The object of the study is operational planning in decision support systems (DSSs) for prosumers. The study addresses a lack of explicit flexibility modeling in DSSs and a limited understanding of how forecast quality impacts planning results.

A novel control module for short-term planning of flexible energy demand and battery dispatch in prosumers is presented. The proposed solution improves prosumers' information support by integrating consumption and generation forecasts, user-defined flexibility preferences, and battery constraints to reduce operational costs and increase profit from energy sales via optimal planning. Unlike methods that obscure decision logic, the module enables explicit flexibility modeling, enhancing transparency and better reflecting individual behaviors. Validation using real-world data across diverse prosumer segments confirms the module's robustness and effectiveness in achieving cost savings.

The module maintained positive cost improvements under realistic and extreme forecast errors (up to 75%) across most flexibility settings, with performance influenced by forecast accuracy and flexibility configuration. A linear dependency was found between forecast error and cost savings. In rare edge cases – very low flexibility and high forecast error – the control plans led to underperformance. Increasing flexibility relaxes accuracy requirements, highlighting an important trade-off. Higher flexibility led to stronger initial performance but faster degradation as forecast errors increased. Lower flexibility setups declined more slowly but were more prone to underperformance in edge conditions.

These findings offer practical insights into flexibility modeling and forecast error tolerance, enabling improved planning and control design for prosumers

Keywords: decision support system, prosumers, photovoltaics, operational planning, forecast error

UDC 004.89:621.31
DOI: 10.15587/1729-4061.2025.340758

IDENTIFYING THE IMPACT OF FORECAST ERRORS AND FLEXIBILITY PREFERENCES IN DECISION SUPPORT FOR OPTIMAL DAY-AHEAD PROSUMER OPERATIONAL PLANNING

Oleh Lukianykhin
Corresponding author
PhD Student*
E-mail: oleh.lukianykhin.a@gmail.com
Vira Shendryk
PhD, Associate Professor, Head of Department*
*Department of Information Technology
Sumy State University
Kharkivska str., 116, Sumy, Ukraine, 40007

Received 10.07.2025
Received in revised form 11.09.2025
Accepted 22.09.2025
Published 31.10.2025

How to Cite: *Lukianykhin, O., Shendryk, V. 2025). Identifying the impact of forecast errors and flexibility preferences in decision support for optimal day-ahead prosumer operational planning. Eastern-European Journal of Enterprise Technologies, 5 (2 (137)), 107–121. https://doi.org/10.15587/1729-4061.2025.340758*

1. Introduction

Prosumers are now a widespread element of modern power systems. Their presence has steadily increased over the past decades, becoming a key trend in grid development. As prosumers organize into microgrids and participate actively in energy flows, they contribute to the growing structural complexity of the grid [1]. While integrating individual prosumers already posed technical and operational challenges, managing large numbers of interconnected prosumers introduces new ones [2].

A common source of complexity in both cases is the inherent uncertainty of the physical processes involved. Renewable energy generation is highly stochastic [3], and consumption in distributed settings can become even more variable and harder to predict than in centralized systems [4]. This uncertainty presents serious challenges for power system operators and prosumer facility managers, particularly in areas such as short-term and long-term planning or efficient resource allocation [5].

While many operational processes can be partially automated, human involvement is still required for key decisions [6], which is also true for the power system domain [7]. Human operators or facility owners must frequently make planning and operational decisions under the aforementioned uncertainty. In such a context, decision support systems (DSS) can assist by helping operators and facility owners navigate uncertainty and make informed decisions, for example, in wind farm management [8]. To this end, such systems should combine technical system information with user-specific preferences to provide actionable recommendations. This combination allows for better efficiency and adoption, as shown in studies [9] and [10], where user experience is taken into account in the integration of electric vehicle into the grid and prosumer DSSs, respectively.

Decision support systems of different types and applications are common in the power systems domain. They are used at various scales and levels of the power grid, but often include a key component that can be characterized as a control module, as in study [11]. By control module, let's mean the part of the DSS that identifies the optimal course of action suggested to the decision-maker responsible for the task, e.g., a power system operator in a control room or the operator of a prosumer facility.

Therefore, research aimed at improving control modules in DSSs for prosumers is relevant. It allows for increasing the overall efficiency of DSSs and, therefore, improving the results of prosumer planning.

2. Literature review and problem statement

In [12], the authors employ optimization algorithms to improve the integration of a large number of prosumers into the energy market. Rule-based systems are also frequently applied, as shown in the review of expert systems for power plants [13]. These studies demonstrate how classical methods can be successfully applied, particularly due to their well-studied properties and their ability to meet formal requirements for implementation in real grids. However, such approaches are unable to address the growing structural complexity and scale of modern energy systems. This creates a need for the development of new methods.

Recently, as discussed in reviews [14, 15], AI approaches have gained popularity, including a wide variety of machine learning (ML) methods applied to different parts of DSS. Despite their growing popularity, both reviews show that the application of AI in energy systems remains rather basic, even primitive. Thus, there is a need for further research, as existing applied solutions are not yet mature, while the use of AI models and ML methods offers considerable potential. In some cases, machine learning (ML) models are trained to directly predict the optimal scenario or course of action, or highlight an issue. For example, in [16], reinforcement learning is used to smooth electricity consumption peaks through a voltage controller. However, such automated solutions leave the issue of practical implementation unresolved, particularly regarding compliance with formal network regulatory requirements. One potential approach to address this problem is the development of hybrid systems. In such a system, ML models predict future states of the energy system (e.g., generation forecasts), while actual control suggestions are generated based on these predictions. The creation of these suggestions most often relies on classical methods, such as fuzzy logic, or even rule-based systems, as in [17, 18]. In a number of studies, a DSS just presents ML model output to the user. For example, in an efficient format, as in [8], where generation forecasts are provided to the user along with corresponding visualizations. Alternatively, a system may issue warnings about potential system failures in specific future scenarios, as in [17]. Despite the advantages and effectiveness of hybrid systems in these studies, unresolved issues remain in integrating complex ML methods with non-trivial classical methods in DSSs.

Numerous studies focus on improving the performance of ML models for specific tasks, such as generation forecasting. The authors in [19, 20] aim to identify general patterns and guidelines for effective forecasting of renewable energy sources. At the same time, studies [21, 22] focus on enhancing forecast accuracy for wind and solar generation, respectively. However, the number of studies on integrated design of control modules within DSSs, combining advanced classical methods with ML approaches, remains limited. Existing work, such as [23], often integrates ML models with simple postprocessing logic, typically rule-based systems, or aims at developing fully automated control solutions rather than DSSs. The literature becomes even sparser when the objective is to build a DSS that explicitly incorporates prosumer operator preferences into its control module, rather than relying on hard-coded constraints. Although a few energy management systems do account for user comfort, they are primarily focused on building or HVAC applications, not on prosumers. For example, the system described in [24], aims to optimize the functioning of a building's energy system, including from the perspective of comfort. However, this system cannot be directly applied to prosumer facilities, as it aims to optimize the use of available energy resources rather than the possibility of generating profit. Nevertheless, such examples suggest the feasibility of combining ML models with optimization methods while explicitly incorporating user preferences into the solution design.

Regardless, ML models are rarely fully precise and thus introduce additional uncertainty into the DSS planning process, i.e., identifying control suggestions. In [25], authors investigate the impact of data availability on the performance of model predictive control (MPC) for a building with smart energy storage. This indirectly addresses investigating forecast error impact on MPC performance in control planning, but the focus remains on the data aspect and energy system of a building. That is, the impact of forecast accuracy on planning outcomes remains an open question. In study [26], impact of forecast uncertainty on grid expansion planning from an economic perspective is analyzed. Similarly, in study [27] the economic implications of forecast error on the operation of a simulated virtual power plant are investigated. These studies highlight the importance of moving beyond forecast accuracy metrics and assessing the impact of forecast precision on downstream task performance. However, in the power system domain, it remains scarcely studied how forecast quality influences the performance of the optimal planning stage of the decision support process, particularly in the context of DSS for prosumers.

Therefore, there is an evident research gap in prosumer DSSs at the intersection of two directions. First, the gap relates to the development of integrated prosumer DSSs that combine ML-based forecasting with classical mathematical methods while accounting for prosumer flexibility preferences. Second, there is a gap in understanding how forecast quality affects the efficiency of operational planning for prosumers. Consequently, research is needed to address these gaps. Filling these gaps has practical significance for the further development of both real-world implementations and academic research in the field of prosumer DSSs.

3. The aim and objectives of the study

The aim of this study is to determine the impact of prosumer flexibility preferences and forecast quality on the efficiency of operational planning. This will enable the improvement of prosumer DSS performance in operational planning tasks through the use of optimal combinations of forecast quality and prosumer flexibility. To achieve this aim, the following objectives were set:

– to develop a control suggestion module for a prosumer DSS with explicit modeling of prosumer flexibility preferences;

– to conduct experiments assessing planning efficiency under different flexibility configurations;

– to conduct experiments evaluating DSS performance under varying levels of forecast error in combination with different levels of flexibility.

4. Materials and methods

4. 1. Object of the study

The object of this study is operational planning in DSSs for prosumers.

The main hypothesis of the study is that suggestions for prosumer facility management can be effectively generated based on consumption and generation forecasts, using optimization methods and taking user preferences into account. This hypothesis relies on the assumption that the mathematical formulation of the optimization problem can not only represent the dynamics of the prosumer's operational processes, but also take into account the prosumer's preferences. A further assumption was made that an optimization-based module can generate effective control suggestions for managing a prosumer facility in terms of achieving defined economic objectives.

Several simplifications were used in the research process. First, the available historical data is considered accurate. In other words, the uncertainty introduced by measurement errors or possible data inconsistencies was not explicitly considered as a factor affecting the final planning result. Second, the evaluation of planning quality is based on the operator's strict compliance with the proposed plan, which may not always be realistic.

