Renewable Energy, Environment, and Power Quality Journal (REE&PQJ)
ISSN:3020-531X
Volume 26, July 2026

A Risk-Aware Market Selection Framework for Prosumers in Multi-Market Energy Environments

R. Estudillo[1], G. Fernandez[1], R. Rocca[1,2], M. Gallego[1], M. Garcia[1] and D. Ferreira[3]

[1] CIRCE Technology Centre
50018, Zaragoza (Spain). e-mail: restudillo@fcirce.es, gfernandez@fcirce.es, rrocca@fcirce.es, mgallego@fcirce.es, mgarcia@fcirce.es

[2] ENERGAIA Mixed Research Institute (University of Zaragoza and CIRCE Technology Centre)
50018, Zaragoza (Spain)

[3] URBENER S-L. — Sistemas Urbanos de Energías Renovables
50004, Zaragoza (Spain) email: david.ferreira@urbener.com

Abstract. With the ongoing transition towards Smart Grids, power systems are increasingly characterized by the integration of distributed energy assets, the electrification of loads, and the deployment of advanced monitoring and control infrastructures. While these developments enable more efficient operation, they also introduce new operational challenges, particularly at distribution level, such as congestion and voltage issues. As a result, the use of flexibility and the emergence of new energy markets have gained relevance, enabling distributed resources to actively support system operation. In this context, the prosumer becomes a key actor. One of the main challenges prosumers face is the lack of knowledge related to energy markets and power system operation, particularly regarding energy prices and uncertainty associated with flexibility service activation in the day-ahead horizon. Although energy prices can be predicted with reasonable accuracy, deviations from actual future values remain unavoidable. This uncertainty, combined with multiple market options, introduces additional risk when deciding which market to participate in. To address this challenge, this paper proposes a novel algorithm that evaluates market-specific risk for each time window based on a configurable risk aversion parameter and selects the optimal market for buying or selling energy, considering price prediction uncertainty and probability of market activation.

Key words. Flexibility, energy market, prosumer, smart grid, optimal market selection

1. Introduction

The ongoing transition towards Smart Grids is reshaping power systems through the large-scale integration of distributed energy resources (DERs), the electrification of demand (e.g., electric vehicles and heat pumps), and the deployment of advanced monitoring and control infrastructures [1]. These trends are moving electricity systems away from a traditionally centralized and unidirectional paradigm towards decentralized distribution networks in which end-users can also produce, store, and manage energy. Prosumers (entities that both consume and produce electricity) have therefore become key actors in distribution-level operation and market participation [2], [3]. While DER integration enables more efficient and sustainable operation, it also introduces new operational challenges at distribution level, where networks were not originally designed for bidirectional flows and high local injections. In practice, high penetrations of intermittent renewables may lead to voltage constraint violations and thermal congestion, limiting further DER hosting capacity and degrading power quality if not properly managed. Recent reviews emphasize that voltage fluctuations and congestion are among the most recurrent technical barriers in RES-dominated distribution grids, and that purely "fit-and-forget" operation is no longer sufficient [4]. Traditionally, these issues have been addressed through network reinforcement, but this approach is often expensive and slow compared with operational alternatives. A growing body of literature therefore investigates flexibility-based congestion management, where controllable loads, storage, and DERs are activated to relieve constraints. A comprehensive design perspective shows that DSOs can combine multiple mechanisms—such as smart network tariffs, local market-based procurement, and even direct control—to mitigate congestion events, each with different trade-offs in efficiency, complexity, and susceptibility to strategic behaviour [5].

In this context, Local Flexibility Markets (LFMs) have gained prominence as market-oriented mechanisms that allow DSOs to procure flexibility services from DERs and aggregators for constraint management [6],[7]. Also peer-to-peer (P2P) energy trading has emerged as a decentralized paradigm where prosumers exchange energy directly, typically enabled by digital platforms and coordination mechanisms. A broad review of the literature identifies P2P trading as a promising route to increase prosumer participation and local renewable utilization, while also underlining open challenges related to scalability, market clearing, network constraints, and realistic modelling of participant behaviour [8].

