Modeling and Demonstrating the Effect of Human Decisions on the Distribution Grid

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***Abstract*—Demand-side management methods such as flexibility and local electricity market studies often do not include varying human decisions, guided by behavior and preference, and the effect these have on the markets and, consequently, on the load of the distribution grid. Studies have shown that, given the right driving motive, human decisions can have an effect and are essential to consider. However, human decisions and their motives are complex and challenging to model, and the effects are not entirely known. Therefore, there is a need to break down human decisions and their motives into modeling parameters to see how these affect the distribution grid. This study aims to model human decisions and see the effect of varying the motives behind these decisions on the operation of distribution grids. First, social factors are explored to determine relevant human decisions. Second, by determining what and how motives drive these decisions. Finally, varying motives and changing human decisions are implemented and simulated in fixed extreme cases. It was found that human decisions can have significant positive and negative effects on the operation of distribution grids depending on the motive and that these motives should be treated delicately.**

***Index Terms*—Human Decisions, Behavior, Electricity Market, Demand-Side Management, Distribution Grid**

I. Introduction

Numerous demand-side management methods have shown to be a promising solution to expected future distribution grid congestion caused by the transition from non-renewable to renewable energy sources [1]. For example, in [2], a market framework is proposed that allows participants to provide flexibility to prevent congestion. Many of these new approaches allow direct market participation by consumers and producers of all sizes.

However, this participation also increases the number of human decisions in the distribution grid. Human decisions in the distribution grid can be preferences or specific behavior characteristics. For example, if and when someone wants a coffee or how an electric vehicle (EV) is used. Both examples affect the distribution grid as they impact power consumption, possibly positively or negatively. For example, one study showed that market participants motivated by economic gains might reduce a local electricity market's trading effectiveness by strategically curtailing their photovoltaic panels (PV) [3]. Another study found that human decisions in the form of bidding strategies can increase a market's energy trading performance [4]. Incentives could affect the operation of the distribution grid as well. For example, one study determined that a combination of incentives, such as net-metering and feed-in tariffs, can increase the installed capacity of PV panels [5]. These incentives, however, do not encourage self-consumption and could lead to increased peak generation congestion.

Human decisions can affect demand-side management and the congestion of distribution grids and are, therefore, essential to consider when developing demand-side management methods such as flexibility and local electricity markets. However, most flexibility and local electricity market studies do not include human decisions and consequently do not take the effects of these individual decisions on their performance and the grid into account [1]. Pilots of these markets are, however, conducted in real-life and hence include human decisions. The problem with pilots is that these are often incentivized or exciting for participants affecting the motive behind human decisions and hence do not necessarily reflect actual conditions.

However, it is not straightforward to include human decisions in the mechanisms, as humans make many daily decisions. Therefore, there is a need to break down human decisions into modeling parameters for demand-side management and understand how various motives drive these decisions and affect the distribution grid. The authors believe it is essential first to understand the effect of extreme cases, where motives significantly change human decisions, to apply these to future studies better.

This study aims to model human decisions and analyze the effect of varying the motives behind these decisions on a distribution grid. This is done by first exploring the different social factors and the corresponding human decisions relevant to the distribution grid, secondly, by determining which motives are relevant and how they affect human decisions, and thirdly, by modeling these decisions and motives for household consumption, EV charging, and PV production, as these are currently the most prevalent DERs. Finally, the effect of human decisions on the operation of distribution grids is determined by simulating various motives in fixed extreme cases. The main contributions of this paper are:

- A breakdown of social aspects and motives into modeling parameters for human decisions

- An analysis of two motives that affect human decisions
- A demonstration of the effect human decisions have on a distribution grid

The paper divides as follows. In Section II, the current state of research in the area of social aspects and human behavior in energy is shortly highlighted, and human decisions are determined. In Section III, various motives and how these affect human decisions are discussed. Section IV introduces the implementation of motives and human decisions in this study, discusses the simulation, and then proceeds with a detailed analysis and discussion of the results. Section V summarizes the main findings and provides future research directions.

II. Human Decisions

A. Social Aspects and Human Decisions

A recent literature review analyzed the social aspects of the energy transition by asking, "what is the current representation of social factors in energy models?", [6]. This literature review considers the question from a broader perspective by analyzing the social aspects used in models, aiming to predict the roll-out of the energy transition from a national level.

