SINERGI Vol. 29, No. 3, October 2025: 819-832
http://publikasi.mercubuana.ac.id/index.php/sinergi
http://doi.org/10.22441/sinergi.2025.3.022

TE-LSTM: winding temperature prediction for induction motors in the oil and gas industry

Joko Supriyono[1,2]*, Imam Mukhlash[3], Mohammad Iqbal[3], Dimas Anton Asfani[4]
[1]Interdisciplinary School of Management and Technology, Institut Teknologi Sepuluh Nopember Surabaya, Indonesia
[2]Saudi Aramco, Saudi Arabia
[3]Department of Mathematics, Institut Teknologi Sepuluh Nopember Surabaya, Indonesia
[4]Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember Surabaya, Indonesia

Abstract
Induction motor winding repair takes longer than other types of failures, such as bearing failures. This research introduces a hybrid deep learning framework, TE-LSTM, to predict winding temperatures in induction motors used in oil and gas operations. It aims to address the challenges of accurately forecasting potential winding failures and enabling proactive maintenance strategies. The TE-LSTM model combines a transformer encoder-based architecture with long short-term memory to effectively model intricate temporal relationships and sensor dynamics within the dataset. The study utilized data collected from January 2016 to December 2024 at 1-minute intervals from induction motors equipped with stator winding temperature sensors. These motors were designed with Class F insulation and had stage 1 and stage 2 alarms set at 257°F and 285°F, respectively. The findings highlight the efficiency and performance of the TE-LSTM model in predicting winding temperatures, which can significantly reduce unplanned downtime and associated costs, thereby optimizing maintenance operations and enhancing the reliability of the motor.

Keywords:
Induction Motor;
LSTM;
Predictive Maintenance;
Transformer;
Winding Temperature;

Article History:
Received: January 5, 2025
Revised: February 8, 2025
Accepted:
Published:

Corresponding Author:
Joko Supriyono,
SIMT, Institut Teknologi Sepuluh Nopember Surabaya Indonesia;
Saudi Aramco, Saudi Arabia.
Email:
Joko.Supriyono@gmail.com

INTRODUCTION

Faults in induction motors can disrupt factory production lines, causing downtime and leading to significant economic and operational losses. Ensuring reliable motor operation is therefore essential to minimize these impacts [1]. Induction motor (IM) drives are utilized in a wide range of applications, including conveyors, cranes, ventilation systems, and the petroleum industry [2]. The reliability and performance of induction motors are critical for ensuring efficient and safe industrial operations. The distribution of failures in IM components is as follows: bearing-related faults account for 40%, stator winding faults for 38%, rotor-related faults for 10%, and other faults for 12% [3] .

IMs are critical in industry, consuming 40-50% of the capacity generated. Induction motors (IM) are prone to various faults, and a standard industry guideline states that for every 10°C increase in temperature, the insulation's lifespan is reduced by half [4]. Detecting faults early can help avoid expensive failures and production downtime. Diagnosing faults in electrical motors involves analyzing various components, such as insulation, bearings, shafts, stators, and rotors. It also relies on multiple diagnostic signals, including acoustic, vibration, and infrared signals [5]. The demand for condition monitoring has grown significantly due to the increasing prevalence of automation, which has reduced direct human interaction with machines for supervising system operations. Condition monitoring provides a visual representation of machine parameters, enabling the detection, analysis, and resolution of issues before failures occur. Early fault detection in induction motors is essential to prevent production downtime and avoid catastrophic failures [6]. Reliability Condition Monitoring (RCM) is a critical and highly efficient method for evaluating and optimizing the maintenance requirements of plants and equipment during operation. Its primary objective is to reduce equipment failures and improve preventive maintenance practices, enabling industrial facilities to manage their machinery effectively and efficiently. Consequently, Prognostics and Health Management (PHM) for induction motors has emerged as a significant area of research [7]. Accurately predicting the remaining useful life (RUL) of induction motors is critical for optimizing condition-based maintenance (CBM) strategies, enhancing operational reliability, and minimizing maintenance costs [8]. PHM shifts maintenance strategies from reactive approaches such as post-failure repairs, routine scheduled servicing, and ad-hoc corrective actions to data-driven predictive maintenance. Central to this transition is the accurate estimation of remaining useful life (RUL), which enables operators to forecast equipment degradation and optimize maintenance interventions.

Figure 1. Induction Motor

Induction Motor

Three-phase AC motors account for approximately 60% of the total industrial electricity consumption, with induction motor (IM) drive systems being extensively utilized across various applications. AC induction motors are among the most used motors in industrial settings. Typically, these motors deliver higher power factors (PF) and greater efficiency when operating at or near full load conditions [9]. Figure 1 illustrates the basic structure of an induction motor (IM). The windings, made of copper, are distributed across the machine. The stator and rotor cores are constructed from laminated silicon steel sheets.

Additionally, the rotor bars are positioned near the top of the rotor and close to the air gap to minimize leakage flux [10]. Motor winding can be seen in Figure 2. Three temperature sensors are typically installed at the motor winding to monitor the winding's condition and prevent overheating.

Induction motors are essential for ensuring uninterrupted operations in the oil and gas industry. These motors, a widely used type of electric motor, are valued for their simplicity, high reliability, and cost-effectiveness, making them a preferred choice in various industrial applications [11]. These motors typically employ Class F insulation, which has a standard maximum winding temperature of 311°F (155°C), as outlined in IEEE standard 43.

However, when monitoring capabilities are limited, this threshold is often adjusted for safety reasons. In scenarios where only three sensors monitor the winding temperature, a more comprehensive approach is necessary. It is often adjusted by lowering the alarm set point of the winding temperatures.

To account for potential temperature variations that could cause inaccurate information due to measurements taken only in a specific area, the maximum allowable temperature was reduced to 287°F (approximately 142°C). These precautionary measures help to safeguard motor integrity and longevity. Based on this adjusted limit, a two-tier alarm system was implemented as follows:

Figure 2. Motor Winding

(1) The initial alarm (H) was activated at 257°F (about 125°C).
(2) The critical alarm (HH) was triggered at 285°F (around 141°C).

This tiered system allows for graduated responses to rising temperatures. When the H alarm sounds at 257°F, it provides an early warning that allows operators to initiate preventive actions. The HH alarm at 285°F serves as a final caution signal, indicating that the temperature is approaching the adjusted maximum. Advanced predictive models are being explored to enhance this protective strategy. In this study, a TE-LSTM model combines the transformer encoder and LSTM architecture used to forecast potential alarm triggers. By anticipating these critical events, operators can implement more proactive maintenance strategies, thereby reducing the risks of unexpected shutdowns, production interruptions, and other operational hazards associated with motor overheating.

