Residential demand response: evaluating how much consumers could actually save

Johan Westö[a,*], Hafiz Imam[a]

[a]Technology and Seafaring, RDI, Novia University of Applied Sciences, Wolffskavägen 33, Vasa, 65200, Finland

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ABSTRACT

The renewable energy supply needed for the energy transition is often intermittent. A successful transition, therefore, requires additional grid flexibility to maintain balance between supply and demand. Residential demand response, in which consumers shift usage in response to a market signal, is considered a largely untapped source of green flexibility. However, assessing its potential is difficult because participation often shifts price risks from retailers to consumers, savings can be relatively small, and investment costs are unknown, making it challenging to assess consumers' willingness to participate. Here, we developed a framework to 1) obtain consumption profiles for representative groups of residential consumers, and 2) determine the absolute savings that consumers within each group could obtain for various levels of load shifting flexibility. We used the framework to assess potential savings for residential consumers in Finland, using real consumption data, when providing implicit flexibility (day-ahead spot market) or explicit flexibility (mFRR reserve market). Our findings show that consumers appear risk-averse, as those already offering the most flexibility have fixed-price contracts that limit their financial compensation. In addition, we find that the potential savings scale similarly across most consumer groups but are currently likely too low to motivate the investments needed to automate loads and provide demand response at a larger scale. The results thus provide important insights for designing future policies and for considering the pace at which the achievable residential demand response potential might grow.

1. Introduction

Electrification is a key driver for the energy transition from fossil fuels to renewable sources. Demand for electricity is therefore expected to double by 2050 [1, 2], requiring substantial growth in renewable generation, primarily wind and solar, to meet rising demand and to replace existing fossil-based production. While we are not there yet, renewable sources are already projected to supply 90 % of the global demand growth in the coming years [3].

The increased reliance on intermittent renewable generation, such as wind and solar, nonetheless comes with its own challenge: the supply from these sources does not necessarily coincide with demand. Integration of large shares of wind and solar thus requires additional solutions to help balance supply and demand, often referred to as flexibility options or sources [4–6]. Typical flexibility options include flexible generation, interconnection, energy storage, and demand response [7, 8]. Currently, the flexibility needed to balance intermittent renewable sources is often provided by natural gas-fueled flexible generation units [6, 9, 10]. However, this has two severe drawbacks: 1) Renewable generation will not be carbon-free as long as it has to be balanced by fossil-based generation [11]. 2) It introduces severe geopolitical risks as the price of electricity becomes highly dependent on the price of natural gas whenever renewable generation is unable to cover the demand, as recently seen during the 2022 energy crisis in Europe [10, 12]. A successful energy transition thus hinges on incorporating new cost-efficient green flexibility options, and the economic feasibility of new options is continuously evaluated [13].

Demand response (DR), in which the demand side deviates from its normal consumption pattern in response to a market signal, is one promising and largely untapped source of green flexibility [14, 15]. DR is divided into implicit (price-based) and explicit (incentive-based) demand flexibility: implicit corresponding to consumers reacting to market prices and explicit to consumers selling flexibility as a service [6, 16, 17]. Interest in both types has grown in the 21st century, and recent developments also consider the potential of residential consumers [18–20]. Finland, Sweden, and Norway are often highlighted as countries with particularly high potential for cost-efficient residential DR. The reasons

*Corresponding author
johan.westo@novia.fi (J. Westö); hafiz.imam@novia.fi (H. Imam)
ORCID(s): 0000-0002-6215-9047 (J. Westö); 0009-0002-6575-8798 (H. Imam)

being that roughly two-thirds of total home energy consumption is used for heating [21], and that all three countries have a high share of homes using electrical heating [22, 23]. Consequently, the residential DR potential per consumer is expected to be high.

Evaluating the potential for residential DR is nonetheless tricky. The relative savings from residential DR can be small, while consumer response fatigue often necessitates automated solutions [18, 24, 25]. The attainable savings with respect to required investment costs are therefore often unclear. In addition, consumers tend to be risk-averse and unwilling to accept price risks from retailers [6, 26]. Studies evaluating DR potential, therefore, typically focus on the theoretical, technical, or economic potential rather than the achievable potential [19, 22, 27–29]. Although the economic potential should include DR implementation costs [29], studies tend to ignore them or assume they are minimal, effectively treating residential DR as nearly cost-free for homeowners [22, 30–32]. Derived potentials thus essentially assume that all residential loads that can participate will, irrespective of any discomfort it may cause or the costs required to make them controllable through automation. However, disregarding consumers' willingness to participate, and acquire and install the required hardware risks giving an unrealistic view of the achievable potential and the pace at which residential DR could be realized.

There is thus a clear gap in understanding the achievable DR potential, that is, how much of the published potentials remain once the savings and the consumers' willingness to participate and acquire the required equipment are factored in. Only a few studies have attempted to quantify consumers' willingness to participate in DR [29]. Existing data are consequently scarce and largely extrapolated from responses to a mix of real and hypothetical scenarios [33], and often based on typical savings as a percentage rather than grounded in real attainable absolute values [34]. This is problematic because potential savings may vary widely across consumer groups, and since participation rates in hypothetical scenarios appear overly positive [33, 35]. It would therefore be important to quantify savings in realistic situations across consumer groups to improve estimates of consumers' actual willingness to participate.

This work addresses the concerns above by proposing a framework to determine realistic savings for residential consumers using real consumption data. In particular, we 1) present a method using modern tools for visualizing consumption data and for extracting representative consumption profiles for various consumer groups at arbitrary detail, 2) develop and release an optimization routine for quantifying the possible savings for each group for various levels of load shifting flexibility, and 3) utilize the proposed framework to evaluate absolute savings for consumers in Finland when providing both implicit and explicit load shifting flexibility. Finland has the same sequential market structure common to Europe in general [36–38], whereby implicit flexibility corresponds to adjusting consumption to day-ahead spot prices and explicit flexibility to selling flexibility to any of the reserve markets. The situation in Finland is also representative of Europe in many other respects, as developments on the Finnish electricity market reflect a European-level push for greater flexibility from DR in the grid.

2. Materials and Methods

The proposed framework for determining realistic DR savings for consumers is based upon: 1) extracting representative consumer groups and their average profiles from real data, and 2) shifting loads optimally to minimize costs. In addition, we modelled the hourly consumption for each group to estimate the hourly heating demand. Below, we present each step in detail, from raw hourly measurement data to savings from optimal load shifts.

2.1. Preprocessing of the hourly consumption data

The consumption dataset was obtained from a Finnish retailer and included all consumers within Vasa Elnät's (local DSO) area who had main fuses rated below 100 A. The dataset included hourly measurement values from 2023 and metadata for each consumer, including tariff type (e.g., normal, day/night), contract type (e.g., fixed price, real-time spot-based), and consumer category (e.g., detached house or low-rise dwelling). The dataset was cleaned to remove consumers whose profiles clearly did not match what would be expected for a place where people live continuously. This included profiles with longer periods (>3 weeks) of no consumption, and consumers with consumption concentrated in a specific month that cannot be explained by heating of living spaces (e.g., drying of crops at the end of the summer). Lastly, consumers were filtered by total consumption, removing all with an annual consumption below 5000 kWh.

2.2. Extraction of representative consumer groups

Our approach to extracting representative consumer groups differs from most prior work in that we do not limit ourselves to daily profiles and do not rely on any handcrafted features [39–41]. Instead, we used Uniform

Manifold Approximation and Projection (UMAP; [42]) to reduce dimensionality and visualize high-dimensional hourly data from a whole year, and custom clustering techniques to extract representative groups from the visualization. These techniques complement each other: UMAP captures local structure, while the clustering techniques provide complementary global organization.

2.2.1. Dimensionality reduction of hourly consumption data

We applied UMAP directly to the raw hourly measurement data to reduce dimensionality from 8760 to 2 (params: n_neighbors=30, min_dist=0.0, metric=cosine, and n_epochs=500). UMAP preserves local similarity structure, thus ensuring that data points (consumers) that are close in the high-dimensional space remain close in the 2-dimensional space. By further using the cosine distance as the metric for UMAP, the dimensionality reduction effectively keeps consumers with similar consumption profiles, that is, consumers who use electricity at similar times, close together. Although one does not know beforehand where various types of consumers end up in the 2-dimensional space, it is easy to inspect afterwards, as the characteristic feature of any region can be found by simply plotting the average profile of all consumers in that region.

