# Average Energy Consumption Prediction for Gumi Industrial Platform using LSTM

Odinachi Udemezuo Nwankwo, Ukamaka Vivian Ihekoronye, Dong-Seong Kim, Jae Min Lee
Department of IT Convergence, Kumoh National Institute of Technology, Gumi, South Korea
{odinachi, vivian, dskim, ljmpaul}@kumoh.ac.kr

***Abstract*—This research presents a Long Short-Term Memory (LSTM)-based framework for predicting the average energy consumption of the Gumi Industrial Complex using data from 2021 and 2022. The study addresses the growing need for advanced forecasting models, driven by the Gumi Industrial Complex's efforts to enhance energy efficiency through the replacement of outdated equipment and devices (19.5%) and the establishment of energy monitoring systems (4.3%). After 20 Epochs of training using Adam optimizer and learning rate of 0.0001, our LSTM model achieved a training mean square error (MSE) of $2.0 \times 10^{-5}$ and a testing MSE of approximately $0.5 \times 10^{-5}$, indicating effective learning and satisfactory predictions. However, the mean absolute percentage error (MAPE) varied between 200% and 1400%, suggesting further tuning is required to improve robustness. Despite this, the results highlight the potential of LSTM models for industrial energy forecasting, supporting the demand for predictive analytics as a critical component of energy management in industrial settings.**

***Index Terms*—LSTM, Energy Prediction, Gumi Industrial Complex**

## I. Introduction

Efficient energy management is crucial for industrial complexes, especially in the face of rising energy demands and the need for sustainability. Accurate forecasting models play a vital role in optimizing energy usage and integrating renewable sources into industrial operations. This study is divided into subsequent sections. Section II discusses the literature review, focusing on prior work. Section III outlines the motivation and contributions of this research.The experimental setup and results are described in Section IV, highlighting the methods and key findings. Finally, Section V presents the conclusion and suggests directions for future research.

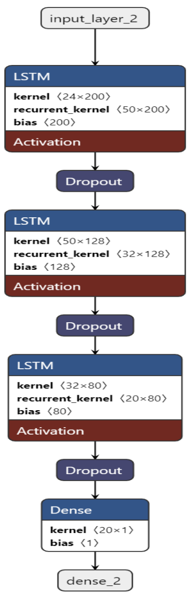


Fig. 1. Long Short Term Memory Model

## II. Literature Review

Literature Review In recent years, predictive models have played a pivotal role in energy management, enabling industries to achieve cost efficiency and energy conservation. Studies leveraging deep learning, such as Convolutional Neural Networks (CNN) and LSTM, have proven effective in time-series forecasting [1] [2]. Prior research has explored energy prediction in industrial settings, but the focus has largely been on building-level consumption or solar energy generation alone. This paper extends the application of LSTM models to predict energy consumption for an entire industrial complex, integrating both demand and solar energy data.

## III. Motivation and Contribution

Industrial complexes often face challenges associated with high energy consumption and changing energy needs. Managing energy effectively in such environments is important to ensure smooth operations and reduce costs. The Gumi Industrial Complex is working to improve energy efficiency and become self-sufficient by using renewable sources like solar power. However, the changing energy demands in an industrial setting require a forecasting model that can accurately predict energy usage based on these unique patterns. This research contributes to the field by:

Developing a forecasting model tailored to the unique energy consumption patterns in an industrial complex. Providing experimental evidence on the feasibility of LSTM for predictive energy management in large-scale industrial environments.

## IV. Experimental Setup and Result

The dataset used for this study includes hourly energy consumption and solar power data merged for the years 2021 and 2022. The input features include category, industry classification, and timestamped hourly consumption data, while the output target is the mean energy consumption per day. The data was split into training and testing sets (80/20).

The LSTM model was implemented in TensorFlow/Keras with hyperparameters tuned through grid search. Key metrics such as MAE, MSE, and MAPE were used for performance evaluation.

### Error Metrics

In the formulas below, $n$ is the number of observations, $y_i$ represents the actual value for the $i^{th}$ observation, and $\hat{y}_i$ is the corresponding predicted value.

**1. Mean Squared Error (MSE):**

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{1}$$

**2. Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

**3. Mean Absolute Percentage Error (MAPE):**

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \tag{3}$$

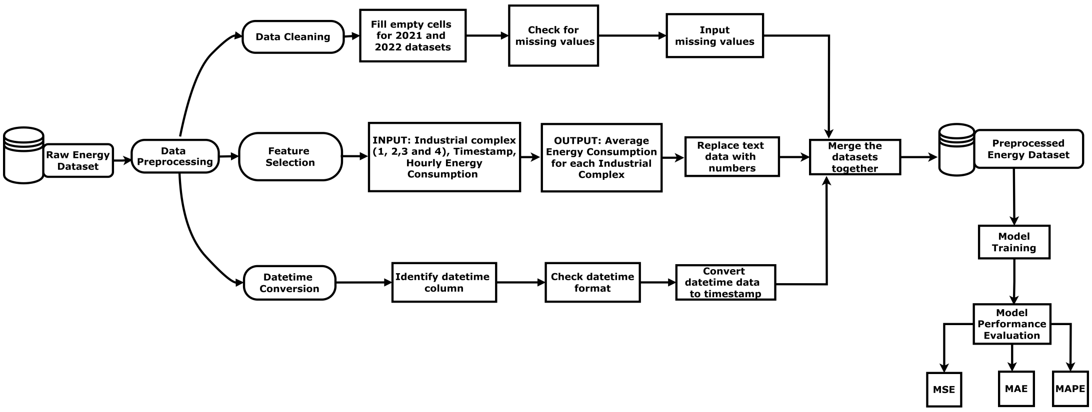


Fig. 2. The proposed system workflow: The proposed system collects historical energy usage and solar power generation data from 2021 and 2022, preprocesses it by handling missing values, normalizing data, and encoding categorical features. The LSTM model is trained on sequential input data to forecast average energy consumption for future periods. Performance is evaluated using metrics such as MSE, Mean Absolute Error (MAE) and MAPE.

