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Methods for studying policies and regulations impacting demand response in Dutch wholesale day-ahead power market

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***Abstract*—Decarbonisation of the electricity sector has led to the adoption and deployment of a large number of consumer-sited flexible assets. Simultaneously, consumers are becoming increasingly aware of their consumption patterns and are eager to reduce their energy expenses making demand response a significant source of flexibility in energy markets. In this paper, we discuss the policy measures that influence a consumer's ability to respond to price signals and offer flexibility in the day-ahead market. We propose two methods to quantitatively analyse these policy instruments through their inclusion in market clearing models for the Dutch day-ahead power market. A single-level optimisation model with social welfare maximisation objective can be used to perform a simplified assessment of changes in demand bids due to policy-based financial influences. This model is suitable for studying simple policies such as time-independent taxes but unsuitable for complex policies such as network tariffs and subsidies. A bi-level optimisation model with consumer surplus maximisation on the upper level and social welfare maximisation on the lower level allows more sophisticated modelling of policies but is limited by its scalability and computational complexity. The two methods can be compared on the basis of their ability to incorporate different policy instruments and market design choices, model consumer bidding behaviour, their computational complexity and challenges to implementation.**

***Index Terms*—Electricity market model, demand response, flexible demand, bi-level optimisation**

I. Introduction

The call for climate change mitigation has put renewable energy at the forefront as the panacea for tackling growing energy demand while reducing emissions. However, widespread adoption of renewable energy resources such as solar PV and wind has also brought with it several challenges, both anticipated and unanticipated. Increasing penetration of variable renewable energy, electrification of end-uses, and proliferation of decentralised assets have collectively created an energy market with increasing variability while reducing the predictability of both supply and demand. The system, thus, requires resources that are capable of adapting their behaviour to techno-economic signals provided by the system, commonly termed as flexible resources or just flexibility.

A relatively untapped source of this flexibility is demand response in the form of load shifting and load shedding [1], [2]. To effectively utilise this resource, we must i) assess its potential, ii) identify the barriers to its utilisation, and iii) adapt policies, regulations and market design to eliminate these barriers. The objective of our research is to contribute to the understanding of policy and regulatory barriers to the participation of demand-side flexibility in electricity markets and designing a conducive regulatory environment. To achieve this, we propose the development of a market clearing model that incorporates the financial and market design aspects of different policies and regulations. This model is developed from the perspective of the market operator and policymakers and seeks to maximise social welfare across the market participants.

There are several approaches to include policy-related financial instruments in market models. It is necessary to understand the differences between these approaches for two important reasons:

i. Understanding these approaches will lead to more robust studies in energy policy and economics and will provide deeper insights into the use of policy instruments to encourage demand response
ii. Several consumers ranging from large industries to aggregators are becoming increasingly interested in the dynamics of electricity markets. They foresee higher electricity consumption on account of the phase-out of fossil-fuel-based energy sources. Consequently, they are concerned about the impact of not only electricity prices but also regulated, non-market charges such as taxes and tariffs. The approach we choose must be compatible with modelling consumers' interests.

To this end, this paper explores two methodologies for incorporating policy, regulatory and market design aspects in market models. These are single-level and bi-level optimisation methods. The overarching goal of both these methods will be to represent market clearing with different parameters and decision variables. We will analyse the relative merits and drawbacks of these methods and their suitability for studying different policies and market design parameters. The focus of this study will be on the Dutch electricity sector, more specifically, the day-ahead auction-based market. In the following section, we provide a brief overview of the Dutch electricity sector policies and governance as well as a review of market modelling methods used in other studies.

II. Literature Review

1) Dutch electricity sector regulations: The Dutch electricity sector is governed and regulated by two primary agencies: the Ministry of Economic Affairs and Climate Policy (Ministerie van Economische Zaken en Klimaat) and The Netherlands Authority for Consumers & Markets (Autoriteit Consument & Markt). Apart from the Ministry and the Authority for Consumers & Markets (ACM), the Dutch energy market must also comply with legislation and directives issued by the European Union.

