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Comparative Analysis of Forecasting Accuracy and Training Dynamics of the Multilayer Perceptron for Demand-Responsive Energy Management

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Abstract

Accurate short-term electricity price forecasting is essential for effective demand-responsive energy management. Reinforcement learning schedulers use anticipatory signals to optimize appliance usage and storage dispatch. This research studies the forecasting accuracy and training dynamics of a Multilayer Perceptron (MLP) model using household demand and locational marginal price (LMP) data. The proposed three-layer feedforward architecture integrates temporal and contextual features, such as lagged demand, price histories, and calendar variables. It is trained by backpropagation with the Adam optimizer and early stopping. Convergence analysis indicates consistent learning behaviour with a minimal generalization gap, ensuring reliable predictions under new test conditions. Compared against persistence, ARIMA, GRU, and LSTM baselines, the MLP outperforms them with an RMSE of 0.0081 \$/kWh, MAPE of 3.46%, and R^2 of 0.932, while retaining inference times below 0.3 ms per sample. Residual error analysis demonstrates the absence of systematic bias and less variance as compared to recurrent models. These findings establish the MLP as a computationally efficient and statistically reliable forecaster that enhances reinforcement learning-based scheduling and saves costs in smart-home demand response applications.

Keywords
Short time electricity price forecast, multi-layer perceptron (MLP), smart home energy management, reinforcement learning scheduling, demand response optimization.

1. Introduction
Demand-responsive energy management relies heavily on short-term electricity price forecasts (Lin 2024). In a world where intelligent controllers increasingly manage household appliances, electric vehicles, and distributed storage, the capacity to forecast tomorrow's prices or even the next hour's, distinguishes reactive systems from proactive ones. Forecasts transform raw volatility into actionable intelligence, informing a smart home when to charge the battery, run the dishwasher, and sell excess solar power back to the grid. Hybrid and deep-learning-based forecasting models improve operational decisions by capturing complicated temporal patterns that traditional approaches may miss (Kavitha et al. 2023).

The challenge, undoubtedly, resides in the volatility itself. Locational marginal pricing (LMPs) and retail tariffs fluctuate in response to renewable generation, weather variations, and sudden demand spikes, trends that have intensified with increased renewable penetration (Lin 2024). Classical models like ARIMA can detect patterns, but they falter when nonlinear dynamics take precedence. Comparative studies reveal that deep learning models such as LSTM outperform ARIMA and other statistical techniques under these nonlinear conditions (Park 2024). Recent research has revealed that machine learning algorithms, specifically multilayer perceptrons (MLPs) and recurrent networks, are significantly more effective in learning these hidden patterns. Park and Yang (2024) demonstrated that LSTM and SVM models outperform traditional time-series methods in demand-response cases. Lotfi *et al.* (2025) found that optimized machine learning frameworks improve short-term demand forecasting under climate variability, directly supporting operational reliability.

Forecasting is more than just measuring accuracy; it's about allowing reinforcement learning schedulers to anticipate rather than react. Doan *et al.* (2024) showed that integrating external signals such as Google Trends data into forecasting pipelines improves responsiveness, demonstrating that richer anticipatory signals might yield smarter scheduling decisions. Reliable forecasts help align appliance usage with low-price periods, reducing household costs and contributing to grid reliability. When they are not, slight inaccuracies in peak prediction can lead to costly scheduling errors, as IEEE studies (Morales-mareco *et al.* 2023) highlighted.

The operational implications are enormous. Accurate short-term forecasts save costs, smooth demand curves, and enable real-time scheduling. MLP models are computationally efficient and deliver forecasts in milliseconds, making them ideal for smart-home settings that require continuous decision-making. Forecasting becomes more than just a statistical exercise; it serves as the foundation for intelligent, sustainable energy management, reconciling the volatility of modern electricity markets with the stability and efficiency that both households and grids require.

