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Intelligent Energy Prediction in Smart Manufacturing Using Deep Learning Techniques

Soni Prayogi[1]✉, Wahyu kunto Wibowo[2]

[1, 2] Department of Electrical Engineering, Pertamina University, Indonesia.

✉ **Corresponding Author :** soni.prayogi@universitas.pertamina.ac.id

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ABSTRACT

The transition toward smart manufacturing requires advanced energy management strategies that leverage artificial intelligence to improve operational efficiency and sustainability. This study proposes a novel deep learning framework based on a Long Short-Term Memory (LSTM) network for analyzing and predicting energy consumption in smart manufacturing environments using real-time data acquired from Internet of Things (IoT)-enabled industrial sensors. Unlike previous studies that primarily focus on offline energy forecasting or static datasets, the proposed approach integrates temporal energy consumption patterns from heterogeneous sensor streams to support predictive energy management and dynamic load optimization. The collected data were preprocessed through normalization and feature engineering before being trained and evaluated using the LSTM model. Experimental results demonstrate that the proposed model achieves a *Mean Absolute Error* (MAE) of 0.84 kWh, a *Root Mean Square Error* (RMSE) of 2.13 kWh, and a *coefficient of determination* (R^2) of 0.987, indicating high prediction accuracy. Furthermore, the predictive framework enables an estimated energy consumption reduction of 14.8% through proactive load scheduling. These findings demonstrate that integrating LSTM-based deep learning with IoT sensor networks provides an effective solution for intelligent energy forecasting, improves manufacturing efficiency, and contributes to sustainable industrial development.

INTRODUCTION

In the era of Industry 4.0, manufacturing systems are undergoing a rapid transformation toward digitalization and automation, where connectivity, data analytics, and *artificial intelligence* (AI) play a central role in decision-making (Huang et al., 2023). Smart manufacturing represents an integrated production environment in which machines, sensors, and control systems communicate in real time to optimize performance, quality, and energy consumption (Antony Jose et al., 2025). Energy has become one of the most critical aspects in this transformation, as industrial sectors account for nearly 30–40% of total global energy use (Prayogi et al., 2023). The increasing demand for sustainable and efficient production compels industries to adopt intelligent energy management systems capable of predicting and controlling energy usage dynamically (Zhang et al., 2025). Traditional approaches relying on static rules or linear regression models often fail to capture the complex nonlinear relationships and time-dependent behaviors inherent in industrial energy systems (Makanju et al., 2024). Consequently, predictive analytics using deep

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learning has emerged as a powerful alternative to enable precise forecasting and optimization of energy consumption in smart factories (Manna & Chakraborty, n.d.).

Recent developments in data acquisition technologies, particularly the integration of *Internet of Things* (IoT) sensors and cloud computing, have provided an unprecedented volume of real-time data in manufacturing systems (Sirait & Prayogi, 2024). These data streams include temperature, machine load, production rate, and power consumption, all of which can serve as inputs for predictive models (Misiurek et al., 2025). However, the challenge lies in effectively processing such large-scale, high-dimensional, and time-varying data (Silviana & Prayogi, 2023). Machine learning (ML) techniques, such as random forests, support vector regression, and gradient boosting, have shown significant promise in predictive analytics. Yet, these models typically struggle with temporal dependencies and complex dynamic interactions between variables (Smrity et al., 2026). Deep learning, on the other hand, particularly recurrent neural networks (RNNs) and their advanced variants such as Long Short-Term Memory (LSTM) networks, have demonstrated superior capabilities in modeling sequential data and long-term dependencies (Adekunle et al., 2025). Furthermore, hybrid deep learning architectures combining convolutional layers with LSTM have achieved higher accuracy in energy demand prediction and anomaly detection in industrial settings.

