Modeling and Analyzing the Effect of Human Preferences on a Local Electricity Market

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***Abstract*—Local electricity markets (LEMs) have progressed significantly in recent years, but a research gap exists in understanding the influence of human preferences on the effectiveness of LEMs when home energy management systems (HEMSs) are involved. Motivated by this, this work aims to model and integrate human preferences into a HEMS, bridging the gap between end-participant and LEM. A sensitivity analysis of the parameter choices of the HEMS and their impact on the performance and outcomes of a LEM is done. Hereby, a behavior model is used to formulate the preferences and motives of households within a LEM in a bottom-up approach. Various distributed energy resources are modeled and controlled via a HEMS, allowing households to input their preferences and motives to output a tailor-made bidcurve for the LEM. A sensitivity analysis reveals that different preference settings result in different consumption profiles, which to a large extent align with the preferences. In addition, the importance of aligning market mechanisms and steering signals with the participants' goals is highlighted.**

***Index Terms*—Distribution grid, home energy management system, human preferences, local electricity market.**

I. Introduction

THE energy transition is significantly gaining in importance and speed, affecting many parts of the electricity distribution. Along with this transition, problems such as congestion or more fluctuating demand and supply arise and must be addressed to ensure a stable electricity distribution in the future. One promising approach to these problems are local electricity markets (LEMs), in which small-scale end participants, such as individual households, can trade with each other or with wholesale electricity markets [1], [2]. These LEMs typically operate in the distribution grid and can thereby connect households within a neighborhood or city with each other. Quite some progress has been made with LEMs in recent years, though challenges for large-scale implementation still exist [1], [2]. The most prominent difference to wholesale electricity markets, such as the day-ahead wholesale market, is the ability of small end-users, such as households, to participate directly. In addition, LEMs usually operate in a much smaller area than classical electricity markets.

One of these challenges is the effect human behavior may have on the effectiveness of LEMs [1], [3], for example, by strategically curtailing photovoltaic (PV) generation [4]. It is clear that human decisions affect distributed energy resources (DERs), such as electric vehicles (EVs) and PVs, via charging and usage preferences [5]. Furthermore, in LEMs, small-scale end participants can create bids for the DERs in their houses [6]. Hereby, these participants create these bids on their own or via individual settings in a home energy management system (HEMS). As such, human preferences, behavior, and decisions (regarding DERs and objectives) will be a part of LEMs and should therefore be considered when designing or analyzing LEMs. However, both [1] and [3] point out that this is rarely done. Within the area of energy management approaches, on the other hand, the idea of using multiple objectives, potentially representing different human preferences, has already been proposed, [7], [8], [9]. At the same time, most of these approaches focus on a microgrid level and include objectives that may not be of interest to individual households (e.g., voltage constraints, [8], [9]) some of the literature already relates the different objectives of a multi-objective energy management system to human behavior and preferences, [7]. This modeling on a household level allows the prosumer to integrate their own individual preferences into the energy management system. With the inclusion of electricity markets, the focus shifts more to multi-objective portfolio optimization, [10], or to multi-objective planning within industries, [11], and therefore does not consider the impact of human preferences. Hence, what is still missing in current research is the link between human behavior and LEMs and the impact of different preferences on the performance and outcome of such a LEM.

LEM research, on the other hand, has focused mainly on optimal bidding strategies for individuals ([12], [13]) as well as market frameworks for flexibility services [14]. Research on bidding often uses game-theoretic tools to analyze the impact of individual bids on markets and to derive optimal strategies [3]. However, these approaches often rely on very simplistic settings, considering only one DER, and therefore do not fit well for future scenarios where households will have multiple DERs. On the other hand, market-oriented research on LEMs often overlooks the impact of human preferences within market design [1]. Human preferences can change the requirements for

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DERs, affecting how market participants bid and reducing the effectiveness of LEMs. With access to HEMSs, humans can optimize their bidding strategies, which may negatively impact LEM performance [13].

Hence, a research gap exists in understanding the influence of human preferences on the effectiveness of LEMs. Currently, limited attention has been given to incorporating multiple DERs and considering the impact of human preferences on bidding strategies and market design. Further research is needed to bridge this gap by integrating human preferences, considering the complexities of future scenarios with multiple DERs, and exploring the role of HEMSs in optimizing bidding strategies while ensuring the overall performance of LEMs. To do so, this work uses the Attitude-Behavior-Context (ABC) model, [15], to integrate human preferences into HEMSs. The ABC model hereby combines internal motives with external factors to model and explain human behavior. The study translates the ABC model into a mathematical optimization model as the central part of the HEMS, which then creates tailor-made bidcurves for the individual household. Based on this, a sensitivity analysis is carried out on the impact of human preferences in the form of HEMS parameter preferences on the LEM's ability to operate, trade energy, and reduce grid congestion. The main contributions of this paper are:

- A bottom-up approach linking the Attitude-Behavior-Context (ABC) model, [15] with human preferences and distributed energy resources in the context of participation in a local electricity market (LEM).
- A case study highlighting the importance of aligning steering signals of LEMs with the participants' goals to ensure proper working of the market.
- A sensitivity analysis emphasizing the need to properly analyze the interactions between different motives/goals before the implementation to avoid unwanted side effects.

This paper continues earlier work and, therefore, shares similarities in approach and methodology with [5]. Major extensions are the introduction of a LEM, the usage of a behavior model, as well as additional considered DERs and motives. Furthermore, the central mathematical formulation, which depicts the applied behavior model, is newly introduced.

The paper is structured as follows: Section II explores human preferences and behavior models and the method used. The LEM is presented in Section III. In Section IV, the household bidding model is introduced. The results are presented and analyzed in Section V. We summarize the results and discuss our work in Section VII.

II. Methodology

This section builds toward the overall method of modeling human preferences and understanding its effect on LEMs used in this study. This is done by first specifying the understanding of behavior within this study and, second, by introducing different concepts for modeling human preferences and elaborating on the used approach in more detail. The section is concluded by applying the above-mentioned approach to the considered setting.

A. Understanding of Behavior

Turning off the lights, lowering the temperature settings, or charging the battery is not directly human behavior but is the consequence or result of human behavior. Within the area of energy-related topics, human behavior has already been studied and researched for many decades [16], [17].

Most of the work on this topic has focused on changes in human behavior in energy consumption and savings [16], [18]. While many of these results are still valid, the situation in which households must make decisions has changed considerably within the last few years and will continue to change drastically within the coming years [19]. LEMs give individual household access to electricity markets, either directly, or indirectly via an intermediary, such as an aggregator. However, in both cases, DER flexibility and human preferences will influence the bidding in markets.

