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# The assessment of residential demand-side management in Hungary

Abstract: This paper assesses the electricity bill savings potential of nationwide demand-side management programs in the residential sector. The analysis provides br oad insights into how time-of-use optimization could bring economic benefits while accelerating the deployment of renewable energy sources. We have built an electricity model with detailed household electricity consumption. Using survey data, we have created a baseline scenario that represents the current appliance usage habits of households in Hungary providing useful information on their shiftable electricity demand. We have then used time-of-use optimization of household appliances that do not affect thermal comfort in order to minimize electricity bills. Assuming different levels of participation in the demand-side management program, we reschedule the use of washing machines, dishwashers and dryers. Load optimization has a peak shaving impact on the total load, ranging from 2.2 to 3.6%. During winter, the potential for peak shaving is around –205 MW, whereas in summer, it is approximately –166 MW. Although solar energy is abundant and cheap during the day in summer, motivating households to shift their load, there is less shiftable load in the late evening hours. Therefore, the peak shaving potential is higher during winter due to the earlier peak. Modelling results from the Hungarian electricity market illustrate that smartening the grid has a bill saving potential of

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6.1%, or EUR 700 million in Hungary, assuming that all households are equipped with smart meters. However, half of this reduction can be achieved with only a 25% participation rate.

KEYWORDS: demand-side management, load shifting, flexibility, system-wide modelling

# Introduction

In July 2023, European electricity prices made headlines by plummeting below zero, driven by a surge in renewable energy sources. Headlines read, "European electricity prices fall below zero again as solar output surges" (Bloomberg 2023) and "European electricity prices tumble into negative territory amid glut of green energy" (Markets Insider 2023). Negative prices in the electricity market, where producers are willing to compensate consumers for their electricity usage, showcases the transformative impact of renewable energy sources. It also brings to light the existing unpreparedness among European countries in fully harnessing the potential of wind and solar power. In addition, the global energy crisis has accelerated the deployment of renewables to unprecedented levels. The increasing intermittent output from renewables can lead to even greater volatility in the electricity market. As a result, there is a strong need for more flexibility in the system, which can help stabilize electricity prices.

Demand flexibility measures, such as dynamic pricing schemes, offer a viable solution by enabling consumers to adapt their consumption patterns in response to price signals from suppliers, thereby aiding in the maintenance of the balance between available capacity and current load requirements. In response to this need, electricity providers have implemented demand response programs. An example of this is that on January 23, 2023, households in Great Britain were incentivized with discounts to reduce their electricity usage for an hour, effectively curbing energy consumption (BBC 2023). Another example is the "Defeat the Peak" pro-social demand response program, where the utility provider identified six peak events during the summer of 2018 and requested consumers to decrease their energy consumption during specific time periods (Pratt and Erickson 2020).

The prerequisite of these programs is equipping European households with smart meters that enable two-way communication between suppliers and consumers. The roll-out of smart meters has been on the EU's agenda for a while. The EU's "Third Energy Package" legislative package which came into force in 2009 set out that at least 80% of consumers shall be equipped with intelligent metering systems by 2020 (Directive 2009/72/EC of the European Parliament and of the Council 2009). As of 2018, 34% of all electricity metering points were equipped with a smart meter and it was estimated that by 2020, the penetration rate would increase to 43% (Tounquet and Alaton 2019). Therefore, the infrastructural requirements of demand flexibility measures are still missing in various countries, particularly in the Central and Eastern Europe (CEE) region, where smart meter roll-out is even below 20% (Vitiello et al. 2022) as shown in Figure 1.

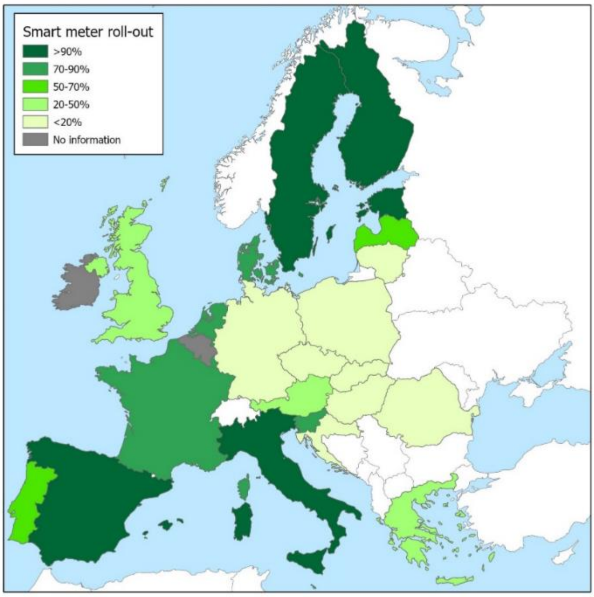


Fig. 1. Progress on national smart-meter roll–outs in 2020 (Vitiello et al. 2022)

Rys. 1. Postępy w krajowych wdrożeniach inteligentnych liczników w 2020 r.

Although, there is limited experience with smart grid technology and residential demand response programs, numerous quantitative models have estimated their potential impacts. Some articles use game theory approach to model demand response in smart grid systems (Lüth et al. 2018; Mondal et al. 2017; Nguyen et al. 2012; Yang et al. 2012), while others use cost optimization algorithms to schedule household electronic device usage (Mota et al. 2022; Bharathi et al. 2017; Taik and Kiss 2019). However, these analyses focus only on the benefits to consumers participating in the programs. There are only a few models that estimate how consumers outside the programs benefit from lower electricity prices and assess the system-wide impact of demand-side management solutions (Freire-Barceló et al. 2021; Kirkerud et al. 2021; Misconel et al. 2021). However, these analyses focus on heating and cooling appliances, the use of which is not fully shiftable. Furthermore, none of them cover the CEE region in detail, where smart meter roll-out is low and where it is essential to highlight the benefits of demand-side solutions.

This paper presents a quantitative model to assess the system-wide potential of demand-side management programs in the residential sector, assuming different levels of national participation rates. Through time-of-use (ToU) optimization of household appliances, the model demonstrates the ability to reduce electricity prices, shave peak loads and reduce overall electricity costs. First, we establish the baseline by estimating the load curve of shiftable appliances, such as washing machines and dishwashers. We then use supply-side data and price feedback to re-estimate the load by strategically rescheduling the use of appliances, with the aim of minimizing the total daily energy cost. We build four scenarios, assuming 25, 50, 75 and 100% smart meter penetration and that all smart metered households participate in the demand response program. These optimized scenarios reflect an ideal case where all actors are assumed to be perfectly informed and rational.

We assess the implications of the proposed scenarios using the Hungarian electricity market as an example. The baseline is based on household survey data on appliance usage habits (Kökény and Hortay 2020); therefore, it accurately reflects how the shiftable appliances are currently used in Hungary. There is very limited information available in the literature on the shiftable electricity demand of households, especially in the CEE region. Therefore, a disaggregated representation of the Hungarian residential electricity demand by appliance can be a useful input for the development of different types of studies. The Hungarian grid has recently faced significant challenges due to the rapid expansion of solar photovoltaic (PV) installations across the country powered by the generous net metering support system for residential consumers. In the first three quarters of 2023, the total installed capacity of household-sized small solar power plants increased by almost 0.7 GW (MEKH 2024). The soaring demand for solar power has reached unsustainable levels, requiring immediate action. Consequently, the government has responded by imposing a temporary suspension on new grid connections, limiting owners of solar panels to self-consumption of the energy generated in their homes.

The remainder of this paper is organized as follows. Section 2 provides a brief summary of the relevant literature, while Section 3 outlines the model built. Section 4 presents the data used in the analysis and Section 5 describes the current state of the Hungarian electricity market. This leads to Section 6, where we discuss the results of the modelling exercise and the cost reduction potential of demand-side management programs. Finally, Section 7 summarizes our conclusions and ideas for future work and Section 8 describes the limitations of the analysis.

