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A novel prediction approach for condition-based maintenance of class II machines via optimized neural network

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Condition-based maintenance (CBM) utilizes the real conditions of the components to make a decision when to replace and/or maintain the components, thus maximizing the life span of the machineries, whilst minimizing the count of service interferences. Particularly, CBM system identifies the noteworthy variations and fluctuations of signals and variables on the basis of sensor information so as to avoid or prevent the breakdown in machines. Thereby, this work develops a new prediction model on CBM in class II machines, where vibration velocity and average time are considered as input parameters and accordingly, the availability and reliability are predicted. Here, the proposed scheme consists of 2 chief phases like (1) feature extraction and (2) prediction. At first, feature extraction is performed, wherein statistical and higher-order statistical features are extracted. Subsequent to this, the extracted features are given to the Neural Network (NN) classifier that predicts the final output (availability and reliability of machines). To enhance the prediction accuracy of the classifier, the weights of NN are fine-tuned via Levy Flight Adopted Grey Wolf Optimization (LF-GWO). At last, the supremacy the presented approach is proved with respect to varied measures.

Keywords: CBM, class II machines, neural network, availability and reliability, LF-GWO algorithm.

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Introduction

"Condition-Based Maintenance (CBM) is defined by EN13306:2010 as Preventive maintenance that includes a combination of condition monitoring and/or inspection and/or testing, analysis and subsequent maintenance actions" [9, 10] "ISO 13372:2012 standard defines CBM as Maintenance performed as governed by condition monitoring programs". CBM examines the conditions of systems and components for determining dynamic protective schedules [11–13].

CBM is gradually turning out to be general in a manufacturing system, enhancing the changeover from maintaining techniques, which merge run-to-fail and programmed preventative preservation to more proficient maintenance techniques [1, 14, 15]. In current decades, the manifestation of reliable and cheaper ICT-like wireless tools, private digital device, and intellectual sensors have permitted a raise in the effectiveness of the CBM program [31]. In automatic industrialized plants, CBM is favored anywhere as it is financially viable and technically practicable [16–19].

The conventional industrialized outlook of CBM is largely concerned on the usage of CM-like thermography, vibration examination, tribology or acoustic discharge [14]. The current growth of the PHM discipline is endorsing a novel CBM, offering powerful abilities for substantial knowledge of valuable existence of system via dynamic pattern recognition. These abilities permit us to efficiently treat new maintaining demands in modern applications and systems. This novel CBM [1, 20, 21] is the most important support for the execution of E-maintaining policies, wherein, CBM build up its full prospective via more practical maintaining management. Nevertheless, there is yet a large gap for effectual execution of such novel CBM programs comprehensively in industry, mostly due to the intricacy of these solution and its life cycles [22–25]. The neural network is known for its flexibility towards characteristics of application [47, 48].

The contribution of the work is given below.

- Introduces a novel prediction model on CBM for class-II machines with the exploitation of optimized NN.
- Proposing a novel algorithm known as Levy Flight Adopted Grey Wolf Optimization (LT-GWO) for fine-tuning the weights of NN.

The paper is organized as: Section 1 describes reviews on traditional CBM frameworks. Section 2 describes the data collection by the case study conducted in class II machines. Section 3 portrays the proposed prediction model for condition-based maintenance of class II machines. Further, Section 4 addresses the extraction of features. The optimized NN model for prediction via the LF-GWO algorithm is specified in Section 5. The results and are elucidated in Section 6.

1. Literature survey

1.1. Related works

In 2016, Antonio et al. [1] presented a technique along with a pattern for clarifying the structure and concepts behind specified CBM solutions. This work discussed regarding the requirement of CBM maintaining schemes in multifaceted contest such as E-maintaining policies. The template complemented the RCM tables, which almost compiled the data of present CBM solution.

In 2020, Muhammad et al. [2] have formulated a distinctive technique of summing up supplementary sensors for monitoring machine's condition with the intention of learning and deploying higher reliability state indicator. The consolidations of realistic sensor information and processing control signal yield higher-dimensional datasets. Further, automated segmentation helped in optimizing the quantity of data mining and data processing ahead of fault analysis.