Despite these opportunities, a central challenge for prosumers is that decision-making becomes increasingly conditioned by uncertainty and risk. In wholesale markets, day-ahead prices can be forecasted with increasing accuracy, but the realized values remain uncertain and can deviate significantly under non-stationary conditions (e.g., changes in generation mix, regulatory context, or market shocks). Probabilistic forecasting and scenario generation approaches are widely used to quantify uncertainty and provide inputs for downstream decision-making under uncertainty [9]. In addition, emerging flexibility arrangements introduce a second uncertainty layer: the activation of flexibility services is not guaranteed in each time slot and depends on local grid conditions and market outcomes.

To handle these uncertainties, the literature increasingly relies on risk-aware optimization tools (e.g., chance constraints, distributionally robust formulations, and explicit risk measures) to capture risk aversion and avoid unfavourable outcomes. For instance, risk-averse prosumer behaviour has been modelled using distributionally robust chance-constrained equilibrium formulations, showing that both uncertainty magnitude and risk preference materially affect optimal strategies and payoffs [10]. Similarly, risk-averse participation of prosumer coalitions in local markets has been studied, emphasizing that uncertainty at coalition level can significantly impact economic results and strategic bidding decisions [11].

Motivated by these gaps, the remainder of this article builds on this body of work to support prosumer decisions in multi-market environments where both price forecast errors and market activation uncertainty affect profitability.

2. Methodology

Within REEFLEX Project, the prosumer/aggregator is expected to interact with multiple markets (e.g., day-ahead, intraday, and emerging local/probabilistic options such as LFM and P2P). A practical issue observed in the project is that choosing the "best" market is not trivial: markets differ not only in expected price, but also in execution certainty (continuous/cleared markets vs. activation- or matching-dependent markets) and in the risk introduced by forecast errors.

This real operational need motivates the creation of the Optimal Market Selection Tool (OMST) designed to generate an optimal buy/sell market decision per time slot for the next day. At a conceptual level, the tool follows a modular global structure (Fig. 1). In general terms, OMST integrates:

1) Input blocks containing price data for each market (day-ahead, continuous, intraday, and flexibility constraints). Given the lack of real P2P data, its price is estimated as the average in each time interval between the minimum market sell price and maximum market buy price. Furthermore, as LFM and P2P activation data is unavailable, a 3-hour activation is assumed during daily peak demand and another 3-hour window during peak generation.

2) Configuration block, where the user can adjust the value of the aversion parameter $\boldsymbol{A}$. This is a key design element that allows the tool's behaviour to be adapted to the prosumer's profile: low values of $\boldsymbol{A}$ promote more aggressive strategies based on expected profitability, whereas high values penalize uncertainty more strongly, prioritizing more stable decision-making.

3) Calculation block, where the tool processes as inputs the predicted prices for the following day, together with the historical information required to characterize the reliability of the predictor and, in those market schemes where execution is not guaranteed, an activation history used to estimate the probability that the transaction will be executed. All these data are managed under a homogeneous structure to enable direct comparison between markets across all time intervals. The score calculation module is responsible for calculating the score for each market to determine the best market choices for the following day.

4) Outputs block contains the results produced by the tool. The outcome of the process is two csv files, which includes, for each time interval of day d+1, the recommended market for buying and/or selling for each 15 minutes interval. This output enables the market selection to be consumed by an aggregator or their prosumers facilitating its integration within control and operational architectures such as those deployed in REEFLEX.