## 1. Related literature

Demand response (DR) programs aim to strategically influence consumption patterns through different signals to address system imbalances (Babatunde et al. 2020). Through the promotion of customer interaction and the responsiveness of customers, DR has the potential to improve market efficiency and reduce peak demand over the long term. Furthermore, DR can lower both plant and capital costs and delay the necessity for network upgrades (Siano 2014). Understanding household behaviour and consumption patterns is vital for enhancing demand-side flexibility. These patterns serve as a baseline to assess the impact of DR programs.

Electricity consumption varies due to multiple factors such as time of day, seasons, weather, and significant events like sports matches (Khatoon and Singh 2014). While commercial and industrial consumption remains stable, the daily fluctuations are mainly due to households. Household consumption patterns are influenced by various factors such as household size, economic status, and socio-demographics (Hayn et al. 2014; Sanquist et al. 2012; Schipper et al. 1989).

Lifestyle characteristics like environmental awareness and occupation also have a strong influence (Lutzenhiser 1993). The uptake of solar panels and batteries in households further impacts consumption patterns, enabling off-grid electricity generation and cost smoothing (Linssen et al. 2017; O'Shaughnessy 2018).

## 1.1. Demand-side management programs

Encouraging residential consumers to shift their electricity usage is crucial for ensuring a secure and affordable national energy supply amidst a transition to higher levels of intermittent renewable energy sources (Nicolson et al. 2018). Fixed electricity tariffs fail to incentivize households to adjust their daily consumption patterns, as they pay the same price regardless of peak or off-peak periods, when system costs significantly differ.

Demand-side flexibility services can be classified into two categories: (1) Explicit demand-side flexibility services and (2) Implicit demand-side flexibility services (van der Veen et al. 2018). In this paper, we focus on the implicit flexibility services which include dynamic ToU optimization, control of the maximum load ($kW_{max}$ control), self-balancing services and controlled islanding. The implementation of these programs may not always reduce energy consumption but can influence consumption patterns. However, when consumption is interrupted, consumers may need to compensate for the lost time, often resulting in a rebound effect where energy is not saved, and a new peak may even be generated (Palensky and Dietrich 2011).

There are several examples for demand response programs. In the United Kingdom, the National Grid introduced the Demand Flexibility Service in winter 2022/23 and over 1.6 million households and businesses participated, providing approximately 350MW of flexibility to the system (ESO 2023). The service was offered for the first time on January 22 and 23, 2023, from 16:30 to 18:00, and those who had signed up got discounts on their bills if they reduced their electricity consumption. National Grid said it paid suppliers between £3 and £6 for every kilowatt-hour of energy saved between 17:00 and 18:00 (BBC 2023).

In the Defeat the Peak pro-social demand response program, analyzed by Pratt and Erickson (2020) and conducted in 2018 by the Burlington Electric Department in Burlington, Vermont, customers received a signal to make short-term reductions in their energy consumption during annual peak periods. Six peak events were identified during the summer of 2018 and the consumers were asked to curtail energy use during specific time periods. The incentive to reduce electricity consumption was a $1000 donation from the municipal utility to a local charity. The results indicate that the program achieved a 13.5% reduction in energy use during the peak annual events in August 2018. The estimated annualized savings achieved by the program is almost $190,000 while the rough cost estimate is around $16,000, resulting in an 11 to 1 return on investment.

Laicane et al. (2015) conducted a survey on a four-person household to investigate user activities and appliance usage. The study focused on the load shifting potential of two appliances:

a washing machine and a dishwasher. The findings indicated that load shifting of these appliances resulted in an average reduction of peak load for the dwelling by 24 and 13.5%, respectively.

## 1.2. Modelling exercises

There are several models in the literature that evaluate smart grid technology and its benefits. Mota et al. (2022) introduced a novel genetic algorithm-based approach to model flexible load shifting to minimize electricity bills. The proposed solution incorporates distributed generation, dynamic pricing, and load shifting to minimize energy costs and achieve bill reductions of up to 15% in real household load scenarios. A genetic algorithm is also used by Bharathi et al. (2017) and achieves a reduction in electricity use during peak hours of almost 22%. Lüth et al. (2018) model a small community, revealing that smart grid and energy storage technologies can lower electricity spending by up to 31% for consumers, facilitating peer-to-peer trading and enhancing energy efficiency. Mondal et al. (2017) examine microgrids with households equipped with energy storage and facing dynamic electricity pricing. Using a Stackelberg game model, they demonstrate that these microgrids effectively meet consumer demand at lower prices.

However, none of the above analyses consider the potential positive impact of DR at a system level. Recently, a few articles have appeared in the literature that examine the wider impacts of these programs. Misconel et al. (2021) assessed the economic benefits of DR from a system perspective in two contrasting decarbonization pathways for a decentralized and for a centralized European energy system. However, in their analysis, the hourly DR potentials are exogenous and taken from the REFLEX data repository (2019). The system-wide DR potential has been estimated endogenously for Spain (Freire-Barceló et al. 2022) and the Northern European countries (Kirkerud et al. 2021). In both cases, the DR potential of heating and cooling appliances is considered; however, these appliances cannot be rescheduled without compromising user comfort. The system-wide potential of other shiftable appliances, such as washing machines and dishwashers, has not yet been estimated. Furthermore, in the CEE region, where the penetration of smart meters is considerably low and their economic evaluation would be essential, no analysis has yet been performed.

# 2. Load shifting model

The model proposed in this paper aims to estimate the system-wide energy cost reduction potential of residential demand-side management programs. It is a perfect foresight model that applies dynamic ToU optimization to the shiftable load schedule to minimize energy costs. A schematic representation of the model is illustrated in Figure 2. First, the model uses household data to determine the number of different appliances, their appliance usage habits and how frequently they are used each week. Then, using this information and the load curve of the appliances, the baseline load for the shiftable household appliances is established. Finally, the model adjusts this schedule within a specified time window by considering price feedback, aiming to minimize electricity costs. An iterative process is applied to compute energy costs for all possible solutions for the distribution of the shiftable load. In essence, it constantly reshapes the shiftable load, adjusts electricity prices and determines the total electricity cost. Then, the algorithm selects the most cost-effective option at the system level.

In this way, the model comprehensively assesses the dynamics of appliance usage, electricity prices and electricity bills, thereby providing valuable insights into the effectiveness of system -wide demand-side management programs.

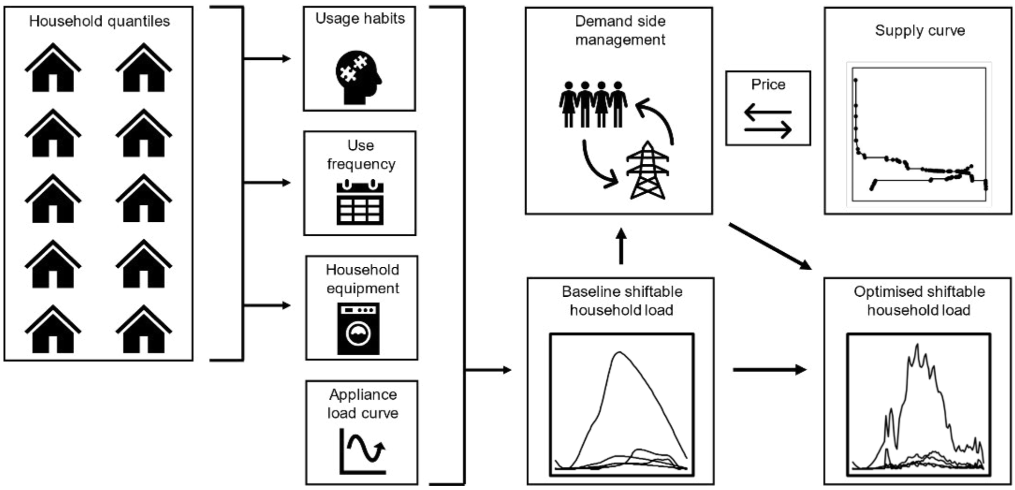


Fig. 2. Proposed model structure

Rys. 2. Proponowana struktura modelu

The model evaluates two scenarios: (1) a baseline scenario, which represents the current state of the electricity load; (2) an optimized scenario, in which the considered household appliances are scheduled to minimize electricity costs. In the scenarios, we only consider the use of appliances that can easily be shifted and that do not cause any loss of comfort, such as washing machine, dishwasher and dryer, similar to Mota et al. (2022) and Laicane et al. (2015).