Key policy and regulatory factors that can influence a consumer's bidding behaviour include:

- Electricity tax: electricity tax is determined and imposed by the Dutch tax authority, Belastingdienst. In 2024, the taxes are categorized by annual consumption levels and consumer types [3].
- Network tariffs: network tariffs are regulated by ACM and imposed by respective network operators. They are categorized by consumer size and connected capacity [4].
- Net-metering scheme: net-metering scheme is offered to small consumers that choose to install rooftop solar systems. Here, the consumer is reimbursed for any excess solar power it injects into the grid. The period of settlement and rate of reimbursement is determined by the electricity provider [5].
- Subsidies such as SDE++ (Stimulering Duurzame Energieproductie en Klimaattransitie) are offered to entities that either produce renewable electricity or reduce carbon emissions such as heat conversion technologies. Consumers that can benefit from SDE++ include user of heat pumps, electric boilers, electrolysers, etc. [6]

A detailed review of these policies is outside the scope of this paper. However, it can be observed that each policy is uniquely structured in its application and requirements. Thus, creating a model that can accurately incorporate these intricacies is a complex task.

2) Modeling methods: The impact of energy policies and regulations is often studied using energy system models and integrated assessment models. Results and analyses produced by these models are used to guide policy-making across the world, including The Netherlands. As an example, the Climate and Energy Outlook report (Klimaat- en Energieverkenning) published annually by The Netherlands Environmental Assessment Agency (PBL) uses results from the COMPETES model built by PBL and TNO [7]. A plethora of both open source and commercial energy system models exist today covering a wide range of objectives, formulations, spatial and temporal resolutions, and methodologies [8]. A significant number of these models perform unit commitment and economic dispatch with a cost minimisation objective. While these models are rich in terms of sectors, technologies and techno-economic details, they lack an adequate representation of flexible demand. In some cases, a simplified implementation of flexibility is performed by designating a portion of the total demand as flexible under a set of conditions [1]. Other studies perform a more technically detailed assessment of availability and impact of demand response in complex enregy system models that accounts for load recovery and saturation [9]. However, in these implementations, the flexibility is not allocated an explicit economic value. From the perspective of demand response, this approach fails to capture a consumer's willingness to accept load shifting or its willingness to pay for power at any given time. Thus, consumers are only passive participants in the market. However, in an actual market, consumers will not only express their willingness to pay for electricity in the bids they submit to the market but also expect remuneration for modifying their behaviour and providing grid services. Their willingness to modify their behaviour and expected financial benefit will be based on the opportunity cost of forgone economic or non-economic activity and the consumer's perception of market signals. Determining this combination of volume and price of flexibility provision is at the centre of flexibility studies.

Inclusion of consumers' price elasticity and willingness to pay (WTP) necessitates the creation of market clearing models that aim to maximise social welfare (consumer surplus + producer surplus) [10], [11]. There is a large body of operations research on the development of auction-based market clearing models for European markets. There are also a large number of studies on the incorporation of flexible resources in such models. Several of these studies analyse the interaction of different stakeholders with the market [10], [12]–[14].

It is noted that a large number of studies on interaction of stakeholders with the market utilise equilibrium based methods such as Stackelberg game, bi-level and multi-level optimisation. Jiang et al. created a two-stage market clearing model coupled with a virtual power plant's (VPP) internal scheduling model and solved using ADMM to study the participation of VPPs in electricity and flexibility markets [10]. Wang et al. used a bi-level optimisation approach to simulate the decision-making of an electric vehicle aggregator and its interactions with the electricity market [12]. Hong et al. used a bi-level model to study the behaviour of a strategic retailer with flexible power demand with respect to its interaction with the day-ahead wholesale market, local power exchange and its consumers [15]. However, there is a relative lack of studies on the incorporation of policy and regulatory instruments in such models. Thus, from the perspective of market operators as well as energy market regulators, the need arises for the development of a publicly available methodology and model with which to study the impact of market design and policies on consumer bidding behaviour and, consequently, social welfare. We propose methods to fill this gap in this paper. In the following section, we expand on two methods for designing such models and provide their formulations, applications, merits and drawbacks.

III. Methodology

As mentioned previously, the primary objective of this paper is to propose methods for incorporating and studying policy, regulatory, and market design instruments in market clearing models. We have chosen the Dutch wholesale day-ahead market as our focus is on the Dutch policy and regulatory environment. The Dutch (and by extension, European) day-ahead electricity market provides a range of options to meet the varying requirements of both consumers and suppliers in the form of several types of bids including hourly, stand-alone bids and interdependent, block bids. In addition, price elastic demand and supply can submit up to 256 bids in each time period [16]. We capture this market design in our model by inputting hourly supply and demand bids and clearing the market over a 24-hour optimisation horizon. Each consumer is allowed to submit multiple bid pairs in each time step.

