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Multi-Level Modeling of Process Variability in Industrial Systems

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Abstract
The implementation of Industry 4.0 technology in manufacturing operations creates a large quantity of heterogeneous and multidimensional datasets from the industry, thereby necessitating variability modeling to assure production quality and faults to achieve efficiency in manufacturing operations. However, traditional methods of building models often do not account for temporal information as well as structural relations between different machinery and procedures at different levels of operations in industries, hence resulting in poor performance predictions in such a dynamic setting. For this reason, an intelligent multi-level variability modeling approach based on the Long Short-Term Graph Neural Network (LST-GNN) is designed. The data produced from the industrial smart factory is pre-processed using Min-Max normalization method, and Linear Discriminant Analysis (LDA) is used for extracting features that are compact and informative but retain variability information. LSTM extracts time dependencies within the sequential data generated by the manufacturing process, while GNN learns structure dependencies in the network of interconnected machines, sensors, and production systems. It is shown that our LST-GNN model outperforms conventional approaches in terms of predictive accuracy, with Mean Absolute Error (MAE) and R^2 values being 0.030000 and 0.939500, respectively. Our proposed model provides higher accuracy, lower error, and higher robustness when used for process control and fault prediction within the domain of smart manufacturing. The LST-GNN is developed using Python programming language with support from TensorFlow, PyTorch Geometric, Scikit-learn, NumPy, Pandas, and Matplotlib libraries.

Keywords: Smart Manufacturing, Industrial system, Process Monitoring, Process Variability, Multi-Level Modeling, Industry 4.0.

1. Introduction

Different phases of evolution have been witnessed by the manufacturing industry due to different industrial revolutions that have experienced advancements in mechanical manufacturing, electrical manufacturing, automated manufacturing, and digital manufacturing. One such industrial revolution that has arisen due to different emerging growth in the form of digital manufacturing, Internet of Things (IoT), and Artificial Intelligence (AI) [1] in Industry 4.0. Industrial revolution 4.0 has brought changes to manufacturing processes with the advent of new technology, which includes data-driven predictive maintenance due to the use of IoT, Big Data, and Machine Learning (ML) technology [2]. Manufacturing quality control uses the technology of AI to detect any type of defect in production and increase efficiency. However, conventional manufacturing technologies are not able to control the production variability; therefore, there exists a great need for adopting predictive inspection technologies to deal with such production variability issues [3]. Additive manufacturing has become an essential part of the manufacturing industry in the present age due to the manufacture of complex structures with minimum losses of materials. There exist certain challenges in additive manufacturing technologies, which are being addressed at the moment [4]. Sustainable manufacturing has become the key process that helps find the equilibrium across economic development, environmental concerns, and social considerations [5]. Technologies of Industry 4.0 drastically improve manufacturing processes due to introduction of smart connectivity, automation, and data analytics. The gears of industry system are to cope with such issues as vibrations, wear-and-tear, and, consequently, breakdowns. Vibration analysis and the use of the Internet of Things through ML is a very efficient way to do that. Multilevel industrial systems interact in various complex cross-level processes where the failure of some component reduces the system's efficiency but does not result in its total crash [6]. Such intermediate operation regimes are called gray states. The traditional system reliability prediction methods are incapable of capturing the dynamics inherent in gray states because of the so-called state-space explosion effect [7].

Research Aim: The goal involves introduction of intelligent multi-level model for analyzing variability in Industry 4.0 manufacturing processes. The Stream of Variation (SoV) approach is integrated with Graph Neural Networks (GNNs) and Long Short-Term Memory (LSTM) to predict variability propagation across machine, process, and production-line levels.

Research Organization: Section 1 discusses the issues faced in Industry 4.0 manufacturing, process variability, and research motivation. Section 2 summarizes the background literature in relation to predictive maintenance, DL models, and multi-level modeling techniques. The proposed methodology is explained in Section 3, covering data acquisition, data processing, feature extraction, and the proposed LST-GNN approach to model process variability. Outcomes and discussions provided inside Section 4, and Conclusion are provided in Section 5.