2.2.2. Formation of representative groups

We created an initial set of consumer groups by plotting the 2-dimensional UMAP representations of each consumer as a scatter plot, and then effectively "tessellating" it using the standard k-means algorithm to split it up into regions (dotted black lines in Figure 2a). We used $k = 50$, but the exact choice does not really matter; it is merely a question of how small regions (few consumers per group) one wants to study. However, because UMAP preserves only local structure during dimensionality reduction, certain neighbouring regions might be much more similar to each other than others. We therefore added a second agglomerative clustering step, in which regions are iteratively merged based on similarity in the original high-dimensional space, to support any number of representative groups between k and 2. This is very useful, as there is generally no single correct number of representative groups; rather, the research questions determine how small differences among consumers must be considered.

The agglomerative clustering utilized normalized consumption data (unit norm) and a merge cost (Δ) between groups defined as:

$$\Delta(\mathbf{g}, \mathbf{h}) = \|\mathbf{g}\|_2 + \|\mathbf{h}\|_2 - \|\mathbf{g} + \mathbf{h}\|_2.$$

where $\mathbf{g}$ and $\mathbf{h}$ are sum vectors, that is, the sum of all consumers' normalized hourly consumption in each group. The merge cost is thus close to zero if the two sum vectors point in nearly the same direction, which occurs when the two groups contain consumers with similarly shaped consumption profiles. Although this merge cost is typically not implemented in agglomerative libraries, it is still the agglomerative equivalent to the coherence objective used by spherical k-means, where coherence of a group is defined by its sum vector [43].

2.2.3. Profile cost

The consumer profile cost is defined as the ratio of the cost (spot price) for the real consumption profile to that for a flat profile with the same amount of energy. This ratio is typically determined monthly because it forms the basis for the final price charged to a customer under new hybrid contracts. Here, it was also determined monthly, then compressed into a single value for each consumer as the volume-weighted average over all 12 months. The values shown per group in Figure 2i are thus the average volume weighted average for all consumers in each group.

2.3. Modelling of the hourly consumption for each group

Measurement data only gives the total consumption per hour. We therefore fitted a linear model to the average consumption profile for each group to estimate the hourly heating demand. The input matrix ($\mathbf{X}$) for the model had 73 columns (features) derived from the time of day, day type (workday or weekend), outdoor temperature, and solar irradiation. The first 48 (24 + 24) features were dummy variables indicating the hour of the day and whether it was a weekday or a weekend (Saturday/Sunday); only one had a value of 1, and the rest were 0. The following 24 features were hour-specific heating degrees, defined as $\max(0, T_{\text{base}} - T_{\text{outdoor}})$. That is, the feature for the hour in question contained the heating degrees, whereas all other 23 features were 0. Lastly, the final feature was simply the solar irradiation. The estimated model coefficients could thus be interpreted as a daily profile for workdays, a daily profile for weekends, hour-specific heating coefficients, and a solar impact coefficient. The models were fit using cvxpy by minimizing the squared prediction error across all 8760 hours, that is, the difference between the model's output and the group's average consumption for each hour. The hyperparameter T_{base} used to define heating degrees was set separately for each group via 5-fold cross-validation.

2.4. Optimization of load shifting to maximize savings

Achievable DR savings for each representative group were determined by identifying optimal load shifts for the group's average consumption profile, with optimal meaning either maximal savings or minimal procurement cost for the electricity used. The optimization problem can be formulated as a convex linear program, and the found optimum is thus guaranteed to be global. We have here generalized the problem definition by formulating it as optimizing an original demand profile ($\mathbf{d}^{\text{ori}}$) to obtain an optimally load-shifted demand profile ($\mathbf{d}^{\text{opt}}$) given known prices ($\mathbf{p}$). The group's average consumption profile thus corresponds to $\mathbf{d}^{\text{ori}}$ in this more general formulation.

2.4.1. Problem formulation and implementation

Load shifting was implemented via a transfer matrix ($\mathbf{T}$) denoting load transfer from hour i to hour j (Figure 3a), with all values constrained to be larger than or equal to zero. The flexibility level, which denotes how many hours a load can be shifted earlier or later, determines which elements in $\mathbf{T}$ are allowed to be non-zero. For example, for a flexibility level of ± 2 hours, only elements in the two neighbouring columns and rows for each diagonal element are allowed to take on non-zero values. From the definition of $\mathbf{T}$, one further gets that the row sums denote the total load removed in each hour, and this must be equal to or less than the available demand in that hour (given by $\mathbf{d}^{\text{ori}}$). Similarly, the column sums denote the total load added to each hour and must be equal to or less than the difference between the maximum power permitted ($P^{\max}$) and the original load (given by $\mathbf{d}^{\text{ori}}$). The demand after load shifting is thus given by:

$$d_i^{\text{opt}} = d_i^{\text{ori}} + \sum_i T_{ij} - \sum_j T_{ij}$$

and the objective function is to minimize the cost of the procured electricity over all hours:

$$\min_{\mathbf{T},\mathbf{d}^{\text{opt}}} \sum_i d_i^{\text{opt}} p_i$$

2.4.2. Rolling horizon

In practice, prices are only known within a short horizon into the future. For example, day-ahead spot prices for the next day are presented around 14:00 each day. The optimization problem above thus needs to be solved daily with a rolling horizon to mimic the real-world scenario (Figure 3b). However, this introduces additional bookkeeping, as loads from day n might be shifted to hours in day $n + 1$, thereby imposing historical constraints when solving the optimization problem for day $n + 1$. This was implemented by extending the transfer matrix to include historical hours and forcing the row and column sums for historical hours to equal their corresponding sums from the previous day.

2.4.3. Day-ahead spot versus mFRR prices

Savings from implicit DR by shifting loads based on known day-ahead spot prices were determined as outlined above. Explicit DR savings from mFRR participation, in turn, require a few additional steps. The added complexity stems from mFRR-based savings, which require a reference profile to determine the DR action or the imbalance that another DR action might have caused. The savings presented in Figure 5d to h therefore assume that the consumer initially found the optimal load shift for the spot prices, after which the resulting spot-optimal profile was taken as the reference profile when determining the upper bound on mFRR-based savings. That is, the optimization presented above was run twice, first against spot prices and then against balancing prices, and the solution from the first run was used as the reference profile when determining the mFRR-based savings from the second run.

2.4.4. Price correction

The day-ahead spot and mFRR prices for the period 15:00 on 24 November 2023 to 00:00 on 25 November 2023 were set to zero. There was a highly unusual bidding event that resulted in extreme prices on this day, and the actual prices cannot be considered to reflect normal variation during the affected hours [44].

2.5. Code and data availability

Our implementation of the optimization routine to determine potential savings for a given consumption profile is available via our load-shift-optimizer GitHub repository. The remaining code used in this work is tailored to the consumption dataset and cannot be shared in full, but fragments are available upon reasonable request. The consumption data used is from a Finnish retailer, and it cannot be made publicly available or shared in any form. Similarly, we are not permitted to share the day-ahead spot prices, but these were obtained from Nordpool's Data Portal. The outdoor temperature data used for modelling heat demand were obtained from the Finnish Meteorological Institute's (FMI) observation station at Vaasa Airport and are freely available from FMI. The solar radiation data for Vaasa were, in turn, obtained from a weather station located at the Meteoria Visitor Center. This data is not publicly available but can be shared upon reasonable request. Lastly, the imbalance and mFRR prices in Finland were obtained from Fingrid's Open data platform (license CC 4.0 BY), where they are freely available.

3. Results

We have established a framework to identify representative groups of residential consumers and to evaluate possible DR savings for each group. We used the framework to determine DR savings for residential consumers in Finland and to better understand which consumers might be most willing to contribute to DR. Below, we first present the data used and provide a high-level overview of the framework. Later, we present the identified consumer groups, their potential savings from implicit DR, their potential heating-based savings from implicit DR, and lastly, their potential heating-based savings from providing explicit DR to the mFRR market. All analyses are conducted for the year 2023.