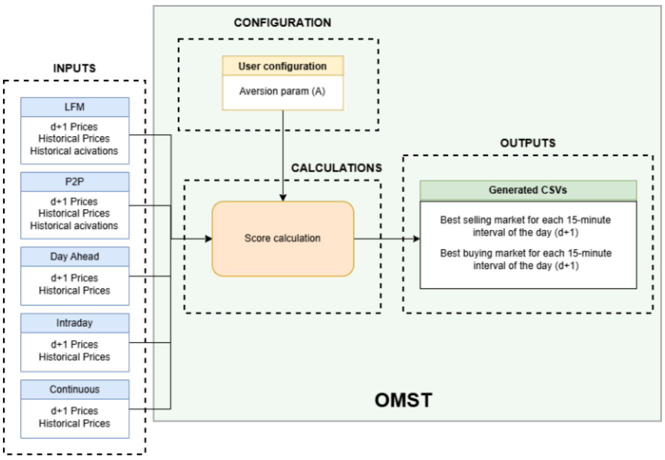

Fig. 1. Global architecture of OMST

In OMST, the risk term is constructed based on the uncertainty associated with the price prediction error, since the market decision is made using forecasted values provided by an external tool rather than real values. For each market $\boldsymbol{e}$ and time interval $\boldsymbol{t}$, the prediction error is defined as in (1).

$$\epsilon_e(t) = P^{Real}{}_e(t) - P^{Pred}{}_e(t) \tag{1}$$

Where $\boldsymbol{P^{Real}{}_e(t)}$ is the real market price of market e at time interval $\boldsymbol{t}$ and $\boldsymbol{P^{Pred}{}_e(t)}$ is the predicted market price of market $\boldsymbol{e}$ on day $\boldsymbol{d}$, at time interval $\boldsymbol{t}$. This error is particularly relevant because prediction errors are typically non-stationary: they depend on the day, the time slot, the system operating conditions, and the quality of the forecasting model. For instance, it is common for the predictor to perform better during certain hours of the day, or to experience temporary degradation when meteorological or market conditions change. Likewise, if the predictor improves its performance over time, the conditional variance naturally assigns higher weight to predictions closer to the present day. To estimate this conditional variance in a practical and robust way using short historical windows, OMST employs an Exponential Weighted Moving Standard Deviation (EWMSD)-type estimator [12], which assigns higher weight to more recent prediction errors (2).

$$EWMSD_e(t) = \sum_{n=0}^{n=7}(1-\lambda) \times \lambda^n \times \epsilon_{e,n}(t)^2 \tag{2}$$

Where $\boldsymbol{EWMSD_e(t)}$ is the conditional variance for market $\boldsymbol{e}$, at time interval $\boldsymbol{t}$, on day $\boldsymbol{d+1}$. $\boldsymbol{\lambda}$ is the decay factor, which typically ranges between 0.94 and 0.97. $\boldsymbol{\epsilon_{e,t,n}{}^2}$ is the prediction error for market $\boldsymbol{e}$, at time interval $\boldsymbol{t}$. The value of $\boldsymbol{n}$ is an integer ranging from 0 (day $\boldsymbol{d}$) to 7 (day $\boldsymbol{d-7}$). This approach is selected for several reasons.

First, the tool operates with high temporal resolution (96 daily time intervals) and therefore requires a computationally efficient method that can be rapidly recalculated for each interval and for each market.

Second, the exponential weighting scheme introduces a mechanism such that, if the predictor starts performing worse during the most recent days, the estimator reacts quickly by increasing $\boldsymbol{EWMSD_e(t)}$, thereby penalizing the market score for that interval. Conversely, if recent errors decrease, the risk measure is reduced, and the market becomes attractive again. This property makes EWMSD particularly suitable for real and dynamic contexts, where extensive historical datasets are not available or where stationarity assumptions are undesirable.