4. 2. Data

The dataset used in this study is publicly available prosumer data from Estonia, originally released by Enefit (Eesti Energia) as part of a Kaggle competition under the CC BY-NC-SA 4.0 license [28], which permits non-commercial research use. It contains historical hourly records of energy generation, consumption, and electricity prices from September 1, 2021, to May 30, 2023. The dataset covers 69 distinct prosumer microgrid segments of varying sizes, including both private households and business entities. While energy purchase prices are provided, the dataset does not specify separate prices for energy sales. To prepare the data for further utilization, the following pre-processing steps were performed:

1. Linear interpolation was applied to fill missing values in consumption and generation data. For instance, if values at hours 1 and 3 are available but missing at hour 2, the hour 2 value is estimated by linear interpolation between hours 1 and 3.

2. Missing installed capacity values were also linearly interpolated; where interpolation was insufficient due to extended gaps, backfill imputation was used to fill missing data.

3. Electricity prices were normalized by scaling down by a factor of 1,000 to convert units from EUR/MWh to EUR/kWh, ensuring consistency with the consumption and generation data units.

4. 3. Experiment procedure

By running an experiment with the same setup and the same random seed, it is possible to conduct a valid comparison of how results depend on a single changed parameter. In the case of the set objectives, it is reasonable to compare the module's performance with different levels of prosumer flexibility and different levels of forecast error.

To obtain a more robust estimate of the module performance, evaluation can be conducted over an extended time period available in the data. Final results can be aggregated for comparison using summary statistics, such as the mean and median of relative daily improvements.

The software implementation for conducting experiments was developed using the Python programming language with the SciPy library [29] for the main parts of the solution related to the control suggestion module and, in particular, optimization.

The solution to optimization problems that appear in planning in DSSs is often obtained using numerical methods. In particular, a constrained nonlinear programming approach with the Sequential Least Squares Programming (SLSQP) method is popular. For instance, the problem may be modeled with a linear cost function (total grid cost balance over time) and mostly linear equality and inequality constraints, with some nonlinear components. SLSQP has the following particularities:

– it fully supports nonlinear equality and inequality constraints, which are necessary for modeling battery state-of-charge (SoC) dynamics and energy balance accurately;

– it is efficient for problems with tens to hundreds of variables;

– it works well with dense constraint systems;

– it provides fast and computationally lightweight performance, which is important for its intended use as a control module in prosumer decision support systems.

Known limitations of the SLSQP method include its sensitivity to infeasible starting points and its difficulty handling highly nonconvex problems.

5. Results of the analysis of the impact of prosumer flexibility preferences and forecast quality on planning results

5. 1. Control suggestions module with flexibility preferences

5. 1. 1. Control module suggestions

The general goal of economics-aware prosumer planning is to minimize electricity costs and/or maximize profits from energy sales while satisfying prosumer needs. The proposed control module generates an optimal 24-hour action plan for a prosumer by leveraging forecasts of energy generation and consumption, as well as day-ahead electricity prices provided by the grid operator. It also incorporates individual preferences specified by the prosumer operator, which are discussed later in this section. Thus, the module implements the operational logic of the power system, taking into account the needs of prosumers. A schematic overview of the control module workflow is presented in Fig. 1.

It is important to note that the module is part of the DSS, meaning that the calculated optimal plan serves as a control suggestion for the prosumer operator, rather than as a plan to be executed automatically. This distinguishes the proposed system from fully automated solutions.

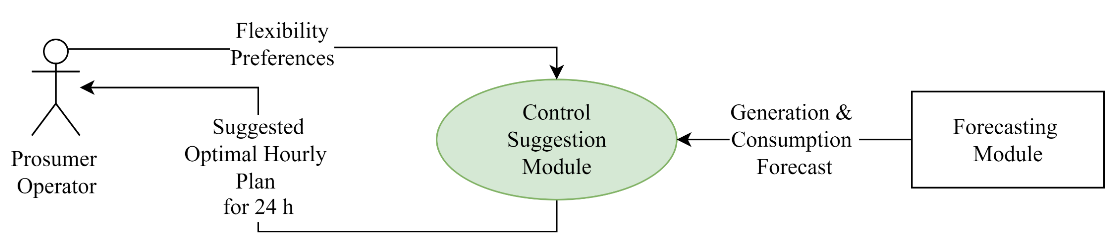

Fig. 1. The workflow of a control suggestion module in a decision support system

5. 1. 2. Proof of concept and flexibility preferences

First, a fundamental version of the prosumer planning problem was addressed: optimal consumption planning based on day-ahead electricity prices. This formulation served to validate the feasibility of the proposed approach and to provide a proof-of-concept implementation. Importantly, it also demonstrated how prosumer preferences can be integrated into a mathematical optimization framework. The optimization is defined over a 24-hour horizon, indexed by $i = 0, 1, ..., 23$.

The inputs of the planning process are:

– p – vector of electricity prices for each hour;

– c – estimated hourly energy consumption profile;

– w – maximum allowed relative deviation from the original profile, expressed as a proportion of each hourly consumption c_i. This parameter represents the prosumer's flexibility preference. It determines how much the consumption in the optimal plan can differ from the initial estimate. The deviation is relative to the original estimate. For example, $w_{10} = 0.1$ means that consumption at hour 10 can be adjusted within $\pm$ 10% of c_{10} in the optimized plan.

Let $x = (x_0, x_1, ..., x_{23}) \in R$ denote the vector of adjusted hourly consumption values – decision variables to be optimized. Then the target function that is being minimized (1)

$$\sum_{i=0}^{23}\left(x_i \cdot p_i\right) \to \min. \tag{1}$$

The constraints for this problem were formulated as follows:

1. Hourly deviation constraints: each adjusted consumption value x_i must remain within a symmetric interval centered around the corresponding baseline value c_i, bounded by a fraction w of c_i (2)

$$c_i\left(1-w_i\right) \le x_i \le c_i\left(1+w_i\right). \tag{2}$$

2. Total consumption constraint: the total adjusted daily consumption must equal the original daily sum (3)

$$\sum_{i=0}^{23} x_i = \sum_{i=0}^{23} c_i. \tag{3}$$

3. Non-negativity bounds: all adjusted consumption values must be non-negative: $x_i >= 0$.

The initial point of the optimization process is defined as $x_i = c_i$ for all hours i, which is feasible by construction and satisfies all imposed constraints. This problem formulation facilitates the development of a proof-of-concept and verification of the implementation. Moreover, it also demonstrates how prosumer flexibility preferences can be integrated into a more advanced formulation of the daily prosumer planning problem.

5. 1. 3. Design of prosumer control suggestion module

The problem formulation was extended to represent a more realistic prosumer setup, incorporating battery storage dynamics, local generation, and the optional capability to sell excess energy back to the grid. Additionally, user flexibility preferences were modeled within the mathematical formulation.

This results in a constrained optimization problem for daily prosumer operation planning, involving scheduling battery charging/discharging, grid purchases, and potential generation curtailment or energy sale. The objective is to minimize total daily energy costs or maximize profit from energy sales, while satisfying demand and operational constraints. Inputs of the problem are:

– g_i, $i = 0, ..., 23$ – hourly local generation;

– c_i, $i = 0, ..., 23$ – hourly electricity consumption;

– p_i, $i = 0, ..., 23$ – hourly grid electricity prices;

– w_i, $i = 0, ..., 23$ – relative deviations in consumption, permitted by the prosumer, representing their flexibility preferences;

– b_0 – initial battery state of charge;

– $b_{\max}$ – maximum battery capacity;

– l_{ch}, l_{dc}, l_{st} – losses associated with battery charging (*ch*), discharging (*dc*), and storage (*st*), respectively; storage loss here refers to the self-discharge of an idle battery.

Then, the decision variables are defined as follows:

– x_i – energy drawn from the grid during hour i, $i = 0, ..., 23$;

– $bflow_i$ – net energy flow from/to the battery in the prosumer energy balance during hour i, $i = 0, ..., 23$, where positive values indicate charging and negative values indicate discharging;

– cr_i – curtailed or sold locally generated energy during hour i, $i = 0, ..., 23$.

Formally, the optimization problem operates over the concatenated decision vector

$$v = [x_0, ..., x_{23}, bflow_o, ..., bflow_{23}, cr_0, ..., cr_{23}].$$

Given the inputs and introduced decision variables, the objective function is as follows if no sale of generated energy back to the grid is allowed (4)

$$\sum_{i=0}^{23}\left(x_i \cdot p_i\right) \to \min. \tag{4}$$

If the sale of generated energy back to the grid is allowed (5)

$$\sum_{i=0}^{23}\left(x_i \cdot p_i\right) - \sum_{i=0}^{23}\left(cr_i \cdot p_i\right) \to \min. \tag{5}$$

The constraints of the formulated problem reflect prosumer operations conditions:

1. Hourly energy balance with flexible demand satisfaction: for each hour, the energy balance must lie within an interval defined by the prosumer's flexibility preference. Specifically, if the allowed relative deviation parameter w_i is greater than zero, the energy balance should satisfy the inequality (6)

$$c_i\left(1-w_i\right) \le x_i - bflow_i + g_i - cr_i \le c_i\left(1+w_i\right). \tag{6}$$

If $w_i = 0$, meaning no deviation is permitted, a small epsilon margin is added to the equality constraint to transform it into an inequality. This modification enhances numerical stability during the optimization process, resulting in (7)

$$c_i - \varepsilon \le x_i - bflow_i + g_i - cr_i \le c_i + \varepsilon, \tag{7}$$

where ε is a small positive constant.

2. Daily energy balance: although hourly consumption deviations are permitted within specified margins, the prosumer is not expected to change their total daily consumption. Therefore, while the optimized plan allows redistribution of consumption across hours within the permitted flexibility, the total daily consumption must remain unchanged (8)

$$\sum_{i=0}^{23} x_i - bflow_i + g_i - cr_i = \sum_{i=0}^{23} c_i + \varepsilon, \tag{8}$$

where small ε is added for stability of the optimization process.