We begin with a simple analysis of the day-ahead spot data to get the big picture. At first sight, the spot price for electricity appears to have fluctuated drastically in Finland during 2023 (Figure 1a). However, the price difference between the evening peak (around 19:00) and the dip in the middle of the night was still only ≈ 5 cents/kWh on average (Figure 1b). Shifting a dishwasher to run at night instead of after dinner would thus have saved at most 20 € per year, if it had been shifted every single day. The price difference between the most expensive and cheapest hours of the day was larger, averaging ≈ 9 cents/kWh (Figure 1c). However, the price difference between the second, third, etc., most expensive hours and the cheapest hour of the day quickly drops, and the average savings from concentrating a uniform load profile on the cheapest hour of the day, a rather extreme DR, is around 3.9 cents/kWh. Although real profiles are not uniform, this still provides a rough upper estimate of what might be achievable when trying to shift consumption within a day. It also indicates that a considerable annual consumption is required for savings to accumulate, as 3.9 cents/kWh corresponds to 39 €/1000 kWh per year.

More detailed savings estimates require access to real consumption data. Here, we used consumption data from residential consumers near Vasa, Finland (Figure 1d). The dataset contains hourly values for all of 2023 for 15854 consumers with an annual consumption above 5000 kWh and main fuses below 100 A. Almost all are classified as residential consumers by the electricity retailer (Figure 1e), and most have annual consumption below 30 000 kWh (Figure 1f), as expected for residential consumers. The average consumption for all consumers is shown in Figure 1g. Two typical features of Finnish residential consumers are clearly visible: 1) there is a strong temperature dependence highlighting the impact of the heating demand on the total consumption, and 2) daily evening peaks from consumers with loads (typically water heaters) that turn on shortly after the distribution system operator's (DSO's) cheaper nighttime tariff begins.

The proposed framework for determining realistic savings for residential consumers is outlined in Figure 1h. Starting from a data table containing hourly consumption values for all consumers, we first perform dimensionality reduction to two dimensions while preserving similarity between consumption profiles. Next, we group neighbouring consumers, extract the average profile for each group, and finally shift consumption optimally to evaluate savings from either implicit (day-ahead spot) or explicit (reserve mFRR) DR.

3.1. Extracted groups exhibit clearly distinct consumption profiles

The original high-dimensional consumption data from all consumers is difficult to visualize. We therefore reduced it to only two dimensions so that each consumer could be visualized as a point in a scatter plot, but in such a way that consumers with similar consumption profiles end up as points close to each other in the scatter plot (see Methods for a more detailed description of the UMAP method used; Figure 2a). The characteristic feature of a group of neighbouring consumers can then be visually identified by simply plotting the group's average profile. Previous work has shown that various consumer types can be easily identified in this way [45]. Here, we build upon this observation and create 50 initial groups to cover all consumers by tessellating the UMAP scatter plot (dotted black lines in Figure 2a), and subsequently merge these groups hierarchically based upon similarity to let us study groups at an arbitrary level of detail (anything between 50 and 2 groups). The colors in Figure 2 show the merged groups at a detail level of 12 groups. This was considered a suitable tradeoff that still covers most of the easily distinguishable groups without overcomplicating the analyses.

The 12 representative groups are split into two clear clusters: consumers with loads that systematically turn on at night are concentrated in the right cluster (groups 7–12), and those that don't are in the left (groups 1–6). However, the UMAP-based dimensionality reduction also organises consumers within each cluster, meaning that a consumer at one end of a cluster can be radically different from one at the other. The fact that they are in the same cluster merely reflects a gradual transition from one end to the other. Figure 2b highlights this gradual transition for the left cluster (groups 1–6), where the climate's impact on the consumption systematically increases as you transition from group 2 to group 5. The average profile for group 2 shows a fairly small difference between winter and summer, whereas the difference increases systematically through group 5. Group 6 (not shown) has even lower consumption during the summer, as this group appears to be where consumers with solar panels are concentrated.

The groups in the right cluster (groups 7–12) all exhibit a nighttime peak, but of varying magnitude and at slightly different times (Figure 2c). Groups 7, 9, and 10 are examples of consumers with water heaters that are most likely controlled by the DSO and set to go on between 22:00 and 23:00, when the tariff changes and the DSO's transmission fee is lower. Groups 11 and 12, in turn, have a much higher peak that also lasts longer. These groups most likely reflect consumers with a water-based heating system, in which electricity is used to heat both tap water and the heating system water at night. Lastly, group 8 reflects consumers who have a peak occurring clearly later, at 01:00–02:00, which is much closer to when the spot price typically takes on its lowest value during the night (see Figure 1b).

The groups presented above were extracted solely from patterns in the hourly consumption data. We therefore further validated them by checking the types of contracts the consumers in each group had and how certain group properties systematically changed across the UMAP-based groups. Figure 2d shows the fraction of consumers with a day/night tariff distribution contract in each group (cheaper transmission fee between 22:00 and 07:00), and it clearly shows how the consumers with a day/night tariff contract are concentrated in the right cluster. Figure 2e similarly shows that consumers with real-time (spot) hourly-price contracts are concentrated in groups 6 and 8. Group 6 appears to be where consumers with solar panels are located, and group 8 shows a nighttime peak closer to when prices tend to be lowest. In addition, we can see that most consumers are located in the left cluster (Figure 2f), that the consumers with highest consumption is located furthest to the right (Figure 2g), and that the horizontal UMAP direction appears to encode how much of the energy that is used during the day Figure 2h. All in all, Figure 2b to h indicate that the UMAP-based dimensionality reduction organized the consumers in a very systematic way that appears to capture real patterns in the data.

Lastly, we quantified the degree to which the extracted consumer groups already concentrate consumption on cheaper hours using the profile cost (Figure 2i). The profile cost compares each group's average profile against a flat profile: a value greater than 1 indicates that consumers tend to use electricity when it is more expensive than the average, and a value less than 1 indicates the opposite. Most consumers have a value greater than 1, but it is clearly below 1 for groups 8, 11, and 12. Group 8 had a nighttime peak closer to the cheapest hours, and groups 11 and 12 had a large fraction of their total consumption during the night. Interestingly, real-time contracts were only common in group 8 (Figure 2e). Groups 11 and 12, which have the most flexibility to offer and have already shifted consumption to nighttime, do not benefit financially from the cheaper spot prices because these consumers predominantly have fixed-price contracts.

3.2. Implicit DR savings scale similarly for most groups but remain modest

Having established a way to obtain representative profiles for 12 consumer groups, we next set out to evaluate the potential savings from shifting consumption in time for each profile. We defined the flexibility level as the number of hours the consumption in a particular hour can be moved, either earlier or later. The optimally shifted profile for any flexibility level can then be found by defining a transfer matrix that indicates the transfer from hour i to hour j and solving for the transfer coefficients that minimize the cost of procured electricity. This is a linear programming problem, as there are constraints to keep shifts within the flexibility window and to ensure that final consumption is between 0 and the maximum value allowed by the main fuses (Figure 3a). However, consumers would not know prices for the whole year. Day-ahead spot prices for the next day are published around 14:00; we therefore run the optimization daily with a rolling horizon of 34 hours when determining the optimally shifted profile for the whole year (Figure 3b).

We first focused on determining the full range of potential savings for each group by assuming that all consumption can be shifted by a given flexibility level. Figure 3d shows how savings per kWh increase for each consumer group (Figure 3c) as the flexibility level increases. The savings grow at almost the same pace across most consumer groups, despite the fact that many of them have radically different consumption profiles to begin with. Most reach a savings potential close to 4 cents/kWh at ±12 hours, as expected from the simple analysis in Figure 1c. Only groups 8 and 11 stand out with a potential of roughly 3 cents/kWh at ±12 hours, and group 12 with the lowest potential of roughly 2 cents/kWh at ±12 hours. The explanation being that these groups already have a profile with consumption somewhat concentrated to cheaper hours, as indicated by the low profile cost in Figure 2i.

The potential yearly savings for each consumer at each flexibility level were estimated by multiplying the per-kWh savings by each consumer's annual consumption. The methodology for grouping consumers considered only the shape of their consumption profiles. Consequently, the annual consumption for consumers in each group varies widely (Figure 3e), and this carries over to the annual savings. Figure 3f depicts the distribution for yearly savings at a flexibility level of ±12 hours. Groups 1 and 2 tend to have the lowest yearly savings, but overall, all groups are represented on both sides of the median. We therefore focus more on the distribution over all groups for various flexibility levels. For a flexibility level of ±1 hour, 90 % of all consumers have yearly savings below 200 €, whereas the equivalent number is roughly 700 € at a flexibility level of ±12 hours (Figure 3g). Another way to look at these yearly savings is to ask how many consumers exceed a given savings threshold at each flexibility level. For example, for a threshold of 400 €, a fairly low compensation for trying to make all loads flexible, 0 %, 10 %, 36 %, and 55 % of the consumers reach this threshold for the flexibility levels ±1, ±3, ±6, and ±12 hours, respectively (Figure 3h).

