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Load scheduling optimization for user-centric residential demand response leveraging time use surveys

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HIGHLIGHTS

- Empirical time use survey data are integrated into residential demand response scheduling optimization.
- A novel algorithm balances electricity costs and user convenience using dynamic weighting.
- Dynamic buffer zones and alternate schedules enhance practical user flexibility and adherence.
- The method is validated using Austrian data, confirming the method's effectiveness under real pricing and usage patterns.
- The approach is scalable and adaptable for diverse markets using standardized survey data.

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ABSTRACT

This paper presents a novel optimization algorithm that integrates user behavior into day-ahead load scheduling for residential demand response (DR) by utilizing data from the Harmonized European Time Use Survey (HETUS). The proposed algorithm schedules the operation of household appliances, such as laundry, dishwashing, cooking, and cleaning, based on dynamic pricing and user preferences, aiming to minimize electricity costs while mitigating the impact on user convenience. A sensitivity analysis is conducted to optimize the weighting factor between cost and behavior, ensuring a balanced trade-off. The algorithm introduces buffer zones and alternative scheduling to provide additional flexibility for users. The methodology is tested using data from Austria, showing significant cost savings of up to 50 % with minimal disruption to user behavior. The results provide the basis for a more personalized energy management solution, potentially increasing user participation and improving the effectiveness of residential DR programs.

1. Introduction

1.1. Context and motivation

As energy systems undergo a major transformation with the transition toward higher shares of renewable energy sources (RES), electricity grid management faces increasing challenges [1]. The intermittent and unpredictable nature of RES, such as solar and wind power, creates significant volatility in power generation, which in turn affects the stability of the electricity market [2]. This volatility is amplified by changing consumption patterns and increasing peak demand periods [3]. As a result, balancing supply and demand in real-time has become a critical issue for electricity grid operators, policymakers, and energy service providers [4]. The traditional top-down approach to electricity grid management, where generation is adjusted to meet demand, is no longer sufficient to ensure grid stability. Therefore, a shift to enable more active and responsive demand-side management is necessary [5]. Demand response (DR) has emerged as a key strategy to address these challenges by enabling end-users to adjust their electricity consumption patterns in response to price signals or other incentives [6]. However, current DR strategies, particularly in the residential sector, have yielded limited customer participation. A number of issues contribute to this, including limited user awareness, sub-optimal financial returns for participants, and a mismatch between user routines and optimal load scheduling [7]. Additionally, the complexity of dynamic pricing options and the challenges associated with transitioning from fixed-price payments to

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dynamic pricing further deter participation [8]. Many existing DR frameworks focus solely on cost minimization and ignore the importance of aligning energy consumption with user routines and preferences [9]. At the same time, technological advancements in the form of smart meters, home energy management systems (HEMS), and dynamic pricing mechanisms offer new opportunities to refine DR strategies. Smart meters provide real-time data on electricity consumption and enable consumers to respond to dynamic tariffs [10]. However, the extent to which residential consumers will change their behavior to align with these signals remains unclear. A key determinant of the effectiveness of DR programs is the degree of personalization provided to users [11]. By tailoring recommendations and scheduling to align with the specific behaviors and preferences of individual households, DR schemes can enhance user participation. This increased engagement could significantly boost the potential for load shifting and peak shaving, thereby maximizing the overall benefits of the program [12]. In this context, the integration of user behavior into day-ahead load scheduling represents a promising avenue for improving residential DR outcomes. By aligning DR efforts with the daily routines and preferences of users, it is possible to strike a better balance between cost savings and convenience, thereby increasing user engagement.

1.2. Research objective

This paper introduces a novel optimization algorithm that optimally schedules household loads. The algorithm leverages behavioral data from the Harmonized European Time Use Survey (HETUS) data. HETUS provides detailed insights into how individuals allocate their time across various activities, allowing the algorithm to incorporate user behavior directly into the scheduling process. In contrast to existing approaches, which prioritize cost minimization without regard to user convenience, this study takes a more user-centric approach by developing load schedules that minimize disruption to daily routines. The proposed algorithm not only schedules the operation of household appliances, such as laundry, dishwashing, and cleaning, to minimize electricity costs but also introduces buffer zones and alternative scheduling options to provide users with added flexibility. This flexibility is key to ensuring that users have control over when their appliances run, making it more likely that they will adhere to the proposed schedules.

Given the context presented above, we formulate the following research question: How can an optimization algorithm leveraging HETUS data effectively incorporate user behavior to schedule household loads while balancing cost savings and user convenience?

1.3. Overview of the paper

The paper is structured as follows: Section 2 contains a literature review, Section 3 presents our methodology, Section 4 illustrates the results of simulating the algorithm, Section 5 discusses the significance and implications of the results, and Section 6 presents our conclusions and outlook.

2. Literature review

This section presents a literature review of research relevant to the scope of this paper. This review is structured into three sub-sections, Section 2.1 discusses various approaches to DR in the residential sector, Section 2.2 focuses on studies investigating user behavior and consumer engagement in DR, and Section 2.3 describes algorithms in the literature that have been utilized for DR optimization while considering the user. Subsequently, Section 2.4 highlights the key contributions of this paper, delineating them clearly from the preceding literature review subsections.

2.1. Demand response in residential energy systems

Building on the need for more personalized DR solutions, this section reviews existing research in residential energy systems and highlights the key strategies for optimizing DR.

The impact of DR in the residential sector is a broad research topic that has been extensively studied, with a primary focus on ensuring grid stability and reducing peak demand. Traditional DR schemes typically rely on economic incentives such as dynamic pricing and time-of-use tariffs to motivate consumers to alter their consumption patterns, as comprehensively reviewed in [13]. Recent technological advances, particularly the increasing accessibility of smart meters and smart home devices, have enabled more sophisticated DR strategies. These technologies facilitate real-time monitoring and automated control, allowing for greater DR impact at the household level. A significant body of research is now focused on leveraging these advancements to enhance DR effectiveness in residential areas, with the twin goals of achieving substantial cost savings and improving the load profile on the grid. For instance, [14] addresses challenges faced by demand-side microgrids by optimizing home energy management through appliance scheduling and DR programs, achieving a net present cost reduction of 21.95 % with grid connection and 5.71 % without, using the HOMER tool. In another approach, an efficient incentive-based DR scheme was developed by Dewangan et al. [15], focusing on optimizing flexible load scheduling via HEMS, which reduces error accumulation and ensures fairness in a decentralized, real-time setup. A community-based HEMS is presented by Abbasi et al. [16], where particle swarm optimization improves peak demand shaving and flattens power demand in microgrids, leveraging electric vehicles (EVs) and battery storage to achieve a 7 % improvement in peak shaving. Furthermore, [17] utilizes a machine learning-based framework to assess and identify DR potential at the individual household level, mapping electricity consumption characteristics to DR capacity under dynamic tariffs and achieving high classification accuracy. In [18], a hybrid energy system integrates EV charging, DR, and net metering to achieve significant cost, emission, and resilience improvements in a multi-residential complex. Another innovative approach is presented by Alfaverh et al. [19], where a peer-to-peer energy sharing framework integrates a HEMS with a dynamic pricing mechanism, achieving significant energy cost savings and promoting fairness among households equipped with local generation and storage. A review by Pallonetto et al. [20] highlights progress in residential DR programs, emphasizing the building of energy flexibility, control algorithms, and market frameworks, while also identifying challenges such as technology adoption, standardization, and the impact of user behavior.

It is important for research on this topic to incorporate a geographical overview as differences exist from one country to another. [21] analyzes the economic potential and market impacts of large-scale DR in Northern Europe, highlighting significant peak shaving potential, particularly in Norway and Sweden, driven by electric space and water heating, with varied economic outcomes based on market conditions. [22] analyzes the impact of residential DR programs on different archetypical electricity grids in Canada, finding that grid composition significantly influences the effectiveness of DR, particularly in grids with high renewable energy sources. Hofmann and Lindberg [23] examine residential DR during Norway's 2021/22 energy crisis, revealing 11.4 % energy savings in winter and notable load shifting among households utilizing real-time price monitoring and smart EV charging, which supports the promotion of spot price contracts to enhance demand flexibility. Avordeh and Gyamfi [24] use K-means clustering to analyze household electricity consumption patterns in the Greater Accra Region, Ghana, identifying key factors influencing appliance use and optimizing DR strategies based on consumer behavior insights. Davarzani et al. [25] review recent literature and pilot implementations of residential DR in active distribution network management, highlighting DR activation strategies, challenges, and future directions, with a focus on innovation trials in Great Britain. [26] develops a HEMS for Morocco, applying dynamic pricing and appliance load scheduling to reduce energy bills by up to 66 %, depending on the scenario, by shifting loads to align with renewable energy generation.

