Time-Series Prediction of Networked Sensor Data in Control Systems Using LSTM Networks

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***Abstract*—Industrial systems, such as pumps, turbines, and compressors, always work in dynamic conditions that demand continuous monitoring in order to ensure safety and efficiency. Current monitoring approaches are based on threshold alarms or offline data analysis, which often miss the early warning of a fault. This paper presents a time-series prediction framework based on Long Short-Term Memory for industrial sensor data. The proposed model uses multivariate sensor inputs comprising temperature, humidity, vibration, and pressure in order to forecast further sensor values. Synthetic sensor data is generated for simulating realistic operating conditions in industries. The data is divided into training and test sets, and an LSTM network is trained using the Adam optimizer. Experimental results demonstrate that the proposed model learns the temporal dependencies of sensor values to predict future sensor readings. The proposed approach will be particularly suitable for predictive maintenance, anomaly detection, and intelligent condition monitoring in industrial automation systems.**

***Index Terms*—LSTM, Time-Series Prediction, Predictive Maintenance, Industrial Sensor Data, Condition Monitoring**

I. INTRODUCTION

Modern industrial automation solutions heavily rely on network sensors for the continuous monitoring of the operational environment for industrial equipment in real time [1] [2]. Machines such as pumps, turbines, and compressors are the backbone of important industries like the energy, manufacturing, oil and gas, and water industries [3] [4]. The machines work around the clock in changing conditions involving changing operational loads and changing environmental conditions [5]. Machines generate huge quantities of information related to temperature, humidity, vibrations, pressure, and other relevant conditions from sensors [6]. It is important for these machines to be continuously monitored for reliability, efficiency, and safety.

In most cases, classical monitoring approaches employed by industrial systems often follow threshold or rule-based techniques of monitoring. In all the three systems, alarms are often raised whenever values read by any sensor exceed certain thresholds [7]. Even though these approaches are easy to employ and are simple by nature, they often fail to identify any small changes observed within systems. In most cases, potential problems often go unnoticed until they develop to alarming conditions [8].

In consequence of the enhanced accessibility of sensor data caused by the popularity of IIoT technologies, data-driven techniques have started to attract more attention. The importance of the effectiveness of machine learning and deep learning techniques in analyzing time-series data in industrial systems has been recognized as critical [9]. These techniques have the power to identify complex pattern dynamics and hidden nonlinear relationships in sensor data. Among the various deep learning techniques employed, Long Short-Term Memory (LSTM) networks have proven to be one of the most efficient techniques for time series prediction tasks [10]. LSTMs are a special class of recurrent neural networks (RNNs) engineered to deal with long-term dependencies in data sequences. LSTMs provide the ability to keep useful historical data while discarding unwanted information. This feature makes LSTMs useful

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for forecasting tasks from industrial sensors.

In such a setting, this proposed work intends to concentrate on the prediction framework based on LSTM techniques for certain industrial devices such as pumps, turbines, and compressors. These devices tend to produce continuous data sets from various sensor devices and are significant to the operational environment of industries. Predicting the future readings of the sensors can assist in maintaining a more reliable regime in the context of industrial automation.

II. LITERATURE SURVEY

Industrial systems produce big amounts of time series sensor data, and predicting such data precisely is very important for predictive maintenance, fault detection, and optimization, etc. Various statistical models, machine learning models, and deep learning models have been proposed in the last few years for solving time series forecasting problems in industrial environments.

Traditional statistical models, such as Autoregressive Integrated Moving Average (ARIMA), have been adopted for forecasting time-series data [11]. The models are effective for linear and stationary time-series data due to their ability to include autoregressive, differentiating, and moving average components, making them applicable for forecasting time-series data [12] . However, it is difficult for traditional methods, such as ARIMA, to cope with complex environments involving multiple sensors, as they can only cope with univariate data. As for the growing industrial IoT, this field tends to be more attractive for machine learning techniques. It also involves time-series prediction tasks, where different methods were applied: from SVM and KNN to regression trees and artificial neural networks [13]. In contrast to statistical methods, advanced methods provide better nonlinear relationship modeling, but they all usually cannot be able to capture long-term temporal dependencies in sequential data.

