EPJ Web of Conferences **326**, 02005 (2025) https://doi.org/10.1051/epjconf/202532602005
COFMER'05

Smart Building Electrical Energy Optimization Through Neural Network Techniques

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Abstract. This paper presents a new approach to optimizing the use of electrical energy in smart buildings using neural network techniques. The proposed method has two main objectives: (i) to achieve energy efficiency through the application of intelligent load management; (ii) to ensure stable building system operation through the prediction of energy demand trends. A neural network-based control algorithm was developed and implemented in the building electrical systems for real-time energy optimization. This approach was validated by applying it to a smart building case, with a real-time monitoring and control prototype. Comprehensive analysis, including simulation and experiment tests, validated the system's effectiveness in reducing energy consumption while maintaining operational stability and being an effective solution to sustainable building energy management.

Keywords: Neural Networks (NN); Intelligent Control Algorithm (ICA); Energy Efficiency Optimization; Real-Time Control (RTC); Sustainable Building Energy Systems; Smart Building (SB).

1. Introduction

In the context of growing urbanization and sustainability challenges, optimizing energy consumption in smart buildings has become a key research priority. Intelligent energy management systems (IEMS) have emerged as promising solutions, enabling real-time supervision and dynamic optimization of energy flows [1]. Among the most advanced approaches, neural network-based techniques offer predictive capabilities that allow energy systems to anticipate demand fluctuations and reduce waste, while ensuring operational efficiency [2,3].

Governments and institutions are actively encouraging the deployment of smart building infrastructures through fiscal incentives and grants, accelerating innovation in building energy management. Modern smart buildings typically rely on a dual-source energy architecture, integrating a primary energy source (PES)—often based on renewable technologies such as photovoltaic panels—and a secondary energy source (SES), typically composed of battery storage systems [4–6]. This hybrid setup enhances both the availability and flexibility of energy supply.

However, renewable energy sources alone are often insufficient to meet the highly variable demands of smart buildings. To address this challenge, energy storage systems (ESS)—including batteries and supercapacitors—are integrated to provide rapid energy support during peak loads or unexpected consumption shifts [7,8]. The effective coordination of these components requires robust control mechanisms capable of ensuring energy balance, minimizing losses, and maintaining system reliability.

Numerous strategies have been proposed to achieve such optimization, but many face limitations in adapting to nonlinear energy usage patterns or rapidly changing environmental conditions [9–10].

In this work, we introduce a neural network-based control algorithm specifically designed to improve energy optimization in smart buildings. By leveraging predictive models and adaptive learning, the system ensures precise control, stability, and responsiveness to dynamic operational needs [3–6].

The remainder of this paper is organized as follows: Section 2 presents the modeling of energy demand and renewable generation.

Section 3 details the design of the neural network-based control system. Section 4 provides simulation results and analysis.

2. System Architecture and Modelling

2.1 Energy Storage and Supply System

The smart building energy system proposed in this study is based on a hybrid architecture combining renewable energy sources—primarily photovoltaic (PV) panels—and energy storage systems (ESS), such as batteries or supercapacitors. These components are interconnected through a bidirectional DC–DC converter, which regulates the power exchange between the energy generation units, storage modules, and building electrical loads.

To ensure continuous and stable power delivery, the primary energy supply is provided by the PV system, while the secondary storage units compensate for demand peaks or supply interruptions. The energy management controller oversees this coordination, adjusting flows in real time to maintain system efficiency and reliability.

Key elements such as the power converter and load distribution unit play a crucial role in balancing

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consumption and generation. They enable seamless integration of variable renewable inputs with the dynamic energy needs of the building.

3.Sliding Mode Controller Design and Stability Analysis

In this section, a Sliding Mode Control (SMC) strategy is proposed to regulate energy flow within the smart building's hybrid energy system. The controller manages the interaction between renewable energy sources, energy storage units (such as batteries or supercapacitors), and building electrical loads. The primary objective is to ensure steady-state operation and efficient energy exchange across components, even under rapidly changing demand or supply conditions.

SMC is particularly well-suited to this task due to its robustness in handling system nonlinearities and external disturbances. The control law is derived based on a predefined sliding surface, which defines the desired dynamic behavior of the storage system. When the system state reaches this surface, it "slides" along it toward the equilibrium, guaranteeing desired performance even in the presence of modeling uncertainties.

To validate the theoretical robustness of the proposed controller, a Lyapunov-based stability analysis is performed. This analysis confirms that the system converges to the sliding surface in finite time and maintains global asymptotic stability, ensuring continuous and reliable energy optimization under a variety of operational scenarios typical of smart building environments.