Key components of an induction motor consist of

(1) Rotor: The rotating component of an electric motor, driven by the interaction with the magnetic field.
(2) Stator: the stationary part creates a rotating magnetic field. The stator consists of a copper winding or an aluminum winding. Copper or aluminum conductors carry electric current and produce magnetic fields.
(3) Insulation: This material electrically isolates and protects windings. Insulation class defines the thermal capability of motor-winding insulation materials. The two standard classes are F and B, which are described in Table 1.

In recent years, the need for precise and reliable Fault Detection and Diagnosis (FDD) methods for complex industrial systems has grown significantly. The primary objective is to enhance the safety and reliability of these systems while reducing unplanned downtime of machinery or processes. Unscheduled interruptions caused by equipment failures have become a critical concern in production facilities, particularly where machines are required to operate continuously for extended periods.

Table 1. Winding insulation class characteristics

Characteristic	Class F	Class B
Maximum operating temperature	155°C (311°F)	130°C (266°F)
Temp Rise Allowance	105°C (221°F)	80°C(176°F)

Faults within a system or process can occur either independently or simultaneously. While simple faults may be identified through single measurements, complex systems often make it challenging to observe system or process states directly. Consequently, there is a growing demand for more efficient and automated approaches to support FDD in such environments [12][13].

The reliability and availability of induction motors (IMs) are essential for ensuring smooth and continuous industrial operations. However, IMs are subjected to various unavoidable stresses during operation, including mechanical, electrical, thermal, and environmental stresses. These stresses arise from factors such as variations in external loading, power supply deviations, excessive heat, insufficient lubrication, sealing mechanism failures, dusty environments, manufacturing defects, and natural aging. To mitigate the risk of catastrophic motor failures, industries employ early fault detection and diagnosis techniques to identify and address component degradation before significant damage occurs [14][15].

Literature Review

Industrial System Maintenance: Preventive maintenance (PM) involves inspecting and servicing equipment based on a predefined schedule. This approach ensures equipment remains reliable and operational during regular use while minimizing the risk of unexpected failures. By proactively addressing potential issues, PM helps avoid costly downtime and the economic losses associated with sudden equipment breakdowns [16]. Recent developments in industrial maintenance have emphasized various strategies, including preventive maintenance (PM), condition-based maintenance (CBM), predictive maintenance (PdM), and hybrid approaches. These methods focus on enhancing system reliability, minimizing downtime, and optimizing operational efficiency, particularly for complex and critical machines [17]. The following summarizes the key developments and approaches across these maintenance strategies:

(1) Preventive Maintenance, A novel Preventive Maintenance Strategy Optimization (PMSO) model was introduced to balance system reliability and cost. The proposed model uses a two-level surrogate model to estimate failure probabilities and optimize maintenance intervals across different operational periods. The proposed approach has demonstrated effectiveness in reducing operational costs and improving lifecycle

safety through multiple case studies. Although this model offers significant structural reliability improvements, it lacks real-time adaptability to dynamic system conditions and external environmental factors, such as temperature and humidity. Incorporating IoT and machine learning into real-time maintenance adjustments can enhance a model's flexibility and responsiveness. Most preventive maintenance is based on inspecting components and operations, whether they are normal or experiencing failure. Maintenance operations consist of the repair, replacement, or upgrading of components or equipment itself [18].

(2) Reliability-Centered Maintenance (RCM) is a systematic approach to optimizing maintenance strategies for physical assets, focusing on preserving their operational functions in the current operating context. This methodology defines economical maintenance practices to restore and maintain the operational ability of components while emphasizing asset management and cost reduction. RCM achieves these goals by carefully balancing preventive and corrective maintenance strategies. The maintenance process involves a comprehensive analysis of system functions, potential failures, and their consequences, leading to the development of tailored maintenance plans that prioritize critical components and eliminate unnecessary tasks [18].

(3) Condition-Based Maintenance: CBM has become increasingly important for ensuring reliable operations. A significant contribution is the development of a CBM strategy for redundant systems using reinforcement learning (RL). The proposed method dynamically optimizes maintenance by reducing both the cost and system downtime. It is particularly effective in redundant systems, outperforming traditional strategies in terms of cost-effectiveness and reliability. CBM is an advanced maintenance strategy that uses real-time monitoring and data analysis to determine when maintenance activities should be performed. This method can benefit from integration with more advanced machine learning techniques, such as deep learning, to handle real-time, high-dimensional data more effectively [19]. This strategy allows maintenance decisions to be adjusted dynamically based on real-time environmental conditions, such as temperature and humidity. Condition-Based Maintenance (CBM) analyzes real-time system data to assess equipment health and initiate maintenance when parameters (e.g., vibration, temperature) exceed predefined thresholds. In contrast, Predictive Maintenance (PdM) leverages advanced analytics, machine learning, and historical trends to forecast potential failures [20] .

It is critical to integrate multiple PDMs to forecast early warnings that indicate an IM is nearing failure [21]. The implementation of PDM for induction motors in the oil and gas operations requires a structured approach. The key steps include prioritizing critical assets, deploying appropriate sensors, integrating diverse data streams, and developing machine learning models. Establishing clear thresholds for maintenance actions and providing staff training on new technologies are critical for successful adoption. Condition monitoring (CM) is essential for PdM because it allows continuous tracking of machinery performance. Hybrid models offer substantial improvements in fault detection accuracy, as demonstrated in industrial applications like mine water inflow prediction.

METHODS

Deep Learning Hybrid Model

Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have become integral to predictive maintenance (PdM) frameworks due to their ability to process the multidata representations such as sensor time-series data, vibration patterns, and thermal profiles [21][22]. A dynamic PdM strategy utilizing a combination of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) models demonstrated superior performance in predicting the RUL of systems, which led to more informed maintenance decisions. This approach was validated using NASA's turbofan engine dataset, which highlighted its ability to improve both system reliability and maintenance efficiency. Although promising, this method focuses on individual components and can be extended to multicomponent systems. Additionally, integrating this predictive approach with decision-support systems can enhance the capacity of the system to automate real-time maintenance decisions [11][23].

Recent research has applied the Transformer architecture and hybrid CNN-LSTM models for early fault forecasting in large induction motors, yielding highly accurate predictive results. These hybrid deep learning frameworks, which integrate Transformer networks, have gained prominence as practical solutions for analyzing complex multivariate time-series data (e.g., vibration, thermal, and current signals). The combined use of preventive maintenance and predictive techniques has evolved into a more comprehensive approach to increasing industrial system reliability. A practical strategy involves using a decision table to combine predictive maintenance with constraints related to under-resourcing, such as budgeted costs or labor availability. This enables maintenance planners to optimize schedules, improving the sustainability of any system dynamically. Despite this, the application of advanced AI methods, such as deep reinforcement learning, to real-time maintenance scheduling for complex, high-dimensional systems has not been explored [11]. Precise forecasting of winding temperatures enables optimized scheduling of production workflows and data-driven maintenance strategies, enhancing operational efficiency while minimizing downtime and maintenance costs [24]. The Transformer and Long Short-Term Memory (LSTM) models are foundational deep learning architectures used in time-series forecasting and sequence modeling.