This study therefore focuses on the consequences of human behavior and preferences on the considered DERs and their effect on the LEM. Other decisions, such as turning off the lights, or long-term investments, such as improving the house's insulation, are not considered.

B. Behavior Models

Three different behavior models, which have been applied to pro-environmental behavior research focusing on energy consumption, are presented in the following.

The *Rational Choice Theory* from economics suggests that consumers evaluate the pros and cons of all possible actions and choose the best one based on external factors like prices and energy savings, [16], [18]. However, this model does not consider internal factors like norms, beliefs, and habits.

In contrast, Sterns' *Value Belief Norm Theory* [20] includes these internal factors and links several theories from psychology and social science to explain pro-environmental behavior. It creates a causal chain among five internal variables and is mainly based on internal factors, unlike the Rational Choice Theory, which only considers external factors.

A model that combines both internal and external factors is the *Attitude-Behavior-Context* (ABC) model [15]. The core idea behind this model is that "behavior (B) is an interactive product of personal sphere attitudinal variables (A) and contextual factors (C)" ([21], p. 415). The ABC model closes the gaps between the Rational Choice Theory and the Value Believe Norm Theory by including internal and external factors. These factors and variables can be described as follows:

- Attitude: These are the internal variables and factors, such as norms, motives, (inner) beliefs, or values.
- Behavior: Within this model, the behavior can be observed via decisions or outcomes.
- Context: The context contains the external factors influencing the behavior. Among these are monetary incentives such as costs or profit, access to technology or devices, social norms in the form of peer pressure, regulatory frameworks, and laws.

In addition, the ABC model not only includes both types of factors but also explains how these factors may interact with each other. It claims that the influence of attitude on behavior is strongest when the context is neutral and that a strong context leaves little room for the attitude. Stern also provides evidence for this claim in the form of a research project on recycling, see [15]. The model has been applied in behavior research, mainly in pro-environmental behavior analysis, such as energy savings or usage [22], [23], [24], [25].

C. Applying the Attitude-Behavior-Context Model

The main principles of the ABC model fit well into the setting of a LEM that is affected by human behavior. This allows us to model human preferences (attitude) and their DERs (context) influencing the bidcurve (behavior) that affects the LEM from the bottom up. The general attitudes, behavior, and context factors and variables in this context are defined as follows:

- Attitude: Three main internal variables in the form of motives are introduced. The first one is an *ecological motive*, in which households prefer to use electricity from fossil-fuel-free energy generation, such as PV or wind power. The second motive is the *comfort motive*, which tries to minimize temperature deviations from the desired set point and charge the EV as fast as possible. The last motive is the *financial motive*, which aims to maximize the profit gained from buying and selling electricity at different time slots. Both ecological and financial motives have been used extensively throughout behavior research in energy savings [26], [27], and are, therefore, included in this study. The comfort motive has yet to see much attention in electricity savings or management, which can partially be attributed to the past's lack of electric heating and mobility opportunities. However, this will likely change soon with the increase of EVs and HPs [28], [29]. In addition, early behavior research on energy savings by Becker et al. [17] already analyzed the importance of house temperature as an indicator of energy savings. Furthermore, EV range anxiety makes people want to charge when the state of charge (SoC) is lower [30]. Therefore, we integrate these factors into this study by including the house temperature and the SoC of the EVs as factors for the comfort motive. The remaining DERs in the form of PV and batteries, on the other hand, do not affect the comfort. Apart from these four DERs, comfort is also affected by household load. This load is, however, assumed to be non-steerable.
  In addition to these motives, different household preferences that may affect the operation of DERs are also considered. These preferences are a temperature range in which the house temperature should be and a desired SoC for the EV. Note that setting an individual temperature range also limits the loss of comfort, which has been shown to reduce the willingness of prosumers to participate in energy management approaches, [31].
- Behavior: In this research, behavior is represented by the bids of the household on the LEM, as bidcurves are the output of a HEMS.

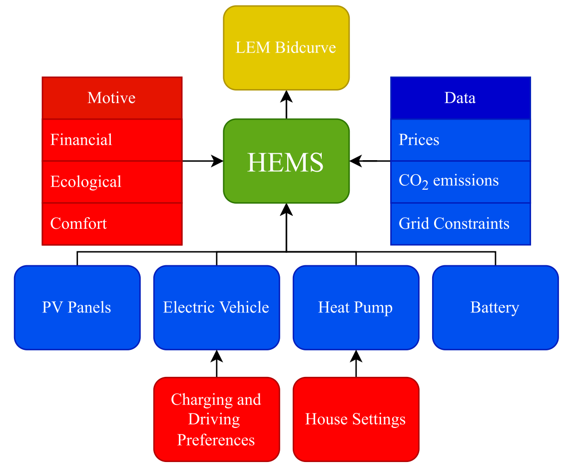

Fig. 1. Overview of the applied Attitude-Behavior-Context model in a bottom-up approach, with the attitude variables in red, the contextual factors in blue, and the behavioral outcome in yellow; the household preferences and distributed energy resources at the bottom provide flexibility, while the motives and other data inputs mostly define the preferred usage of flexibility.

- Context: This study focuses on a future scenario where households can access various DERs. These DERs are PV, batteries, EVs, and HPs, as these devices are among the most common DERs in LEM literature, [32], and the sales of HPs and EVs are rising [28], [29]. Apart from these DERs, we consider electricity prices, CO_2 emissions, and grid constraints as external factors. The interactions between households, such as peer pressure within a neighborhood, are deliberately excluded from this study.

Note that depending on the setting or situation, the proposed ABC model can easily be extended by further internal motives, such as risk adverseness, or external DERs, such as washing machines or dishwashers.

This general list of internal and external factors and variables must be adjusted for every household to make up for personal preferences and conditions. Regarding the three different motives, households may have different preferences and do not simply follow a single motive. Hence, we introduce the (individual) motive weights w_e, w_c, and w_f corresponding to the ecological, comfort, and financial motives and representing the individual preferences of each household over these motives. It is assumed that $w_e + w_c + w_f = 1$ and $w_e, w_c, w_f \geq 0$. Therefore, these weights can be seen as percentages of the corresponding motives on the overall attitude of each household. Note that even though these motive weights may be changed over time, we assume them to be fixed for the time horizons considered in LEMs.

