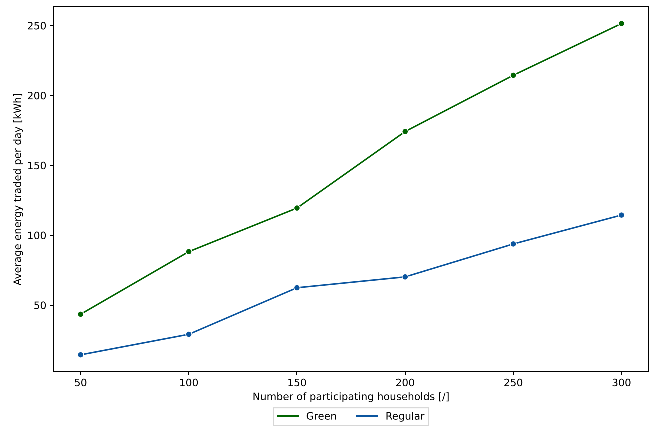
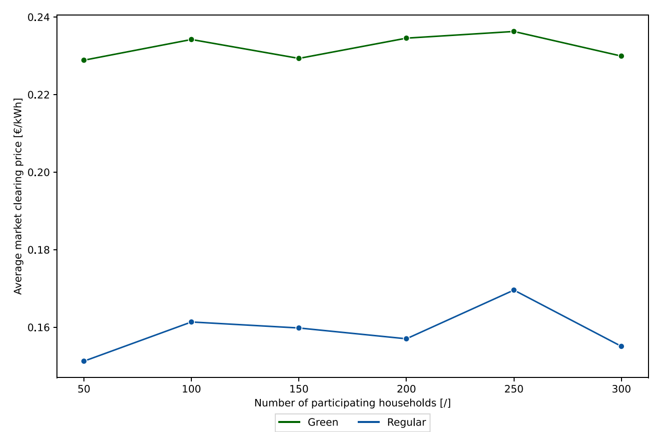


Fig. 12. Market clearing results with participants from different clusters.



(a) Average and min-max range of energy cleared



(b) Average and min-max range of market-clearing price

Fig. 13. Market clearing results for a varying number of market participants.

as the clearing prices. Thus, the desirability of a certain product or attribute and the willingness to pay for it have an impact on both the design and the outcomes of the market.

Varying number of market participants. User-centric markets can have a varying number of participants. Therefore it is of interest to evaluate the influence of the number of participants on the market outcomes and its scalability. The results for a range of 50 to 300 households are presented in Fig. 13. The average energy that is cleared for the two products increases linearly with the number of participants as seen in Fig. 13(a). The prices are not affected by the changing number of participants in Fig. 13(b). Thus, markets with fewer participants will have similar prices as markets with more participants, and they are not negatively affected by the smaller size. This means that establishing a P2P market is beneficial in terms of prices regardless of the number of participants, although the volume of energy cleared will likely differ.

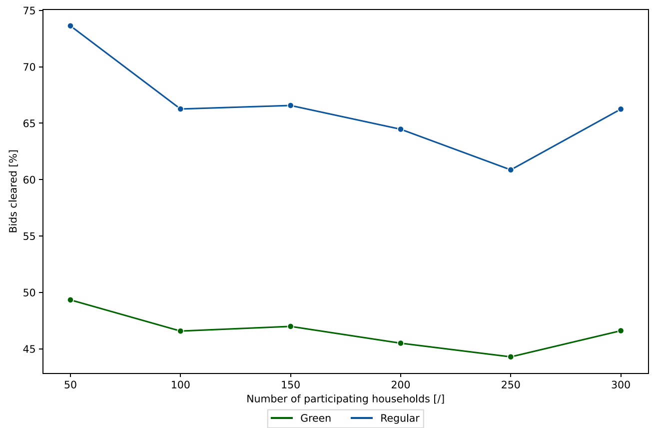
The average percentage of bids and offers that are cleared compared to those that are submitted to the market for varying market sizes is shown in Fig. 14. The average is calculated over all time intervals and for 10 independent runs per market size. The percentage of bids for green electricity that is cleared is between 45 and 50% regardless of the market size, whereas the percentage of cleared bids for regular electricity is consistently higher, between 60 and 75%. Since green electricity is a more desired product for both clusters, there are more submitted bids, so higher demand, for this product, compared with regular electricity. When looking at the percentage of offers cleared in Fig. 14(b), it is evident that for both products, the percentage of offers that are cleared is very high. In principle, there is more demand than supply in the market, which is expected since the electricity that

Table 10
Out-of-sample analysis costs for households per cluster over the simulated period [€].