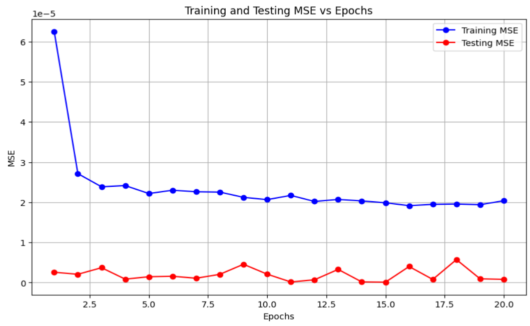


Fig. 3. From the graph, the training MSE appears to converge to approximately $2.0 \times 10^{-5}$, and the testing MSE fluctuates around $0.5 \times 10^{-5}$ towards the later epochs.

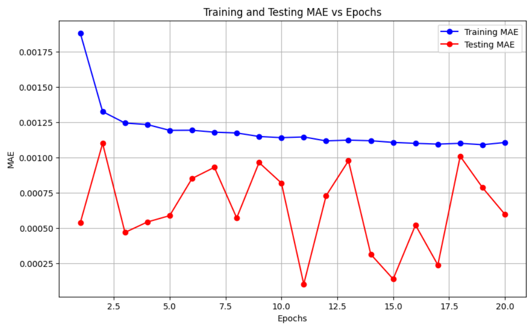


Fig. 4. From the graph, the Training MAE stabilizes around 0.0012 towards the later epochs, and the testing MAE fluctuates mostly between 0.0005 and 0.0010.These values indicate that the model's predictions for both training and testing data are quite close to the actual values.

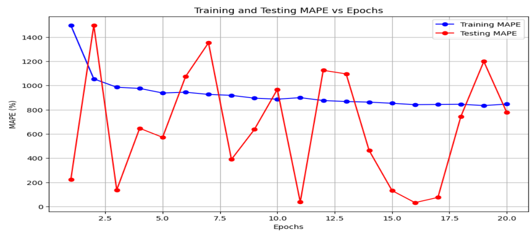


Fig. 5. The graph shows that training MAPE appears to stabilize around 900% after a few epochs.Testing MAPE fluctuates widely, ranging from 200% to 1400% across different epochs.

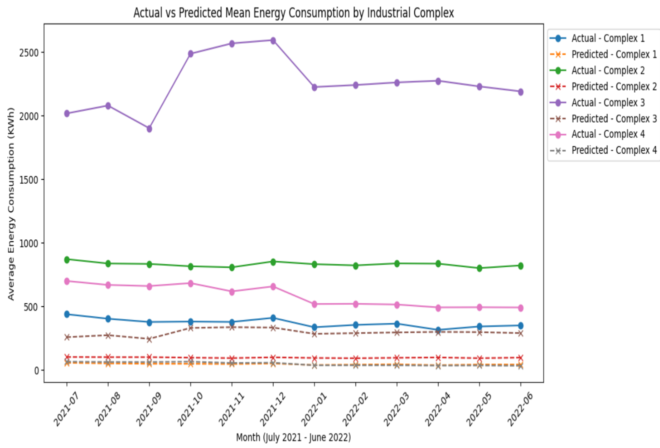


Fig. 6. Actual vs. Predicted Mean Energy Consumption (KWh) for each industrial complex from July 2021 to June 2022. The plot compares the actual and predicted energy consumption trends across four industrial complexes, highlighting the performance of the LSTM model.

## V. Conclusion and Future Work

The LSTM model achieved strong performance in both training and testing, demonstrating its capability to forecast energy consumption accurately. While the variability in MAPE suggests opportunities for further optimization, these results confirm the model's applicability to large-scale energy management. Future improvements will explore advanced tuning and external data integration to further enhance forecasting precision.

## Acknowledgement

This work was partly supported by Innovative Human Resource Development for Local Intellectualization program through the Institute of IITP grant funded by the Korea government(MSIT) (IITP-2024-RS-2020-II201612, 25%) and by Priority Research Centers Program through the NRF funded by the MEST(2018R1A6A1A03024003, 25%) and also This research was conducted using data provided by the Energy Self-Sustaining Infrastructure Development Project, funded by Korea Industrial Complex Corporation (KICOX, 25%), Korea and by the MSIT, Korea, under the ITRC support program(IITP-2024-RS-2024-00438430, 25%) supervised by the IITP

## References

[1] L. A. C. Ahakonye, G. C. Amaizu, C. I. Nwakanma, J. M. Lee, and D.-S. Kim, "Classification And Characterization Of Encoded Traffic In SCADA Network using Hybrid Deep Learning Scheme," *Journal of Communications and Networks*, vol. 26, no. 1, pp. 65–79, 2024.

[2] L. A. C. Ahakonye, C. I. Nwakanma, J. M. Lee, and D.-S. Kim, "Time-Efficient Deep Learning-Based Energy Consumption Prediction For Smart Factory," in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 879–882.