Transformer Model

In the context of temperature prediction for induction motors, transformers excel at capturing long-range dependencies in sensor data, which is crucial for accuracy. Below is the sequence of building the models:

(1) Data Encoding: The preprocessed data are converted into tensors for efficient processing by the neural network model.
(2) Positional Encoding: Position information is embedded in the input sequence to preserve the temporal context.
(3) Transformer Encoder Module: The Transformer Encoder serves as a critical component for analyzing sequential and time-series data, leveraging self-attention mechanisms to capture temporal dependencies and contextual patterns across the input.
(4) LSTM Decoder with Attention: The transformer output is then processed by an LSTM decoder employing an attention mechanism. This combination enables the model to focus on the relevant input sequences, thereby enhancing its predictive performance.

In model performance evaluation, the loss value is calculated using the mean square error, and optimization was performed to minimize the loss, typically using the Adam optimizer [25]. Finally, the model's performance was evaluated using the mean absolute error and root mean squared error as key metrics.

Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) network, developed by Hochreiter and Schmidhuber in 1997, is a specialized recurrent neural network (RNN) designed to overcome the vanishing gradient problem, a critical limitation in traditional RNNs that impedes learning of long-range dependencies in sequential data. LSTM uses gating mechanisms to control the flow of information through the network, enabling it to maintain information over long sequences. The key components of an LSTM unit include:

(1) Input Gate: This gate controls the input data information.
(2) Forget Gate: The gate decides the information to discard from the cell state.
(3) Memory-cell Gate: The gate updates the cell state with new information.
(4) Output Gate: This gate determines the output at each time step.

Memory-cell gate in the LSTM helps preserve long-term dependencies, making it suitable for sequence prediction tasks, such as predicting future temperature values based on previous readings. The LSTM's ability to learn temporal dependencies from time-series data complements the Transformer's self-attention mechanism [26]. While the Transformer captures global relationships, the LSTM focuses on learning temporal dynamics, and the combination of both architectures is effective for predicting winding temperatures in induction motors.

Hybrid Transformer and Long-term Short Memory (TE-LSTM)

The TE-LSTM model combines the Transformer's global attention mechanism with the LSTM's strength relative to learning sequential dependencies. The proposed hybrid model is beneficial for time-series data because understanding both long-term dependencies and short-term trends is crucial for accurate forecasting. The overview of the proposed model architecture is described as follows:

The model takes as input time-series data, i.e., the winding temperature readings of the induction motors. Positional Encoding involves converting the token embedding into a positional embedding to help the transformer-encoder model understand the sequence order, as shown in (1) and (2) [27].

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{\text{model}}}}}\right) \quad (1)$$

$$PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{\text{model}}}}}\right) \quad (2)$$

With pos is the position, i is the dimension, and d_{model} is the model size.

Positional embeddings are fed through the layers of the encoder. Each layer applies Self-Attention and Feedforward layers to extract functional patterns from the data. Transformer-Encoder Block: The core of the Transformer is its self-attention mechanism, which computes attention scores for each pair of elements in a sequence. This allows the model to weigh the importance of each element in the sequence when making predictions. Mathematically, the self-attention mechanism can be defined as (3):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3)$$

with:
Q represents the query matrix, and
K is the key matrix, and
V is the value matrix, and
d_k is the dimension of the matrix K.
This mechanism allows the Transformer-Encoder to focus on different parts of the input sequence depending on the importance of each part, which makes it highly effective for time-series forecasting.

LSTM decoder with attention mechanism, where the output from the transformer encoder is input to the LSTM decoder. The concept behind the LSTM block, which focuses explicitly on capturing temporal dependencies in the data and using an attention mechanism, is that it can look back to relevant time stamps, facilitating better predictions. Learn attention scores with linear layers + tanh between the Recognition Exception squad. Output Layer: Finally, the LSTM decoder produces predictions of the temperature for the next step in accordance with the learned temperature from the prior steps. TE-LSTM combines the Transformer-Encoder with a global attention mechanism with LSTM to allow learning from sequential dependencies. In this study, we propose a schematic representation of the process of developing a TE-LSTM model (Transformer-Encoder Long Short-Term Memory) to predict the winding temperature and useful life of electrical machines. The key steps involved in this process are as follows and can be seen in Figure 3.

(1) Data Collection and Data Processing: Sensor Data Acquisition: Real-time data from multiple sensors, including winding temperature, vibration, and electrical current, are collected at minute intervals.
(2) Data Cleaning: Duplicate entries are eliminated, and missing values are addressed using appropriate cleaning methods. After preprocessing, the dataset is split into two parts: 90% is allocated for training the model, while the remaining 10% is reserved for validation, ensuring robust and reliable model performance.
(3) Sliding Window Method [28]. The time series data are organized into sequential windows to capture temporal dependencies [29].

The study utilized motor winding temperature records from motors that had been running for more than 10 years. This creates the following series of processing steps, and the analysis workflow is as follows:

(1) The actual temperature data of the induction motors were represented as a time series. This is a widespread use of positional Encoding because it preserves the order or sequence, allowing the model to understand the time aspect of data.
(2) The Transformer Encoder: The encoder takes the input sequence and processes it with multiple attention heads to model long-range dependencies in the temperature data. This allows the model to remember past sensor readings when predicting future temperatures.
(3) LSTM Decoder with Attention: The LSTM decoder reads the encoded sequence and pays attention to both short-term and long-term trends inside it. The attention mechanism provides additional context to the LSTM, calculated by weighing the critical time steps; thus, the LSTM can be used to
(4) LSTM Decoder with Attention: The LSTM decoder reads the encoded sequence and pays attention to both short-term and long-term trends inside it. The attention mechanism provides additional context to the LSTM by weighing the critical time steps, enabling the LSTM to make more accurate temperature predictions.
(5) Predictions: This is the final step where a temperature prediction is made for the next step, allowing verification of whether it approaches alarm levels H and HH.

Research Gap

To have a better intuition of our contributions, we summarize a few significant research gaps in this work.