Recurrent Neural Networks were introduced to handle sequential learning problems, which included feedback connections so that information could persist across time steps [14]. While RNNs can model temporal patterns, they do suffer from the vanishing gradient problem and hence are unable to learn long-term dependencies effectively. To handle this shortcoming, Long Short-Term Memory networks were developed [15]. In LSTM networks, memory cells and gating mechanisms maintain the important information over very long sequences, making them quite apt for performing time-series prediction tasks [16]. Recent studies indicate that there are higher chances of better performance from the LSTM model rather than statistical models. An example of this is that studies that compared the performance of the model revealed that for fluctuating and nonlinear data sets, LSTM outperformed ARIMA models. For stable and linear environments, ARIMA proved to be better. In contrast, studies that compared and analysed the performance of both models revealed that there were improved accuracy levels together with minimized errors using LSTM's sequential models.

In the context of predictive maintenance, LSTM architectures have emerged as the popular choice for predictive maintenance models. Predictive maintenance models based on LSTM architecture have demonstrated promising results for improving the efficiency of plant operations and accuracy in predicting faults. Promising results have also been obtained for prediction accuracy based on LSTM architecture for sensor-based forecasting. Current research trends are focused on the inclusion of the LSTM model in the context of the industrial IoT domain, specifically Industry 4.0. It is noteworthy that ”predictive maintenance systems powered by IoT technology combined with advanced analytics enable companies to proactively detect equipment failures before they happen, thereby improving equipment uptime and lowering maintenance costs.” Lstm-based models were reported to outperform all other deep learning-based models while implementing industrial control systems.There have also been suggestions for hybrid techniques that integrate both statistical methods and deep learning methods. For example, the ARIMA-LSTM hybrid method for ARIMA models with LSTM as residuals incorporates linear trend models with non-linear residuals to reduce the error in the forecasting results.

From the literature, there is a clear transition from traditional statistical-based models to deep learning for the prediction of industrial time series as shown in table 1. Although statistical-based models have their place for simple and stationary signals, the results on complex and nonlinear industrial sensor signals highlight the superiority of the LSTM-based models.

TABLE I
COMPARISON OF TIME-SERIES PREDICTION MODELS

Category	**Model**	**Key Characteristics**	**Limitations**
Statistical	ARIMA	Effective for linear and stationary time-series data	Poor performance on nonlinear and multivariate data
Machine Learning	SVM, KNN, ANN	Capable of modeling nonlinear relationships	Lack inherent temporal memory
Deep Learning	RNN	Supports sequential and temporal learning	Suffers from vanishing gradient problem
Deep Learning	**LSTM**	Captures long-term dependencies and nonlinear dynamics	High computational and training cost
Hybrid	ARIMA–LSTM	Combines linear and nonlinear modeling strengths	Increased model complexity and tuning effort

III. PROPOSED METHODOLOGY

The proposed framework aims to predict future sensor readings of industrial equipment using a LSTM network. The methodology is uniformly applied to three critical industrial systems pump, turbine, and compressor as shown in “Fig. 1”,which continuously generate multivariate time-series data. The objective is to learn the temporal dynamics of sensor signals and forecast future values to enable predictive maintenance and intelligent condition monitoring.

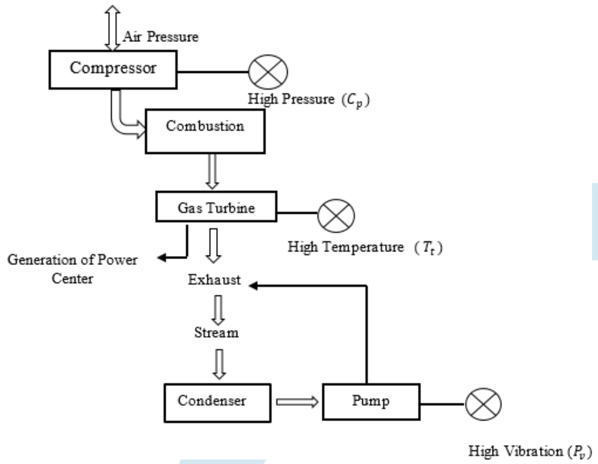

Fig. 1. Proposed Multivariate Sensor Monitoring in Industrial Systems

The overall workflow of the proposed methodology consists of five main stages: *sensor data generation, data preprocessing, sequence formation, LSTM model training, and prediction with performance evaluation*. The same pipeline is followed for all three case studies to ensure consistency and scalability.