To model flexibility, it is essential to first define and categorise it, particularly the difference between flexibility and elasticity. Conventionally, demand flexibility is interpreted as the ability to shift load temporally, which may or may not be in response to a price signal. Such load shifting and shedding have been studied extensively in both technological and economic contexts. Conversely, price elasticity of demand is the sensitivity of demand to changes in prices. While flexibility does not possess a fixed mathematical or economic definition, elasticity is a well-defined economic concept and is expressed mathematically as $(\Delta Q/Q)\big/(\Delta P/P)$. In order to effectively value demand response, we must study both flexibility as well as elasticity of demand. This can be achieved by either defining demand as a function of price and providing exogenous values of elasticity and prices or by specifying sets of price-quantity pairs. In our study, we have chosen to utilise price-quantity pairs to reflect the WTP of demand in order to represent the EPEX day-ahead market clearing mechanism. By allowing multiple bids per consumer per timestep, it is possible to capture both price elasticity and temporal flexibility. In the following sections, we provide the rationale, formulation and use cases for single and bi-level market models utilising elastic demand representation.

A. Single-level optimisation

This method uses a simple day-ahead market clearing model with the assumption that all consumers submit bids at their true willingness to pay in the absence of any external policy influence. The fundamental premise behind this model is that the market operator is privy to only the bidding data (price-volume pairs) submitted by the participants. The individual participant's internal optimisation and strategic decisions are not known to the operator. Thus, the operator's objective is to clear the market with the aim of maximising social welfare. The objective function for the market operator is:

$$\max \sum_{t=1}^{T} \left[\sum_{i \in D} \sum_{k \in K_i} \left(q^D_{i,k,t} WTP^D_{i,k,t} \right) - \sum_{j \in G} \left(c^G_{j,t}\, q^G_{j,t} \right) \right] \quad (1)$$

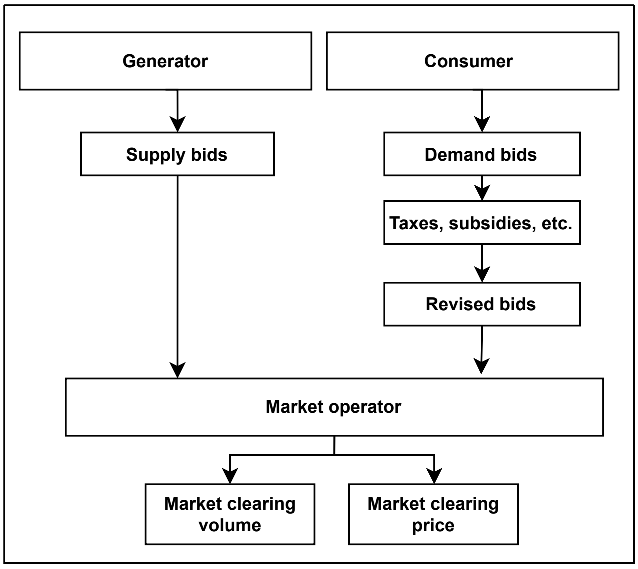

Fig. 1. Single-level model structure

subject to constraints:

$$\sum_{i \in D} \sum_{k \in K_i} q^D_{i,k,t} = \sum_{j \in G} q^G_{j,t} \quad \forall t \in T \quad (2)$$

$$q_j^{G_{\min}} \leq q^G_{j,t} \leq q_j^{G_{\max}} \quad \forall t \in T \quad (3)$$

$$p_t^{\mathbf{min}} \leq WTP^D_{i,k,t} \leq p_t^{\max} \quad \forall t \in T \quad (4)$$

$$0 \leq q^D_{i,k,t} \leq Q^D_{i,k,t} \quad \forall t \in T \quad (5)$$

$$Q^{D_{\min}}_{i,T} \leq \sum_{t=1}^{T} q^D_{i,k,t} \leq Q^{D_{\max}}_{i,T} \quad \forall i \in D \quad (6)$$

where $q^G_{j,t}$ is the power generated by generator j in timestep t, $q^D_{i,k,t}$ is the demand met of bid pair k of demand i in timestep t, $Q^{D_{\min}}_{i,T}$ and $Q^{D_{\max}}_{i,T}$ are the minimum and maximum demand met over the time horizon T, $WTP^D_{i,k,t}$ is the willingness to pay of demand i in timestep t for quantity $q^D_{i,k,t}$, and $p_t^{\mathbf{min}}$ and $p_t^{\max}$ are the minimum and maximum bid prices for timestep t. The decision variables in this problem are demand met and generation ($q^D_{i,k,t}$, $q^G_{j,t}$).