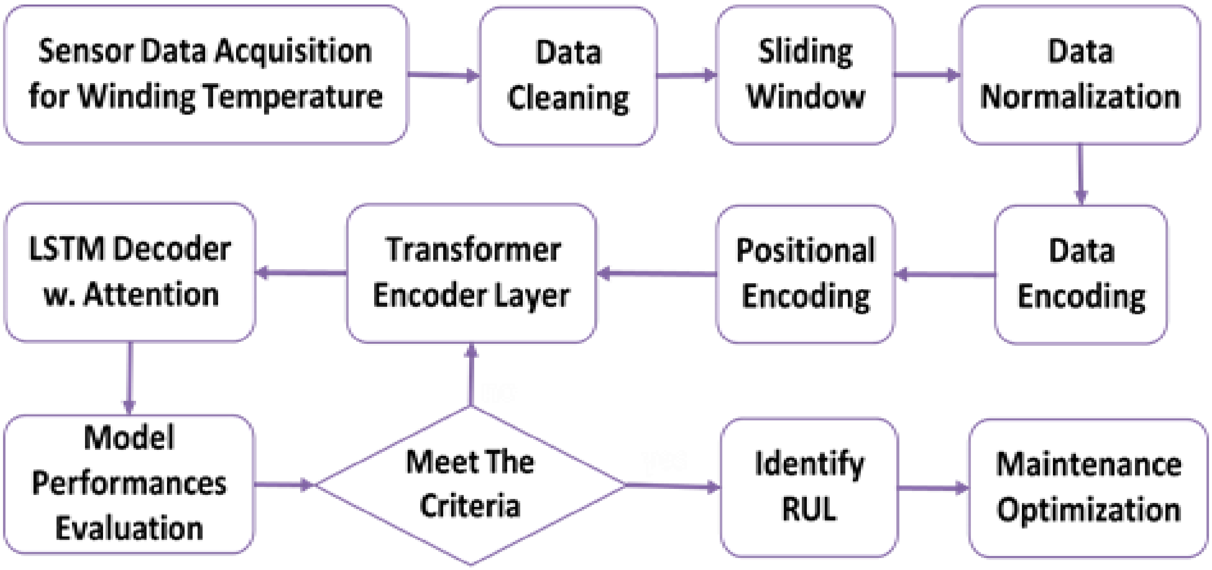

Figure 3. A framework of TE-LSTM for Winding temperature prediction

Although many strides have already been made in the predictive maintenance of induction motors, we can still mention some challenges, as follows:

(1) Deep Learning model: This work introduces a hybrid deep learning model that stands apart from existing approaches, such as [27] and [21]. The previously mentioned models combined an LSTM with no Transformer-based model. In that case, they may fail to capture the long-term dependencies of the sensor data because the Transformer is designed to process sequential data.

(2) This work introduces winding temperature predictions, especially for their early warning and failure time. To the best of our knowledge, this work is the first study to analyze IM winding temperature using the TE-LSTM model.

(3) Primary Data: This work observed the winding temperature of induction motors using actual operational data from the oil and gas industry, which will be available upon request. In this work, the study aims to alleviate some of these limitations by introducing a hybrid TE-LSTM that effectively addresses both long-term dependencies and local patterns in motor temperature data, thereby creating an opportunity base for better interpretability and cross-domain transfer learning tasks [30].

RESULTS AND DISCUSSION

This hybrid approach leverages the benefits of Transformer and LSTM architectures, allowing better capture of long-term dependencies and short-term patterns in the temperature data, which can help a model produce more accurate predictions for winding temperatures in induction motors. In this study, data from two motors were collected. Both motors were specified with a voltage level of 4.16 kV, 3-phase, 60 Hz, asynchronous motors. Motor A's power output was 470 HP, and Motor B's was 600 HP. Motor A and B data were collected between January 2016 and December 2024. This resulted in over two million data points per motor, which were recorded at 1-minute intervals.

Two methods were used to handle missing data: replacing it with a fixed value of 90°F and removing the affected data. The replacement value of 90°F was chosen because during periods when the motor was not in operation, the winding temperature stabilized around 90°F while the motor's space heater was still in operation. The data were then normalized using both Z-score and Min-Max normalization techniques, and the dataset was split into training (90%) and testing (10%) sets. The model is trained using a time-series dataset with 90% allocation for training and 10% for testing. The trained model then predicts when critical temperature thresholds H would be reached, providing valuable information for proactive maintenance decisions. Winding temperature data for both Motor A and B can be seen in Figures 4 and 5. Loss for this model is also indicated in Figure 8.

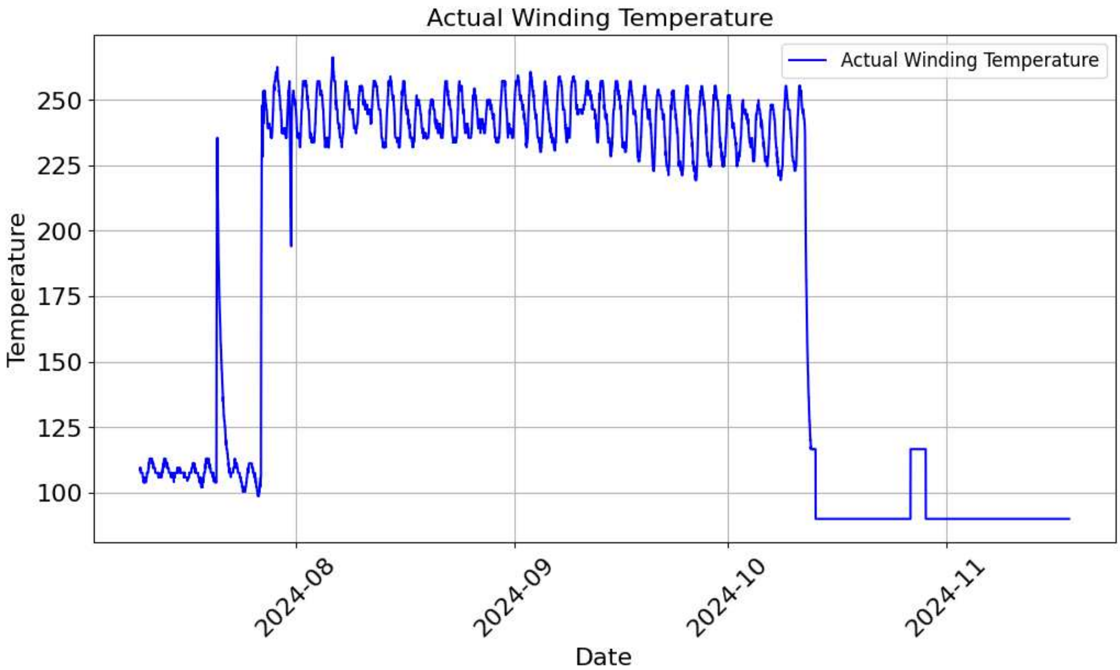

Figure 4. Winding temperature of Motor A (4.16 kV, 470HP) from 1/1/2021 to 31/12/2024