2.2. User behavior and consumer engagement in residential DR

While technology plays a critical role, equally important is the consideration of consumer behavior, as outlined in this section. Consideration of consumer behavior and corresponding patterns is crucial to the success of DR strategies. A thorough review of factors impacting user engagement is presented in [7]. Many previous studies have emphasized the importance of addressing user behavior in DR programs. For example, [27] critically reviews residential consumer engagement with DR, identifying key limitations and proposing strategies to accelerate adoption in the UK, such as promoting smart technologies, supporting EV adoption, and enhancing digital comparison tools for better decision making. Gamification techniques are explored by Lampropoulos et al. [28], who propose a user-centered design for a game-enhanced tool aimed at increasing consumer participation and collaboration in energy management systems. Another study, [29], analyzes consumer behavior in aggregated demand scheduling, using both non-automatic and machine learning methods to identify factors influencing performance, highlighting the impact of demand volume and flexibility while addressing limitations in electricity consumption datasets. Meanwhile, [30] investigates the expectations of designers in an active demand management project, focusing on three themes: idealized electricity consumption, alignment with technological innovations, and economically rational consumers, emphasizing the need for designs tailored to real users. Schweiger et al. [31] present a comprehensive review of the development and implementation of user-centric business models in energy systems, discussing the necessary data, computational methods, psychological aspects of consumer participation, and identifying key challenges and future research needs. In a related context, [32] model the electricity demand flexibility potential of residential appliances across 564 households, identifying clothes dryers as having the greatest potential for demand reduction, with significant opportunities for optimizing grid efficiency through appliance load shifting in the mid-continent independent system operator in the North American region. Wang et al. [33] propose a semi-supervised learning approach for household profile identification using smart meter data, demonstrating improved accuracy over supervised methods when labeled data is limited, with the wrapper feature selection method yielding the best performance. Similarly, [34] survey 400 small electricity users in Poland, revealing low awareness but strong interest in demand-side response programs, with a preference for incentive schemes over dynamic tariffs, highlighting financial benefits as the primary motivation for participation. In a cooperative framework, [35] integrate consumers and prosumers in sustainable smart communities, focusing on demand reallocation based on renewable energy supply, and analyzing demand flexibility, aggregation, and microgeneration policies in Spain. The role of accurate predictions of user behavior is further explored by Tabatabaei and Klein [36], who find that while energy efficiency remains unchanged, financial benefits from a smart heating system using a pre-heating strategy are realized during colder months. Anuebunwa et al. [37] examine the impact of consumer discomfort in DR programs, identifying schedulable loads and applying tailored load scheduling via genetic algorithms, while also addressing system robustness and security against potential cyber-attacks.

2.3. Integration of user behavior in load scheduling of appliances

Now that DR in residential energy systems and the role of user behavior have been surveyed, the next step is to investigate their intersection in load scheduling. An overview of techniques and methodologies utilized to address this multi-faceted problem is provided in [38]. Researchers in [39] develop a HEMS that optimizes appliance scheduling using historical data, dynamic pricing, and solar energy, while prioritizing user comfort, achieving up to 63.48 % cost savings. In another approach, [40] proposes a home appliance scheduling framework that focuses on user comfort while optimizing AC usage and reducing electricity costs, utilizing the grey wolf and crow search optimization algorithms under real-time price signals. Similarly, [41] presents a load scheduling algorithm that balances cost efficiency with consumer preferences, aiming to minimize lifestyle disruptions while optimizing energy consumption and reducing costs in DR programs. Further exploring this area, [42] details a power scheduling algorithm for smart homes that balances cost efficiency and user discomfort by using a fractional programming approach to optimize both consumption efficiency and satisfaction while minimizing costs. Additionally, [43] introduces a DR scheduling method for residential buildings, employing a multi-objective optimization algorithm to minimize electricity costs and inconvenience, while effectively shifting peak loads and maintaining occupant comfort. A related study by Mota et al. [44] presents a residential load scheduling algorithm that uses a genetic algorithm (GA) to optimize energy costs and load shifting for DR events, incorporating user-defined comfort constraints such as appliance operating windows and load order. Javadi et al. [45] present a home energy management model that minimizes electricity bills and user discomfort, using a novel discomfort index to account for user preferences in appliance scheduling. Authors in [46] propose an activity-based energy demand model that links occupants' activity schedules to appliance usage events, enabling the identification of population segments with high DR potential and supporting the design of targeted flexibility interventions. A study in [47] proposes a residential load scheduling approach integrating electrical and thermal loads, electric vehicle charging, and renewable generation under uncertainty, modeling user behavior through preferred appliance and thermal load operation time windows, and optimizing schedules using a binary particle swarm optimization algorithm to balance cost and user comfort. Pamulapati et al. [48] develop a multi-objective evolutionary scheduling framework that implicitly models user satisfaction from past appliance usage via energy disaggregation and incorporates interactive priority weighting to generate customized trade-off schedules across multiple time resolutions.

Table 1 summarizes the key elements of these studies and highlights the specific contributions and novelty of the present work.

2.4. Key contributions and novelties

As summarized in Table 1, prior studies have incorporated user behavior into residential demand response scheduling through a range of approaches, from static comfort constraints and heuristic indices to implicit user satisfaction derived via data-driven methods. However, these approaches lack integration of large-scale empirical behavioral data and often rely on fixed or manually assigned parameters without adaptive balancing of cost and convenience. Building on the identified limitations in the literature, this paper introduces the following three novel contributions:

- Unlike previous works that rely on abstract comfort models or manual preference settings, this study leverages comprehensive empirical behavior data from HETUS time diaries to inform load scheduling. This approach enables adaptive modeling of diverse user routines at scale, thus better aligning DR schedules with real-life behavior patterns. This is realized through an optimization algorithm that integrates these data directly into the scheduling process.
- The optimization algorithm employs data-driven parameter tuning to determine the optimal weighting factor between cost and user convenience for each load through sensitivity analysis determines the weighing factor between cost and user convenience for each load via sensitivity analysis. This approach replaces reliance on fixed or manually selected parameters.
- Beyond producing a single cost-optimal schedule, the algorithm introduces buffer zones and alternate schedules to provide users with flexible options, addressing practical adherence challenges often neglected in rigid scheduling frameworks.

Table 1
Summary of recent studies on residential demand response scheduling incorporating user behavior, outlining their key distinctions.

Ref	Approach	Behavioral input	Optimization	Output	Key distinction
Waseem et al. (2020)	AC scheduling under RTP	Fixed comfort preferences; non-adaptive.	Grey Wolf + Crow Search	Minimized electricity costs	Static constraints for comfort; no user diversity.
Jiang et al. (2020)	Load scheduling with user preference balancing	Manual preference input; limited generalization.	Cost-efficiency model	Reduced costs, minimized disruptions	Static user preferences; limited flexibility.
Jiang et al. (2025)	Smart home scheduling	Discomfort modeled via cost penalties; parameter-heavy.	Fractional programming	Improved satisfaction and profiles	Parameter-based dissatisfaction modeling; lacks empirical data.
Chen et al. (2022)	Multi-objective DR optimization	User-defined inconvenience metrics; not empirically derived.	Multi-objective algorithm	Cost reduction and comfort preservation	Uses abstract comfort models; lacks real-world behavior base.
Mota et al. (2022)	GA-based appliance scheduling	Predefined appliance time windows and order	Genetic Algorithm	DR event participation schedules	Static input constraints; no behavioral modeling.
Javadi et al. (2021)	HEMS with discomfort index	Synthetic index without real validation.	Heuristic	Minimized bills and discomfort	Index-based comfort modeling; not grounded in data.
Barsanti et al. (2024)	Activity-based energy demand modeling	Activity schedules; analytical only, no scheduling optimization.	Pattern-based classification	Segment-specific DR potential	Insightful segmentation; lacks operational scheduling.
Kanakadhurga et al. (2024)	Appliance scheduling integrating thermal and electrical loads, EV and renewables	User preferences modeled as preferred operation time windows for appliances and thermal loads	Binary Particle Swarm Optimization	Optimal appliance schedules maintaining comfort with uncertainty and EV battery degradation modeling	Explicit comfort constraints and comprehensive uncertainty analysis
Pamulapati et al. (2020)	Multi-objective home appliance scheduling	Implicit user satisfaction derived from past usage via energy disaggregation; interactive priority weights	Multi-objective evolutionary algorithm	Set of representative trade-off schedules balancing cost and user dissatisfaction	User behavior implicitly modeled from past appliance usage via energy disaggregation.
Present study	Load scheduling using HETUS and dynamic prices	Empirical behavior from HETUS time diaries; enables adaptive modeling and alternative scheduling.	Linear optimization with λ sensitivity	Optimal, buffered, and alternate schedules	Behavior-driven DR with data-based appliance use patterns. Approach that algorithmically balances cost and convenience.

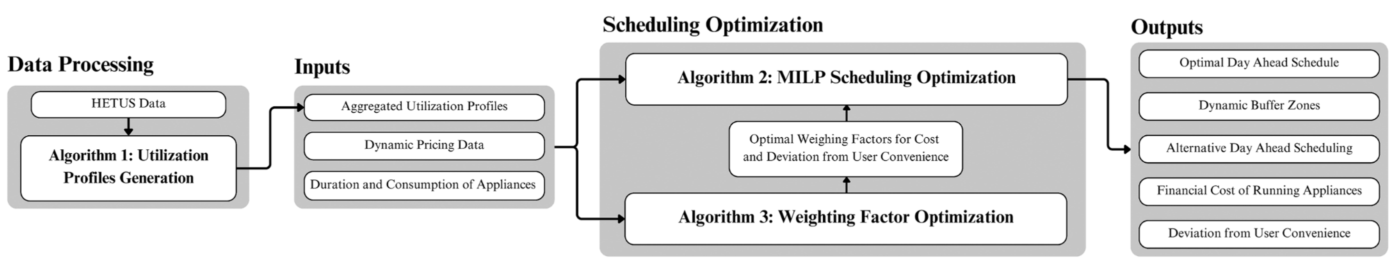

Fig. 1. Methodology of the paper.

3. Methodology

The overall framework of the proposed methodology for behavior-driven load scheduling in residential demand response is presented in Fig. 1.

The process begins with the generation of utilization profiles from HETUS data, followed by the integration of dynamic pricing data and appliance-specific characteristics as inputs. The scheduling optimization process comprises two algorithms: a weighting factor optimization algorithm to balance cost and user convenience, and a mixed integer linear programming (MILP) algorithm for day-ahead scheduling. The outputs include an optimal day-ahead schedule, buffer zones, alternative scheduling options, and quantification of financial costs and deviations from user preferences.

