AI-Driven Flexibility Market Platform for Dynamic Demand Regulation in Eco-Industrial Cluster

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***Abstract*—This study presents an Artificial Intelligence(AI)-driven local flexibility market platform designed to enhance grid resilience and support sustainable energy integration within eco-industrial clusters. As industrial energy demand grows and grid congestion intensifies, scalable solutions are essential to balance supply and demand. The proposed platform introduces a bidirectional demand regulation system, enabling industries to optimize flexibility market participation, mitigate grid constraints, and generate financial incentives for adaptive energy behavior. At its core, an Extreme Gradient Boosting (XGBoost) model delivers high-precision demand forecasting, capturing daily, weekly, and seasonal variations across industrial sectors. Unlike traditional models, it integrates feature-engineered balancing price predictions, empowering industries with strategic bidding capabilities. A Danish eco-industrial cluster case study, interfacing with the DK1 wholesale aggregator, validates the platform's scalability and real-world applicability, demonstrating its ability to transform industries into proactive market participants, enhancing economic benefits while strengthening grid stability**

***Index Terms*—Local Flexibility electricity markets, Industrial demand response, AI driven demand forecasting of industry, Flexibility market simulator, Eco-industrial clusters, AI-driven flexibility markets**

I. INTRODUCTION

The transition to sustainable energy has increased power grid complexity. With rising industrial energy use and grid congestion, scalable solutions are needed to balance supply and demand efficiently. Local Flexibility Markets (LFMs) enhance grid stability, enabling industrial consumers to participate in demand-side response (DSR) while optimizing financial returns [1]. These markets also integrate distributed energy resources (DERs) to improve supply-demand matching and mitigate grid constraints [2] .

1) AI and Machine Learning in Demand Flexibility: Advancements in artificial intelligence (AI) and machine learning (ML) have significantly improved energy forecasting and flexibility market operations. Traditional demand-side management (DSM) approaches rely on static schedules and fixed tariffs, limiting adaptability to real-time market conditions [3].In contrast, AI-driven models—particularly Extreme Gradient Boosting (XGBoost)—effectively handle large datasets, capture nonlinear dependencies, and improve forecasting accuracy [4].These capabilities enable industries to optimize market participation and enhance profitability [5]. Recent research demonstrates the effectiveness of XGBoost-based forecasting in predictions [6]. Feature engineering techniques further refine predictive accuracy, enabling dynamic adjustments [7]. AI-powered real-time demand response mechanisms also enhance grid stability and market efficiency [8].

2) Research Contributions: This study enhances AI-powered flexibility trading by: (1) Extending existing platforms [9] with interactive visualizations, improved forecasting, and enhanced trading mechanisms. (2) Developing a high-precision AI-driven forecasting model, integrating real-time grid conditions and balancing price fluctuations. (3) Implementing a strategic bidding system to optimize market participation, improving prior bidding strategies. (4) Demonstrating the platform's real-world applicability via a case study on Danish eco-industrial clusters, interfacing with the DK1 wholesale market aggregator.

3) Research Challenges and Motivation: Despite AI-driven forecasting's success, existing models focus mostly on short-term load predictions, often neglecting real-time balancing price dynamics. Ensuring accurate price forecasting and optimal bidding in LFMs remains challenging [10], [11]. Prior research highlights real-time data analytics as critical for optimizing industrial flexibility trading [12], reinforcing the need for AI-driven participation frameworks [13]. This study addresses these gaps by integrating a feature-engineered balancing price forecasting model with real-time bidding optimization, enabling proactive and profitable market engagement.

The remainder of this paper is structured as follows: Section II presents the XGBoost-based forecasting methodology. Section III describes the AI-driven flexibility market platform, while Section IV evaluates performance through a real-world case study. Section V concludes with key findings and future research directions.

II. METHODOLOGY

A. Extreme Gradient Boosting (XGBoost) Algorithm for Industrial Electricity Consumption

XGBoost leverages parallel processing to enhance computational efficiency and features an intrinsic mechanism for handling missing values by allowing user-defined placeholders

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[4]. Unlike conventional forecasting algorithms, which halts tree expansion on negative loss, XGBoost supports user-defined tree depth, enabling deeper learning representations and improving predictive performance.

