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Practice of a Load Shifting Algorithm for Enhancing Community-Scale RES Utilization

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Abstract: Amidst the recent energy crisis, the pivotal roles of resource efficiency and renewable energy sources (RES) for sustainable development have become apparent. The transition to sustainability involves decentralized energy solutions empowering local communities to generate, store, and utilize their energy, diminishing the reliance on centralized systems and potentially transforming them into resources for power flexibility. Addressing the above necessities, amongst other elements, the adoption of advanced demand-side management (DSM) strategies. In response, we introduce a versatile algorithm investigating the impact of DSM on the community scale, designed to maximize the utilization of renewable energy produced from local installations. Integrated as an ancillary module in a research data management platform, the algorithm underwent testing using historical datasets collected from end-consumers and a small-scale RES installation. This study not only offers insights for energy stakeholders, but also establishes theoretical parameters that can inform subsequent decision-making processes in the field.

Keywords: demand side management; load shifting; energy communities; renewable energy sources



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1. Introduction

The recent energy crisis underscores the pivotal role of energy and resource efficiency alongside further exploitation of renewable energy sources so as to achieve sustainable development. Shifting towards a sustainable future involves decentralized energy solutions [1] and local communities [2] generating, storing, and using their own energy, gradually diminishing reliance on centralized systems [3], or even positioning them as flexibility resources [4,5]. Above all, this transition is driven by the adoption of energy storage technologies [6,7], with battery storage holding a key role in the support of distributed RES power generation.

To that end, although storage costs are assumed to decrease in recent years [8], value-adding aspects of advanced energy management featuring sophisticated forecasting techniques [9,10] and demand side management (DSM) [11] can also be identified. Regarding DSM, its value comes down to the non-capital-intensive character of similar solutions in addressing the mismatch between the variable RES power generation and the inelastic—in principle—load demand, alongside additional services, such as with the support of system resilience in times of extreme weather events [12].

At the same time, however, it should be noted that the degree of DSM implementation is very much dependent on pricing incentives [13], as well as on end-user behavioral aspects [14]. Having said that, it may be argued that the beneficial character of DSM could be better reflected at the community and/or cooperative level, since, at the given scale, greater flexibility is anticipated due to the grouping of end-users [15] and the appreciation of a certain complementarity between different load demand profiles, which may in turn allow for a more effective application of DSM. This is, of course, relevant for either microgrid

(e.g., central PV station at the community level) or distributed (e.g., residential rooftop PVs) scale application of RES, with the second option also suggesting the development of narrower aggregation schemes, i.e., limited pools of end-users within a grid-bounded geographical community (e.g., (virtual) mini-grids within microgrids), addressing at the same time any land-use constraints regarding the development of centralized RES at the community level [16].

Acknowledging the above, we have developed a versatile algorithm to investigate the impact of DSM at the community scale [17–20], with the ability to examine different groups of end-users. The algorithm is designed to tap a predetermined, hypothetical flexibility potential, inherent in electricity demand, with the objective of maximizing the direct utilization of energy generated from local RES installations. Moreover, it stands as an ancillary software module, deployable in data-driven energy management platforms [21], while it can also take the form of a stand-alone design tool.

In its operational form, the proposed module queries day-ahead forecasts and feeds them into an optimization algorithm, which is tasked with identifying hour-long load demand adjustments that ultimately maximize the daily energy consumption covered by local RES installations. The adjustments maintain the daily energy demand unchanged, meaning that the proposed DSM strategy falls under the category of “Load Shifting”. The module iteratively executes this process, relating various adjustment levels with the direct consumption of RES, as detailed in the subsequent section. Such relations not only provide insights for energy stakeholders, but also offer theoretical thresholds to be taken into account in posterior optimization processes and decision-making modules.

2. Materials and Methods

The Materials and Methods section details the use case and the proposed framework.

2.1. The Use Case

In the present use case, a DSM strategy is employed to make the most of the electricity produced from a local RES installation. This involves tapping the flexibility of consumers’ electricity demand. The above is accomplished using an optimization algorithm. This algorithm utilizes time series of load demand and RES power generation to determine the most efficient load demand reallocation. In the present study, these time series extend over a 24 h period.

The load demand of a six-consumers group can be met by the grid and/or by a local solar photovoltaic (PV) installation. Both consumers and the RES installation are located on the island of Tilos [22], with the developed algorithm being, however, applicable in different settings and scales, able to cover both more centralized and distributed energy schemes. The optimization algorithm adjusts the initial load demand profile within specified margins to maximize alignment with solar PV power generation. These adjustments maintain the total energy demand unchanged, meaning that the proposed DSM strategy falls under the category of “Load Shifting”. Importantly, the solar PV power generation is upscaled. The actual nominal power of the installation is 3.36 kW_p, and the upscaled power is 10 kW_p.

The DSM strategy is applied in a day-ahead fashion, with hour-long timesteps. To carry this out, in this paper, we adopted the perfect forecast approach, i.e., using unaltered measurements registered to a particular time period.

A day’s worth of random load demand data is merged with the scaled measurements of the solar PV installation’s power output. This combined dataset acts as input for the optimization algorithm, accompanied by a set of hyperparameters defining the maximum allowable adjustments in load demand. The algorithm mainly generates two 24 h time series, indicating whether, and at what degree, the load demand should increase or decrease.

This process is iterated for various combinations of hyperparameters, using the same datasets. In each iteration, the consumption directly met by the solar PV installation is calculated, mapping the relationship between load shifting and the utilization of the local RES installation.

2.2. The Framework

The proposed framework evaluates the impact of DSM on RES utilization, under different levels of adjustments in load demand, in a repetitive fashion. To streamline this process, the framework steps are integrated into a pipeline, automating its execution.

Initially, the optimization horizon and the combinations of the maximum allowed power adjustments—towards both greater and lower values at each time step of the optimization horizon—are defined. Subsequently, the pipeline is executed repeatedly, according to the combinations' number, for a particular time period. The pipeline comprises the following six steps:

1. **Data acquisition and cleaning.** The pipeline commences with the retrieval of two datasets for the chosen time frame. After retrieval, data cleaning is rigorously performed based on the specific characteristics of each dataset. The cleaning process aims to remove duplicates—common when merging datasets from various sources—to correct structural inconsistencies (e.g., converting textual numerical data to their proper format), identify and remove outliers, and address missing entries, often represented as blank spaces, “NaN” (Not a Number), or placeholder values (e.g., −9999);
2. **Power upscale.** The cleaned datasets are upscaled, matching a hypothetical upscale in the nominal power of the local RES installation;
3. **Forecasting.** The processed datasets are tailored to meet the specific requirements of an external module, which generates predictions of the RES production and of the aggregate load demand. The prediction horizon is also provided to that module, as it should match the optimization horizon;
4. **Decision-making.** The obtained predictions are fed to an optimization algorithm, which computes the power adjustments for each time step within the optimization horizon;
5. **Performance evaluation.** The values of a set of Key Performance Indicators (KPIs) are computed;
6. **Storage of computations.** The raw, processed and forecasted data are stored, along with the given scenario characteristics, in a database. The database contents are visualized using an open-source monitoring platform, e.g., Grafana.

