Iraqi Journal of Computers, Communications, Control and Systems Engineering
Journal homepage: https://ijccce.uotechnology.edu.iq

Intelligent Power Management Model for Buildings Using Deep Neural Networks

Marwa Mushtaq Talib[1*], Muayad Sadik Croock[2]

[1] University of Mosul, Computer Engineering Department, Mosul, Iraq
[2]University of Technology, Electrical Engineering Department, Baghdad, Iraq
[1] marwa.21enp1@student.uomosul.edu.iq, [2] muayad.s.croock@uotechnology.edu.iq

DOI: https://doi.org/10.33103/uot.ijccce.25.1.2

HIGHLIGHTS

- DNN-Based Power Management .
- Feature Reduction for Efficiency
- High Accuracy

ARTICLE HISTORY

Received: 21/December/2024

Revised: 10/February/2025

Accepted: 06/March/2025

Available online: 30/April/2025

Keywords:
Power management, Smart building, PCA, Bourta and Deep Neural Network.

ABSTRACT

Power management aims to maximize energy use while saving building expenses and raising their efficiency. Minimizing energy consumption and supporting environmental preservation by automation depends on intelligent power management systems in buildings. This paper presents a performance evaluation to assess the deep learning approach using an intelligent model that preserves power consumption in smart buildings. A deep Neural Network (DNN) model is presented to manage building power usage by utilizing three classes named "modes". Full mode is where the power is in full usage, Select mode presents power in selective consumption, and Shutdown mode is when there is no power consumption. Moreover, Boruta and Principal Component Analysis (PCA) feature reduction techniques were employed to minimize the complexity of the approach. The suggested model is trained and tested using a measured dataset taken from a university building over one year. The DNN paired with the Boruta feature reduction approach grabs greater consideration for classification accuracy of 99.8% and a classification duration of 1.19 seconds according to the results of the suggested model. The high accuracy results for DNN-Bourta prove that this model is an ideal approach to be implemented in real-time intelligent power management systems.

I. INTRODUCTION

A big challenge for reaching environmental sustainability in modern society is energy efficiency. The viability of a smart city depends on the development of infrastructure and energy-efficient services. With one-third of annual greenhouse gas emissions and more than 40% of world energy consumption attributed to the building and construction industry, it is a major and increasing factor of global warming[1]. An improved method of tracking and regulating a building's energy consumption is building energy management systems or BEMS. Apart from controlling energy, the system might control and oversee a broad spectrum of other building components, weather it is home, commercial, or industrial[2]. The extensive implementation of smart monitoring and control technologies presents significant opportunities for energy conservation and a robust return on investment, applicable to both newly constructed and retrofitted buildings. At present, a range of methodologies is being employed to regulate energy consumption within buildings. The notion of smart buildings advocates for the integration of cutting-edge technology and energy resources within architectural frameworks. The primary emphasis in this context is on automation, efficient use of resources, user convenience, and energy conservation, facilitated by wireless sensor networks (WSNs) [3]. In wireless sensor networks, sensors within smart buildings have the capability to gather data regarding various environmental variables. This data collection facilitates improved decision-making processes that can optimize resource utilization while ensuring the maintenance of desired operational behaviors. The concept of WSN is not only related to smart buildings, but its obviously integrated in rather large and varied domains as clarified in [4],[5],[6],[7] ,[8] ,[9] and [10]

The incorporation of digital methodologies in the energy sector is clearly advantageous, as evidenced by the amalgamation of artificial intelligence (AI) with concepts aimed at enhancing energy efficiency. Advanced learning systems grounded in strong artificial intelligence can facilitate complex decision-making processes regarding the management of technologies that are energy-efficient. Based on what was mentioned before, this work's objective is to employ AI methods for managing the consumption of energy in buildings. This is utilized by data gathered from the building to develop a model that is proficient in managing the energy use in buildings, thereby minimizing power consumption to the most economical levels[11].