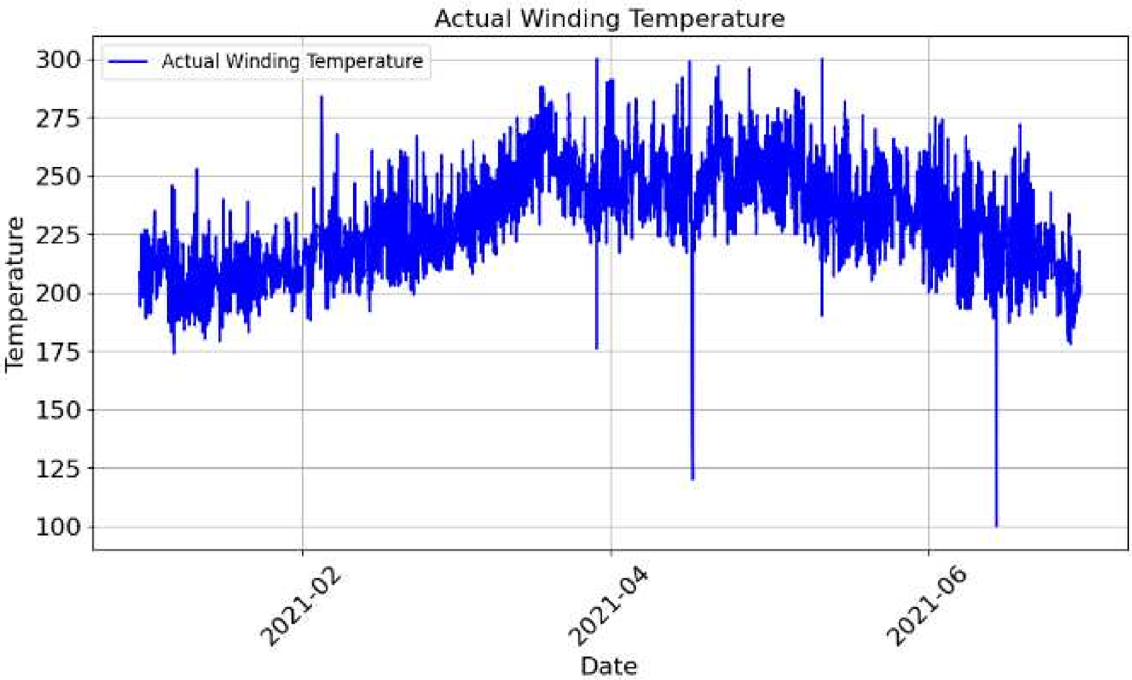

Figure 5. Winding temperature of Motor B (4.16 kV, 600 HP)

Model predictions for both motors can be seen in Figure 6 and Figure 7. The TE-LSTM model was evaluated for its prediction capabilities. The model's predictions were highly accurate for both early warning winding temperatures at 257 °F and at 285 °F. The graphs show the performance of the two motors, highlighting the strengths and limitations of the predictive models. The predicted winding temperature (orange line) for Motors A and B matches the actual winding temperature (blue line) throughout the period, demonstrating the model's proficiency in tracking overall temperature trends. The motor usually operates within 100°F to 125°F, but spikes above 275°F indicate possible overheating or atypical operation.

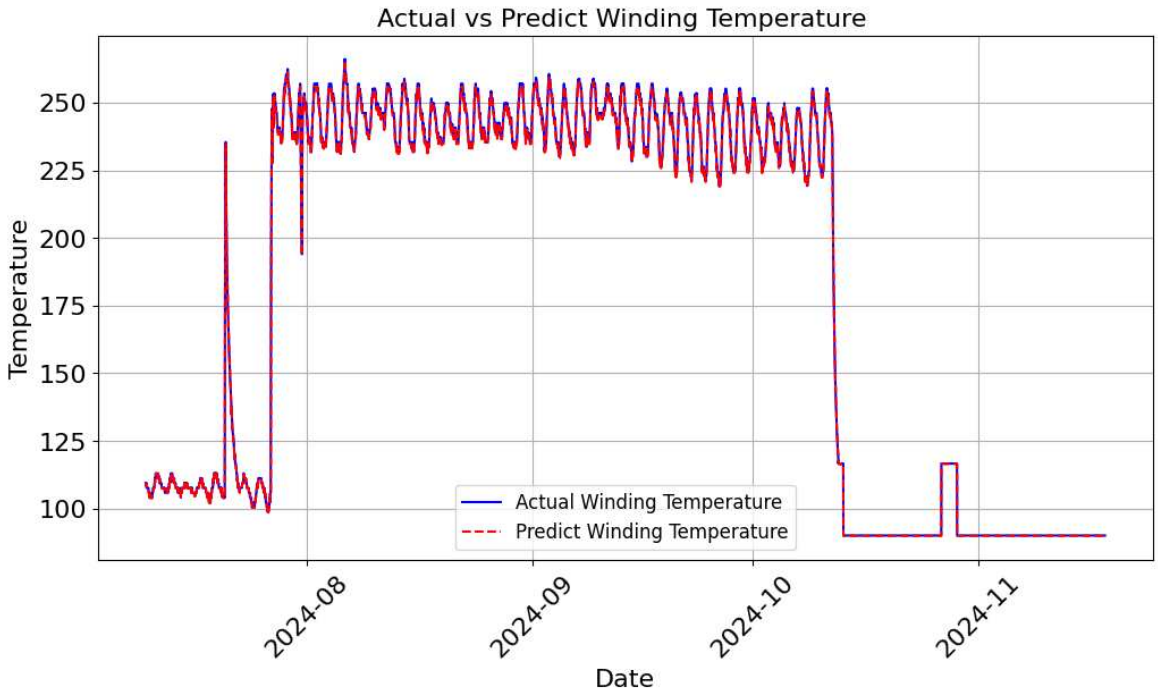

Figure 6. Winding Temperature Estimation for Motor A: 470 HP, 4.16 kV, 3P, and 60 Hz from TE-LSTM. The estimated winding temperature reaches 257°F on July 26, 2024, matching the actual temperature

The TE-LSTM model for Motor B demonstrated its ability to capture the overall temperature trends, closely following the actual winding temperature variations from early February to mid-March. The actual temperature fluctuated rapidly between 200°F and 275°F, and the model effectively predicted these changes, although with a smoother profile. These results show that the Transformer-LSTM model successfully identified the underlying temperature patterns

The TE-LSTM model was also evaluated for model prediction. The model's predictions were highly accurate for both early and late failure detection. The graphs depict the performance of the two motors, highlighting the strengths and limitations of the predictive models. The predicted winding temperature (orange line) for Motor A generally matches the actual winding temperature (blue line) throughout the period, demonstrating the model's proficiency in tracking overall temperature trends. Nonetheless, discrepancies in the magnitude and timing of significant temperature spikes are noted, especially in early July and mid-September. The motor usually operates within 100°F to 125°F, but spikes above 275°F indicate possible overheating or atypical operation. The TE-LSTM model for Motor B demonstrated its ability to capture the overall temperature trends, closely following the actual winding temperature variations from early February to mid-March. The actual temperature fluctuated rapidly between 200°F and 275°F, and the model effectively predicted these changes, although with a smoother profile. These results show that the Transformer-LSTM model successfully identified the underlying temperature patterns; however, further tuning is required to enhance the model's responsiveness to sharp temperature fluctuations. Validating thermal models under operational conditions has been a focus of prior research, highlighting the importance of accurate winding temperature prediction for optimizing machine performance. In summary, although the models exhibit strengths in tracking general temperature trends, the observed discrepancies in the spike magnitudes and sharp variations indicate areas for model refinement.