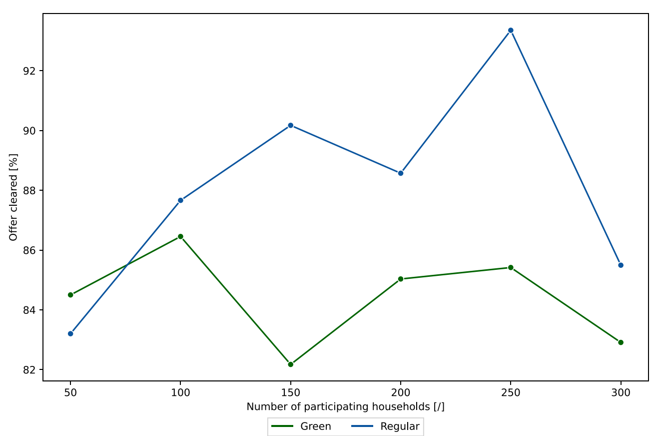
Cluster	C^{SSD}		C^{AC}	
	mean	SD	mean	SD
Cluster 1	3.13	1.07	5.59	1.54
Cluster 2	1.90	0.73	4.61 1	1.55

is offered for sale is generated by small PV installations and a limited surplus of EV battery charge. Hence, there is room for more generation installations in the market, regardless of the market size, according to the balance of supply and demand. Finally, even though the percentage of cleared bids seems to slightly decrease with the increase in the number of participants, the same cannot be said for the percentage of cleared offers, where there is no evident trend.

Out-of-sample analysis. Lastly, an out-of-sample analysis is done for the 10 independent runs of the case with 100 households and sequential market clearing. To perform this, the actual smart meter measurements are used as realizations for the inflexible load consumption and PV production. The clearing prices from the sequential market-clearing are used as realizations of the P2P market prices. The first stage variables, i.e. the power that is scheduled to be bought or sold to different suppliers are fixed. The deviations from the scheduled values from the actual production, consumption, and price realizations in the second stage are minimized to obtain the results. The resulting expected cost per household per cluster is shown in Table 10, in the column C^{SSD}, where SSD stands for second-stage deviations. Here it is assumed that all



(a) Percentage of cleared bids



(b) Percentage of cleared offers

Fig. 14. Percentage of cleared bids and offers for a varying number of market participants.

scheduled quantities can be cleared in the P2P market. Hence the total costs are actually lower than the in-sample expected costs. However, in reality, not all bids and offers are cleared in the market. If only those quantities are charged at the P2P market-clearing prices and the remaining uncleared quantity is actually traded with the retailer, in the corresponding category of green or regular electricity, the actual costs C^{AC} are higher than the in-sample expected costs. This is expected since the possibility of not matching is not considered in the optimization model. Moreover, this refers to the need to improve the coordination between the offers and bids in terms of time and quantity, to achieve a higher percentage of cleared offers and prices. This will be the subject of future work.

5. Conclusions

The design of P2P electricity markets that include desirable products and enable the fulfillment of objectives that are relevant for end-users is crucial for their development and successful deployment. To elicit user preferences and attitudes toward participation in P2P electricity markets specifically in the context of the focus country, a survey that includes a discrete choice experiment was conducted in the Netherlands. In comparison to other studies, attributes that are directly related to electricity as a product were the focus of the experiment, based on which product differentiation in the P2P market is made possible. The survey results indicate that the possibility to buy renewably generated electricity and the resulting costs are more important factors for making decisions regarding electricity trading, compared to whether exchanges will be done within a P2P market or a conventional retailer or having the possibility to set your own selling price for electricity. User preferences and objectives derived from the discrete choice experiment were incorporated into the multi-objective optimization model of a home energy management system, as part of an integrated approach of combining descriptive and prescriptive analytics. Uncertainty in the realization of market prices and own production and demand was also considered through stochastic optimization. The resulting stochastic multi-objective optimization model is solved through stochastic goal programming. A case study that combined the results from the survey and actual data from the Netherlands was presented. The results demonstrate that the decision-support tool is able to reflect the user preferences of different clusters of users automatically in the scheduled commitments in the P2P market. Moreover, the possibility for a recourse action in the two-stage stochastic optimization provides a method of how market participants can respond to changes to their scheduled market commitments in real time, thus ensuring that the scheduled trades will take place. A forward double-sided auction-based P2P electricity market with product differentiation was proposed and simulated. The product differentiation is based on the results of actual choices made by respondents during the survey, rather than assumptions based on literature study or self-expressed intentions. The forward auction provides sufficient time to plan ahead and coordinate with other stakeholders if necessary, it encourages truthful bidding and results in efficient market operation. However, the proposed decision support for HEMS can also be used in other market-clearing mechanisms. The results from the market clearing show that participants can fulfill their objectives in the P2P electricity market. The percentage of different types of users influences the proportion of different products that are cleared whereas the total energy cleared in the market remains relatively the same. Finally, it is shown that participation in P2P electricity markets is beneficial for the users, regardless of the number of total participants. In future work, methods to improve coordination in the market from mechanism design will be investigated. In addition, an analysis of the impact of the market on the distribution network will be performed and potential coordination strategies will be considered.

CRediT authorship contribution statement

Irena Dukovska: Conceptualization, Methodology, Investigation, Software, Data curation, Writing – original draft. **J.G. (Han) Slootweg:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Nikolaos G. Paterakis:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The link to the dataset containing the data of the survey is provided.

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