2. Related Work

The estimation of the useful life of gear hobbing cutting tools is studied using Deep Neural Network (DNN) and Artificial Neural Network (ANN) models in [8]. The accuracy reached is 0.9665 for the DNN model; however, the performance of this model relies highly on proper feature selection and adequate data pre-processing. An anomaly detection solution for Industrial Internet of Things (IoT)applications using a Bidirectional Long Short-Term Memory–Variational Autoencoder (BiLSTM-VAE) model with dynamic adaptive loss functions is introduced in [9]. The suggested model is able to reach high accuracy levels (up to 98%), but the achieved results are sensitive to the environmental conditions and require regular re-training. Predictive Maintenance (PdM) model combining ML techniques of a multi-criteria decision-making approach, Best-Worst Method (BWM) is proposed in [10]. XGBoost and Gradient Boosting algorithms allow obtaining accuracy of 95.2%; however, the results depend on data quality and processing conditions. Fault diagnosis for IM bearing systems by analyzing vibrations using Support Vector Machine (SVM),ANN, and Principal Component Analysis (PCA) in IoT applications is described in [11]. The achieved accuracy of the suggested solution exceeds 95%; however, the effectiveness of this technique is highly sensitive to the operating conditions and feature quality. Fault Diagnosis in multiple components is improved by the use of ML classifiers such as SVM with radial basis function (SVM-RBF),ANN, and Decision Tree (DT)in [12]. Fusion of features improves classification accuracy to 83.84%; however, the ability to diagnose bearing faults is relatively poor. In [13], a Denoising Domain Adversarial Network (DDAN) for diagnosing faults in wheel hub motor with noisy operation is presented. The accuracy rate of this technique to classify in a cross-domain fashion is 84.93% with improved Signal-to-Noise Ratio (SNR), while the performance deteriorates considerably when there are high levels of noise. Worker activity recognition and generation of instructions for Industry 4.0 are discussed in [14], where Convolutional Neural Network (CNN), CNN-SVM, and You Only Look Once version 3 Tiny (YOLOv3-Tiny) techniques are used. The accuracy rate is 94% in this case, but it depends largely on the quality of video material and variety of activities performed by workers. A Cyber-Physical System (CPS) security approach for Industry 4.0 production environment is proposed in [15]. In particular, LSTM, CNN, and PLO algorithms are utilized to develop this CPS security architecture, and the achieved accuracy is 91.66%. Yet, the model is mostly tested within simulation environments only. Finally, error prediction in multi-stage machining processes is provided in [16]. It involves block manufacturing based on Stream of Variation (SoV). However, this approach necessitates highly accurate modeling and adaptability across machining processes. Process parameter optimization in industrial processes [17] with a Multi-Level Progressive Parameter Optimization (MLPPO) model. The model obtains a MAE of 0.035219, RMSE of 0.048677, and R^2 value of 0.927054, which indicates improved predictive power of the MLPPO model. Nevertheless, such dependence on correlation and distributional nature of the datasets restricts the ability of the MLPPO model to generalize.

3. Methodology

The designed approach has an established pipeline to establish models that address process variability at several different levels of the process in industry, as depicted in Figure 1. First of all, the data obtained from the industrial process are normalized to stabilize the numbers while scaling the heterogeneous parameters acquired from sensors and machines. Then, linear discriminant analysis (LDA) is used to extract the necessary features for the process to increase separability between classes. The model used here consists of LSTM and Graph Neural Network (GNN). Lastly, hyperparameters are tuned to provide stable learning before model training is executed on a Graphics Processing Unit (GPU).