After completing the sixth step, the process returns to Step 4 and uses the next combination of the maximum allowed power adjustments as input. Once all the combinations are tested, the process is terminated.

2.3. Integration with Research Platform and Database

The -customized for the use case- pipeline was integrated with a research platform and database, as illustrated in Figure 1. The process begins by sourcing data from two repositories: one on the island of Tilos, and the other at the University of West Attica. These repositories provided data related to a 3.36 kW_p solar PV installation and load demand for a given pool of local consumers. Among these consumers, data related to the load demand for a subset of six consumers were maintained. Both connections were facilitated through the platform.

The datasets retrieved underwent a data cleaning process aimed at removing outliers, rectifying inaccuracies resulting from equipment malfunctions or communication errors, and filling in missing data. The detailed procedures for cleaning the data were tailored to the specific case and dataset in question, as further described in the following Section 2.4.

Additionally, the power-related intermediate dataset was upscaled to align with the output of a 10 kW_p installation, representing a potential upgrade from the current installation. Subsequently, the datasets were customized to fulfill the specific criteria of the forecasting module, i.e., set to perfect forecasting mode (with outputs matching inputs). Following this, data were directed to the optimization algorithm, computing operational signals for each time step within the optimization horizon. This involves typical actions for building an optimization model. Next, designated KPIs were computed. In this paper, only the RES utilization and the RES share in load demand were computed. Moreover, the

pipeline was executed multiple times for each of two fixed reference time-periods, enabling a comprehensive assessment of the DSM impact on RES shares.

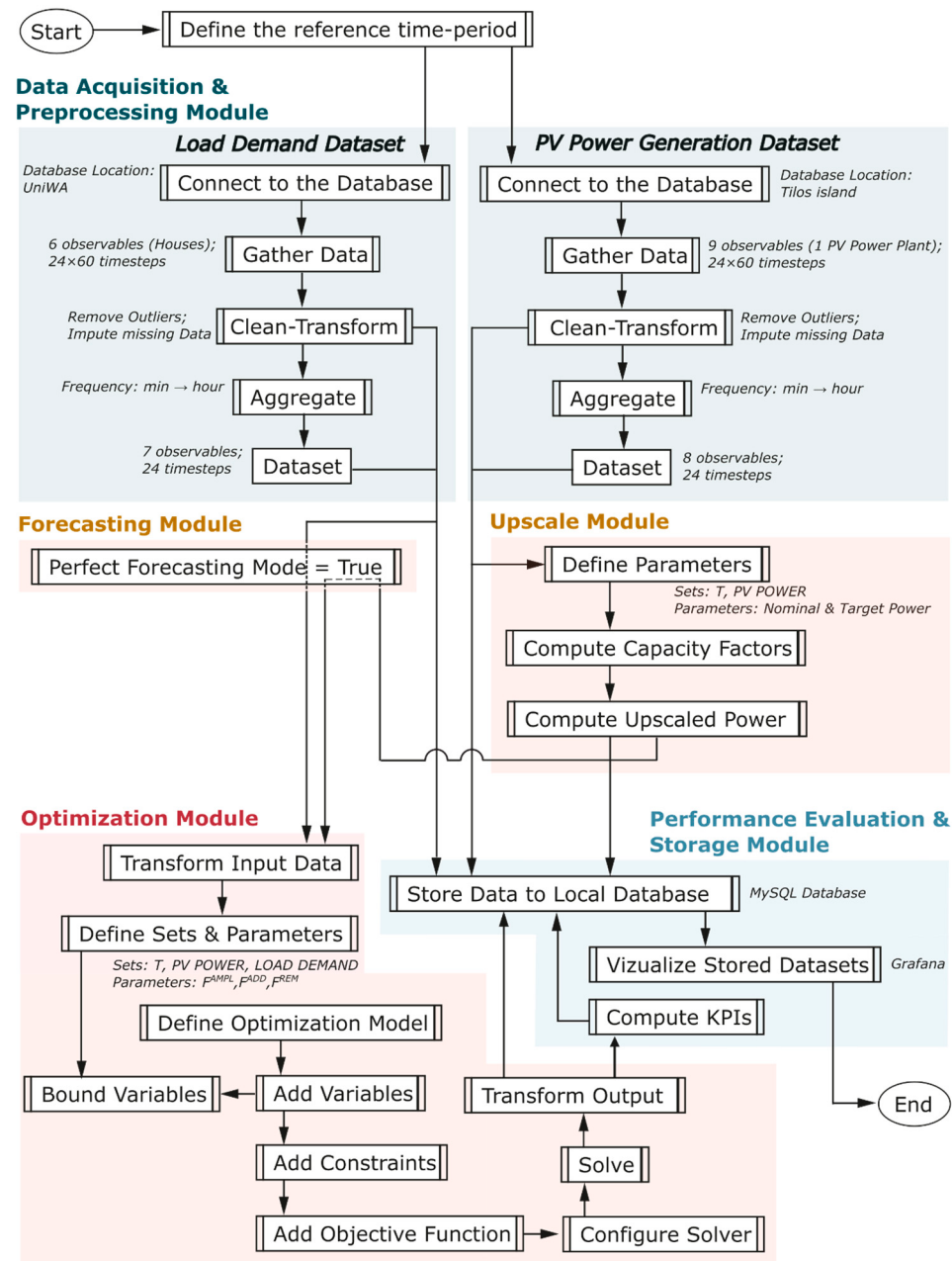


Figure 1. The flow chart of the pipeline.

2.4. Data Acquisition and Cleaning

Data used for the scope of the paper were retrieved in the context of a research project pilot implementation, concluded recently [21]. This was enabled through a data management research solution deployed by the University of West Attica and the Municipality of Tilos for the purpose of the project, integrating two, residential-scale photovoltaic installations, and a group of representative facilities for different types of end-uses (public buildings, households, commercial stores, hotels, electric vehicle chargers, and water pumping stations). The research platform, which supported the elaboration of services tailored to different stakeholders, was hosted in a central data server using custom algorithms for polling and pushing packets from/to final end points (facilities). The latter was then responsible for forwarding these data to a second collecting system for further processing,

i.e., design of management strategies and services, with the proposed pipeline comprising one of the designed services.

