Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

AN ENERGY EFFICIENT DATA AGGREGATION MANAGEMENT FOR CYBER PHYSICAL SYSTEM TO DETECT THE RECESSIVE DISTURBANCES USING LONG SHORT TERM MEMORY

UMAPATHI G R
Department of Information science and engineering, Acharya Institute of Technology, Bangalore, India.

Dr. RAMESH BABU H S
Sai Vidya Institute of Technology, Bangalore, India.

Abstract

Manufacturing is an embodiment of the national economy as well as a pillar industry for creating human wealth. Cyber Physical System have been increasingly deployed in manufacturing industries to achieve the dynamics in manufacturing. Energy management system playing a key role to improve the energy efficiency of Cyber Physical System. However efficient energy management system are error-prone, still inefficient and difficult to achieving better accuracy. In order to overcome these issues a LSTM (Long Short Term Memory) is proposed for detecting the recessive disturbances in Cyber Physical System. The Agglomerative clustering is used for data cleansing and PCA is used for data reduction. The pre-processed data is given to the LSTM classifier for detecting the recessive disturbances The simulation analysis shows that the proposed method obtain 100% accuracy for NPP data, 0 % error, precision is 100%, specificity is 100% and so on. This shows that the proposed method attain better performance compared to other existing approaches among four datasets. Based on this proposed classification the anomalies prediction can be improved and provide energy efficient management in cyber physical system.

Keywords: Cyber physical system (CPS), energy efficient management, Data aggregation, recessive disturbances, agglomerative clustering, PCA, LSTM.

1. Introduction

Manufacturing is a major embodiment of a country's national economy and overall national strength, as well as a cornerstone industry for building human wealth [1]. Increased energy and resource use in industry has generated worries about long-term economic development in several countries [2].. As a result, mining heterogeneous industrial Big Data to manage energy-efficient manufacturing operations is becoming increasingly important [3].

Smart technologies such as sensor networks, cloud computing, and artificial intelligence are enabling manufacturing to become hyper-connected [4]. Smart manufacturing systems can connect with one another and configure themselves quickly to meet changing production demands [5]. Companies have substantial challenges in maintaining the manufacturing quality and great energy performance, as well as and productivity [6].

To deal with the shifting dynamics, smart sensors, Cyber physical systems, and Big Data analytics are gradually being deployed in various industries [7]. Cyber physical

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

systems are characterised as systems in which the physical and software components are closely interwoven to produce a variety of diverse behavioural patterns [8]. The Cyber-physical system has emerged as a new creation of IoT vision for realising this linkage through the combination and reasoning of extracted knowledge buried in industrial processes, with the ultimate aim of connecting the physical as well as the virtual worlds. This vision suggests a means to deal with the increased complexity that comes with massive individualization in smart manufacturing workshops [9].

However, due to the enormous volume of obtained dynamism of manufacturing processes, manufacturing data, relevant data reduction and the complexity, and association analysis to assist energy-efficient manufacturing are still inefficient and high error especially for discrete manufacturing factories [10]. Many deep learning algorithms has been developed for detecting anomalies during manufacturing process. Several existing methods based on cyber physical systems have been adopted to improve the classification accuracy of energy management systems, but these mehods are still unable to detect anomalies with good results. In order to overcome these issues a Long Short Term Memory is proposed. Furthermore a LSTM classifier have the potential to attained high accuracy comparing to other deep learning techniques.

The key objectives of the proposed method is given below

- ❖ To detect the recessive disturbances an energy efficient management system based on Cyber Physical System using LSTM is proposed.
- ❖ In order to detecting the anomalies raw data’s are collected from manufacturing industries which is denoted in the physical energy layer of Cyber Physical System.
- ❖ For pre-processing the raw data agglomerative clustering and principal component analysis is used which is denoted in the cyber physical layer of cyber physical system.
- ❖ To detect the recessive disturbances in Cyber Physical System an LSTM classifier is used which is denoted in the knowledge driven management layer of cyber physical system.

The remaining part of the manuscript is structured as follows, section 2 describes several researches related to the existing epileptic disease prediction system using various machine learning algorithms. Section 3 containing the proposed methodology of energy efficient management system using LSTM classifier. Section 4 discuss the results attained through the implementation of the proposed method. Section 5 contain the conclusion of the proposed model.

2. Literature Review

Several relevant reviews about efficient energy management system based on Cyber Physical System using various techniques have been reviewed in this section.

Bevilacqua M et al., [11] had designed the industrial sector, big data analytics approaches have been applied to energy management

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

Campatelli G et al., [12] had performed in the processing of carbon steel, a surface response method was used to optimise process parameters and reduce power usage.

Delgado-Gomes V et al., [13] had designed MaSnufacturing and production systems should be aware of their energy use.