3.1. Harmonized european time use survey (HETUS)

3.1.1. Overview

HETUS is a standardized survey that aims to collect data on how people in European countries allocate their time across a wide range of activities [49]. It is a valuable asset for understanding the daily lives of people and analyzing their behavior. In the context of DR, HETUS data provides a gateway to understanding the end user's energy consumption activities and identifying any relevant underlying patterns for DR strategies.

In general, time use surveys are based on time diaries collected from individuals. Each person participating in the survey fills out their activities throughout the day, typically from 4:00 AM to 4:00 AM the next day, in increments of 10 min. Inputting the activity is accomplished through a distinct 3-digit code describing the main activity during that timeslot, and another 3-digit code describing a secondary activity that may have been performed in parallel. The respondent then fills in a 2-digit code describing the location in which these activities were conducted. Finally, the respondent includes information about whether they were alone, or with someone they know (i.e., with partner, parent, or other household member). Table 2 provides selected examples of the most commonly selected activity codes in the HETUS dataset, while Table 3 illustrates a set of location codes. Further details on the activity codes can be found in [50].

In addition to the time diaries, further description of the responses is provided. Standard metadata such as country, day, month, and year are included. Household information such as the size, type, appliances, age of members, and net monthly income is provided to give a deeper understanding. Further occupational, demographic, and economic data are included.

Table 2
Activity codes and corresponding descriptions.

Code	Activity
011	Sleep
821	Watching TV, Video or DVD
111	Working time in main and second job
021	Eating
999	Unspecified activity

Table 3
Location codes and corresponding descriptions.

Code	Location
11	Home
12	Weekend home
13	Workplace or school
15	Restaurant, cafe, or pub
10	Unspecified location

HETUS data include datasets from 17 countries in Europe, namely: Austria, Belgium, Germany, Estonia, Greece, Spain, Finland, France, Hungary, Italy, Luxembourg, The Netherlands, Norway, Poland, Romania, Serbia, and the United Kingdom. In order to test the methodology presented in this paper, the focus will be on the Austrian case. The reasoning for this selection is as follows.

Austria is characterized by a progressive energy policy that strongly supports measures involving energy flexibility through various initiatives [51]. However, the penetration of smart meters in the country, which are crucial elements in enabling flexibility, only reached upwards of 47 % in 2022 according to [52]. This places Austria in a critical position in comparison to other countries with a similar penetration of intermittent energy resources in their energy mix, such as Denmark and Sweden, which have already reached the 100 % mark. The country has set 2024 as the deadline for reaching a 80 % rollout of smart meters. This ambitious target presents an interesting opportunity to analyze the impact of DR in a country that is in the midst of a significant transition to smart metering. Another important factor in this selection is the data Austrians have access to as well as the different tariff contract opportunities available for consumers. According to [52], Austria is the only country in Europe to provide all of the following elements to its consumers:

- Cumulative data for 3 years or up to the beginning of contract
- Near real-time data offered through the internet for time of use
- Information about environmental impact
- Energy price differentiation according to intra-day, weekdays, and weekends
- Hourly or real-time energy pricing
- Consumption remote control

By utilizing HETUS data, the aim is to take advantage of this opportunity to analyze the potential impact of the presented methodology in the Austrian context.

3.1.2. Data extraction

With a comprehensive understanding of HETUS, the next step is to extract and utilize data relevant to energy consumption activities for this study. The data extraction process begins by identifying the energy consuming activities that are to be targeted. Four activities have been identified; laundry, dish-washing, cooking, and cleaning. This selection was based on perceived flexibility of the associated appliances and their expected potential effectiveness pertaining to load scheduling. Other activities, such as ironing, watching TV, and heating water, were initially considered but eventually excluded due to a relative lack of flexibility compared to the selected loads. The exact activity codes for each selected load were used to identify when each load was happening (Laundry: 331, Dish-washing: 312, Cooking: 311, and Cleaning: 321 as described in [50]).

3.1.3. Profile development

A detailed set of information is provided for each respondent's diary entry. Only three of these are essential to our study:

- Main Activity: This 3-digit code indicates the primary activity that a respondent was performing or occupied with during that.
- Second Activity: This 3-digit code indicates another activity that the respondent was performing in parallel with the main activity at that time.
- Location: This 2-digit code indicates the location of the user at the time when the activity was happening.

To create a utilization profile (UP) corresponding to each respondent, the algorithm iterates over all timeslots, and records when the targeted activity has been performed. The algorithm then verifies that the location code corresponds to that of their home and excludes all activities performed elsewhere (i.e., at work or at another home). As the main interest is the household rather than the individual user, the profiles are aggregated to create a distinct profile for each household where the activities of all members are grouped. Finally, the resulting household profiles for each appliance are multiplied by the household weight in order to reflect the statistical representation of the population. When examining the temporal variations in energy consumption behavior, the main factor is related to the activity differences between weekdays and weekends, which are primarily driven by the working schedules of the population. Other socio-economic or seasonal factors have a secondary impact. This is confirmed by a study in [53], which argues that activity-based differences between weekdays and weekends represent the primary driver of residential electricity load curve variations, with all other seasonal or demographic factors remaining constant. Thus, the final step in the approach involves categorizing the profiles as weekday and weekend profiles as illustrated in Algorithm 1.

The generated UPs for Austria are illustrated in Fig. 2.

On weekdays, laundry usage has spread-out peaks during the day from 9:00 to 17:00, while cooking and dishwashing are more concentrated around meal times (morning and evening). Cleaning peaks primarily during morning hours. On weekends, laundry and cleaning start earlier, with concentrated usage in the morning and midday, indicating increased flexibility for these tasks compared to weekdays. Cooking and dishwashing follow similar patterns but show a greater spread across the day. These profiles represent user convenience and flexibility pertaining to each load and are fed into the algorithm. Once the utilization profiles are established, they serve as key inputs to the optimization algorithm, which is described next.

Algorithm 1 Generating utilization profiles.

Require: P_h, the diary of a person P part of household h
Require: $M_{act,t}$, the main activity at timeslot t
Require: $S_{act,t}$, the secondary activity at timeslot t
Require: L_t, the location at timeslot t
Require: Target Activities
for each P_h **do**
  for $t = 1$ to 144 **do**
    if $M_{act,t}$ or $S_{act,t}$ is a target activity **and** L_t is home **then**
      Update utilization profile for the activity at the timeslot.
    end if
  end for
end for
Aggregate profiles across household members.
Aggregate profiles by day type.
Output utilization profiles for each activity.

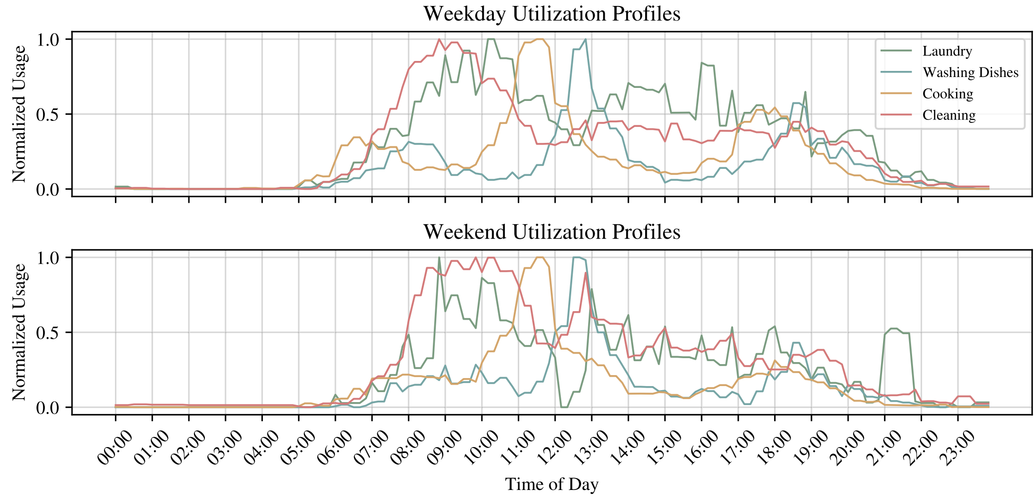

Fig. 2. Generated utilization profiles for austrian households on weekdays and weekends.

3.2. *Optimization algorithm design*

The optimization component is developed to effectively provide a day-ahead load scheduling of selected household activities. The scheduling is expected to minimize costs while considering user behavior. This section describes the optimization problem as well as its mathematical formulation. For clarity and brevity in the results section, the abbreviations listed at the bottom of Table 4 will be used.

3.2.1. *Optimal scheduling*

For each appliance, the algorithm determines the most cost-effective time frame for performing a given activity while providing a certain level of flexibility for the user. It takes as input the generated UP for each appliance, the hourly day-ahead pricing, and the expected activity duration. The algorithm then outputs three forms of scheduling. The main one is the optimal schedule, then a buffer zone is calculated to enable flexibility around the optimal scheduling, and finally, an alternate scheduling is presented to the user as a second-best option. It is important to note that both the dynamic pricing and the UP are normalized to a common scale ranging from 0 to 1 in order to ensure balance in the objective function. Normalization is a necessary data preprocessing step that enables the algorithm to treat both parameters with equal importance. This ensures that any influence on the scheduling decisions is related solely to the weighting factor in the objective function. The specific method used to this end is min-max normalization, where for any given data point X, the normalized value is calculated by subtracting the minimum value in the dataset from X, and then dividing the result by the range of the data as described in Eq. (1).