Fig. 1 depicts the ABC model applied to the process of creating a bid for an individual household. The HEMS, connecting all aspects, corresponds to the automated implementation of the ABC model, which is explained in detail in Section IV. Note that the households can control all of the attitude variables, apart from the driving decisions. These driving decisions are assumed to be fixed and already included in the EV data. All of the contextual factors are also fixed and cannot be controlled directly by the households.

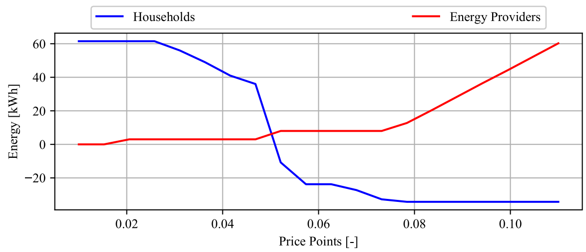

Fig. 2. Created example of an aggregated household bidcurve and the combined bidcurve of the three energy providers for twenty price points.

III. Market and Energy Provider

A. Local Electricity Market

Due to the scoping of this study, the LEM needs to allow humans to set parameters in a HEMS influencing the bidcurve, meaning that the HEMS creates a bidcurve based on parameter values and constraints set by the households. Therefore, the LEM chosen for this study is similar to the LEM in [33] and focuses on the low-voltage sections of the distribution grid, enabling small-scale participants, such as individual households, to submit bids and thereby directly participate in the energy market. The LEM allows participants to bid directly into the LEM, but an energy supplier purchases electricity for the neighborhood day ahead on the wholesale market to ensure sufficient market liquidity.

The considered LEM is based on a double-sided auction and operates in an intraday fashion, meaning that it works with fifteen-minute time slots and the price-forming process takes place just before the start of each time slot. Due to the time slot length, households need to use forecasts and predictions of their household demand to compute the bidcurves submitted to the LEM. Deviations in these predictions mainly stem from a varying utilization of wet appliances, however, it has been shown that clever usage of the flexibility of DERs may alleviate these deviations sufficiently [34].

It should be noted that the LEM focuses on electricity procurement rather than flexibility. However, the HEMS uses the flexibility of DERs to optimize for its objective. For each market iteration, there are two bidcurves in a double-sided auction. In this study, the demand bidcurve of the households represents the possible buying decisions and actions of the household, whereas a negative value of the bidcurve implies the intention of selling electricity. The energy providers submit supply bidcurves, in which a positive value represents selling electricity to the households, while a negative value represents the action to buy electricity. Fig. 2 displays an example of these two bidcurves. It should be noted that both bidcurves can represent buying and selling of electricity and that each bidcurve consists of pairs of prices and corresponding energy.

The market mechanism works as follows: After receiving the bidcurves from the households and from the energy supplier and providers, the household bidcurves are first aggregated. The same happens for the bidcurves of the energy supplier and providers. Next, the crossing point of the two aggregated bidcurves is determined. This point then defines the initial clearing price and the corresponding energy volume. If the volume of cleared energy is within the grid constraints, the clearing price is communicated to the participants, who then act according to their submitted bidcurves. Otherwise, if the initial clearing volume exceeds the grid constraints by consuming or producing too much power, the clearing price is adjusted to the corresponding volume within the grid limits. This procedure is introduced and explained in detail in [35]. Any imbalance between demand and supply caused by this approach is then assumed to be handled by predetermined agreements between the energy supplier and balancing responsible parties, which are not part of this study.

B. Energy Providers

In this study, the focus is on human preferences in the household and, therefore, does not consider its effect on the bidcurves of the energy providers. The LEM presented in the previous subsection allows for an energy supplier and multiple energy providers to provide a bid. This could involve multiple suppliers, various local PV plants, wind turbines, or other entities in a real-world scenario. However, in this study, a limited number of fifty households is considered requiring a more controlled approach. Therefore, we ensure that whatever the household bids, there is always a match between the bidcurves.

The aggregated bidcurve of the energy providers for a fixed time slot t_0 consists of three parts. The first part corresponds to the purchases of an energy supplier at the clearing price of the wholesale day-ahead market. The amount the supplier buys or sells is decided based on its prediction of the energy demand of all households. This prediction is based on the household loads, the PV generation and the demand for the HPs and EVs:

$$\sum_{h \in house} \left(p_{t_0}^{h} - p_{t_0}^{PV,h} + g^{HP}(h, t_o) \right) + c^{EV}(t_0) \cdot \bar{p}^{EV}, \quad (1)$$

In this (1), $c^{EV}(t_0)$ represents the expected share of EVs connected to the grid at time slot t_0, while $\bar{p}^{EV}$ corresponds to the average EV demand based on historical data. $g^{HP}(h, t_o)$ estimates the required power to keep the desired house temperature of house h given the outside temperatures at time slot t_0. $p_{t_0}^{h}$ and $p_{t_0}^{PV,h}$ correspond to the estimated household demand, respectively PV generation of household h during time slot t_0. To account for the bids of the remaining energy providers, we reduce this predicted demand by a factor α, $0 < \alpha < 1$. In this study, the other energy providers are a wind power farm and providers of short-term flexibility.

The second part of the bidcurve represents a surplus of wind generation compared to the expected wind generation. This surplus may be sold at the local intraday market. Given the intermittent nature of wind generation, this leads to higher fluctuations in the aggregated bidcurve of the providers over time. The amount of wind surplus is a percentage of the purchased energy from the energy supplier to ensure a match between the provider and household bidcurves. This percentage depends on the national wind production in the Netherlands [36] and is chosen in such a way that the overall energy at the market is in the same order of magnitude as the bidcurve of the households, but differences may still occur.

Algorithm 1: Bidcurve Model for Time Slot t_0 for a Single Household.

initialize $BidCurve = [0, 0, \ldots, 0, 0]$ of length N
initialize $PriceSteps$ (equal for each household)
for $i \in [1, .., N]$ **do**
  solve $localHEMS(t_0, t_0 + Hz, PriceSteps[i], Data)$
  $BidCurve[i] = x_{buy} - x_{sell}$ is the market interaction given price $PriceSteps[i]$
  save PV, battery, EV, and HP usage
end for
Interpolate $BidCurve$
return $BidCurve$ and other saved data points

To ensure that in this limited market setup, an intersection always exists between the bidcurves of the households and the energy provider, we introduce an additional energy provider, offering expensive, short-term flexibility. We assume that this energy provider can sell and buy energy from the LEM, thereby ensuring that the two bidcurves intersect.