Decision tree models include a built-in feature importance attribute, which highlights the most influential features in making predictions. This importance is determined using criteria such as Gini impurity or entropy-based information gain, helping to identify which features contribute the most to decision-making. The main formulations used for XGBoost algorithm are given in Eq (1) - (5).

1. **Objective Function:**

$$\mathcal{O}(\phi) = \mathcal{L}(\phi) + \Psi(\phi) \tag{1}$$

where $\mathcal{L}(\phi)$ is the loss function measuring model performance, and $\Psi(\phi)$ is the regularization term controlling complexity to prevent over fitting.

2. **Model Prediction:**

$$\hat{z}_i = \sum_{q=1}^{Q} g_q(s_i), \quad g_q \in \mathcal{G} \tag{2}$$

where Q is the number of trees, and $\mathcal{G}$ represents the space of all regression trees, ensuring ensemble learning through boosting.

3. **Regularization Term:**

$$\Psi(g_q) = \delta U + \frac{1}{2}\kappa \sum_{j=1}^{U} v_j^2 \tag{3}$$

where U is the number of leaves, v_j is the weight for leaf j, and δ, κ are regularization parameters that control tree complexity and mitigate overfitting.

4. **Second-Order Taylor Expansion of Loss Function:**

$$\mathcal{O}^{(p)} \approx \sum_{i=1}^{m} \left[a_i g_p(s_i) + \frac{1}{2} b_i g_p^2(s_i) \right] + \Psi(g_p) \tag{4}$$

where a_i and b_i are the first and second derivatives of the loss function with respect to prediction $\hat{z}_i$, facilitating efficient gradient-based optimization.

5. **Optimal Weight Calculation for Each Leaf Node:**

$$v_j^* = -\frac{\sum_{i \in J_j} a_i}{\sum_{i \in J_j} b_i + \kappa} \tag{5}$$

where J_j represents all instances in leaf j, ensuring that leaf weights are adjusted based on loss gradients to optimize tree splits.

B. Methodology for Deriving Optimal Hours for Up-regulation and Down-regulation for Industrial Consumers

Eco-industrial clusters consist of industries with varied or similar load profiles located within close proximity. These industries can leverage demand-side flexibility by participating in electricity markets through up-regulation (contributing energy to the grid) and down-regulation (reducing consumption to support grid stability). Aggregators facilitate these transactions by tracking wholesale electricity volumes, prices, and market conditions.

To determine the optimal hours for demand-side flexibility, this methodology employs correlation analysis between predicted factory energy consumption and forecasted grid load, followed by price-based decision-making using machine learning techniques. The approach assumes that industrial consumers have access to on-site generation or battery storage to facilitate energy balancing. Furthermore, the flexibility potential is set at 10% of the factory's maximum consumption.

For simplicity, this study considers only participation in balancing ancillary services markets; however, the proposed platform is also designed to support other energy services. In this context, the balancing ancillary services market operates after the intraday market, with spot prices already determined. Additionally, it is assumed that the factory procures electricity from the grid at day-ahead market spot prices. Consequently, selling electricity at a price lower than the spot price would be economically unfeasible, and such cases are excluded from consideration.

This algorithm determines the best hours for up-regulation and down-regulation based on strong positive and strong negative correlations, ensuring that participation in the balancing market is financially viable

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Algorithm 1 Optimal Demand-Side Flexibility Algorithm
Require: Predicted factory consumption, predicted grid load, predicted balancing up prices, $P_{\text{up}}$ and predicted balancing down prices, $P_{\text{down}}$ and spot prices, $P_{\text{spot}}$ from Energinet API
Ensure: Optimal flexibility decision per hour

Step 1: Correlation Analysis
  • Compute Pearson correlation coefficient ($r$) between predicted factory consumption and predicted grid load.
  • If $r \leq -0.50$ then: Label as Strongly Negative.
  • Else if $r \geq 0.50$ then: Label as Strongly Positive.
  • Else: Ignore hour.

Step 2: Store Selected Hours
  • Store hours with Strongly Negative/Positive correlation in Selected_Hours.