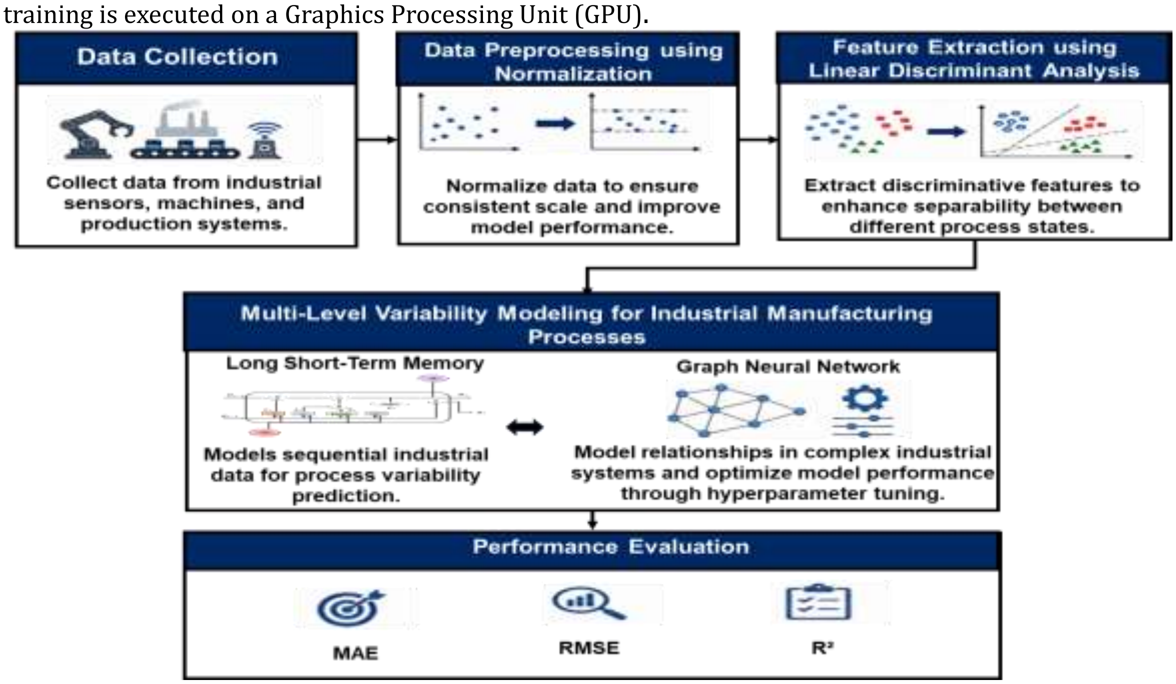

Figure 1: Workflow of the Introduced Method

3.1 Collection of Data

Dataset used is extracted via Kaggle (https://www.kaggle.com/datasets/rauffauzanrambe/industrial-smart-factory-automation-dataset-2026). The dataset is used for designing and verifying the developed multi-level model of process variability. The dataset comprises approximately 1L records containing industrial data gathered from a smart factory environment that include sensor readings, information concerning the machines used in manufacturing operations, inspection information, environmental conditions, and process monitoring attributes. It enables performing variability analysis, fault prediction, and quality control in advanced Industry 4.0 factories. For experimenting the performance of the developed models, the training-testing splitting method in an 80/20 ratio is used.

3.2 Data Pre-processing using Min-max normalization

The normalization technique ensures that the values of industrial variables are scaled into a range of 0 to 1, thereby avoiding any biasing effect caused due to wide variations in parameters. The process of normalization facilitates easy convergence and training of models while making variability analyses more efficient for smart manufacturing systems.

$$H_{norm} = \frac{H_{ft} - H_{Min}}{H_{Max} - H_{Min}} \quad (1)$$

In Equation (1), H denotes the feature of the industrial process, H_{norm} denotes the value of normalization, H_{ft} denotes the parameter of industrial input derived from sensors, machining facilities, and production systems, H_{Min} depicts the minimum measure of the attribute in the industrial dataset, and H_{Max} indicates the maximum attribute measures in the industrial dataset.

3.3 Feature Extraction using Linear Discriminant Analysis (LDA)

LDA used for feature selection to enhance the analysis of process variability and classification of defects in the industrial manufacturing system. LDA is a dimensionality reduction technique used for enhancing the separation between various classes of industrial operations. The main purpose of implementing LDA is the identification of important manufacturing features that affect the predictions of defects, process variability, and manufacturing quality.

$$|E(D)| = \frac{|D^v K_f D|}{|D^v K_D D|} \quad (2)$$

$$K_f D = \lambda K_D D \quad (3)$$

In Equation (2 & 3), E depicts the similarity function of kernel, D is the matrix of projection, $E(D)$ indicates the function of the criterion, $|E(D)|$ refers to the determination of the criterion function, v denotes the function of transpose, D^v is the transpose of the matrix D, K refers to the function of kernel, f denotes the mapping of feature, K_f denotes the state of industrial process, K_D represents the Class-internal scatter matrix, and λ denotes the eigenvalue associated with D.