The TE-LSTM model's predictions closely mirror the actual winding temperature curve, although it has a less erratic profile. The actual temperature fluctuates swiftly between 200°F and 275°F. Although the model accurately forecasts these variations, it might benefit from additional adjustments to more accurately reflect these abrupt changes. Researchers have emphasized the importance of accurately predicting winding temperatures to fully exploit motor performance, as well as the need to validate thermal models under operational conditions to ensure their efficacy.

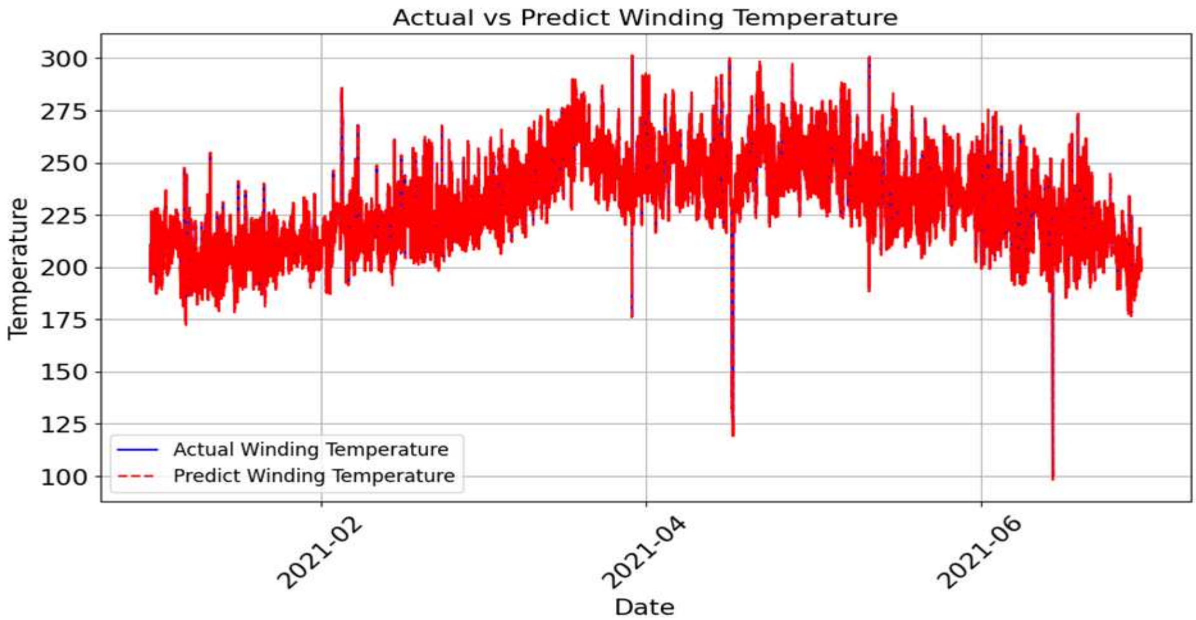

Figure 7. Winding Temperature Estimation of Motor B for 600 HP, 4.16 kV, 3P, and 60 Hz from TE-LSTM. The estimated winding temperature reached 257°F on February 8, 2021, matching the actual temperature