2.4.1. Load Demand

The utilized mean power measurements, or load demand, refer to six end-users and have a variable frequency, which for the majority of the dataset is 4 min. The raw data have 91,906 rows (timesteps) and 6 columns. The measurements start from 1 March 2022 00:04:00 and end on 7 March 2023 16:54:00, meaning that the time-length is 371 days and 16.8 h.

In the data validation stage, the processing steps are as follows:

1. Data time-index confinement. Data registered to the testing period of the installations that log the information are removed. This is in the period between 1 March 2022 00:04:00 and 20 March 2022 23:00:00. The new dataset's first timestamp is 21 March 2022 00:00:00;
2. Removal of potential data entry errors. Considering that the time series relies on real measurements and power usage naturally fluctuates, large numbers of consecutive identical values often suggest data entry errors. To address this, a sliding window test is used. This test identifies if a value is identical to the three preceding and three following values, flagging it for removal. The flagged values are then discarded, ensuring their replacement in subsequent steps. Importantly, the primary purpose of implementing this test is to eliminate extended periods, spanning several hours, during which data from the power meters are not received or are not correctly stored due to various faults, rather than removing single data points. Hence, the number of consecutive values tested in the procedure should be chosen to effectively eliminate these extended periods;
3. Outliers' replacement. Outlier replacement involves detecting and substituting outliers with empty entries marked by the symbol NaN (representing Not a Number) using the Z-score method for each end-user. The Z-score method is a statistical technique used to assess how far a data point is from the mean of a dataset, measured in terms of standard deviations. This method helps identify outliers by flagging data points that fall beyond a certain threshold from the mean. Common Z-score thresholds typically range from around -3 to $+3$ standard deviations from the mean. However, the specific threshold chosen can vary depending on the context and the desired level of sensitivity to outliers [23]. A Z-score threshold of ± 3 is more conservative and identifies extreme outliers, aligning with the goals of the analysis;
4. Time series resample. The 6 time series, one for each end-user, are resampled with a 1 h frequency. The missing values are filled with NaNs;
5. Data imputation or removal. Missing data are imputed using linear interpolation. If there is a substantial time gap in the missing data, values from the same time step on the previous day are employed as a substitute, if they are available;
6. Aggregations. The aggregate load demand is computed by summing the mean hourly power consumption of the six end-users.

The intermediate data have a shape of 8441 rows (hourly timesteps) and 7 columns. Their frequency is constant and does not contain any NaNs. In Figure A1 in the Appendix, the processed timeseries per end-user is illustrated. The aggregate load demand is shown in Figure 2. Two distinct days being part of this dataset are exploited in the present study.

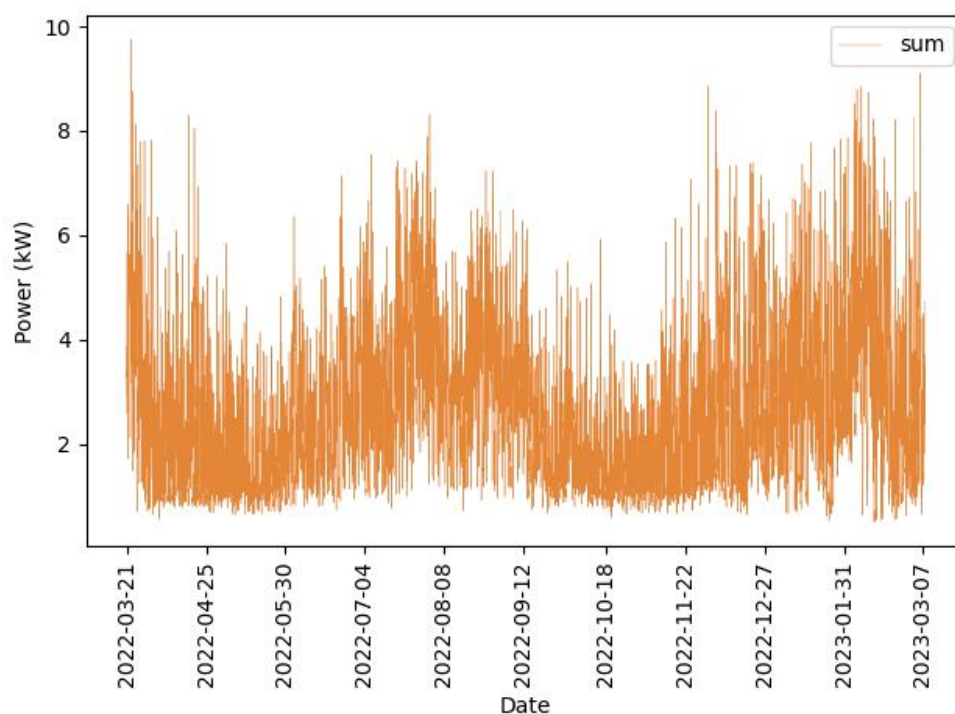


Figure 2. The aggregate load demand data, after the cleaning process.

2.4.2. Solar PV Power Generation

The data regarding solar PV power generation are registered to an installation of 3.36 kW_p. The installation is located on the island of Tilos. The retrieved data have nine columns, corresponding to the observables recorded by the installation's inverter, and 1440 rows (timesteps), as they correspond to one day's worth of data at a one-minute frequency.

The measurements start on 15 October 2023 00:00:00 + 03:00 and end on 15 October 2023 23:59:59 + 03:00. It should be noted that data during the very morning and afternoon, when solar PV generation is zero, are not logged; thus, one has to impute missing data accordingly. More specifically, the following steps are carried out in order to validate the data:

1. Data time-index confinement and resampling. Data are resampled, using the same frequency, in order to reindex them, so as to contain exactly 1440 timesteps, which correspond to one day. The missing values are filled with NaNs;
2. Data imputation or removal. Missing data are imputed using linear interpolation. If there is a substantial time gap in the missing data, values from the same time step of the previous day are employed as a substitute, if available;
3. Data resample. The data are resampled into an hourly frequency. The employed aggregation function is the mean. Various aggregation functions yield distinct strategies for managing uncertainty in the power generation side. For instance, choosing the first quartile (q1) is a safer alternative than opting for the third quartile (q3).

The resampled data are illustrated in Figure 3. The total energy production is ~17 kWh. These data are upscaled, as explained in the following section and subsequently consumed by the proposed DSM algorithm.