The most important inputs of the model are as follows:

- *period*: vector of periods in day, typically hours or quarters;
- *day*: vector of days considered in the analysis;
- *app*: vector of shiftable appliances considered in the analysis;
- *quant*: vector of household income quantiles considered in the analysis;
- *l. curve:* vector of appliance load curve lengths in terms of number of periods;

- *tot. load*: variable which represents the overall electricity consumption, encompassing the total load on the system and defining the demand-side of the electricity market, dimensions: [*period*, *day*];
- $S(i,j,load_{i,j})$: supply curve function representing the relationship between the quantity of electricity (*load*) that suppliers are willing to generate and sell at different prices on a specific day ($j$) and period ($i$);
- *price*: the price of electricity in a given time period, dimensions: [*period*, *day*];
- *part.rate*: the share of households participating in the demand-side management program, constant;
- *load.curve*: appliance load curve which represents the electricity load pattern of an individual appliance during its periods of use, dimensions: [*l.curve,app*];
- *tot.appliance*: the number of different appliances owned by households, dimensions: [*quant,app*;
- *op.window*: operation time window defining specific time periods during which appliances can be utilized by the optimization algorithm, dimensions: [*period*];
- *use.freq*: weekly frequency per resident with which appliances are typically used by households, dimensions: [*app*];
- *use.habit*:: distribution of appliance usage over the day (shown in Figure A.1 in the Appendix). Defines the probability of an appliance being started for each time period of the day, dimensions: [*app,period*].

By incorporating and analyzing these fundamental variables, the model aims to simulate and evaluate electricity market dynamics, consumption patterns, and the potential impact of various demand-side interventions or pricing strategies. The model utilizes discrete time periods to represent time.

## 2.1. Baseline scenario

The baseline scenario is defined as the estimated reference load of household appliances included in the analysis during the observation period. This load is specifically referred to as the total shiftable load as only those appliances that can be shifted without compromising user comfort are integrated into the model. Due to the unavailability of nationwide appliance or household load data, the model is utilized to approximate the baseline shiftable load, which serves as a benchmark for comparison. To reflect the current state of the residential electricity market, the baseline shiftable load is distributed throughout the day, taking into account observed household usage patterns.

From the weekly frequency of usage per resident, a daily use probability is calculated by household income quantile (by taking into account the average number of household residents). Each day of the observation period, a random variable, following a standard uniform distribution, is assigned to all appliances. If the value of the random variable is lower than the probability of the corresponding appliance, the appliance is used that day. After computing the total number of appliances used within a day, the timing of their usage is determined based on the appliance usage patterns (use.habit). The number of appliances started in a given period by household quantile and by appliance is stored in the start variable (with dimensions: [quant, app, period, day]).

The baseline shiftable load is represented by:

$$shift.load = start \cdot load.curve \tag{1}$$

which is an [*quant*,*app*,*period*,*day*] matrix. This distribution of shiftable load is crucial for accurately representing the load's temporal dynamics. Therefore, it is essential that the *start* matrix is well specified. We compare the impact of demand-side management programs to this scenario to assess their cost reduction potential.

On the supply side, we use historical electricity prices observed throughout the observation period. As the baseline scenario is used as a reference case reflecting the current state of the household electricity market, historical data is the most appropriate when available.

## 2.2. Optimized scenario

This scenario focuses on evaluating the potential of smart technologies equipped with appliance ToU optimization for load shifting. The ToU rates used in this analysis are based on the hourly day-ahead supply curves. The rates change dynamically to reflect the actual cost of generating electricity, allowing optimization to achieve minimum cost at system level. The objective is to achieve an optimized distribution of appliance usage throughout the day that minimizes the electricity costs while maintaining the same total daily electricity consumption as the baseline scenario. The starting time of appliance use is optimized iteratively by household income quantile and by appliance type in random order.

The ToU optimization algorithm is run for each day of the observation period. The shiftable load is rescheduled for day $d$ as follows:

1. Random selection: the algorithm randomly selects a household quantile, denoted by $q$, and an appliance, denoted by $a$, from the pool.

2. Program participation: the number of the selected appliances owned by the selected household quantile that are started on the given day ($start_{q,a,:,d}$, where ‘:’ marks all values of a dimension) is multiplied by the participation rate (*part.rate*) to obtain the number of appliances included in the optimization:

$$part.appliance_{q,a} = part.rate \cdot start_{q,a,:,d} \tag{2}$$

3. Shiftable load removal: the load of the participating appliances included in the optimization is removed from the total load:

$$adj.load = tot.load - part.rate \cdot shift.load_{q,a,:,:} \tag{3}$$

where $shift.load_{q,a,:,d}$ refers to the shiftable load of appliance $a$ owned by the household quantile $q$ in all periods of day $d$.

4. Re-adding the shiftable load: the algorithm gradually reintroduces the previously removed load by optimally rescheduling it in batches. Batch processing ensures that the reintroduction of the load does not lead to new price peaks during the day. Each batch, typically consisting of around 100 appliances, is strategically scheduled to minimize overall system costs, factoring in price dynamics. The algorithm estimates, for each period $p_0$ of the load operating time window, what the total load would be if the batch of appliances were started in that period ($b.load_{p_0,:,d}$, dimensions: [*period*,*period*,*day*]). Starting the batch of appliances in period $p_0$ also increases the adjusted load in the following periods while the appliances are running ($lc_a$ is the periods of operation of the load curve of appliance $a$):

$$add.load = load.curve_a \cdot batch \tag{4}$$

$$b.load_{p_0,p,d} = \begin{cases} adj.load_{p,d}, & p < p_0 \text{ or } p_0 + lc_a \le p \\ adj.load_{p,d} + add.load_{p-p_0+1}, & p_0 \le p < p_0 + lc_a \end{cases} \tag{5}$$

5. Cost calculation: the electricity prices are then recalculated for all $p_0$, where $p_0 \in op.window$ and the total daily electricity costs are estimated by multiplying the prices and the *b.load*:

$$c_{p_0} = \sum_{p=1}^{\max(period)} S\left(p, d, b.load_{p_0,p,d}\right) \cdot b.load_{p_0,p,d} \tag{6}$$

where $c_{p_0}$ is the total daily system-wide electricity bill if the batch of appliances are started in period $p_0$. The cost values calculated for all $p_0 \in op.window$ are gathered in the *cost* vector.

6. Optimal time period: the algorithm selects the time period with the lowest electricity costs:

$$optimal\ period = arg\ min_p(cost) \tag{7}$$

All appliances in the batch are scheduled to start during in the *optimal period*.

7. Iteration through batches: the optimization process is performed iteratively. Once all the selected appliances have been optimized in batches, the algorithm restarts by randomly selecting a new household quantile and appliance. After each iteration, the total load and electricity prices are updated based on the latest modifications.

This iterative optimisation approach aims to achieve a cost-effective distribution of electricity usage for different households and appliances, thereby potentially reducing overall electricity costs and enhancing load management efficiency.

Through the scenarios, we aim to assess the maximum cost reduction potential of demand-side management program as the difference between the optimized costs and the baseline costs. The difference between the costs reflects the benefits of smartening the grid by installing smart meters in the households and thus enabling demand-side management programs. In the following section, we present the capabilities of the proposed model and assess the potential of residential demand response using the Hungarian electricity market as a case study.

## 3. Hungarian electricity market

After the 2010 parliamentary elections, the new government in Hungary implemented policy actions to address high electricity prices. They announced a residential price cap on universal services in July and introduced regulatory price legislation in 2011. Over the following years, they gradually reduced universal service prices, aiming to address social problems caused by high electricity costs and potentially reclaiming state property by taking over private companies (Szőke et al. 2021). As a result, Hungarian households have become insensitive to the fluctuating energy prices and the challenges of the energy transition. As the residential price cap became unsustainable due to the soaring energy prices in 2022, from August 1, residential customers have only been able to benefit from the reduced tariffs for electricity and natural gas up to the average consumption. Residential customers are charged approximately EUR 0.0953 per kWh for electricity consumption below a certain limit (2523 kWh per year). Above this limit, the tariff almost doubles to EUR 0.1845 per kWh.