3.4 Multi-Level Variability Modeling for Industrial Manufacturing Processes

The LSTM network is an architecture related to Recurrent Neural Networks (RNNs) that attempts to train sustained correlation in industrial data, successfully overcoming problems such as vanishing and exploding gradients with gated memory cells. The GNN model captures structured dependencies in the industrial system via the aggregation of nodes, which are machines, sensors, or inspection units, representing spatial dependencies in the system. The combination of both models LST-GNN in the hybrid architecture is trainable temporal correlations from ordered records alongside capturing spatial dependencies of the system structure via graphs.

Long Short-Term Memory (LSTM): LSTM is an architecture related to RNNs which learn long-term dependencies within sequence data. LSTM addresses issues such as vanishing and exploding gradients faced by conventional RNNs through gates in memory cells. LSTM is appropriate for industrial time-series data obtained from sensors, machinery, and manufacturing records. LSTM enhances learning stability, forecasting performance, and temporal pattern identification, making it applicable for process variability studies and fault predictions. Figure 2 represents the internal structure of an LSTM network where forget gate, output gate, and input gate control the flow of information.

$$D_s = e_s \odot D_{s-1} + j_s \odot \widehat{D}_s \quad (4)$$

In equation (4), D_s denotes the state of cell, s refers to the index of the time step, D_s and D_{s-1} denotes the present and prior state of the cell at the step of time, e_s refers to the output of the forget gate, $\odot$ denotes the multiplication of each element, j refers to the input gate result, j_s represent input gate output at s, $\widehat{D}_s$ represents the cell state of the candidate, $\widehat{D}_s$ refers to the cell state of the candidate from the input of industrial data.

$$g_s = p_s \odot \tanh(D_s) \quad (5)$$

In Equation (5), g denotes the output of the hidden state, s refers to the index of the time step, g_s refers to the hidden state at the step of time, p refers to the gate of the output, p_s represents the output gate at the step of time, $\odot$ denotes the multiplication of each element, tanrefers to the tangential function, tang denotes the tangential function of the hyperbola, D_s denotes the state of cell, D_s denotes the present state of the cell at the step of time, and $\mathrm{tang}(D_s)$ represents the tangent activation of the hyperbola.

$$\begin{bmatrix} \widehat{D}_s \\ p_s \\ j_s \\ e_s \end{bmatrix} = \begin{bmatrix} tang \\ \sigma \\ \sigma \\ \sigma \end{bmatrix} (X[{w_s \atop g_{s-1}}] + a) \quad (6)$$

In Equation (6), $\widehat{D}_s$refers to the cell state of the candidate,s refers to the index at the step of time, $\widehat{D}_s$ represents cell position of the candidate from the input of industrial data, p refers to the gate of the output, p_s represents the output gate at the step of time,j_s represent input gateoutput at s,e_s refers to the output of the forget gate,an refers to the tangential function, tang denotes the tangential function of the hyperbola,σ refers to the activation function of sigmoid, X denotes the feature matrix of the input, w depicts the matrix of weight, w_s represents the weight matrix corresponding to input mapping at time instant, g denotes the output of the hidden state, $g_s$and g_{s-1}refers to the present and prior hidden state at the step of time, and a refers to the term of bias.

$$Z_S = [g_{S-m,}g_{S-m+1,}\cdots, g_{S+1}] \quad (7)$$

In Equation (7), Z refers to the sequence of the output feature, s refers to the index of the time step,Z_S denotes a series of hidden states that form temporal variability features, g denotes the output of the hidden state,s refers to the index of the time step, g_s refers to the hidden state at the step of time,m denotes the window size that determine the number of past time periods,g_{S-m} and g_{S-m+1} represents the states of hidden layer in the previous and next window sequence, and g_{s+1} refers to the upcoming hidden state at the step of time.