Complementarily, OMST introduces the activation probability $\boldsymbol{Z_{e,d+1}(t)}$ for those market schemes in which a transaction may not actually be executed. This element is critical to represent the difference between markets with guaranteed execution and environments where the transaction depends on external conditions (for instance, the existence of local congestion, the need for the service by the system operator, or sufficient counterparty availability in P2P trading). Instead of assuming a fixed activation value, OMST estimates $\boldsymbol{Z_{e,d+1}(t)}$ through an Exponentially Weighted Moving Average (EWMA) (3) applied to a binary activation history for each market.

$$\begin{aligned} Z_{e,d+1}(t) = \lambda\gamma_e(t) + \lambda(1-\lambda)\gamma_{d-1}(t) \\ + \lambda(1-\lambda)^2\gamma_{d-2}(t) + \cdots \\ + \lambda(1-\lambda)^8\gamma_o \end{aligned} \tag{3}$$

Where $\boldsymbol{Z_{e,d+1}(t)}$ represents the activation probability, computed using an EWMA estimator for market $\boldsymbol{e}$, at time interval $\boldsymbol{t}$, for day $\boldsymbol{d+1}$. $\boldsymbol{\lambda}$ is the smoothing factor, which may take a value of 0.2. $\boldsymbol{\gamma_{e,d-n,}(t)}$ is the binary activation indicator for market $\boldsymbol{e}$, at time interval $\boldsymbol{t}$, on day $\mathbf{d}-\boldsymbol{n}$ and $\boldsymbol{\gamma_o}$ is the initial binary activation value, configured as 1. Similarly to the risk estimation case, the use of exponential weighting allows the model to better capture the recent behaviour of the market. If the market has frequently been activated during a specific time slot over the last days, $\boldsymbol{Z_{e,d+1}(t)}$ will tend towards 1, increasing the attractiveness of operating in that interval. Conversely, if activation has been scarce or null in recent days, the estimated probability will decrease, automatically penalizing the score even if the expected price is favourable. This approach also provides practical advantages: it does not require complex classification or probabilistic estimation models, it adapts well to short historical windows, and it enables a direct and traceable implementation. Finally, both the conditional dispersion term $\boldsymbol{EWMSD_e(t)}$ and the activation probability $\boldsymbol{Z_{e,d+1}(t)}$ are integrated into the computation of a risk-adjusted score function, where the final score simultaneously reflects the expected profitability, the uncertainty associated with the predictor, and the feasibility of execution. In this way, OMST does not only evaluate markets based on their expected price but also accounts for the likelihood of the transaction being performed and the confidence in the forecast. For the selling decision, OMST computes the risk-adjusted score as in (4).

$$\begin{aligned} S_{sell(d+1,e)}(t) = \mu_{d+1,e}(t) - \frac{1}{2}A \\ \cdot EWMSD_{(d+1,e)}(t) - A \\ \cdot \left[1 - Z_{e,d+1}(t)\right] \\ \cdot EWMSD_{(d+1,e)}(t) \end{aligned} \tag{4}$$

whereas for the buying decision, OMST evaluates as following (5).

$$\begin{aligned} S_{buy(d+1,e)}(t) = \mu_{d+1,e}(t) + \frac{1}{2}A \\ \cdot EWMSD_{(d+1,e)}(t) + A \\ \cdot \left[1 - Z_{e,d+1}(t)\right] \\ \cdot EWMSD_{(d+1,e)}(t) \end{aligned} \tag{5}$$

In these expressions, the term $\boldsymbol{Z_{e,d+1}(t)}$ acts as an execution feasibility modulator: when the probability of activation is low, the expected value of operating in that market is reduced, even if the predicted price is favourable. This allows OMST to naturally penalize markets such as LFM or P2P when their recent activation history indicates low likelihood of execution for a given time slot. Similarly, the term involving $\boldsymbol{A}$ and $\boldsymbol{EWMSD_e(t)}$ introduces a risk-aversion mechanism based on the reliability of the price predictor. Markets exhibiting high dispersion of prediction errors for a given time interval are penalized, reducing the probability that OMST selects an apparently profitable but unstable option. The parameter $\boldsymbol{A}$ therefore enables adaptation to different prosumer profiles: low values lead to more profit-driven strategies, while high values result in more conservative decisions that prioritize stability and reduced exposure to forecast uncertainty. Overall, the combined use of EWMSD (risk quantification) and EWMA-based activation probability $\boldsymbol{Z_{e,d+1}(t)}$ enables OMST to produce more realistic market participation decisions, capturing the inherent trade-off between expected profit and risk exposure. This provides a consistent and traceable criterion for optimal market selection in each time interval of the day-ahead horizon. Once the risk-adjusted score values are computed for all the markets $\boldsymbol{M}$ and for each time interval t in equation (6), OMST performs the market selection step by applying a direct optimization criterion.