Step 3: Decision Making
  • For each hour in Selected_Hours:
      – Retrieve $P_{\text{up}}$, $P_{\text{down}}$, $P_{\text{spot}}$.
      – If $P_{\text{up}} > \max(P_{\text{down}}, P_{\text{spot}})$ then:
          * Decision: Balancing Up-Regulation (Supply energy to grid).
      – Else if $P_{\text{down}} > P_{\text{spot}}$ then:
          * Decision: Balancing Down-Regulation (Reduce consumption).
      – Else:
          * Decision: No Action (Not profitable).
```

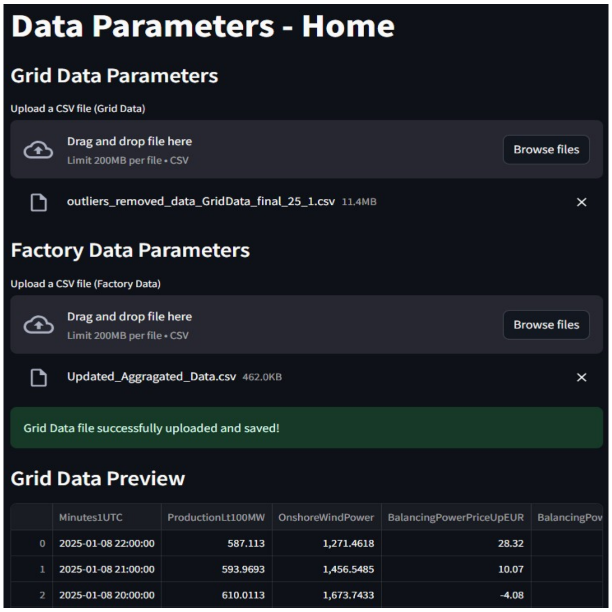
C. *AI-Driven Flexibility Market Platform for Eco Industrial Clusters*

This work extends the market-driven platform introduced in [9], integrating new interactive views and enhancements. The platform employs Streamlit for the graphical user interface (GUI) and Google Firebase as a cloud database for bid storage and clearance pricing. The backend, developed in Python 3.9, utilizes libraries such as scipy, sklearn, Streamlit, and Firebase, ensuring efficient data handling and seamless frontend-backend interaction.

This study improves performance of the platform with the integration of interactive analytics. Users can upload factory energy consumption and grid data and predict grid conditions, and forecast energy demand. The strategic bidding interface leverages AI to suggest optimal trading hours, bidding prices, and market participation types (balancing up/down regulation).

The data parameter view (Fig.1). enables industrial participants to upload and visualize grid and factory data for AI-driven market predictions, ensuring transparency before bidding. The strategic bidding view (Fig.7) provides insights into flexibility opportunities and market participation strategies.

By integrating AI-driven algorithms and interactive views, the platform enhances data-driven decision-making, enabling industrial participants to optimize bidding strategies, maximize revenue, and improve operational efficiency.



outliers_removed_data_GridData_final_25_1.csv 11.4MB

Updated_Aggragated_Data.csv 462.0KB

Grid Data file successfully uploaded and saved!

	Minutes1UTC	ProductionLt100MW	OnshoreWindPower	BalancingPowerPriceUpEUR	BalancingPov
0	2025-01-08 22:00:00	587.113	1,271.4618	28.32	
1	2025-01-08 21:00:00	593.9693	1,456.5485	10.07	
2	2025-01-08 20:00:00	610.0113	1,673.7433	-4.08	

Fig. 1. Uploading input files for strategic bidding in the platform

III. RESULTS AND DISCUSSIONS

A six-year historical dataset of balancing up-regulation prices, balancing down-regulation prices, spot prices, imbalance energy (MWh), renewable energy production, total grid load, and other conventional energy production data for the DK1 price area has been collected from Energinet, the Danish transmission system operator (TSO), via their datahub API [14]. Similarly, a two-year dataset of energy consumption and flexibility potential from a Danish industrial facility has been gathered for this study.