Absent any distortionary external factors, a consumer will bid at its willingness to pay (WTP) for a certain quantity of electricity. Thus, in the above function, $WTP^D_{i,k,t}$ is used in place of $p^D_{i,k,t}$.

1) Incorporating policy instruments: From the perspective of the market operator, when a consumer is exposed to policy-related financial distortions, the change in their bidding behaviour will reflect a rational adjustment of their bids. In the single-level optimisation approach, bid prices are modified by reducing them by the value of the financial distortions while keeping the bid quantity unchanged. It implies that the willingness to pay of the consumer for a certain quantity remains the same but the bid price will be different.

Below, we provide a general formulation for incorporating fixed or time-varying distortions such as electricity taxes and network tariffs in the model. Their inclusion will modify the objective function to:

$$\max \sum_{t=1}^{T} \left[\sum_{i \in D} \sum_{k \in K_i} q_{i,k,t}^{D} \left(\mathrm{WTP}_{i,k,t}^{D} - N_{i,t}^{\mathrm{var}} \right) - \sum_{j \in G} c_{j,t}^{G} \, q_{j,t}^{G} \right] \tag{7}$$

where $N_{i,t}^{\mathrm{var}}$ is the variable component of the distortion.

B. Bi-level optimisation

This method utilises a bi-level, single-leader – single-follower, model that allows strategic decision-making by a consumer to account for external policy influence . The upper level is built from the perspective of the consumer that seeks to maximise their welfare while anticipating market prices. In the lower level is the market operator that clears the market based on social welfare maximisation objective. The lower level takes demand bids as inputs form the upper level and its output, market clearing price, is used as an input in the upper level. In addition, non-strategic demand and supply bids are provided as inputs to the market clearing model.

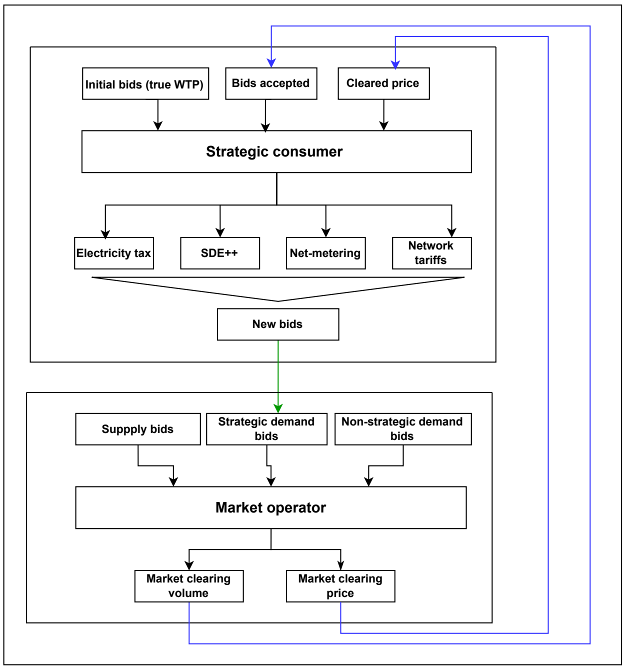

Fig. 2. Bilevel model structure

The model is formulated as below:

Upper-level problem: Market clearing using social welfare maximisation objective

$$\max \sum_{t=1}^{T} \left[(WTP_{i,t} - \lambda_t) Q_{i,t}^{D} \right] \tag{8}$$

subject to:

$$0 \leq \; Q_{i,t}^{D} \leq Q_{i,t}^{D_{\max}} \quad \forall t \in T \tag{9}$$

$$Q_{i,T}^{Dmin} \leq \sum_{t=1}^{T} Q_{i,t}^{D} \leq Q_{i,t}^{Dmax} \quad \forall t \in T \tag{10}$$

where $Q_{i,t}^{D}$ is the volume bid by the strategic consumer in time t and is the variable in the upper level problem. The WTP (bid price) and λ_t are parameters.

Lower level problem: Social welfare maximisation

$$\max \sum_{t=1}^{T} \left[WTP_{i,t} \, Q_{i,t}^{D} + \sum_{-i \in D} \sum_{k \in K_i} \left(q_{-i,k,t}^{D} \, p_{-i,k,t}^{D} \right) - \sum_{j \in G} \left(c_{j,t}^{G} \, q_{j,t}^{G} \right) \right] \tag{11}$$

here, i refers to the strategic consumer while -i denotes the set of non-strategic consumers.