For the selling decision, OMST selects the market that maximizes the score function as defined in (6).

$$e^*_{sell,d+1}(t) = \arg\max_{e\in M} \; S_{sell(d+1,e)}(t) \qquad (6)$$

Similarly, for the buying decision, OMST selects the market that minimizes the associated score as given in (7).

$$e^*_{buy,d+1}(t) = \arg\min_{e\in M} \; S_{buy(d+1,e)}(t) \qquad (7)$$

As a result, the tool produces, for each time slot $\boldsymbol{t}$ of day $\boldsymbol{d+1}$, the optimal market recommendation for buying and/or selling energy, ensuring that the decision reflects not only the expected price but also the risk linked to forecasting uncertainty and the probability of execution in probabilistic market schemes.

3. Optimal Market Selection Tool

The Optimal Market Selection Tool (OMST) has been implemented as a lightweight, modular Python application within the REEFLEX framework. While the previous section describes the methodological foundations of the tool, this section focuses on its practical realization, software architecture, and testing procedure. OMST is implemented entirely in Python, following a pipeline-oriented design that facilitates traceability and reproducibility. Market data ingestion is handled through CSV files which are generated automatically from ESIOS API responses, containing real and predicted prices for the day-ahead and intraday markets, as well as synthetic representations of continuous, P2P, and LFM markets. This approach allows OMST to operate transparently on real or simulated datasets without modifying the core logic. Internally, all market data are reshaped into homogeneous data structures indexed by day and quarter-hour, ensuring consistent comparison across markets.

The score calculation processing layer directly reflects the estimators introduced in the methodology section. EWMA and EWMSD calculations are applied per market and per time interval using vectorized NumPy operations, which ensures computational efficiency even at high temporal resolution (96 intervals per day). Special care has been taken to guarantee numerical robustness: negative or undefined prices are clipped to zero. This safeguard prevents extreme or unrealistic cases from propagating into the decision stage and ensures stable execution under typical data imperfections. Scores are computed independently for each market and time interval. The final market choice is obtained through argmax/argmin operations, complemented by a tie-breaking mechanism that prioritizes higher execution feasibility and lower risk exposure.

As a result, OMST produces a single score for each quarter-hour of the next-day horizon. In addition, the tool generates two CSV output files: one containing the markets with the highest score for selling, and another with the markets with the highest score for buying. From a software point of view, OMST uses only common and widely used Python libraries. It relies on pandas for handling time series and organizing data, and numpy for numerical calculations. The requests library is used to retrieve data from APIs when needed. This simple setup makes OMST easy to use and deploy, even in limited environments.

The tool has been tested on a standard personal computer (AMD Ryzen 5 Pro 7535U with Radeon Graphics, 16 GB RAM) under a typical scientific Python environment. The tool has been validated using real Spanish electricity market data from March 5 to March 11, 2026, to determine the optimal selection for March 12, 2026. The dataset includes all the following markets: day ahead, continuous, intraday, P2P (estimated) and LFM, where the latter corresponds to the average quarter-hourly price of system constraints.