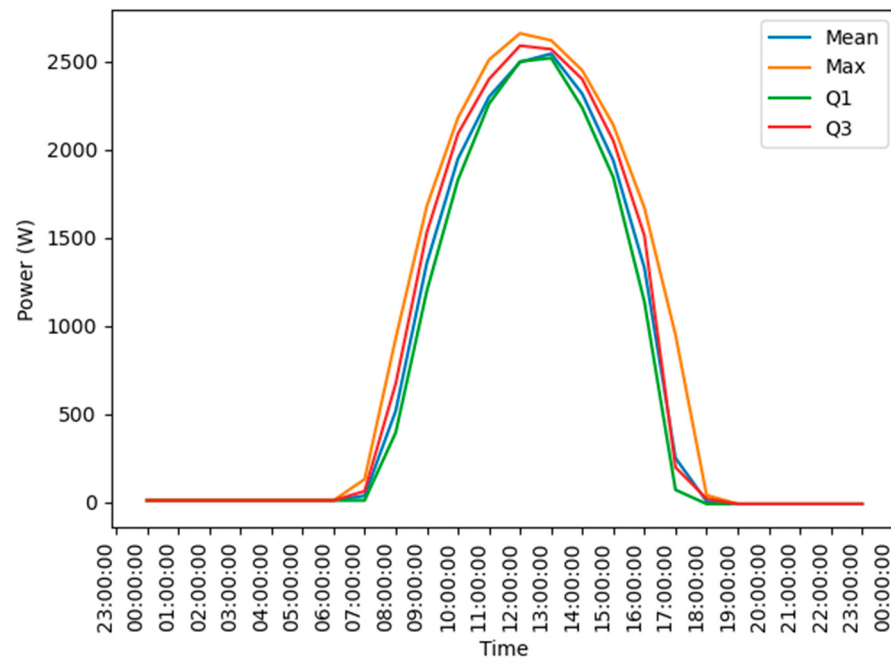


Figure 3. The power generation of the local solar PV installation, after the cleaning process.

2.5. Power Upscale

The power generation of the local solar PV installation is upscaled, matching a hypothetical upscale in the nominal power capacity. To carry this out, the capacity factor of the installation is initially computed for each timestep. Subsequently, the capacity factor is applied to the desired power capacity, yielding the scaled-up power generation curve.

2.6. Forecasting

In this paper, we opted for the perfect forecasting approach, as the influence of uncertainty is beyond the scope of our study. As a result, both the inputs and outputs of the forecasting module represent the processed measurements. Subsequently, those measurements are directed to the optimization module.

2.7. Decision Making

The decision making is carried out by an optimization model, which is based on linear programming. Its objective function minimizes the sum of the amplified violations v^{AMPL} , over the optimization horizon T , which, in our case is set to 24 timesteps t , as shown in Equation (1).

$$\text{Minimize} \left(\sum_t v_t^{AMPL} \forall t \in T \right) \quad (1)$$

The computation of v^{AMPL} is based on the violation v^{NRM} of the balance between the power p^{RES} , generated by the solar PV plant, and the proposed load demand l^{DSM} . The magnified value of v^{NRM} gives more weight to violations that occur when the RES power is increased, based on Equation (2).

$$v_t^{AMPL} = v_t^{NRM} * p_t^{RES} \quad (2)$$

The balance between p^{RES} and l^{DSM} is monitored through the constraint of Equation (3). Any imbalances are stored in the variable v^{NRM} .

$$p_t^{RES} - l_t^{DSM} - v_t^{NRM} = 0 \quad (3)$$

The l_t^{DSM} is linked to the original load demand (Baseline), l_t^{BL} , via Equation (4). In particular, the l_t^{DSM} is determined as the l_t^{BL} altered towards higher values by the variables p_t^{ADD} and towards lower values by the variable p_t^{RED} .

$$l_t^{DSM} = l_t^{BL} + p_t^{ADD} - p_t^{RED} \quad (4)$$

The power addition is limited to a fraction of the original load demand by the factor F^{ADD} , at each timestep of the optimization horizon, as shown in Equation (5). Similarly, the power reduction is limited using the factor F^{RED} , as shown in Equation (6).

$$p_t^{ADD} \leq l_t^{BL} * F^{ADD} \quad (5)$$

$$p_t^{RED} \leq l_t^{BL} * F^{RED} \quad (6)$$

Also, any power additions are meaningful only during timesteps where p_t^{RES} exceeds l_t^{BI} . The latter is introduced to the optimization model through Equation (7). Given that both p_t^{RES} and l_t^{BI} are known at the start of the optimization process, there is no requirement to model the if statement exclusively using binaries. Instead, this condition is integrated as a parameter, i.e., a list comprising zeros and ones.

$$p_t^{ADD} = 0 \text{ if } p_t^{RES} < l_t^{BI} \quad (7)$$

The opposite also stands for any power reductions. Those are meaningful only during timesteps where p_t^{RES} is available, thus p_t^{RES} being greater than zero. Given that p_t^{RES} is known at the start of the optimization process, the if condition is integrated as a parameter through Equation (8),

$$p_t^{RED} = 0 \text{ if } p_t^{RES} \geq 0 + F^{SEN} \quad (8)$$

where F^{SEN} is a sensitivity factor that mitigates the influence of measurements near zero. In the present study, that parameter is set to 100 W.

In the final step, Equation (9) is incorporated into the optimization algorithm, guiding the allocation of energy reductions across the two halves of the optimization horizon,

$$F^{fh} * \sum_{t=0}^{t=\lfloor \frac{T}{2} \rfloor} p_t^{RED} = F^{sh} * \sum_{t=\lfloor \frac{T}{2} \rfloor + 1}^{t=T} p_t^{RED} \quad (9)$$

where F^{fh} plus F^{sh} equals unity. Currently, these parameters are set to 0.5, evenly distributing the energy reductions across the two halves of the optimization horizon.

2.8. Performance Evaluation

The impact of DSM on RES Utilization is evaluated for each set of operational conditions. This involves computing RES Utilization for both the baseline scenario, $S = BL$, and the scenario incorporating DSM, $S = DSM$, as explained hereunder.