Park K. T et al., [14] had performed the industrial internet of things and manufacturing big data, a cyber-physical energy system has been designed to save energy during the dyeing process.

Zhang, C et al., [15] had designed an RFID-enabled ubiquitous environment, To satisfy the requirement for real-time production control, a deep learning approach for energy-efficient control of CNC machine tools has been developed. The experiment results reveal that the developed method is effective and efficient for the energy efficient control problem of machine tools.

Shuaiyin Ma et al. [16] had developed an energy-Cyber-Physical System enabled management for energy-intensive manufacturing enterprises.

Shuaiyin Ma et al. [17] has suggested a data-driven sustainable intelligent manufacturing for energy-intensive industries, based on demand response is being developed. The medium and small scale companies find it hard to swap equipment due to high cost.

Chaoyang Zhang et al. [18] has introduced discrete manufacturing workshops, Production anomaly detection and an energy-efficient production decision method were made possible by edge computing.
These methods assumed that the data was sampled from a specific distribution, which may or may not be accurate [11], There are still a lot of things that can be done to make manufacturing more energy efficient [12], Small and medium-sized factories are finding it difficult to benefit from these advancements [14], This strategy could also have major negative consequences in terms of resource usage and pollution [15], This method may also have significant negative consequences in terms of resource use and pollution [16], Due to the high expense of updating equipment, medium- and small-sized businesses find it difficult to do [17], The raw energy data is always huge, isolated, and messy, so it can't be used to analyse production irregularities directly [18], In order to overcome these issues LSTM classifier was proposed to predict the anomalies in energy efficient management system.

3. Proposed Methodology for energy efficient management system

Industry is consider as a major energy consumer so, manufacturers are try to reducing the manufacturing costs. Industrial production management systems are looking for ways to reduce energy use without lowering outputs. Cyber Physical Systems, Smart sensors and Big Data analytics are expanding and it used in manufacturing workshops to deal with the changing dynamics.. In order to overcome the issues an energy efficient management system based on LSTM is proposed to detect the recessive

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

disturbances. In figure 1 the diagrammatic representation of the energy efficient management system is shown.

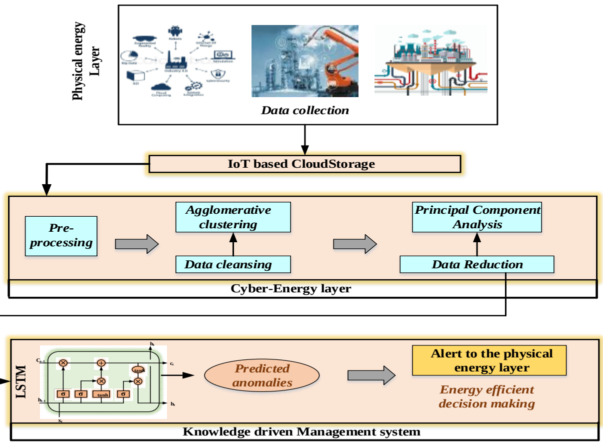


Figure 1: Architecture of proposed energy efficient management system

3.1 Data collection

The data's are collected from various manufacturing industries for detecting the anomalies which is present in the physical- energy layer of Cyber physical system.

3.2 Pre-processing

The Raw data is used as an input for the pre-processing procedure. To improve the system's performance, data pre-processing is utilised to convert raw data into valuable information for subsequent procedures. For pre-processing the raw data we used two approaches which is agglomerative clustering and Principal Component Analysis. Data cleansing is done by using Agglomerative clustering and for reducing the data we use principal component analysis.

Data cleansing

Raw data is fed as an input for the data cleansing process.. For grouping the messy data's we used agglomerative clustering.

<u>Agglomerative clustering</u>

A type of hierarchal clustering algorithm is agglomerative clustering. it can be viewed as a method of constructing multi-granular information for the original data. Mathematically, for n_c initial clusters $C = \{C_1, C_2, \ldots, C_{n_c}\}$, each iteration of the algorithm attempts to select two clusters C_a and C_b using Eq. (1) [19]

$$\{C_a, C_b\} = \operatorname{argmax} A\left(C_i, C_j\right) ;\ C_i, C_j \epsilon C_{i \neq j} \qquad (1)$$

Where $A\left(C_i, C_j\right)$ is a function for calculating cluster affinity complete linkage, and average linkage, single linkage are the most used methods for measuring the affinities between two clusters. PIC creates a structural description for clusters on a similarity network and assumes that two clusters have a strong affinity if their structural descriptors dramatically change when they are combined into one. These methods are usually based on the K-nearest-neighbour network, which uses Eq.(2) to create the similarity matrix. [19]

$$W_{ij} = \begin{cases} \exp(-\frac{\|x_i - x_j\|_2^2}{\delta}, & \text{if } x_j \epsilon N_i^K \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Where N_i^K is the set of K-nearest neighbours of x_i and δ is a trade-off parameter.