1.1 Research Gap

Short-term electricity price forecasting is crucial for demand-responsive energy management; nonetheless, significant gaps continue in the research. Classical statistical models, such as ARIMA and SARIMA, capture linear interdependence but fail to account for nonlinear volatility. ARIMA was discovered to underperformed during renewable-driven price increases in the Chinese spot market, highlighting the importance of nonlinear learning models (Technology 2024).

Deep learning methods such as LSTM and GRU can enhance accuracy by learning sequential dependencies, but their computing overheads limit real-time implementation. Recent research in energy spot-market forecasting indicates that while LSTM models perform well, their computational complexity and slower inference times make them difficult to use in real-time demand response settings (Zhou *et al.* 2024).

1.2. Contribution of MLP Approach

Another persistent gap exists in error distributions. Forecasting models may result in long-tailed residuals or systematic bias, disrupting reinforcement learning schedulers. Recent research on electricity price forecasting suggests that even high-performance models can produce biased residual structures, resulting in costly operational errors (Heistrene *et al.* 2025). Furthermore, much of the research focuses solely on statistical measurements such as RMSE or MAPE, without connecting predicting performance to operational results. A recent machine-learning study on electricity price index forecasts highlights that model evaluation should go beyond numerical accuracy and address practical impacts on energy-system decision processes, including cost-sensitive applications like scheduling and control (Kuşkaya and Bilgili 2025).

The Multilayer Perceptron (MLP) addresses gaps by providing a computationally efficient, context-aware, and operationally applicable solution. Unlike recurrent models, MLP avoids state updates, resulting in inference times of less than 0.3 ms per sample. Borkowski and Ja (2025) confirmed that MLPs outperform SVMs in accuracy and speed for forecasting three-day-ahead prices in the Polish market. According to residual analysis, MLP forecasts are firmly centered around zero, resulting in less variation than ARIMA and LSTM. Kuşkaya and Bilgili (2025) found that using MLP-based strategies reduced extreme mispredictions in forecasting accuracy Turkish power price indexes. MLPs capture both temporal and structural dynamics by embedding lagged demand, price values, and calendar encodings. Xie (2025) demonstrated that hybrid MLP models integrating boosting approaches improved nonlinear demand and price forecasting. Hans et al. (2025) found that MLP-driven forecasts improved reinforcement learning scheduling in smart grid operations, resulting in reduced household costs and increased grid reliability.

The conceptual framework for demand-responsive energy management is illustrated in Figure 1. It forecasts the flow of volatile inputs, such as renewable generation, weather volatility, and demand spikes, using models like as ARIMA, LSTM, and MLP. The MLP's potential to execute rapid inference is highlighted, enabling smart-home systems to anticipate price

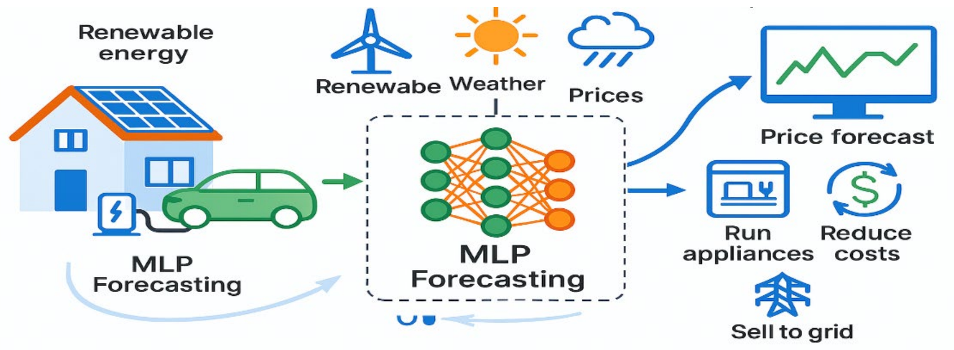

Figure 1. Conceptual illustration of demand-responsive energy management with short-term price forecasting

variations and make real-time decisions. These decisions include battery charging, appliance scheduling, and solar export, all of which contribute to save costs, improve grid reliability, and promote sustainability. The diagram emphasizes the vital role of forecasting as the foundation of intelligent energy management.