3. Battery state of charge (*SoC*) constraints: given the physical nature of the battery, there are constraints for the battery's *SoC*. Let *SoC* at hour i be (9):

$$SoC_i = SoC_{i-1} \cdot (1 - l_{st}) + charge \cdot (1 - l_{ch}) - \frac{discharge}{(1 - l_{dc})},$$
$$SoC_{-1} = b_0,\ charge = \max(bflow_i; 0),$$
$$discharge = \min(blfow_i; 0). \tag{9}$$

Here, charge and discharge are split into two components for better process stability. The SoC is constrained by the physical battery limits: $0 \le SoC \le b_{\max}$.

4. Battery charging is limited to available generation (10)

$$g_i - bflow_i - cr_i \ge 0, \text{ when } bflow_i > 0. \tag{10}$$

5. Discharging is limited by battery availability, i.e., the battery cannot discharge more energy than it has stored (11)

$$\frac{bflow_i}{(1 - l_{dc})} + SoC_{i-1} \ge 0, \text{ when } bflow_i < 0. \tag{11}$$

6. Physical bounds: the amount of energy the prosumer imports from the grid cannot be negative because selling energy is modeled separately. Therefore, $x_i \ge 0$. Similarly, the curtailment or sale amount cannot be negative and must not exceed the local generation during that hour, meaning, i.e., $0 \le cr_i \le g_i$.

The optimization is initialized with a heuristic feasible starting point x^0 constructed as follows:

– grid purchase assumes full use of available generation, with the grid covering any shortfall: $x_i^0 = \max(c_i - g_i; 0)$;

– the battery remains idle in the initial guess, so the battery flow is zero: $bflow_i = 0$;

– any excess generation beyond the consumption is either curtailed or sold, depending on whether sale is allowed: $cr_i^0 = \max(g_i - c_i; 0)$.

This initial point is feasible by construction with respect to all defined constraints and serves as the solver's starting solution. It is possible that the optimization may fail to improve upon this point or encounter numerical issues resulting in failure. In such a case, the initial point is retained in the subsequent aggregated statistics, with an associated cost improvement value of zero.

The solution is obtained using a constrained nonlinear programming approach with the Sequential Least Squares Programming (SLSQP) method. Known limitations of the SLSQP method mentioned in 4. 3 are addressed in the proposed design, as the formulated problem avoids complex nonlinearities, and the initial point used in the optimization is feasible by construction.

To evaluate the module, the improvement in cost can be calculated as the difference between the cost at the initial point (baseline solution) and at the optimized solution (12)

$$old\ cost = cost(x^0),\ new\ cost = cost(x^{opt}). \tag{12}$$

Here, the cost function depends on whether the sale of excess generated energy is allowed (13) or not (14):

$$cost_{no\ sell} = \sum_{i=0}^{23} (x_i \cdot p_i), \tag{13}$$

$$cost_{sell} = \sum_{i=0}^{23} (x_i \cdot p_i) - \sum_{i=0}^{23} (cr_i \cdot p_i). \tag{14}$$

The cost here represents the net balance of the prosumer's energy purchases and sales, meaning it can be negative if more energy is sold than purchased. All the formulas account for this possibility. The total cost saving and relative improvement are then defined as follows (15):

$$cost\ saving = old\ cost - new\ cost,$$
$$impr = \frac{cost\ saving}{|old\ cost|}. \tag{15}$$

To obtain a more robust estimate of the module performance, evaluation was conducted according to description in 4. 3. In the case of prosumer preferences, it is reasonable to compare module performance with different levels of prosumer flexibility reflected in the parameter w. Final results are presented with summary statistics, such as the mean and median of relative daily improvements, as well as the total cost savings.

From a practical perspective, scaling the inputs of the optimization problem can improve both the stability and speed of the optimization process. To this end, before applying any optimization logic, the input energy variables are scaled to the range [0, 1] or [–1;1] using the following transformation (16):

$$g_{scaled} = \frac{g}{f_e},\ c_{scaled} = \frac{c}{f_e},\ b_{0\ scaled} = \frac{b_0}{f_e},\ b_{\max\ scaled} = \frac{b_{\max}}{f_e},$$
$$f_e = \max[1; \max(g); \max(c); b_{\max}]. \tag{16}$$

Prices are scaled in the same way if necessary. After scaling the input data, the optimization process is run. After optimization, the optimal solution is rescaled back to the original units before being returned to the user (17)

$$x^{opt} = x_{scaled}^{opt} \cdot f_e,\ cr^{opt} = cr_{scaled}^{opt} \cdot f_e,$$
$$bflow^{opt} = bflow_{scaled}^{opt} \cdot f_e. \tag{17}$$

It's expected that values of input data and variables in [0;1] (generation and consumption, grid purchases, curtailment) or [–1;1] (battery flow) ranges will improve the stability of the solution process.

All the proposed methods are based on the operational logic of the processes and are driven by the practical need to account for forecast errors and prosumer flexibility.

5. 1. 4. Validation of the proposed module

First, the general feasibility of the proposed approach to module development was tested using the consumption redistribution planning problem. In this problem, electricity consumption is adjusted from the original schedule according to day-ahead prices. This experiment validated both the conceptual soundness of the approach and the correctness of the implemented experimental pipeline developed in Python, using the SciPy library [29]. Fig. 2 shows the result of a daily optimal planning for September 1, 2021, with a flexibility limit of plus or minus 10% for each hour. In this example, the battery capacity was set to approximately 20% of the median daily generation (i.e., $b_{\max} = 200$ kWh, prosumer segment ID 60).

The observed behavior aligns with expectations: the control module suggests shifting peak consumption to periods with lower prices. Next, the full problem formulation was applied to the same setup. The full formulation incorporates energy generation, battery storage usage, and the sale of generated energy, as described in the previous section. A visualization of the planning results is presented in Fig. 3. Here and in the following analysis, battery-related losses were modeled as follows: 3% monthly self-discharge loss [30], 5% losses during both discharging and charging [31]. These charge and discharge losses are consistent with typical prosumer storage systems, e.g., Tesla Powerwall has a round-trip efficiency around 90%.

In this example, introducing generation and battery storage increased cost savings from 1.56% in the base case to 4.4% in the full problem formulation. This result aligns with expectations and supports the validity of the setup. A further example was examined to test more complex user preference constraints. Specifically, if the operator does not allow increased consumption during nighttime hours, this can be modeled by setting $w = 0$ for $i = 0, \ldots, 5$. Under this constraint, the improvement over the baseline was 3.54%. Fig. 4 illustrates the baseline and optimized control plans for this case.

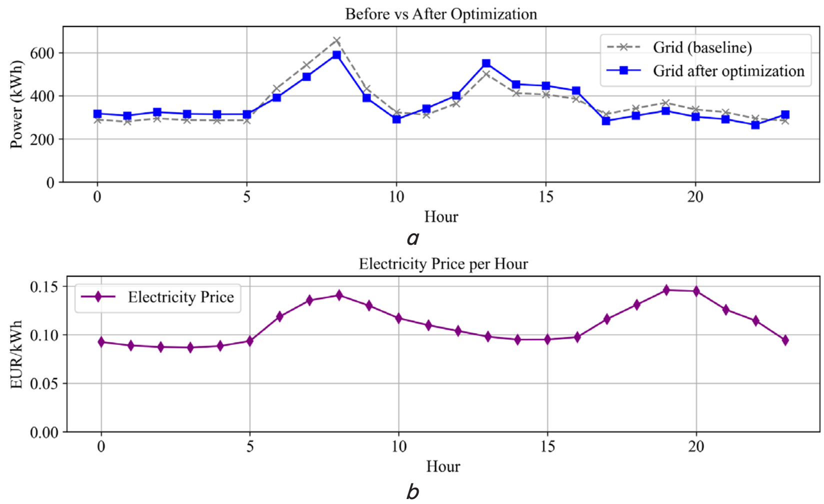

Fig. 2. Results of the daily planning for a simplified problem formulation: *a* – energy purchase from the grid, *b* – prices

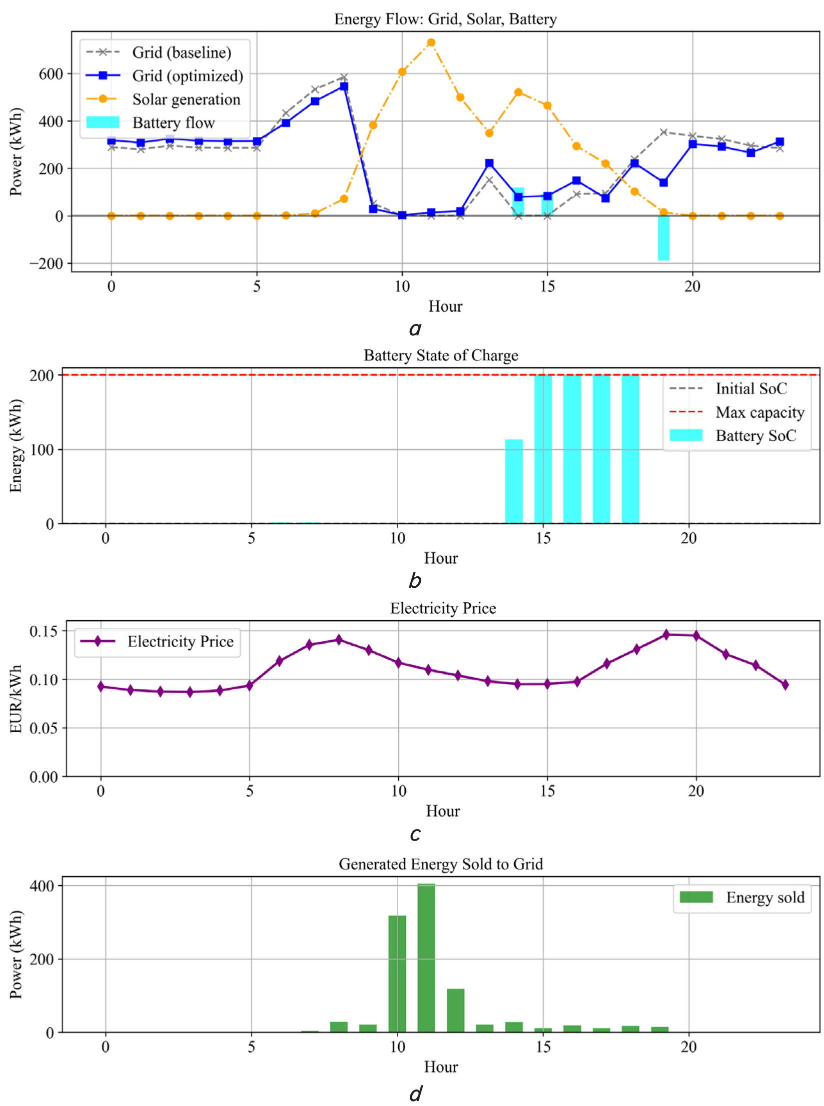

Fig. 3. Results of the daily planning for a full problem formulation: *a* – energy generation and purchases from the grid, *b* – battery state of charge, *c* – prices, *d* – energy sold