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

For example, consider day-ahead electricity prices ranging from 0.10 €/kWh to 0.40 €/kWh. A mid-day price of 0.25 €/kWh would normalize to (0.25–0.10)/(0.40–0.10) = 0.5, representing the midpoint of the price range. Similarly, the highest peak price of 0.40 €/kWh normalizes to 1, while the lowest off-peak price of 0.10 €/kWh normalizes to 0.

The objective of the optimization is to minimize the total cost Z, which balances the electricity price with the deviation from the user's default UP:

$$\text{Minimize} \quad Z = \sum_{i\in\mathcal{A}} \sum_{t=1}^{T} x_{i,t}\left(C_t + \lambda(1 - U_{i,t})\right) \tag{2}$$

Subject to:

Single start time constraint

Each activity i must start exactly once within the available s:

$$\sum_{t=1}^{T-d_i} s_{i,t} = 1, \quad \forall i \in \mathcal{A} \tag{3}$$

Activity duration constraint

For each activity i, if it starts at t, it must continue for its entire duration d_i:

$$x_{i,t} = \sum_{t'=\max(1,t-d_i+1)}^{\min(t,T-d_i)} s_{i,t'}, \quad \forall t = 1,\ldots,T, \quad \forall i \in \mathcal{A} \tag{4}$$

Table 4
Glossary of terms used in the describing the scheduling optimization.

Term	Description
$\mathcal{A}$	Set of activities (laundry, dishwashing, cooking, cleaning)
T	Total number of time slots (15-min) in a day
d_i	Duration of activity i (number of time slots)
$s_{i,t}$	Binary variable: 1 if activity i starts at time t, 0 otherwise
$x_{i,t}$	Binary variable: 1 if activity i is active at time t, 0 otherwise
C_t	Normalized day-ahead electricity price at time t (€/kWh)
$U_{i,t}$	Utilization profile value for activity i at time t
λ	Dimensionless weighting factor balancing cost and user preference
Z	Total cost objective to minimize
λ_{opt}	Optimal weighting factor determined via sensitivity analysis
Λ	Set of tested λ values in sensitivity analysis
$D(\lambda)$	Deviation from user preferences for weighting factor λ
$Z(\lambda)$	Total cost associated with weighting factor λ
t_{opt}	Optimal start time for activity a
t_{end}	End time of activity a, i.e., $t_{\text{opt}} + D_a - 1$
$\text{Buffer}^{\text{before}}_{a,t_{\text{opt}}}$	Set of time slots before t_{opt} within cost threshold
$\text{Buffer}^{\text{after}}_{a,t_{\text{end}}}$	Set of time slots after t_{end} within cost threshold
$\text{Buffer}_{a,t_{\text{opt}}}$	Combined buffer zone (before and after) for activity a
$\mathcal{B}_a$	Set of excluded time slots in buffer zone for alternate scheduling
LS	Laundry scheduling
DWS	Dish-washing scheduling
CS	Cooking scheduling
CLS	Cleaning scheduling
OS	Optimal schedule
ESB	Earliest start in buffer zone
LSB	Latest start in buffer zone
AS	Alternate schedule
WD	Weekday
WE	Weekend

where:

- $\mathcal{A}$ is the set of activities (laundry, dishwashing, cooking, cleaning).
- $s_{i,t}$ is a binary decision variable that is 1 if activity i starts at time t, otherwise 0.
- $x_{i,t}$ is a binary decision variable that is 1 if activity i is ongoing at time t, otherwise 0.
- C_t is the cost related to the normalized day-ahead price at time t.
- $U_{i,t}$ is the utility for activity i at time t.
- d_i is the duration of activity i in s.
- λ is a weighting factor that balances the cost against user convenience.
- T is the total number of s.

3.2.2. Buffer zone

In order to provide supplementary flexibility to the user, a buffer zone is implemented for the proposed scheduling. This time range is calculated based on the optimized scheduling. Once the algorithm identifies the optimal, it analyzes timeslots before and after the optimized operation with the goal of assessing whether performing the activity earlier or later than recommended is feasible without a considerable increase in cost. Specifically, the algorithm sets a threshold of a 5 % price increase, considering timeslots at a maximum of 50 % of the activity's duration. If the price change remains within this threshold, the buffer zone is extended to include those. The selected buffer zone parameters are practically reasonable as they provide meaningful scheduling flexibility without substantially compromising the primary cost-minimization goal. They represent a realistic allowance for users' minor schedule adjustments, enhancing user acceptance while maintaining cost effectiveness. These parameters are intended to be adapted by the user to tailor the algorithm to their needs. This approach allows users supplementary flexibility in scheduling while still adhering to cost-effective energy usage.

Let t_{opt} be the optimal start time for an activity a. The buffer zone before the optimal start time is defined as:

$$\text{Buffer}_{a,t_{\text{opt}}}^{\text{before}} = \left\{ t \mid t = t_{\text{opt}} - i,\ 1 \le i \le \frac{D_a}{2},\ \frac{\text{Price}_t}{\text{Price}_{t_{\text{opt}}}} \le 1.05 \right\} \tag{5}$$

Let t_{end} be the optimal end time for an activity a such that $t_{\text{end}} = t_{\text{opt}} + D_a - 1$. The buffer zone after the optimal end time is defined as:

$$\text{Buffer}_{a,t_{\text{opt}}}^{\text{after}} = \left\{ t \mid t = t_{\text{end}} + i,\ 1 \le i \le \frac{D_a}{2},\ \frac{\text{Price}_t}{\text{Price}_{t_{\text{end}}}} \le 1.05 \right\} \tag{6}$$

The complete buffer zone for an activity a is the union of the buffer zones before and after the optimal time:

$$\text{Buffer}_{a,t_{\text{opt}}} = \text{Buffer}_{a,t_{\text{opt}}}^{\text{before}} \cup \text{Buffer}_{a,t_{\text{opt}}}^{\text{after}} \tag{7}$$

3.2.3. Alternate scheduling

The next step in the algorithm's operation is to provide a completely alternative scheduling. This would serve as a second option for the user in case the first recommendation is not suitable. This particularly aims to address occurrences where the user faces unforeseen circumstances or other practical constraints. The alternate scheduling is generated by adapting the optimization problem to exclude the optimal schedule and its corresponding buffer zone. This exclusion establishes a gap that ensures no overlap with the initial recommendation, making for a more meaningful alternative. In addition to the primary optimization constraints, the alternative scheduling process introduces a new constraint to avoid overlap with the buffer zones of the optimal schedule. This constraint ensures that the second-best scheduling does not occur within these excluded zones, preserving flexibility while avoiding conflicts with the optimal recommendation.

Algorithm 2 MILP scheduling optimization.

```
Require: Day-Ahead Electricity Prices of 365 Days D_n.
Require: Utilization Profiles U_p for activities.
Require: Consumption C_a, Duration D_a, and λ_opt for each activity.
Require: Define activities, s, and user behavior data.
Require: Define buffer zones and alternate scheduling parameters.
Normalize day-ahead price and utilization profile.
for each activity do
    Minimize: Z = Σ_{t=1}^{T} x_{a,t} (C_t + λ(1 − U_{a,t}))
    Subject to: Single start time and activity duration constraints.
    Calculate total cost and deviation from user behavior.
end for
Output optimal schedules for each activity.
```

The added constraint for alternative scheduling is formulated as:

$$s_{a,t} = 0, \quad \forall t \in \mathcal{B}_a,\ \forall a \in \mathcal{A} \tag{8}$$

where $\mathcal{B}_a$ is the set of elements that fall within the buffer zones of the optimal scheduling for activity a. The MILP optimization approach is illustrated in Algorithm 2.

3.2.4. Weighting factor optimization

In this study, λ is set initially to 1, providing a balanced emphasis between the cost and behavior components of the objective function. However, determining the optimal value of λ is crucial to achieving the best trade-off between cost minimization and adherence to user preferences. In order to identify the optimal weighting factor, a sensitivity analysis is necessary. This involves running the optimization for various values of λ across a predefined range, evaluating the trade-off at each point. The goal is to find the λ value where the cost and deviation from the user's preferred usage profile are most balanced. Analytically, this optimal λ corresponds to the point where the slope of the cost function intersects with that of the deviation from the UPs.

Objective function

The original optimization problem can be formulated as:

$$\text{Minimize} \quad Z(\lambda) = \sum_{i \in \mathcal{A}} \sum_{t=1}^{T} x_{i,t} \left(C_t + \lambda(1 - U_{i,t}) \right) \tag{9}$$

where:

- $Z(\lambda)$ is the total cost for a given λ.
- λ is the weighting factor that balances cost (C_t) and deviation from user behavior ($U_{i,t}$).

Parameter variation

λ is varied over a range of values $\lambda \in [0, 2]$ in steps of $\Delta\lambda = 0.25$. The chosen increments for λ reflect deliberate intervals that clearly illustrate the shift from pure cost-driven optimization ($\lambda = 0$), to balanced cost-convenience optimization ($\lambda = 1$), and finally to scenarios strongly prioritizing user convenience ($\lambda = 2$). This granularity sufficiently captures the trade-off dynamics without excessive computational overhead.

Specifically, let $\Lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_n\}$ be the set of λ values tested, where $\lambda_i = 0 + (i-1) \times 0.25$, for $i = 1, \ldots, n$, covering the full range. For each value of λ, the optimization problem is solved, yielding different schedules and associated costs $Z(\lambda)$. To put this into perspective from a user experience point of view, $\lambda = 0$ prioritizes maximum cost savings with significant schedule adjustments, $\lambda = 1$ balances moderate savings with reasonable routine changes, and $\lambda = 2$ minimizes disruption while accepting higher costs. For example, $\lambda = 0.25$ may shift activities 2–3 hours from preferred times for maximum savings, while $\lambda = 1.5$ keeps adjustments within 1-hour windows.