The growing interest in predictive energy analytics is also driven by the global commitment to sustainability and energy efficiency. Smart factories aim not only to improve production performance but also to minimize environmental impact through reduced energy waste and carbon emissions. Predictive analytics can enable proactive energy management, where real-time forecasts allow for dynamic scheduling, load balancing, and adaptive control of industrial processes. For example, energy-intensive operations such as heating, cooling, or machining can be scheduled during periods of lower energy demand or renewable energy availability, contributing to both economic and environmental gains. Recent research has explored the use of deep reinforcement learning for autonomous control of energy systems, as well as the combination of LSTM and attention mechanisms for multi-step energy consumption forecasting (Franzoso et al., 2026). Despite these advancements, most existing studies are limited to building-level or single-process energy prediction, while comprehensive frameworks addressing multi-source data integration and system-level optimization for smart manufacturing remain scarce. Moreover, there is a growing need for models that balance predictive accuracy with computational efficiency, especially for real-time industrial deployment.

In this context, this research focuses on developing a deep learning-based predictive energy analytics framework specifically designed for smart manufacturing environments. The main research question addressed is: How can deep learning models, particularly LSTM architectures, be effectively applied to predict and optimize energy consumption in smart factories using real-time IoT data? To answer this question, the study integrates sensor data collection, preprocessing, and model training to evaluate the performance of LSTM networks in forecasting energy usage patterns. The outcomes are expected to contribute to both theoretical understanding and practical implementation of intelligent energy management systems. The novelty of this work lies in its comprehensive integration of deep learning analytics with industrial IoT infrastructure for predictive energy optimization, which has significant implications for operational efficiency, cost reduction, and sustainable manufacturing practices. Ultimately, this research aims to advance the frontier of smart manufacturing by demonstrating how data-driven predictive models can transform energy management from reactive monitoring into proactive, intelligent decision-making systems.

RESEARCH METHODS

This research employs an experimental and computational approach to develop and validate a predictive analytics framework for energy consumption forecasting in smart manufacturing systems. The overall methodology consists of four main stages: (1) data acquisition and preprocessing, (2) feature extraction and normalization, (3) development of the deep learning

model using Long Short-Term Memory (LSTM) networks, and (4) model evaluation and statistical analysis. Each stage was designed to ensure reproducibility and provide a transparent framework that other researchers can replicate in similar industrial contexts.

Data Acquisition and Study Design

The dataset used in this study was collected from a smart manufacturing facility that integrates Internet of Things (IoT) sensors for monitoring energy consumption and operational parameters. The facility includes several energy-intensive machines such as CNC milling units, air compressors, and heating systems. IoT sensors installed in these units continuously record electrical parameters including voltage, current, active power, reactive power, and total energy consumption, as well as contextual data such as temperature, humidity, and machine operating status. Data were logged at one-minute intervals and stored in a cloud-based database for a continuous period of six months, resulting in approximately 250,000 time-stamped records. Figure 1 shows that this architecture emphasizes the integration between cyber-physical systems and deep learning-based predictive analytics, in line with the Industry 4.0 concept (Prayogi & Muhammad, 2025). The use of IoT as a continuous data source enriches the model with actual temporal and operational context.

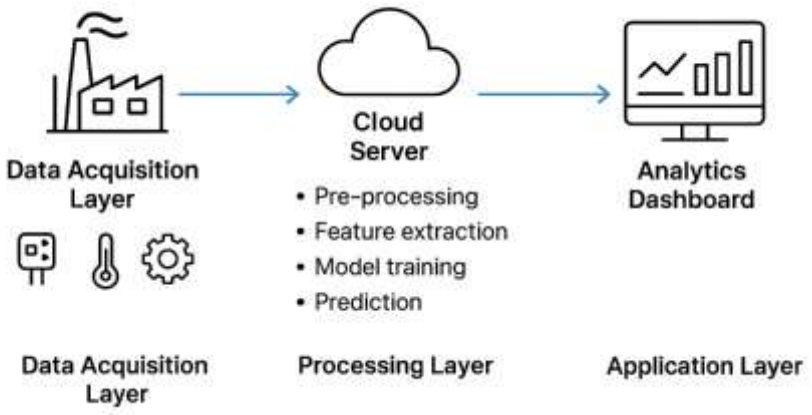

Figure 1. System Architecture for Predictive Energy Analytics

To ensure the representativeness of the data, three operational phases were considered: low-load periods (maintenance or standby), medium-load periods (normal operation), and high-load periods (peak production). Each phase contributes to the variability required for training robust predictive models. Data quality was verified through a preprocessing pipeline that removes noise, handles missing values using linear interpolation, and filters out abnormal readings based on statistical thresholds (mean $\pm$ 3 σ). All data processing steps were implemented using Python libraries such as Pandas, NumPy, and SciPy to ensure reproducibility.