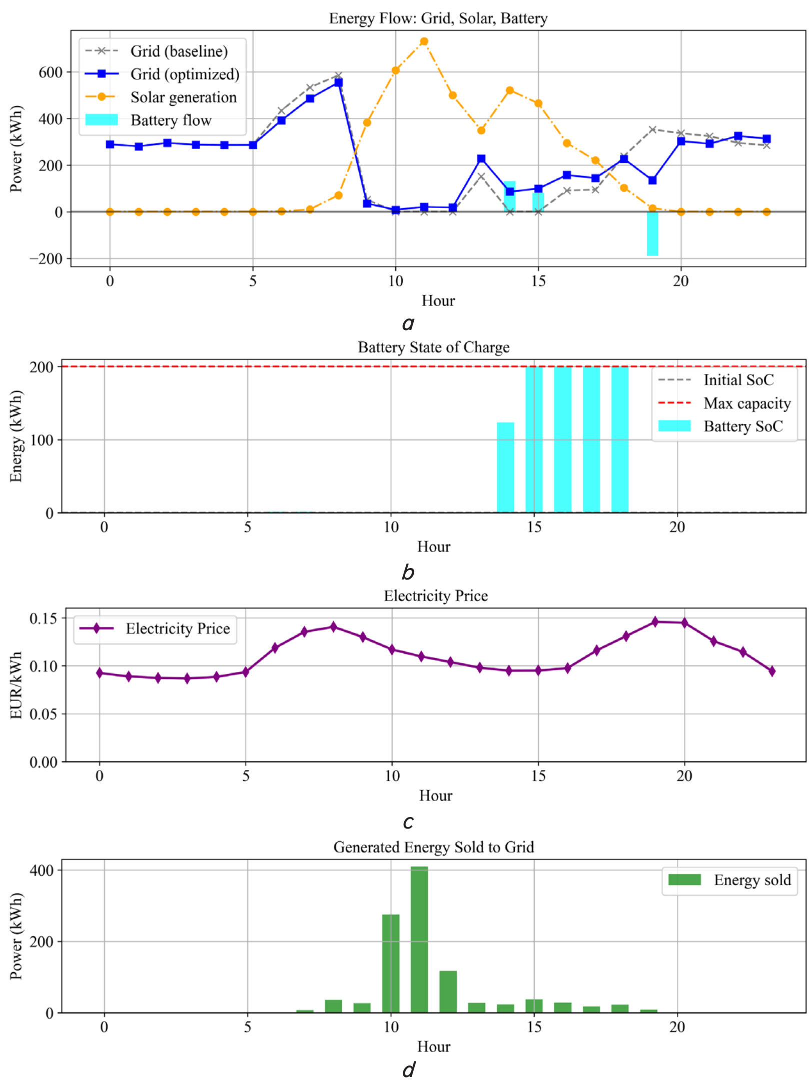

Fig. 4. Results of the daily planning for a full problem formulation with complex flexibility preferences: *a* — energy generation and purchases from the grid, *b* — battery state of charge, *c* — prices, *d* — energy sold

As expected, restricting the control module's flexibility in shifting consumption leads to smaller improvements. However, limiting control over 25% of the daily period resulted in only a 0.86% decrease in performance, demonstrating the module's robustness and potential for cost savings.

5. 2. Planning efficiency under different flexibility preferences

Next, a comparison of the impact of different user preferences was conducted for two prosumer segments identified in the historical data: a private household segment (ID 26) and a business prosumer segment (ID 60). For the household segment, battery capacity was set to approximately the median daily generation (20 kWh), whereas for the business segment, it was set to 20% of the median daily generation (200 kWh). The results for both segments are summarized in Table 1.

Considering the significant difference between the average and median relative improvement, the distribution of improvements appears to be skewed, with a few outliers increasing the mean. Therefore, the median is used as the primary measure of performance in this analysis. Additionally, the standard deviation is omitted, as it provides limited insight in the context of skewed distributions.

Table 1

Performance of the planning process depending on the prosumer's flexibility preference for big and small prosumer segments

User flexibility preference	Small prosumer (ID = 26, $b_{max} = 20$)			Big prosumer (ID = 60, $b_{max} = 200$)		
	Average improvement	Median improvement	Number of failed optimizations	Average improvement	Median improvement	Number of failed optimizations
$w = 0.1$	46.86%	4.92%	0	14.41%	3.86%	0
$w = 0.25$	88.92%	9.64%	0	25.00%	8.50%	0
$w = 0.5$	158.30%	17.21%	0	42.46%	15.96%	0
$w = 0.75$	226.99%	24.81%	0	59.32%	23.40%	0

It was observed that the greater the prosumer's flexibility in redistributing consumption, the higher the savings, with median performance improvement increasing from 4.92% to 24.81% for the smaller prosumer segment and from 3.86% to 23.40% for the larger segment. Notably, the improvement is positive on all evaluated days.

To investigate whether increased battery capacity enables higher cost savings, an experiment was conducted using a battery sized at 200% of the installed PV capacity for a small prosumer. This corresponds to storage capable of holding the theoretical maximum generation over a two-hour period. The results are presented in Table 2.

Table 2

Performance of the planning process depending on the prosumer's flexibility preference for increased and decreased storage capacity

User flexibility preference	Small prosumer (ID = 26, b_{max} = 2x installed PV capacity)			Small prosumer (ID = 26, b_{max} = 5)		
	Average improvement	Median improvement	Number of failed optimizations	Average improvement	Median improvement	Number of failed optimizations
$w = 0.1$	50.62%	4.92%	0	35.69%	4.22%	0
$w = 0.25$	92.39%	9.71%	0	78.91%	9.11%	0
$w = 0.5$	161.90%	17.24%	0	150.76%	16.64%	0
$w = 0.75$	231.12%	24.81%	0	221.89%	24.42%	0

Increasing battery capacity beyond the median daily generation did not result in significant performance improvements. A smaller battery configuration, corresponding to approximately 25% of the median daily generation ($b_{max} = 5$ kWh), was also evaluated, as presented in Table 2. Downsizing the battery led to a minor decrease in performance.

Following the initial experiments, the analysis will focus on scenarios with limited battery capacities. These cases present more challenging conditions and better highlight key relationships, as the results are not heavily influenced by large battery storage.

Table 3 presents the estimated time required to run daily optimal planning for a prosumer across different setups. It was observed that greater flexibility results in longer optimization times, which aligns with the problem formulation and the associated expectations.

The initial experiments highlighted the importance of optimized implementation. Initially, experiments were conducted sequentially, with the initial battery state b_0 of each day set to the remaining battery capacity from the previous day. However, in all cases, the optimal profile involved fully utilizing the stored energy. Based on this observation, the experiments were parallelized and run with $b_0 = 0$ for all days, enabling faster and independent execution. This modification resulted in a 360% increase in running speed compared to the sequential approach for the same experiment. Furthermore, the proposed scaled approach significantly accelerated the experiments, reducing runtime from 92,075 seconds to 11,268 seconds (an 717% speed increase) for a specific experiment involving a larger prosumer segment. This approach also improved the numerical stability of the optimization process, decreasing the failure rate from 2.35% to 0.02%.

Table 3

Average time for daily planning for different prosumer's flexibility preferences for different prosumer setups

Prosumer flexibility preference w	Average time for daily planning, s			
	Small prosumer (ID = 26, b_{max} = 5)	Small prosumer (ID = 26, b_{max} = 20)	Small prosumer (ID = 26, b_{max} = 2x installed PV capacity)	Big prosumer (ID = 60, b_{max} = 200)
$w = 0.1$	0.446	0.482	0.300	0.586
$w = 0.25$	0.501	0.498	0.380	0.603
$w = 0.5$	0.532	0.540	0.340	0.677
$w = 0.75$	0.573	0.554	0.346	0.781

5. 3. Planning efficiency under different forecast error

5. 3. 1. Machine learning forecast uncertainty impact

The ML forecast may negatively affect the downstream planning task because of the additional uncertainty it introduces. To address this, a controlled environment with a defined forecast error rate was proposed (Fig. 5).

The main parameter of the process is the error rate, which represents the size of uncertainty that should be imposed on the control module inputs. Since this needs to be controlled, the decision was made to use historical data with added noise instead of using a set of ML models with different error rates.

The uniform noise was chosen to reflect the assumption of reasonable modeling. This means that the forecasting models are assumed to be built with the best available knowledge, resulting in forecast errors (residuals) that are uniformly distributed. In other words, if the errors follow a specific distribution, the modeling process should be revisited to incorporate the structure of the residual distribution and improve model performance. Additionally, this is a fairly generic assumption that does not limit the applicability of the analysis. Moreover, it is not an overly optimistic assumption compared to normally distributed errors, since large deviations from actual values are more likely with uniform noise.