Algorithm 3 Weighting factor optimization.

```
Require: Day-Ahead Electricity Prices of 365 Days D_n.
Require: Utilization Profiles.
Require: Consumption and Duration of Activities.
for D = 1 to 365 do
    for each activity do
        Identify Day Type.
        for λ = 0 to 2 step 0.25 do
            Generate optimal schedule.
            Calculate total cost and deviation.
            Identify λ_opt.
        end for
        Calculate average λ_opt.
    end for
end for
Output final λ_opt for each activity for each day type.
```

Output metrics

For each $\lambda \in \Lambda$:

- Optimal cost $Z(\lambda)$ is computed.
- Deviation $D(\lambda)$ from the user's preferred schedule is computed and can be represented as:

$$D(\lambda) = \sum_{i \in \mathcal{A}} \sum_{t=1}^{T-d_i} s_{i,t} \sum_{k=0}^{d_i-1} \left(1 - U_{i,t+k}\right) \tag{10}$$

Intersection point

The optimal λ for each activity can be identified as the value where the trade-off between cost and deviation is most balanced. This can be interpreted graphically as the intersection point between the cost curve and the deviation curve.

Mathematical representation

The sensitivity analysis can thus be framed as finding:

$$\lambda_{\text{optimal}} = \arg\min_{\lambda \in \Lambda} (Z(\lambda) + D(\lambda)) \tag{11}$$

or finding the point where $Z(\lambda)$ and $D(\lambda)$ intersect, which could be described as solving for λ where:

$$Z(\lambda) = D(\lambda) \tag{12}$$

Algorithm 3 illustrates the process of reaching the optimal λ.

4. Results

4.1. Assumptions and baseline scenario

In order to assess the algorithm's performance, certain assumptions are necessary. The parameters in Table 5 are set for the estimated duration and consumption of each activity. These duration and consumption values reflect typical operation patterns for household appliances, commonly referenced in residential energy management studies and appliance usage guidelines. All MILP day-ahead scheduling optimizations were solved using the CBC solver via PuLP, with runtimes under 1 s per appliance scheduling problem on an AMD Ryzen Threadripper PRO 5975WX.

Table 5
Assumptions on duration and consumption of each activity.

Activity	Duration (hour)	Consumption (kWh)
Laundry	2	1.5
Dish-washing	1.5	2.25
Cooking	1	2.5
Cleaning	0.5	1

To effectively compare the results, a baseline scenario that is reflective of a normal real-life operation of the selected loads needs to be established. To this end, the utilization profiles are leveraged to create such a scenario. The loads in the baseline are set to occur during the most popular timeslot for each activity. More specifically, these are the timeslots that maximize the area under the curve of the utilization profiles. The baseline also includes representative profiles of dynamic pricing extracted from the transparency platform of the European Network of Transmission System Operators for Electricity (ENTSOE) [54]. The weekday pricing profile corresponds to Friday July 21st 2023, and the weekend pricing profile corresponds to Saturday July 22nd 2023. Figs. 3 and 4 illustrate this scenario.

As illustrated in the figures, the baseline operation for the selected activities is differentiated using distinct colors; green corresponds to laundry, blue to washing dishes, yellow to cooking, and red to cleaning. Each subplot shows the normalized day-ahead price as a dotted black line and the corresponding UP in the respective color of the load. As can be observed in the graphs, the baseline scheduling corresponds to the peaks of the UPs of each activity.

Two metrics are selected to assess the performance of the algorithm in the simulation:

- Cost: The total financial cost of performing a certain activity at the optimal time range, quantified in EUR
- Deviation: The deviation of the optimal schedule from the UP of the activity, quantified as the difference between 1 and the normalized UP

4.2. Analysis of optimal load scheduling with $\lambda = 1$

This section illustrates and analyzes results for one weekday and one weekend day. The weighting factor λ will then be optimized as described in the methodology. Finally, the load scheduling will be simulated once more with the optimal weighting factors pertaining to the different activities and day types. The initial run of the simulation will be referred to as "$\lambda = 1$", while the second one will be referred to as "optimal λ".

Figs. 5 and 6 illustrate the resulting load scheduling from running the algorithm for one weekday and one weekend respectively.

The optimal scheduling is shown in a dark shade, while the buffer zones, if available, are shown in a light shade. The alternate schedule is shown in a hatched pattern of the corresponding color. For this case, the optimization algorithm aligns appliance usage with both user behavior and electricity prices for a weekday. The laundry schedule peaks in the afternoon, capturing a lower price period while providing a buffer zone for flexibility starting only after the optimal operation. Dishwashing follows a similar pattern with optimal scheduling at around noon, aligned with a low-cost time. Cooking is scheduled during late morning, while an alternate evening option is provided for lower-cost flexibility. Cleaning is optimally scheduled in the afternoon, leaning more toward cost minimization than user convenience, with an alternate time scheduled a couple of hours later.

For the weekend, the optimization shifts the laundry schedule later in the day from morning to around noon, aligning with lower prices and higher user activity during this period, while the alternate schedule in this case perfectly matches the baseline. This means that the alternate option here proposes a full compliance with user behavior, despite the higher price period. Dishwashing is optimally scheduled from 12:00 to 13:30, taking advantage of a low-price window, with an earlier alternate schedule provided in the morning as well as buffer zones both before and after. Cooking follows a similar pattern to weekdays, with the optimal time scheduled for late morning, and an alternate afternoon timeslot as a second option. Cleaning is optimally scheduled around noon, again

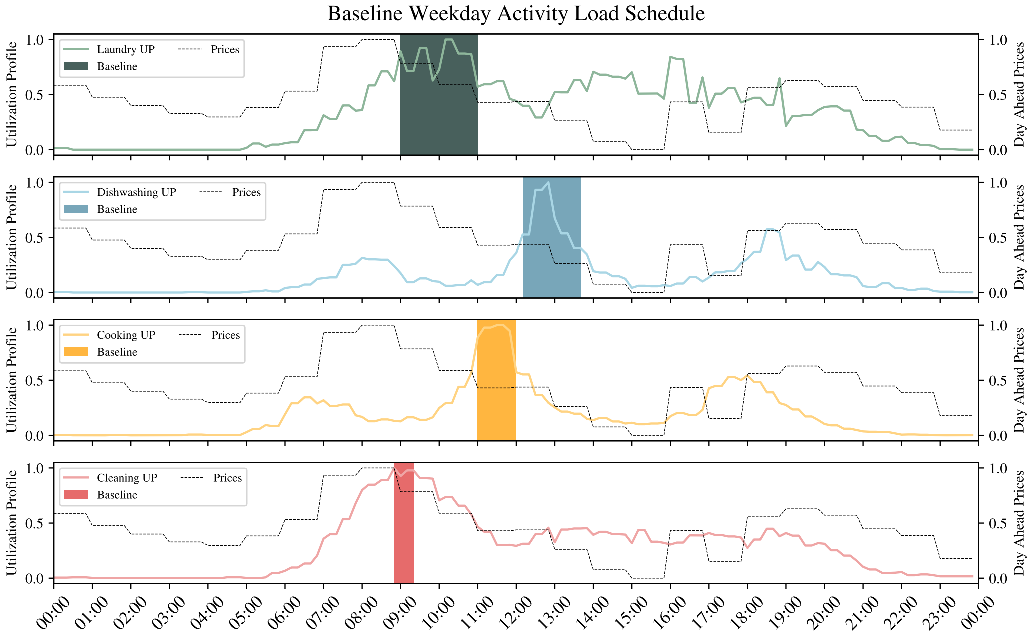

Fig. 3. Baseline scenario for a weekday.

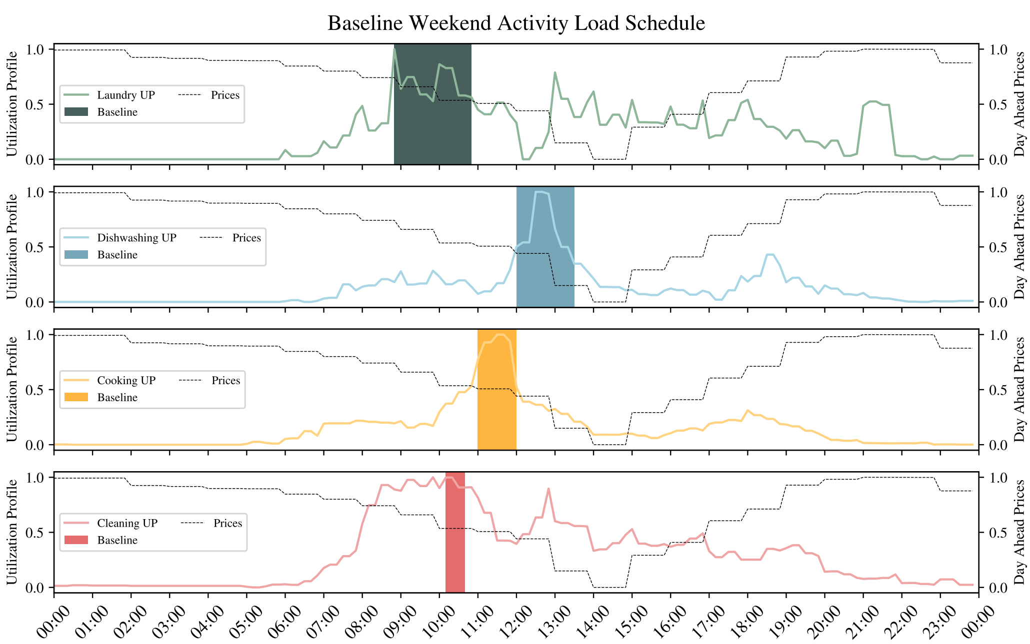

Fig. 4. Baseline scenario for a weekend.

matching user behavior, while an alternate cleaning time is suggested for earlier in the morning.