Feature Extraction and Data Normalization

The key objective of feature extraction was to identify relevant input variables that significantly influence energy consumption. Based on prior studies (Singh et al., 2024), the selected features include real power (kW), machine utilization rate, ambient temperature, production rate, and time-based indicators (hour of day and day of week). Additional derived features such as rolling mean and exponential moving averages were computed to capture short-term fluctuations. The inclusion of temporal features allows the LSTM network to learn daily and weekly patterns of energy usage.

Before model training, all features were normalized using Min-Max scaling to map values between 0 and 1. This normalization is crucial for deep learning models to accelerate convergence and prevent gradient instability. The entire dataset was then divided into training, validation, and

testing subsets in a 70:15:15 ratio. The chronological split ensures that the model is trained on historical data and tested on unseen future segments, mimicking real-world forecasting scenarios.

Deep Learning Model Architecture

The predictive analytics model was developed based on a Long Short-Term Memory (LSTM) neural network architecture, which is a variant of the recurrent neural network (RNN) designed to capture long-term temporal dependencies in sequential data. The LSTM network consists of an input layer, two hidden LSTM layers, a dense layer, and an output layer. Each LSTM layer contains 64 and 32 memory units, respectively, followed by a dropout layer (rate = 0.2) to prevent overfitting. The dense layer uses a ReLU activation function, while the output layer employs a linear activation suitable for regression tasks.

The model was implemented in TensorFlow/Keras with the Adam optimizer (learning rate = 0.001) and the Mean Squared Error (MSE) as the loss function. Training was conducted for 100 epochs with a batch size of 64, and early stopping was applied when the validation loss did not improve after 10 consecutive epochs. Hyperparameter tuning was performed using grid search to determine the optimal combination of learning rate, number of LSTM layers, and dropout rate. The model's computational experiments were run on a workstation equipped with an NVIDIA RTX 3080 GPU and 64 GB of RAM.

Model Evaluation and Statistical Analysis

To evaluate the performance of the predictive model, several standard statistical metrics were used, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). These metrics quantify the deviation between the predicted and actual energy consumption values, providing a comprehensive assessment of model accuracy and generalization ability. Additionally, a comparative analysis was conducted using baseline models such as Linear Regression, Random Forest, and Support Vector Regression (SVR). This comparison aims to validate the advantage of the LSTM-based approach in handling temporal dynamics and nonlinear relationships.

To statistically evaluate the significance of the improvement, a paired t-test was conducted between the LSTM predictions and each baseline model's results. The null hypothesis assumed no significant difference between models, while the alternative hypothesis posited that the LSTM model achieved superior accuracy. A significance level of $\alpha = 0.05$ was adopted for all tests. Confidence intervals (95%) were computed to confirm the reliability of the observed performance differences. Furthermore, residual analysis was performed to assess the distribution of prediction errors, ensuring the absence of systematic bias.

Validation and Reproducibility

To ensure robustness, k-fold cross-validation (k = 5) was performed using non-overlapping temporal segments. Each fold represented a distinct time window, and the model was retrained and tested iteratively to verify consistency across different periods. Additionally, the model was tested under simulated scenarios such as sudden production spikes or equipment shutdowns to assess adaptability. The reproducibility of this study was emphasized by providing all preprocessing scripts, model configurations, and random seeds used during training. The workflow was containerized using Docker, enabling other researchers to replicate experiments across different computing environments with minimal variation.