The amount of energy u that is produced by the RES installation and is directly consumed by the consumers is computed using Equation (10), over each time step t of the optimization horizon T , for each scenario S . The equation specifies that u equals the load demand, l , when the latter is less than the power generated from the local RES installation, p , and vice versa.

$$u_t^S = \begin{cases} l_t^S & \text{if } l_t^S < p_t^{RES} \\ p_t^{RES} & \text{if } l_t^S \geq p_t^{RES} \end{cases} \quad (10)$$

The load demand can be satisfied either by the grid or by the local RES installation. The RES share, s , is calculated for each day, d , as shown in Equation (11). The improvement, I , of RES share between the baseline scenario and the DSM scenario is computed using Equation (12).

$$s_d^S = \frac{u_d^S}{I_d^{S=BL}} \quad (11)$$

$$i_d = \frac{u_d^{DSM} - u_d^{BL}}{u_d^{BL}} \quad (12)$$

3. Results

The intraday behavior for different scenarios of load demand flexibility, i.e., defined by the level of permitted power adjustments, is next presented. Following this, the balance between load shifting and direct exploitation of RES is elucidated.

3.1. Intraday Behaviour of the DSM Algorithm

The DSM algorithm is designed to adjust loads according to the available solar PV power generation, with the goal of minimizing reliance on grid-supplied electricity. This section evaluates the intraday behavior of the algorithm across two distinct occasions and under four different load demand flexibility scenarios, which are as follows:

- Mild adjustments scenario. In this scenario, the hyperparameters limiting upward (F^{ADD}) and downward load demand adjustments (F^{RED}), in relation to load demand at a given timestep, are set to 10%;
- Moderate adjustments scenario. Both hyperparameters are set to 20%;
- Ample adjustments scenario. Both hyperparameters are set to 30%;
- Unrestricted additions scenario. The hyperparameter F^{ADD} is set to 100%, while allowing moderate reductions in load demand (F^{RED} is set to 20%).

Each occasion involves a random day's worth of load demand data and solar PV power generation. In particular, the first intraday behavior analysis involves load demand data recorded on 17 May 2022 and solar PV power generation data on 15 October 2023. The aggregate energy demand is 44.3 kWh, and the solar PV energy yield is 50.9 kWh. The second analysis involves load demand data registered to 26 April 2022, with a corresponding energy demand of 105.9 kWh, while maintaining the same data regarding the RES power generation.

In terms of the algorithm's load demand reallocation priorities, it is directed to slightly prioritize increasing load demand during time periods when RES power is elevated. Additionally, the algorithm is guided to evenly distribute decreases in load demand between the first and second halves of the day.

The intraday behavior for the scenario with mild adjustments is shown in Figure 4a. Starting at the beginning of the day and continuing until the solar PV installation starts generating power, the optimization algorithm chooses to reduce load demand. Subsequently, the algorithm chooses to increase load demand until the afternoon (16th timestep), when solar PV power generation decreases significantly. The increase is directly proportional to the initial load demand curve, resulting in greater load demand values receiving greater load demand increases, and vice versa. Also, with the daily energy demand remaining constant, these additions are enabled by the choice to reduce load demand again during the afternoon (after the 18th timestep).

Increasing the adjustment limits, F^{ADD} and F^{RED} , makes the load demand significantly more flexible, resulting in further reductions in grid-supplied energy. This is illustrated in Figure 4b,c, where the limits increase to 20% and 30%, respectively, shifting more loads beneath the solar PV power curve. The adjustment pattern remains consistent with that of the scenario with mild adjustments. However, both reductions and additions in load demand are proportionally larger.

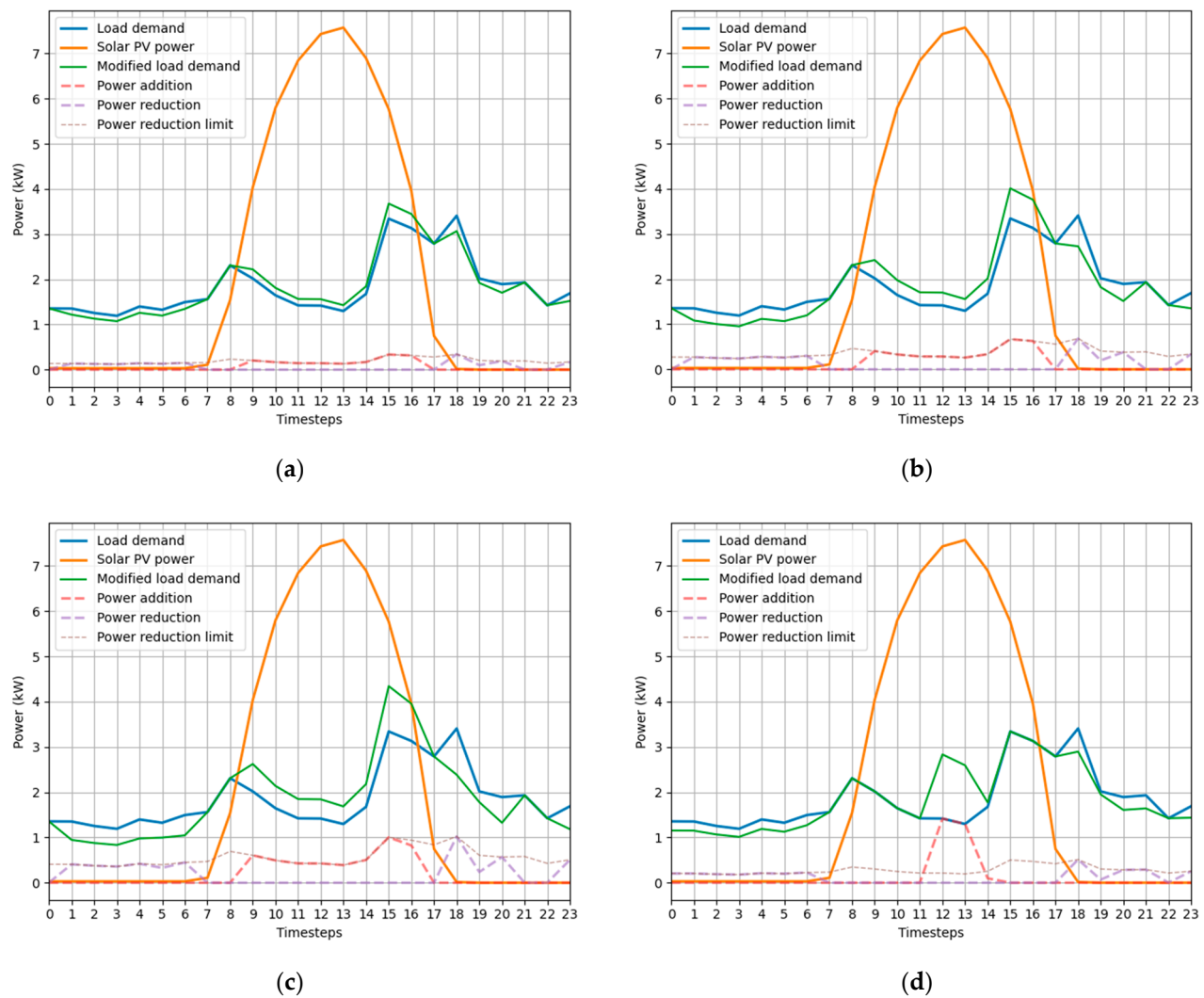


Figure 4. The intraday behavior for 44.3 kWh of energy demand with (a) mild; (b) moderate; (c) ample; and (d) unrestricted increase and moderate decrease limits.