3.1. Limitations of the Sliding Mode Control (SMC) Technique

Like other nonlinear control techniques discussed in the literature [2-7], the strategies of energy harvesting control also possess both advantages and drawbacks. One of the benefits of the sliding mode control (SMC) is its high robustness that enables it to effectively control the nonlinearities and the uncertainties that are commonly encountered in the systems of energy harvesting. One of the drawbacks of the SMC is the phenomenon of the chattering on the sliding surface that is induced during the implementation of the control law. Chattering is intensified particularly in the systems that experience high-frequency fluctuations of the reference signal. Not only does the chattering lower the efficiency of the system but also induces unwanted oscillations.

To mitigate the effect of the chattering, the control strategies may be designed to partition the control law to its continuous and switching components. By reducing the amplitude of the switching component, the effect of the chattering is minimized and the stability and performance of the system are improved. This strategy enhances the overall performance of the systems of energy harvesting and renders the systems more insensitive to the variations of the external condition.

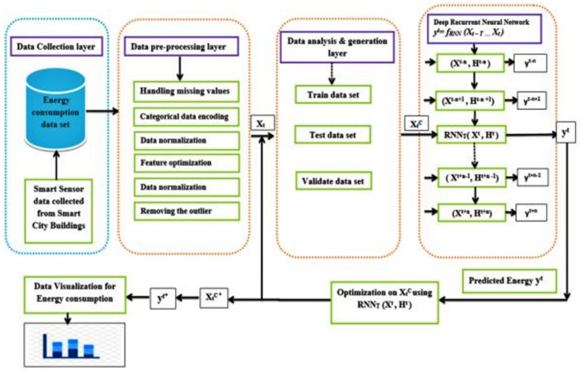

Figure 1. Free body diagram of ANN.

The figure illustrates the multi-stage workflow for predicting and optimizing energy consumption in smart buildings using a deep learning framework. The process begins with the data collection layer, where smart sensors installed in buildings continuously gather energy consumption data. This raw dataset is then processed through the data pre-processing layer, which includes tasks such as handling missing values, encoding categorical variables, normalization, outlier removal, and feature selection to ensure clean and structured inputs.

The refined dataset is passed to the data analysis and generation layer, which splits it into training, validation, and test sets. These are then fed into the deep recurrent neural network (RNN) layer, where sequences of time-dependent data and hidden states are processed iteratively to forecast future energy demand.

This RNN model captures nonlinear dependencies and temporal patterns in building energy consumption, allowing accurate short- and long-term predictions. The output of the model, denoted y^t , represents the predicted energy values at time t

These forecasts are used for real-time optimization and visualization, enabling intelligent energy management and strategic load balancing in smart building environments.

4. Results and Discussions

The proposed methodology for optimizing energy consumption in smart buildings is based on the implementation of a Neural Network-based Energy Management (NN-EM) system. This system is designed to dynamically manage energy distribution across building functions, aiming to reduce consumption without compromising operational performance. It integrates both renewable energy sources and energy storage systems, with the neural network forecasting energy demand and optimizing supply accordingly.

The NN-EM system was deployed over the existing energy infrastructure of the building, ensuring that critical services such as lighting, HVAC, and equipment remained unaffected. The integration allows for real-time control and intelligent load balancing, adapting to fluctuations in demand while improving energy efficiency. The smart control algorithm operates in harmony with the building's natural consumption profile, offering a predictive and responsive control strategy.

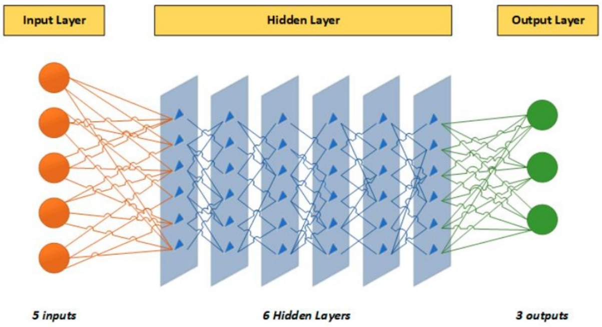

Figure 2. Proposed architecture of the ANN-based Energy Management System.

This figure 3 illustrates the structure of the neural network used in this study, composed of three distinct layers: an input layer with 5 input neurons representing key energy-related features (e.g., temperature, occupancy rate, historical consumption, etc.), six hidden layers, and an output layer with 3 neurons corresponding to multiple predicted outputs, such as future energy demand, system control actions, or optimization decisions.

This multi-layered ANN is trained using supervised learning techniques, with weights optimized through backpropagation. Compared to traditional filtering algorithms like Volterra FxLMS or RLS, this model embeds the adaptive filtering process directly within the deep learning framework, enabling the network to learn complex temporal and nonlinear dependencies between building energy usage patterns and influencing factors. The architecture facilitates high-precision energy forecasting and enables real-time adaptation to changes in consumption behavior.