In contrast, this study focuses on the social aspects of demand-side management participants on a distribution grid level. Hence, many social factors, such as politics and technological advancements, considered in [6], are not important for the modeling in this study. One factor that is important for both the energy transition and various demand-side management approaches is the behavior and lifestyle of households as it directly relates to the usage of distributed energy resources and smart devices, which in turn influence the operation of distribution grids. Hence, human behavior and lifestyle strongly influence the decisions taken by humans each day and affect the load of the distribution grid.

According to another study, most energy-consuming behavior, and thus human decisions, are based on preferences formed by habits and routines [7]. For example, a routine could be to always charge an EV to 100% or wash clothes during the day. An example of a habitual decision could be arriving home from work at 18:00 and plugging in the EV to charge.

B. Human Decisions in Households

As preferences determine human decisions relevant to the distribution grid, it is important to dive deeper into this subject and determine the preferences and human decisions. Therefore, this study investigates human decisions for three essential and well-used devices and loads: household load, PV, and EV charging, see Fig. 1. Given the importance of human decisions and, as outlined above, the influence of lifestyle and behavior on human decisions, these decisions, and corresponding parameters must be chosen in a way that they represent a wide range of preferences.

Electric Vehicle: The authors believe that human decisions regarding EVs can be divided into two categories, driving decisions and charging decisions. The former decisions are relevant when the EV is moving, while the latter decisions are

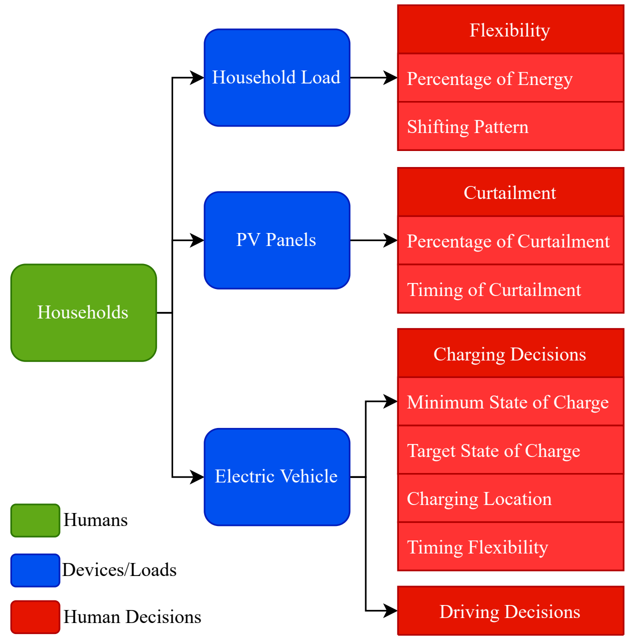

Fig. 1. An overview showing the human decisions per device/load derived and converted from social aspects. Driving decisions are taken from [8].

taken when the EV is connected to a charging station. The driving decisions can be characterized by the following parameters: departure and arrival times, the driving distance, and corresponding energy consumption. In previous research, the authors have already investigated driving decisions, including charging decisions that do not take place at the home charging station, see [8]. The charging decisions can be modeled via the following parameters. The first one is a minimum state of charge (SOC), indicating when to charge the EV. As soon as the SOC of the EV drops below the minimum SOC, the EV starts to charge. Another behavior parameter is the target SOC, up to which the EV is charged. Note that the minimum SOC parameter is strictly smaller than the target SOC. Both can be used to model individual range anxiety, a critical behavioral aspect of EVs [9]. Finally, there is the human decision to plan and shift EV charging according to certain motives.

Photovoltaic Panels: Households can only affect PV production by curtailing the generation in the inverter, reducing the power the PV panel produces. There are two major decisions to take when curtailing: the time slots when to curtail and the percentage of energy generation curtailed.