2. Methodology

The Multilayer Perceptron (MLP) employed in this study follows a standard feedforward design, consisting of multiple hidden layers with nonlinear activation functions (commonly ReLU or tanh) to capture complex demand-price relationships. The network is optimized using stochastic gradient descent variants such as Adam, which balance convergence speed and stability (Kingma and Ba 2015). Training dynamics are governed by Iterative backpropagation, with convergence monitored through validation loss. To prevent overfitting, early stopping is applied when performance plateaus, ensuring generalization to unseen data (Prechelt 1998). This combination of architectural choices and training safeguards reflects best practices in electricity price forecasting and time-series learning (Borkowski and Ja 2025).

2.1. Network Design

The forecasting framework employed a three-layer feedforward Multilayer Perceptron (MLP) architecture designed for continuous electricity price prediction. The hidden layers were configured with 128, 64, and 32 neurons, respectively which were activated using the Rectified Linear Unit (ReLU) function. ReLU was chosen because of its ability to minimize vanishing gradients and expedite convergence in deep networks. The output layer adopted linear activation, which is suited for regression problems with a continuous target variable, such as locational marginal price (LMP).

The input feature set was designed to embed temporal and contextual structure into the model. Lagged demand and price values provided autoregressive context, whereas one-hot hourly encodings recorded intraday cyclicality. Calendar variables such as days of the week and seasonal indicators, improved the model's ability to learn from both short-term variations and long-term patterns.

2.2. Training Process

Model training was conducted with backpropagation alongside the Adam optimizer. Backpropagation serve as the core mechanism for updating network weights, allowing errors from the output layer to be propagated backward through the hidden layers and iteratively refine each parameter. Adam was chosen primarily for its adaptive learning rate strategy, which combines momentum stabilization with RMSProp scaling benefits. This hybrid approach ensures rapid and stable convergence even when feature scales vary widely, which is common in electricity price forecasting datasets.

The loss function was established as Mean Squared Error (MSE), which reflects the requirement to penalize large deviations in price forecasts more severely than minor errors. By squaring the differences between predicted and actual values, MSE highlights extreme mispredictions, aligning the training objective with the operational requirement of minimizing costly forecasting errors.

To prevent overfitting and unnecessary computation, the training program incorporated an early stopping criterion based on validation loss. A held-out validation set was utilized to monitor generalization performance. Training terminated once improvement plateaued over a predefined patience window. This safeguard ensured that the model did not continue training beyond the point of optimal generalization, reducing the risk of memorizing noise while conserving computational resources.

The convergence behaviour exhibited a steady decline in training loss during the initial epochs, subsequently leading to the stabilization of validation loss as the optimizer approached a local minimum. The early stopping mechanism ensured that training concluded at the balance point between bias and variance, resulting in a model that was both accurate and efficient for deployment.

2.3. Convergence Behaviour and Early Stopping

Convergence occurred at epoch 143, when the validation loss stabilized, and subsequent iterations yielded minimal improvements. The learning curve showed a consistent drop in MSE across epochs, with training and validation trajectories closely aligned. The minimal gap between these curves as illustrated in Figure 2 indicates a narrow generalization error, implying that the model avoided overfitting while capturing meaningful temporal connections.