IV. Household Bidding Model

In this section, we introduce a bidding model for an individual household based on the ABC model whose output fits the input of the previously presented LEM. We first provide the general framework for computing the bidcurve and then present insights into the details of the mathematical formulation.

A. Framework

Given the presented LEM, each household must submit a bidcurve to clear the LEM, which occurs at the beginning of each time slot. As introduced, the bidcurve for the LEM consists of a set of price-volume pairs. To reduce the computational burden, we choose a fixed number N of price points, equally distributed within the given price range, and compute the optimal buying and selling decisions for each given price point individually. Based on this, we linearly interpolate the solution between the price points and construct the bidcurve, which can then be submitted to the LEM. Algorithm 1 displays the scheme for approximating the individual bidcurve for a given household for time slot t_0.

- $BidCurve$ is a vector used to store each price's buying and selling decisions.
- $PriceSteps$ represents the given choice of price points within the price range.
- $localHEMS$ is the local decision problem of finding optimal buying and selling decisions for a price point $PriceSteps[i]$, a time horizon $[t_0, t_0 + Hz]$ with $Hz \in \mathbb{N}_{>0}$, as well as the house-dependent $Data$, such as the individual motive weights, the DER parameters, or further information, such as prices or weather data.

Based on this framework to compute the bidcurve for a single house, the decision problem of finding optimal buying and selling amounts ($localHEMS$ in Algorithm 1) can be specified in more detail. For this, we use a mathematical optimization model to achieve a tractable approach, allowing the usage of standard software solvers to get an optimal solution. Within the model, the operating limits of the DERs are represented as constraints, while the different motives build up the objective function. Let $\mathcal{T}'$ denote the time horizon $[t_0, t_0 + Hz]$, and w.l.o.g. index the time slots, such that the first one starts with 1.

B. Variables

The variables used in the bidding model are:

- $x_t^{PV} \geq 0$ denotes the energy of the PV system, which is not curtailed during time slot t.
- $x_t^{B,C} \geq 0$ and $x_t^{B,D} \geq 0$ denote the charged and discharged energy of the battery within time slot t.
- $x_t^{EV,C} \geq 0$ denotes the charged energy of EV during time slot t.
- $x_t^{HP} \geq 0$ denotes the charged electrical energy of the HP during time slot t. Closely connected, h_t^{HP} denotes the heating output of the HP within time slot t, while $h_t^{HP,house}$ denotes the heat taken out of the buffer tank during time slot t to heat the house. Furthermore, $t_t^{HP,tank}$ denotes the tank temperature of the buffer tank at the beginning of time slot t, while $t_t^{HP,house} \in \mathbb{R}^4$ is a vector of length four, denoting four different temperature points within the house, see [37] for further details.
- $x_t^{buy} \geq 0$ and $x_t^{sell} \geq 0$ denote the volume of bought and sold energy of the household for time slot t.

C. Constraints

The given variables are the base for the device constraints, describing the flexibility offered by the devices and the human preferences:

PV constraint: The PV generation p_t^{PV}, which depends on the solar input and the size of the installed system, can be curtailed:

$$x_t^{PV} \leq p_t^{PV} \quad \forall t \in \mathcal{T}'. \tag{2}$$

Battery constraint: The energy within the battery for each time slot has to be between 0 and the capacity C^B of the battery, given the charging and discharging efficiency $0 < \gamma^B \leq 1$. The charging and discharging energy is limited by constraint (4), which limits the sum of charging and discharging energy to the battery's maximum energy limit U^B. The maximum energy limit is equal to the maximum power limit divided by the number of time slots per hour:

$$0 \leq iE^B + \sum_{s=1}^{t} \gamma^B x_s^{B,C} - \frac{1}{\gamma^B} x_s^{B,D} \leq C^B \quad \forall t \in \mathcal{T}', \tag{3}$$

$$x_t^{B,C} + x_t^{B,D} \leq U^B \quad \forall t \in \mathcal{T}'. \tag{4}$$

EV constraint: The energy within the EV has to be within 0, and it is capacity C^{EV} given the charging decisions $x_t^{EV,C}$, and its energy demand p_t^{EV}, and the EV can only be charged when it is available. Let $I(EV) \subseteq \mathcal{T}'$ denote the set of time slots when the EV is not at home. In addition, the charging energy is limited to the maximum charging power. In contrast to the battery, the EV does not consider charging efficiencies, as no discharging to the grid is allowed:

$$0 \leq iE^{EV} + \sum_{s=1}^{t} x_s^{EV,C} - p_s^{EV} \leq C^B \quad \forall t \in \mathcal{T}', \tag{5}$$

$$x_t^{EV,C} \leq U^{EV} \quad \forall t \in \mathcal{T}', \tag{6}$$

$$x_t^{EV,C} = 0 \quad \forall t \in I(EV). \tag{7}$$

HP constraint: The HP model is substantially more complex than the previous DER models. For this study, we use the model introduced in [37], as both model and data are freely available. In general, the HP model can be split up into three parts: the HP, the hot water buffer tank, and the house. The model of the HP contains the transformation of electrical energy to heat energy (8) and a capacity limit (9), while the buffer tank accounts for the changes in temperature in the tank (10) and its limits (11). Note that no loss of heat over time is considered in this formulation. The house model considers the thermo-dynamics of the household based on the heat input into the house, the individual parameter of insulation of the house as well as time-dependent parameters, such as the sun's influence on the house's heating or the outside temperature (12). The thermo-dynamic changes are modeled utilizing a linear function $f(\cdot)$. In addition, the user-dependent house temperature limits are modeled (13) and may differ between households:

$$x_t^{HP} = \frac{h_t^{HP}/\Delta t}{COP(t_t^a, t_{set}^{tank})} \quad \forall t \in \mathcal{T}' \tag{8}$$

$$h_t^{HP} \leq C^{HP} \quad \forall t \in \mathcal{T}' \tag{9}$$

$$t_{t+1}^{HP,tank} = t_t^{HP,tank} + \frac{h_t^{HP} - h_t^{HP,house}}{m_{tank} c_{p,water}} \quad \forall t \in \mathcal{T}' \tag{10}$$

$$l_t^{HP,tank} \leq t_t^{HP,tank} \leq u_t^{HP,tank} \quad \forall t \in \mathcal{T}' \tag{11}$$

$$t_{t+1}^{HP,house} = f(t_t^{HP,house}, h_t^{HP,house}, house) \quad \forall t \in \mathcal{T}' \tag{12}$$

$$l_t^{HP,house} \leq t_t^{HP,house} \leq u_t^{HP,house} \quad \forall t \in \mathcal{T}', \tag{13}$$

where Δt corresponds to the time slot length in seconds. The cooling function of the HP is modeled in a similar way, with a different coefficient of performance function, and without the buffer tank. For further details of the HP model, see [37].