For a more detailed analysis, it is important to look into how these schedules reflect cost and deviation. The summary of results is presented in Tables 6 and 7.

The table provides a detailed comparison of the baseline schedule and the optimized schedule $\lambda = 1$ in terms of cost, deviation from user behavior, and start times for various household activities. The optimization significantly reduces costs across all activities, particularly for laundry, where the cost drops from 1.888 EUR to 0.897 EUR. Other activities, like dishwashing, see smaller reductions, with a slight decrease of 0.034 EUR. In terms of deviation from user behavior, most activities experience a modest increase in deviation, such as laundry, which shifts from 0.156 to 0.397, reflecting the trade-off for cost savings. Cooking retains the same deviation, indicating that having the schedule remain the same as the baseline is the better option for this case. The start times of activities are also detailed, with laundry shifting from 09:00 in the baseline to 14:00 in the optimized schedule to capture lower energy prices, while activities like cooking maintain the same start time. Alternate schedules offer additional flexibility, proposing different start times, such as moving laundry to 09:50 or dishwashing to 17:10, which provides users with more convenient options while still achieving cost savings.

The results for the weekend do not differ drastically from those of a weekday. In this case as well, optimization significantly reduces costs, particularly for laundry, where the cost drops from 1.312 EUR to 0.391

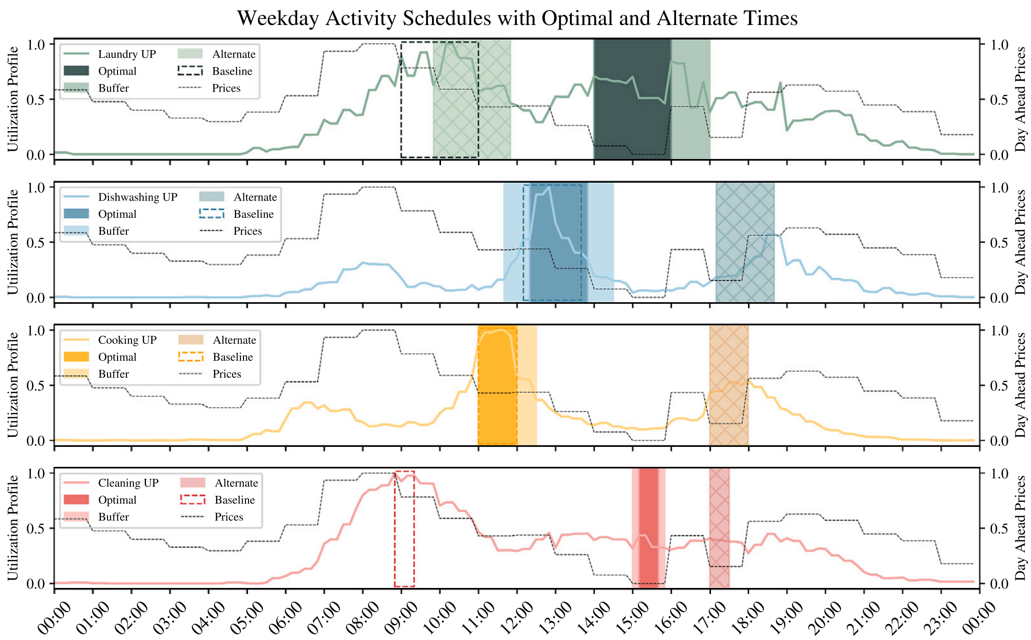

Fig. 5. Load scheduling for a weekday.

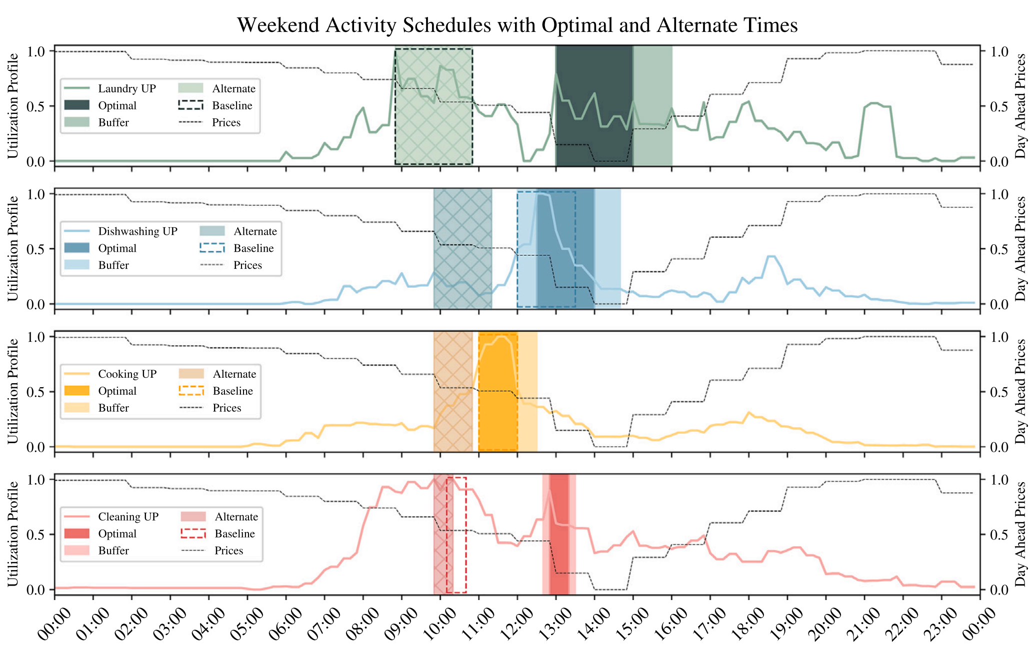

Fig. 6. Load scheduling for a weekend.

EUR. Dishwashing also sees a reduction, with the cost decreasing by 0.186 EUR. In terms of deviation, most activities experience a moderate increase, such as laundry, which shifts from 0.290 to 0.541, reflecting the trade-off for cost savings. Cooking, similar to the weekday case, maintains the same deviation, indicating that this activity in particular displays higher rigidity. The start times show adjustments as well, with laundry shifting from 08:50 to 13:00, while alternate schedules provide more flexibility, such as moving dishwashing to 09:50, offering a convenient alternative for users.

From analyzing the results illustrated in both tables, it is clear that substantial cost savings can be achieved without major impact on convenience of the user. While the initial results show promise, optimizing the balance between cost and user convenience requires further refinement. The following subsection looks into optimizing λ for each individual activity on both days separately, resulting in 8 separate weighting factors.

4.3. Optimizing the weighting factor

As outlined in the methodology, a sensitivity analysis is conducted for the optimization of load scheduling. The value of λ is varied from 0 to 2 in increments of 0.25, and the resulting cost and deviation values are used to identify the optimal trade-off point. A key aspect worth highlighting is that this sensitivity analysis is performed over 365 days, with a new real dynamic pricing profile used for each day. This approach ensures that the weighting factors are evaluated across diverse pricing

Table 6
Weekday comparison of schedule costs, deviations, and start times for different activities (baseline vs. $\lambda = 1$).

Load	Type	Cost (EUR)			Deviation			Start times	
		Base	$\lambda = 1$	Δ	**Base**	$\lambda = 1$	Δ	**Base**	$\lambda = 1$
LS	OS	1.888	0.897	−0.991	0.156	0.397	0.241	09:00	14:00
	ESB	1.888	0.897	−0.991	0.156	0.397	0.241	09:00	14:00
	LSB	1.888	1.170	−0.718	0.156	0.401	0.245	09:00	15:00
	AS	1.888	1.662	−0.226	0.156	0.253	0.097	09:00	09:50
DWS	OS	1.562	1.528	−0.034	0.326	0.339	0.014	12:10	12:20
	ESB	1.562	1.660	0.098	0.326	0.400	0.074	12:10	11:40
	LSB	1.562	1.287	−0.275	0.326	0.616	0.290	12:10	13:00
	AS	1.562	1.519	−0.043	0.326	0.707	0.381	12:10	17:10
CS	OS	1.246	1.246	0.000	0.035	0.035	0.000	11:00	11:00
	ESB	1.246	1.246	0.000	0.035	0.035	0.000	11:00	11:00
	LSB	1.246	1.251	0.005	0.035	0.229	0.194	11:00	11:30
	AS	1.246	0.894	−0.353	0.035	0.520	0.485	11:00	16:00
CLS	OS	0.358	0.140	−0.218	0.032	0.599	0.567	08:50	15:10
	ESB	0.358	0.140	−0.218	0.032	0.599	0.567	08:50	15:00
	LSB	0.358	0.140	−0.218	0.032	0.603	0.571	08:50	15:20
	AS	0.358	0.179	−0.179	0.032	0.603	0.571	08:50	17:00

Table 7
Weekend comparison of schedule costs, deviations, and start times for different activities (baseline vs. $\lambda = 1$).