Existing agglomerative clustering is based mainly on the pairwise distance, to the best of our knowledge. Although this method retains the data's local structure effectively, it is susceptible to noise and outliers. As a result, these methods will struggle with datasets that contain noise and outliers.

Data Reduction

Data reduction is a way to decrease the size of original data so that it may be stored in a tiny size. While lowering data, data reduction solutions maintain data integrity. In this way, the data is reduced using the Principal Component Analysis approach.

Principal Component Analysis (PCA)

PCA stands for Principle Component Analysis, which is an unsupervised linear method for reducing the variables of a huge data set into a smaller one. Figure 2 the each step by step procedure in PCA is shown.

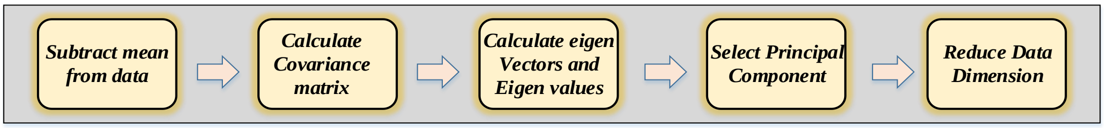


Figure 2: Diagrammatic representation of PCA procedure

Step 1: A dataset is contemplate (consider) as essential that is named as M, $A = [M_1, M_2 \ldots\ldots M_N]$ and x is the size of the dataset followed that, mean associated to this dataset is calculated. That is calculated by using eqn. (3) [20].

$$\sigma = \frac{1}{x}\sum_{k=1}^{x} x_i \quad (3)$$

Where the k value is vary from 1 to x, from above equation and the total number of sample considered for analysis is denoted by x and mean calculation is denoted by σ terms.

Step 2: Then the covariance matrix is computed with the assist of obtained mean value. This matrix is calculated by using Eqn. (4)

$$\rho = \frac{1}{x}\sum_{k=1}^{x}(a_1 - \sigma)(a_i - \sigma)^T \quad (4)$$

Calculated mean value is denoted by σ and covariance matrix related to sample set is represented by ρ.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

Step 3: By using covariance matrix the Eigen vectors feature values are calculated using following equations.

$$\rho = \mathcal{H}.\mathcal{S}\,\mathcal{H} \tag{5}$$

$$\mathcal{S} = \mathrm{diag}(\omega_1, \omega_2 \ldots\ldots \omega_m) \tag{6}$$

$$\mathcal{H} = (h_1, h_2 \ldots . h_n) \tag{7}$$

By using this matrix with feature values k, $\mathcal{S}$ signifies the diagonal was created by using Eqn. (7). Where the feature values is denoted by ω_m and feature matrix was represented by $\mathcal{H}$ that incorporated with the correlated feature vectorh_n.

Step 4: In order to estimate the cumulative variance contribution rate, the calculated feature vectors, feature values are used that is related to beginning v-row element that is shown in Eqn. (8)

$$\delta = \sum_{i=1}^{v} \omega_i / \sum_{j=1}^{v} \omega_j \tag{8}$$

The estimated value δ must be more than or equal to the 0.9 in eqn (8). For the first v-row elements, the contribution rate with cumulative variation is expressed by δ. The value of δ is used to choose the issue that has been identified. The considered sample information can be discovered by selecting the value of in the v-row element.

Step 5: The v-row feature vector, which is indicated in the following equations, is used to reduce the dimension in the given sample dataset.

$$\mathcal{B} = \mathcal{H}_v \tag{9}$$

$$\mathcal{N} = \mathcal{B}.A \tag{10}$$

The Feature matrix is illustrated by B, and the Feature vectors associated to the starting v-row elements are included in this feature matrix. The dataset A is renamed B, and the x-dimension is decreased to the v-dimension. N stands for a dimension-reduced dataset. PCA is used to reducing the original dataset, which achieve effective dimension reduction. By using dimensionality reduction the classification accuracy is enhanced

3.3 Classification

The extracted data's are given as an input to the classifier in order to detect the recessive disturbances which is present in the knowledge driven management layer of cyber physical system. The classification is achieved by using Long Short Term Memory (LSTM). Figure 3 shows the architecture of LSTM at time step t.