Grid constraint: The buying and selling decisions are limited to the energy capacity of the household connection to the grid:

$$x_t^{buy} + x_t^{sell} \leq C^{house} \quad \forall t \in \mathcal{T}'. \tag{14}$$

Balancing constraint: The buying and selling decisions and the device consumption and production for each time slot $t \in \mathcal{T}'$ have to match the fixed household demand p_t^h:

$$x_t^{buy} - x_t^{sell} + x_t^{PV} + x_t^{B,D} - x_t^{B,C} - x_t^{EV,C} - x_t^{HP} = p_t^h. \tag{15}$$

Constraints (2)-(15), and the non-negativity constraints of the variables describe the set of feasible solutions of our model. Note that all constraints are linear, resulting in a convex polyhedron. This implies that the convex combination of any two feasible solutions lies within the polyhedron and is, therefore, feasible. Hence, we can interpolate any two feasible solutions and again receive a feasible solution.

D. Objective Function

The objective function is a combination of the already introduced three motives. We first formulate each motive as an individual objective function before combining them into the final objective function.

Ecological Motive: The goal of the ecological motive is to account for and reduce the CO_2 emissions of the consumed electricity, leading to the following objective function:

$$\min OF_e = \sum_{t \in \mathcal{T}'} \lambda_t x_t^{buy}, \tag{16}$$

where λ_t is a forecast of the time-varying average grid emission factor [38].

Comfort Motive: Within this study, we define comfort as related to the house temperature as well as the SoC of the EV. Hence, maximizing comfort relates to minimizing the deviations in temperature from a pre-defined preferred temperature, as well as to maximizing the SoC of the EV:

$$\min OF_c = \sum_{t \in \mathcal{T}'} \left(t_{t,1}^{HP,house} - t_t^{house,set} \right)^2 - \eta SoC_t^{EV}, \tag{17}$$

Where $t_t^{house,set}$ denotes the preferred temperature in time slot t, and SoC_t^{EV} denotes the SoC of the EV at the end of time slot t. Note that SoC_t^{EV} can be computed by dividing the energy balance of constraint (5) by its capacity C^{EV}. The additional factor $\eta \geq 0$ represents the individual balance between the two components of the objective function.

Financial Motive: The financial motive aims to decrease the costs and increase the profit of participating in the LEM. Hence, the objective function is based on the buying and selling decisions:

$$\min OF_f = \sum_{t \in \mathcal{T}'} \pi_t^{buy} x_t^{buy} - \pi_t^{sell} x_t^{sell}. \tag{18}$$

The main challenge with the financial objective is that it depends on the future clearing prices π_t of the LEM, which are not known yet and which can be seen as a highly correlated, stochastic process. Hence, the decision problem of submitting a bidcurve is a highly complex problem, which depends on future, uncertain demands and supplies of households and energy providers. However, the LEM operates in an iterative fashion, in which only the bidcurve for the current time slot t_0 is required. Therefore, we restrict the price dynamics to the current time slot. For future prices, we use predictions of the clearing price of the LEM, which, in this case, are based on the day-ahead market clearing prices. These prices are slightly adapted to reflect the decisions of the supplier side by assuming a small increase in price for buying decisions and a small decrease for selling decisions. The price dynamic for time slot t_0 is based on the price range *PriceSteps*, as introduced in Algorithm 1. This choice of modeling the prices is an approximation of the underlying stochastic pricing process. However, due to the limited impact of a single household bidcurve on the clearing process of the

LEM, as well as the increasing uncertainty for future demand and supply, this decomposition of the pricing process still holds approximately.

The individual motive weights are used to combine the three objective functions. However, similar to the *linear scalarization* method from multi-objective optimization [39], we first normalize each objective function to the interval [0,1] by analytically deriving upper and lower bounds on each objective function. This normalization process ensures that the weights actually represent the intended preferences and that no single motive dominates the others due to a large objective value, even if its motive weight may be small. Let OF_e', OF_c', and OF_f' represent the normalized versions of the objective functions. Then the final objective function is:

$$\min w_e OF_e' + w_c OF_c' + w_f OF_f'. \tag{19}$$

Combing the constraints, describing the set of feasible solutions, with the objective function (19), gives the optimization problem for the current time slot t_0 for a single household to decide how much to buy or sell based on the given price. This procedure can be applied to each household, and the resulting bidcurves can be added up for the final bidcurve for the LEM.

V. Numerical Results and Analysis

A. Simulation

It is possible to analyze the effect of specific motives behind human decisions on the LEM using the introduced LEM and bidding models. The following gives the data considered, time horizon, and motive weights.

Data: All test scenarios include a LEM with fifty households, each equipped with PV, an EV, a battery, and an HP. The household and PV data is taken from [33], and the household load is based on the yearly average Dutch household load profile and scaled to match an average yearly consumption of 3250 kWh. The PV generation is created by combining solar irradiance data with the expected yearly PV generation, corrected for roof area and angles of the Dutch city of Arnhem.

The EV data is taken from [40], where EVs have a 50 or 75 kWh battery and a home charger of 11 kW. As mentioned in Section II, the driving decisions and EV demand are included in the data and assumed to be known to the household. The battery is modeled after a Tesla wall-mounted battery with a capacity of 13.5 kWh and charging and discharging limits of 5 kW. The HP is a simplified version of the HP model presented in [37], whereby differences are the lack of a minimum operating limit and the omission of a minimum downtime requirement. In addition, the demand for domestic hot water is not considered.

The wind data used as input for the bidding model of the energy provider comes from [36]. The day-ahead prices used for the LEM and the financial motive are from the Dutch wholesale market in the year 2020, and the average CO_2 emissions are based on the energy contribution per production type in the Netherlands during the year 2020 [41], [42]. The price range considered in the LEM ranges from the day-ahead price in kWh minus 0.03€/kWh to the day-ahead price plus 0.07€/kWh to align with the aggregator's purchase. The household grid limit is $3 \times 25A$ or 17.25 kW to allow the households to use the DERs simultaneously. The grid limit where LEM intervenes and adjusts the bidcurves is 141 kW.