However, solar PVs have become exceptionally popular. As of July 1, 2023, the total installed capacity of Hungarian solar systems exceeded 5,000 MW. In 2022, the expansion was 1,100 MW, which was an annual record, while in the first half of 2023, 1,023 MW had already been installed. The National Energy and Climate Plan, which is currently under review, anticipates a doubling of installed capacity by the beginning of the next decade, compared to the 6 GW previously expected by 2030 (Ministry of Energy 2023). Consequently, the Hungarian grid is encountering significant challenges due to imbalances between the inflexible demand and the increasingly intermittent supply. In October 2022, the government imposed a temporary suspension on applications for new grid connections, limiting owners of solar panels to self-consumption of the energy generated in their homes.

In Hungary, Kökény and Hortay (2020) analyzed the demand elasticity potential of Hungarian household appliances. For their research, they conducted a representative opinion poll with 1001 respondents in terms of type of settlement, age of household head and education level. They found that around two-thirds of the population had a negative attitude towards shifting their consumption, partly because they were not satisfied with the 10% discount on electricity costs offered in return. However, it is important to reiterate that Hungarian electricity prices are well below the EU average as a result of electricity price cuts. Removing the rebates could significantly increase households' willingness to pay as the savings potential would also be much higher.

# 4. Data

In the model, we take the 2022 fifteen-minute load data for Hungary from ENTSO-E, day-ahead supply curves and electricity prices from HUPX, and decile level household data from the Hungarian Central Statistical Office (KSH) (for more details please see Table A.1 in the Appendix). Incorporating decile level data allows for the introduction of heterogeneity into the model. While household-level data would offer greater accuracy, it is seldom available for analysis.

We calculate our baseline load curve for shiftable household appliances (washing machine, dryer, and dishwasher) relying on the survey of Kökény & Hortay (2020) about electricity consumption habits of Hungarian households. Additional details regarding the assumptions of the baseline scenario are presented in Figure A.1, Table A.2, and Table A.3 in the Appendix.

# 5. Results and discussion

In this section, we present the most important outcomes of the modelling exercise. In the baseline scenario, we use the historical electricity prices and the total load of Hungary in 2022 and then compare the results of the optimized scenario with these. The energy crisis that unfolded in 2022 had a severe impact on Hungarian electricity prices. While the average daily electricity prices at the beginning of the year were around 200 EUR/MWh, the average price in August was 486 EUR/MWh, reaching an annual peak of 1045 EUR/MWh. The significant increase in electricity prices followed the trend in TTF gas prices, which also peaked in August. The soaring electricity prices triggered a strong demand response. The average Hungarian load in 2022 was between 4500 MW and 5500 MW, but the annual peak reached 7100 MW on 25 January, before the war in Ukraine broke out. After the war started and the prevailing energy crisis hit the electricity markets, the load gradually decreased, with the average daily load falling from 5700 MW in January to 4700 MW in the summer.

In Figure 3, the 2022 mean total load and electricity prices of Hungary are depicted. As can be seen, the peak load is around 7:30 p.m. when the sun is usually already down and no solar power is available. Consequently, prices also peak at around the load peak. Also, there is a smaller morning peak leading to increased prices from 8 a.m. to 9 a.m. We can conclude that during the high electricity consumption periods, prices also reach their daily highest values.

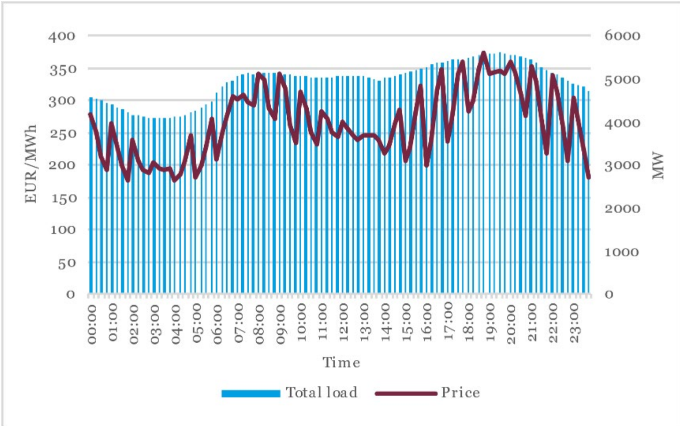


Fig. 3. Average 15-minute electricity load and electricity prices in Hungary in 2022 (ENTSO-E, HUPX)

Rys. 3. Średnie 15-minutowe obciążenie prądem i ceny prądu na Węgrzech w 2022 r.

## 5.1. The impacts of a nationwide demand-side management program

First, we estimate the baseline load of shiftable household appliances and then apply the optimization algorithm to all the households (approximately 4.1 million in Hungary) to minimize electricity bills using the methodology described in Section 3.2. The baseline shiftable load is estimated based on the appliance usage habits, the weekly frequency of usage and the appliance load curves. Further details of the assumed inputs are given in the Appendix. Figure 4 shows the baseline shiftable load by appliance including all Hungarian households. Washing machines are mostly used in the late morning and at noon, while dishwashers and dryers are often started in the afternoon or evening. The greatest potential for demand-side management is in the scheduling of washing machines. As almost 99% of households have a washing machine, its total load is significantly higher than that of dishwashers or dryers.

The baseline load of shiftable appliances peaks at 444 MW around midday (see Fig. 5), which is favorable from a system point of view as there is usually ample solar power available at this time. Nevertheless, the shiftable load is still significant during the evening peak hours, around 300 MW at 7 p.m. when prices also reach their daily maximum. In our analysis, we consider these baseline results as the estimated shiftable load curve of Hungarian households.

In the optimized scenario, we assume that all Hungarian households participate in the demand-side management program and that the system operator can schedule all the washing machines, dishwashers and dryers in the country, approximately 5.3 million appliances in total. This scenario assesses the hypothetical maximum potential of introducing a nationwide demand-side management program in Hungary. The optimization algorithm reschedules the start of the electrical appliances to minimize electricity bills. The results shown in Figure 5 are in line with the intuition – the algorithm shifts a substantial amount of appliance usage from the evening hours to

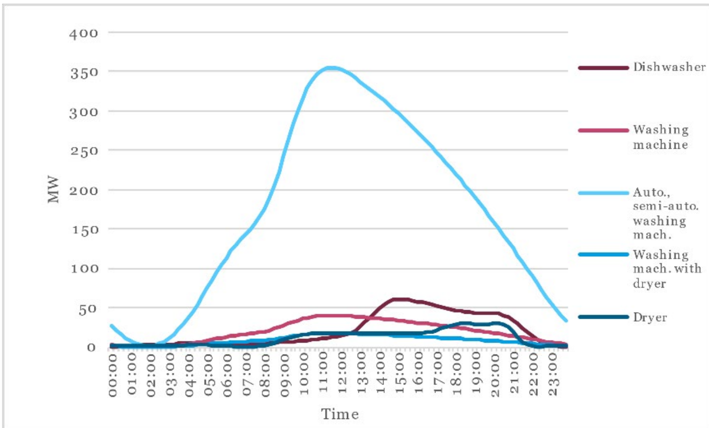


Fig. 4. Average shiftable household load by appliance in the baseline scenario

Rys. 4. Średnie zmienne obciążenie gospodarstwa domowego według urządzenia w scenariuszu bazowym

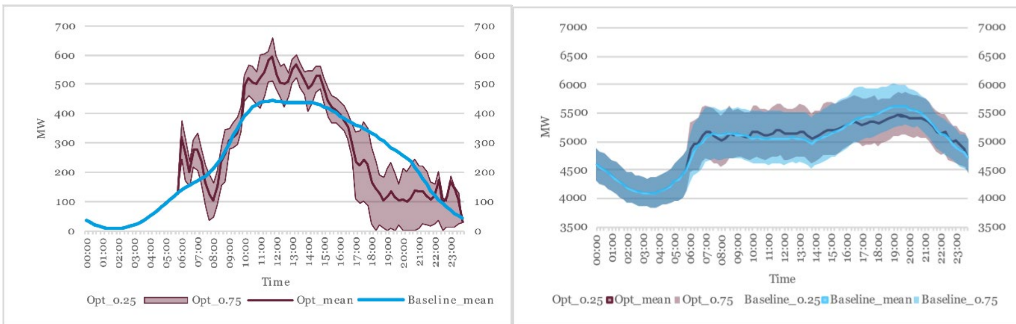


Fig. 5. Average shiftable load (left) and total load (right) in the baseline and optimized scenario. The shaded areas represent the interquartile range of the variables

Rys. 5. Średnie obciążenie zmienne (po lewej) i obciążenie całkowite (po prawej) w scenariuszu bazowym i zoptymalizowanym. Zacienione obszary przedstawiają rozstęp międzykwartylowy zmiennych

the midday and the early morning hours. This is consistent with the findings of the literature that demand response has a smoothing effect on the total load (Kirkerud et al. 2021).