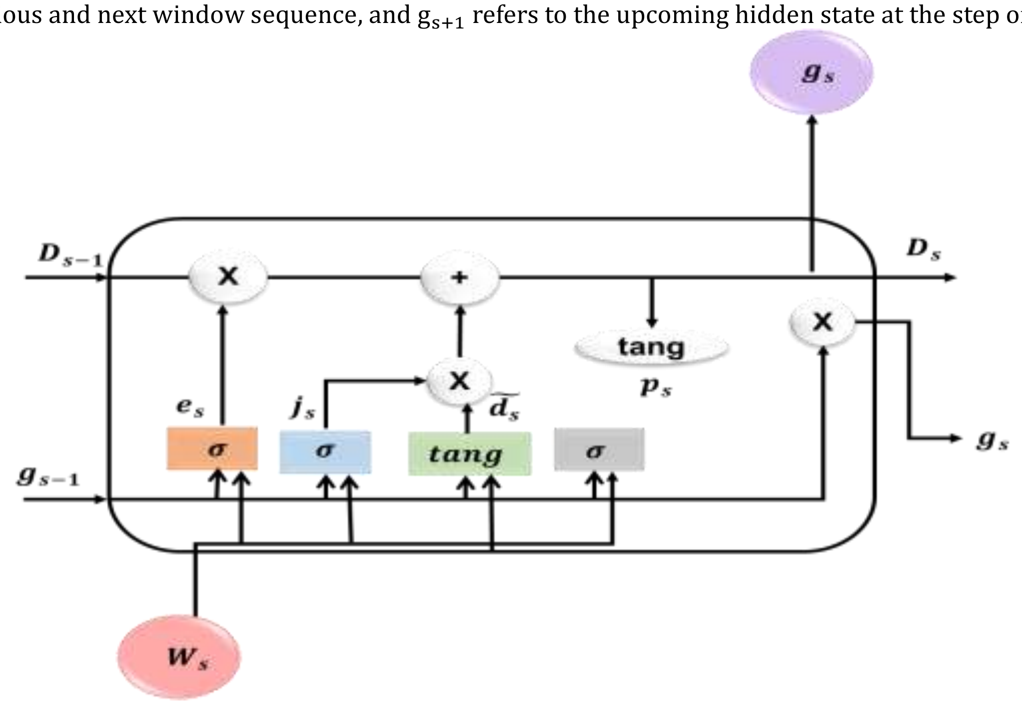

Figure 2: Architecture of LSTM

Graph Neural Network (GNN): GNNs are DL architectures that can work on graph-based data by representing the graph nodes through the aggregation of the neighboring nodes' information. When applied in the modeling of industrial process variation, GNNs are able to represent complex associations between the machines, sensors, inspection stations, and processes in the plant. Each layer represents the nodes in the graph using learned transformations and nonlinearity by aggregating neighboring nodes' information.

$$g_u^{(k+1)} = \sigma (X^{(k)}.\mathrm{AGGREGATE} ((g_v^{(k)} : v \in M (v)\} + a^{(k)}) \quad (8)$$

In equation (8), g denotes the feature of the node, u denotes the target of the node,k and $k+1$denotes the current and the upcoming index of the layer, $g_u^{(k+1)}$ denotes the representation of the updated feature, σ refers to the activation function of non-linear feature, X represents the matrix of weight, $X^{(k)}$ denotes the matrix of the learnable weight, AGGREGATE(.) denotes the function that combines the information with the nodes of the neighbor, v denotes the neighboring node,$g_v^{(k)}$ represents the feature of neighbor node,∈ denotes the element belongs, $v \in M(v)$ represents the membership of the neighboring set, M represents the set of neighbor, $M(v)$ indicates the neighbor set connected with the nodes, $g_v^{(k)} : v \in M(v)$ denotes the feature of the neighboring nodes belongs to the membership of the neighboring set, a denotes the term bias, and $a^{(k)}$ denotes the bias term of the learnable.

Hyperparameter of the suggested model: The hyperparameters that were used in configuring this model ensure stability and efficient learning during training. The use of a learning rate of 0.001 in conjunction with Adam, an Adaptive Moment Estimation optimizer, allows for the adaptive adjustment of gradients, while a batch size of 64, along with 100 epochs of training, balances speed and performance in learning. Dropout with a value of 0.30 and weight decay of 0.0001 minimizes overfitting. In terms of architecture, there are 128 LSTM units that allow for temporal feature learning, alongside 64 hidden units from Graph Neural Networks that operate on 3 graph layers using ReLU as the activation function and mean aggregation strategy. Sequence Length is set to 20.