Each simulation run was conducted for one week with a time slot of fifteen minutes, resulting in 672 runs of the LEM. Two weeks, one winter and one summer week, are chosen based on outside temperature and solar irradiance.

Horizon: The time horizon for the optimization model and data availability is set at four hours or sixteen-time slots. In a sensitivity analysis, this duration was found to be a good balance between results, future knowledge, and simulation duration. The data for these four hours available to the HEMS is the outside temperature, EV arrival/leave times and energy requirements, future PV generation, wholesale day-ahead prices for the financial motive, and emission factors for the ecological motive. In this window, HEMSs cannot access LEM data such as wind generation and clearing prices.

Motive Weights: To analyze the impact of the parameters on the LEM, three main lines of scenarios, each corresponding to one defining motive, are created to cover large parts of the parameter space. All individual scenarios are built up as follows: The defining motive has a motive weight of α, while the remaining two motives equally share the remaining weight, that is $(1-\alpha)/2$ for $\alpha \in [0.1, 0.9]$. This choice of α, coupled with the objective functions leads to a non-increasing bidcurve for the households. Individual scenarios are referred to via the defining motive and the α value.

Number of Price Points: The influence of the number of price points N on the bidcurves, and thereby on the clearing of the LEM, is mainly based on the distance between the price points. Given the used price range around the day-ahead price of 0.1€, we choose $N = 20$, resulting in a distance of 0.00526€ between two consecutive price points. Therefore, the clearing price is at most 0.00263€ away from the nearest price point and thereby from an optimal solution. We deem this difference to be small enough in a real-world implementation to assume that the difference between an optimal solution at the clearing price and the submitted bid is negligible.

B. Results

Fifty simulations are run in total, whereby each of the twenty-five motive scenarios (the balanced is identical for all) is used once for the winter and once for the summer week. Fig. 3 shows the results of the various scenarios regarding the cost and the CO_2 emissions. Fig. 4 displays the grid-oriented metrics, namely how often the consumed power was within 5% of the grid limit as well as the root-mean-square differences (RMSD), which measures the differences in power from one-time slot to the other. Given a power profile p of length T, it is computed as follows:

$$RMSD = \sqrt{\frac{1}{T-1} \sum\nolimits_{i=1}^{T-1} (p(i) - p(i+1))^2}. \tag{20}$$

Fig. 5 shows the overall power profile for the extreme and balanced motive scenarios for the winter and summer. Note that the scales during the summer and winter weeks are different.

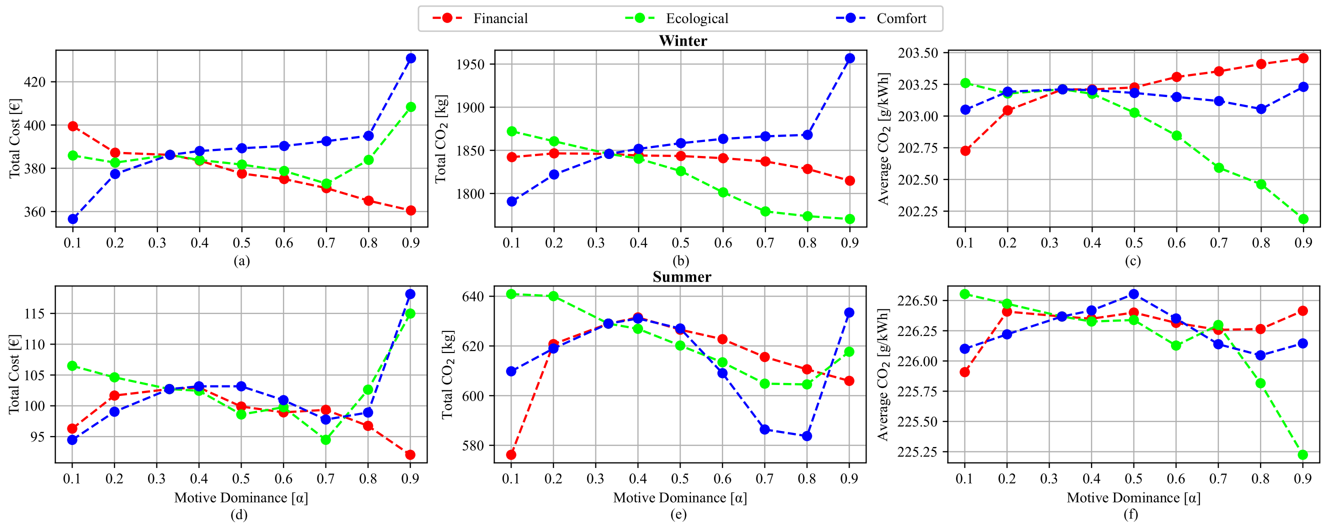

Fig. 3. Overview of the individual objectives (total cost, total CO_2 emissions, average CO_2 emissions) for all three scenario lines (motive dominance ranging from 0.1 to 0.9) for winter and summer. The comfort objectives (EV SoC, house temperature) showed no unforeseen behavior and are thus left out.

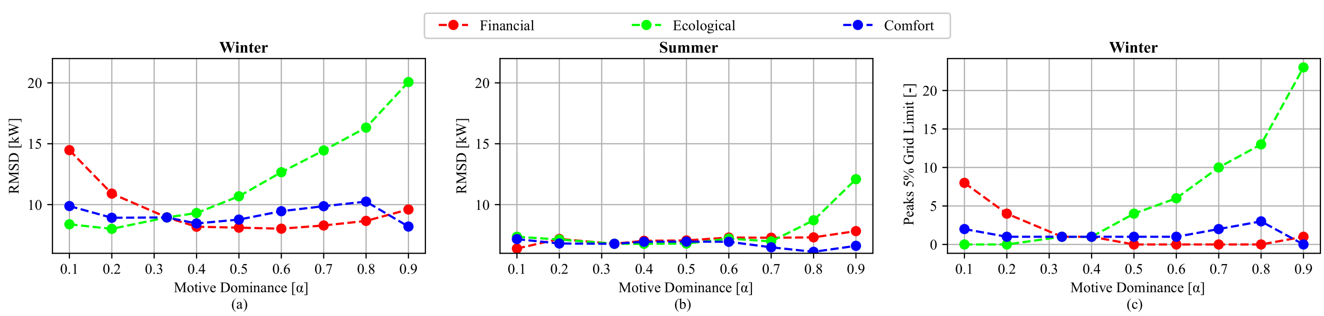

Fig. 4. Overview of the grid metrics for all three scenario lines (motive dominance ranging from 0.1 to 0.9). The grid limitation metric is only shown for the winter simulation, as the summer simulation showed non-zero values only for large α values for the ecological scenario line.