Load	Type	Cost (EUR)			Deviation			Start times	
		Base	$\lambda = 1$	Δ	**Base**	$\lambda = 1$	Δ	**Base**	$\lambda = 1$
LS	OS	1.312	0.391	−0.921	0.290	0.541	0.251	08:50	13:00
	ESB	1.312	0.391	−0.921	0.290	0.541	0.251	08:50	13:00
	LSB	1.312	0.513	−0.799	0.290	0.622	0.332	08:50	14:00
	AS	1.312	1.312	0.000	0.290	0.290	0.000	08:50	08:50
DWS	OS	0.956	0.770	−0.186	0.308	0.376	0.068	12:00	12:30
	ESB	0.956	0.956	0.000	0.308	0.308	0.000	12:00	12:00
	LSB	0.956	0.456	−0.500	0.308	0.712	0.404	12:00	13:10
	AS	0.956	1.339	0.383	0.308	0.829	0.521	12:00	09:50
CS	OS	0.940	0.940	0.000	0.072	0.072	0.000	11:00	11:00
	ESB	0.940	0.961	0.021	0.072	0.313	0.241	11:00	10:30
	LSB	0.940	0.893	−0.047	0.072	0.293	0.221	11:00	11:30
	AS	0.940	1.010	0.070	0.072	0.639	0.567	11:00	09:50
CLS	OS	0.196	0.114	−0.082	0.032	0.306	0.274	10:10	12:50
	ESB	0.196	0.142	−0.054	0.032	0.289	0.257	10:10	12:40
	LSB	0.196	0.086	−0.110	0.032	0.410	0.378	10:10	13:00
	AS	0.196	0.208	0.012	0.032	0.034	0.002	10:10	09:50

patterns, offering a more accurate reflection of real-life scenarios. Fig. 7 illustrates the dynamic pricing data utilized for each day.

The pricing data reflects both short-term fluctuations and long-term trends. Significant price spikes can be observed during certain periods, particularly in the colder months of January, February, and the end of the year, likely reflecting the increased demand during winter. Conversely, prices appear to be more stable during the summer months. It is expected that including data for an entire year in the study allows for a comprehensive evaluation of each load's flexibility across these various fluctuations and trends. This approach also accounts for seasonality by calculating the optimal λ over the full year, ensuring that the scheduling algorithm adapts to changes in energy consumption and pricing across different months. Table 8 shows the results of running the sensitivity analysis for one day, and Fig. 8 plots these results to show the intersections.

For the pricing profile shown in Fig. 7, intersections were identified in 7 out of the 8 cases. These intersections were recorded across multiple dates, with the average over one year being selected as the optimal λ. It is important to note that not all simulations produce an intersection, as seen in this case. When an intersection is absent, the run for that activity is discarded and labeled as N/A. By removing these cases, the analysis focuses solely on λ values where a genuine trade-off occurred, leading to a more robust and meaningful result. Table 9 shows the averaged λ results for one day, three months, six months, and one year.

For all activities, the λ values tend to change as the time period lengthens, indicating that over time, the balance between cost savings and user deviation becomes more refined. Over time, the changes from one period to the next become smaller, indicating convergence toward the optimal value. For instance, LS-WD begins at 1.02 after 1 day but steadily drops to 0.56 after one year, showing a clearer alignment with the optimal trade-off. In cases like DWS-WD, where no intersection is observed in the 1-day analysis, a more stable λ emerges as data accumulates. The next step is to perform the optimal load scheduling on the same pricing profile utilized earlier, and compare the results for that day using the optimal weighting factors. Table 10 presents a comparison of costs and deviation between the first simulation and the one with the optimal weighting factors.

Table 10 demonstrates the impact of applying the optimized λ values on both cost and user deviation for different appliances on weekdays and weekends. The optimized λ shows significant improvements in cost reductions across most activities, particularly for dishwashing, where the cost decreases by 0.540 EUR on weekdays and 0.283 EUR on weekends compared to the $\lambda = 1$ scenario. However, the reduction in cost is often accompanied by an increase in user deviation, especially for DWS, which experiences a deviation increase of 0.576 on weekdays and 0.277 on weekends. For cooking, the cost drops by 0.547 EUR on weekdays and 0.720 EUR on weekends, but user deviation also rises significantly, showing the trade-off between cost savings and convenience. In some cases, such as laundry scheduling and cleaning, the costs remain largely unchanged, indicating that the optimization primarily balances cost and user behavior without drastically altering the schedule. Additionally, alternate schedules for certain activities exhibit notable cost reductions, such as for LS on weekdays, where the cost decreases by 0.519 EUR while still providing a moderate improvement of 0.151 in user deviation. It can be deduced that the optimized λ values allow for a more nuanced balancing of cost and user deviation, providing flexibility and better cost savings without severely impacting user comfort.

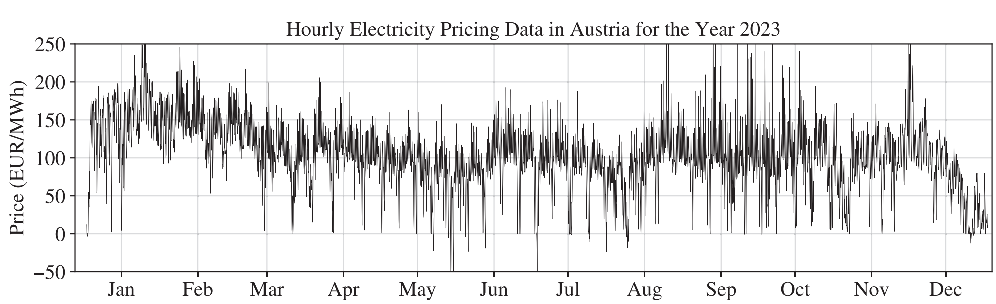

Fig. 7. Hourly pricing utilized to optimize weighting factor λ (source: ENTSO-E).

Table 8
Sensitivity analysis for weighting factor λ.

λ	LS-WD		DWS-WD		CS-WD		CLS-WD		LS-WE		DWS-WE		CS-WE		CLS-WE	
	Cost	Dev.	Cost	Dev.	Cost	Dev.	Cost	Dev.	Cost	Dev.	Cost	Dev.	Cost	Dev.	Cost	Dev.
0.0	0.06	0.38	0.03	0.62	0.0	0.8	0.0	0.6	0.27	0.54	0.14	0.8	0.0	0.91	0.0	0.66
0.25	0.06	0.38	0.17	0.36	0.63	0.04	0.0	0.55	0.27	0.54	0.63	0.33	0.67	0.07	0.18	0.31
0.5	0.06	0.38	0.29	0.33	0.63	0.04	0.0	0.55	0.27	0.54	0.68	0.31	0.67	0.07	0.43	0.03
0.75	0.17	0.37	0.29	0.33	0.63	0.04	0.98	0.04	2.0	0.33	0.68	0.31	0.67	0.07	0.43	0.03
1.0	0.17	0.37	0.29	0.33	0.63	0.04	0.98	0.04	2.34	0.29	0.68	0.31	0.67	0.07	0.43	0.03
1.25	2.87	0.16	0.29	0.33	0.63	0.04	0.98	0.04	2.34	0.29	0.68	0.31	0.67	0.07	0.43	0.03
1.5	2.87	0.16	0.29	0.33	0.63	0.04	0.98	0.04	2.34	0.29	0.68	0.31	0.67	0.07	0.43	0.03
1.75	2.87	0.16	0.29	0.33	0.63	0.04	0.98	0.04	2.34	0.29	0.68	0.31	0.67	0.07	0.43	0.03
2.0	2.87	0.16	0.29	0.33	0.63	0.04	0.98	0.04	2.34	0.29	0.68	0.31	0.67	0.07	0.43	0.03

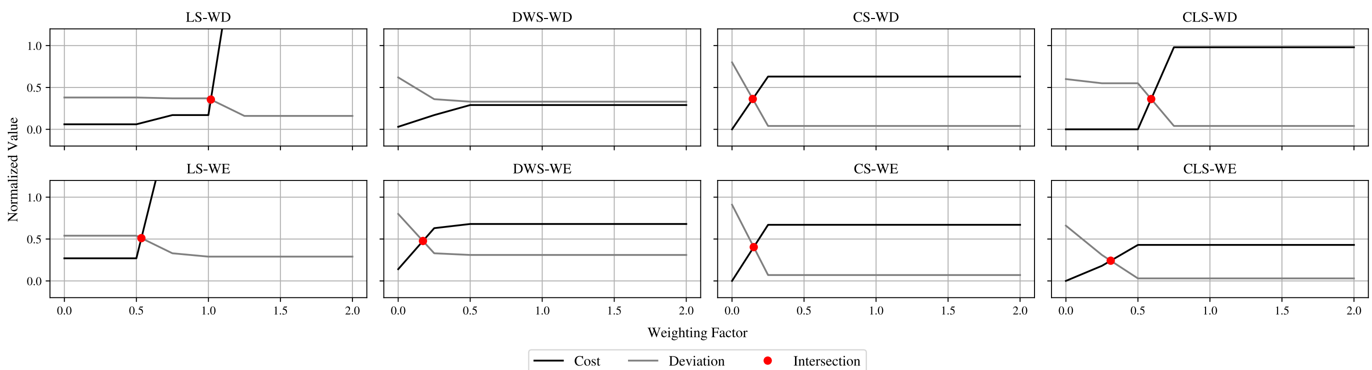

Fig. 8. Intersection identification from sensitivity analysis.

Table 9
Lambda intersection results.