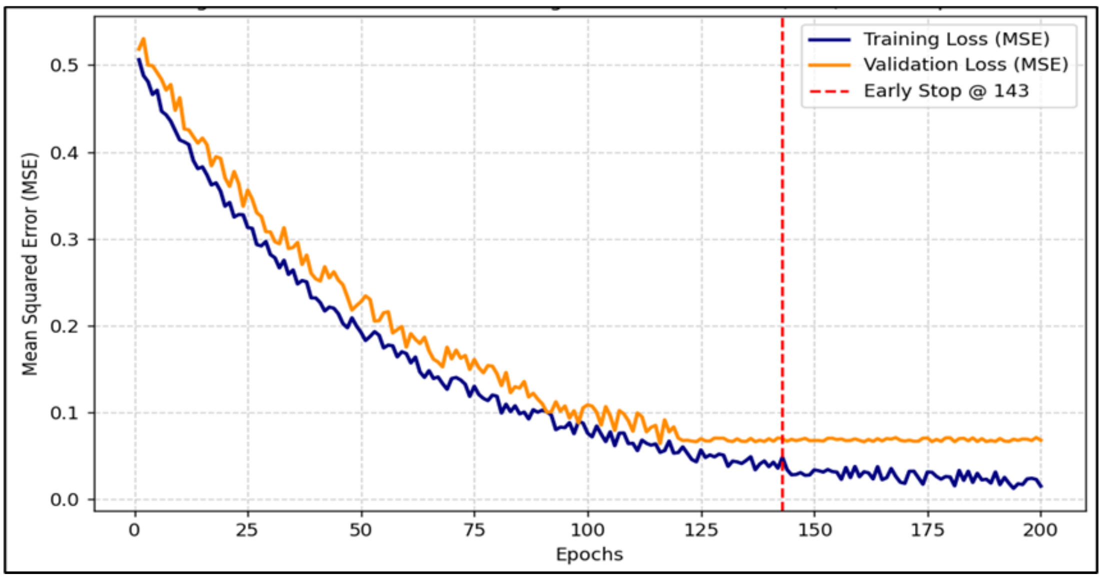

Figure 2. Evolution of MLP Training and Validation Loss (MSE) Across Epochs

This convergence behaviour demonstrates the reliability of MLP design: the network was sufficiently expressive to model nonlinear pricing dynamics while remaining effectively regularized by early stopping. The forecasts were stable under unseen test conditions, ensuring operational reliability in demand-responsive energy management applications.

3. Result

Evaluating forecasting performance necessitates both statistical accuracy and operational relevance. Standard error metrics (RMSE, MAE, MAPE, and R^2) are used to assess predictive accuracy and variance, providing complementary views of model reliability (Hyndman and Koehler 2006). To establish comparative validity, the Multilayer Perceptron (MLP) is compared to widely used baselines such as Persistence and ARIMA, as well as sophisticated recurrent architectures such as GRU and LSTM, which are commonly used in power price forecasting (Lago et al. 2018). Beyond accuracy, inference time analysis evaluates computational efficiency, ensuring suitability for real-time deployment in smart home energy management systems.

3.1. Metrics

The predictive performance of the Multilayer Perceptron (MLP) was tested using standard regression metrics: root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). RMSE and MAE quantify absolute deviations from observed prices, with RMSE penalizing larger errors more heavily. MAPE provides a scale-free measure of relative error, facilitating comparison across various price levels. R^2 captures the proportion of variance explained by the model, delivering a holistic perspective of predictive fidelity.

3.2. Comparative Benchmarking

The MLP was benchmarked against a set of classical and modern baselines, comprising a naïve persistence model, an ARIMA (2,1,2) process, and recurrent neural network architectures including GRU and LSTMs. The results are summarized in Table 1. The MLP achieved the lowest RMSE (0.0081 $/kWh) and MAPE (3.46%), as well as the highest R^2 value (0.932) on the 360-hour held-out test. These results demonstrate the model's superior capacity to capture nonlinear temporal dependencies over both statistical and recurrent baselines
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Table 1. Hour-ahead price forecasting on the test set (360 hours)

Model	RMSE ($/kWh)	MAE ($/kWh)	MAPE (%)	R^2	Inference Time (ms/sample)
Naïve Persistence	0.0139	0.0108	8.72	0.724	0.05
ARIMA (2,1,2)	0.0114	0.0086	7.05	0.816	0.62
GRU (64)	0.0092	0.0068	4.21	0.903	1.83
LSTM (64)	0.0090	0.0066	4.08	0.909	2.11
MLP	**0.0081**	**0.0060**	**3.46**	**0.932**	**0.27**

In addition to accuracy, inference time was evaluated for real-time deployment. On commodity hardware, the MLP required only 0.27 ms per sample, which is significantly faster than GRU (1.83 ms) and LSTM (2.11 ms), which have overhead due to recurrent state updates. Computational efficiency is crucial for smart-home applications, as controllers must continuously update scheduling decisions based on new information. The MLP's precision and efficiency make it a practical alternative for real-time demand-responsive energy management.