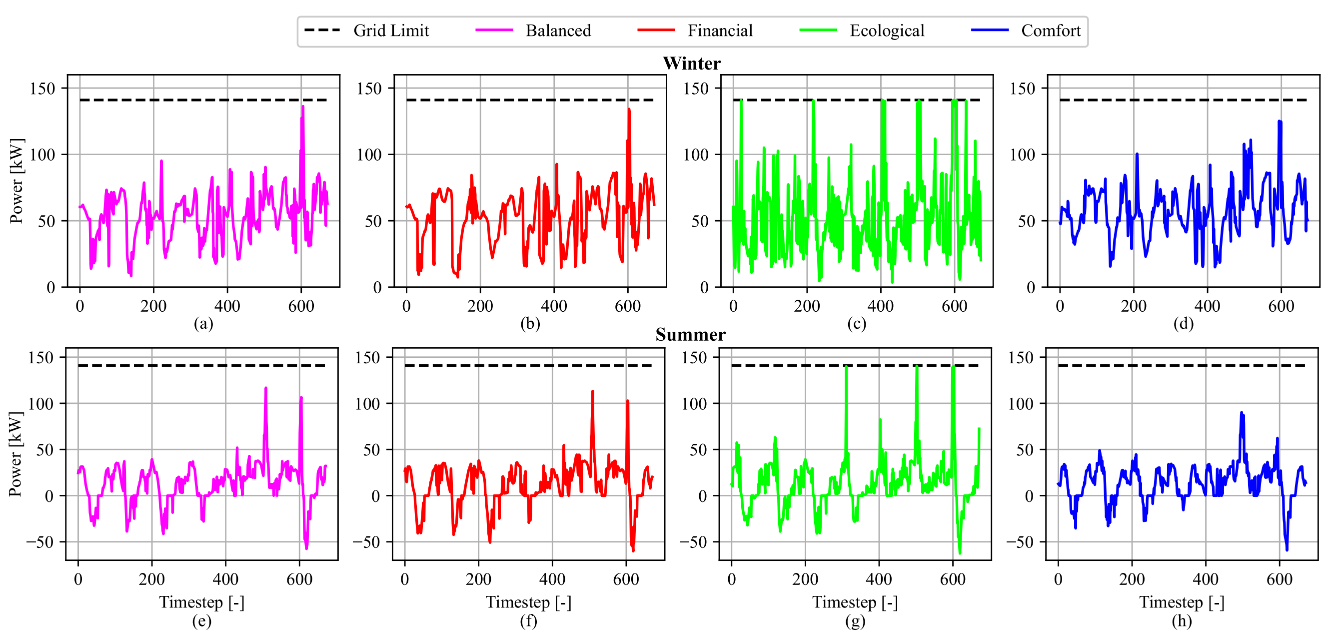

Fig. 5. Aggregated power profile of all households for winter (a-d) and summer (e-h) simulations of the balanced 0.33 and 0.9 scenarios.

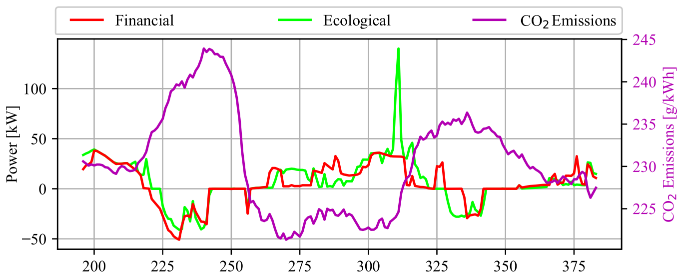

Fig. 6. Aggregated power profile of all households for the 0.9 ecological and 0.9 financial scenarios and the CO_2 emission factors for the summer week.

Fig. 6 overlays the power profile of the extreme ecological motive in summer with the CO_2 emissions as well as the power profile of the extreme financial motive.

C. Analysis

Three main insights can be observed from the results. First, based on Fig. 3, it can be observed that, in general, the motives accomplish their respective goals. A clear trend regarding its corresponding objective can be seen for each of the three motives. In general, it holds that the higher the weight of the motive, the better the corresponding objective, independent of the summer or winter week. However, that does not necessarily imply that no other motive mixture may perform better, as can be seen for the total CO_2 emissions, in which comfort-oriented scenarios outperform the ecological motive. The considered extreme scenarios, with weights of 90% and 5%, perform the best compared to all other motive mixtures, except for the extreme ecological scenario in summer.

This outlier can be explained by analyzing how the market and HEMSs work. Given the large weight of the ecological motive, a household's HEMS suggests buying most of the necessary electricity at the one time slot during the considered time horizon, in which the CO_2 emission is the lowest. As the underlying CO_2 data and motive weights are the same for all households, all households want to buy a large amount of electricity simultaneously. Given these bidcurves, the LEM has to clear the market given the grid constraints, which often limits the amount of traded electricity, as shown in Fig. 6 at time step 311 for the ecological scenario. Due to this electricity limitation, households are forced to consume less during this time slot and therefore have to shift their electricity to buy at a later time, in which the CO_2 emissions are already higher. Other motive mixtures with a smaller weight on the ecological motive do not strictly aim to buy electricity at one specific time slot, resulting in solutions in which electricity is already bought beforehand, e.g., at time slots 280-300 in Fig. 6, in which the CO_2 emissions are lower. Hence, the problem of the ecological motive is the focus on buying at specific time slots coupled with the market clearing of the LEM, potentially resulting in worse results compared to other motive mixtures.

This analysis of the extreme ecological motive also explains why more balanced motives usually perform quite well regarding all considered objectives. As no single motive dominates the others, the bidcurves allow a larger range of flexibility w.r.t. buying and selling electricity, which works better for the LEM clearing mechanism. In addition, devices such as batteries, EVs, or the buffer tank of the HP provide enough flexibility to buy electricity beforehand and only use it later on. This also explains the good performance of the 0.6 to 0.8 comfort scenario for the total CO_2 emissions for summer (Fig. 3(e)). Instead of trying to sell surplus PV generation, as done by the financial or the ecological scenarios, it stores it in the EV battery or the HP. It can thereby reduce the total amount of electricity to buy compared to, for example, the 0.8 ecological scenario. Hence, even though, in total, it consumes more electricity to run the HP or charge the EV, it needs to buy less from the LEM, resulting in lower CO_2 emissions.