3.3. Heating-based DR still requires high flexibility

The previously derived potential savings from shifting all consumption appear fairly low, especially considering the effort and hardware required to automate all loads in a home. Another extreme case is to only consider potential savings from the loads with the highest potential, namely those with high annual consumption and high flexibility. The obvious first choice in Nordic homes is the heating system. We therefore fitted a model to each group's average profile to predict heating demand. The model took as input the time of the day, the outdoor temperature (heating degrees; the difference between the outdoor temperature and a heating threshold), and the solar irradiation, and predicted the hourly total consumption and heating demand (Figure 4a). This fairly simple model works well as all consumers are from a geographically local region, and as the average profiles for most groups show a very clean pattern with daily fluctuations on top of a heating demand that scales linearly with heating degrees (Figure 4b). The fitted models explain around 95 % of the variance in the average profile for most groups (Figure 4c), the only clear exception being group 1, which has a profile with a much weaker temperature dependence and stronger daily oscillations. We also used the model to extract additional group properties from its parameters, namely the peak solar impact and the fraction of total consumption used for heating. The peak solar impact clearly indicates that consumers with solar panels are concentrated in group 6 (Figure 4d), and the heating fraction shows that all groups except 1 and 2 predominantly use some form of electricity-based heating system (heating fraction between 40 and 70 %; Figure 4e).

We next used the predicted hourly heating demand for each group to investigate how savings per kWh increased with a higher flexibility level (Figure 4g). That is, we optimized the predicted hourly heating demand for various flexibility levels using the method in Figure 3a and b. The maximum allowed power was set to 1.2 times the predicted heating demand at −29 °C, as the heating systems for buildings in this region of Finland must be dimensioned for −29 °C [46]. The overall pattern is very similar to that in Figure 3d, where we optimized total consumption. However, the annual savings differ because the fraction of total consumption used for heating varies across groups; groups 1 and 2, with non-electrical heating, differ from the rest, with only marginal savings even at a flexibility level of ±12 hours. Overall, though, 90 % of all consumers have yearly heating-based savings below 100 € at a flexibility level of ±1 hours, and this increases to roughly 360 € at ±12 hours. Looking at a specific savings threshold like 200 €, assuming some hardware and an electrician to install it, 0 %, 12 %, 34 %, and 48 % of the consumers reach it for the flexibility levels ±1, ±3, ±6, and ±12 hours, respectively (Figure 4j). The level of heating-based flexibility a building can provide is highly building-specific, but likely around ±3 to ±6 hours at best (see subsection 4.3). Typical yearly savings would therefore be roughly 100 to 200 €.

3.4. Explicit (mFRR) DR contributes less than implicit DR

We next investigated whether it would be possible to increase heating-based savings by having consumers, in addition to implicit spot-based DR, also sell explicit demand flexibility to the mFRR reserve market. There are two possible mFRR products, corresponding to up- or down-regulation, respectively. Up-regulation occurs when demand exceeds supply in the grid, and down-regulation occurs when supply exceeds demand. Residential consumers could provide up-regulation by dropping a load and deferring its use to a later time, and vice versa for down-regulation.

Although multiple reserve products exist, the two mFRR reserve products have the slowest response time requirement in Finland and, thus, in theory, can be combined with all types of electric heating systems. The mFRR market is also where most of the reserve energy is traded, and in 2023, balancing energy prices were set by mFRR prices. Participation, nonetheless, requires an aggregator that takes a fraction of the profit, as the minimum bid size is 1 MW, far beyond what a residential unit can provide.

Explicit DR from load shifting is, however, a fairly complex process due to the retailer's balancing responsibility. Any explicit load-shifting DR action requires a complementary action in the opposite direction; for example, dropping a load for one hour will require additional consumption at a later hour. There is no guarantee that this additional consumption, also called a rebound [47], can be bought before the time of consumption, forcing the retailer to pay the balancing energy price for it. It is thus reasonable to assume that the rebound is priced at the balancing price, which can vary widely and is revealed only after delivery (Figure 5a). However, the balance price is formed from the mFRR up- and down-regulation prices (Figure 5b), meaning it also determines the values for the initial DR action. The optimal explicit DR can thus be found through the same optimization as before, but with the balancing price rather than the spot price. The interpretation is different, though, because balancing prices are not known in advance. The savings from optimizing against balancing prices thus constitute an upper bound, whereas they reflect actually achievable savings when optimizing against spot prices. We can nonetheless determine this upper bound to understand what is possible. A first rough estimate can be obtained from the simple example used for spot prices in Figure 1c, namely by determining the possible savings from concentrating all consumption from a uniform consumption profile on the cheapest hour. This gives 8.4 cents/kWh, which can be compared to 3.9 cents/kWh for the spot price (Figure 1c), thus indicating an increased savings potential.

To get better estimates of the upper bound, we ran the daily optimization for each group's (Figure 5d) hourly heating demand against the balancing price. The savings potential for most groups approaches 6 to 7 cents/kWh as the flexibility level is increased to $\pm$12 hours (Figure 5e). By subtracting out the contribution from implicit spot-based DR, we see that the additional savings from explicit DR to the mFRR market appear to saturate around 2.5 cents/kWh for most groups (Figure 5f). The reason is that balancing price dips tend to be short, and the heating system's maximum power is too low for most groups to provide the heating energy required to cover longer breaks from brief charges. The exceptions are groups 11 and 12, which have more power available, as these groups have a system intended to charge a heat storage during nighttime. Focusing on the group of consumers as a whole, 90 % of all consumers have a yearly heating-based upper mFRR DR savings bound below 170 € at a flexibility level of $\pm$1 hours, and this increases to roughly 290 € at $\pm$12 hours (Figure 5g). These savings are again fairly modest and most likely smaller than those achievable with implicit spot-based DR, as only a fraction will be available in practice, where prices are not known in advance, and the final profit must be shared with an aggregator. In addition, the hardware requirements for explicit DR are clearly higher than for implicit spot-based DR. Focusing at a specific savings threshold like 200 €, a reasonable lower threshold due to unknown prices and profit sharing, 4 %, 13 %, 24 %, and 29 % of the consumers reach it for the flexibility levels $\pm$1, $\pm$3, $\pm$6, and $\pm$12 hours, respectively (Figure 5h).

4. Discussion

The increasing share of intermittent renewable energy sources, such as wind and solar, requires additional grid flexibility to balance supply and demand. DR, where demand deviates from normal consumption patterns, is considered an untapped source of flexibility with high theoretical potential. Here, we sought to better understand the achievable potential and timeframe for residential DR by evaluating realistic savings for residential consumers. We developed a framework to evaluate savings from both implicit (price-based) and explicit (incentive-based) DR and applied it to residential consumers in the Vasa region of Finland, using hourly data from 15854 consumers in 2023. The framework consisted of a novel method for grouping these consumers by the shape of their consumption profiles and an optimization routine for evaluating savings across all groups by optimally shifting consumption across various flexibility levels. Our findings show that potential savings grow similarly across most groups with greater flexibility, that implicit spot-based DR is likely more profitable than explicit mFRR-based DR, but that realistic savings remain modest. Below, we put these findings in perspective to see how they affect the achievable residential DR potential and how the potential might evolve in the future.

4.1. Risk aversion and contract types

The determined savings assumed that consumers already had a contract that allowed them to benefit from providing implicit spot-based DR. However, it is well known that consumers are risk-averse [6, 26], and the majority of consumers, both in this dataset and in Finland and Europe overall, still have fixed-price contracts [23, 48]. This was also clearly evident in the examined dataset: consumers with the most flexible loads still predominantly had fixed-price contracts and thus did not benefit financially, despite already concentrating consumption during low-priced nighttime hours (see Figure 2e and i). DR potential is thus likely withheld due to contractual reasons, as consumers do not find contracts that strike the right balance between perceived risk and DR savings. There is a push at the European level towards hybrid contracts to address this issue [6], and electricity retailers in Finland began offering a special type of hybrid contract in 2024 [49]. This hybrid contract consists of a fixed component per kWh and a spot-based consumption component equal to the difference between the consumer's profile cost and a flat profile cost for the same energy. The spot-based component is thus negative for consumers who tend to use electricity when it is cheaper, effectively lowering their total cost (these are the consumers with a profile cost below 1 in Figure 2i). Hybrid contracts thus pass along the benefits of implicit spot-based DR to consumers without exposing them to the full price risk of volatile spot prices. An interesting follow-up to this study would be to evaluate whether consumers with the most flexible loads switched to these newer contracts, and, if not, why.