Activity	λ Intersection after N Days			
	1	90	180	365
LS-WD	1.02	0.72	0.63	0.56
LS-WE	0.53	0.80	0.67	0.68
DWS-WD	N/A	0.53	0.44	0.46
DWS-WE	0.17	0.50	0.44	0.46
CS-WD	0.14	0.48	0.37	0.37
CS-WE	0.15	0.53	0.36	0.37
CLS-WD	0.59	0.65	0.61	0.57
CLS-WE	0.31	0.67	0.73	0.73

5. Discussion

The results presented in this study demonstrate the potential of incorporating user behavior into day-ahead load scheduling, specifically through the use of time-use data from HETUS. The optimization algorithm successfully balances two key factors: reducing electricity costs and maintaining user convenience. This dual focus marks a shift from traditional DR strategies that prioritize cost reduction while often neglecting the behavioral patterns of end users. The approach used here allows for a more personalized energy management system, which aligns energy consumption with user routines, potentially increasing user participation and overall satisfaction in DR programs. The sensitivity analysis provides further insight into the role of the weighting factor λ in balancing cost and user deviation. The results reveal that while significant cost reductions are achievable, they often come at the expense of increased deviation from user preferences. This trade-off was particularly pronounced for activities such as dishwashing and cooking, where cost savings were substantial but user behavior deviated notably from their usual routines. Conversely, in cases like laundry scheduling, the algorithm was able to find a more balanced trade-off, achieving cost savings without significantly altering user behavior. Another important aspect highlighted by the study is the role of alternate scheduling and buffer zones. These mechanisms introduce additional flexibility for the user, allowing them to choose an alternative schedule that, while not the absolute lowest-cost option, still provides substantial savings with minimal disruption to their routines. Specifically, buffer zones inform users that starting slightly earlier or later than the optimal time is still acceptable, while the alternate schedule offers a secondary option, further simplifying adherence to load shifting recommendations. This feature is particularly relevant in real-world applications, where users may not always be able to adhere to the optimal schedule but would still benefit from a second-best option. However, one challenge that emerged from the sensitivity analysis is the difficulty in achieving a clear balance between cost savings and user convenience across all activities. For some loads, such as cooking, the optimization led to higher user deviation as the algorithm heavily favored cost minimization. In such cases, the user-centered design approach must be refined to better reflect the varying levels of flexibility for different types of activities. Real-world implementation would encounter user acceptance challenges including varying comfort with using technology interfaces, resistance to routine changes, and diverse household schedules that may not align with average behavioral patterns. These challenges underscore the importance of the flexibility mechanisms integrated into this methodology, including buffer zones and alternative scheduling options. Since the presented method utilizes HETUS, a standardized dataset, it ensures straightforward adaptability and scalability to other European countries. The harmonization across surveys enables the replication of this methodology in diverse geographical contexts, thus enhancing its general applicability and usefulness for pan-European DR strategies. From a computational perspective, the algorithm scales linearly with household count due to independent optimization of each activity, making it suitable for practical multi-household DR applications.

The limitations of this study include the reliance on static HETUS data which limits adaptability to real-time changes in user behavior. Uniform assumptions about appliance flexibility and preferences ignore

Table 10
Comparison of schedule costs, deviations, and start times for different activities on weekdays and weekends ($\lambda = 1$) vs. λ_{opt}.

Load	Type	Cost (EUR)			Deviation			Start times	
		$\lambda = 1$	λ_{opt}	Δ	$\lambda = 1$	λ_{opt}	Δ	$\lambda = 1$	λ_{opt}
Weekday									
LS	OS	0.897	0.897	0.000	0.397	0.397	0.000	14:00	14:00
	ESB	0.897	0.897	0.000	0.397	0.397	0.000	14:00	14:00
	LSB	1.170	1.125	−0.045	0.401	0.401	0.000	15:00	14:50
	AS	1.662	1.143	−0.519	0.253	0.404	0.151	09:50	12:50
DWS	OS	1.528	0.988	−0.540	0.339	0.915	0.576	12:20	14:30
	ESB	1.660	1.031	−0.629	0.400	0.873	0.473	11:40	14:00
	LSB	1.287	1.124	−0.163	0.616	0.932	0.316	13:00	14:50
	AS	1.519	1.357	−0.162	0.707	0.525	−0.182	17:10	12:50
CS	OS	1.246	0.699	−0.547	0.035	0.893	0.858	11:00	15:00
	ESB	1.246	0.699	−0.547	0.035	0.893	0.858	11:00	15:00
	LSB	1.251	0.975	−0.276	0.229	0.849	0.620	11:30	15:30
	AS	0.894	0.894	0.000	0.520	0.520	0.000	17:00	17:00
CLS	OS	0.140	0.140	0.000	0.599	0.599	0.000	15:10	15:10
	ESB	0.140	0.140	0.000	0.599	0.599	0.000	15:00	15:00
	LSB	0.140	0.140	0.000	0.603	0.603	0.000	15:20	15:20
	AS	0.179	0.179	0.000	0.603	0.634	0.031	17:00	17:00
Weekend									
LS	OS	0.391	0.391	0.000	0.541	0.603	0.062	13:00	13:00
	ESB	0.391	0.391	0.000	0.541	0.541	0.000	13:00	13:00
	LSB	0.513	0.492	−0.021	0.622	0.605	−0.017	14:00	13:50
	AS	1.312	0.818	−0.494	0.290	0.680	0.390	08:50	11:50
DWS	OS	0.770	0.487	−0.283	0.376	0.653	0.277	12:30	13:00
	ESB	0.956	0.487	−0.469	0.308	0.653	0.345	12:00	13:00
	LSB	0.456	0.423	−0.033	0.712	0.822	0.110	13:10	13:40
	AS	1.339	1.032	−0.307	0.829	0.331	−0.498	09:50	11:50
CS	OS	0.940	0.220	−0.720	0.072	0.902	0.830	11:00	14:00
	ESB	0.961	0.220	−0.741	0.313	0.908	0.595	10:30	14:00
	LSB	0.893	0.427	−0.466	0.293	0.909	0.616	11:30	14:30
	AS	1.010	0.940	−0.070	0.639	0.072	−0.567	09:50	11:00
CLS	OS	0.114	0.044	−0.070	0.306	0.573	0.267	12:50	14:30
	ESB	0.142	0.044	−0.098	0.289	0.617	0.328	12:40	14:20
	LSB	0.086	0.072	−0.014	0.410	0.530	0.120	13:00	14:40
	AS	0.208	0.196	−0.012	0.034	0.032	−0.002	09:50	10:10

socio-economic and cultural diversity, requiring finer modeling. The fixed λ range in the sensitivity analysis may miss key trade-offs, suggesting adaptive optimization. Focusing only on Austria limits the findings' applicability, emphasizing the need for cross-country validation. While this study focuses on Austrian households to establish and validate the methodological framework, future research should implement the approach across multiple European countries to assess its robustness under different load structures, pricing mechanisms, and societal contexts. Additionally, excluding high-impact loads like EVs and heating systems limits the potential impact of the algorithm. Future work should explore how the algorithm performs in different pricing environments and with other forms of time-dependent pricing mechanisms, such as real-time pricing or critical peak pricing. Future research could also extend the user-centric approach to analyze aggregate grid benefits such as peak reduction and load smoothing across multiple households.

6. Conclusion

Building on the insights discussed in the previous section, the conclusion explores the practical considerations and next steps for implementing this algorithm in real-world settings. When considering the real-world implementation of this algorithm, several important factors must be addressed. First, the success of this approach in shifting user behavior and influencing the timing of their activities relies heavily on a user-friendly interface. This could be an online platform that provides users with a clear overview of the day-ahead schedule. A better alternative is a smartphone application, offering a more streamlined, accessible experience. The advantage of a mobile application is its ability to deliver push notifications, allowing real-time updates and reminders, which further enhance user engagement. Crucially, users must retain full autonomy to manually start appliances whenever needed, ensuring the system serves more as a recommendation tool rather than a restrictive control system. Second, certain parameters need to be provided by the user. While a primary goal of this algorithm is to minimize user input, especially when it is inconvenient or time-consuming, some level of user involvement can enhance its flexibility. Key parameters include buffer zone thresholds, appliance energy consumption, and activity duration. Additionally, users should have the option of adjusting weighting factors and modifying how alternate scheduling is optimized. For instance, they could create larger gaps between the optimized schedule and alternative timings to better fit their preferences. In general, this increases the algorithm's adaptability, enabling users to input data specific to their habits and the settings available on their appliances. Third, the algorithm is intended to function as a default, out-of-the-box solution for home energy management. Ideally, the behavioral component should adapt over time based on user habits. One potential enhancement is to allow the system to learn from user behavior tracking whether they follow the proposed schedule, and gradually shift from generalized profiles, such as those based on HETUS, to user-specific profiles. This would provide a more tailored solution, potentially leading to greater user engagement and impact. This highlights the fact that, ultimately, the success of the system depends on the user's willingness to participate and adhere to it. While this approach simplifies the process and makes it highly accessible, it is fundamentally reliant on changing user behavior and ensuring the system provides enough value to make it worthwhile for them. Although the activities selected in this study have limited DR potential due to their relative lack of flexibility, they are important because they are prevalent in every household and performed regularly by most families. While more impactful loads, such as EV charging and heat pumps, offer greater potential for DR, they are not yet as widespread as they could be.

In this study, Austria has served as an excellent testbed for this algorithm. The consistent cost savings achieved in both simulations highlight how user behavior aligns with dynamic pricing, revealing real potential for DR. With Austria's evolving smart meter rollout, these results provide motivation to accelerate the deployment and offer more options for residential consumers to engage in such programs. For future work, it would be well worth testing the algorithm on real users by developing an app and conducting a study to assess its impact on load shifting and DR behavior. Incorporating additional activities would also be of interest. The authors plan to monitor the next release of HETUS data closely to see if it includes other more relevant loads, such as EV charging, plug-in heaters, or other DR-related activities that could be integrated. While this study focuses on Austrian households, the methodology's foundation on a harmonized dataset enables direct application to other European countries. Thus, expanding the study beyond Austria to include other European countries and exploring the impact of increased user adherence and acceptance of DR strategies on the grid could provide exciting new research directions.

CRediT authorship contribution statement

Reda El Makroum: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Zwickl-Bernhard:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **Lukas Kranzl:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition. **Hans Auer:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the authors used ChatGPT to refine writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Reda El Makroum reports financial support was provided by Horizon Europe. Reda El Makroum reports financial support was provided by Swiss State Secretariat for Education Research and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share the data.

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