Subject to constraints:

$$Q_{i,t}^{D} \; + \sum_{i \in D} \sum_{k \in K_i} q_{i,k,t}^{D} = \sum_{j \in G} q_{j,t}^{G} \quad \forall t \in T \tag{12}$$

$$q_{j}^{G_{\min}} \leq q_{j,t}^{G} \leq q_{j}^{G_{\max}} \quad \forall t \in T \tag{13}$$

$$0 \leq q_{-i,k,t}^{D} \leq q_{-i,k,t}^{Dmax} \quad \forall t \in T \tag{14}$$

In the lower level problem, $q_{j,t}^{G}$ and $q_{-i,k,t}^{D}$ are the variables. λ_t is the market clearing price, which is the dual variable of the power balance constraint, equation (12).

1) Incorporating policy instruments: When a consumer is exposed to external policy influences, it will react by modifying its bid quantity against a modified bid price. Thus, the upper level problem can be altered as follows:

$$\max \sum_{t=1}^{T} \left[(WTP_{i,t} - \; N_{i,t}^{\mathrm{var}} \; - \; \lambda_t) Q_{i,t}^{D} \right] \tag{15}$$

Bi-level problems are known to be challenging to solve given their non-convexity and potential non-linearity [17]. In the current case, given the convexity of lower level (market clearing) problem, it can be replaced by its KKT conditions, which are then added as constraints to the upper level problem. The bilinear term can be linearised using strong duality theorem on the lower level objective function. Finally, complementarity constraints can be linearised using the Big M method [18]. However, it must be noted that even with these approximations and conversions, finding a global optimal solution to a bilevel problem may be challenging.

IV. Comparison - Applications and Limitations

In this section we will discuss the relative merits and drawbacks of the two methods described previously and their utility in studying energy policies and regulations.

i. Rational vs. strategic behaviour: a very important distinction to make when choosing a method is whether the consumer is expected to alter its bids rationally to account for policy impact or behave strategically and attempt to alter market outcome. When considering rational behaviour, a consumer is not expected to anticipate market outcome. Thus, in such a case, a single-level market clearing optimisation method may be used. On the other hand, a strategic consumer will anticipate the market outcome when determining its bid. A bilevel optimisation model may be more suitable for a such a study.

ii. Representation of demand elasticity: the single-level optimisation method allows explicit incorporation of demand elasticity in the model in the form of multiple bid pairs per time step. Bilevel model, on the other hand, can only generate one, optimal, bid pair per timestep for the strategic consumer. Thus, if the objective of a study is to assess the variation in demand elasticity under different circumstances, a single-level model is more suitable, particularly in cases where elasticity varies across time periods.

iii. Representation of demand flexibility: both methods can provide insights into the shifting of demand across time periods as well as curtailment under different policy scenarios.

iv. Inclusion of other decision variables and parameters: these considerations are relevant for consumers that have access to substitutes to grid electricity, such as gas, self generation from rooftop solar, etc.. In such cases, a consumer will optimise its power procurement from the electricity market not only against the anticipated market prices, but also against the cost of substitutes. Such parameters (e.g. gas prices) and variables (e.g. self consumption of solar power) cannot be included in a simple, centralised market clearing model. A bilevel model is better able to capture the effect of substitutes on a consumer's behaviour by adding it as an additional follower (lower level) problem.

v. Scalability: a centralised market clearing model as conceptualised by the single-level optimisation method is mathematically less challenging to scale up to include a large number of market participants. On the other hand, bilevel models with multiple leaders (in this case, strategic consumers) and single or multiple followers are demonstrably more challenging to solve [19] and have higher computational expense. Additionally, selectively studying the behaviour of one strategic consumer under different policy scenarios in a single-leader model will yield misleading results.

V. Conclusion

In this paper, we have proposed two methods for studying the influence of policy instruments on demand elasticity and flexibility. Both approaches have their merits and drawbacks. The single-level optimisation approach is relatively straightforward to implement and has low computational expenses. It can also be used to study the collective impact varying policies on a diverse set of consumers that are both elastic and flexible. However, it is limited in evaluating the impact of policies on that have access to alternatives to grid power. Conversely, a bilevel model is more suitable for capturing the decision making of strategic consumers that seek to anticipate and alter market outcomes. They are also able to incorporate multiple energy carrier options for consumers with alternate sources. However, such models are limited in their ability to study elasticity of demand and their scalability. A quantitative assessment of the two methods is the subject of ongoing research, the results of which will be shared in future publications.

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