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Work-in-Progress: Layer 1 ANN-Based Next-Hour Price Prediction for a Smart Residential Microgrid

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Abstract
A microgrid is a small, self-contained power system capable of integrating renewable energy and maintaining operation during main grid outages. As microgrids become increasingly relevant to the future electric grid, they provide an effective platform for teaching renewable energy integration and intelligent energy management at a practical scale. This Work-in-Progress paper presents the development of Layer 1 of a two-stage Artificial Neural Network (ANN) designed to predict next-hour Real-Time electricity prices at the Citizens Electric node within PJM Interconnection, a regional transmission organization in the United States that coordinates wholesale electricity markets and grid operations across multiple states. The forecasting framework is implemented within a smart residential microgrid at Bucknell University using real operational market data. Because Real-Time prices are published after market operation, the model performs hour-ahead prediction using historical Day-Ahead prices and previously published Real-Time prices. Forecasted weather variables are part of the broader instructional platform design but are not included in the current Layer 1 results. This structure intentionally exposes students to uncertainty and delayed information inherent in electricity markets. The data acquisition system operates on a low-cost Raspberry Pi–based controller that automatically retrieves market data for instructional use. Layer 1 serves as the forecasting foundation for a future Layer 2 phase that will integrate predicted prices with smart meter measurements to support intelligent microgrid control. The goal is to provide a simple, accessible predictive framework that enhances students' understanding of how electricity markets, economic signals, and engineering decisions intersect within modern energy systems.

1. Introduction

Smart residential microgrids are increasingly used as instructional platforms for teaching renewable energy integration, data-driven decision-making, and the interaction between engineering systems and electricity markets. Prior research in engineering education has consistently shown that hands-on and active learning approaches improve student engagement, confidence, and conceptual understanding when compared to purely lecture-based instruction [1]-[3]. These findings remain highly relevant as artificial intelligence tools become more common in engineering workflows.

In organized electricity markets such as the PJM Interconnection, a regional transmission organization (RTO) that coordinates wholesale electricity markets and grid operations across multiple states in the United States, Locational Marginal Prices (LMPs) reflect real-time supply-demand balance, network congestion, and operational constraints [4]. Because these prices are published after market operation, students must confront the reality that engineering decisions often rely on forecasted rather than perfect information. Introducing price prediction into an educational microgrid context provides a practical setting for systems thinking, uncertainty awareness, and data-driven reasoning, which are emphasized in broader shifts in engineering education [5].

Recent ASEE work has highlighted the importance of using artificial intelligence as a supportive educational tool, rather than as a replacement for foundational understanding [6], [7]. Within this context, next-hour electricity price prediction provides a natural, low-risk entry point for exposing students to AI-enhanced analysis while preserving transparency and interpretability.

This Work-in-Progress paper presents Layer 1 of a two-stage ANN framework implemented within a smart residential microgrid for instructional purposes. Layer 1 focuses on next-hour PJM's LMP prediction and serves as a preparatory stage for future intelligent control activities. The emphasis of this paper is on educational structure and student learning engagement, rather than algorithmic performance or optimization. Evidence of student learning is documented through artifact-based assessment, structured model analysis activities, and guided interpretation of forecast performance within the instructional setting.

2. Instructional Context and Platform Overview

2.1 Educational Setting and Microgrid Platform

The instructional activities are conducted using an existing residential microgrid originally commissioned in 2015 [8] and later restored and modernized in 2025 for educational use. The original system architecture and design specifications are documented in detail in [8], providing a foundation for the present instructional expansion. The platform includes a photovoltaic array, controllable residential loads, and a Raspberry Pi–based controller integrated with a power meter. This configuration enables students to work with authentic operational data rather than simulated examples.

For instructional purposes, the controller retrieves publicly available PJM market data and local weather forecasts. Day-Ahead LMPs are treated as forward-looking market signals, while Real-Time LMPs, published on the following business day, are used for validation. This intentional preservation of data latency exposes students to realistic market timing, uncertainty, and operational constraints.

The ANN modeling environment is implemented in Python using Google Colab to provide a cloud-based, license-free platform that supports accessibility and interpretability in an educational setting. The modeling workflow emphasizes understanding input selection, timing, and economic meaning rather than tuning network complexity.

2.2 Data Acquisition and System Implementation

The instructional platform is built around a Raspberry Pi 4 controller that serves as the central data acquisition and logging unit for the microgrid forecasting module. The Raspberry Pi communicates with PJM Data Miner 2 through its public API [4] to automatically retrieve Day-Ahead and Real-Time market pricing data for the Citizens Electric node (PNODE 3387777).