4. Analysis

The graphical results illustrate the operational behaviour of OMST in comparison with a purely price-driven baseline strategy. For benchmarking purposes, a simple baseline strategy is defined that operates independently for each quarter-hour. In the selling case, the baseline selects, at every quarter-hour interval, the market with the highest predicted price, disregarding any consideration of risk or execution uncertainty. Conversely, for buying decisions, the baseline selects the market with the lowest predicted price at each quarter-hour, again without accounting for forecast errors or activation probabilities. In contrast, OMST incorporates both forecast uncertainty and activation probability into a risk-adjusted score formulation.

The predicted price comparison (Fig. 2) shows that the tool sometimes selects markets with higher prices, while the baseline consistently chooses the lowest prices. This occurs because the score can be higher in markets with slightly higher prices when their associated risk is significantly lower, resulting in a better overall score.

The score comparison (Fig. 3) illustrates the improvement in the score for each decision, comparing both the baseline and the selections generated by OMST. The improvement plot (Fig. 4) makes this effect even clearer, showing how the score increases when deviating from the lowest-price market chosen by the baseline. If the risk aversion parameter ***A*** were smaller, the decisions made by OMST would more closely resemble those of the baseline, since a lower value of ***A*** implies a higher tolerance for risk.

For selling decisions, a similar pattern is observed. The baseline selects, at each quarter-hour, the market with the highest predicted price, while OMST may choose markets with slightly lower prices. This happens because the score can be higher in markets where the risk is significantly lower or the probability of activation is higher, leading to a better overall outcome despite not having the maximum price.

The score comparison (Figures 5 and 6) shows how the score improves for each decision when comparing the baseline with OMST. The improvement graph (Fig. 7) makes this effect clearer, highlighting how the score increases when deviating from the highest-price market selected by the baseline. If the risk aversion parameter A were reduced, OMST decisions would become closer to the baseline, since a lower value of Aimplies a greater willingness to accept risk in exchange for higher expected prices.

The timeline representations (Figs. 8 and 9) provide a clear visualization of the selected markets across the full day-ahead horizon. They show how OMST dynamically switches between markets at a quarter-hour resolution, reflecting the combined effect of price, risk, and activation probability.

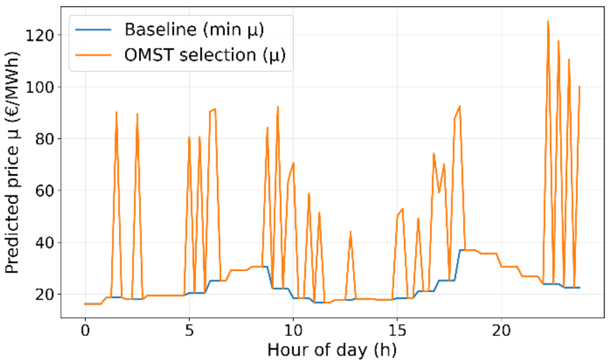

Fig. 2. Buy predicted price comparison (Baseline vs OMST).

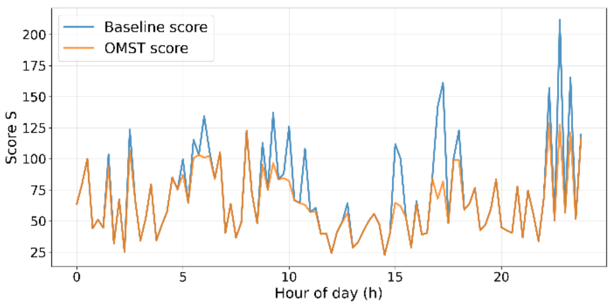

Fig. 3. Buy score comparison (Baseline vs OMST).

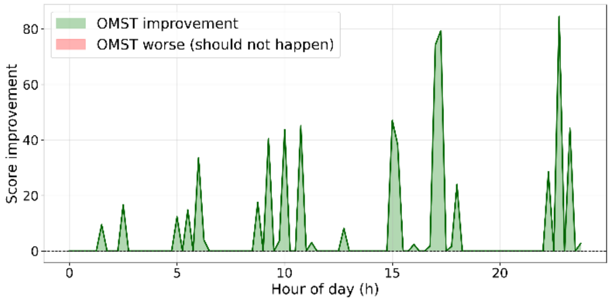

Fig. 4. Buy score improvement of OMST over baseline.