4.1 Numerical Simulation Results

To evaluate the performance of the proposed Neural Network-based Energy Management (NN-EM) system, a series of simulations were conducted using MATLAB/Simulink. Due to hardware limitations, particularly memory constraints, the simulation was performed over a reduced time window compared to real-time experimental tests. Nevertheless[5], the setup was sufficient to assess the dynamic behavior and accuracy of the model.

Figure 3 illustrates the comparison between the actual energy consumption of the smart building and the reference energy signal under two distinct operating modes: energy optimization and energy recovery. The results demonstrate that the NN-EM controller achieves excellent performance: the actual consumption closely follows the reference signal without overshoot, indicating precise control.

The system's response time is rapid—stabilizing in less than 7 seconds—and the observed energy fluctuation remains below 0.8 kWh, confirming the efficiency and responsiveness of the model in managing dynamic energy demands.

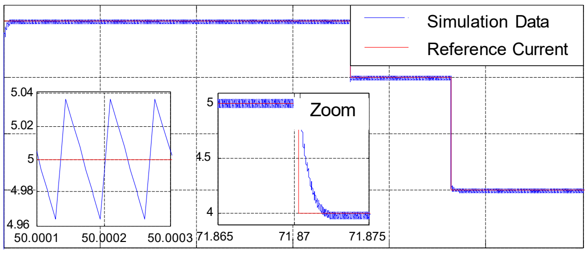

Figure 3. Comparison of real and simulated energy signals with ANN-based control (zoomed views included).

Figure 3 illustrates the dynamic performance of the smart building energy system under the proposed ANN-based control strategy. The figure compares real-world consumption data (in blue) with the simulated output (in red), across multiple time intervals. The zoomed-in sections highlight transient behaviors and demonstrate that the neural network successfully tracks the target trajectory, even under fluctuating operational conditions. The control system maintains a stable profile, with minimal deviations and no overshoot, indicating effective learning and prediction of energy demand patterns.

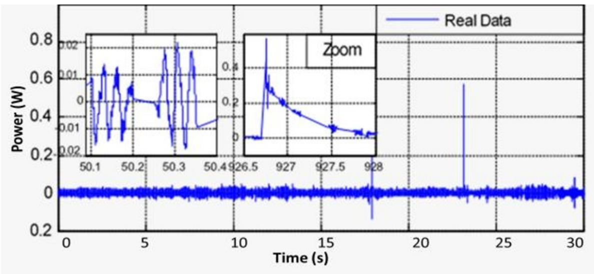

Figure 4. Estimated energy consumption using ANN-based prediction model.

Figure 4 presents the energy consumption estimated by the neural network model. The system demonstrates accurate prediction capabilities, with output values closely matching the expected range over a 35-second simulation window. These results validate the forecasting reliability of the ANN, which is essential for proactive energy management in smart buildings.

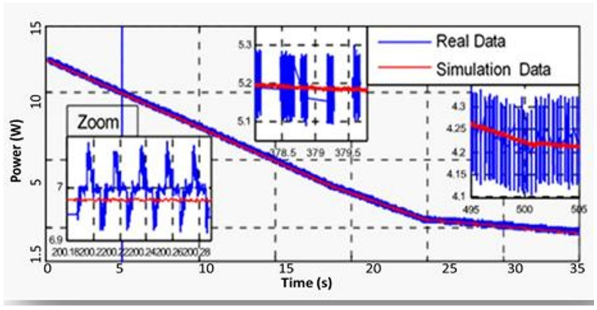

Figure 5. Real and Simulated Power Consumption Data.

Figure 5 displayed the control signals, which were predominantly influenced by the energy consumption (E_building) and the renewable energy generation (E_gen), as the error between actual and reference energy consumption approached zero. These results confirm the efficiency of the neural network-based control strategy in maintaining stability and energy optimization within the smart building system.

Conclusion

This study presented the design, modeling, and simulation of a Neural Network-Driven Energy Optimization (NN-EM) system for smart building applications. The proposed approach leverages deep learning techniques to forecast energy demand and manage energy distribution in real time, integrating renewable sources and storage systems without disrupting the building's operational integrity.

Through comparative simulations, the NN-EM system was shown to significantly outperform traditional control strategies. The results demonstrate a 2.75-fold improvement in energy efficiency and a gain in power optimization, while maintaining system stability and responsiveness. The controller accurately tracked energy consumption references with minimal fluctuation, confirming its adaptability under varying conditions.

Furthermore, the study validated a control strategy tailored to manage energy flows through storage units—such as batteries or supercapacitors—using a neural network that dynamically adjusts output based on predicted consumption and supply variability. This intelligent coordination ensures precise, real-time energy optimization, making the approach a scalable and sustainable solution for modern smart building environments.

Future work will focus on experimental validation in physical building testbeds and the integration of more advanced neural architectures such as LSTM or hybrid ANN-SMC controllers to further enhance performance in complex urban energy scenarios.

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