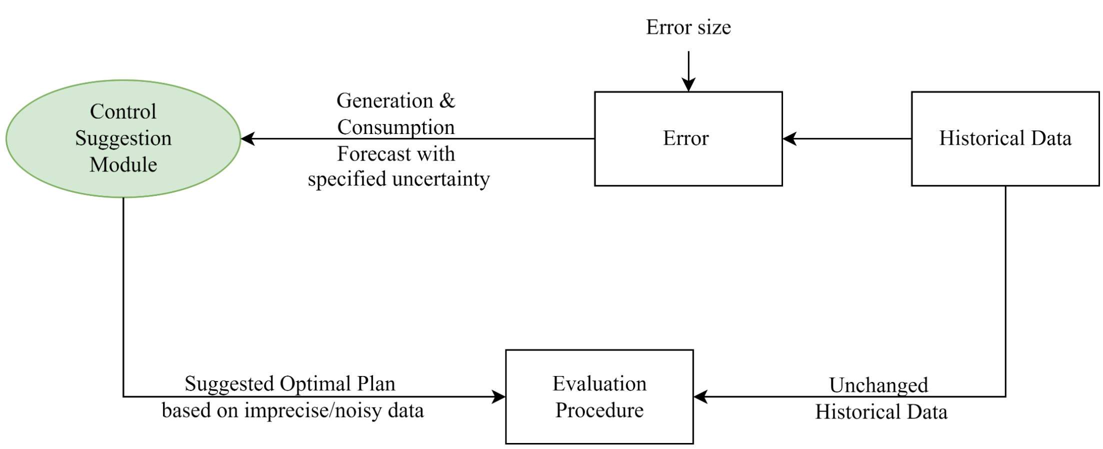

Fig. 5. A controlled environment for evaluating the error impact on the planning process

In particular, the noise is applied as follows:

1. A sample *mle* of size 24 is drawn from the uniform distribution [$-ml\_error$; $+ml\_error$], where *ml_error* is a parameter of the process and $ml\_error \in [0; 1]$.

2. The true values for generation or consumption are adjusted using the formula (18)

$$a_i^{err} = a_i \cdot \left(1 + mle_i\right). \tag{18}$$

The optimization problem is solved using noisy consumption and generation estimates as inputs, simulating a real situation with imprecise forecasts. However, the optimization process itself assumes that the forecasts are accurate. In other words, the optimization algorithm does not explicitly handle forecast errors.

The results of the planning are evaluated against true (noiseless) consumption and generation data. This approach models a forecast-informed plan applied to real conditions, simulating real-world degradation of plan effectiveness. In particular, the baseline cost is calculated based on the correct data, representing an optimistic benchmark. This baseline assumes the prosumer can plan the sale of the exact amount of generated energy and successfully deliver it to the grid. Then, the actual consumption is calculated using the given plan and the observed generation, illustrating what occurs when the operator implements a plan based on a noisy forecast, which is inaccurate due to forecast errors (19)

$$c_i^{actual} = x_i^{opt} - bflow_i^{opt} + g_i - cr_i^{opt}. \tag{19}$$

Then, the additional (penalty) cost is calculated based on the difference between the observed consumption and the planned consumption (20)

$$added\ cost = \max\left(0; \max\left(p\right) \cdot \sum_{i=0}^{23}\left(c_i - c_i^{actual}\right)\right). \tag{20}$$

This means that if a prosumer needs to urgently purchase more energy than planned, they pay the maximum price – a pessimistic but reasonable assumption. If the prosumer does not need to buy more, no added cost is incurred. However, they may miss additional profit because some excess energy was not sold. Using the maximum price for the penalty reflects a conservative estimate of potential costs in the optimized plan. Then the full new cost is a sum of new cost and added cost.

5. 3. 2. Experimental results of the controlled forecast error change

As the next step, the influence of uncertainty in machine learning forecasts on prosumer planning was investigated. To this end, experiments were conducted comparing planning performance across different error rates for both the small (ID = 26, $b_{\max} = 20$ kWh) and large (ID = 60, $b_{\max} = 200$ kWh) prosumer segments. Results for the smaller segment (ID = 26, $b_{\max} = 20$ kWh) are presented in Fig. 6–8.

It is observed that the performance of the planning process deteriorates approximately linearly with increasing forecast error, as demonstrated by both median improvement (Fig. 6) and total cost savings (Fig. 7). Even at a 50% error rate, results remain positive across all values of the prosumer flexibility parameter. However, a decrease in cost savings due to ML forecast errors is also observed, as shown in Table 4.

As shown in Fig. 8, the relationship between the number of negative daily improvements and the machine learning forecast error is nonlinear. However, the rate at which the number of negative observations increases depends on the prosumer flexibility preference parameter. In the more conservative case ($w = 0.1$), the number of negative observations rises rapidly, exceeding 20% at an error rate of 0.25, whereas the most flexible prosumer ($w = 0.75$) experiences no negative observations at this error rate. For values of w greater than 0.1, the increase is slower, indicating that higher user flexibility corresponds to fewer negative cases.

From another perspective, it is worth highlighting that the prosumer with $w = 0.75$ experiences a much lower proportion of negative daily outcomes (just above 10 percent) compared to more than 50 percent for the conservative case with $w = 0.1$. However, the drop in median performance at the same error level shows an opposite trend: the more flexible prosumer ($w = 0.75$) experiences a larger decline of 8.57% than the conservative one ($w = 0.1$), which drops by 6.32%.

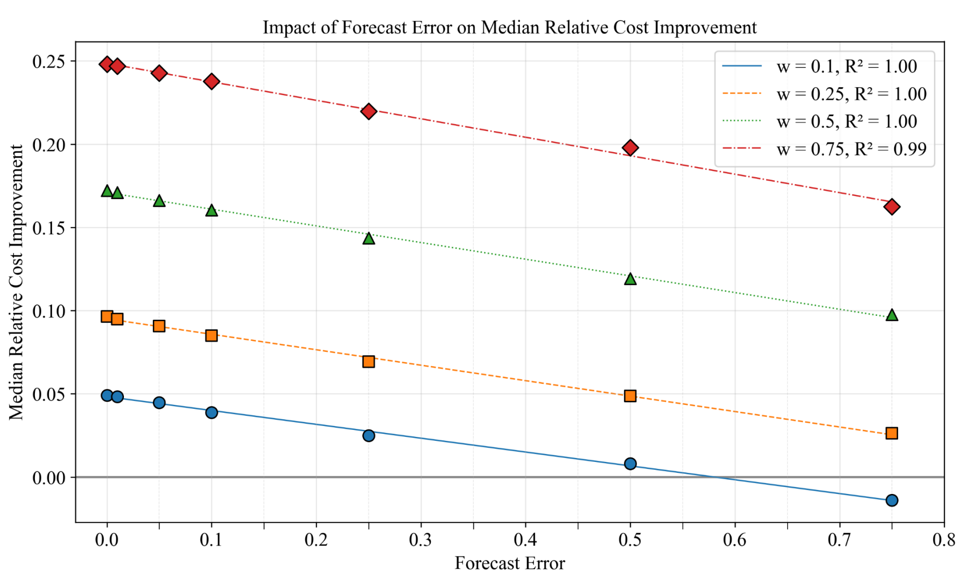

Fig. 6. Impact of the forecast error on median relative cost improvement across different flexibility preferences for the smaller prosumer segment (linear approximation)

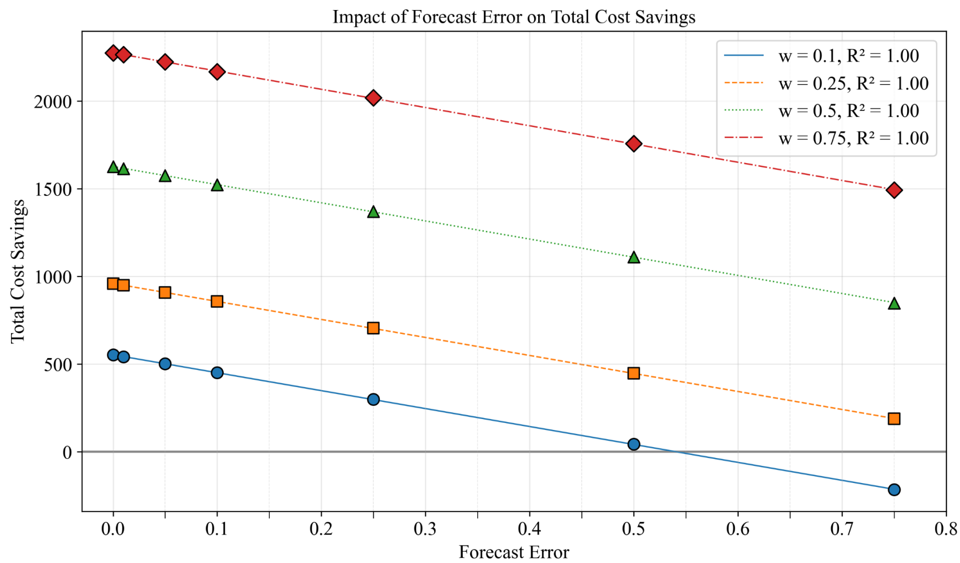

Fig. 7. Impact of the forecast error on total cost savings across different flexibility preferences for the smaller prosumer segment (linear approximation)

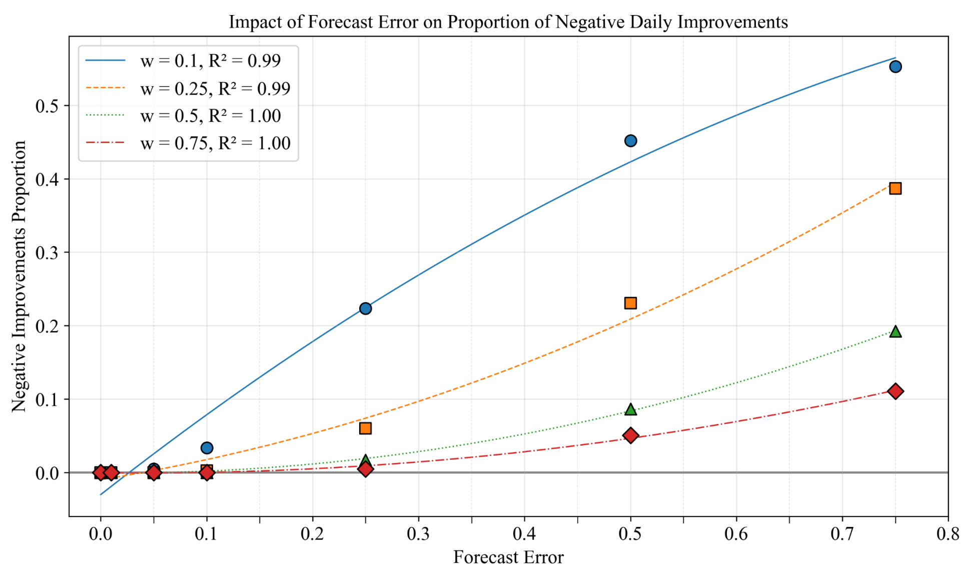

Fig. 8. Impact of the forecast error on the proportion of negative daily improvements across different flexibility preferences for the smaller prosumer segment (quadratic approximation)

Table 4

Median relative cost improvement at perfect forecast and 0.75 error rate, along with their difference, for the considered flexibility preferences in smaller prosumer segment

w	Perfect forecast	Forecast error 0.75	Difference
0.1	4.92%	–1.40%	6.32%
0.25	9.64%	2.62%	7.02%
0.5	17.21%	9.76%	7.45%
0.75	24.81%	16.24%	8.57%

The results of the forecast error experiments for the larger prosumer segment (ID = 60, b_{max} = 200) are presented in Fig. 9–11.