In Figure 4d, where load demand additions are unrestricted, a different adjustment pattern is observed. The optimization algorithm concentrates the load demand near the 12th timestep, where solar PV power maximizes. This behavior is a direct result of the constraint as shown in Equation (2). Thus, for an exceedingly high setting of F^{ADD} , the load demand pattern becomes less uniformly distributed in time.

Using the load demand data registered on the 26 April 2022, where the energy demand is more than double compared to the first analysis, load shifting is primarily driven by the hyperparameter F^{ADD} . On the given day, load demand is high during the early and late timesteps when solar PV power generation is zero, while during time periods with significant solar PV power generation, load demand is low. This load demand pattern, with identical settings for F^{RED} and F^{ADD} , results in significantly larger power reduction limits compared to power addition limits. Consequently, increasing the setting of F^{ADD} is more crucial for overall load demand flexibility compared to F^{RED} . These observations become prominent in Figure 5a–d.

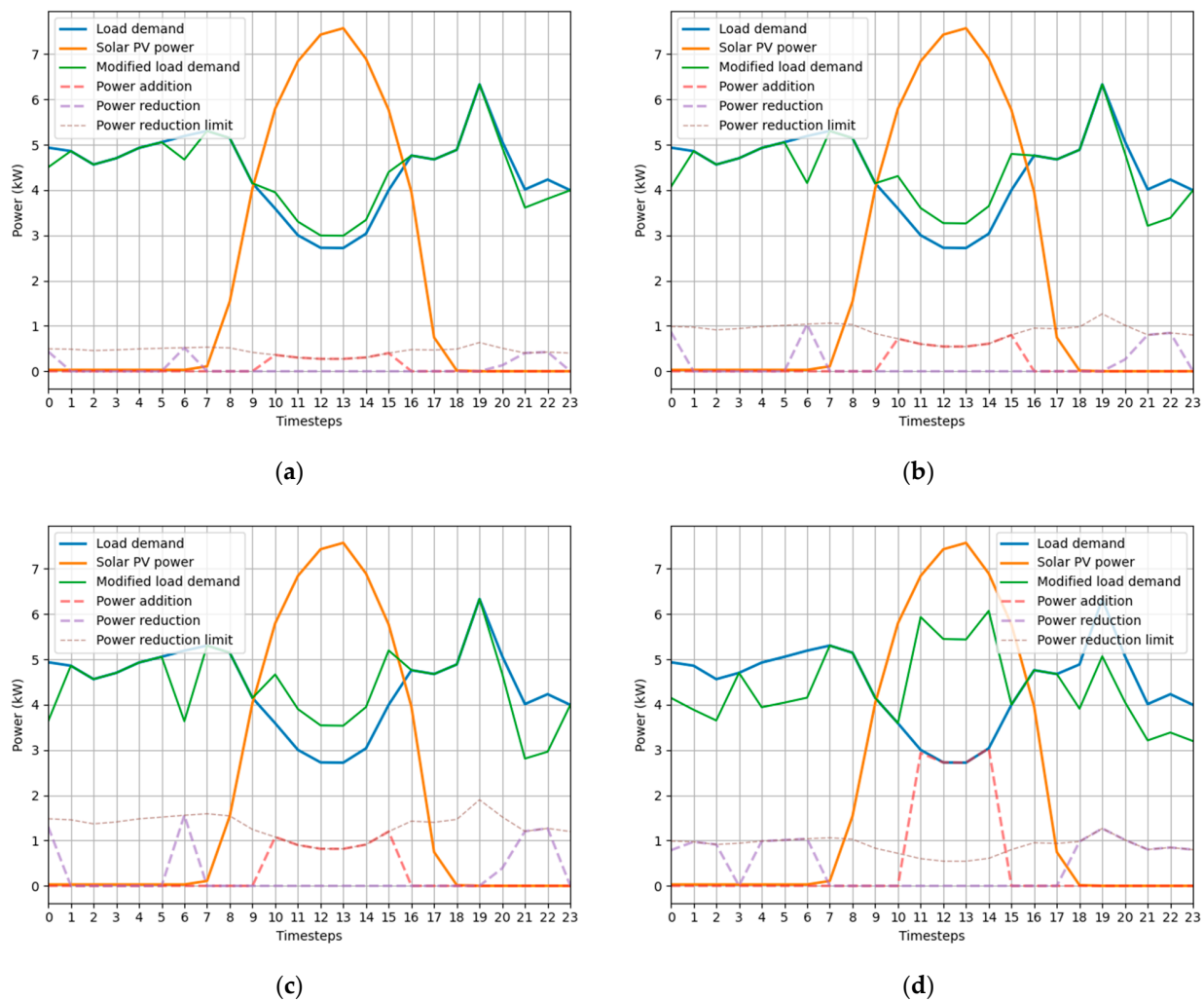


Figure 5. The intraday behavior for 105.9 kWh of energy demand with (a) mild; (b) moderate; (c) ample; and (d) unrestricted increase and moderate decrease limits.