4.2. Hybrid heating systems

Electrical heating is very common in Finland, Sweden, and Norway [22, 23], and official statistics for Finland report over half a million dwellings with electrical heating (ground heat excluded) [50]. This would imply a huge potential for residential DR. However, detached houses with direct electrical heating are expected to easily reach an annual consumption above 20 000 kWh, and yet these are rare in the dataset used (Figure 1e). Others have noted a similar discrepancy and attributed it to official statistics assuming that households only utilize one heating system, whereas hybrid heating systems appear to be the norm [51]. In fact, Numminen et al. [51] recently found that only 2 % of detached houses rely solely on direct electrical heating, and 79 % have a hybrid heating system using 2 or 3 heating sources, with the most common combination being wood, direct electrical heating, and air-to-air heat pumps. So, although many dwellings probably initially relied on direct electrical heating, that is no longer the case. This transition to hybrid heating systems has two implications when it comes to load shifting DR: 1) the saving potential will be smaller than expected, as the real yearly consumption will be lower than for direct electrical heating only, and 2) the investment cost might be higher, as many systems need to be automated instead of just one. Both negatively affect the savings-to-cost ratio, making it less likely that a consumer will participate in load-shifting DR. The hybrid solutions nonetheless facilitate load shedding as electricity-based heating might be replaced with other sources like wood, and this likely helped lower the electricity consumption in the Nordics during the 2022 energy crisis [25, 51]

The findings in [51] were based on survey data, but the described transition towards hybrid heating systems is also clearly evident in the data analyzed here. The fraction of electricity consumed for heating is expected to lie between 60 and 70 % for buildings with direct electrical heating [21], but most groups have a heating fraction below this. Only group 5 stands out with a heating fraction clearly above the rest. However, cabins appear to be common in this group. The high fraction, therefore, most likely indicates that group 5 contains several smaller houses kept warm by direct electrical heating, with very low other consumption, as they might not be inhabited all the time. For the remaining groups, hybrid heating systems are most evident in groups 9 and 10. These have heating fractions below 50 % (Figure 4e and f), despite having an evening peak around 22:00-23:00, indicating the presence of a water heater. It is thus very likely that these consumers initially relied primarily on direct electrical heating due to the presence of the water heater, but have since been retrofitted with an air-to-air heat pump; alternatively, they rely partly on wood. Nonetheless, our data strongly support the notion that the half a million dwellings with electrical heating reported in official statistics provide a highly misleading view of the achievable DR potential, as hybrid heating systems appear to be the norm. This observation is probably not specific to Finland but applies broadly, as hybrid heating systems are common elsewhere in the world [52, 53]. The observation rather highlights the complexity of estimating achievable DR potentials.

4.3. Load-shifting and thermal mass

Our results clearly indicate that even large loads, such as the heating system, must be able to shift loads by ±3 hours, and preferably more, before the yearly savings clearly exceed 100 €. This requires a heat storage that can release heat to keep indoor temperatures fairly stable even when the heating system is switched off. The storage could nonetheless be the building itself, in which case the building's mass and materials determine the storage capacity. A common building practice globally is to build detached houses and low-rise dwellings on concrete slab foundations, and the majority of such dwellings in Finland are built on insulated concrete slabs that can provide storage capacity [54]. The concrete slab is typically around 100 mm thick ([55]) and thus provides a mass of around 240 kg/m^2 ($\rho = 2400$ kg/m^3), and a heat capacity of 240 kJ/(m^{2}K) ($c = 1$kJ/(kgK)).

The heating demand per unit floor area and heating degree is around 1.5 W/(m^{2}K), closer to 1 for newer buildings and closer to 2 for older [56]. This is roughly 5 kJ/(m^{2}hK) or 75 kJ/(m^{2}h) when the outside temperature is around 0 °C (15 heating degrees). Consequently, the concrete slab could, in theory, provide floor heating for 3 hours for every degree it can be heated (1 or 2 hours more in newer buildings). Modern detached houses (from 2000 onwards) often combine geothermal heating with a water-based floor-heating system in which pipes are embedded in the concrete slab, thereby heating the slab directly. Such buildings might therefore manage to keep indoor temperature fluctuation within ±1 °C while providing a flexibility level of ±3 hours throughout most of the year, and perhaps up to ±6 hours or more if there is additional wall mass (stone or log houses). In contrast. dwellings categorised with electric heating tend to be older and have air-to-air heat pumps, or heating panels or radiators under the windows that heat the inside air instead. The concrete slab is therefore heated only indirectly, via radiation from walls and roofs, followed by conduction through the floor material. Consequently, it becomes more challenging to use the concrete slab for heat storage and floor heating. These older buildings are therefore less likely to reach a flexibility level of even ±3 hour without causing discomfort.

So, although Finland has half a million dwellings with electric heating, the achievable load-shifting DR contribution is likely much smaller than the theoretical potential would imply. The majority of these dwellings have hybrid heating systems that heat the air rather than the concrete slab. The level of load-shifting flexibility is thus likely too low to yield sufficient savings to motivate automating the various subsystems. More modern buildings, in contrast, are better insulated and often equipped with water-based floor heating and air-to-water or geothermal heat pumps. This makes it possible to more effectively use the concrete slab as a heat storage, and, consequently, these buildings are better suited for load-shifting DR. For newer heat pumps, it is even possible to activate implicit DR with the push of a button, effectively making the investment cost zero [57]. Counterintuitively, load-shifting DR is thus likely to grow in proportion to the number of homes equipped with water-based floor heating and new heat pumps, as this combination offers greater flexibility and near-zero additional investment cost for implicit DR.

4.4. Timeframe for Future residential DR growth

The identified savings potential across all consumer groups is modest, suggesting that load-shifting DR is likely to be initially implemented in situations with high annual consumption, high flexibility level, and low investment costs. This includes primarily newer heat pumps and electric vehicle chargers, for which the software might already support implicit DR with zero additional investment. Consequently, the achievable DR potential is expected to grow gradually as older systems and appliances are replaced with newer ones that include built-in DR support. However, there are a couple of exceptions to this. New legislation coming into force during the fall of 2026 will require DSOs in Finland to allow consumers to give third parties control over the relays in their smart meters [58]. Most water heaters that turn on systematically between 22:00 and 23:00 are already controlled by these relays and could, in theory, become price-controlled without rewiring or additional hardware. This legislation might therefore make a large share of the daily peaks seen in Figure 1g and Figure 2c follow the spot price through implicit DR (the end-to-end latency of current smart meters is insufficient for explicit DR [59]). A second exception is the new hybrid contracts, which should suit certain consumer groups well, in particular those who already have a large water tank (heat storage) and heat both tap water and the heating system water at night (groups 11 and 12). A simple change from a fixed-price contract to a hybrid contract ought to lead to considerable savings, and there is a good chance the load can be price-controlled with a fairly small investment, since it is already time-controlled. In fact, in many cases, these loads are likely already controlled by the smart meter's relay. In addition, groups 11 and 12 had the highest potential for additional earnings from explicit DR on the mFRR reserve market, and their loads are likely responsive enough to sell flexibility to other reserve markets as well.

Dishwashers, washing machines, fridges, and freezers are unlikely to contribute to DR at current electricity prices, despite being mentioned in most residential DR potential estimates and surveys [19, 22, 27, 29, 31–34]. Modern fridges and freezers typically consume a couple of hundred kWh per year. Assuming a flexibility level of ±3, this implies a savings potential around 2 cents/kWh, or roughly 4 €/year (Figure 3d). Similarly, the dishwasher's realistic potential was found to be roughly 20 €/year at best, assuming usage shifted from dinner time to the middle of the night every single day. The washing machine has similar values as it consumes roughly the same amount of energy as the dishwasher. Consumers might thus be unwilling to pay for a DR feature in these appliances, and widespread adoption would likely require regulation that mandates that all new appliances include one. However, it is also questionable whether people would think these savings are enough to bother running these appliances based on spot prices, even if a DR feature was built in. In addition, consumers in Finland and Europe in general are likely to face power tariffs in the future, as DSOs try to prevent consumers from concentrating too many loads in the cheapest hour/quarter [60]. These appliances would thus also have to coordinate with heat pumps and EV chargers, which most likely already use cheap hours/quarters, to avoid adding loads when consumption is already high and incurring extra costs.