Day-Ahead LMP data, typically posted daily between 12:00 p.m. and 1:30 p.m. ET, are automatically downloaded each evening to serve as forward-looking market inputs for the forecasting model. Real-Time LMP data, which are published on business days between 11:00 a.m. and 12:00 p.m. ET and represent the previous day's actual market performance, are also retrieved automatically and used as validation targets during ANN training. For example, Monday postings include the complete weekend data.

Local weather data is obtained using a Davis Vantage Pro2 weather station connected through a TP-Link TL-MR3020 router operating in access-point mode with Meteobridge firmware. The system interfaces with the OpenWeatherMap API to retrieve 24-hour local weather forecasts, including irradiance (W/m^2), temperature (°F), humidity, wind speed (mph), and pressure (inHg). These data are stored in CSV format for alignment with market price inputs. Although the weather pipeline is established as part of the broader instructional platform, forecasted weather variables are not yet included as model inputs in the current Layer 1 results reported here.

All automated downloads and logging operations are scheduled using the Linux crontab utility to ensure consistent daily data retrieval without manual intervention. This infrastructure enables students to work with authentic, time-stamped operational data rather than simulated datasets.

2.3 Layer 1 ANN Modeling Framework and System Architecture

Figure 1 illustrates the two-layer control architecture implemented within the instructional microgrid platform. The framework follows a staged philosophy: Predict → Decide → Protect.

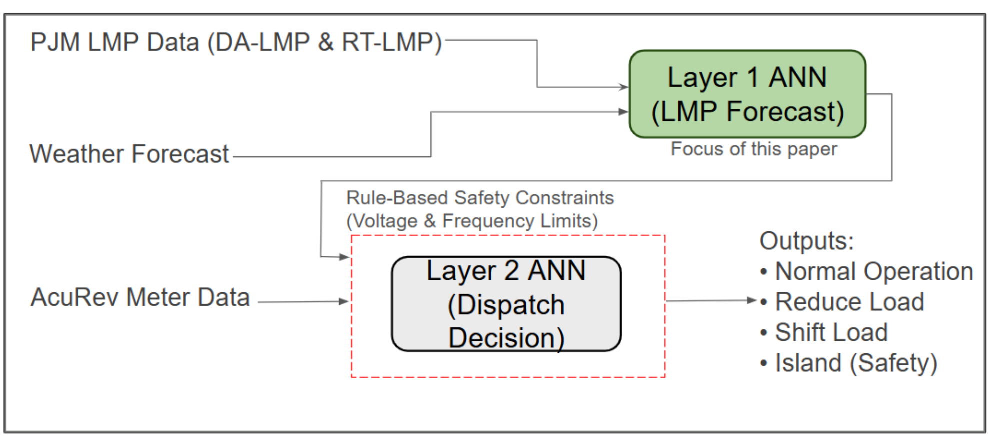

Figure 1. *Two-Layer ANN architecture for instructional microgrid price prediction and dispatch. Forecasted weather inputs are shown as part of the planned system design but are not included in the current Layer 1 results reported in this Work-in-Progress paper.*

Layer 1 focuses on next-hour electricity price forecasting. Inputs to Layer 1 include Day-Ahead and previously published Real-Time Locational Marginal Price (LMP) data from PJM Interconnection. The system architecture also incorporates forecasted local weather parameters as planned inputs; however, the current Layer 1 instructional implementation focuses on market-based inputs only. The output of Layer 1 is a single predicted next-hour Real-Time LMP value.

Layer 2, shown for context but not the primary focus of this paper, integrates the predicted price with real-time electrical measurements from an AcuRev power meter, including voltage, current, and real power. Dispatch decisions such as normal operation, load reduction, load shifting, or islanding are generated in response to economic signals.

Importantly, rule-based safety constraints enforce voltage and frequency operating limits to ensure stable system performance. This hybrid structure intentionally demonstrates to students that artificial intelligence–based optimization must operate within engineering safety standards.

The architecture is implemented on a low-cost Raspberry Pi–based platform, enabling reproducibility and accessibility in instructional settings.

2.3.1 Data Collection

Layer 1 utilizes publicly available market and environmental data to create an authentic forecasting environment for students. Hourly Day-Ahead (DA) and Real-Time (RT) Locational Marginal Price (LMP) data are retrieved from PJM Interconnection's Data Miner 2 API for the Citizens Electric pricing node and stored as comma-separated value (CSV) files aligned by timestamp.

The platform was designed to additionally incorporate forecasted weather variables; however, consistent multi-year forecast-aligned weather data were not available for the full study period. Therefore, the current Layer 1 instructional implementation focuses on market-based inputs, while weather integration remains under development.

By working with authentic electricity market data rather than synthetic datasets, students confront realistic variability, delayed market postings, and imperfect information conditions that mirror operational engineering practice.