On average, the appliances in the optimized scenario are started forty-five minutes earlier then in the baseline. During the peak hours, the difference between the optimized and the baseline scenario reaches –200 MW and the largest increase in demand compared to the baseline occurs in the beginning of the optimization window at 6 a.m. (182 MW) and just before noon at 11:45 a.m. (150 MW), as shown in Figure 6. The adjusted shiftable load results in a more smoothed total load curve with lower peak and higher off-peak demand. The peak shaving impact of the optimization algorithm on the total load curve ranges from 2.2% to 3.6% between 6 p.m. and 8:30 p.m.

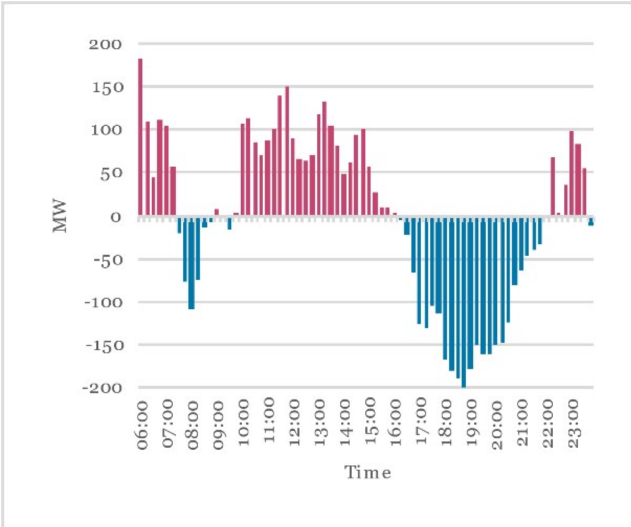


Fig. 6. Difference between shiftable load in the optimized and in the baseline scenario

Rys. 6. Różnica pomiędzy obciążeniem zmiennym w scenariuszu zoptymalizowanym i bazowym

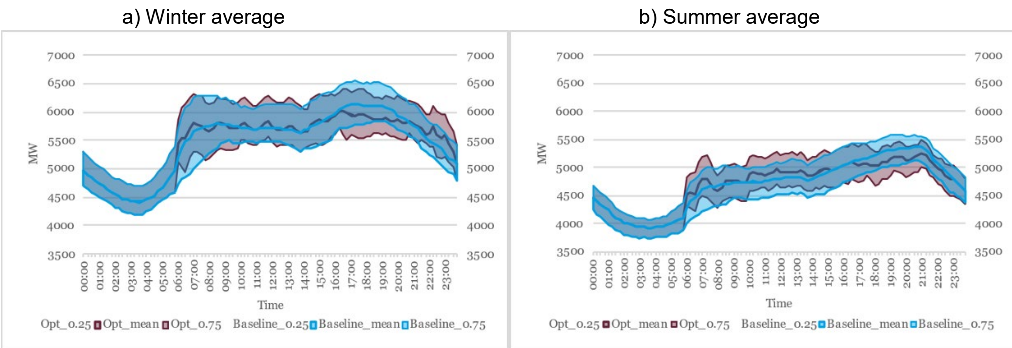


Fig. 7. Average total load in the baseline and optimized scenario during winter (left) and summer (right). The shaded areas represent the interquartile range of the variables

Rys. 7. Średnie całkowite obciążenie w scenariuszu bazowym i zoptymalizowanym zimą (po lewej) i latem (po prawej). Zacienione obszary reprezentują zakres międzykwartylowy zmiennych

The load shifting potential varies depending on the season. In Hungary, the total load pattern differs between summer and winter. Figure 7 presents the average baseline and optimized load during both seasons. During winter, the average load is significantly higher than in summer, ranging between 4,400 MW and 6,100 MW daily, compared to 3,900 MW and 5,350 MW in summer. Additionally, the daily peak occurs at 5:15 pm in winter and at 8:45 pm in summer. As a result, the potential for load shifting varies between seasons. In winter, the potential for peak shaving is around –205 MW, whereas in summer, it is approximately –166 MW. Although solar energy is abundant and cheap during the day in summer, motivating households to shift their load, there is a less shiftable load in the late evening hours. Therefore, the peak shaving potential is higher during winter due to the earlier peak.

The optimization algorithm reschedules the household appliances so as to minimize electricity bills. It endogenously recalculates the electricity prices and selects the start time where the running costs are the lowest. Consequently, price changes follow load changes (see Fig. 8). Nevertheless, the price impacts of the optimization are even more substantial. As the supply curve of the electricity generation is non-linear, lowering the peak demand by a few percentage points ends up in a 21–28% decrease in the electricity prices between 6 p.m. and 8:30 p.m.

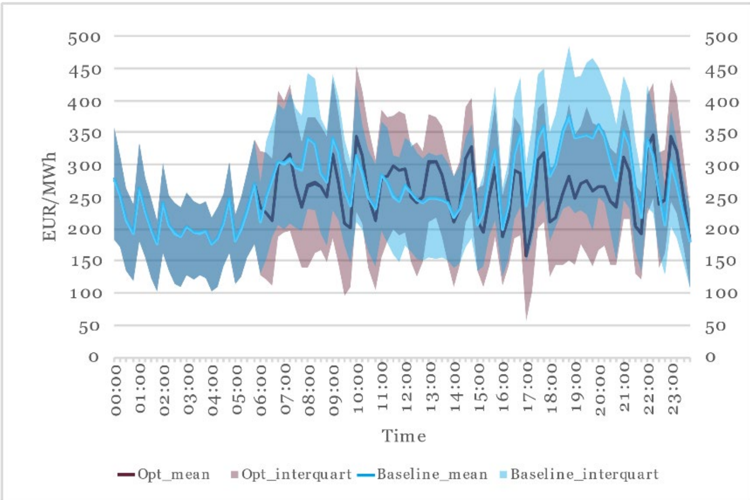


Fig. 8. Average electricity prices in the baseline and optimized scenario. The shaded areas represent the interquartile range of the variables

Rys. 8. Średnie ceny energii elektrycznej w scenariuszu bazowym i zoptymalizowanym. Zacienione obszary reprezentują zakres międzykwartylowy zmiennych

The overall electricity bills in the scenarios can be simply calculated from the fifteen-minute electricity prices and load. In the baseline scenario, the total electricity bill in 2022 in Hungary was EUR 11.8 bn. The reduction achieved by the optimization algorithm reaches 6.1% of the overall electricity costs which is approximately EUR 700 million, as shown in Figure 9. The substantial cost reduction is mostly achieved by the average electricity price decrease. Price changes do not only impact the households which are involved in the demand-side management program but also the other actors. Comparing the cost reduction to other quantitative analyses, the 6.1% reduction might seem low at first sight. Household demand-side management programs are estimated to achieve a 20–30% electricity bill reduction (Awais et al. 2015; Bharathi et al. 2017; Jiang and Xiao 2019; Rajamand 2020) but these studies do not consider any restriction on the time window of the optimization. Mota et al. (2022) considered both a time window and load order estimated a reduction of 14.7%. However, these studies assessed only the household bill reduction potential of demand-side programs while the model proposed in this paper estimated the system-wide bill reduction potential of the programs.