Household Load: The household load consists of all connected appliances, such as lights, electronics, and wet appliances. This load is usually represented by a load profile where each entry corresponds to the household's energy demand for a specific time slot. These profiles contain all the possible human decisions considering household appliances. Most of these appliances are considered inflexible [10] and will thus be unaffected by motives. Another study proposes to limit the flexibility of wet appliances, such as washing machines, tumble dryers, and dishwashers, to minimize the impact on

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comfort [11]. Within this work, these appliances define the flexibility of households, characterized by the two decision parameters of the total magnitude of household flexibility and the pattern of shifting this flexibility.

III. Motives Driving Human Decisions

A. Motives

There is only limited research on human behavior within the area of energy consumption. One branch deals with segmenting current energy consumers into different archetypes, each following similar behavior, [12], [13]. One common approach among these studies is to use different characteristics, ranging from socioeconomic over sociodemographic to behavioral aspects, to cluster similar consumers. While most segmentation approaches are based on socioeconomic- and demographic aspects, such as age, gender, or income, some approaches also include the drivers behind human behavior and decisions - namely motives - into their approach. Among the most common motives in the area of energy consumption and savings are the financial and pro-ecological motives, [13], [14]. In [7], further information on different behavior models and their connection to motives is given. It is important to note that, in general, behavior is not the consequence or outcome of a single motive but a unique mixture of different motives. Therefore, households may react differently to the same incentive, such as a pricing structure. Within the remainder of this study, the considered main motives are referred to as financial motive and ecological motive.

B. Scenarios

Based on the insights into the motives behind human decisions, three different scenarios are introduced to observe and analyze the impact of different motives on the distribution grid. As stated in the introduction, the authors believe it is essential first to understand the effect of extreme cases in which all households only consider one motive. Therefore, two extreme scenarios are implemented, where all households have a financial or an ecological motive driving their decisions. The third scenario can be seen as a base comparison for the two extreme scenarios as it follows the natural mixture of motives.

Based on these scenarios, it is possible to discuss the different motives' influences on the human decision parameters. The parameters related to driving decisions are expected not to be affected by the various motives. Furthermore, it is assumed that humans will not continuously watch and act on motives themselves but that they automate the progress by programming and planning appliances and devices [10].

Financial Scenario: At the moment of writing, in the Netherlands, one can only shift consumption into the night, following a night tariff structure with lower prices from 23:00 to 7:00 compared to the prices over the day. Due to financial motivation, humans shift flexible demand into this time window. The shape of the shifted household load flexibility is expected to follow a modified sinus function as displayed in Fig. 2. This shape should represent more realistic human decisions regarding smart programmable devices during the

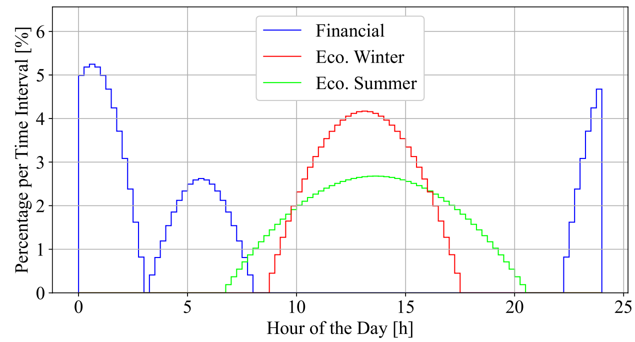

Fig. 2. Figure shows the percentage effect on household flexibility of human decisions per fifteen-minute change for financial and ecological scenarios.

night, in which devices, such as the washing machine, are expected to run around 23:00 or before 7:00 as people are not expected to get up in the middle of the night to load/unload these appliances. EV charging does not follow this function but is expected to be programmable and charges at full power during time slots between 23:00 and 7:00 until the target SOC is met. Note that arrival and departure times of EVs are additional constraints for the charging process.