This research utilizes deep neural networks to develop a model aimed at reducing energy consumption in buildings. A quantified dataset of an open floor area in a university building is utilized to train and test the model. From this dataset, five distinct features have been selected (occupancy, plug load, lighting, temperature, and humidity). Three modes of operation (three classes) namely: Full, Select, and shutdown were implemented to improve the power management, which results in saving consumed power. Occupancy status and building's temperature are considered as the main feature selection for the operational modes. The Full mode is executed when the building is full and temperature is more than 25C or less than 18C unlike Selected mode when the temperature is less than 18C or greater than 25C and the building is partially occupied. While Shutdown is applied when the building is empty. Data preprocessing is done by scaling data; then, two techniques Boruta and Principle Component Analysis (PCA) were applied individually for DNN to reduce features. To select the best method that satisfies the requirements of the proposed model, these techniques have been assessed with respect to accuracy and running times. Precision, recall, and F1-Score were implemented as evaluation metrics to provide a comprehensive picture of every class's performance. In addition to this, an analysis is performed without the implementation of feature reduction techniques to determine the significance of these methods in improving the performance of the system. Following the implementation of the proposed methodology, comparative analyses of the aforementioned model indicated that the DNN-

Bourta classifier attained the highest accuracy, recorded at 99.8%. and the time taken for classification is 1.19 seconds.

The sections are categorized as the following: Section II lists DL-based energy-efficiency solutions derived from a literature study. Section III addresses the suggested system of power management. Section IV aspects results while Section V summarizes the results and emphasizes further research projects.

II. LITERATURE REVIEW

Examining scholarly articles on energy management reveals that, specifically in recent research, machine learning, and deep learning methods have been extensively analyzed within the academic literature. One of the most significant domains in which machine learning and deep learning methodologies can be employed to enhance energy efficiency in construction is building energy management. Power systems can address a variety of issues, including control, planning, and scheduling[12]. The main reason for building such systems is to minimize the electric usage of users by scheduling the overall consumption[13].

Concerning ML techniques, many ML classifiers were studied and compared to assess building energy efficiency. According to [13], The machine learning model predicted unmeasured variables that were derived from a network of sensors. Through the analysis of a six-month dataset derived from Japanese intelligent buildings, they declared that the proposed model was able to determine the internal readings for controlling heating and cooling systems. Though they tried to lower the possible cost by minimizing the number of sensors, their work did not specifically address the possible energy consumption of the structure.

Conversely, DL algorithms are growingly popular for controlling building power consumption, and this is a very important element in building energy economy due to the ability of emission management. The authors of [2] evaluated the performance estimation by using the prediction time and input parameter dimensions, they evaluated the time cost of the prediction model by means of Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) indices. Additionally, in[14] an organizing framework is introduced and a deep learning algorithm to support integrated control and modeling of building power supply and demand. This study investigated various elements that facilitate the oversight and regulation of clean energy production particularly during periods of peak consumption. The implementation of smart user control mechanisms for Heating, Ventilation, Air-conditioning, and Cooling (HVAC) methods resulted to a decrease in power consumption expenses, and that’s leads to user satisfaction. Based on this, an innovative HVAC management architecture has been introduced, which is originally built on a multi-step predicting deep reinforcement learning (MSP-DRL) algorithm[15]. This is achieved by proposing a system that demonstrated its effectiveness, indicating a potential cost savings of over 12% in comparison to alternative approaches that incorporated user control. Research in the domain of deep learning has largely focused on user preferences, while often neglecting the occupancy status of buildings, which can vary from completely empty to fully occupied or partially filled. The optimization of energy utilization in buildings has been the subject of considerable scholarly investigation, especially in the context of managing HVAC systems through the integration of deep learning techniques, as comprehensively reviewed in sources [16], [17], [18], [19], [20], and [21].

III. SUGGESTED INTELLIGENT POWER MANAGEMENT SYSTEM

The proposed research methodology involves an assessment of methods for deep learning without feature reduction in comparison to the application of Bourta/PCA as primary feature reduction techniques. Subsequently, the results will be evaluated to determine the ideal solution for power management. This section is structured as several subsections to clarify the whole concept of this research.

A. General Structure

As *Fig. 1* shows, several actions were carried out consecutively to apply the suggested DNN architecture as a workflow. The first choice is a suitable dataset for this study theme. Following that, preprocessing techniques including data labeling and feature scaling were implemented and feature reduction techniques were applied to evaluate classification results. After that, criterion assessments about correctness and implementation time are computed; lastly, a comparison is done to assess the proposed approach.

B. Dataset Collection

The selected dataset is derived from a study implemented in an open area within a floor in a university [22]. It is gathered under both indoor and outdoor environments during one year from 1/1/2013 to 31/12/2. Indoor features including occupancy status, plug load, temperature, humidity, and light are considered when developing this model. This study focusing on managing the operational status of the buildings in three distinct modes: shutdown, full, and select, the proposed method aims to improve the management of energy as already stated. A new feature is added to the dataset based on occupancy conditions and temperature to classify the model based on the aforementioned modes. *Fig. 2* illustrates the rooms in this office related to the dataset.