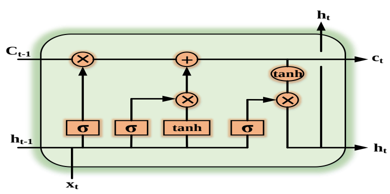


Figure 3: Architecture of Long Short Term Memory

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

A typical Recurrent Neural Network is a LSTM network, by altering the $\tanh$ layer it change the memory cell structure in RNNs and it has a gate mechanism and memory unit. This process determines how to use and update the data stored in the memory cell. Gradient diffusion and detonation are not discussed because of this structure. The input gate, output gate and forgot gates are denoted by i, o, f and c represents the memory cell. The inputs of an input gate is represented by i_t and o_t is represented as an output gate and forgot gate is represented by f_t. At time t that the network receives all vector x_t and its previous hidden size $h_{(t-1)}$. Based on x_t and $h_{(t-1)}$ the gate signals are formed [22].

$$f_t = \sigma(W_{fx_t} + U_{fh_{t-1}} + b_f) \tag{12}$$

$$i_t = \sigma(W_{ix_t} + U_{ih_{t-1}} + b_i) \tag{13}$$

$$o_t = \sigma(W_{ox_t} + U_{oh_{t-1}} + b_o) \tag{14}$$

$$\hat{c}_t = \tanh\,(W_{cx_t} + U_{ch_{t-1}} + b_c) \tag{15}$$

$$c_t = f_t \times c_{t-1} + i_t \times \hat{c}_t \tag{16}$$

$$h_t = o_t \times \tanh(c_t) \tag{17}$$

Where logistic sigmoid function is denoted by σ and f_t is represented as forgot gate, input gate is by i_t, output gate o_t and the memory cell vector activation vector c_t at time step t. In the interval [0, 1] the entries of gating vectors f_t , i_t , o_t and the bias is represented by b, all gates and memory cells are represented as the same size as $h_t \in R_f, W_f, W_i, W_o, W_c \in R_{H\times d}$. Memory dimension of the LSTM is denoted by d and $b_f, b_i, b_o, b_c \in R_H$, and $U_f, U_i, U_o, U_c \in R_{H\times H}$. Figure 4 shows the layer diagram for Long Short Term Memory. Where H and h are the dimensionality of the hidden layer and input respectively.

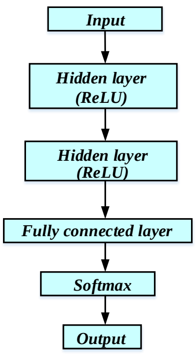


Figure 4: Layer diagram for LSTM

Figure 4 shows that the layer diagram for LSTM classifier. These are the layers present in the Long Short Term Memory which is input layer, hidden layer, fully connected layer, softmax function and output.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

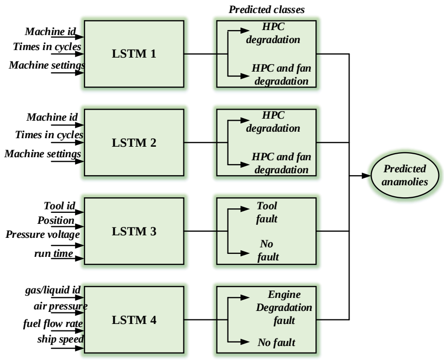


Figure 5: LSTM Architecture for proposed methodology

Figure 5 shows the LSTM architecture for proposed methodology. For the proposed method we create four LSTM net for predicting different type of anomalies that is recessive disturbances.

4. Results and Discussion

The proposed method is developed to detect the recessive disturbances using LSTM based on efficient energy management system. The proposed Long Short Term Memory is evaluated in this section. The testing is performed with the help of MATLAB 2021a The data’s are collected from GitHub website for detecting the anomalies. There we take four type of data’s such as NPP [23], C-MPASS [24], PHM-08 [25], and PHM-18 [26]. The description regarding the dataset is given below.

Navel Propulsion System (NPP) data

NPP data was generated using a sophisticated Gas Turbine simulator mounted aboard a Frigate with a CODLAG (Combined Diesel Electric and Gas) propulsion plant type.

Turbofan engine degradation data (C-MPASS)

The C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) simulator was used to create this data collection. C-MAPSS is a tool for evaluating realistic large commercial turbofan engine data.

Engine degradation data (PHM-08)

The only difference between this dataset and C-MAPSS data is that C-MAPSS data includes actual RUL values, while this dataset does not. Multiple multivariate time series are collected in data sets

Etching Tool fault detection data (PHM-18)

PHM 18 data was provided to examine the wafer manufacturing process's ion mill etch tool fault behaviour. It's a database that captures sensor data from ion mill etching equipment in a temporal sequence under various settings. 20 'train fault' files consist of a total of 1,236 rows and consist of three columns. 20 'train_ttf' files consist of a total