2.3.2 Data Preparation

Prior to training, datasets are cleaned and synchronized to ensure consistent hourly alignment across Day-Ahead and Real-Time LMP time series. Missing entries and minor timestamp discrepancies are corrected through structured preprocessing routines implemented in Python.

Input features are normalized to improve numerical stability during training. Feature selection emphasizes interpretable variables that students can physically relate to system behavior, reinforcing connections between environmental conditions, market dynamics, and price variation.

This preprocessing workflow is intentionally transparent so that students can understand each transformation step rather than treating the ANN as a "black box."

2.3.3 Model Architecture

The Layer 1 predictor is implemented as a supervised feedforward Artificial Neural Network in Python using Google Colab. The model maps historical Day-Ahead and previously published Real-Time LMP values to a single continuous output representing the next-hour Real-Time LMP.

Although weather variables were initially considered as additional explanatory inputs, consistent multi-year forecast-aligned datasets were not available for the full study period. To preserve realistic forecasting conditions and avoid data leakage, the instructional implementation focused on price-only inputs. This constraint provided an opportunity for students to discuss data availability limitations and trade-offs between model complexity and data integrity.

The architecture is intentionally kept interpretable and computationally lightweight to ensure accessibility on low-cost hardware platforms. Emphasis is placed on understanding input-output relationships and prediction behavior rather than pursuing highly optimized hyperparameter tuning.

2.3.4 Training and Validation

The dataset is divided into training and validation segments representing continuous operational periods. Model performance is evaluated using mean absolute error (MAE) and mean absolute percentage error (MAPE), allowing students to quantify forecasting accuracy.

Students compare predicted next-hour prices against subsequently published Real-Time market values, reinforcing the concept that engineering decisions must often be made under forecast uncertainty. This staged forecasting exercise serves as preparation for the subsequent dispatch decision layer of the microgrid framework.

3. Educational Implementation and Learning Evidence

3.1 Semester Integration

Layer 1 forecasting activities are integrated after students develop foundational understanding of renewable energy systems, electricity markets, and microgrid operation. The instructional sequence follows a staged progression aligned with the Predict → Decide → Protect framework introduced earlier.

Students first examine Day-Ahead and Real-Time LMP data to understand market timing and operational latency. Structured exploratory data analysis activities allow students to observe hourly and seasonal price variability and identify characteristic peak patterns. This foundation prepares students to appreciate the need for prediction under delayed information conditions.

Supervised learning concepts are then introduced as analytical tools for forecasting rather than opaque optimization mechanisms. Students transition from data exploration to model-based prediction within a cloud-based Python environment (Google Colab), ensuring accessibility and eliminating local software barriers.

3.2 Student Activities and Artifacts

Student involvement spans data organization, model interaction, and analytical interpretation.

Students:

- Retrieve and organize PJM Day-Ahead and Real-Time LMP data.
- Document posting schedules and market timing differences.
- Align hourly timestamps and prepare structured CSV datasets.
- Analyze daily and seasonal price behavior.
- Implement and modify a simple feedforward ANN in Google Colab.
- Compare predicted next-hour prices against subsequently published Real-Time values.
- Interpret forecast deviations in economic terms.

Artifacts generated include:

- Time-aligned LMP datasets.
- Annotated exploratory plots.
- Colab-based model notebooks.
- Prediction-versus-actual comparison charts.
- Short analytical reflections explaining forecast error sources.

These artifacts demonstrate engagement with authentic operational data and reinforce systems-level reasoning under uncertainty.

To support interpretive analysis, students examine prediction-versus-actual alignment and compute standard validation metrics. Figure 2 shows an example comparison between predicted and published Real-Time LMP values used during instructional discussion.