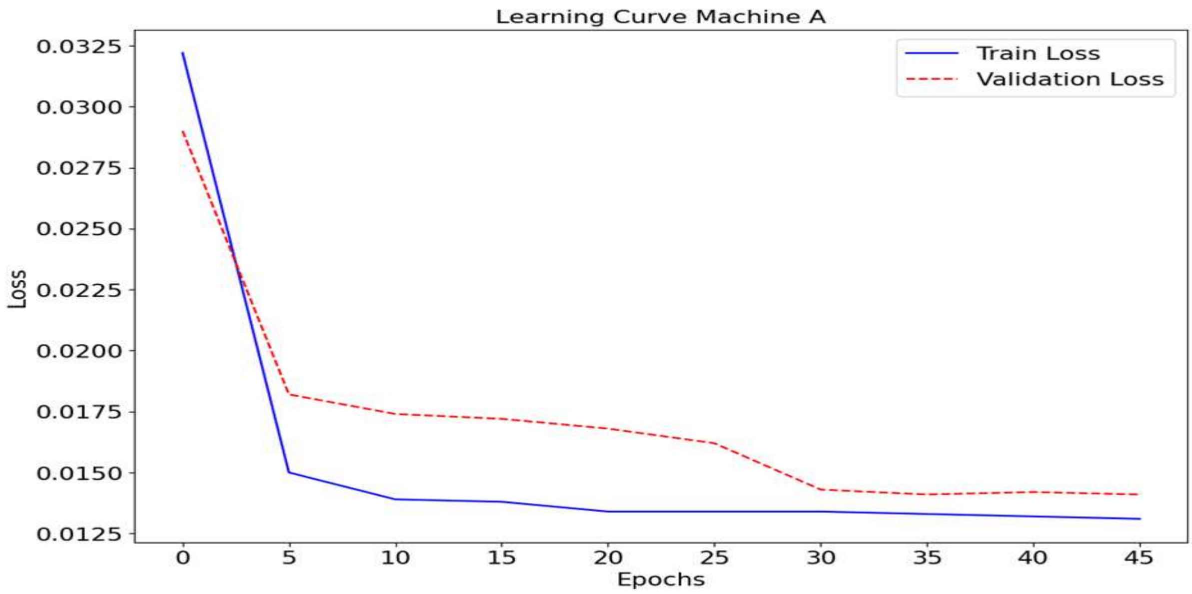

Figure 8. TE-LSTM Model Loss for Motor A

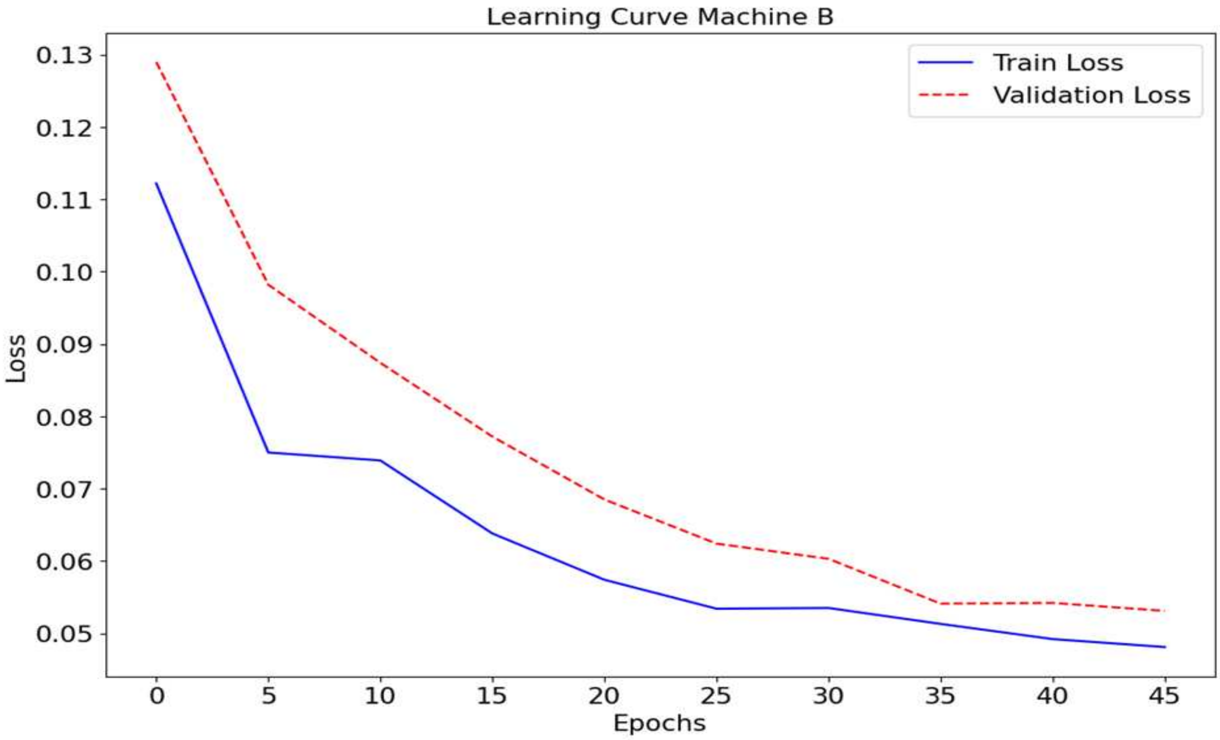

Figure 9. TE-LSTM Model Loss for Motor B.

The Transformer-LSTM model's ability to track overall temperature trends is commendable; further tuning might be necessary to enhance accuracy. The learning curve for both models indicates that the losses can be found in Figures 8 and 9.

The TE-LSTM model for Motor B demonstrated its ability to capture the overall temperature trends, closely following the actual winding temperature variations from early February to mid-March. The actual temperature fluctuated rapidly between 200°F and 275°F, and the model effectively predicted these changes, although with a smoother profile. These results show that the Transformer-LSTM model successfully identified the underlying temperature patterns; however, further tuning is required to enhance the model's responsiveness to sharp temperature fluctuations. Validating thermal models under operational conditions has been a focus of prior research, highlighting the importance of accurate winding temperature prediction for optimizing machine performance. In summary, although the models exhibit strengths in tracking general temperature trends, the observed discrepancies in the spike magnitudes and sharp variations indicate areas for model refinement.

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Performance Evaluation

The Root Mean Square Error (RMSE) of Motor A was 0.803, and Motor B was 0.301, reflecting the error margin between the predicted and actual temperature values or performance degradation over time, as listed in Table 2. The RMSE is commonly used to assess prediction model accuracy, with lower values indicating better fitting between predicted and observed data.

The estimated winding temperature of 257°F for both Motor A and Motor B is accurate, resulting in an early warning detection for the H alarm, matching the actual winding temperature.

Table 2. Performance Evaluation

Motor	RMSE
A	0.301
B	0.803

CONCLUSION

A hybrid Transformer-Encoder with an LSTM architecture (TE-LSTM) considerably improved the temperature alarm prediction of induction motors. This hybrid deep learning model can also predict the performance of motor and other equipment assets, helping change maintenance strategies from reactive to proactive—reducing unplanned downtime while boosting operational effectiveness. This model is beneficial in the oil and gas industry because it mitigates frequent motor failures, which helps to increase reliability, maintain production uptime, and reduce operational costs.

FUTURE DISCUSSION

Despite these advancements, several research gaps remain in the field of maintenance strategies. Most studies focus on either static environments or predetermined damage intervals, which cannot be applied to real-world dynamic situations. Future studies should better incorporate real-time information from IoT devices to gain an accurate and necessary understanding of ICT (Information and Communication Technology) system health. The addition of deep learning capabilities to TE-LSTM means that it can be used in larger industrial systems, resulting in better optimization of maintenance schedules based on prior research. Many predictive maintenance models I have seen and worked on focus on a single part; however, in the real world, it is not that simple because we sometimes deal with multicomponent systems.

Further research is required on multicomponent systems with interdependence, which require sophisticated time-based maintenance scheduling strategies. Resource constraint integration: There is little exploration into integrating resource constraints (e.g., a constrained maintenance budget and workforce) with dynamic types of maintenance. To summarize, these areas can form the foundation for an integrated decision-making framework that will assist in creating sustainable, efficient industrial-based preventive strategies.

REFERENCES

[1] A. Glowacz, M. Sulowicz, J. Zielonka, Z. Li, W. Glowacz, and A. Kumar, "Acoustic fault diagnosis of three-phase induction motors using smartphone and deep learning," *Expert Systems With Applications*, vol. 262, Mar. 2025, doi: 10.1016/j.eswa.2024.125633.

[2] S. Lv, S. Liu, H. Li, Y. Wang, G. Liu, and W. Dai, "A hybrid method combining Lévy process and neural network for predicting remaining useful life of rotating machinery," *Advanced Engineering Informatics*, vol. 61, Aug. 2024, doi: 10.1016/j.aei.2024.102490.

[3] G. Zhong, D. Huang, W. Yu, and Y. Xiong, "A multi-directional attention CNN motor fault diagnosis method for small sample data classification," *Measurement (London)*, vol. 257, Jan. 2026, doi: 10.1016/j.measurement.2025.118638.

[4] D. Bhowmick and S. K. Chowdhury, "Estimation of induction motor equivalent circuit parameters and losses from transient measurement," *ISA Transaction*, vol. 157, pp. 573–590, Feb. 2025, doi: 10.1016/j.isatra.2024.12.012.

[5] A. Glowacz, "Thermographic fault diagnosis of electrical faults of commutator and induction motors," *Engineering Applications of Artificial Intelligence*, vol. 121, May 2023, doi: 10.1016/j.engappai.2023.105962.

[6] S. Shokoohi and J. Moshtagh, "Parity equation model-based fault diagnosis method newly applied to bearing faults in induction motors," *Measurement (London)*, vol. 249, May 2025, doi: 10.1016/j.measurement.2025.117057.

[7] L. Zheng, Y. He, X. Chen, and X. Pu, "Optimization of dilated convolution networks with application in remaining useful life prediction of induction motors," *Measurement (London)*, vol. 200, Aug. 2022, doi: 10.1016/j.measurement.2022.111588.

[8] M. Dadfarnia, M. E. Sharp, and J. W. Herrmann, "Comprehensive evaluations of condition monitoring-based technologies in industrial maintenance: A systematic review," *Journal of Manufacturing Systems*, Elsevier B.V, vol. 82, pp. 449-477, Oct. 01, 2025, doi: 10.1016/j.jmsy.2025.06.015.