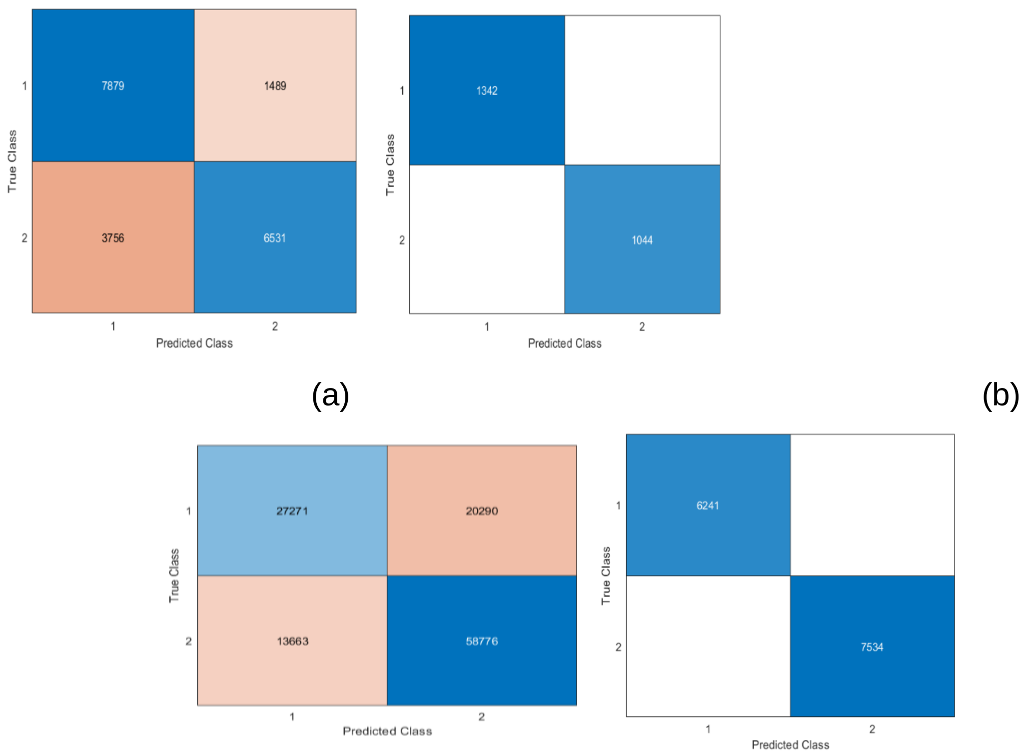
Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

of 82,189,440 rows and consist of four columns. The test data consist of 7,198,948 rows and consists of 24 columns.

Table 1: Parameters of LSTM classifier

Parameters	**Range**
Mini batch	16
Max epoch	100
Number of hidden units	100
Optimizer	Adam
Activation function	softmax
Gradient threshold	1

Table 1 contains the parameters of LSTM classifier. In the proposed and existing technique, the Mini batch size is referred as 16 and the max epoch value is referred as 100, number of hidden units are referred as 100 and the Optimizer used in the classifier is denoted as Adam. Activation function for output layer is soft max then the gradient threshold value is 1.



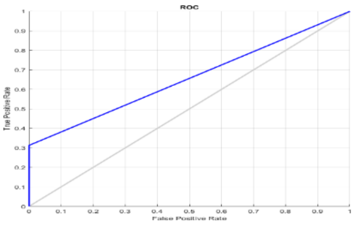
(a) (b)

(c) (d)

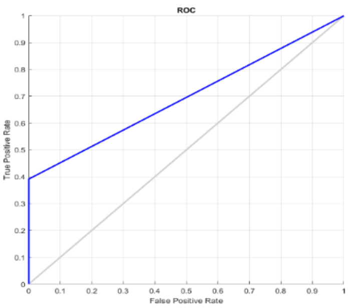
Figure 6: confusion matrix for the proposed LSTM classifier for four different dataset

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

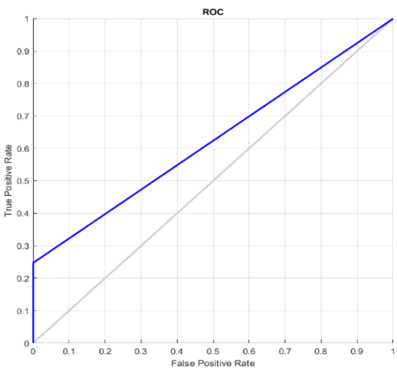
A confusion matrix is a way of summarising the performance of a classification algorithm. Making a confusion matrix can help you figure out which components of your classification model are correct and which are wrong. In figure 6 there are four different confusion matrix are plotted for various type of datasets. Figure 6 (a) confusion matrix is plotted for engine degradation data. For class 1 predicted label is 7879, for class 2 predicted value is 6531. For figure 6 (b) confusion matrix is plotted for engine degradation data. Predicted label for class 1 is 1342 and for class 2 the predicted label is 1044. In figure 6 (c) the confusion matrix is plotted for etching tool fault detection data. For class 1 the predicted label is 27271 and for class 2 the predicted label is 58776. In figure 6 (d) confusion matrix for ship maintenance data is plotted. For class 1 the predicted class value is 6241 and for class 2 the predicted label value is 7534.