## 5.2. Impacts at different levels of participation rates

The potential of a nationwide demand-side management program is vast but optimizing the 100% of shiftable household appliances is ambitious. We therefore rerun the optimization algorithm for the first seven days of each month assuming 25, 50 and 75% participation rate in the demand-side management program. Through this sensitivity analysis, we assess how the marginal benefits of smart meter roll-out and the extension of the demand-side management programs vary depending on the participation rate. The modelling outcomes are summarized in Table 1.

Table 1. Modelling outcomes at different levels of household participation rates

Tabela 1. Modelowanie wyników przy różnych poziomach wskaźników aktywności gospodarstw domowych

| Scenario | Participation rate [%] | No. of appliances | Total savings [%] | Avg. price change [%] | Avg. peak shave [%] |
|---|---|---|---|---|---|
| Optimized 25% | 25 | 1,316,696 | –3.1 | –2.5 | –0.9 |
| Optimized 50% | 50 | 2,633,393 | –4.0 | –3.5 | –1.7 |
| Optimized 75% | 75 | 3,950,089 | –5.0 | –4.6 | –2.3 |
| Optimized 100% | 100 | 5,266,785 | –6.1 | –6.0 | –2.7 |

The results suggest that even a 25% participation rate can achieve half of the savings seen for the fully optimized scenario (Optimised 100%). This is due to the non-linearity of the electricity supply curve; even an average reduction of 0.9% during the peak hours can lead to a 9–15% drop in prices between 6 p.m. and 8:30 p.m. (see Fig. 10). Nevertheless, the difference in savings is still substantial even between the 75% and 100% participation scenarios. Consequently, the economic benefits of equipping the last 25% of households with smart meters and including them in the demand-side management program are still high. Furthermore, the price and peak shaving effects also increase with the participation rate. As well as reducing peak electricity prices, peak shaving has other welcome consequences. In the evening peak hours, demand is often met by gas turbines. Peak shaving therefore helps to decouple fossil fuels from electricity generation by reducing the reliance on gas turbines.

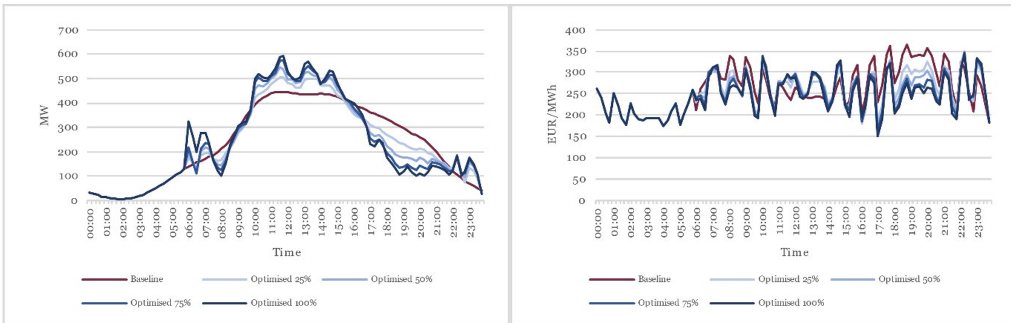


Fig. 10. Average shiftable load (left) and electricity prices (right) in the baseline and optimized scenarios with different participation rates

Rys. 10. Średnie obciążenie zmienne (po lewej) i ceny energii elektrycznej (po prawej) w scenariuszach bazowych i zoptymalizowanych z różnymi wskaźnikami udziału

## Conclusions

The energy transition presents several challenges to the electricity grid, particularly in managing the growing proportion of intermittent renewable energy sources. To address this issue, smartening the grid and enhancing flexibility becomes crucial, and demand-side solutions offer a promising approach by optimizing consumption patterns based on price signals from suppliers.

The modelling results, exemplified by the Hungarian electricity market, underline the significant potential of demand-side management programs that focus on the appliances for which use can be shifted without compromising thermal comfort. Rescheduling household washing machines, dishwashers and dryers not only reduces household electricity bills but also benefits all consumers by reducing peak electricity prices, which is often overlooked in analyses. The total energy cost saving potential of the ToU optimization is 6.1%, or EUR 700 million in Hungary, assuming that all 4.1 million households participate. Nevertheless, half of this reduction can be achieved with only a 25% participation rate. This significant reduction is achieved by optimizing only those appliances that do not affect the comfort of the occupants – washing machines, dishwashers and dryers.

It is crucial to recognise that without appropriate price incentives, households may be reluctant to adjust their electricity consumption to align with the availability of renewable energy. Traditional fixed electricity tariffs do not provide the necessary motivation for households to alter their consumption patterns, as they are charged the same rate regardless of whether it is a peak or off-peak period, despite the significant differences in system costs during these periods. Smart meters are essential in the transformation of the electricity market as they enable the introduction of such pricing schemes. Although smartening the grid requires a substantial investment in smart meters, which has a considerable upfront cost, the improved grid flexibility and the electricity cost savings are likely to outweigh the costs.

Although beyond the scope of this paper, it would be interesting for future work to assess how the increasing number of electric vehicles or household batteries might affect the benefits of demand-side programs. The use of electric vehicles may further increase the daily peak load if households are not discouraged from charging during the evening hours. However, vehicle-to-grid technologies and residential batteries can help to store solar power generated by rooftop PV and reduce residential load during peak hours.

## Limitations

There are various limitations of the modelling exercise. First, due to the absence of household -level data to directly monitor individual appliance usage, we relied on aggregated survey data to approximate household appliance usage patterns. However, this approach fails to capture the inherent heterogeneity in real-life appliance usage, thereby introducing potential inaccuracies in the representation of the model. Despite this, the baseline total shiftable load curve of the model displays a notable peak during midday, when electricity prices are low. In actuality, the load distribution may be more concentrated in the evening hours, indicating the possibility of even greater benefits through optimization, as a larger portion of loads could be shifted away from peak hours.

Second, the optimization process hinges on supply curves tailored to the baseline load conditions. However, in a realistic scenario where suppliers are aware of the potential for household appliance optimization, it is highly likely that day-ahead price curves would adapt accordingly. Additionally, the availability of supply curves was limited to the first Wednesdays and Saturdays of each month in 2022, leading to assumptions of uniformity for both weekdays and weekends within each month. Furthermore, the supply curves are specific to Hungary's current energy mix and therefore cannot be used to model future scenarios. Consequently, these limitations highlight the need for a more comprehensive and nuanced approach to refine the accuracy and practical applicability of the model.

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KULTURÁLIS ÉS INNOVÁCIÓS MINISZTÉRIUM

Új Nemzeti Kiválóság Program

NEMZETI KUTATÁSI, FEJLESZTÉSI ÉS INNOVÁCIÓS HIVATAL

The Authors have no no conflicts of interest to declare.

# References

Awais et al. 2015 – Awais, M., Javaid, N., Shaheen, N., Iqbal, Z., Rehman, G., Muhammad, K. and Ahmad, I. 2015. An efficient genetic algorithm based demand-side management scheme for smart grid. *2015 18th International Conference on Network-based Information Systems,* IEEE, pp. 351–356, DOI: 10.1109/NBiS.2015.54.

Babatunde et al. 2020 – Babatunde, O.M., Munda, J.L. and Hamam, Y. 2020. Power system flexibility: A review. *Energy Reports* 6, pp. 101–106, DOI: 10.1016/j.egyr.2019.11.048.

BBC 2023. Energy saving scheme: National Grid pays people to cut power again due to cold weather. [Online] https://www.bbc.com/news/business-64378224 [Accessed: 2023-09-10].

Bharathi et al. 2017 – Bharathi, C., Rekha, D. and Vijayakumar, V. 2017. Genetic algorithm based demand-side management for smart grid. *Wireless personal communications* 93, pp. 481–502, DOI: 10.1007/s11277-017-3959-z.