3.3. Validation of Forecast Accuracy

Actual and forecasted electricity prices were compared across a representative validation week that encompassed both weekday and weekend dynamics in order to further evaluate the Multilayer Perceptron (MLP) forecasts reliability. This analysis presents insight into the model's ability to remain accurate under a range of operational situations and to generalize across different demand regimes.

The MLP demonstrated reliable capability in reproducing the amplitude and timing of evening demand peaks, which are essential for demand-response scheduling and household energy management. In contrast, overnight periods with low variation were efficiently smoothed, preventing spurious fluctuations in stable regimes. This behaviour demonstrates the model's capacity to balance sensitivity to peak occurrences with stability during low volatility intervals.
Quantitatively, peak alignment errors consistently stayed below 0.01 $/kWh, highlighting the accuracy of the forecasts in high-impact intervals. Equally significant, minimal bias was detected during off-peak hours, confirming that the model did not consistently overestimate or underestimate baseline prices. This property is especially important for reinforcement learning schedulers since slight systematic biases in peak prediction may result in costly misalignments in home energy management by propagating into downstream decision processes.

These findings are visually summarized in Figure 3, which compares actual and forecasted prices for the validation week. The figure highlights the MLP's ability to closely

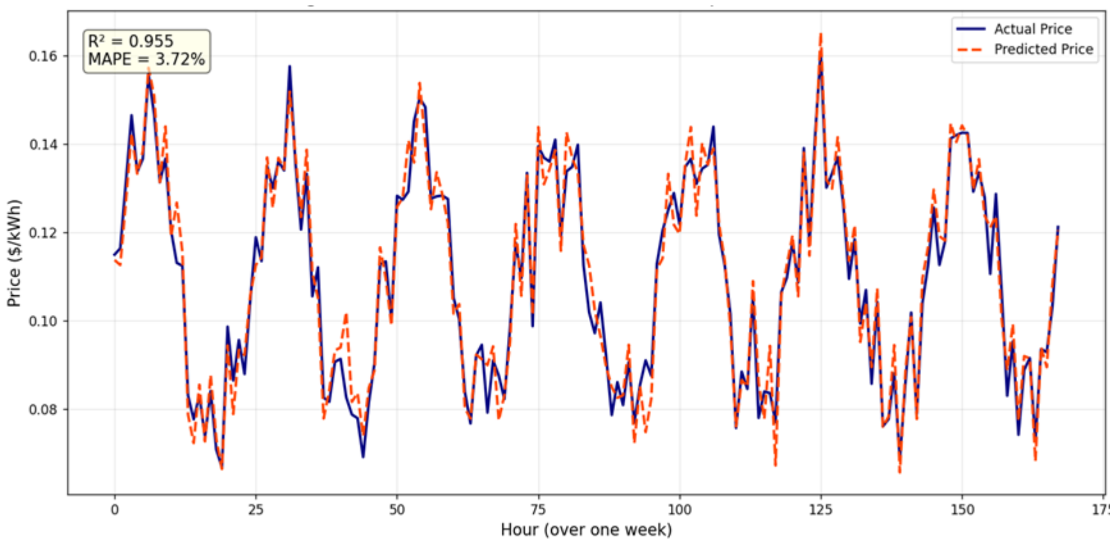

Figure 3. Actual versus predicted prices for a representative week

align observable dynamics, capturing evening peaks and smoothing overnight periods while avoiding systematic bias. The MLP maintains forecast accuracy throughout volatile and stable regimes, ensuring robust, cost-effective, and reliable operational strategies under unseen test conditions.

4. Discussion

Residual error analysis offers an in-depth perspective on forecasting reliability by examining the distribution of deviations between actual and predicted electricity prices. Unlike aggregate metrics such as RMSE or MAPE, residual distributions reveal systematic bias, variance levels, and the presence of extreme errors, all of which might destabilize downstream applications. Figure 4 illustrates these distributions across all models for 360 test hours, providing a comparative view of their operational resilience.