(a)

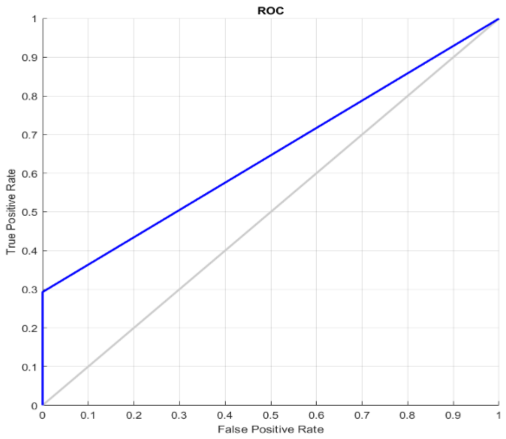


(b)



(c)

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2



(d)

Figure 7: ROC plot for proposed classifier for four different datasets

The ROC curve (Area under the Curve) is an evaluation metric for identifying problems at different threshold levels. The AUC is a measure of separability, while the ROC is a probability curve. It demonstrates how well the model can differentiate between different classes. By plotting the true positive rate (TPR) against the false positive rate (FPR) a ROC curve is created. The genuine positive rate is the proportion of all positive observations that should have been positive. There is no discrimination if the AUC is less than 0.5. A score of 0.7 to 0.8 is regarded satisfactory, 0.8 to 0.9 is excellent, and greater than 0.9 is exceptional. Figure 7 shows that the ROC plot of the proposed classifier. In 7 (a) the ROC value for engine degradation data is 1, for other data also the ROC value is same that is 1. The proposed method reach the value 1, so the proposed classifier shows the better performance.

4.1 Comparison Analysis

The evaluation analysis of the proposed prediction model is performed based on using several metrics. The metrics that are considered for this study are accuracy, error, f1_score, false negative rate, precision, sensitivity and specificity. The proposed approach is evaluated and compared with four datasets like NPP, C-MPASS, PHM-08, and PHM-18. The analysis is performed comparing the proposed technique with some conventional techniques such as, Support Vector Machine (SVM), Naive Bayes (NB), Artificial Neural Network (ANN), and Random Forest (RF).

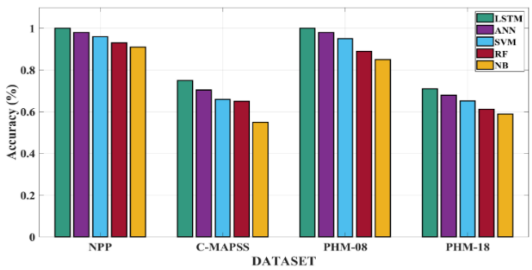


Figure 8: Comparison of proposed and existing accuracy metric for different dataset

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

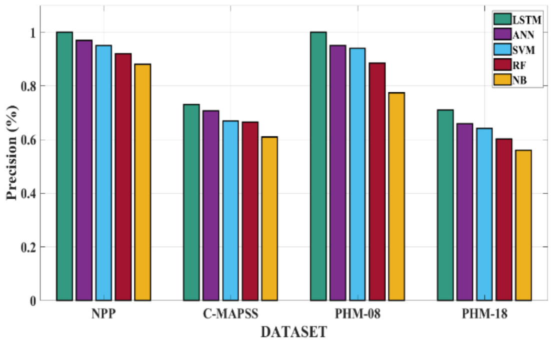


Figure 9: Comparison of proposed and existing precision metric with different dataset

The comparison of proposed and existing accuracy metric for four different datasets are given in figure 8.. LSTM classifier is 100% and it is seen to be greater on comparison on other existing systems such as ANN, SVM, RF, NB whose values for accuracy are 0.98, 0.96, 0.93 and 0.91.

Figure 9 shows that the comparison analysis of precision metric between proposed and existing techniques for four different datasets. For NPP data the precision value for the proposed LSTM classifier is 100% and it is seen to be greater on comparison on other existing systems such as ANN, SVM, RF, NB whose values for accuracy are 0.97, 0.95, 0.92 and 0.88.