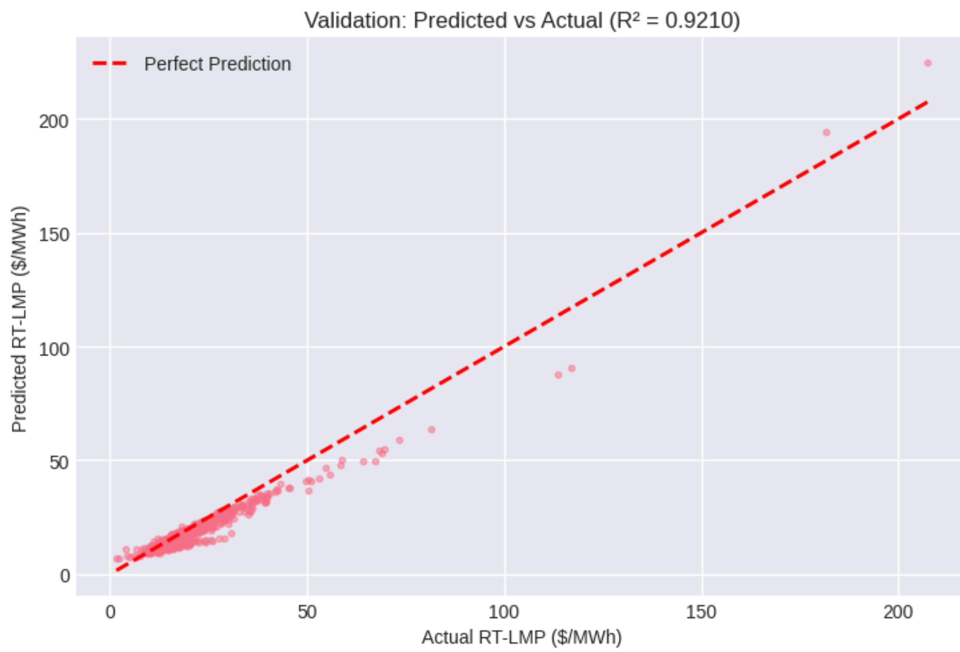

Figure 2. *Predicted versus actual Real-Time LMP values used by students to interpret forecasting accuracy and error patterns.*

Students also review summarized validation performance metrics to quantify forecasting behavior.

Table 2. Validation performance metrics used for instructional analysis.

Metric	**Validation**
MAE ($/MWh)	2.98
MAPE (%)	13.72
R^2	0.921

Rather than emphasizing performance optimization, instructional focus centers on interpreting deviations, recognizing forecast uncertainty, and understanding how prediction accuracy influences engineering decision-making. Validation results provide a realistic but imperfect forecasting scenario appropriate for classroom analysis.

The dataset spans approximately two years of operational data, which is sufficient for instructional demonstration but not intended to represent long-term market generalization. This limitation is explicitly discussed with students to reinforce responsible interpretation of data-driven models.

3.3 Assessment Strategy

Assessment is artifact-based and formative rather than centered solely on model performance metrics. Evaluation focuses on students' ability to:

- Explain the operational differences between Day-Ahead and Real-Time markets.
- Justify the need for forecasting when decisions must precede full information availability.
- Interpret forecasting error using metrics such as mean absolute error (MAE) and mean absolute percentage error (MAPE).
- Recognize conditions under which prediction uncertainty increases.

Grading emphasizes conceptual understanding, reasoning clarity, and economic interpretation rather than optimization of network complexity. The use of Google Colab supports transparent model inspection and iterative experimentation without requiring advanced software licenses.

3.4 Early Observations

As this project remains a Work-in-Progress, evaluation findings are currently qualitative.

Preliminary instructional observations indicate that students demonstrate improved understanding of electricity market timing and operational uncertainty after interacting with real LMP data and implementing forecasting models. Classroom discussions shift from deterministic reasoning ("use the actual price") to anticipatory reasoning ("decisions must be made before final prices are known").

Students increasingly articulate the economic implications of prediction error and recognize that artificial intelligence supports engineering judgment rather than replacing it.

These early observations support the viability of next-hour price forecasting as an effective entry point into intelligent microgrid education.

3.5 Accessibility and Inclusive Design Considerations

The instructional platform was intentionally designed to lower barriers to participation in artificial intelligence-based power systems education. The use of a Raspberry Pi controller and publicly available market data enables replication at relatively low cost. The modeling environment is implemented in Google Colab, which removes licensing requirements and allows students to work from personal devices without specialized software installation.

This approach supports broader participation by reducing financial and technical access constraints often associated with advanced power system laboratories. By integrating real-world data with cloud-based tools, the framework provides an accessible pathway for diverse learners, including those from institutions with limited laboratory resources.

4. Future Work

As a Work-in-Progress effort, the initial training dataset was limited and used to demonstrate the forecasting concept rather than maximize predictive accuracy. The data acquisition pipeline remains in place, enabling additional data to be collected and the model to be retrained as part of ongoing instructional activities. Future instructional cycles will incorporate expanded datasets to allow students to explore seasonal variability and model generalization behavior.

Future efforts will extend this educational framework to Layer 2, where predicted prices are combined with real-time electrical measurements to inform intelligent control decisions. This next phase will introduce students to trade-offs between economic optimization and operational constraints, further reinforcing systems-level thinking. That phase will be reported separately and is intentionally excluded from this paper to maintain a clear focus on Layer 1 educational objectives.

5. Conclusion

This Work-in-Progress paper demonstrates how next-hour electricity price prediction can be used as an effective educational tool within a smart residential microgrid. By engaging students in real data acquisition, forecasting, and interpretation, the project supports learning in energy markets, systems integration, and data-driven reasoning.

Layer 1 forecasting provides a structured and accessible entry point for introducing artificial intelligence concepts into power and energy engineering education. The staged Predict → Decide → Protect framework reinforces the principle that data-driven models must operate within engineering constraints, supporting the development of informed and responsible engineering judgment.

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