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Work-In-Progress: Layer 2 ANN Based Intelligent Load Control for a Smart Residential Microgrid

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Abstract

Microgrids are small, self-sufficient power systems that can operate independently using their own distributed energy sources and can provide services to clients even during main grid outages. Smart residential microgrids can provide a practical and educational platform for testing and teaching renewable energy systems, data analytics, and artificial intelligence based control strategies. This paper presents the development of Layer 2 of a two stage Artificial Neural Network (ANN) framework designed for intelligent operational control of a smart residential microgrid. Layer 1 of the system focused on predicting the next hour of PJM's Locational Marginal Price (LMP) for the Citizens Electric node (PNODE 3387777) at Bucknell University using real operational market data. PJM's Data Miner 2 API provides both Day Ahead (DA) and Real Time (RT) LMP data; however, RT prices are only published the following business day. To enable proactive decision making, Layer 1 was developed to predict the RT price at least one hour ahead of operation time. Layer 2 uses these predicted prices to guide real time control actions within the residential microgrid. The AcuRev 2000 smart meter communicates with a Raspberry Pi controller through an assigned Ethernet port, automatically saving daily CSV logs every 5 minutes via a scheduled crontab task. Under normal operation, each daily AcuRev CSV (e.g., 07152025.csv) contains 288 entries corresponding to 5-minute intervals throughout the 24-hour day with small deviations (±1 row) only during reboots or midnight overlaps. Across July to August 2025, the system achieved 99.2% AcuRev logging uptime and 93.9% Dropbox upload success, confirming high data completeness and reliability. Each CSV records live electrical parameters for multiple residential loads; voltage (V), frequency (Hz), current (I), real power (W), reactive power (VAR), apparent power (VA), and power factor (cosθ), which, combined with hourly weather data (temperature, humidity, pressure, solar irradiance, and wind speed) and the predicted next hour LMP from Layer 1, form the training inputs for the intelligent controller. The training dataset spans July 1 to August 31, 2025, and the validation dataset covers September 1st to September 30th, 2025, a three-month period of continuous, stable operation. The trained controller determines optimal load operation modes, Normal, Load Management, Pre Heating / Pre Cooling every hour and Islanded (Isolation from the grid) every 5 minutes based on cost, grid frequency, and voltage stability constraints. Assessment will compare simulated cost savings, frequency and voltage stability, and ANN accuracy (MAE, MAPE) against a baseline rule-based control done during the grid's inception in 2015. Preliminary results demonstrate reliable data acquisition and the foundation for real time predictive control. This work fits within the ASEE ECE Division topic area "Current ECE Issues and Integration into the Curriculum , AI/ML Applications in Smart Grids and Real Time Analytics." The project has a direct impact on engineering student education, as it provides a hands-on, research driven environment where students apply artificial intelligence, data acquisition, and control theory to a functioning

residential microgrid, bridging the gap between classroom learning and real-world distributed and renewable energy systems.

1. Introduction

Smart residential microgrids provide a valuable instructional platform for exposing students to the interaction between renewable energy systems, electricity markets, and control decision making. While forecasting-based approaches help students understand uncertainty and market dynamics, control-oriented implementations are necessary to translate predictive information into operational actions. Introducing intelligent control in an educational setting requires careful structuring to avoid overwhelming students while preserving transparency in decision logic.

This Work-in-Progress paper presents Layer 2 of a two-stage ANN framework developed within a residential microgrid used for instructional purposes. Layer 1 is presented in a companion Work-in-Progress paper submitted to the same conference, focusing on next-hour electricity price forecasting using ANN models. Layer 2 builds on this foundation by using forecasted price signals together with real-time electrical measurements to guide load-level operational decisions.

By separating forecasting and control into staged instructional layers, the framework promotes progressive learning and systems-level reasoning, consistent with documented shifts toward learner-centered, experiential engineering education and evidence-based active learning practices [1], [2].

This work is implemented within Bucknell University's Electrical Engineering program, primarily involving senior undergraduate (BSEE) and graduate (M.S. Electrical Engineering) students enrolled in courses related to power systems, renewable energy, and intelligent energy systems.

2. Instructional Context and System Overview

Figure 1 illustrates the two-layer control architecture with emphasis on the Layer 2 ANN responsible for dispatch decision-making within the instructional microgrid platform. The framework follows a staged philosophy: Predict → Decide → Protect.