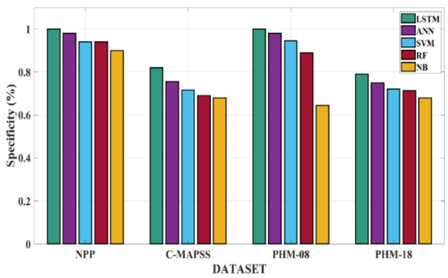


Figure 10: comparison of proposed and existing specificity metric

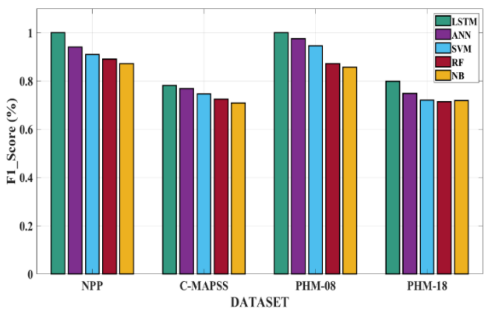


Figure 11: **Comparison of proposed and existing F1-score metric**

The comparison of proposed and existing Specificity metric for four different datasets are shown in figure 10. For NPP data the specificity value for the proposed LSTM classifier is 100% and it is seen to be greater on comparison on other existing systems

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

such as ANN, SVM, and RF and NB whose values for specificity are 0.98, 0.94, 0.94, and 0.90.

. Figure 12 shows the comparison of proposed and existing F1_Score metric. For all datasets the proposed LSTM classifier is 100% and it is seen to be greater on comparison on other existing systems such as ANN, SVM, RF, NB are 0.94, 0.91, 0.89, 0.87 respectively.

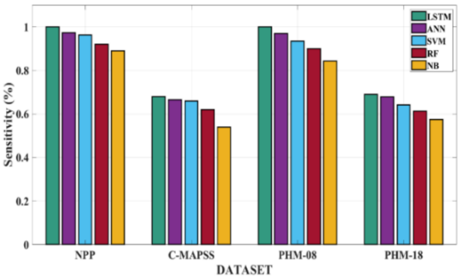


Figure 12: **Comparison of proposed and existing sensitivity metric**

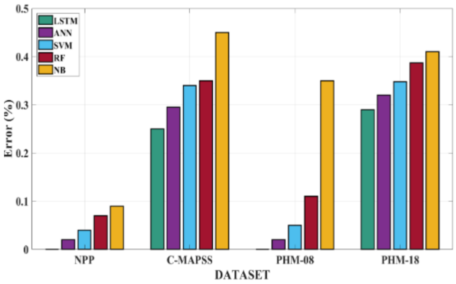


Figure 13: **Comparison of proposed and existing Error metric**

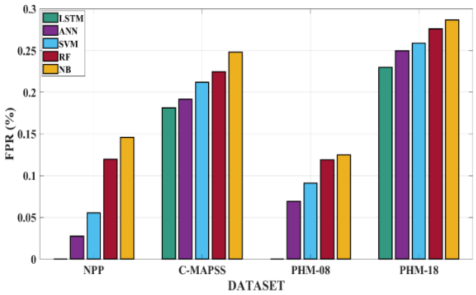


Figure 14: **Comparison of proposed and existing false positive Rate metric**

figure 13. The graph is plotted among the several techniques such as proposed and existing machine learning techniques The error for the proposed method is 0 is less than the existing four methods such as ANN, SVM, RF, and NB are 0.02, 0.04, 0,07,0.09 respectively.

The comparison analysis of False Positive Rate with Proposed and existing machine learning techniques is shown in figure 14. The graph is plotted among the several techniques such as proposed and existing machine learning techniques and the value of FPR rate on both X and Y- labels respectively. The FPR value is low in proposed technique compared to existing techniques. The FPR value for the proposed method

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

is 0 is less than the existing four methods such as ANN, SVM, RF, and NB are 0.02, 0.05, 0.2 and 0.14 respectively.

5. Conclusion

In this paper a long short term memory was proposed to detect the recessive disturbances in Cyber physical System. The execution of the proposed LSTM classifier is compared and examined with some existing techniques such as ANN, SVM, RF and NB. The outcomes exposed that the applied methods executed and that reveals better results as 100% of accuracy for NPP dataset. Result showed that the proposed LSTM classifier can produced optimal solution compared to our existing approaches. Therefore the proposed approach can be a good alternative for improving the existing approaches. The construction of association links between decision-making to realise energy conservation energy and the Big Data will be a focus of future work.

REFERENCES

[1]Liu, C., Cai, W., Jia, S., Zhang, M., Guo, H., Hu, L. and Jiang, Z., 2018. Energy-based evaluation and improvement for sustainable manufacturing systems considering resource efficiency and environment performance. Energy conversion and management, 177, pp.176-189.

[2] Lu, Y., Peng, T. and Xu, X., 2019. Energy-efficient cyber-physical production network: Architecture and technologies. Computers & Industrial Engineering, 129, pp.56-66.

[3] Tao, F., Qi, Q., Wang, L. and Nee, A.Y.C., 2019. Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. Engineering, 5(4), pp.653-661.

[4] Mawson, V.J. and Hughes, B.R., 2019. The development of modelling tools to improve energy efficiency in manufacturing processes and systems. Journal of Manufacturing Systems, 51, pp.95-105.