Bloomberg 2023. European Power Prices Go Below Zero Again as Solar Output Surges. [Online] https://www.bloomberg.com/news/articles/2023-07-04/power-prices-drop-below-zero-as-solar-output-surges-in-europe#xj4y7vzkg [Accessed: 2023-09-20].

Directive 2009/72/EC of the European Parliament and of the Council of 13 July 2009 concerning common rules for the internal market in electricity and repealing Directive 2003/54/EC (2009).

ESO 2023. Demand Flexibility Service (DFS). [Online] https://www.nationalgrideso.com/industry-information/balancing-services/demand-flexibility-service-dfs#Data-Portal [Accessed: 2023-09-20].

Freire-Barcelo et al. 2022 – Freire-Barcelo, T., Martin-Martinez, F., Sanchez-Miralles, A., Rivier, M., San Roman, T.G., Huclin, S., Chaves Ávila, J.P. and Ramos, A. 2022. Storage and demand response contribution to firm capacity: Analysis of the Spanish electricity system. *Energy Reports* 8, pp. 10546–10560, DOI: 10.1016/j.egyr.2022.08.014.

Hayn et al. 2014 – Hayn, M., Bertsch, V. and Fichtner, W. 2014. Electricity load profiles in Europe: The importance of household segmentation. *Energy Research & Social Science* 3, pp. 30–45, DOI: 10.1016/j.erss.2014.07.002.

Jiang, X. and Xiao, C. 2019. Household energy demand management strategy based on operating power by genetic algorithm. *IEEE Access* 7, pp. 96414–96423, DOI: 10.1109/ACCESS.2019.2928374.

Khatoon, S. and Singh, A.K. 2014. Effects of various factors on electric load forecasting: An overview. *2014 6th IEEE Power India International Conference* (*PIICON*), pp. 1–5), DOI: 10.1109/POWERI.2014.7117763.

Kirkerud et al. 2021 – Kirkerud, J.G., Nagel, N.O. and Bolkesjø, T.F. 2021. The role of demand response in the future renewable northern European energy system. *Energy* 235, DOI: 10.1016/j.energy.2021.121336.

Kökény, L. and Hortay, O. 2020. A survey of popular attitudes to deferment of electricity consumption in Hungary (A villamosenergia-fogyasztás elhalasztásával kapcsolatos lakossági attitűd felmérése magyarországon). *Közgazdasági Szemle* 67(7–8), pp. 657–687, DOI: 10.18414/KSZ.2020.7-8.657.

Laicane et al. 2015 – Laicane, I., Blumberga, D., Blumberga, A. and Rosa, M. 2015. Reducing household electricity consumption through demand-side management: the role of home appliance scheduling and peak load reduction. *Energy procedia* 72, pp. 222–229, DOI: 10.1016/j.egypro.2015.06.032.

Linssen et al. 2017 – Linssen, J., Stenzel, P. and Fleer, J. 2017. Techno-economic analysis of photovoltaic battery systems and the influence of different consumer load profiles. *Applied Energy* 185, pp. 2019–2025, DOI: 10.1016/j.apenergy.2015.11.088.

Lutzenhiser, L. 1993. Social and behavioral aspects of energy use. Annual review of Energy and the Environment 18(1), pp. 247–289, DOI: 10.1146/annurev.eg.18.110193.001335.

Lüth et al. 2018 – Lüth, A., Zepter, J.M., del Granado, P.C. and Egging, R. 2018. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. *Applied energy* 229, pp. 1233–1243, DOI: 10.1016/j.apenergy.2018.08.004.

Markets Insider 2023. European electricity prices tumble into negative territory amid glut of green energy. [Online] https://markets.businessinsider.com/news/commodities/european-electricity-prices-negative-green-energy-wind-solar-renewable-demand-2023-7 [Accessed: 2023-09-20].

MEKH 2024. Nem engedélyköteles kiserőművek és háztartási méretű kiserőművek adatai. [Online] https://mekh.hu/nem-engedelykoteles-kiseromuvek-es-haztartasi-meretu-kiseromuvek-adatai [Accessed: 2024-03-15] (*in Hungarian*).

Ministry of Energy 2023. 2023 első felében több, mint 1 gigawattal nőtt a hazai napelemes kapacitás. [Online] https://kormany.hu/hirek/2023-elso-feleben-tobb-mint-1-gigawattal-nott-a-hazai-napelemes-kapacitas [Accessed: 2023-09-25].

Misconel et al. 2021 – Misconel, S., Zöphel, C. and Möst, D. 2021. Assessing the value of demand response in a decarbonized energy system–A large-scale model application. *Applied Energy* 299, DOI: 10.1016/j.apenergy.2021.117326.

Mondal et al. 2017 – Mondal, A., Misra, S. and Obaidat, M.S. 2017. Distributed home energy management system with storage in smart grid using game theory. *IEEE Systems Journal* 11(3), pp. 1857–1866, DOI: 10.1109/JSYST.2015.2421941.

Mota et al. 2022 – Mota, B., Faria, P. and Vale, Z. 2022. Residential load shifting in demand response events for bill reduction using a genetic algorithm. *Energy* 260, DOI: 10.1016/j.energy.2022.124978.

Nguyen et al. 2012 – Nguyen, H.K., Song, J.B. and Han, Z. 2012. Demand-side management to reduce peak-to-average ratio using game theory in smart grid. [In:] *2012 Proceedings IEEE INFOCOM Workshops,* pp. 91–96, DOI: 10.1109/INFCOMW.2012.6193526.

Nicolson et al. 2018 – Nicolson, M.L., Fell, M.J. and Huebner, G.M. 2018. Consumer demand for time of use electricity tariffs: A systematized review of the empirical evidence. *Renewable and Sustainable Energy Reviews* 97, pp. 276–289, DOI: 10.1016/j.rser.2018.08.040.

O'Shaughnessy et al. 2018 – O'Shaughnessy, E., Cutler, D., Ardani, K. and Margolis, R. 2018. Solar plus: A review of the end-user economics of solar PV integration with storage and load control in residential buildings. *Applied energy* 228, pp. 2165–2175, DOI: 10.1016/j.apenergy.2018.07.048.

Palensky, P. and Dietrich, D. 2011. Demand-side management: Demand response, intelligent energy systems, and smart loads. *IEEE transactions on industrial informatics* 7(3), pp. 381–388, DOI: 10.1109/TII.2011.2158841.

Pratt, B.W. and Erickson, J.D. 2020. Defeat the Peak: Behavioral insights for electricity demand response program design. *Energy Research & Social Science* 61, DOI: 10.1016/j.erss.2019.101352.

Rajamand, S. 2020. Effect of demand response program of loads in cost optimisation of microgrid considering uncertain parameters in PV/WT, market price and load demand. *Energy* 194, DOI: 10.1016/j.energy.2020.116917.

REFLEX data repository 2019. Database of the REFLEX Project – Analysis of the European Energy System. [Online] https://data.esa2.duckdns.org/tree/REFLEX [Accessed: 2023-12-20].

Sanquist et al. 2012 – Sanquist, T.F., Orr, H., Shui, B. and Bittner, A.C. 2012. Lifestyle factors in US residential electricity consumption. *Energy Policy* 42, pp. 354–364, DOI: 10.1016/j.enpol.2011.11.092.

Schipper et al. 1989 – Schipper, L., Bartlett, S., Hawk, D. and Vine, E. 1989. Linking life-styles and energy use: a matter of time? Annual review of energy 14(1), pp. 273–320, DOI: 10.1146/annurev.eg.14.110189.001421.

Siano, P. (2014). Demand response and smart grids — A survey. *Renewable and sustainable energy reviews* 30, pp. 461–478, DOI: 10.1016/j.rser.2013.10.022.

Szőke et al. 2021 – Szőke, T., Hortay, O. and Farkas, R. 2021. Price regulation and supplier margins in the Hungarian electricity markets. *Energy Economics* 94, DOI: 10.1016/j.eneco.2021.105098.