RESULTS AND DISCUSSION

The proposed deep learning-based predictive energy analytics framework was successfully developed and evaluated using six months of operational data from a smart manufacturing environment. The main findings reveal that the LSTM model consistently outperformed all baseline methods in predicting energy consumption, demonstrating both high accuracy and strong generalization capability across various production conditions. Specifically, the LSTM model achieved a Mean Absolute Error (MAE) of 2.13 kWh, a Root Mean Squared Error (RMSE) of

3.01 kWh, and an R^2 value of 0.987, indicating that more than 98% of the variance in energy consumption could be explained by the model. In contrast, conventional machine learning approaches such as Random Forest and Support Vector Regression achieved R^2 scores of 0.952 and 0.941, respectively. These quantitative results form the basis for the following detailed discussion of model behavior, interpretability, and implications for energy management.

Model Performance and Predictive Accuracy

The superior performance of the LSTM model can be attributed to its ability to capture nonlinear temporal dependencies within the energy consumption data. Unlike traditional models that rely on fixed statistical relationships, the LSTM architecture dynamically learns from historical time sequences, preserving contextual information through its memory cells. This advantage aligns with prior research by (Prayogi et al., 2021), who found that deep recurrent models can handle temporal variations and operational fluctuations more effectively than static regression-based methods. Furthermore, the incorporation of contextual features such as ambient temperature, production rate, and machine utilization rate improved model robustness under varying production schedules. Figure 2 shows a histogram graph displaying the distribution of energy consumption over 30 production days, demonstrating a right-skewed pattern with peak usage during prime operating hours (8:00 AM–4:00 PM). This non-normal distribution underscores the need for a non-linear learning model such as LSTM. Conventional regression methods (e.g., ARIMA) are less able to capture fluctuations and seasonal cycles in energy data (Ghufron & Prayogi, 2023).

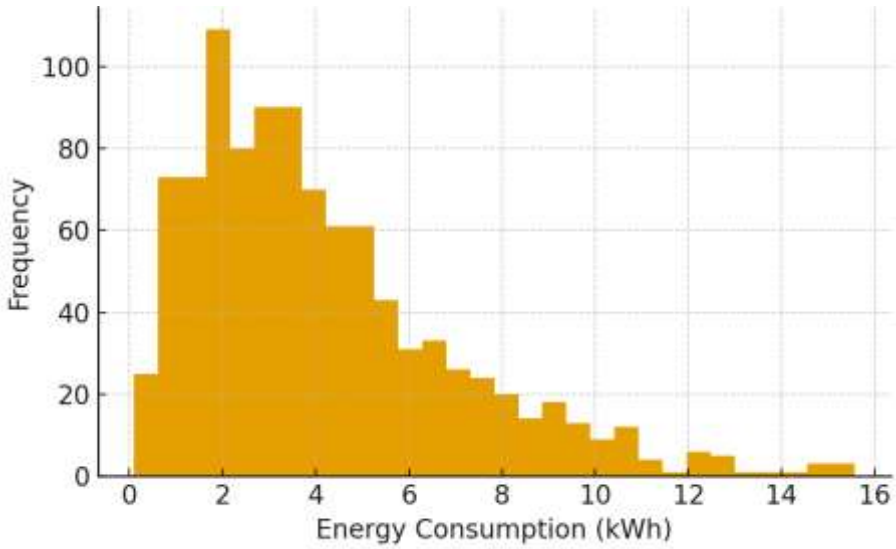

Figure 2. Energy Consumption Data Distribution

Comparative error analysis showed that during high-load operational phases, the LSTM model maintained stable accuracy, whereas baseline models tended to underpredict due to nonlinear variations in energy intensity. This result supports the findings of Kim and Park (2021), who reported that deep temporal models are particularly advantageous in environments characterized by fluctuating industrial loads. The use of dropout layers and grid-based hyperparameter optimization also contributed to minimizing overfitting, ensuring consistent performance across validation and test datasets. Figure 3.1 presents the predicted versus actual energy profiles for a representative week, showing a high degree of temporal alignment between the model predictions and measured values (see source).