It is observed that performance decreases approximately linearly with increasing forecast error. Negative total cost savings are already observed at a flexibility level of w = 0.1 and an error rate of 0.5. However, a decrease in cost savings due to ML forecast errors is also observed in this larger prosumer segment, as shown in Table 5.

It is shown in Fig. 11 that the relationship between the forecast error rate and the number of days with negative improvements follows a similar pattern to the previous prosumer setup. For the lowest flexibility level, this number increases faster than linearly and exceeds 60 percent at the highest considered forecast error of 0.75. In contrast, for the highest flexibility level, it remains below 10 percent even at that same error level.

The percentage of failed optimizations does not exceed 0.01% and 0.02% for forecast error experiments in prosumer setups with IDs 26 and 60, respectively. These failures are caused by numerical issues that can be addressed during the solution refinement phase of implementation.

Table 6 summarizes the difference in median relative improvement between the ideal forecast (error = 0) and the highest considered forecast error (0.75) across the four tested setups.

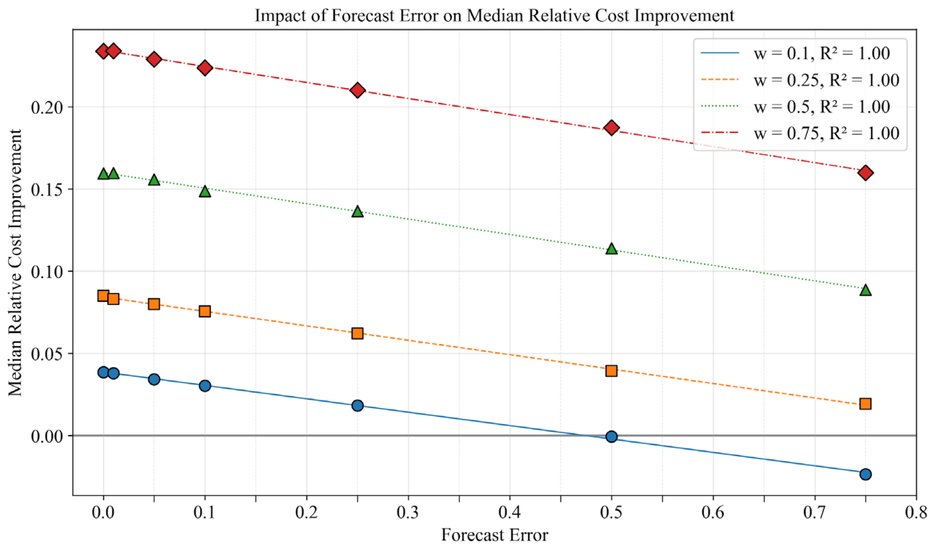

Fig. 9. Impact of the forecast error on median relative cost improvement across different flexibility preferences for the bigger prosumer segment (linear approximation)

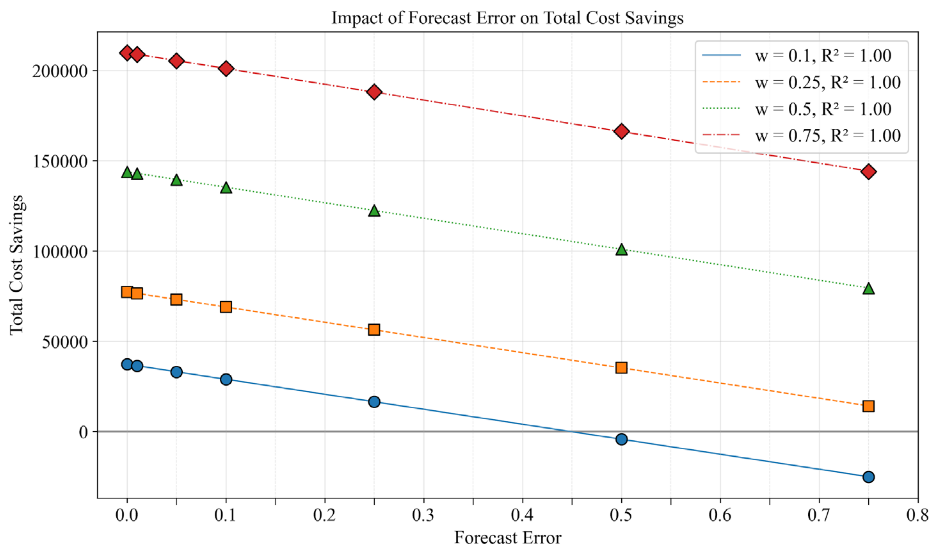

Fig. 10. Impact of the forecast error on total cost savings across different flexibility preferences for the bigger prosumer segment (linear approximation)

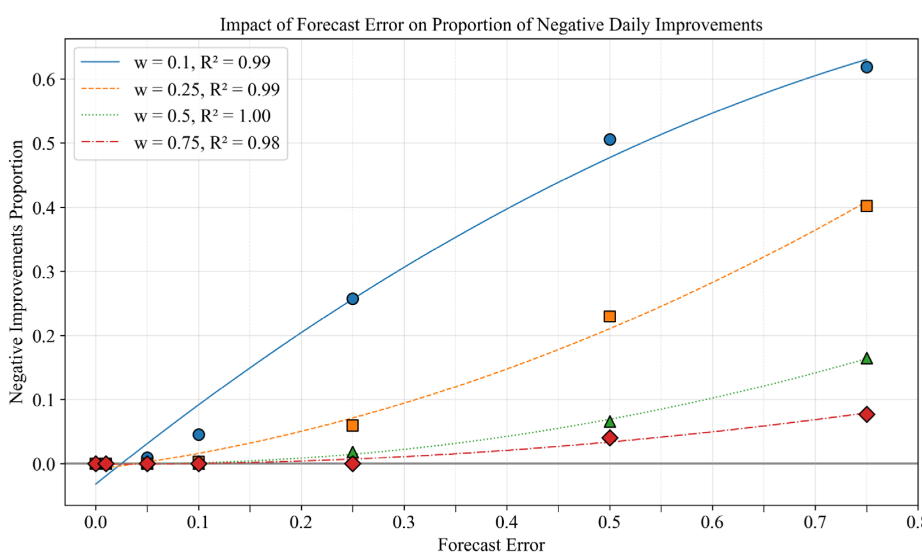

Fig. 11. Impact of the forecast error on the proportion of negative daily improvements across different flexibility preferences for the bigger prosumer segment (quadratic approximation)

Table 5

Median relative cost improvement at perfect forecast and 0.75 error rate, along with their difference, for the considered flexibility preferences in bigger prosumer segment

w	Perfect forecast	Forecast error 0.75	Difference
0.1	3.86%	–2.36%	6.22%
0.25	8.50%	1.93%	6.57%
0.5	15.96%	8.88%	7.08%
0.75	23.40%	16.00%	7.39%

Table 6

Difference between median relative cost improvement at perfect forecast and 0.75 error rate, for the considered flexibility preferences and prosumer setups

Prosumer flexibility preference *w*	Difference between median relative improvement at 0 and 0.75 errors			
	ID = 26, $b_{\max} = 5$	ID = 26, $b_{\max} = 20$	ID = 26, $b_{\max}$ = 2x installed PV capacity	ID = 60, $b_{\max} = 200$
0.1	6.84%	6.32%	6.13%	6.22%
0.25	7.57%	7.02%	6.94%	6.57%
0.5	7.66%	7.45%	7.48%	7.08%
0.75	8.78%	8.57%	8.03%	7.39%

The only consistent pattern observed is that the performance drop is greater for setups with higher prosumer flexibility.

6. Discussion of prosumer planning efficiency under changing forecast uncertainty and flexibility preferences

The study focuses on an applied problem: daily optimal planning for a prosumer with one-hour resolution. The task is to generate an optimal operational plan for the prosumer for the upcoming day, based on hourly electricity prices and forecasts of energy generation and consumption, battery constraints, and prosumer flexibility preferences. If a battery is available, its charging and discharging must also be planned. The optimization goal depends on whether energy sale to the grid is allowed. If sale is not allowed, the objective is to minimize the total cost of electricity purchased. If sale is allowed, the objective becomes maximizing net profit, defined as the difference between revenue from energy sold and the cost of energy purchased. In all cases, the plan must satisfy the demand and respect system constraints. Prosumer's flexibility preferences are defined as the willingness of the prosumer or prosumer operator to redistribute energy consumption throughout the day. These preferences specify the maximum allowed deviation of the optimized plan for a given hour on the following day from the forecasted consumption for that hour, for example, by 10% or 25%. This option was chosen as a balanced compromise. On the one hand, it sets clear constraints for planning, moving away from the trivial creation of any plan that ignores the prosumer's preferences. On the other hand, it can be reasonably assumed that while the prosumer may agree to adjust their consumption, they will not accept arbitrary changes, even in the form of redistribution, and this problem formulation explicitly accounts for such limitations.