3.2. Analysis of the Load Demand Flexibility Impacts on the RES Shares

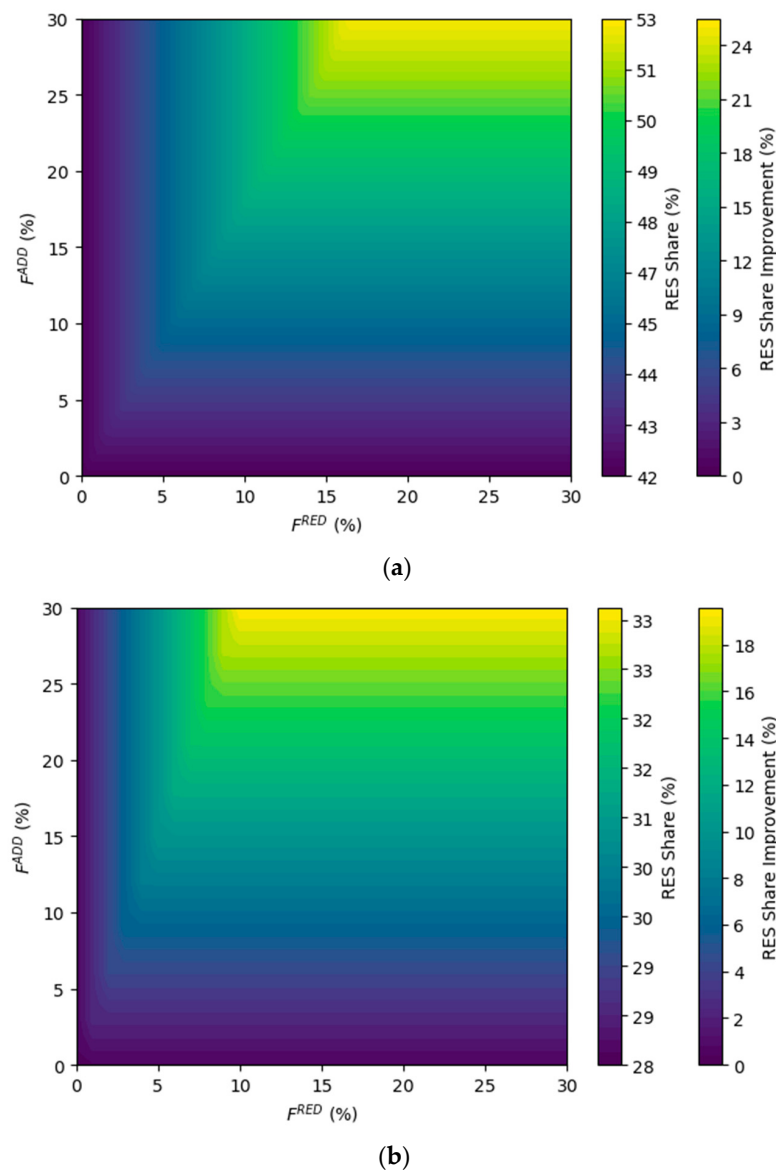
The load demand can be satisfied either by the grid or by the local RES installation. The RES share for each load demand dataset and each flexibility scenario (combination of F^{ADD} and F^{RED}), discussed in the previous section, is reported in Table 1.

By setting both parameters, F^{ADD} and F^{RED} , to 30%, i.e., an increased limit, the RES share can reach up to approx. 52%. This represents a substantial improvement of 25% compared to the baseline scenario, where load shifting is prohibited. In the case of a higher energy demand (i.e., 105.9 kWh), the improvement tops at 19.3%, which is considerably lower than the achieved improvement when there is a lower energy demand (i.e., 44.3 kWh).

Examining the flexibility scenario wherein F^{ADD} and F^{RED} are set to 100% and 10%, respectively, results in further enhancements in RES shares, reaching 38.5% for the higher-energy-demand dataset and 30.3% for the lower-energy-demand dataset. While the improvement is substantial in both cases, it follows a different path (pairs of F^{ADD} and F^{RED}) for each scenario, indicating that different combinations of F^{ADD} and F^{RED} prove to be more suitable for distinct load demand curves that present different intraday behaviors. This becomes evident in Figures 6a and 6b, where the RES share is depicted in relation to the F^{ADD} and F^{RED} parameters. Both figures illustrate that increasing the value of F^{ADD} exerts a more significant impact on RES shares compared to increasing F^{RED} , up to a specific point, beyond which further enhancements are constrained. That point is approx. (15%, 27%) and (10%, 27%) for the lower- and higher-energy-demand datasets, respectively.

Table 1. The RES utilization for different load demand flexibility scenarios.

Energy Demand (kWh)	Flexibility Scenario	RES Consumption (kWh)	RES Share (%)	Improvement (%)
44.3	Baseline	18.6	41.9%	-
	Mild	20.2	45.5%	8.6%
	Moderate	21.8	49.1%	17.2%
	Ample	23.2	52.4%	25.1%
	Unrestricted Additions	24.2	54.6%	30.3%
105.9	Baseline	29.7	28.0%	-
	Mild	31.6	29.8%	6.4%
	Moderate	33.5	31.6%	12.9%
	Ample	35.4	33.4%	19.3%
	Unrestricted Additions	41.1	38.8%	38.5%

**Figure 6.** The influence of the load demand flexibility in RES shares for a daily energy demand of (a) 44.3 kWh and (b) 105.9 kWh.

Comparing Figures 6a and 6b also indicates that for the particular load demand patterns, when the daily energy demand grows, for a given F^{ADD} , a smaller F^{RED} is necessary for improving the RES share by the same amount. Thus, smaller adjustments in load demand are necessary, in terms of percentages.

4. Discussion

The examination of the intraday behavior of the DSM algorithm reveals its responsiveness to different load demand flexibility scenarios, under different daily energy-demand datasets. The algorithm demonstrates that increased flexibility, as expressed by higher load-demand adjustment limits (F^{ADD} and F^{RED}), results in a more pronounced reduction in grid-supplied energy. The algorithm prioritizes load adjustments during periods of increased RES power generation, distributing load decreases evenly throughout the day. Also, under scenarios with unrestricted additions, the algorithm concentrates load demand near peak solar PV power generation, leading to a less uniform distribution over time.

The analysis of the load demand flexibility impact on the achieved RES shares showcases the algorithm's ability to optimize load shifts for exploiting RES. The algorithm's ability to shift load demand according to F^{ADD} and F^{RED} settings significantly influences RES utilization, ranging from 6% to 25% for smaller to larger interventions in the load demand curve.

Also, the analysis exhibits the significance of tailoring distinct combinations of F^{ADD} and F^{RED} to specific load demand and power generation patterns, with the optimal choice contingent upon the desired intraday behavior. The impact of increasing the adjustment limits on RES shares is more pronounced up to a certain threshold, beyond which further enhancements are constrained. This insight underscores the critical consideration of load demand patterns and associated parameters in optimizing DSM algorithms for enhanced RES integration.

In prospective research endeavors, attention could be directed towards the practical application of the cascading optimization approach. This involves the sequential stacking of two models, where the output of the initial model becomes the input for the second. Within this framework, there is a specific focus on leveraging the outputs generated by the presented DSM algorithm, using a second optimization model, for the optimal allocation of the load demand adjustments to distinct energy-intensive appliances. The investigation will center on exploring the practicality and effectiveness of this approach, as well as on evaluating the scalability and efficiency of this cascading optimization framework, especially as the optimization timestep duration decreases from hourly to minute intervals.

Moreover, future research could also encompass extension of our model both in terms of involved components and KPIs, which, for example, may refer to the incorporation of storage and/or back up diesel genset models, coupled with DSM strategies, towards, e.g., the improvement of end users' resilience against events of adverse weather conditions.