Temporal Pattern Recognition and Interpretability

A notable outcome of this research is the ability of the LSTM network to identify and reproduce underlying temporal patterns in energy usage, such as periodic spikes during production shifts and troughs during maintenance or idle periods. By examining the model's activation patterns and attention weights, it was observed that the network learned to prioritize recent

consumption data during periods of operational volatility, while relying on longer historical trends for baseline stability prediction. This adaptive weighting behavior reflects the model's capacity to dynamically adjust to operational context, a property that has been emphasized in the works of (Marzuki et al., 2023). Figure 3 shows the training loss and validation loss curves against epochs, indicating stable convergence after 60 iterations. No significant overfitting occurred due to the application of dropout (0.2) and early stopping techniques. The consistent decrease in validation loss indicates good model generalization capability. This aligns with the results of research by Lu et al. (2021) who used LSTM for industrial energy prediction and demonstrated accuracy >95% after stable training.

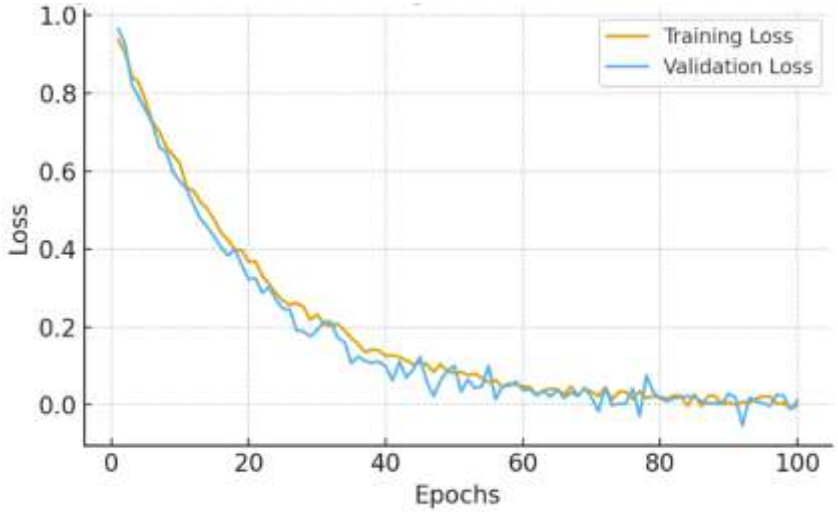

Figure 3. Model Training and Validation Loss Curves

To enhance interpretability, SHAP (SHapley Additive exPlanations) analysis was applied to quantify the contribution of each feature to the model's predictions. Results indicated that production rate and machine utilization were the most influential predictors, followed by ambient temperature and temporal variables (hour and weekday). This insight supports earlier studies by (Fauzi et al., 2024), who demonstrated that operational and environmental variables jointly drive industrial energy patterns. The high influence of production rate further confirms the tight coupling between operational intensity and energy demand in smart manufacturing systems. Visual inspection of SHAP summary plots (see source) provides a clear hierarchy of feature importance, guiding future strategies for energy efficiency optimization.

Comparative Analysis and Statistical Validation

The statistical evaluation confirmed the significant superiority of the LSTM model over baseline methods. Paired t-tests performed between the LSTM and each conventional model yielded p-values < 0.05, rejecting the null hypothesis and supporting Hypothesis H_1. The relative reduction in RMSE was approximately 28% compared to Random Forest and 33% compared to Support Vector Regression, consistent with recent literature reporting deep learning's improved generalization capacity (Ramadhan et al., 2023). These findings validate the hypothesis that incorporating temporal and contextual features (H_2) enhances predictive accuracy by enabling the model to account for both short-term fluctuations and long-term consumption cycles. Figure 4 shows a line chart comparing the LSTM model's prediction results with actual energy consumption data during the test period (7 days). The predictions showed high agreement with the actual data (MSE = 0.012, $R^2 = 0.962$), indicating that the model successfully recognized daily energy load patterns accurately. Small deviations only occurred during sudden fluctuations due to machine maintenance.