A. Sensor Data Generation

In industrial environments, sensors continuously measure physical parameters such as temperature, humidity, vibration, and pressure. Synthetic time-series data is generated to emulate realistic operating conditions of rotating machinery.

Each sensor signal is modeled using a sinusoidal function with additive Gaussian noise as shown in "Eq. (1)":

$$S(t) = A\sin(\omega t + \phi) + N(t) \tag{1}$$

In (1), $S(t)$ denotes the sensor value at time t, A represents the amplitude, ω is the angular frequency, ϕ is the phase shift, and $N(t) \sim \mathrm{N}(0, \sigma^2)$ denotes zero-mean Gaussian noise with variance σ^2.

For each industrial system, four sensor streams are generated as given in "Eq. (2)":

$$\{Temp(t),\ Hum(t),\ Vib(t),\ Pres(t)\} \tag{2}$$

B. Data Preprocessing and Multisensor Integration

The individual sensor readings are combined into a multivariate feature vector as expressed in "Eq. (3)":

$$\mathbf{S}(t) = \begin{bmatrix} Temp(t) \\ Hum(t) \\ Vib(t) \\ Pres(t) \end{bmatrix} \in \mathrm{R}^4 \tag{3}$$

Over T time samples, the dataset is represented as in "Eq. (4)":

$$\mathbf{X} = \{\mathbf{S}(1), \mathbf{S}(2), \ldots, \mathbf{S}(T)\} \tag{4}$$

To stabilize neural network training, Min–Max normalization is applied as defined in "Eq. (5)":

$$\mathbf{S}_{norm}(t) = \frac{\mathbf{S}(t) - \mathbf{S}_{min}}{\mathbf{S}_{max} - \mathbf{S}_{min}} \tag{5}$$

In "Eq. (5)", $\mathbf{S}_{min}$ and $\mathbf{S}_{max}$ denote the minimum and maximum values of each sensor feature, respectively.

C. Sequence Formation

A sliding window of length L is used to construct supervised learning samples.

The input sequence is defined in "Eq. (6)":

$$\mathbf{X}_t = \{\mathbf{S}(t - L + 1), \ldots, \mathbf{S}(t)\} \in \mathrm{R}^{L\times 4} \tag{6}$$

The prediction target is given by "Eq. (7)":

$$\mathbf{Y}_t = \mathbf{S}(t + 1) \tag{7}$$

Thus, the learning objective becomes as "Eq. (8)"

$$f_\vartheta(\mathbf{X}_t) \approx \mathbf{Y}_t \tag{8}$$

where $f_\vartheta(\cdot)$ represents the LSTM model parameterized by ϑ. The dataset is divided into training (80%) and testing (20%) subsets.

D. LSTM Network Architecture

To capture temporal dependencies, an LSTM network is employed. The internal operations of an LSTM cell are described as follows.

The forget gate is computed using "Eq. (9)":

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{9}$$

The input gate is defined in "Eq. (10)":

$$i_t = \sigma\left(W_i[h_{t-1}, x_t] + b_i\right) \tag{10}$$

The candidate cell state is obtained from (11):

$$\tilde{C}_t = \tanh\left(W_c[h_{t-1}, x_t] + b_c\right) \tag{11}$$

The cell state update is performed using "Eq. (12)":

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{12}$$

The output gate is computed as in "Eq. (13)":

$$o_t = \sigma\left(W_o[h_{t-1}, x_t] + b_o\right) \tag{13}$$

Finally, the hidden state is obtained using "Eq. (14)":

$$h_t = o_t \odot \tanh(C_t) \tag{14}$$

In (9)–(14), x_t denotes the input vector, h_t the hidden state, C_t the memory cell state, $\sigma(\cdot)$ the sigmoid activation function, and $\odot$ the element-wise multiplication operator.