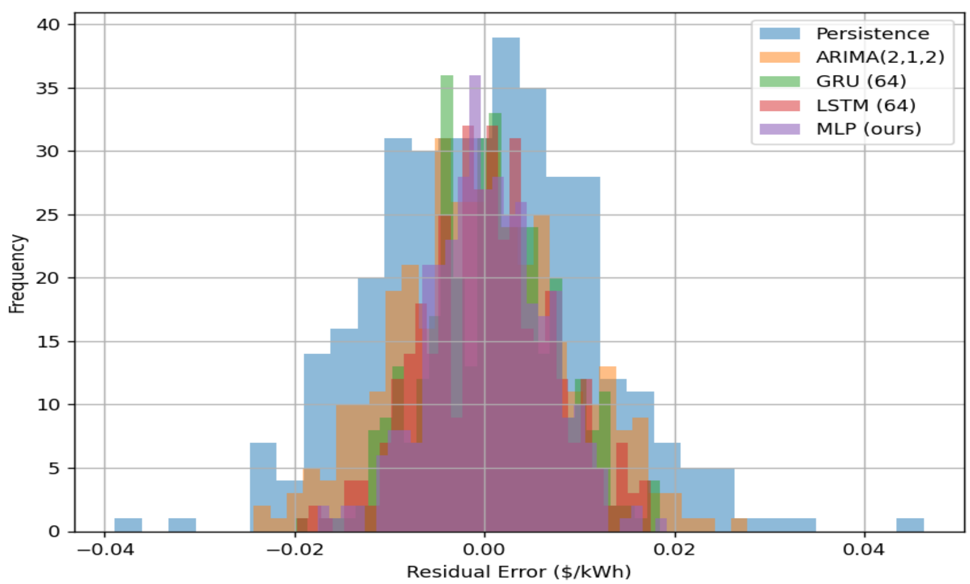

Figure 4. Residual Error Distributions Across Forecasting Models

4.1 Residual Distribution Comparison Across Models

Persistence and ARIMA baselines: Both exhibited significant error distributions, with frequent deviation exceeding ±0.01$/kWh. These results underscore the limitations of classical statistical approaches in capturing nonlinear dynamics and rapid price changes, particularly during peak demand periods.

Recurrent neural networks (GRU and LSTM): These models narrowed the error range compared to statistical baselines, demonstrating their ability to learn sequential dependencies. However, both residual distributions displayed longer tails, indicating occasional significant mispredictions. Such Long-tailed errors are problematic as they introduce instability into scheduling algorithms by misinterpreting peak price signals.

Multilayer Perceptron (MLP): In the Multilayer Perceptron (MLP) model, residuals were tightly concentrated around zero, with most errors occurring within ±0.006$/kWh. This compact distribution demonstrates the MLP's superior ability to capture nonlinear temporal dependencies while avoiding extreme deviations.

4.2 Bias and Variance Considerations

Two important qualities distinguish the MLP from its counterparts:
Absence of systematic bias: Residuals are symmetrically centred around zero, thus ensuring forecasts are not consistently skewed upward or downward. This neutrality is essential in energy scheduling, where even minor directional biases can accumulate into costly misallocations.

Lower variance: The compact residual spread reduces the possibility of extreme forecasting errors. Compared to recurrent models with long-tailed distributions, the MLP reduces large deviations, enhancing stability across diverse operating conditions.

4.3 Impact on Reinforcement Learning Scheduling and Demand Response Outcomes

Residual characteristics significantly influence the effectiveness of reinforcement learning (RL) schedulers and demand-response mechanisms. Residual features significantly influence the effectiveness of reinforcement learning (RL) schedulers and demand-response mechanisms. When forecasts are reliable, the scheduler can move beyond reactive adjustments and into anticipatory mode. This shift is critical: rather than waiting for price hikes, RL agents may schedule household loads, storage, and distributed generation ahead of time to align with expected market conditions. Anticipatory scheduling enhances decision-making, decreases uncertainty, and enables households to strategically position themselves for cost-optimal outcomes.