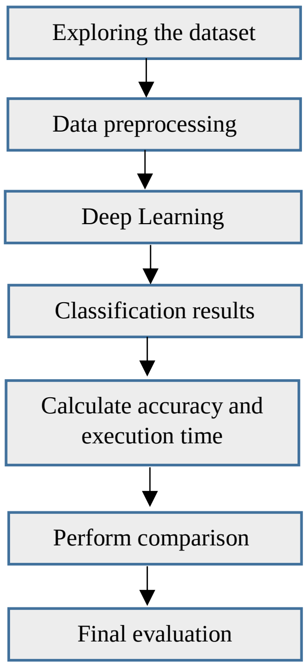

FIG. 1. SUGGESTED SYSTEM WORKFLOW OF THE PROPOSED SYSTEM.

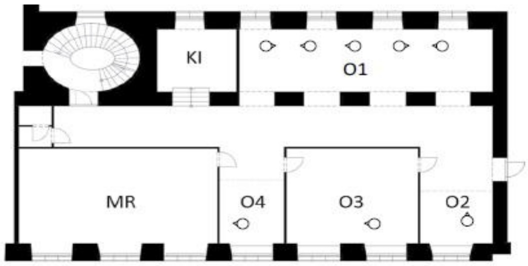

FIG. 2. STRUCTURE OF THE OFFICE IN THE BUILDING [22].

C. Dataset Preprocessing

Refining raw, frequently insufficient data to ensure accuracy and dependability in the classification model depends on the phase of data preparation. Data are gathered from the rooms depending on the predefined features. Subsequently, the data is categorized into three different classes: Full, Select, and Shutdown, which are designated with the numerical values of 0, 1, and 2, respectively. Feature scaling is used following labeling to unify the range of values, therefore guaranteeing that no one feature dominates distance computations—a necessary condition for the improvement of DNN algorithm accuracy. This technique gets the data ready for more exact and effective study[23].

D. Methods for Features Reduction

Using a machine learning-based feature reduction method, redundant elements are eliminated and the most important ones are targeted to improve accuracy. This work compares the DNN-based power management model using two techniques: Boruta and Principal Component Analysis (PCA). Boruta retains only the most pertinent real features by building a shadow dataset from the original data, randomly permuting feature columns, and contrasting their value with these shadows [24]. Conversely, PCA lowers dimensionality by converting features into orthogonal components, therefore modifying the variance ratio to 0.95 and preserving 95% of the volatility in the data. Accuracy and execution time guided evaluations of both approaches.

E. Proposed Deep Learning Model

DL-DNN is applied to categorize power management modes in a more efficient approach. *Fig. 3* shows the fundamental DNN architecture whereby each feature requires one neuron from the input vector. Inputs of the neural network consist of occupancy level, plug loads, humidity, temperature, and light.

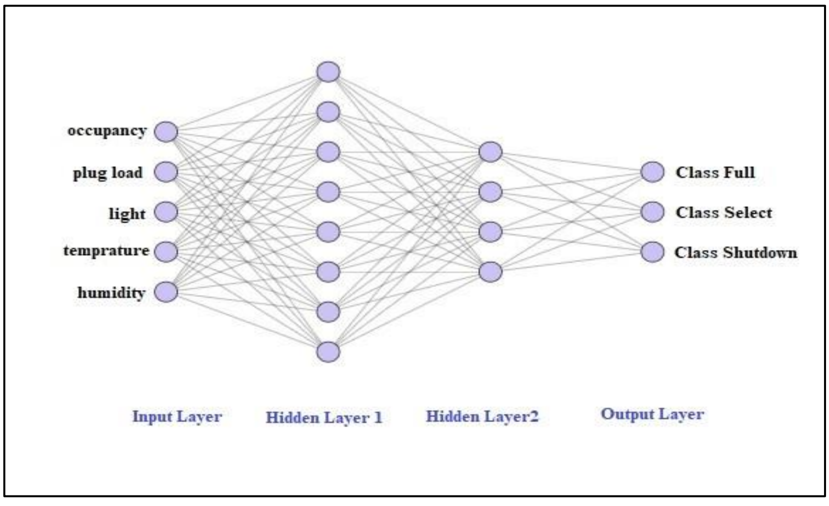

FIG. 3. CONFIGURATION OF DNN.

The neural network is comprised of two hidden layers, while the output layer involves three neurons corresponding to each of the three operational modes: Full, Select, and Shutdown. The ReLU function, an acronym for Rectified Linear Unit, serves as the activation function for the hidden layers [25].