E. Model Training

The LSTM network is trained by minimizing the Mean Squared Error (MSE) loss defined in “Eq. (15)”:

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{15}$$

where y_i and $\hat{y}_i$ denote the actual and predicted sensor values, respectively, and N is the number of samples.

F. Prediction and Performance Evaluation

After training, the model predicts future sensor values for unseen sequences. The prediction accuracy is evaluated using standard regression metrics.

The Root Mean Squared Error is defined in “Eq. (16)”:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{16}$$

The Mean Absolute Error is given in “Eq. (17)”:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{17}$$

The coefficient of determination is computed using “Eq. (18)”:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{18}$$

G. Application to Industrial Case Studies

The proposed methodology is applied to three industrial systems: pump, turbine, and compressor. For each application, multisensor data is processed through the same pipeline, and the LSTM model predicts future temperature, humidity, vibration, and pressure values. This unified framework demonstrates strong generalization capability across different rotating machinery.

1) Predicting Data for Turbine Sensor: In the first case study, the framework is implemented using a dynamic condition for a given turbine system. Synthetic sensor data for the turbine, such as temperature, humidity, vibration, and pressure, are created and processed. A training set of 80%, along with a corresponding test set of 20%, from the created dataset labels the features of the problem domain. The trained LSTM model successfully predicts the future sensor values for the corresponding turbines. The predicted curve fits well with the actual trend of the respective sensor data.

2) Prediction of Compressor Sensor Data: The second case study is concerned with a compressor system, in which compressor sensor data is created, visualized, and then transformed to input-target pairs. The LSTM architecture is successful in detecting both dynamic and nondynamic variations in sensor data. The similarity in the predicted and real values proves the effectiveness of the architecture for monitoring the condition of the compressor.

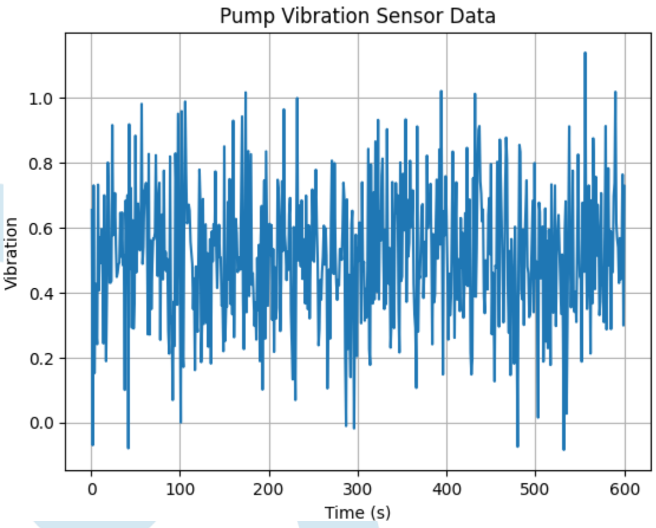

Fig. 2. Pump Vibration Sensor Data

3) Pump Sensor Data Prediction: For the third case study, the proposed framework has been implemented for a pump system. For the proposed LSTM network, the capacity to learn the dynamic characteristics of the sensor data of the pump is successfully demonstrated. Also, correct predictions of temperature, humidity, vibration, and pressure signals have been achieved. These results prove the capability of the proposed model in learning slow-changing as well as fast-changing parameters of the pump system.

IV. RESULT ANALYSIS

The performance of the proposed LSTM-based prediction framework was evaluated on three industrial systems pump, turbine, and compressor using multisensor time-series data comprising temperature, humidity, vibration, and pressure. The evaluation focuses on the model’s ability to learn temporal dependencies and accurately forecast future sensor readings under varying operating conditions.

From “Fig.2” and “Fig.3” pump sensor data exhibits continuous dynamic behavior with moderate variations in temperature and humidity and relatively low-amplitude vibration signals. The comparison between actual and predicted outputs shows a strong overlap across all four parameters. The LSTM model effectively captures the underlying temporal patterns and maintains low prediction error throughout most of the operating range. Small deviations are observed only near abrupt peaks, which is typical for short-horizon time-series prediction. These results confirm that the proposed framework is capable of reliable pump condition monitoring and can support predictive maintenance strategies.