5. Conclusion

We introduced a novel methodology for grouping electricity consumers and used it to evaluate realistic savings for residential consumers in Finland from both implicit and explicit load shifting DR. The results indicate that savings scale similarly across consumer groups as flexibility in time increases, meaning the ability to shift loads over longer periods, but remain modest. In addition, the results confirm three important observations for estimating achievable DR potentials. 1) Residential consumers appear risk-averse, as the consumers with the most flexibility to offer predominantly had fixed-price contracts. 2) Hybrid heating systems are the norm; only a small fraction of consumers had a consumption matching the expectation for direct electric heating, whereas many showed clear signs of hybrid heating systems. 3) The possible savings for many household appliances are so small that it is questionable whether consumers would ever consider DR for them. Overall, the results highlight that previous studies that focused on the economic potential of DR likely overestimated the contribution of households with electrical heating. The realistic yearly savings are typically so low that retrofitting older systems might be considered too costly, and the achievable DR potential is therefore more likely to grow slowly over time as older systems and buildings are replaced. These findings provide important insights for estimating the achievable DR potential in general, and the proposed framework generalizes to estimate achievable DR savings in other countries.

CRediT authorship contribution statement

Johan Westö: Conceptualization, Methodology, Software, Writing - Original Draft, Visualization. **Hafiz Imam:** Software, Visualization.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Grammarly and Copilot in order to detect and correct grammatical errors and unclear statements. After using these tools, the authors reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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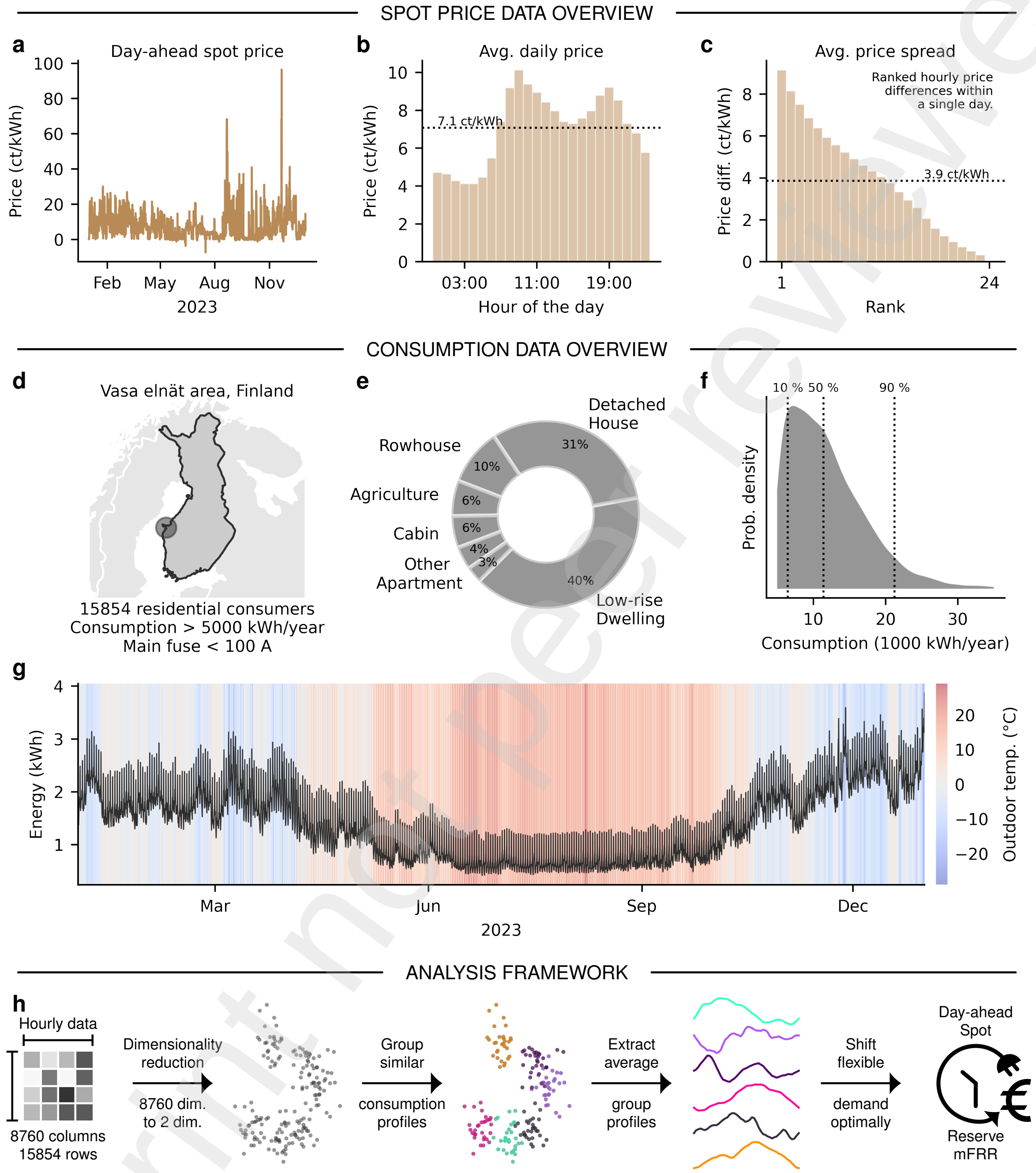

Figure 1: Overview of the datasets and the analysis framework. **a)** Hourly Finnish spot electricity prices in 2023 (including 24 % VAT). **b)** Average hourly spot price across all hours of the day; the dotted black line denotes the average price. **c)** Average intra-day price spread: the difference between the most expensive hour, the second most expensive hour, etc., and the cheapest hour; the dotted black line shows the mean of all 24 differences. **d)** Map showing the approximate area of Vasa Elnät where the analysed consumers are located. **e)** The retailer's categorisation of the analysed consumers. **f)** Annual electricity consumption of all consumers. **g)** Average hourly consumption for all consumers during 2023. **h)** High-level overview of the analysis framework going from hourly consumption data to potential savings from implicit (day-ahead spot) or explicit (mFRR reserve market) DR.