[5] Lawrence, A., Thollander, P., Andrei, M. and Karlsson, M., 2019. Specific energy consumption/use (SEC) in energy management for improving energy efficiency in industry: Meaning, usage and differences. Energies, 12(2), p.247.

[6] Cain, W., Liu, C., Lai, K.H., Li, L., Cunha, J. and Hu, L., 2019. Energy performance certification in mechanical manufacturing industry: A review and analysis. Energy Conversion and Management, 186, pp.415-432.

[7] Liu, T., Tian, B., Ai, Y. and Wang, F.Y., 2020. Parallel reinforcement learning-based energy efficiency improvement for a cyber-physical system. IEEE/CAA Journal of Automatica Sinica, 7(2), pp.617-626.

[8] Mohamed, N., Al-Jaroodi, J. and Lazarova-Molnar, S., 2019. Leveraging the capabilities of industry 4.0 for improving energy efficiency in smart factories. Ieee Access, 7, pp.18008-18020.

[9] Leng, J., Zhang, H., Yan, D., Liu, Q., Chen, X. and Zhang, D., 2019. Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop. Journal of ambient intelligence and humanized computing, 10(3), pp.1155-1166.

[10]Zhang, C., Wang, Z., Ding, K., Chan, F.T. and Ji, W., 2020. An energy-aware cyber physical system for energy Big data analysis and recessive production anomalies detection in discrete manufacturing workshops. International Journal of Production Research, 58(23), pp.7059-7077.

[11] Bevilacqua, M., Ciarapica, F. E., Diamantini, C., & Potena, D. (2017). Big data analytics methodologies applied at energy management in industrial sector: A case study. International Journal of RF Technologies, 8(3), 105-122.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online): 0493-2137
E-Publication: Online Open Access
Vol:55 Issue:06:2022
DOI 10.17605/OSF.IO/GVZE2

[12] Campatelli, G., L. Lorenzini, and A. Scippa. 2013. “Optimization of Process Parameters Using a Response Surface Method for Minimizing Power Consumption in the Milling of Carbon Steel.” Journal of Cleaner Production 66 (1): 309–316.

[13] Delgado-Gomes, V., J. A. Oliveira-Lima, and J. F. Martins. 2017. “Energy Consumption Awareness in Manufacturing and Production Systems.” International Journal of Computer Integrated Manufacturing 30 (1): 84–12.

[14] Park, K. T., Y. T. Kang, S. G. Yang, W. B. Zhao, Y. Kang, S. J. Im, D. H. Kim, S. Y. Choi, and S. Do Noh. 2019. “Cyber Physical Energy System for Saving Energy of the Dyeing Process with Industrial Internet of Things and Manufacturing Big Data.” International Journal of Precision Engineering and Manufacturing-Green Technology.

[15] Zhang, C., and P. Jiang. 2020. “RFID-Driven Energy-Efficient Control Approach of CNC Machine Tools Using Deep Belief Networks.” IEEE Transactions on Automation Science and Engineering 17 (1): 129–141

[16] Ma, S., Zhang, Y., Lv, J., Yang, H. and Wu, J., 2019. Energy-cyber-physical system enabled management for energy-intensive manufacturing industries. Journal of cleaner production, 226, pp.892-903

[17] Ma, S., Zhang, Y., Liu, Y., Yang, H., Lv, J. and Ren, S., 2020. Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries. Journal of Cleaner Production, 274, p.123155.

[18] Zhang, C. and Ji, W., 2020. Edge computing enabled production anomalies detection and energy-efficient production decision approach for discrete manufacturing workshops. IEEE Access, 8, pp.158197-158207.

[19] Cain, Z., Yang, X., Huang, T. and Zhu, W., 2020. A new similarity combining reconstruction coefficient with pairwise distance for agglomerative clustering. Information Sciences, 508, pp.173-182.

[20] Granato, Daniel, Jânio S. Santos, Graziela B. Escher, Bruno L. Ferreira, and Rubén M. Maggio. "Use of principal component analysis (PCA) and hierarchical cluster analysis (HCA) for multivariate association between bioactive compounds and functional properties in foods: A critical perspective." Trends in Food Science & Technology, vol: 72, pp. 83-90, 2018.

[21] Filzmoser, P. and Hron, K. Correlation analysis for compositional data. Mathematical Geosciences, 41(8), pp.905-919.

[22] Rao, G., Huang, W., Feng, Z. and Cong, Q., 2018. LSTM with sentence representations for document-level sentiment classification. Neurocomputing, 308, pp.49-57.

[23] https://github.com/makinarocks/awesome-industrial-machine-datasets/tree/master/data-explanation /Naval %20Propulsion%20Plants

[24] https://github.com/makinarocks/awesome-industrial-machine-datasets/tree/master/data-explanation/C-MAPSS