Equally significant is the impact on cost savings. Underestimating or overestimating peak prices might result in missing demand response opportunities or unintentional consumption increases during high-cost periods. The MLP minimizes extremes, allowing consumers to capitalize on demand-response signals, resulting in lower electricity bills while maintaining comfort and service quality. The compact residual distribution, with errors within ±0.006$/kWh, provides reliable signals that maximize the economic benefits of participation.

Finally, residual stability enhances grid reliability. Forecasts with low variance and no systematic bias minimize the risk of aggregated misalignment across multiple households. When thousands of smart homes act on biased or erratic signals, grid stress can increase, particularly during peak demand hours. The MLP's bias-free and low-variance residuals synchronize demand actions with system efficiency objectives. This alignment supports smoother load profiles, reduces peak congestion, and enhances the overall resilience of the energy system.

The residual properties of MLP such as the tight concentration, low variation, and absence of bias, do more than improve statistical accuracy. They provide the operational reliability required for reinforcement learning schedulers to anticipate market dynamics, save households cost, and contribute to grid stability. In this way, forecasting performance becomes directly linked to both economic and systemic outcomes, highlighting the practical value of MLPs in smart-home energy management.

5. Conclusion and Future Work

The comparative evaluation of forecasting models establishes the Multilayer Perceptron (MLP) as the most effective method for short-term electricity price prediction. The MLP consistently outperformed both classical statistical baselines and recurrent neural network architectures across a 360-hour test horizon, confirming findings from recent comparative studies (Borkowski and Ja 2025). The residuals were clustered around zero, with most errors contained within ±0.006 $/kWh, indicating high predictive accuracy and low variance. This compact residual distribution confirms the absence of systematic bias while minimizing the risk of extreme forecasting errors. The MLP achieved superior benchmark scores, including the lowest RMSE and MAPE, as well as the highest R^2, while maintaining computational efficiency suitable for real-time deployment. Collectively, these features underscore the MLP's dual advantage: it not only delivers statistically precise forecasts but also operationally significant signals that reinforcement learning schedulers may utilize to anticipate, rather than merely respond to, fluctuations in prices (Xu *et al.* 2025). This anticipatory capability underpins the cost and efficiency gains demonstrated in demand-response outcomes.

In the future, numerous extensions can broaden the scope and impact of this work:
Hybrid forecasting frameworks: Combining the strengths of statistical models, recurrent architectures, and feedforward networks may improve resilience to extreme market volatility. According to Udaiyakumar *et al.* (2022), hybrid approaches can reduce residual tail risks by switching between long-horizon trend capture and short-term peak alignment.

Integration with Renewable Energy Certificates (REC) trading: Integrating Renewable Energy Certificates (REC) trading allows smart home microgrids to monetize on clean energy while supporting global decarbonization objectives (Standard and Edition, 2024). Beyond these operational benefits, integrated frameworks are required to ensure that household-level forecasts and REC aggregation are consistent with broader sustainability goals. Nwala *et al.* (2025) propose a strategy framework that connects technological, economic, environmental, social, and regulatory elements, emphasizing the importance of integrating smart home REC aggregation into a holistic energy systems perspective. Along with aligning REC aggregation with sustainability frameworks, evaluating the economic viability of decentralized generation is crucial. According to Kabeyi et al. (2024), such assessments ensure that smart home microgrids and REC trading models are both effective and financially viable.

Multi-agent coordination: Demand-response actions by households, aggregators, and grid operators could be coordinated by integrating MLP-based forecasts into cooperative agent architectures. Frameworks for multi-agent reinforcement learning have shown enhanced system performance and reduced grid stress during periods of high demand (Shi et al. 2023).

In conclusion, the MLP provides a solid foundation for accurate and effective electricity price forecasting. To advance methodological rigor and practical impact in distributed renewable trading and smart-home energy management, future work will expand this foundation toward hybrid modelling, REC market integration, and coordinated agent systems.