Ecological Scenario: The ecological motive results in households trying to consume as much as possible during PV production hours by shifting their flexible load into time windows around PV production. This window is not as strict as the night tariff as it is not seen as an incentive but a personal motivation. Therefore, this window differs between households to account for personal preferences, such as leaving for work and running devices beforehand, and the possible difference in PV system orientation. In addition, at least two versions of time windows should be considered to account for the differences in PV generation (and decisions) during winter and summer. Generally, it is assumed that, depending on the season, the time windows start between 5:00 and 10:00 and end between 16:00 and 22:00, corresponding to Dutch sunrise and set times. Various programmable household loads are planned during the day, and sometimes the EV will be at home too [8]. The flexible load is not spread equally among all-time slots within the time window but mimics the shape of the PV generation to maximize the self-consumption. Hence, the flexible load follows a quadratic distribution, as displayed in Fig. 2. Even though the flexibility of devices of a single household cannot mimic this shape perfectly, given that a sufficient number of households are considered, the total flexibility is assumed to follow the quadratic form. The EV charging does not follow this shape but charges at full power in time slots within the time window as long as the target SOC is not yet met.

Base Scenario: No particular motive is preferred within the base scenario, and households follow their mixture of motives. Therefore, the flexible demand is not assigned to specific time windows, but the original demand vector is used. EVs start charging as soon as they arrive until their target SOC is met, or they must depart again.

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IV. Results and Discussion

A. Simulation

The effects of human decisions, varied by the motives of the financial, ecological, and base scenario, on the distribution grid can now be determined and analyzed using EV, PV, and household load modeling parameters. For this, a simulation consisting of 100 households is done in a simulation environment based on and consisting of data from earlier work. Given that the aim is to investigate extreme cases, each household is given an EV, PV, and household load with the human decision modeling parameters determined in Section II. The simulation runs for one year for each of the three scenarios, where the decision parameters are adjusted accordingly.

Electric Vehicle: The EV data comes from [8] and consists of EVs with $50kWh$ or $75kWh$ batteries and home chargers of $3.7kW$ or $11kW$ and also contains the driving behavior. The parameters related to driving decisions are assumed not to be influenced by the various motives determined previously. The human decisions related to home charging can vary depending on the motives, as discussed in Section III. The vehicles will always charge to 100% SOC. For the base scenario, all vehicles will immediately charge when arriving home. In the financial scenario, the vehicles will charge as much as possible between 23:00 and 7:00. Finally, in the ecological scenario, the charging depends on winter (October through March) or summer (April through September). During the winter, a random starting time in fifteen-minute intervals between 7:00 and 10:00 and an end time between 16:00 and 19:00 is drawn for each household. For the summer, a random starting time between 5:00 and 8:00 and an end time between 19:00 and 22:00 is drawn.

Photovoltaic Panels: The PV data is created by matching solar irradiance to expected yearly PV generation, given the roof area and angles [15]. This creates an individual PV generation profile for each simulated household. As the motives do not change the human decisions regarding PV, the PV generation profile is identical for the three motives.

Household Load: For the household load, average Dutch consumption profiles are used [16]. These profiles corresponded to typical Dutch consumption rates for households ranging from $2300kWh$ to $5450kWh$ with an average of $3250kWh$ [17]. These profiles are directly used as the household load in the base scenario. As discussed in Section II, the flexibility in household loads comes from the dishwasher, washing machine, and dryer. The consumption of these devices can reach up to 30% of the average total household consumption [18], but this depends on the type and efficiency of these devices, and not every household has all three [11]. Therefore, a safe margin is considered, putting the flexibility of households to 10% of the total consumption. This flexibility can be shifted over the day, as discussed in Section III and shown in Fig. 2. For the financial scenario, this time window is from 22:00 until 8:00, as it is expected that humans will not time their devices perfectly. The winter and summer times determined for the EV are used in the ecological scenario.

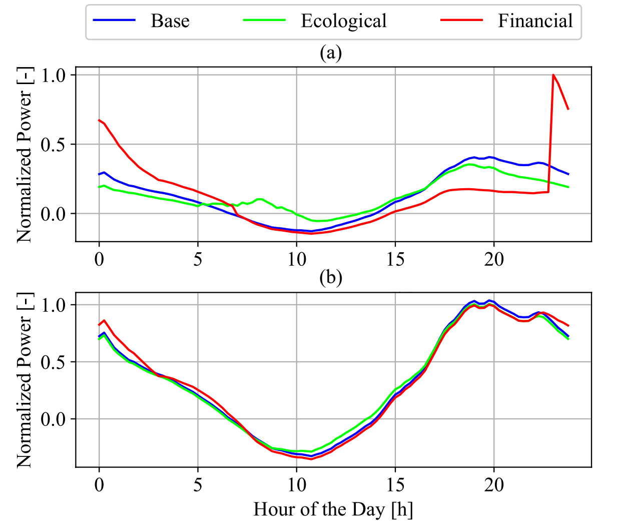

Fig. 3. Overlaying the normalized, average daily power profiles of all households for the three scenarios (a) and for the three scenarios with all EV decisions taken from the base scenario (b)