F. Testing of The Model

The confusion matrix serves as a straightforward and efficient tool for assessing the performance of a model with respect to particular classes. Precision, recall, and F-score are also taken into consideration along with accuracy results to be recognized as evaluation metrics to assess the efficiency of the classification method [26]. *Fig. 4* presents a straightforward representation of a confusion matrix. The completion of the testing process yields four values that populate a table consisting of the expected labels as well as actual labels: true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). This framework facilitates the computation of accuracy derived from the aforementioned table. The equations numbered 1, 2, 3, and 4 demonstrate the calculation of precision, recall, precision, F-score, and accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

$$F - score = \frac{2 * Precision * Recall}{Precision * Recall} \qquad (4)$$

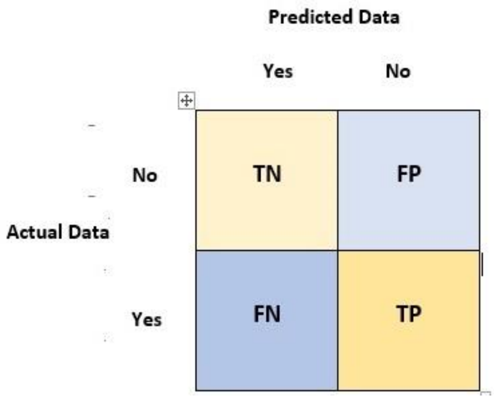

FIG. 4. CONFUSION MATRIX.

Execution time is also considered to calculate the duration taken for each method required when applying Bourta and PCA individually.

IV. RESULTS AND DISCUSSION

Various case studies are taken into account to test and assess the suggested DNN classification model. This covers the potential confronted issues and related remedies following training of the proposed intelligent models utilizing the chosen dataset. Important factors to be taken into account while choosing the best model to be applied in this work are accuracy and execution time. Furthermore, for in-depth class study analysis precision, recall, and f1-score are taken into consideration. This methodology primarily seeks to attain optimal accuracy while maintaining a reasonable classification duration.

A. First Case Study

The first case study addresses the effects of applying the DNN model without any feature reduction techniques. Here the results revealed that the model's accuracy is 99.6% and that the execution time is 1.62 s. Table I presents the suggested model's confusion matrix, illustrating the estimated values for the three different classes alongside the diagonal values corresponding to each class. This arrangement effectively reflects the true positive values predicted by the model. *Fig. 5* presents the classifying metrics about accuracy, recall, and F1-score for each class, as obtained from the scores of the testing dataset.

TABLE I. FIRST CASE STUDY: A CONFUSION MATRIX.

Classifier		**DNN**	
mode	**Full**	**Select**	**Shut down**
Full	799	36	1
Select	0	435	6
Shutdown	36	33	26686

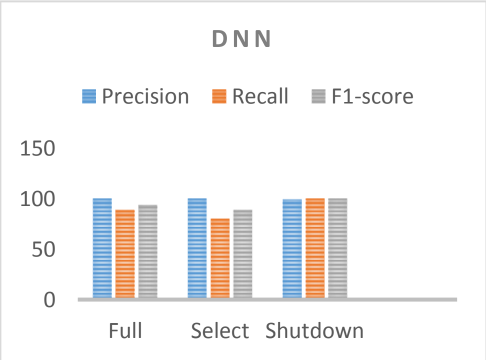

FIG. 5. CLASSIFICATION EVALUATIONS FOR EVERY CLASS IN THE FIRST CASE STUDY.

B. Second Case Study

The employment of Boruta and PCA within the framework of the DNN paradigm is presened in this case study. Table II presents a comparative analysis of the time consumed alongside the corresponding accuracy metrics. Despite the equivalence in time duration across the two scenarios, the accuracy outcomes associated with the utilization of Boruta-DNN surpass those obtained through PCA-DNN. Table III provides the confusion matrix for the proposed model, while DNN-Boruta and DNN-PCA classification results were clarified in *Fig. 6*, taking into consideration the F1-score, recall, and precision.

TABLE II. SECOND CASE STUDY ACCURACY AND TIME EFFICIENCY.

DNN model	**Accuracy**	**time/Boruta**	**time/PCA**
DNN	99.8% Boruta 95.53% PCA	1.19s	1.19s

TABLE III. SECOND CASE STUDY: A CONFUSION MATRIX.