4. Result

The proposed approach uses DL tools and high-end hardware configuration to perform various tasks. The model is coded in Python (version 3.11), TensorFlow (version 2.16), PyTorch Geometric (version 2.5), NumPy version 1.26, Pandas version 2.2, Scikit-learn version 1.5, Matplotlib version 3.9, and Compute Unified Device Architecture (CUDA) Toolkit (version 12.2), with execution in Jupyter Notebook under Anaconda 2024 environment. Hardware comprises Intel Core i7 13th generation Central Processing Unit (CPU), NVIDIA RTX 4060 (8 GB) GPU, 32 GB Double Data Rate 5 Synchronous Dynamic Random Access Memory (DDR5RAM), and 1 TB Solid State Drive (SSD). The model is executed on a 64-bit Windows 11 Pro computer system.

Explorative Data Analysis: Figure 3 indicates industrial temporal variation and energy consumption. Figure 3(a) illustrates the levels of energy consumed by various factory units, such as assembly, Computer Numerical Control (CNC), logistics, robotics, and welding units. The welding unit consumes the most amount of energy while the inspection and cooling units consume relatively lesser amounts of energy, and Figure 3(b) depicts the fluctuations in energy consumption in relation to various timestamps. This fluctuating line reveals that have been many instances where energy consumption reached unexpected peaks and then drastically dipped down. This analysis allows one to observe erratic consumption trends.

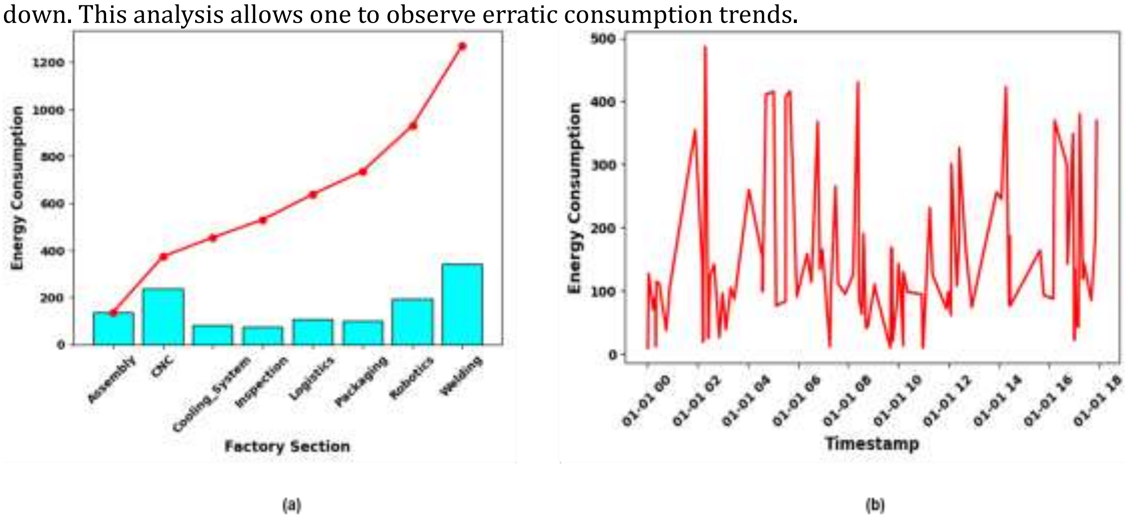

Figure 3: Visualization of (a) Analysis of Factory Energy (b) Energy Time Variation

Figure 4 represents an analysis of the pressure and humidity pattern over time; Figure 4(a) shows the fluctuations in the levels of pressure through time. The data used in this figure is based on original pressure and moving averages of the same. Purple line depicts fluctuation in the readings of pressure whereas yellow line represents the smoothing of those variations, and Figure 4(b) displays the humidity decomposition based on the trend and seasonal components throughout the period. The trend component is responsible for indicating the behavior of humidity through time, whereas the seasonal component explains the repetitive fluctuation and periodic nature of humidity.