A. *Forecasting Model Performance-Validation on Danish Market Data.*

1) Balancing Up and Down Regulation Price: Figure 2 illustrates the feature importance ranking for balancing up-regulation prices. It can be observed that biomass, other renewable energies, and fossil hard coal remain resources for addressing balancing up-regulation requirements, highlighting the continued reliance on conventional energy sources during supply shortages. Using feature engineering and XGBoost algorithm, the balancing up-regulation price forecast is generated for the year 2024. The forecast results are depicted in Figure 3, showing expected price variations based on market conditions.

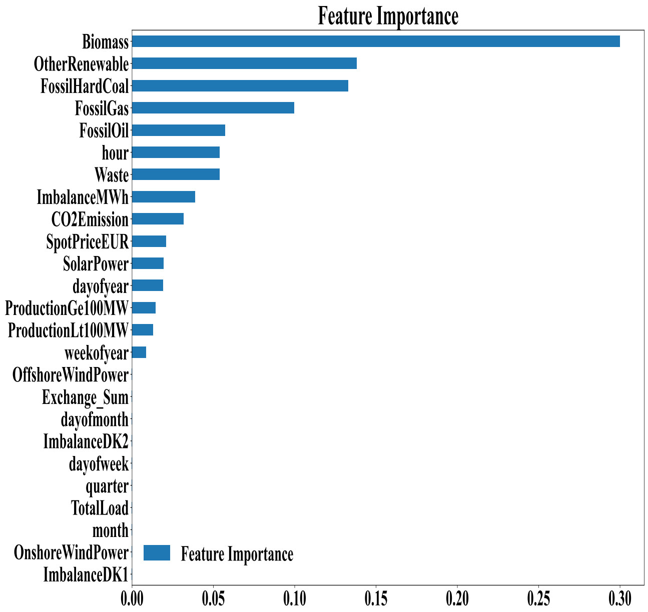


Fig. 2. Feature engineering of balancing up regulation price

Similarly, the balancing down-regulation price is forecasted using the same approach. The resulting forecast is shown in Figure 4.

Table I presents the evaluation metrics for balancing up-regulation and balancing down-regulation forecasts, demonstrating strong predictive accuracy. The Root Mean Square Error (RMSE) of 12.95 and the Mean Absolute Error (MAE) of 9.458, along with Theil's Inequality Coefficient (Theil's U) of 0.0826, validate the model's effectiveness. Given price fluctuations between 0–200 EUR/MWh, these results suggest profitable bidding opportunities. For balancing down-regulation, a similar trend is observed, albeit with slightly higher errors (RMSE = 13.99, MAE = 10.013, Theil's U = 0.1243). The Mean Absolute Percentage Error (MAPE) is infinite due to instances of zero-price values, which impact percentage-based error calculations. Additionally, a baseline

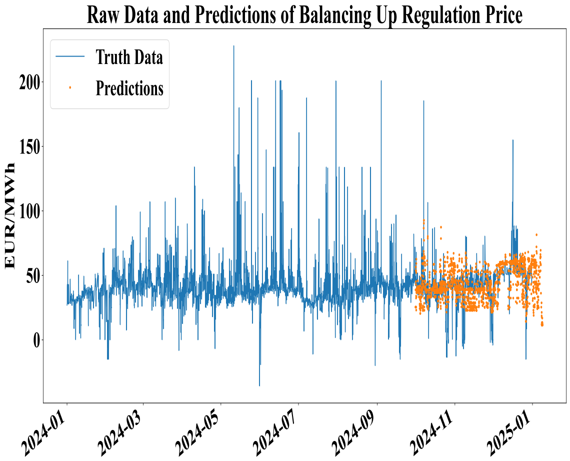


Fig. 3. Forecasting of balancing up regulation price

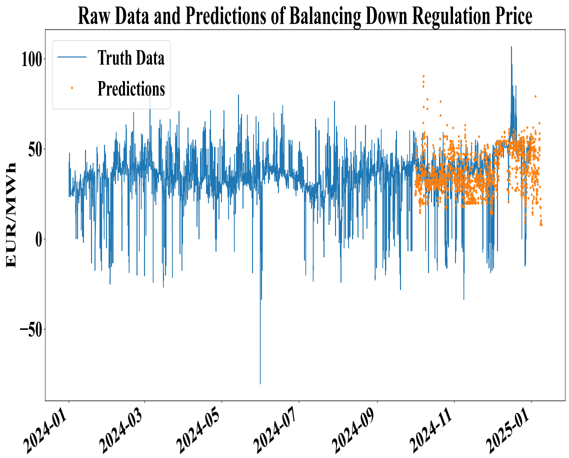


Fig. 4. Forecasting of balancing down regulation price

comparison with linear regression is conducted, demonstrating that the XGBoost model outperforms the baseline model in both balancing up-regulation and balancing down-regulation scenarios.

TABLE I
EVALUATION METRICS FOR THE BALANCING UP AND DOWN REGULATION PRICE MODELS

Metric	**Model (Up)**	**Baseline (Up)**	**Model (Down)**	**Baseline (Down)**
RMSE	12.95	30.42	13.99	27.05
MAE	9.458	24.32	10.013	21.38
MAPE (%)	inf	inf	inf	inf
Theil's U^2	0.0826	0.4573	0.1243	0.4649

2) Factory Energy Consumption: Using XGBoost algorithms, the model effectively predicts factory energy consumption while accounting for daily, weekly, and seasonal variations. This provides a robust foundation for optimizing energy usage scheduling. The temporal features—daily, weekly, and seasonal patterns—are extracted and analyzed to assess their significance in forecasting factory energy consumption.