Classifier	**DNN/Boruta**		
Mode	**Full**	**Select**	**Shutdown**
Full	820	4	12
Select	14	415	12
Shutdown	2	4	26749
Classifier	**DNN/PCA**		
Mode	**Full**	**Select**	**Shutdown**
Full	165	0	671
Select	38	0	403
Shutdown	140	0	26615

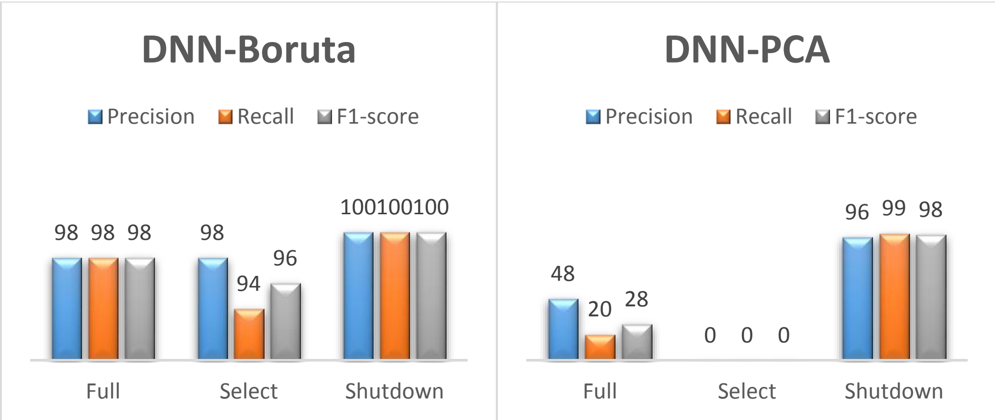

FIG. 6. THE CLASSIFICATION OUTCOMES OF THE SECOND CASE STUDY UTILIZING DNN-BORUTA AND DNN-PCA.

C. Comparative Case Study Analysis

Clarifying the accuracy findings shown in *Fig. 7*, DNN-Bourta classifier had the best accuracy of 99.8%. Regarding the implementation time, DNN-Bourta and DNN-PCA both scored the lowest at 1.19 seconds according to *Fig. 8*.

After examining Table III, shows that DNN-PCA misses classifying all the instances in class Select unlike DNN-Bourta which classifies class Select to a reasonable rate, this could be justified by the fact that the Boruta most certainly preserves all pertinent characteristics, including those that might reflect complicated or nonlinear interactions, which would help to improve classification performance unlike PCA chooses components not in line with their relevance to the classification criteria but rather based on overall variance. PCA might not retain the features required to produce reliable predictions for this class if the variance linked with the 'Select' mode is not substantial when compared to other modes. This is most likely the reason the PCA classifier failed to forecast any instances of the "Select" class (0 predictions), therefore producing total misclassification. This again makes DNN-Bourta the optimal method to be implemented in the suggested model.

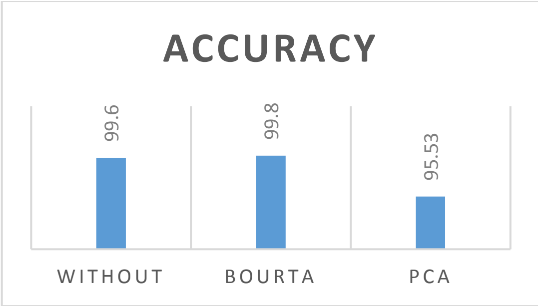

FIG. 7. ACCURACY RESULTS.

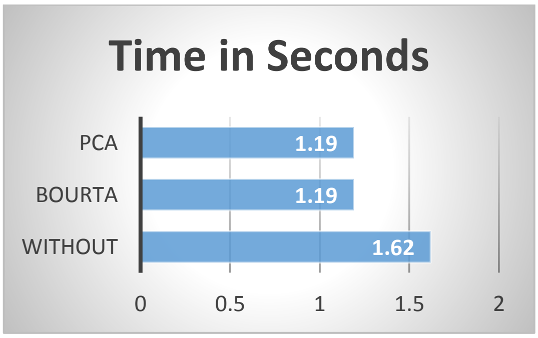

FIG. 8. CLASSIFICATION TIME.

V. CONCLUSION

This article presents an intelligent power management system based on Deep Neural Networks (DNN) applying Boruta and PCA feature reduction methods. The suggested approach effectively categorized building consumption of energy into three modes: Full, Select, and Shutdown, so maximizing energy use and preserving comfort. By means of a thorough analysis, the DNN-Boruta approach exceeded DNN-PCA and attained the best classification accuracy of 99.8%, together with a less execution time of 1.19 seconds. The results show the effectiveness of DNNs in managing complicated building management situations. Regarding future work, real-time integration of the model in real building administration systems would enable thorough testing under real-world situations, so offering insightful analysis on savings in energy and system efficacy.

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