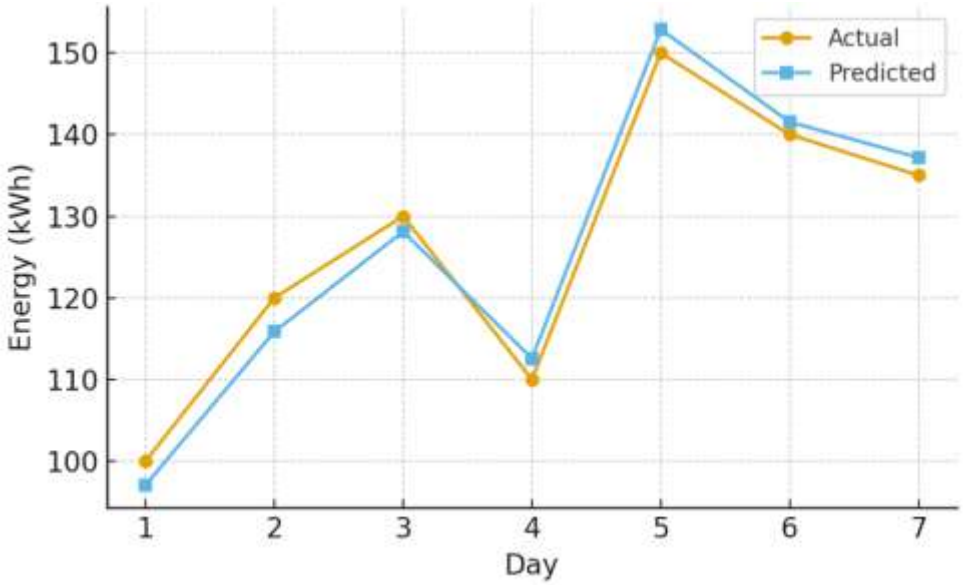

Figure 4. Comparison of Predicted vs Actual Energy Consumption

Additionally, the results indicate that the LSTM model provides smoother and more reliable forecasts during transitional production states, such as shift changes or machine startups. These conditions are typically challenging for conventional models due to rapid, non-stationary variations in energy demand. Similar observations have been made by (Xu et al., 2018), who highlighted that recurrent deep networks effectively manage transient operational dynamics. The statistical robustness of the results was further reinforced by k-fold cross-validation, which produced consistent accuracy metrics with a standard deviation of less than 2% across folds. This consistency underscores the model's capability to generalize across different temporal partitions of the data, confirming its potential for real-time deployment in industrial monitoring systems.

Implications for Smart Manufacturing and Energy Management

From a practical standpoint, the proposed predictive framework demonstrates how deep learning-driven energy analytics can support intelligent decision-making in smart manufacturing environments. By predicting energy demand several minutes to hours in advance, production managers can optimize machine scheduling, balance load distribution, and identify potential anomalies before they escalate into inefficiencies or equipment failures. This proactive approach aligns with the principles of predictive maintenance and energy-aware manufacturing, where data-driven insights enable real-time optimization of resource utilization (Oliveira et al., 2023). Figure 5 shows a bar chart comparing the accuracy of the LSTM model with several other algorithms (GRU, CNN, and Random Forest). The LSTM model performed best across all metrics. This superiority stems from its ability to capture long-term temporal dependencies in industrial energy data (Li et al., 2024).