The proposed module optimizes the total net energy cost, accounting for both energy purchases and potential profits from energy sales. At the same time, it ensuring flexible demand satisfaction by utilizing local generation, curtailment, and battery storage. The constraints guarantee feasible battery operation and enforce demand-supply balance within the prosumer's flexibility preference bounds. Additionally, the operator can impose varying limits on consumption deviations from the baseline plan at the hourly level, including the option to fix consumption during specific time periods. This design enables operational cost minimization and, where permitted, profit maximization through energy sales via optimal adaptive scheduling that incorporates user-defined flexibility preferences.

The proposed mathematical formulation in the module design reflects both the prosumer's operational processes and the operator's ability to specify their preferences in the input data to the DSS. In particular, this allows users not only to limit the deviation but also specify periods where adjustments of consumption shouldn't be allowed (7). For example, private households are often unlikely to increase consumption in night hours. Therefore, they may want to disallow the control module from suggesting scenarios with such an increase.

The proposed module design allows for additional features of the prosumer facilities to be taken into account in the DSS. For example, the minimum state of charge, below which the battery should not be discharged, is often recommended to be around 20% of the maximum capacity to preserve battery performance. This condition can be effectively represented in the model by setting the lower *SoC* bound to zero (9). This means that the zero *SoC* level in the optimization corresponds to 20% of the actual physical capacity, which is never utilized. Therefore, this formulation is equivalent to explicitly enforcing a minimum *SoC* limit. In such cases, the maximum battery capacity parameter should be adjusted accordingly to represent the usable capacity above this minimum threshold.

The results indicate that the proposed control module effectively incorporates prosumer preferences for consumption flexibility during planning and demonstrates relative robustness to forecasting errors from ML models. However, the acceptable forecast error threshold should be determined for each prosumer setup and calibrated based on the level of prosumer flexibility to ensure optimal application. These findings provide important insights into prosumer planning strategies under uncertainty.

The observed differences between prosumer segments in Table 1 can be attributed to varying structural ratios between energy consumption, generation, installed PV capacity, and battery storage. These differences influence the dynamics of energy use, self-consumption, and storage efficiency, directly affecting the achievable cost savings. Although the median improvements are comparable across segments, structural differences may produce occasional high-performance outliers, skewing the distribution and reinforcing the median as a more reliable measure of typical performance.

The battery-related experiment outcomes shown in Table 2 are likely due to the assumption in the problem formulation that the battery charges exclusively from generated energy and not from the grid. Therefore, when the available battery capacity exceeds the daily generation, the additional capacity remains unused and does not contribute to further cost savings. Furthermore, while energy storage plays a role in optimal prosumer operation, the majority of the observed cost savings are achieved through consumption redistribution and the sale of surplus generated energy. These findings highlight the importance of proper storage sizing in prosumer systems and demonstrate the capability of the developed control module to support such analyses. A more detailed assessment of storage sizing strategies utilizing the control module is recommended for future work.

From a technical perspective, results (including Table 3) highlight the importance of experiments' parallelization and the positive impact of using a scaled optimization problem. In particular, for all setups, the planning time for one day remained below one second, demonstrating feasibility for practical application and emphasizing the benefits of employing an algorithm appropriately tailored to the complexity of the optimization problem.

Results in Fig. 6, 7, 9, 10 suggest that the proposed control module maintains sufficient robustness to forecast errors at considered levels when applied in the examined prosumer segment. Slightly smaller robustness to forecast errors for a bigger prosumer, shown in Fig. 9, 10, is likely due to the lower improvement under perfect forecasts in this prosumer segment. These findings indicate that the module performance may behave differently across setups. Therefore, evaluating the module on historical data is advisable to identify the acceptable forecast error threshold for a specific setup. If both flexibility and forecast accuracy can be adjusted, a more optimal combination may be found. For example, a flexibility level of $w = 0.25$ paired with a forecast error rate of 0.5 delivers performance comparable to that of $w = 0.1$ under perfect forecasts. In other words, increasing flexibility beyond 0.1 allows for a more relaxed requirement on forecast accuracy without compromising overall performance.

Despite the module being effective even under the influence of an imperfect forecast, the performance decrease in Table 4 is observed when the error rate is growing. It is likely because higher flexibility combined with larger forecast errors leads to greater differences between planned and actual consumption, which increases the penalty cost. Consequently, the acceptable level of forecast error depends on the degree of prosumer flexibility. For example, a prosumer willing to implement planning with a flexibility parameter of $w = 0.25$ under a forecast error rate of 0.5 achieves cost improvements comparable to those of planning with $w = 0.1$ (2.5 times more restrictive) and zero forecast error (an unrealistic scenario). The drop in performance for the bigger prosumer segment in Table 5 is slightly smaller, suggesting that it depends on the original performance levels. Specifically, if the baseline performance is more moderate due to lower flexibility or a different prosumer configuration, the impact of increasing forecast errors tends to be less steep. Nevertheless, the overall decline still follows a linear trend.

It is important to emphasize that negative daily cost improvements in this problem formulation arise solely from the penalization term in the new cost value. This term reflects the discrepancy between actual consumption and the consumption in the optimal plan based on inaccurate forecasts. Therefore, it is expected that no negative values occur at a zero error rate, as shown in Fig. 8, 11. The number of negative improvements in Fig. 8 and the drop in performance in Table 4 show opposite trends, likely due to the larger margin for improvement available to more flexible prosumers. While their plans degrade slightly more in terms of median performance, the additional flexibility prevents cost savings from becoming negative, effectively absorbing the impact of forecast errors. The results for bigger prosumers in Fig. 11 are similar. For three out of four tested flexibility values, the increase is slower than linear, which is worth highlighting as a positive sign for the module's robustness: prosumers would generally prefer stable, positive performance. At the same time, it is possible that the relationship is polynomial (e.g., quadratic), meaning that beyond a certain threshold of forecast error, the rate of negative outcomes might increase more rapidly in flexible prosumers than in conservative ones. However, even if such a turning point exists, it likely occurs beyond the 0.75 level, making it irrelevant for practical use cases, where such high forecast errors are unlikely to be tolerated.

The performance results in Tables 4–6 reinforce the importance of jointly calibrating flexibility settings and forecast quality to ensure reliable and resilient performance across varying conditions. In particular, increasing prosumer flexibility allows for more relaxed forecast accuracy requirements, highlighting an important trade-off in operational planning.

Unlike solutions that offer minimal post-processing of ML model results, such as [8] or [17], the developed module combines forecasts with the application of a classical analytical method. Moreover, the proposed solution uses an advanced optimization algorithm, unlike solutions that use the simplest methods, such as rule-based systems and fuzzy logic [13, 17]. Furthermore, the proposed solution focuses on the effectiveness of DSS as a whole, rather than its individual components, such as the forecasting process, as in [19–22]. In contrast to [24], the module allows explicit modeling of user preferences. This work focuses on the impact of uncertainty on planning in the context of prosumers, rather than heating, ventilation, and air conditioning systems [24], automated building control [25], or power grid expansion [26]. Another advantage of the proposed solution is that it is universal for different prosumers, unlike other studies that considered specific objects or network segments, as in [27]. This holds both for the direct application of the management module and for the use of the identified relationships between forecast quality, flexibility preferences, and planning outcomes. Thus, the advantages of this solution are provided by the module design, which allows explicit modeling of prosumer flexibility, as well as a detailed analysis of the relationships between forecast errors, prosumer flexibility, and planning efficiency.

In summary, this study fills the research gaps identified in Section 2. In particular, the developed module is an effective solution that combines ML forecasting with a classical optimization approach in prosumer DSS, explicitly accounting for prosumer consumption flexibility. Such systems are scarcely studied and not widely available for use in prosumers. Moreover, the conducted analysis revealed dependencies on how flexibility preferences and forecasting errors affect planning efficiency. Such studies have not been conducted for prosumer DSS. In addition, the interaction between these two factors was investigated, and practically important dependencies were found. This interaction has not been well researched. These findings provide valuable insights into the modeling of prosumer flexibility, storage sizing, and forecast error tolerance thresholds, enabling improved planning and control design for real-world prosumer DSSs.

This study has several limitations that should be considered when interpreting the results. First, the module is designed to optimize energy use on a daily basis, treating each day independently and thus excluding the possibility of multi-day planning. Second, due to limitations of the dataset, the electricity selling price was assumed to be equal to the purchase price. While this assumption simplifies the analysis, the control module can be directly extended to account for asymmetric pricing, which would provide a more realistic evaluation in many practical settings. Third, battery charge and discharge rate constraints were not incorporated, based on the assumption that a reasonably sized battery can be fully charged or discharged within a one-hour time step. This assumption is generally valid when the battery is reasonably sized relative to the system's generation and consumption, and the time step is one hour. However, it may require revision for setups where power throughput limitations could significantly affect dispatch behavior or when much shorter time steps, such as one minute instead of one hour, are used.

The disadvantage of this study is the lack of evaluation of how forecast quality affects user satisfaction. This may change the outcomes of practical applications in cases where user satisfaction is significantly reduced. While the evaluation procedure accounts for the impact of forecast inaccuracies on planning efficiency, it does not directly assess how such inaccuracies influence user satisfaction. Defining what user satisfaction means in this context and how it should be measured remains a separate research challenge. Consequently, this aspect was not addressed in the present study and represents a valuable direction for future work, such as the development of user-centered performance metrics to support applied solutions and research involving prosumers.

Future development of this study should address the limitations and disadvantages of the study, as well as further enhance the developed approach. First, the penalty applied when implementing a plan based on imprecise forecasts could be revised to more accurately represent real-world consequences, enabling a more precise determination of the maximum tolerable forecast error. Second, investigating how forecast inaccuracies affect user satisfaction, as well as how it should be measured, could provide valuable insights into user-centered performance metrics and support the development of more effective, applied solutions. Third, extending the evaluation to scenarios with asymmetric electricity purchase and sell prices would facilitate the development of context-specific recommendations for acceptable forecast error levels. Finally, the module developed in this study can be reused across various applications, ranging from evaluating different prosumer configurations to optimizing battery sizing for specific setups.