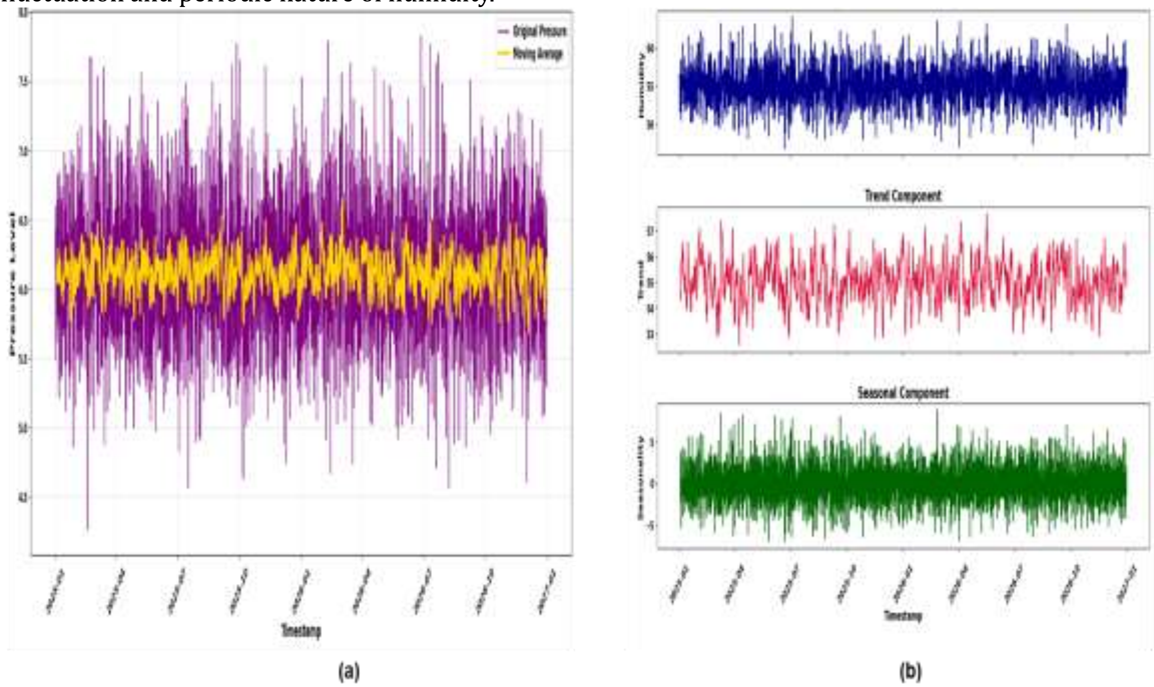

Figure 4: Visualization of (a) Monitoring Pressure Trends, (b) Humidity Factors Analysis

Evaluation Metrics: The performance metrics measure the accuracy of predictions as well as the effectiveness of models. MAE is a metric that considers the mean absolute error for the difference between predictions and observations. This is an indication of prediction accuracy and reliability within industrial settings, where lower MAE values indicate high performance levels. RMSE considers the magnitude of the errors made while putting more weight on larger differences. This makes RMSE more reliable as it accounts for errors in complicated situations. The R^2 is for distribution of the difference demonstrated based on the approach, suggesting how well data relations have been captured; a larger value of R^2 means better explanatory power of the model.

Performance Analysis: The comparative analysis depicted in Table 1 and Figure 5 shows the efficiency of various predictive modeling techniques based on performance measures. Statistical approaches such as Spearman Rank Correlation (SRC)[17] offer predictive capabilities with the help of traditional methods, whereas ML based techniques including XGBoost [17] increase efficiency in recognizing non-linear patterns. The MLPPO technique [17] is even more effective for achieving increased prediction accuracy with the application of optimal learning procedures. DL and hybrid methods, including GNN with LSTM, outperform other approaches by capturing temporal dependencies effectively. Nevertheless, the suggested LST-GNN method offers the highest performance, making the smallest errors, reaching the value of 0.030000 for MAE, 0.046800 for RMSE, and 0.939500 for R^2.

Table 1: Comparative Performance of Current Models and Proposed LST-GNN

Method	MAE	RMSE	R^2
SRC [17]	0.037089	0.050803	0.920540
XGBoost [17]	0.035223	0.048687	0.927024
MLPPO [17]	0.035219	0.048677	0.927054
LST-GNN [proposed]	0.030000	0.046800	0.939500