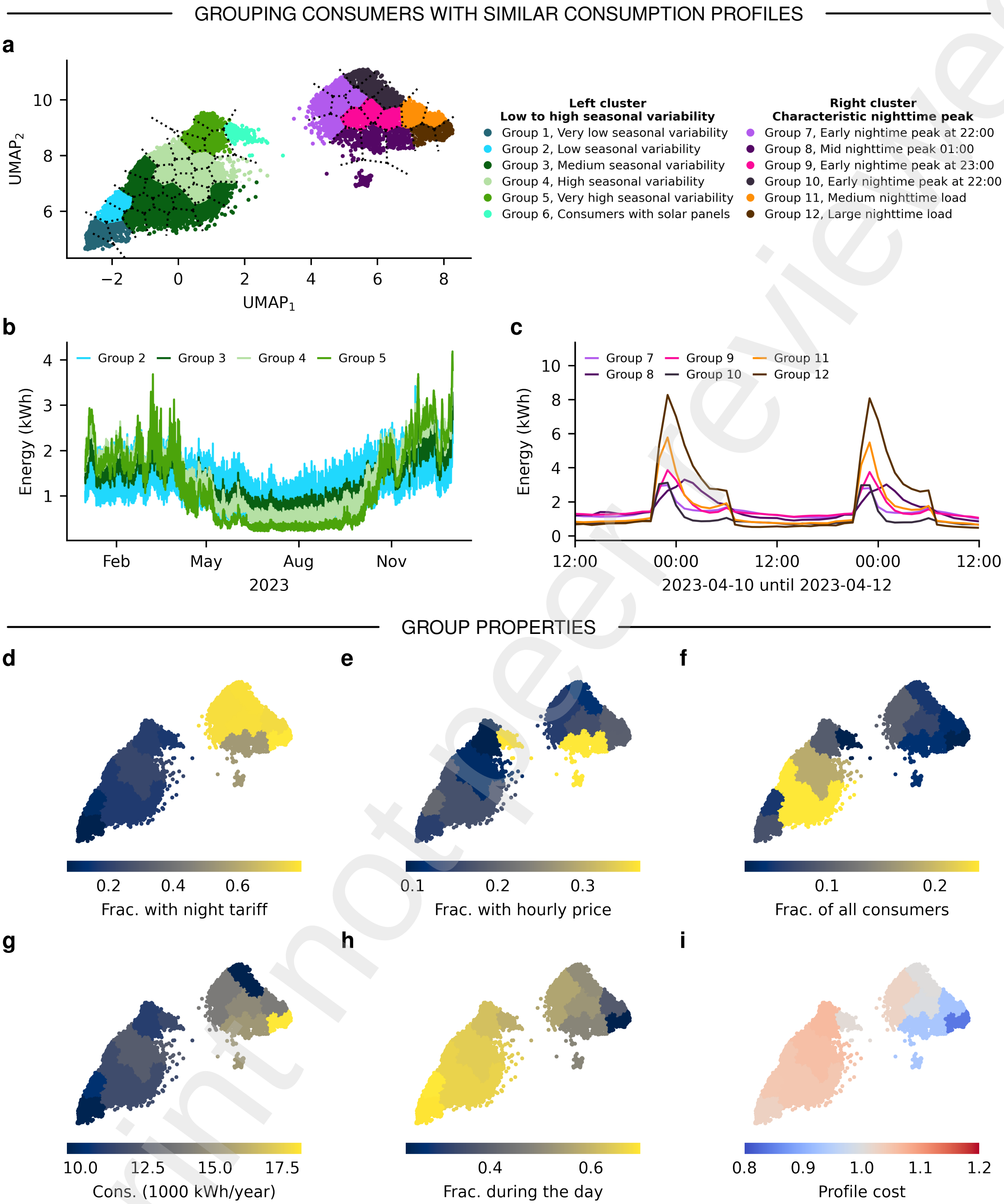

Figure 2: Consumer segmentation and validation into representative groups. **a)** UMAP-based dimensionality reduction visualizing each consumer as a point in a scatter plot, where nearby points are consumers with similar profiles. The tessellated blocks (black dotted lines) represent 50 initial groups with similar profiles, which can be further merged based on similarity to base the analysis on arbitrary detail (the colors depict the used detail level of 12 groups). **b)** Yearly average profiles for the consumers in groups 2 to 5. **c)** Daily average profiles for the consumers in groups 7 to 12, depicting their characteristic nighttime peak. **d)** The fraction of consumers in each group with a day/night tariff. **e)** The fraction of consumers in each group with a real-time hourly spot-priced contract. **f)** The fraction of all consumers located in each group. **g)** The average annual consumption for each group. **g)** The average fraction of all consumption that occurs during daytime (07:00 to 22:00) for each group. **i)** The average profile cost for each group.

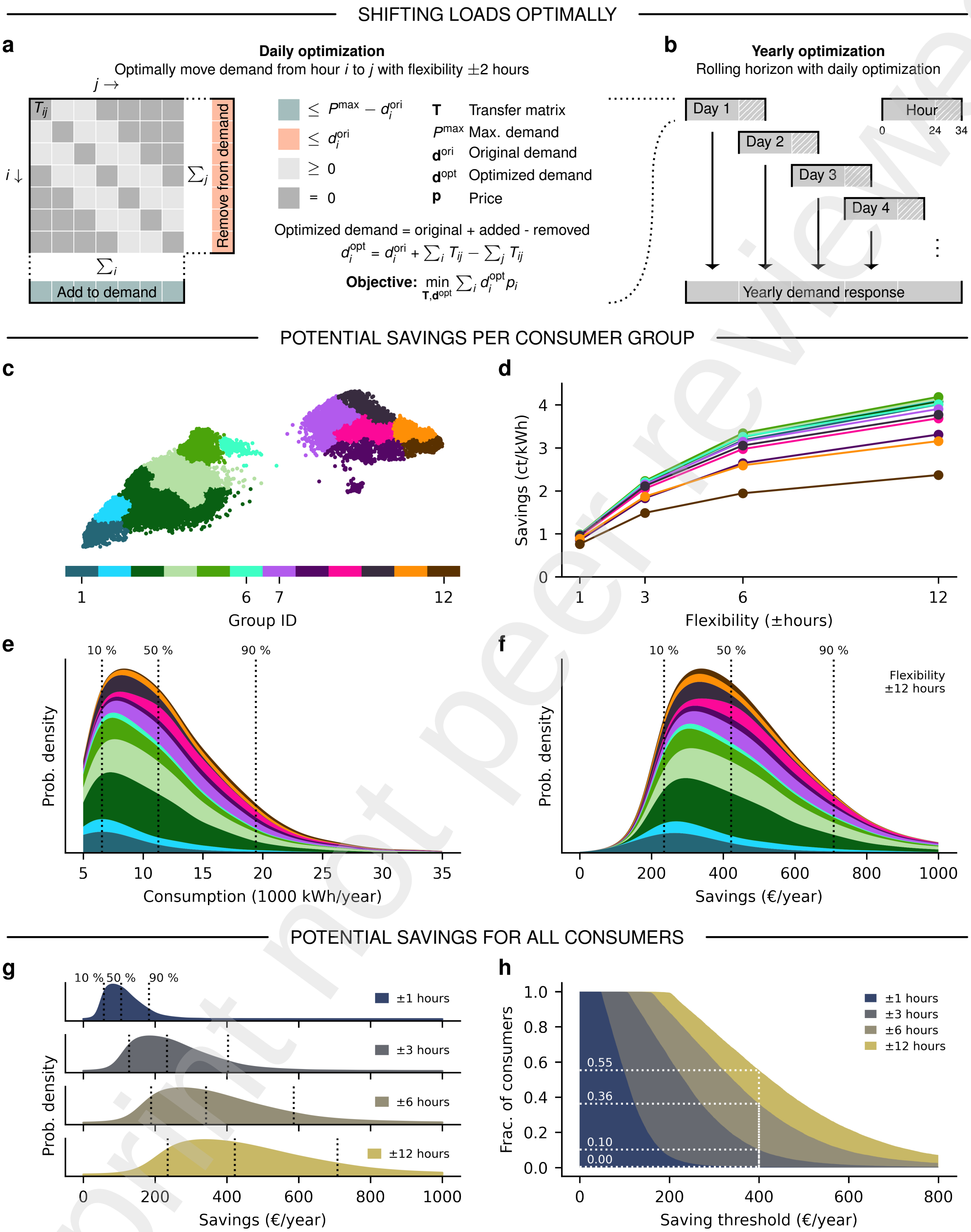

Figure 3: Savings from shifting all consumption optimally with implicit (spot) DR. **a)** Optimal load shifting is formulated as a linear programming problem via a transfer matrix, with the objective of minimizing the cost of procured electricity while satisfying constraints. **b)** The optimization is run daily with a rolling horizon to produce an optimal demand response for the whole year. **c)** The UMAP-based consumer groups analyzed. **d)** Savings per kWh when optimizing the average profile for each group at various flexibility levels. **e)** Annual consumption for the consumers within each group. **f)** Annual savings for the consumers within each group at a flexibility level of ±12 hours. **g)** Annual savings for all consumers at various flexibility levels. **h)** Fraction of all consumers with savings greater than a given threshold at various flexibility levels.

