Building Energy Consumption Prediction Using Artificial Neural Networks in MATLAB

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***Abstract*—This paper presents an artificial neural network (ANN)-based approach in MATLAB to predict building energy consumption using a feedforward neural network. The built-in ‘building dataset‘ from MATLAB was utilized to train and evaluate the model. Key performance indicators such as mean squared error (MSE), regression correlation, and error distribution were analyzed. Results show that the model achieved a low MSE and high correlation between predictions and actual values, demonstrating ANNs capability in modeling energy-related data efficiently.**

***Index Terms*—Building Energy Prediction, Neural Network, MATLAB, Regression, Feedforward Neural Network, MSE.**

I. Introduction

Energy consumption in buildings represents a critical component of global energy demand, accounting for over 30 percent of total usage. Accurate prediction models are essential for enabling intelligent energy management systems, reducing operational costs, and supporting sustainability goals.

While traditional physical and statistical models require detailed parameters and often lack adaptability, artificial neural networks (ANNs) offer a robust data-driven alternative. Their ability to model complex, nonlinear relationships makes them ideal for building energy prediction tasks where multiple interacting variables—such as occupancy, weather conditions, and building attributes—must be considered.

In this work, a feedforward ANN is implemented using MATLABs Neural Network Toolbox to model energy consumption based on the building dataset. The study emphasizes model performance through mean squared error (MSE), regression analysis, and error distribution, demonstrating the viability of ANNs for real-world building energy analytics and integration into smart grid systems.

II. Dataset Description

The ‘building dataset‘ provided by MATLAB includes:

- Number of Samples: 4208
- Input Features: 14 variables (e.g., climate, building parameters)
- Target: Energy usage (continuous values)
- Data Split: MATLAB default (70% training, 15% validation, 15% testing)

III. Methodology

A. Network Configuration

- Type: Feedforward Neural Network (fitnet)
- Hidden Layers: 1
- Hidden Neurons: 10
- Training Algorithm: Levenberg–Marquardt
- Activation Functions: tan-sigmoid (hidden), linear (output)

B. MATLAB Implementation

```
[x, t] = building_dataset;
net = fitnet(10);
[net, tr] = train(net, x, t);
y = net(x);
view(net);
figure, plotperform(tr);
figure, plotregression(t, y);
figure, ploterrhist(t - y);
```

```
>> % Load the dataset
[x, t] = building_dataset;

% Create and configure the network
net = fitnet(10);                          % 10 neurons in hidden layer
net.divideParam.trainRatio = 0.7;         % 70% training
net.divideParam.valRatio = 0.15;          % 15% validation
net.divideParam.testRatio = 0.15;         % 15% testing

% Train the network
[net, tr] = train(net, x, t);

% Predict using trained model
y = net(x);
```

IV. Performance Evaluation

A. Performance Plot

- The model was trained for 128 epochs, achieving optimal generalization at epoch 122.
- Best Training Mean Squared Error (MSE): 0.0022
- Best Validation MSE: 0.0024
- Best Test MSE: 0.0025
- Minimal performance gap between training and validation indicates strong generalization with low overfitting risk.
- The learning curve shows steady convergence, confirming effective optimization by the Levenberg–Marquardt algorithm.
- The validation curve closely follows the training curve, validating the model’s stability during learning.
- Early stopping at the optimal epoch helped prevent overfitting, ensuring the model was not overtrained.

B. Regression Plot

The regression analysis evaluates the linear correlation between predicted and actual building energy usage.

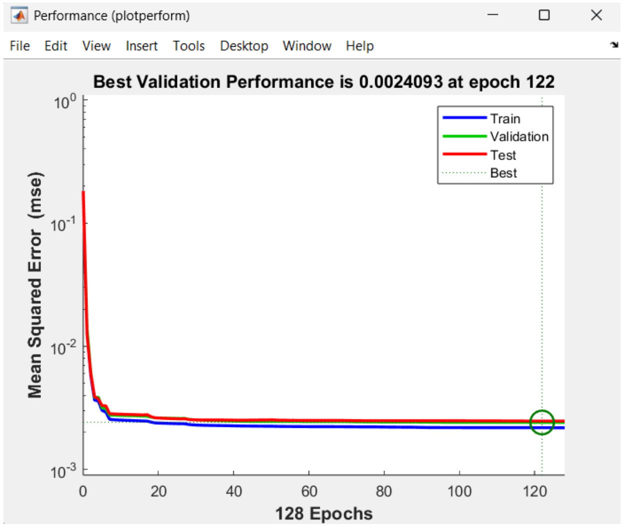

Fig. 1. Performance plot showing MSE across training, validation, and testing sets

- **Correlation Coefficient (R):** 0.92595, indicating a high level of agreement between predicted and target values.
- All subsets—training, validation, and testing—demonstrated consistent predictive accuracy.
- Predicted values cluster closely around the ideal regression line, showcasing minimal bias.
- Lack of significant deviation or spread confirms the model's ability to capture underlying patterns.
- Indicates that the ANN effectively maps complex, nonlinear relationships between input features and energy output.