“Fig.4” and “Fig.5” The turbine dataset presents comparatively higher variability, particularly in the temperature signal, which includes several sharp transient peaks. Despite this increased complexity, the LSTM model demonstrates robust learning capability by closely following the overall trend of the sensor signals. Humidity and pressure fluctuations are

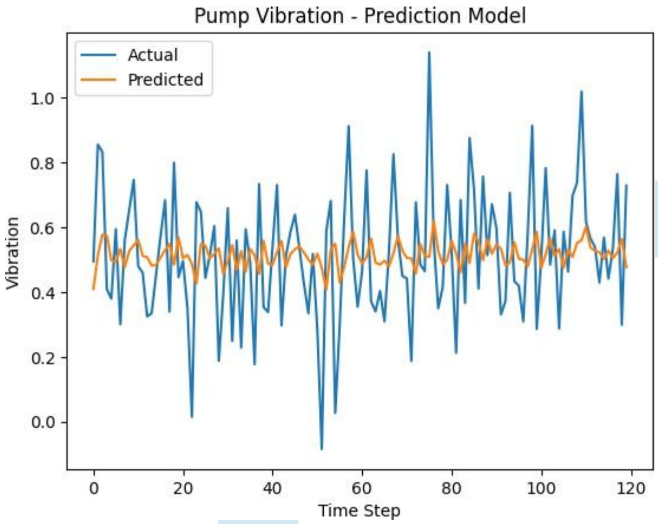

Fig. 3. Predicted Data of pump Vibration sensors

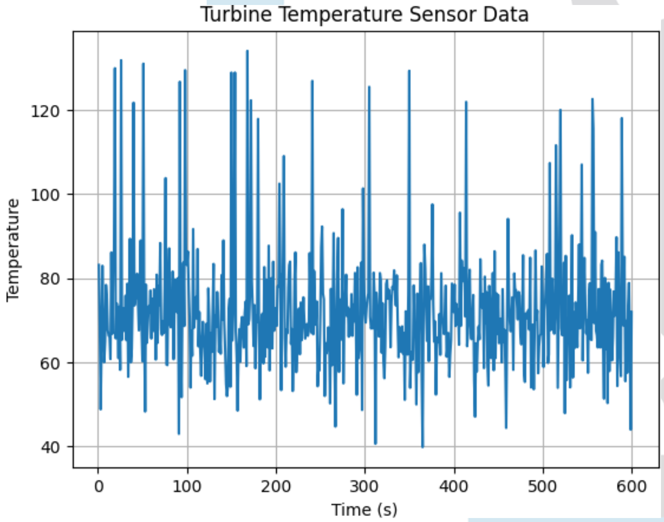

Fig. 4. Turbine Temperature Sensor Data

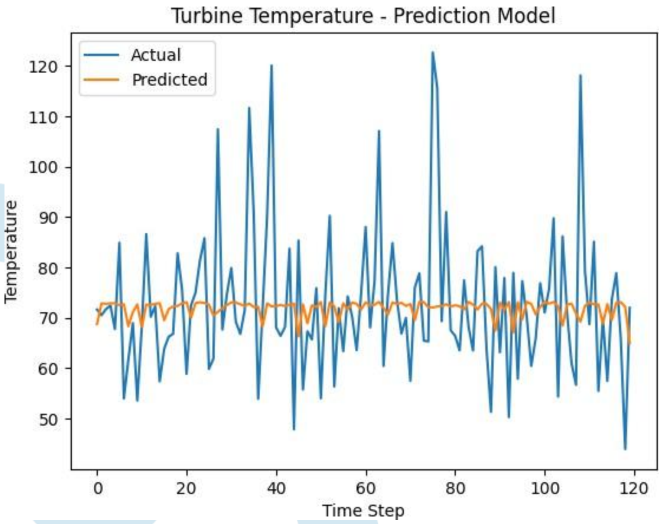

Fig. 5. Predicted Data of Turbine Temperature Sensor

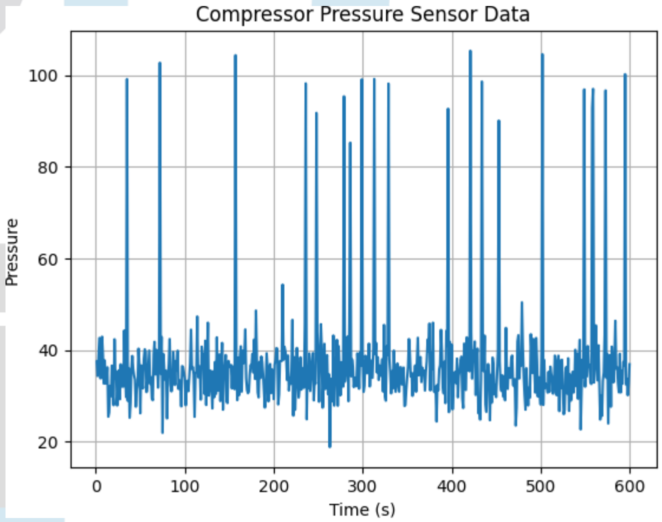

Fig. 6. Compressor Pressure Sensor Data

accurately modeled, while the low-level vibration signal is consistently tracked. The close agreement between measured and predicted values indicates that the proposed approach successfully captures nonlinear temporal dependencies present in turbine operation. This validates the applicability of the model for real-time turbine health assessment and anomaly detection.

The multisensor signals show steady fluctuations corresponding to changing load conditions of compressor system are shown in “Fig.6”, and “Fig.7”. Temperature and pressure demonstrate noticeable variations, whereas vibration remains within a narrow operating band, indicating stable mechanical behavior. The LSTM predictions align closely with the actual sensor readings across the entire test interval. Both gradual trends and short-term variations are effectively modeled, confirming strong temporal generalization. These results highlight the suitability of the proposed framework for compressor performance monitoring and predictive diagnostics.