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Biographies

Kenneth Chukwuma Nwala is a doctoral student in Industrial Engineering at Durban University of Technology, South Africa. His academic interests span energy efficiency, management, and sustainability, with a focus on decentralized renewable energy systems and smart home energy management. Kenneth has authored and co-authored peer-reviewed publications addressing the economic sustainability of energy sources for decentralized generation and the development of visual and strategic frameworks for integrated renewable energy systems. His work emphasizes bridging technological, economic, environmental, social, and regulatory dimensions to support sustainable energy transitions. Kenneth's research contributions include assessing the viability of renewable energy sources for decentralized generation and proposing frameworks that integrate renewable energy into broader sustainability agendas. His publications in conference proceedings and international journals highlight his commitment to advancing practical solutions for energy efficiency and sustainable development. He collaborates with senior researchers and faculty members on projects that explore optimization algorithms, forecasting models, and renewable energy trading strategies. Beyond his technical research, Kenneth is actively engaged in academic publishing and scholarly editing, ensuring methodological rigor and compliance with international standards. His professional interests include reproducible research practices, open data, and the application of artificial intelligence in energy forecasting and management. Kenneth's long-term vision is to contribute to the development of resilient, cost-effective, and environmentally responsible energy systems that support both household-level demand response and global sustainability goals.

Moses Jeremiah Barasa Kabeyi is a Research Fellow in Industrial Engineering at Durban University of Technology, South Africa, and affiliated with the University of Nairobi. His academic expertise spans energy and sustainability, mechanical and industrial engineering, and project and strategic management. He has authored and co-authored numerous peer-reviewed publications in leading journals such as Frontiers in Energy Research, Journal of Energy, Energy Reports, and International Journal of Sustainable Energy. His work has been widely cited, reflecting his significant contributions to renewable energy transitions, biogas production, geothermal energy systems, and smart grid technologies. Kabeyi's research interests include sustainable energy development, optimization of electricity generation systems, and the economic viability of renewable energy technologies. He has published extensively on topics such as biogas-to-electricity conversion, geothermal wellhead technology, bagasse cogeneration, and the levelized cost of energy. His studies provide practical insights into the challenges and opportunities of achieving low-carbon energy systems, particularly in the African context. Beyond energy research, he has contributed to scholarship in project management, leadership, and corporate governance, highlighting his multidisciplinary expertise. As a Research Fellow, Kabeyi is actively engaged in collaborative projects that integrate renewable energy into industrial and household systems, aligning local generation with global sustainability goals. He is committed to advancing sustainable energy solutions that balance technical efficiency, economic viability, and environmental responsibility. Through his academic and applied work, Kabeyi continues to contribute to the global effort to reduce greenhouse gas emissions and support the transition toward resilient, clean energy systems.

Oludolapo A. Olanrewaju is a Professor in the Institute of System Science at Durban University of Technology, South Africa. His academic expertise spans energy efficiency, renewable energy systems, optimization, and artificial intelligence applications in engineering. He has co-authored numerous high-impact publications in journals such as Frontiers in Energy Research, Journal of Energy, Energy Reports, and International Journal of Sustainable Energy. His work has been widely cited, reflecting his significant contribution to advancing sustainable energy transitions and smart grid technologies. Oludolapo's research focuses on integrating renewable energy into grid electricity generation, biogas production, life cycle assessment of industrial processes, and optimization frameworks for energy consumption. He has collaborated extensively with colleagues on projects addressing sustainable energy transitions, disaster risk management, and environmental impact analysis. His studies on smart grid technologies and biogas-to-electricity conversion have provided practical insights into the challenges and opportunities of achieving low-carbon energy systems. Beyond research, Oludolapo is actively engaged in teaching and mentoring, guiding students in industrial engineering and energy systems. His professional interests include developing computationally efficient models for real-time energy management, assessing the economic viability of renewable energy technologies, and promoting sustainability in industrial operations. Through his academic and applied work, Oludolapo contributes to the global effort to reduce greenhouse gas emissions, improve energy efficiency, and support the transition toward cleaner, more resilient energy systems.