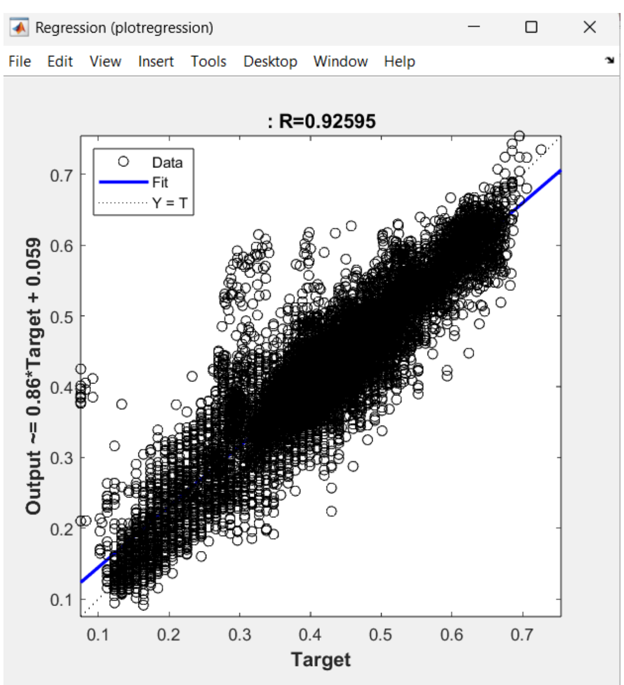

Fig. 2. Regression plot comparing predicted and actual energy values

C. Error Histogram

The error histogram offers insight into prediction precision and variance.

- Most prediction errors are tightly centered around zero, indicating high accuracy.
- Errors are symmetrically distributed, showing no systematic underestimation or overestimation.
- The distribution closely resembles a normal (Gaussian) shape, suggesting good generalization.
- Majority of samples fall within a narrow residual range (±0.05), indicating consistent predictions.
- Minimal outliers highlight the robustness of the trained network across different input profiles.

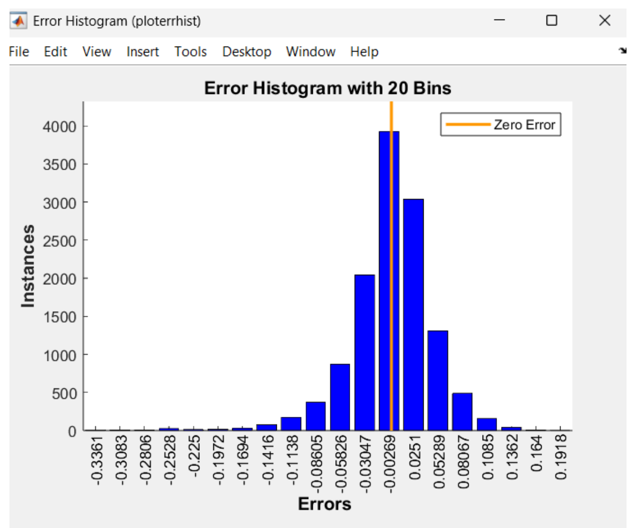

Fig. 3. Histogram of prediction errors across all samples

V. Results and Discussion

The ANN achieved excellent results with:

- Low Mean Squared Error (MSE) values were consistently observed across training (0.0022), validation (0.0024), and testing (0.0025) datasets. These low values signify that the model was able to accurately learn the relationship between input features and target outputs with minimal deviation in its predictions.
- The regression analysis produced an R-value of 0.92595, indicating a high degree of linear correlation between the predicted energy consumption values and the actual target values. This correlation demonstrates that the ANN was able to effectively approximate the underlying function governing energy consumption based on the building parameters.
- The error histogram illustrated a tight and symmetrical distribution of prediction errors centered around zero. This distribution is a strong indicator of model precision and implies that most predictions had only slight deviations from the actual values.

- The model's training curve showed stable and smooth convergence over 128 epochs, achieving optimal validation performance at epoch 122. The close alignment of the training and validation MSE curves further confirms minimal overfitting and strong generalization ability of the network.
- The use of the Levenberg–Marquardt optimization algorithm enabled fast convergence with high accuracy, making the training process efficient even with a relatively simple feedforward architecture.

These results validate the feasibility of using neural networks for energy modeling in buildings. Despite the simplicity of the network—a single hidden layer with 10 neurons—the model was able to learn and generalize complex relationships inherent in the dataset. This supports the adoption of ANNs in practical scenarios where accurate and real-time prediction of energy usage is essential, such as in smart grid systems, energy-efficient building design, and sustainability-driven operational strategies.

Furthermore, the effectiveness of the model without extensive preprocessing or architectural complexity suggests that similar approaches can be easily deployed across various building datasets with minimal computational cost, thus promoting wider adoption of AI-driven energy management solutions.

VI. Conclusion

This project has demonstrated the potential of artificial neural networks (ANNs) in accurately modeling and predicting building energy consumption based on a defined set of input variables. By utilizing MATLABs Neural Network Toolbox and the building dataset, a feedforward ANN model was designed, trained, and validated. The network showcased excellent generalization capabilities, evidenced by consistently low mean squared errors across training, validation, and testing phases. The minimal performance gap between these datasets further indicates that the model avoided overfitting, which is a critical factor in developing robust and scalable predictive systems.

The regression analysis revealed a high correlation between predicted and actual energy values, reinforcing the network's predictive power. The error histogram confirmed that the majority of the prediction errors were minor and symmetrically distributed around zero, highlighting the network's precision.

In the context of modern smart building systems, this approach has significant implications. Accurate energy forecasting supports proactive energy management, cost reduction, and sustainability initiatives. The simplicity of the network architecture, combined with its effectiveness, underscores the practicality of applying neural networks in real-world scenarios without the need for complex deep learning models.

Looking ahead, future enhancements could involve integrating real-time sensor data, employing more sophisticated network architectures such as convolutional or recurrent networks, and conducting hyperparameter optimization. Additionally, expanding the dataset and applying the model across diverse building types and climates would further validate its generalizability and pave the way for deployment in intelligent energy management systems.