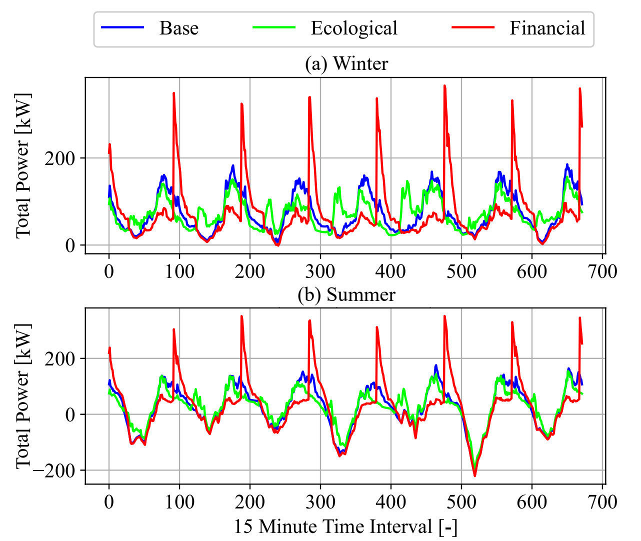

Fig. 4. Showing the total power consumption of all households per time step during one simulated week in both winter (a) and summer (b).

B. Discussion

Starting with Fig. 3a, it can be seen that the ecological and financial motives affect human decisions and impact, in particular, the peak power consumption and, thereby, the operation of the distribution grid. Positively, there is a spread in consumption, especially for the ecological motive, which shifts some parts of the consumption from evening and night to time slots with PV generation, reducing both consumption and generation peaks.

An apparent negative effect is synchronization in the financial scenario, with the night tariff starting at 23:00 and all consumers synchronizing their EV charging, resulting in a massive spike in power consumption. Fig. 4 shows that in both winter and summer, the night-tariff peak is almost doubled compared to the ecological or base scenario. This type of synchronization has been noted and debated as a problem before [19]. The results show that simultaneous price changes may lead to extreme congestion problems in a situation where all households follow the financial motive. In contrast, the ecological scenario showed promising first results. Nevertheless, it should be noted that the assumed flexibility of EV and the household load was insufficient to consume the entire PV production, and, as can be seen in Fig. 4b, significant production peaks may still occur.

Another finding comes from Fig. 3b, where the profiles for the different scenarios with the same EV charging decisions are compared. As can be seen, the differences in the profiles are minimal, leading to the conclusion that decisions regarding EV charging are significantly more potent compared to the considered household flexibility and, therefore, should be the primary focus of research.

Finally, it should be noted that his study only considered extreme cases where all households followed a single motive which will most likely not be the case in real life, but there may still be moments in which human decisions align with each other and may cause similar effects.

V. Conclusion

This study aimed to model human decisions and see the effect of varying the motives behind these decisions on a distribution grid. Different social factors, corresponding human decisions, and affecting motives relevant to distribution grids were explored and converted into parameters for grid simulations. Next, a simulation with varying motives and human decisions for fixed extreme cases was carried out.

It was found that in these cases, human decisions can have significant negative or positive effects on the operation of distribution grids, depending on the motive. Negatively, extreme power spikes caused by the synchronization of consumers show that future grid operators should consider the simultaneity of prices in any case. Positively, with a suitable motive, peak loads can be shifted and spread. A combination of different motives and incentives may allow for further reduction of peaks. Therefore, the human decisions explored in this study show they affect the distribution grid and again highlight the necessity to include human decisions in further research.

In future work, human decisions will be explored for distributed energy resources such as heat pumps and batteries. Furthermore, this study's ecological and financial motives will be adapted and expanded to bidding strategies usable in local electricity markets to see the effect of human decisions on future local electricity markets.

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