Taik, S. and Kiss, B. 2019. Smart household electricity usage optimisation using MPC and MILP. [In:] *2019 22nd International Conference on Process Control* (PC19), pp. 31–36, IEEE, DOI: 10.1109/PC.2019.8815043.

Tounquet, F. and Alaton, C. 2019. Benchmarking smart metering deployment in the EU-28. Tractebel Impact.

van der Veen et al. 2018 – van der Veen, A., van der Laan, M., de Heer, H., Klaasen, E. and van der Reek, W. 2018. Flexibility Value Chain. USEF. [Online] https://www.usef.energy/app/uploads/2018/11/USEF-White-paper-Flexibility-Value-Chain-2018-version-1.0_Oct18.pdf [Accessed: 2023-12-19].

Vitiello et al. 2022 – Vitiello, S., Andreadou, N., Ardelean, M. and Fulli, G. 2022. Smart metering roll-out in europe: Where do we stand? cost benefit analyses in the clean energy package and research trends in the green deal. *Energies* 15(7), DOI: 10.3390/en15072340.

Yang et al. 2012 – Yang, P., Tang, G. and Nehorai, A. 2012. A game-theoretic approach for optimal time-of-use electricity pricing. *IEEE Transactions on Power Systems* 28(2), pp. 884–892, DOI: 10.1109/TPWRS.2012.2207134.

Áron Dénes Hartvig, László Szabó

# Ocena zarządzania popytem mieszkaniowym na Węgrzech

## Streszczenie

W artykule dokonano oceny potencjału oszczędności w rachunkach za energię elektryczną wynikających z ogólnokrajowych programów zarządzania popytem w sektorze mieszkaniowym. Analiza dostarcza szerokich informacji na temat tego, w jaki sposób optymalizacja czasu użytkowania może przynieść korzyści ekonomiczne, przyspieszając jednocześnie wdrażanie odnawialnych źródeł energii. Zbudowaliśmy model energetyczny ze szczegółowym zużyciem energii elektrycznej w gospodarstwach domowych. Korzystając z danych ankietowych, stworzyliśmy scenariusz bazowy, który przedstawia obecne nawyki użytkowania urządzeń w gospodarstwach domowych na Węgrzech, dostarczając przydatnych informacji na temat ich zmiennego zapotrzebowania na energię elektryczną. Następnie zastosowaliśmy optymalizację czasu użytkowania urządzeń gospodarstwa domowego, które nie wpływają na komfort cieplny, w celu zminimalizowania rachunków za energię elektryczną. Zakładając różny poziom uczestnictwa w programie zarządzania popytem, zmieniono harmonogram wykorzystania pralek, zmywarek i suszarek.

Optymalizacja obciążenia ma wpływ na szczytowe golenie obciążenia całkowitego, w zakresie od 2,2 do 3,6%. Zimą potencjał szczytowego golenia wynosi około –205 MW, podczas gdy latem wynosi około –166 MW. Chociaż energia słoneczna jest dostępna w dużych ilościach i tania w ciągu dnia latem, co motywuje gospodarstwa domowe do zmiany obciążenia, w późnych godzinach wieczornych obciążenie jest mniejsze. Dlatego potencjał redukcji szczytu jest wyższy zimą ze względu na wcześniejszy szczyt. Wyniki modelowania węgierskiego rynku energii elektrycznej pokazują, że inteligentniejsza sieć ma potencjał oszczędności rachunków wynoszący 6,1%, czyli 700 mln EUR na Węgrzech, zakładając, że wszystkie gospodarstwa domowe są wyposażone w inteligentne liczniki. Jednak połowę tej redukcji można osiągnąć przy zaledwie 25% wskaźniku uczestnictwa.

Słowa kluczowe: zarządzanie popytem, przenoszenie obciążeń, elastyczność, modelowanie w całym systemie

# Appendix

TABLE A.1 Data table

TABELA A.1. Tabela danych

| Data | Source | Table name, link |
|---|---|---|
| Housing data | KSH | 14.1.1.24. Housing data by income deciles, annual data for Hungary, 2020: https://www.ksh.hu/stadat_files/jov/hu/jov0024.html |
| Household equipment by decile | KSH | 14.1.1.25. Average annual stock of consumer durables by income decile [pieces per 100 households], annual data for Hungary, 2020: https://www.ksh.hu/stadat_files/jov/hu/jov0024.html |
| Usage habits | Kökény & Hortay (2020) | Table F4 Detailed appliance use by time of day: http://real.mtak.hu/112556/ |
| Electricity load | ENTSO-E | Total Load - Day Ahead / Actual, 15-minute data for Hungary, 2022: https://transparency.entsoe.eu/load-domain/r2/totalLoadR2/show |
| Electricity prices | HUPX | HUPX ID market data, 15-minute data for Hungary, 2022: https://hupx.hu/en/market-data/id/market-data |
| Electricity supply curves | HUPX for 2022 | DAM- Aggregated Data, hourly data for Hungary, 2022: https://hupx.hu/en/market-data/dam/aggregated-data (data tables for first Wednesday and Saturday of each months shared by HUPX are confidential) |
| Frequency of usage | Assumption | Frequency of appliance use is shown in Table A.2 |
| Appliance load curve | Assumption | Appliance load curves are shown in Table A.3 |
| Load operating time window | Assumption | The load operating window is between 6 a.m. and 12 p.m. |

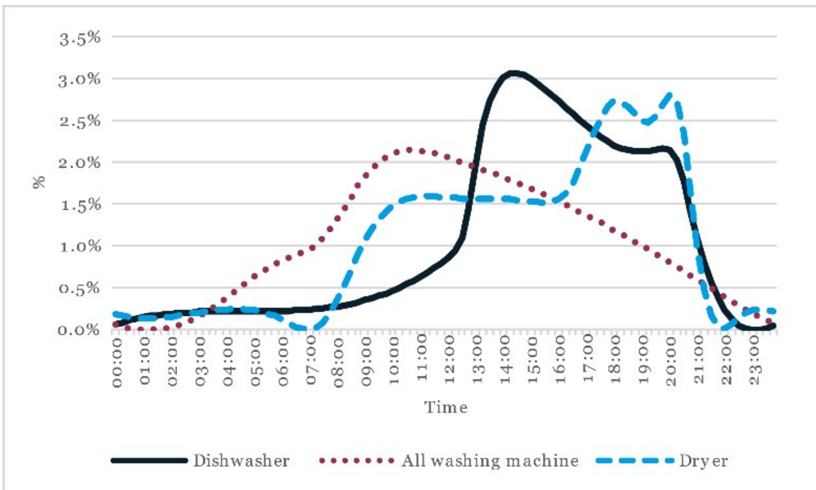


Fig. A.1. Distribution of appliance usage habits by appliance, own calculation based on Kökény and Hortay (2020)

Rys. A.1. Podział nawyków użytkowania urządzeń według urządzenia, obliczenia własne

Table A.2 Frequency of appliance usage per resident

Tabela A.2. Częstotliwość korzystania z urządzenia na mieszkańca

| Appliance | Weekly frequency per resident |
|---|---|
| Dishwasher | 1 |
| Washing machine | 1 |
| Auto., semi-auto. washing mach. | 1 |
| Washing mach. with dryer | 1 |
| Dryer | 1 |

Table A.3 Appliance load curves [kW]

Tabela A.3. Krzywe obciążenia urządzenia [kW]

| Appliance | 00:00 | 00:15 | 00:30 | 00:45 | 01:00 | 01:15 |
|---|---|---|---|---|---|---|
| Dishwasher | 0.53 | 0.27 | 0.03 | 0.27 | 0.57 | 0.13 |
| Washing machine | 1.03 | 0.10 | 0.10 | 1.20 | 1.13 | 1.00 |
| Auto., semi-auto. washing mach. | 1.03 | 0.10 | 0.10 | 1.20 | 1.13 | 1.00 |
| Washing mach. with dryer | 1.03 | 0.10 | 0.10 | 1.20 | 1.13 | 1.00 |
| Dryer | 1.43 | 1.40 | 0.93 | 0.57 | – | – |