Using these selected features, energy forecasting is performed utilizing XGBoost algorithm. As depicted in Figure 5, the predicted values closely align with actual energy consumption data, effectively capturing strong seasonal consumption trends—higher demand in winter months and lower demand in summer.

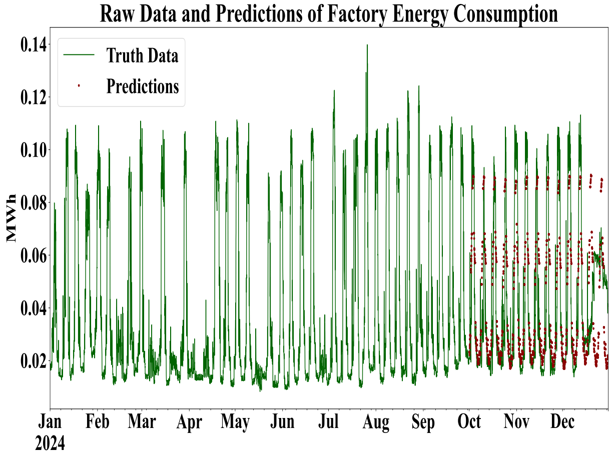


Fig. 5. Forecasting of a factory energy consumption

As shown in Table II, the forecasting model's performance is assessed using standard error metrics. The predicted values from the XGBoost model are compared with those from the baseline Linear Regression model to quantify performance improvements. The results indicate that the XGBoost model outperforms the baseline across all evaluation metrics. Specifically, the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) of the XGBoost model are 0.01905 and 0.01352, respectively, demonstrating lower prediction errors compared to the baseline values of 0.02689 and 0.02286. Furthermore, the Mean Absolute Percentage Error (MAPE) is significantly reduced from 70.37% in the baseline model to 36.48% in the XGBoost model, highlighting improved forecasting accuracy. Additionally, Theil's U^2 statistic is notably lower for the XGBoost model (0.1401) than for the Linear Regression model (0.2789), indicating superior predictive performance. These findings confirm that the XGBoost model provides more reliable and accurate forecasts for factory energy consumption.

TABLE II
EVALUATION METRICS FOR THE FACTORY ENERGY CONSUMPTION MODEL

Metric	**Model**	**Baseline (Linear Regression)**
RMSE	0.01905	0.02689
MAE	0.01352	0.02286
MAPE (%)	36.48	70.37
Theil's U^2	0.1401	0.2789

B. Optimal Demand Regulation Windows

In this study case, 938 hours were found to be strongly negatively correlated, while 754 hours exhibited strong positive correlation with the DK1 grid load in the year 2024. These two categories of hours play a crucial role in the strategic bidding calculations for demand-side management.

Identifying optimal hours for balancing up and balancing down regulation enhances financial efficiency by enabling industries to adjust energy consumption during profitable periods. The platform determines these optimal hours based on predicted balancing prices and factory energy demand patterns.

The simulation results for the factory, presented in Fig. 6, depict the optimal hours available for allocation among different regulatory actions, including balancing up, balancing down, and no action, over the course of 2024.