Across all three industrial applications, the proposed LSTM-based model consistently achieves high-quality predictions with minimal tracking error. The strong correspondence between actual and predicted curves demonstrates effective learning of multivariate temporal relationships. The framework shows good generalization despite differences in signal dynamics among pump, turbine, and compressor systems.

Overall, the experimental results verify that the proposed method is robust, scalable, and well suited for multi-sensor industrial time-series forecasting. The approach can be effectively utilized for real-time condition monitoring, early fault identification, and predictive maintenance in modern industrial automation environments.

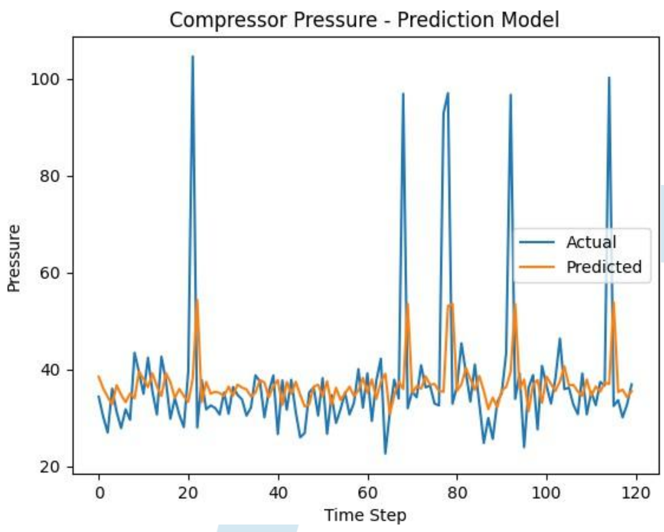

Fig. 7. Predicted Data of Compressor Pressure Sensor

V. CONCLUSION

The proposed study presents an LSTM-based framework for predicting multivariate sensor data from pump, turbine, and compressor systems. The model effectively learns temporal dependencies and generates predictions that closely match the actual sensor readings across all applications. The results demonstrate that the proposed approach is reliable for condition monitoring and predictive maintenance in industrial automation environments. Future work will focus on validating the framework using real industrial datasets and deploying it within real-time IIoT-based monitoring systems.

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