[9] H. C. Chuang, G. De Li, and C. T. Lee, "The efficiency improvement of AC induction motor with constant frequency technology," *Energy*, vol. 174, pp. 805–813, May 2019, doi: 10.1016/j.energy.2019.03.019.

[10] N. Arish, M. Ardestani, and A. Hekmati, "Optimum Structure of Rotor Slot for a 20 kW HTS Induction Motor," *Physica C: Superconductivity and its Applications*, vol. 582, Mar. 2021, doi: 10.1016/j.physc.2021.1353829.

[11] G. Bilal Yıldız and B. Soylu, "Integrating preventive and predictive maintenance policies with system dynamics: A decision table approach," *Advanced Engineering Informatics*, vol. 56, Apr. 2023, doi: 10.1016/j.aei.2023.101952.

[12] A. I. Rohan *et al.*, "Intelligent fault diagnosis in rolling element bearings: Combining envelope spectrum and spectral kurtosis for enhanced

detection," *Results in Engineering*, vol. 27, Sep. 2025, doi: 10.1016/j.rineng.2025.106899.
[13] Ha'imza, Amirullah, and B. Plangklang, "Development of nominal rules on the Fuzzy Sugeno method to determine the quality of power transformer insulation oil using Dissolved Gas Analysis data," *Sinergi (Indonesia)*, vol. 27, no. 1, pp. 31–44, 2023, doi: 10.22441/sinergi.2023.1.005.
[14] P. Gangsar and R. Tiwari, "Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review," *Mechanical Systems and Signal Processing,* Academic Press, vol. 144, 106908, October 2020, doi: 10.1016/j.ymssp.2020.106908.
[15] Y. Lv, F. Fang, T. Yang, and C. E. Romero, "An early fault detection method for induced draft fans based on MSET with informative memory matrix selection," *ISA Transaction*, vol. 102, pp. 325–334, Jul. 2020, doi: 10.1016/j.isatra.2020.02.018.
[16] S. Riaz, A. Saghir, M. J. Khan, H. Khan, H. S. Khan, and M. J. Khan, "TransLSTM: A hybrid LSTM-Transformer model for fine-grained suggestion mining," *Natural Language Processing Journal*, vol. 8, p. 100089, Sep. 2024, doi: 10.1016/j.nlp.2024.100089.
[17] S. Cahyati, S. D. Puspa, R. Himawan, N. R. Agtirey, and J. A. Leo, "Optimization of preventive maintenance on critical machines at the Sabiz 1 plant using Reliability-Centered Maintenance method," *Sinergi (Indonesia)*, vol. 28, no. 2, pp. 355–368, 2024, doi: 10.22441/sinergi.2024.2.015.
[18] M. H. Enjavimadar and M. Rastegar, "Optimal reliability-centered maintenance strategy based on the failure modes and effect analysis in power distribution systems," *Electric Power Systems Research*, vol. 203, Feb. 2022, doi: 10.1016/j.epsr.2021.107647.
[19] Y. Luo, X. Zhao, B. Liu, and S. He, "Condition-based maintenance policy for systems under dynamic environment," *Reliability Engineering and System Safety*, vol. 246, Jun. 2024, doi: 10.1016/j.ress.2024.110072.
[20] B. P. Muliatama, I. Mukhlash, M. Iqbal, N. Hidayat, and M. Kimura, "Raw Mill Engine Failure Detection from Transformer Gated Convolutional Unit Networks," in *Proceedings of 2023 IEEE International Conference on Data and Software Engineering, ICoDSE 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 214–219. doi: 10.1109/ICoDSE59534.2023.10291294.
[21] J. Supriyono, I. Mukhlash, M. Iqbal, and D. A. Asfani, "Early Warning Forecasting of Large Induction Motor in the Oil and Gas Industry from Deep Learning," in *2024 IEEE International Symposium on Consumer Technology (ISCT)*, IEEE, Aug. 2024, pp. 436–442. doi: 10.1109/ISCT62336.2024.10791291.
[22] J. Shi, S. Wang, P. Qu, and J. Shao, "Time series prediction model using LSTM-Transformer neural network for mine water inflow," *Scientific Reports*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-69418-z.
[23] L. Wang, Z. Zhu, and X. Zhao, "Dynamic predictive maintenance strategy for system remaining useful life prediction via deep learning ensemble method," *Reliability Engineering and System Safety,* vol. 245, May 2024, doi: 10.1016/j.ress.2024.110012.
[24] J. Peng, D. Shen, T. Nie, and Y. Kou, "RLclean: An unsupervised integrated data cleaning framework based on deep reinforcement learning," *Information Sciences (NY)*, vol. 682, Nov. 2024, doi: 10.1016/j.ins.2024.121281.
[25] S. K. Purohit and S. Panigrahi, "Novel deterministic and probabilistic forecasting methods for crude oil price employing optimized deep learning, statistical and hybrid models," *Information Sciences (NY)*, vol. 658, Feb. 2024, doi: 10.1016/j.ins.2023.120021.
[26] Y. Dai, J. Wei, and F. Qin, "Recurrent neural network (RNN) and long short-term memory neural network (LSTM) based data-driven methods for identifying cohesive zone law parameters of nickel-modified carbon nanotube reinforced sintered nano-silver adhesives," *Materials Today Communications*, vol. 39, Jun. 2024, doi: 10.1016/j.mtcomm.2024.108991.
[27] B. P. Muliatama, I. Mukhlash, M. Iqbal, N. Hidayat and M. Kimura, "Raw Mill Engine Failure Detection from Transformer Gated Convolutional Unit Networks," *2023 IEEE International Conference on Data and Software Engineering (ICoDSE)*, Toba, Indonesia, 2023, pp. 214-219, doi: 10.1109/ICoDSE59534.2023.10291294.
[28] L. Danay, R. Ramon-Gonen, M. Gorodetski, and D. G. Schwartz, "Evaluating the effectiveness of a sliding window technique in machine learning models for mortality prediction in ICU cardiac arrest patients," *International Journal of Medical Informatics*, vol. 191, Nov. 2024, doi: 10.1016/j.ijmedinf.2024.105565.
[29] F. T. Lima and V. M. A. Souza, "A Large Comparison of Normalization Methods on Time Series," *Big Data Research*, vol. 34, Nov. 2023, doi: 10.1016/j.bdr.2023.100407.
[30] I. B. Abruzi, M. Iqbal, I. Mukhlash, A. M. Rukmi, N. Kurniati, and M. Kimura, "Engine Failure Detection of Raw Mill Machine via Discrete

Variational Auto-encoder," in *Proceedings of 2022 International Conference on Data and Software Engineering, ICoDSE 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 59–64. doi: 10.1109/ICoDSE56892.2022.9972209.