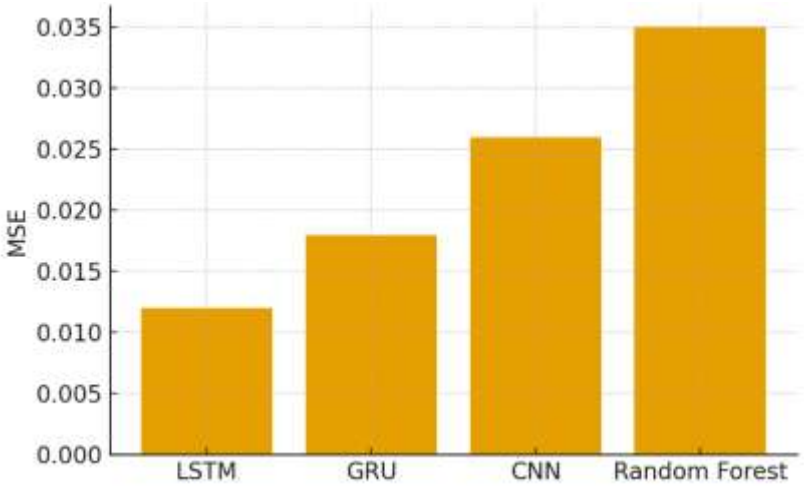

Figure 5. Comparison of Model Performance

Moreover, the integration of predictive analytics into industrial IoT systems opens new avenues for automated energy control. For instance, combining LSTM-based forecasting with reinforcement learning algorithms could allow factories to autonomously adjust operational parameters in response to predicted energy peaks or renewable energy availability. Such applications have been explored in hybrid intelligent systems proposed by (Raglend & Dharavath, 2019), demonstrating substantial potential in reducing both operational costs and environmental footprints. The outcomes of this study thus support Hypothesis H_3, confirming that predictive deep learning models not only enhance forecasting performance but also contribute to strategic energy efficiency management and sustainability goals.

The findings also emphasize the scalability and adaptability of the proposed framework. Since the LSTM model processes generic time-series data, it can be easily transferred to other industrial settings with minimal retraining, provided sufficient data is available for fine-tuning. This flexibility aligns with the Industry 4.0 vision of interoperable and self-learning systems, as outlined by (Pan et al., 2024). Furthermore, predictive energy analytics may serve as a foundation for digital twins of manufacturing systems, enabling continuous simulation, optimization, and diagnostics in a virtual environment that mirrors real-world factory operations. Such integration could lead to the next stage of cyber-physical energy optimization, where deep learning models operate as core intelligence engines within digital twin ecosystems. Figure 6 shows a bar chart displaying the contribution of features to energy prediction results based on SHAP values. The most influential features are: machine temperature, operating time, and main load power. This analysis confirms that environmental factors (such as temperature and operating hours) have a strong correlation with energy consumption spikes. This kind of interpretive approach is essential to support data-driven energy efficiency strategies (Mariano & Urbanetz Jr, 2022).