5. Conclusions

In summary, this study extensively explored the day-to-day behavior and impact of a versatile DSM algorithm, focusing on adjusting aggregate load demands and evaluating the relevant effect on RES shares. The algorithm applied using processed data from consumers and a solar PV power plant situated on the island of Tilos in Greece, aims to maximize renewable energy utilization, providing early insights for DSM applications.

The study underscores the effectiveness of load shifting in reducing grid-supplied energy, also highlighting that increased load-demand flexibility markedly reduces grid-supplied energy. In the baseline scenario, a solar PV power installation with a 10 kW_p nominal capacity covers approximately 42% and 28% of the daily energy demand in low- and high-demand scenarios, respectively. Implementation of DSM resulted in enhancements to RES shares, ranging from 6% to 25%, contingent on load-demand adjustment limits that varied up to 30% of the hourly load demand. Thus, the pivotal role of enhanced load-demand

flexibility, indicative of the ability to shift loads, is underscored in achieving substantial reductions in grid dependency.

The study also emphasizes the critical importance of considering the load demand patterns and associated parameters in optimizing DSM algorithms to strategically prioritize load additions during period of high-RES power, hence enhancing RES integration, with minimum intervention in consumers' behavior, or else the load demand curve.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su16135679/s1>.

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Nomenclatures

T	The optimization horizon
t	The timestep of the optimization
v_t^{AMPL}	The amplified violation of the balance between load demand and power generation
v_t^{NRM}	The violation of the balance between load demand and power generation
p_t^{RES}	The power generated from the local RES installation
I_t^{DSM}	The proposed load demand
I_t^{BL}	The actual load demand
p_t^{ADD}	The suggested increase in load compared to the current load demand
p_t^{RED}	The suggested decrease in load compared to the current load demand
F^{ADD}	The parameter to limit the suggested increase in load demand
F^{RED}	The parameter to limit the suggested decrease in load demand
F^{SEN}	The parameter to mitigate influence of power measurements near zero
F^{fh}	The weight factor for prioritizing reduction in the first half of T
F^{sh}	The weight factor for prioritizing reduction in the second half of T

Appendix A

Appendix A contains the processed load demand data of six consumers, located on the island of Tilos, Greece. The data are registered to the time period between 1 March 2022 00:04:00 and 7 March 2023 16:54:00, and are shown in Figure A1. Moreover, to enhance the reproducibility of the findings and the method and also demonstrate the robustness of the algorithm against the variation in basic hyperparameters, a set of examples employing synthetic load demand and PV production data for a day's period is provided in the form of Supplementary Material.

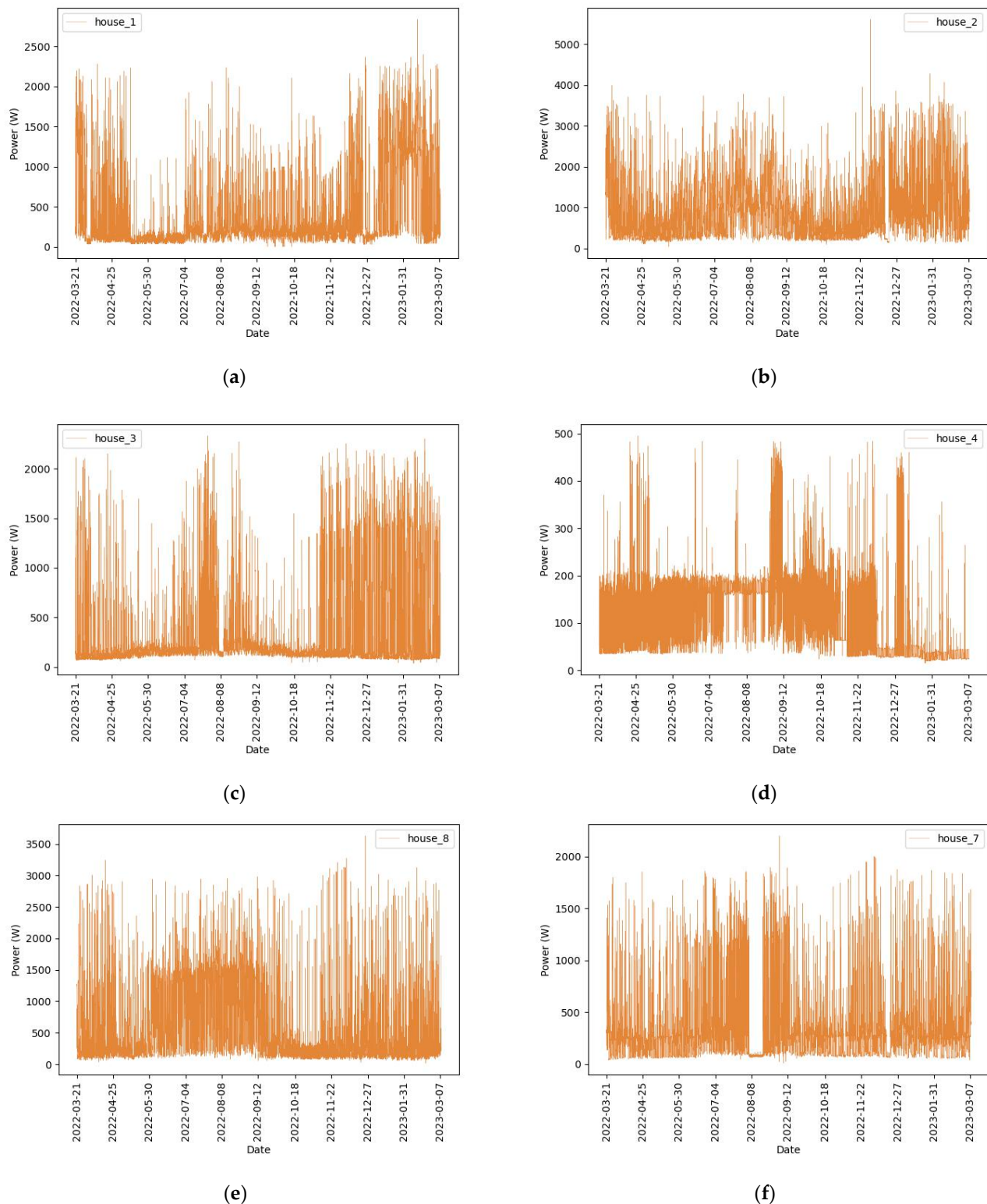


Figure A1. (a–f) The mean hourly load demand data of the six consumers examined after the cleaning process.

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