It is observed that balancing-up actions occur with greater frequency than balancing-down actions in this scenario. This trend may be influenced by specific market conditions, such as energy price volatility or grid stability requirements.

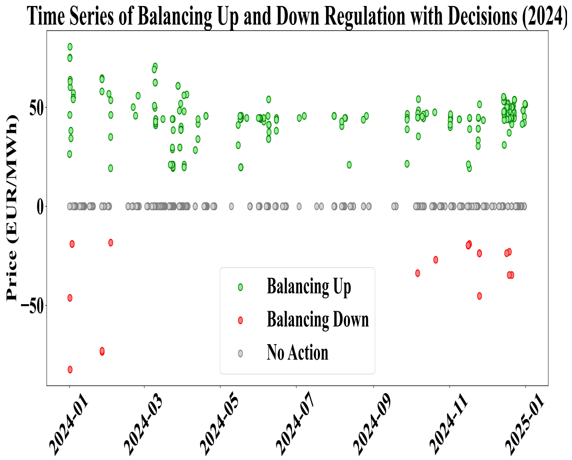
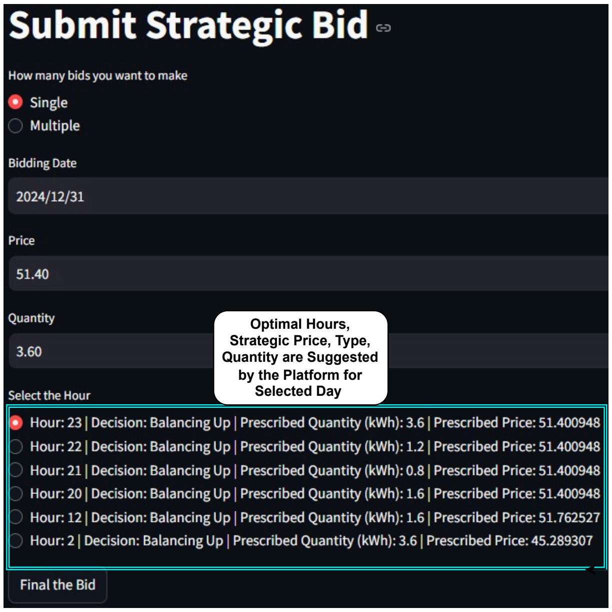


Fig. 6. Optimal hours for balancing up and balancing down regulation identified by AI platform for this use case and for year 2024

C. AI-Driven Flexibility Market Platform Demonstration

The platform bridges the gap between industrial participants and market aggregators, establishing a bidirectional regulation system. By integrating price forecasting, energy consumption forecasting, and demand flexibility constraints, the platform enables industries to optimize their bidding strategies. A strategic bidding interface of the AI-driven flexibility market platform is illustrated in Figure 7. The platform identifies all potential market participation opportunities (including date and time) and provides bid suggestions (covering type and price). Users can override these suggestions if they prefer a different bidding strategy. When submitting a strategic bid, a factory can select the desired date and available hours, along with the suggested strategic price, bid quantity, and the type of service (i.e., balancing up or balancing down).


Submit Strategic Bid

How many bids you want to make

● Single
○ Multiple

Bidding Date: 2024/12/31

Price: 51.40

Quantity: 3.60

Optimal Hours, Strategic Price, Type, Quantity are Suggested by the Platform for Selected Day

Select the Hour

● Hour: 23 | Decision: Balancing Up | Prescribed Quantity (kWh): 3.6 | Prescribed Price: 51.400948
○ Hour: 22 | Decision: Balancing Up | Prescribed Quantity (kWh): 1.2 | Prescribed Price: 51.400948
○ Hour: 21 | Decision: Balancing Up | Prescribed Quantity (kWh): 0.8 | Prescribed Price: 51.400948
○ Hour: 20 | Decision: Balancing Up | Prescribed Quantity (kWh): 1.6 | Prescribed Price: 51.400948
○ Hour: 12 | Decision: Balancing Up | Prescribed Quantity (kWh): 1.6 | Prescribed Price: 51.762527
○ Hour: 2 | Decision: Balancing Up | Prescribed Quantity (kWh): 3.6 | Prescribed Price: 45.289307

Fig. 7. Strategic bidding view in the AI driven platform for industrial consumer

IV. CONCLUSION

This study enhances AI-driven flexibility market participation by integrating XGBoost-based forecasting, balancing price predictions, and strategic bidding mechanisms. The proposed platform optimizes industrial engagement in local flexibility markets, demonstrating its effectiveness through a Danish case study. Future research will refine real-time adaptability and extend market applicability across different energy systems.

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