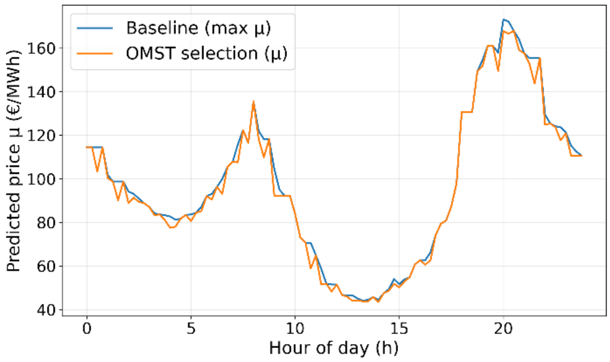

Fig. 5. Sell predicted price comparison (Baseline vs OMST).

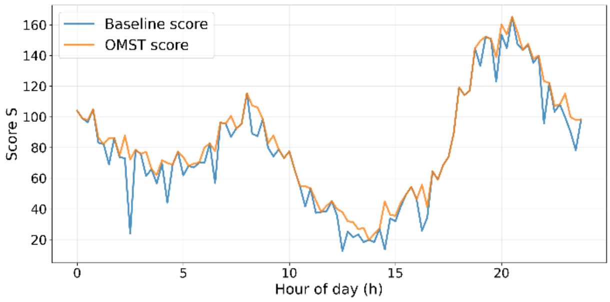

Fig. 6. Sell score comparison (Baseline vs OMST).

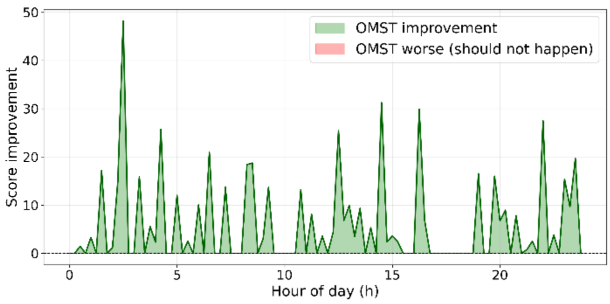

Fig. 7. Sell score improvement of OMST over baseline.

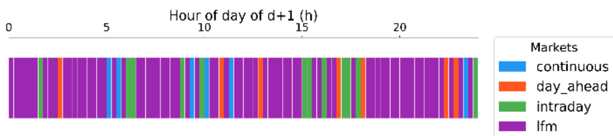

Fig. 8. Hourly market selection timeline for the OMST buying strategy.

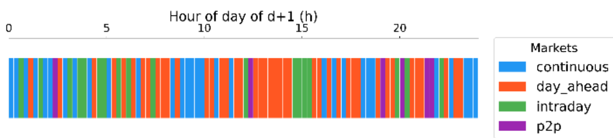

Fig. 9. Hourly market selection timeline for the OMST selling strategy.

Overall, the results indicate that OMST behaves consistently with its theoretical design. It does not aim to outperform the baseline in purely price terms, but rather to improve the expected risk-adjusted outcome by internalizing uncertainty and feasibility aspects. The behaviour observed in the figures is coherent with the implemented score formulation and demonstrates that the tool responds dynamically to variations in forecast dispersion and activation probability.