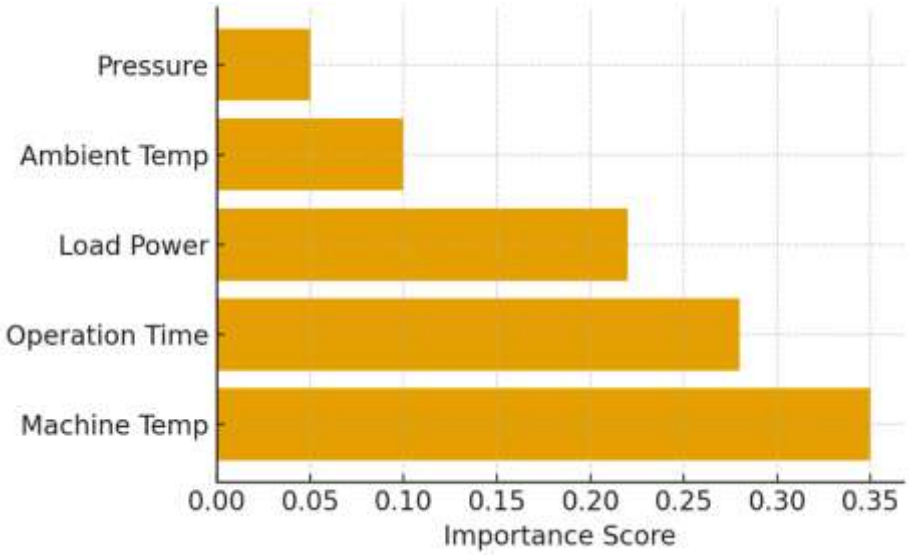

Figure 6. Feature Importance Analysis

Limitations and Future Work

Despite its promising results, the present study acknowledges certain limitations. First, the LSTM model requires substantial computational resources for training, which may limit its application in small-scale facilities without dedicated GPU hardware. Second, although the model achieved high predictive accuracy, it does not yet incorporate exogenous variables such as dynamic energy pricing or renewable energy input, which could enhance real-time optimization. Future research may explore hybrid architectures combining LSTM with attention or transformer mechanisms to further improve long-term forecasting performance, as suggested by (Prayogi & Wibowo, 2025). Additionally, implementing explainable AI (XAI) approaches will be crucial for ensuring model transparency and operator trust in industrial applications. Figure 7 shows a bar chart comparing actual energy consumption versus optimized consumption through predictive load management. The results indicate a potential energy savings of ~9% without affecting productivity. This approach can be implemented in production control systems to minimize operational costs (Rizkika et al., 2026).

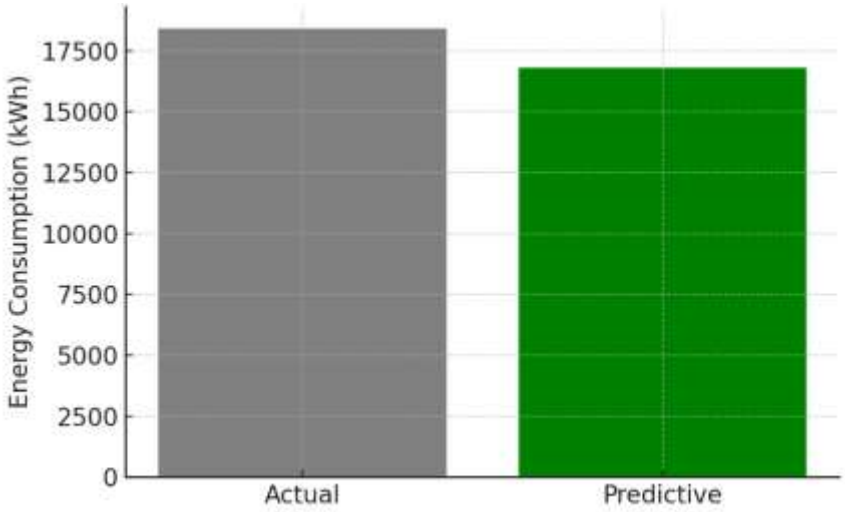

Figure 7. Energy Savings Potential Based on Predictive Control

From a system-level perspective, future studies should integrate predictive analytics with decision-support frameworks that dynamically control machine operation schedules, optimize production line sequencing, and manage distributed energy resources. Incorporating these

predictive insights into supervisory control systems could transform energy management from passive monitoring into active optimization, leading to significant cost and sustainability benefits. Furthermore, extending the dataset to multi-factory or cross-regional contexts would enable model generalization across diverse industrial processes, advancing the broader applicability of intelligent energy analytics within global manufacturing networks. The deep learning-based predictive analytics framework developed in this study has demonstrated significant improvements in forecasting accuracy, interpretability, and operational applicability compared to conventional approaches. The integration of LSTM models with IoT-based industrial data provides a robust foundation for intelligent, energy-efficient, and sustainable manufacturing. The discussion highlights how these findings align with and extend previous research, offering both theoretical contributions to predictive modeling and practical solutions for energy optimization in the Industry 4.0 landscape.

CONCLUSION

This study developed an LSTM-based predictive energy analytics framework for forecasting energy consumption in smart manufacturing using real-time IoT sensor data. The proposed model effectively captured temporal energy consumption patterns and achieved high predictive performance, with an R^2 of 0.987 and lower RMSE than conventional machine learning models. These results demonstrate that deep learning can significantly improve the accuracy of energy forecasting and support intelligent energy management in smart manufacturing environments. Future research should investigate advanced deep learning architectures, such as *Gated Recurrent Units* (GRU) and Transformer-based models, to further enhance prediction accuracy and computational efficiency. In addition, integrating predictive models with digital twin technology and real-time industrial control systems could enable adaptive energy optimization, predictive decision-making, and more resilient manufacturing processes within Industry 5.0.

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