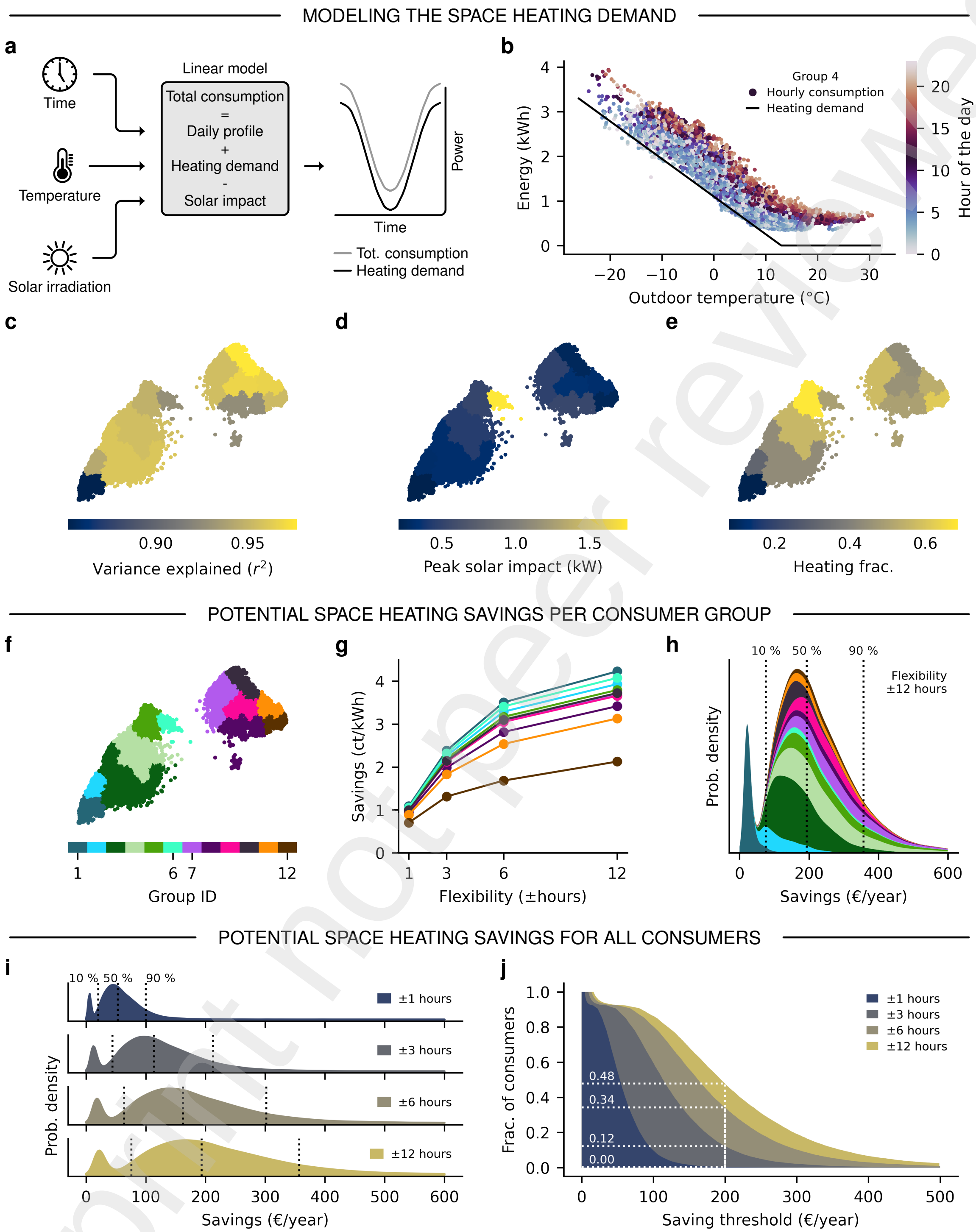

Figure 4: Savings from shifting space-heating-based consumption optimally with implicit (spot) DR. **a)** Linear model used to model total consumption and heating demand. **b)** The average hourly consumption and predicted heating demand for group 4 versus outdoor temperature. **c)** The variance explained (r^2) for the model fitted to each group's average profile. **d)** The peak solar impact from each model's solar irradiation coefficient. **e)** Each group's heating fraction extracted as the annual space-heating demand divided by the total consumption. **f)** The UMAP-based consumer groups analyzed. **g)** Savings per kWh when optimizing the space heating demand for each group at various flexibility levels. **h)** Annual savings for the consumers within each group at a flexibility level of ±12 hours. **i)** Annual savings for all consumers at various flexibility levels. **j)** Fraction of all consumers with savings greater than a given threshold at various flexibility levels.

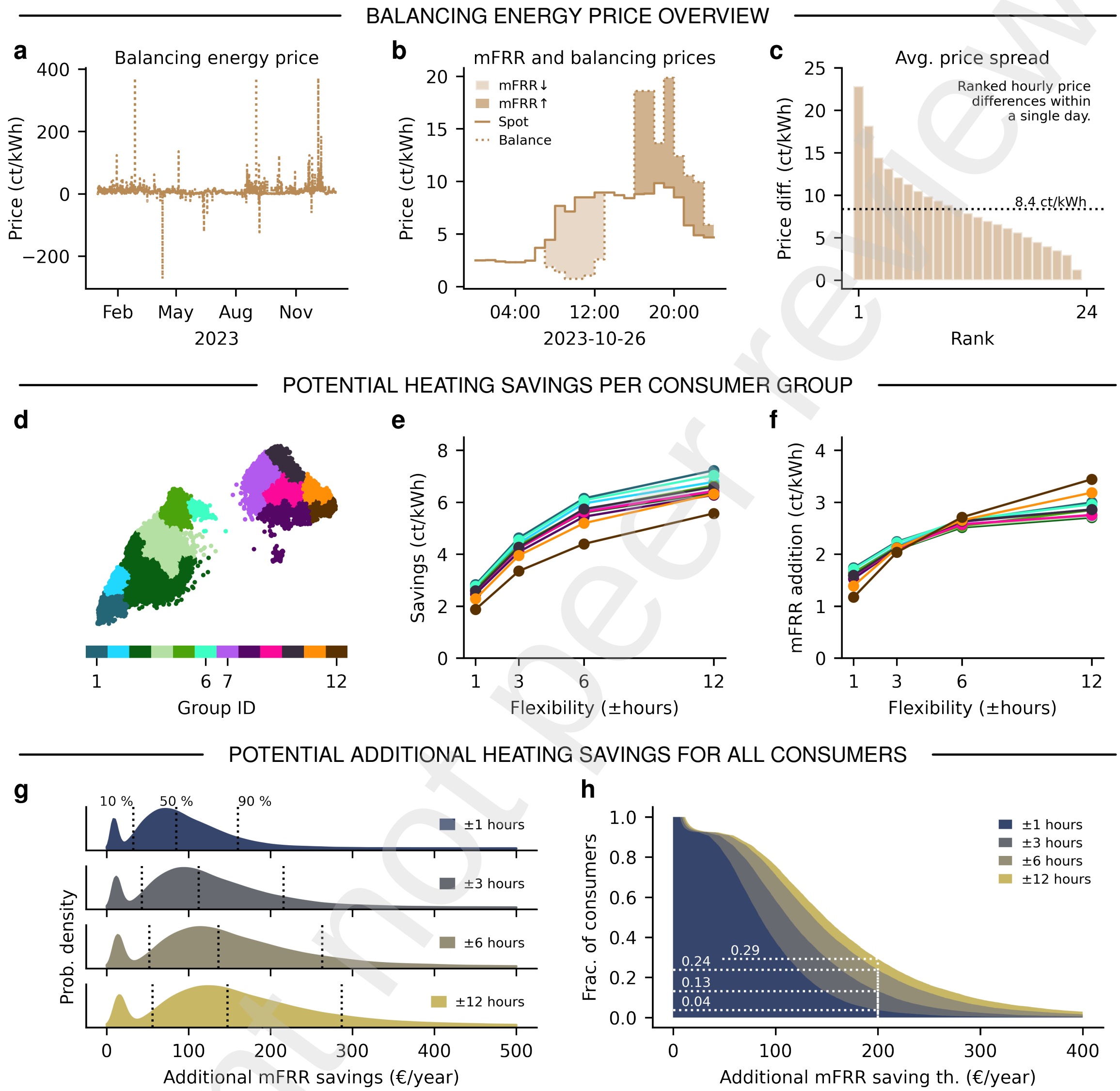

Figure 5: Upper bound for savings from shifting space-heating-based consumption optimally with explicit (mFRR) DR. **a)** Hourly Finnish balancing energy prices in 2023 (including 24 % VAT). **b)** mFRR and balancing energy prices for one example day. **c)** Average intra-day price spread: the difference between the most expensive hour, the second most expensive hour, etc., and the cheapest hour; the dotted black line shows the mean of all 24 differences. **d)** The UMAP-based consumer groups analyzed. **e)** Savings per kWh when optimizing the space heating demand for each group at various flexibility levels against the balancing price. **f)** Additional savings per kWh from explicit (mFRR) DR at various flexibility levels. **g)** Upper bound for the additional mFRR-based savings for all consumers at various flexibility levels. **h)** Fraction of all consumers with an upper bound greater than a given threshold at various flexibility levels.