5. Conclusions

The transformation of distribution networks driven by high penetration of distributed energy resources, electrification of demand, and digitalization is leading to the proliferation of new market mechanisms, including local flexibility markets and peer-to-peer trading schemes. While these markets create new economic opportunities for prosumers, they also introduce additional layers of uncertainty related not only to price volatility but also to execution feasibility. The coexistence of multiple market alternatives with heterogeneous risk profiles makes intuitive decision-making increasingly complex and potentially inefficient. In this context, the Optimal Market Selection Tool provides a structured and traceable framework to support prosumer decision-making in multi-market environments. By combining expected price, forecast uncertainty through an exponentially weighted dispersion measure, and activation probability estimated from recent history, OMST captures the fundamental trade-off between profitability and risk exposure. The preliminary results indicate that the tool behaves coherently with its theoretical formulation and consistently achieves risk-adjusted utilities that are equal to or better than those obtained through a purely price-driven baseline strategy. Although the current model does not yet support intra-day updates, a promising enhancement would be re-executing the tool every 6 hours. This would allow updating market activation values and readjusting predictions based on new real-time data, effectively increasing granularity to improve accuracy. Such refinements, along with further calibration, will ensure the tool's robustness as new flexibility products and probabilistic market schemes continue to emerge in modern electricity markets.

Acknowledgement

This paper shows the results of a through research and work carried out in the REEFLEX project. REEFLEX has received funding from the European Union’s Horizon Europe Research and Innovation program under Grant Agreement No. 101096192.

References

[1] G. Fernández, A. Menéndez, P. Meneses, A. Zubiria, A. García, F. Díez, J. Jimeno, J. Rodríguez-Seco y F. Cortés, «Development and Initial Testing of a Virtual Laboratory for the Build-up and Testing of Microgrid Management Algorithms,» *EA4EPQ,* vol. 20, 2022.

[2] J. Parra Domínguez, E. Sánchez y Á. Ordóñez, «The Prosumer: A Systematic Review of the New Paradigm in Energy and Sustainable Development,» *Sustainability,* 2023.

[3] B. A. Jnr y B. Anthony Jnr, «Distributed energy prosumer communities and the application of emerging technologies: A systematic literature review,» *Sustainable Futures,* vol. 9, 2025.

[4] V. Astapov, N. Shabbir, A. Rosin, L. Kütt, V. Maask y H. Tiismus, «Review of technical solutions addressing voltage and operational challenges in a distribution grid with high penetration of intermittent RES,» *Energy Reports,* vol. 14, 2025.

[5] R. J. Hennig, L. J. de Vries y S. H. Tindemans, «Congestion management in electricity distribution networks: Smart tariffs, local markets and direct control.,» *Utilities Policy,* vol. 85, 2023.

[6] T. Dronne, F. Roques y M. Saguan, «Local Flexibility Markets for Distribution Network Congestion-Management in Center-Western Europe: Which Design for Which Needs?,» *Energies,* vol. 14, 2021.

[7] M. Attar, S. Repo, V. Heikkilä y O. Suominen, «Congestion management in distribution grids using local flexibility markets: Investigating influential factors,» *International Journal of Electrical Power & Energy Systems,* vol. 167, 2025.

[8] E. A. Soto, L. B. Bosman, E. Wollega y W. Leon-Salas, «Peer-to-peer energy trading: A review of the literature,» *Applied Energy,* vol. 283, 2021.

[9] H. Hilger, D. Witthaut, M. Dahmen, L. Rydin, J. Trebbien y E. Cramer, «Multivariate scenario generation of day-ahead electricity prices using normalizing flows,» *Applied Energy,* vol. 367, 2024.

[10] S. Ramyar, T. Makoto y Y. Chen, «Risk-averse and strategic prosumers: A distributionally robust chance-constrained MPEC approach,» *Energy Systems,* vol. 15, 2022.

[11] M. Tostado-Véliz, W. Kareem, P. Siano y F. Jurado, «Risk-Averse Strategic Participation of Prosumers Coalition in Local Community Markets. Sustainable Cities and Society,» 2025.

[12] O. Owolabi, T. Schafer, G. Smits, S. Sengupta, S. Ryan, L. Wang, D. Matteson, M. Sherman y D. Sunter, «Role of Variable Renewable Energy Penetration on Electricity Price and its Volatility Across Independent System Operators in the United States,» 2021.