7. Conclusions

1. This study introduced and thoroughly evaluated a novel control module designed for short-term planning of flexible energy demand and battery storage dispatch in prosumer energy systems. A flexible, optimization-based approach is proposed that seamlessly integrates consumption and generation forecasts, user-defined flexibility preferences, and battery storage constraints. The module was validated using real-world data across prosumer segments of varying sizes, demonstrating robust and scalable performance, achieving significant cost savings under diverse demand-generation profiles. These results confirm the scalability and practical applicability of the module. Unlike black-box methods that obscure decision logic, the proposed system explicitly allows users to specify their willingness to shift their energy consumption. This granularity in flexibility modeling proved essential in tailoring planning results to individual user behavior, thereby increasing transparency and trust in decisions.

2. It was found that prosumer flexibility preferences do not prevent the control module from achieving meaningful cost improvements, although some reduction in savings is expected due to the module's reduced freedom in planning. A linear relationship was also found between the flexibility and overall cost savings and median relative cost improvement when using the module. Increasing prosumer flexibility allows for more relaxed forecast accuracy requirements, highlighting an important trade-off in operational planning. Additionally, higher flexibility settings demonstrate better overall module performance but lead to a slightly faster decline as forecast error increases. In contrast, lower flexibility configurations degrade more slowly with increasing error but generally show more modest performance and may ultimately lead to underperformance.

3. The control module demonstrated robust cost improvements under realistic and even extreme forecast errors (up to 75%), depending on prosumer segment and flexibility preferences. A linear relationship was observed between forecast error rate and both total cost savings and median relative cost improvement when applying the module. Performance becomes negative only in rare corner cases characterized by very limited prosumer flexibility (e.g., flexibility parameter $w = 0.1$) combined with a high forecast error (e.g., 75%).

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The work is supported by the state budget scientific research project of Sumy State University, «Intelligent information technology for proactive management of energy infrastructure in conditions of risk and uncertainty» (state registration number 0123U101852).

Data availability

Manuscript has associated data in a data repository [28].

Use of artificial intelligence

ChatGPT and Claude were used to improve the software implementation, in particular for structuring and optimizing the code, detecting errors, adding comments, and accelerating testing of modifications.

References

1. Lopes, J. A. P., Madureira, A. G., Matos, M., Bessa, R. J., Monteiro, V., Afonso, J. L. et al. (2019). The future of power systems: Challenges, trends, and upcoming paradigms. WIREs Energy and Environment, 9 (3). https://doi.org/10.1002/wene.368
2. Gržanić, M., Capuder, T., Zhang, N., Huang, W. (2022). Prosumers as active market participants: A systematic review of evolution of opportunities, models and challenges. Renewable and Sustainable Energy Reviews, 154, 111859. https://doi.org/10.1016/j.rser.2021.111859
3. Alam, Md. S., Al-Ismail, F. S., Salem, A., Abido, M. A. (2020). High-Level Penetration of Renewable Energy Sources Into Grid Utility: Challenges and Solutions. IEEE Access, 8, 190277–190299. https://doi.org/10.1109/access.2020.3031481

4. Shafiullah, M., Ahmed, S. D., Al-Sulaiman, F. A. (2022). Grid Integration Challenges and Solution Strategies for Solar PV Systems: A Review. IEEE Access, 10, 52233–52257. https://doi.org/10.1109/access.2022.3174555
5. Mišljenović, N., Žnidarec, M., Knežević, G., Šljivac, D., Sumper, A. (2023). A Review of Energy Management Systems and Organizational Structures of Prosumers. Energies, 16 (7), 3179. https://doi.org/10.3390/en16073179
6. Pöhler, J., Flegel, N., Mentler, T., Van Laerhoven, K. (2025). Keeping the human in the loop: are autonomous decisions inevitable? I-Com, 24 (1), 9–25. https://doi.org/10.1515/icom-2024-0068
7. Marot, A., Rozier, A., Dussartre, M., Crochepierre, L., Donnot, B. (2022). Towards an AI Assistant for Power Grid Operators. HHAI2022: Augmenting Human Intellect. https://doi.org/10.3233/faia220191
8. Donida Labati, R., Genovese, A., Piuri, V., Scotti, F., Sforza, G. (2020). A Decision Support System for Wind Power Production. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50 (1), 290–304. https://doi.org/10.1109/tsmc.2017.2783681
9. Krueger, H., Cruden, A. (2020). Integration of electric vehicle user charging preferences into Vehicle-to-Grid aggregator controls. Energy Reports, 6, 86–95. https://doi.org/10.1016/j.egyr.2020.02.031
10. Lukianykhin, O., Shendryk, V. (2025). Use of generative artificial intelligence to improve output message effectiveness in decision support systems for prosumers. Technology Audit and Production Reserves, 4 (2 (84)), 13–23. https://doi.org/10.15587/2706-5448.2025.333726
11. Fotopoulou, M., Rakopoulos, D., Petridis, S. (2022). Decision Support System for Emergencies in Microgrids. Sensors, 22 (23), 9457. https://doi.org/10.3390/s22239457
12. Iria, J., Soares, F. (2019). A cluster-based optimization approach to support the participation of an aggregator of a larger number of prosumers in the day-ahead energy market. Electric Power Systems Research, 168, 324–335. https://doi.org/10.1016/j.epsr.2018.11.022
13. Mayadevi N., Vinod Chandra S. S., Ushakumari, S. (2014). A Review on Expert System Applications in Power Plants. International Journal of Electrical and Computer Engineering (IJECE), 4 (1). https://doi.org/10.11591/ijece.v4i1.5025
14. Lukianykhin, O., Shendryk, V., Shendryk, S., Malekian, R. (2024). Promising AI Applications in Power Systems: Explainable AI (XAI), Transformers, LLMs. New Technologies, Development and Application VII, 66–76. https://doi.org/10.1007/978-3-031-66271-3_8
15. Bose, B. K. (2017). Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems – Some Example Applications. Proceedings of the IEEE, 105 (11), 2262–2273. https://doi.org/10.1109/jproc.2017.2756596
16. Lukianykhin, O., Bogodorova, T. (2021). Voltage Control-Based Ancillary Service Using Deep Reinforcement Learning. Energies, 14 (8), 2274. https://doi.org/10.3390/en14082274
17. Qi, B., Liang, J., Tong, J. (2023). Fault Diagnosis Techniques for Nuclear Power Plants: A Review from the Artificial Intelligence Perspective. Energies, 16 (4), 1850. https://doi.org/10.3390/en16041850
18. Panapakidis, I. P., Koltsaklis, N. E., Christoforidis, G. C. (2021). Forecasting Methods to Support the Decision Framework of Prosumers in Deregulated Markets. 2021 9th International Conference on Modern Power Systems (MPS), 1–5. https://doi.org/10.1109/mps52805.2021.9492725
19. Benti, N. E., Chaka, M. D., Semie, A. G. (2023). Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects. Sustainability, 15 (9), 7087. https://doi.org/10.3390/su15097087
20. Teixeira, R., Cerveira, A., Pires, E. J. S., Baptista, J. (2024). Advancing Renewable Energy Forecasting: A Comprehensive Review of Renewable Energy Forecasting Methods. Energies, 17 (14), 3480. https://doi.org/10.3390/en17143480
21. Xie, Y., Li, C., Li, M., Liu, F., Taukenova, M. (2023). An overview of deterministic and probabilistic forecasting methods of wind energy. IScience, 26 (1), 105804. https://doi.org/10.1016/j.isci.2022.105804
22. Lukianykhin, O., Shendryk, V. (2025). Machine learning-driven photovoltaic generation forecasting for prosumer decision support. Artificial Intelligence, 30 (AI.2025.30 (1)), 107–119. https://doi.org/10.15407/jai2025.01.107
23. Karagiannopoulos, S., Aristidou, P., Hug, G. (2019). Data-Driven Local Control Design for Active Distribution Grids Using Off-Line Optimal Power Flow and Machine Learning Techniques. IEEE Transactions on Smart Grid, 10 (6), 6461–6471. https://doi.org/10.1109/tsg.2019.2905348
24. Linan-Reyes, M., Garrido-Zafra, J., Gil-de-Castro, A., Moreno-Munoz, A. (2021). Energy Management Expert Assistant, a New Concept. Sensors, 21 (17), 5915. https://doi.org/10.3390/s21175915
25. Langtry, M., Wichitwechkarn, V., Ward, R., Zhuang, C., Kreitmair, M. J., Makasis, N. et al. (2024). Impact of data for forecasting on performance of model predictive control in buildings with smart energy storage. Energy and Buildings, 320, 114605. https://doi.org/10.1016/j.enbuild.2024.114605
26. Pineda, S., Morales, J. M., Boomsma, T. K. (2016). Impact of forecast errors on expansion planning of power systems with a renewables target. European Journal of Operational Research, 248 (3), 1113–1122. https://doi.org/10.1016/j.ejor.2015.08.011
27. Matthiss, B., Momenifarahaniy, A., Ohnmeissz, K., Felderx, M. (2018). Influence of Demand and Generation Uncertainty on the Operational Efficiency of Smart Grids. 2018 7th International Conference on Renewable Energy Research and Applications (ICRERA), 751–756. https://doi.org/10.1109/icrera.2018.8566733
28. Eljand, K., Laid, M., Scellier, J.-B., Dane, S., Demkin, M., Howard, A. (2023). Enefit - Predict energy behavior of prosumers. Kaggle. Available at: https://kaggle.com/competitions/predict-energy-behavior-of-prosumers
29. Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D. et al. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods, 17 (3), 261–272. https://doi.org/10.1038/s41592-019-0686-2
30. Knap, V., Molhanec, M., Gismero, A., Stroe, D.-I. (2021). Calendar Degradation and Self-Discharge Occurring During Short- and Long-Term Storage of NMC Based Lithium-Ion Batteries. ECS Transactions, 105 (1), 3–11. https://doi.org/10.1149/10501.0003ecst
31. Kumar, M. (2023). Comparison on study of lithium ion and lead acid charging and discharging characteristics. International Scientific Journal of Engineering and Management, 02 (03). https://doi.org/10.55041/isjem00163