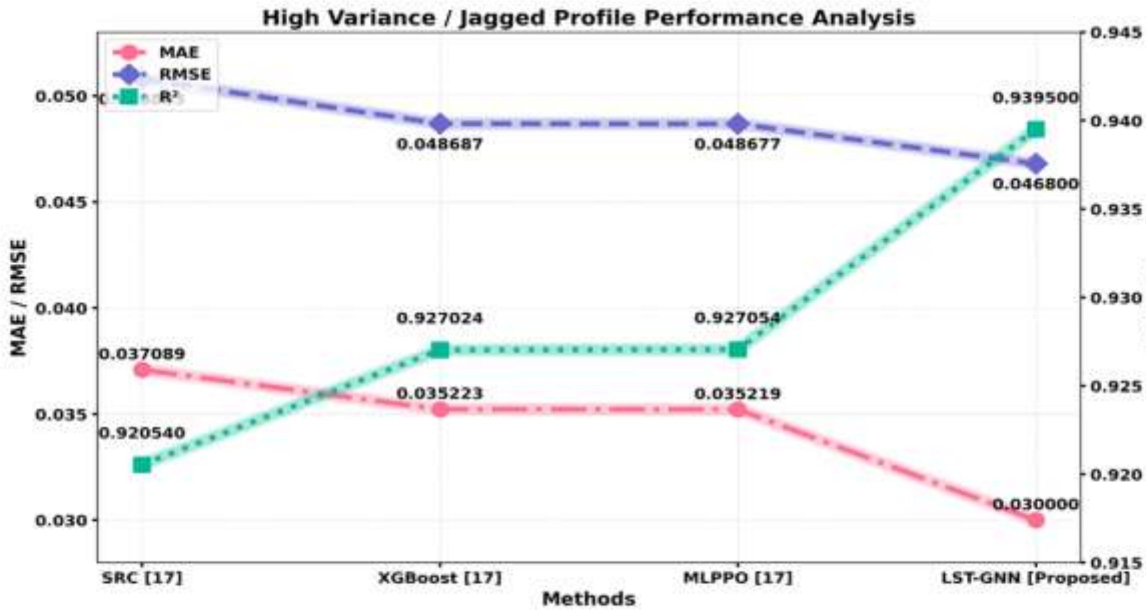

Figure 5: Comparative analysis of Models for Industrial Process Variability Modeling

All the baseline models are retrained with the industrial smart factory automation dataset, with the same experimental configuration as well as the same split between training and testing datasets, as shown in Table 2 below. To provide a fair evaluation against other competing models, the same pre-processing techniques were applied in the form of normalization and feature extraction using LDA. The performance of the models was measured using MAE, RMSE, and R^2. Experimental outcomes highlighting the proposed LST-GNN is surpassing previous approaches because it has more accurate predictions.

Table 2: Retraining Performance Comparison of Industrial Variability Prediction Model

Method	MAE	RMSE	R^2
SRC	0.052400	0.068900	0.881200
XGBoost	0.045700	0.061300	0.902500
MLPPO	0.041200	0.056800	0.918400
LST-GNN [proposed]	0.030000	0.046800	0.939500

Discussion: The models like SRC [17], XGBoost [17], MLPPO [17], and LST-GNN [17] are assessed on the basis of their performance metrics like MAE, RMSE, and R^2 for modeling complex tasks in industries. The SRC [17] model is not capable of handling nonlinear learning and makes simpler assumptions. This affects its adaptation to complex datasets and leads to decreased robustness while dealing with different industrial scenarios. XGBoost [17] addresses the limitation of SRC [17] model but becomes prone to tuning the values of its hyperparameters. It can suffer from overfitting or poor generalization capabilities because of the shift in data distribution or complexity. The MLPPO [17] model further improves the efficiency and optimization capabilities of models but still needs fine tuning and large computational resources for proper functioning. To overcome the drawbacks the suggested LST-GNN surpasses these drawbacks by using long-term temporal learning and graph dependencies, making its representation of the relationships more precise.

5. Conclusion

The intelligent multi-level variability modeling scheme for industrial manufacturing was presented in this research by adopting a hybrid model known as LST-GNN. This new model has successfully captured the dependencies in time and space with regard to Industry 4.0 manufacturing processes owing to the application of both LSTM and GNN methods. The process of data pre-processing and feature extraction via the use of LDA has enhanced model stability and its efficiency in learning. According to the results of experiments conducted, the new algorithm shows good results, surpassing the performance of previously developed algorithms with the metrics MAE = 0.030000, RMSE = 0.046800, and R^2 = 0.939500. The suggested algorithm improves process variability analysis, defect prediction, process monitoring, and process quality improvement in intelligent manufacturing systems. However, the problems associated with this algorithm are related to the computational complexity and data volume. Future research should focus on optimizing the model and its adaptability to changes in conditions.

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