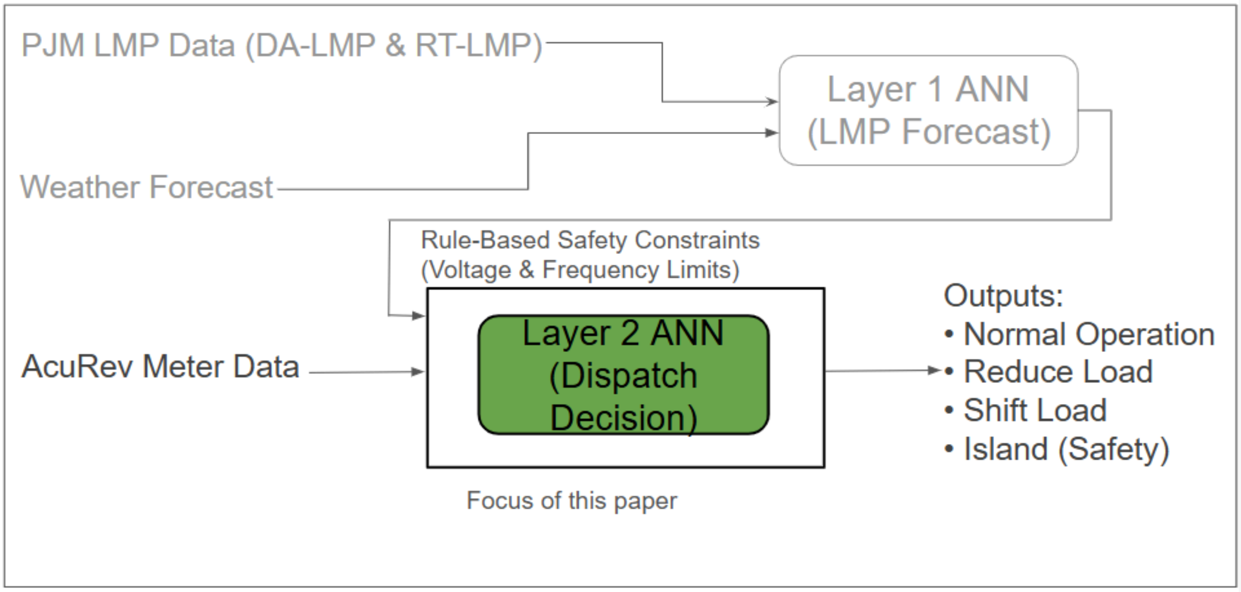

Figure 1. *Microgrid control framework highlighting Layer 2 ANN for dispatch decision-making.*

The instructional activities are conducted using an existing residential microgrid originally commissioned in 2015 and later restored and modernized in 2025 for educational use. The platform includes a photovoltaic array, controllable residential loads, and a Raspberry Pi based controller integrated with a smart power meter. This configuration enables students to work with authentic operational data rather than simulated examples.

For Layer 2 activities, the controller logs electrical measurements at five-minute intervals, including voltage, frequency, current, real power, reactive power, apparent power, and power factor. These measurements are combined with forecasted weather variables and next-hour price forecasts produced by Layer 1. The ANN model is trained using historical microgrid and market data, with input features including time-based variables and electricity pricing signals. All data are stored as timestamped CSV files, which students inspect and analyze as part of the learning process.

Students engage with the system through structured laboratory exercises and project-based activities. These activities guide students to work with real microgrid datasets, implement ANN models, and analyze system behavior under different operating conditions. Student artifacts include data preprocessing scripts, trained neural network models, performance evaluation plots, and written reflections explaining their decision-making process and system behavior.

3. Student Involvement in Control-Oriented Learning

A primary educational objective of Layer 2 is to help students understand how predictive information informs operational decisions under real-world constraints.

3.1 Control Mode Interpretation

Students examine how the intelligent controller selects among predefined operating modes such as normal operation, load management, and pre-heating or pre-cooling. These modes are intentionally designed to be interpretable, allowing students to reason about why specific actions are selected based on price forecasts, voltage and frequency conditions, and time-dependent constraints.

For example, a student may observe that predicted electricity prices are expected to increase in the early evening hours. Based on this forecast, the student can implement a pre-cooling strategy during lower-cost periods to reduce energy consumption during peak pricing. This type of decision-making process helps students connect predictive modeling with practical control actions in a microgrid environment.

3.2 Data Pipeline Interaction

Students engage directly with the data pipeline by validating logging intervals, inspecting daily CSV files, and identifying minor irregularities associated with system reboots or timing offsets. This activity reinforces the importance of data integrity in intelligent control systems and highlights practical challenges encountered in deployed cyber-physical platforms.

3.3 Comparative Reasoning

To support learning, the intelligent controller is conceptually compared with a baseline rule-based control strategy previously used in the microgrid. The emphasis is placed on understanding differences in decision logic, structure, and adaptability rather than numerical performance optimization, consistent with active learning and problem-based learning approaches that prioritize conceptual reasoning and systems understanding [3], [4].

4. Evidence of Student Learning and Educational Impact

Consistent with ASEE expectations for Work-in-Progress contributions, evidence of learning is demonstrated through artifact-based and activity-based outcomes rather than summative assessment.

Students demonstrate learning by explaining how forecasted price information influences control decisions, interpreting relationships between electrical measurements and operating modes, and articulating tradeoffs between cost-oriented actions and grid stability considerations. These outcomes are observed through student-generated analyses of logged data, annotated operational timelines, and guided technical discussions conducted during laboratory and project sessions.

5. Educational Value of the Two-Stage Framework

Separating forecasting and control into two instructional layers mirrors authentic engineering practice while reducing cognitive load for students. Layer 1 introduces uncertainty and market timing, while Layer 2 demonstrates how predictive information is operationalized within physical systems.

This staged approach supports curricular integration and scaffolding of complex concepts, consistent with prior work in integrated engineering education and instructional design [5], [6].

6. Future Work

As a Work-in-Progress effort, the current implementation emphasizes conceptual understanding rather than control optimization. The data acquisition and control infrastructure remain in place, enabling continued data collection and iterative refinement as part of future instructional activities. Extensions involving expanded assessment or additional control objectives are intentionally excluded from this paper to maintain a clear focus on Layer 2 educational objectives.

The implementation of this work is ongoing and is expected to span multiple semesters. Initial deployment involves approximately 10–20 students participating in laboratory and project-based activities. Student assessment is conducted through project deliverables, performance evaluations of implemented models, and reflective analysis of system behavior. Future iterations will expand participation and incorporate more comprehensive evaluation metrics.

7. Conclusion

This paper presents a Work-in-Progress educational implementation of intelligent load control within a smart residential microgrid. By building on price forecasting and integrating real-time electrical measurements, Layer 2 provides students with a practical context for understanding control decision making under uncertainty. The two-stage framework supports progressive learning, systems-level reasoning, and meaningful engagement with artificial intelligence in power and energy engineering education.

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