The second observation focuses on a grid-oriented view of the outcome of the LEM. Human preferences and behavior affect the LEM beyond individual objectives. When analyzing the resulting power profiles, as displayed in Fig. 5, large differences in the quality of the profiles can be observed. In particular, the extreme ecological scenario for the winter week, see Fig. 4(c), seems to perform quite poorly, with many large fluctuations and peaks. Such peaks in power profiles can be explained due to homogeneous bidcurves over many households, which are caused by the usage of the same data and underlying (optimization) models. Fig. 4 also summarizes the power profile for each scenario into a single value using the RMSD (see (20)). These values confirm that the ecological motive is worse in winter and summer than the power profiles of the financial, comfort, and balanced scenarios. The results also show that, in particular, during the summer, the differences in traded electricity between neighboring time slots are much smaller than in the winter week. This insight aligns with the observations of the power profiles in Fig. 5.

The third observation is based on the results of the previous analysis in that even though the LEM may not perform well for extreme cases, it is generally robust against smaller deviations in the motive mixture. In particular, for scenarios where no single motive is larger than 0.7, all considered metrics, both from a grid perspective and the objectives from a household perspective, do not change rapidly and show nearly constant behavior. Only the ecological motive may still cause problems due to its focus on specific time slots, which counteracts the goal of a LEM in distributing flexibility across time.

VI. Implications on Future Markets

Summarizing the results of the previous section, we have seen that different motive mixtures can successfully model human behavior and, in turn, significantly impact the outcome of a LEM, both on an individual level, as well as on a grid level. In the following, we look at the implications of this for the application and design of future LEMs.

First of all, research on household participation in local energy trading and market approaches has identified multiple drivers of participation in LEMs or local trading approaches, ranging from environmental, [43], to financial, [44] or self-supportive (autarky) reasons, [45]. Hence, allowing households to follow their preferences regarding local trading may enlarge the group of potential participants compared to a fixed (black box) approach. This increase in participation aligns well with the European Union's Clean Energy Package, [46]. However, based on the observations and analysis of the results in the previous section, allowing households to follow their preferences may result in additional grid congestion. Therefore, LEM operators must pay close attention to the chosen distribution of the motive weights to ensure a well-working market. This could be achieved by, e.g., limiting extreme motive weights on a household level, restricting the averaged motive weights over the whole set of participating households, or implementing a default mixture, which comes in place in case the grid gets strained for a longer period of time.

Another important insight from the above results can be gained when analyzing the impact of various motive mixtures on the LEM. We have seen that even if the motive objectives do not directly align with the steering signals of the market, the LEM can still produce promising results, as seen for the results of the comfort motive. However, this effect only occurs when the steering signals and the motive objectives are not opposing each other. In the case of the comfort motive, the objective is to consume a sufficient amount of electricity, but the time of consumption is largely not important, while the steering signals focus on when to buy electricity. If, however, the motive objective and the steering signal directly oppose each other (as observed and analyzed for the ecological objective), the steering function of the market becomes ineffective. This highlights the need to pay special attention to the design of the objective function behind the various motives.

In the proposed approach, the households were given a choice between three different motives. However, they could not change the underlying objective functions on their own. Hence, it is possible to alter the underlying objective functions of motives to better align them with the steering signals of the market without deviating too much from the motive. For the ecological motive, an alternative objective could be to maximize the consumption of your own PV generation instead of only considering CO_2 emissions. If the CO_2 emissions should stay the main focus of the ecological motive, a discretization of the CO_2 emissions into pre-defined levels, such as *high*, *medium*, and *low* could shift the focus from a single time slot to a larger set of time slots, which allows the steering signal of the LEM to better reach their goal within each of the levels.

VII. Discussion and Conclusion

This work aimed to model human preferences and motives and analyze the impact of home energy management system (HEMS) parameter choices on the outcome and performance of a local electricity market (LEM). This was done by exploring various motives behind human preferences and using the Attitude-Behavior-Context (ABC) model to combine internal motives with the external flexibility of DERs on a household level to create individual bidcurves. Finally, a sensitivity analysis of the input parameters gave insights in the connections between motives and their impact on a LEM.

It was found that the ABC model, which models human preferences and their motive weights as input to a HEMS, can align the achieved power profiles to the goals of these motives and that a balanced motive mixture accounts for both the individual objectives and the grid constraints. On the other hand, extreme cases and a large weight for the ecological motive can lead to large fluctuations and peaks due to synchronized bidcurves, which is often not desired. The analysis highlights the importance of aligning market steering signals with the participants' motives in future LEM design to ensure a functioning market, as misalignment can lead to undesirable results. Another key insight is the importance of thoroughly analyzing the interactions between objectives and their implementation to avoid undesirable side effects and ensure optimal bidding strategies.

Some limitations to this work should, however, be mentioned. First, the results are based on two simulated weeks with slightly simplified DERs. A longer simulation with more detailed DERs may provide more details and could alter the conclusions of this work. Second, this research focused on household bidding in a LEM rather than on the bidding of the energy providers and other strategic bidding possibilities. Thirdly, only one type of LEM was considered, and different results and conclusions may be found with different LEMs. Fourthly, we assumed human behavior to be static, that is, households do not change or adjust their parameter setting over time or react to previous (undesired) outcomes. This choice was made to reduce additional complexity of the considered problem and also to avoid the problem of specifying when household start changing their motive mixture. In practice, this may happen, however it has also been shown that only a relatively small percentage of people ($10-15\%$) actually change their behavior based on feedback and messages, [47]. Finally, the authors realize that human preferences and behavior are already complex to research in real life, and it is even more challenging in simulations where minor omissions and changes can influence the results considerably.

Nevertheless, the authors believe that the conclusions and results of the analysis are relevant and that future research on LEMs should consider the impact of human preferences as an important aspect. Using the ABC model to include individual motives and preferences as parameter choices of the HEMS is a practical and reasonable approach. Finally, given these insights and conclusions, some interesting research directions for future work arise. Firstly, a study or survey could be done regarding the distribution of the motive weights. In addition to the three considered motives, other driving factors may be identified. Secondly, it may be of interest to extend the chosen price dynamic and investigate the impact on the financial objective. A last research direction could investigate the impact of the similarity of the motives on the outcome. Within the sensitivity analysis, the motive mixtures of each household were the same, while in practice, the motive mixtures may change from one household to another. It would be interesting to investigate whether this would further impact the LEM.

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