In 2018, Guo et al. [3] have optimized the inventory threshold, lot size, overhaul thresholds and preventive preservation jointly in such a way that the whole cost of each unit time was reduced. Accordingly, a stochastic arithmetical approach was formed and resolved by a simulation-oriented optimization model that coupled RSM along with MC Simulation.

At last, sensitivity analysis and descriptive example were offered that demonstrated the developed scheme.

In 2021, Miha et al. [4] have shown a new CBM for TBLW system that performed condition recognition by means of observing the plasma light emission in online with amalgamation of offline scrutiny of SM. A mixture of quality constraints extracted from SM of malfunctioning parts was deployed for identifying process worsening, like optic contamination, minimal laser power or misaligning of opto-mechanical system. The data attained was deployed for making adjustments in predefined procedure on the basis of proficient domain knowledge.

In 2018, Alberto [5] has introduced CBM architecture for managing events and alarm on the basis of global data captivated by numerous sensors that incorporated a folk of CNC machine equipments. The developed approach was separated into 2 modules: "a local system embedded in each machine and a cloud as a service system to supervise the local accuracy based on global system knowledge". At last, an industrialized CPS analysis was carried out depending on a bearing standard, which authenticated the local constancy of CBM in examining the updates provided by global modules.

In 2017, Zhou et al. [6] have developed a "multi-level decision making" technique that optimally planned the maintenance functions of railway transportation consists of numerous modules separated into fundamental units for preservation. Scenario oriented chance-based MPC was exploited at the higher levels for determining an optimum long-term component-wise intervention plan for railway infrastructures, and TIO technique was deployed for converting the MPC crisis to a nonlinear constant optimization crisis.

In 2018, Alessio et al. [7] have shown "how the completion time of a lot is significantly affected by the preventive maintenance policy". It was performed by deploying arithmetical demonstrations attained by deploying both real industrial cases and ad-hoc schemes. The subsequent contribution relied on the adopted technique allowed the modelling of common synchronous generation lines and, specified a lot dimension, the calculation of their related service levels. The method was portrayed such that its expansion to diverse conditions (like dissimilar system outline and asynchronous equipments) was quite uncomplicated.

In 2018, Joeri et al. [8] have united CBM on one (scrutinized) element, with COM and periodic PM on other elements of the similar machinery. Moreover, 2 thresholds were implemented on the deprivation level to make a decision when to check the scrutinized element: while the deprivation level of the scrutinized element surpassed a primary "opportunistic" threshold, the scrutinized element was serviced jointly with another element that requires CM.

1.2. Review

Table 1 shows the review on CBM in machines. At first, FMSA was used in [1] that offers accurate measurement and it also offers better fault detection. However, provided template can be further improved. Nyquist criterion was used in [2] that proffer enhanced efficiency and it also minimizes processing data, but selecting minimal count of relevant features is challenging. Simulation-oriented optimization was deployed in [3] that offers higher sensitivity and it also offers enhanced system reliability. However, it needs more consideration on numerous attributes. In addition, Gaussian blur kernel model was used in [4], which obtains good process condition together with high reliability; nevertheless, it requires concern on online plasma monitoring system. K-NN algorithm was presented in [5] that predicts failure patterns with new stable update, but the reliability is not considered. Moreover, TIO

T a b l e 1. Review on conventional condition-based maintenance schemes in machines

Author	Method	Features	Challenges
Antonio et al. [1]	FMSA model	• Accurate measurement • Better fault detection	Provided template can be further improved
Muhammad et al. [2]	Nyquist criterion	• High efficiency • Minimizes processing data	Selecting minimal count of relevant features is challenging
Guo et al. [3]	Simulation oriented optimization	• High sensitivity • Enhanced system reliability	Needs more consideration on numerous attributes
Miha et al. [4]	Gaussian blur kernel model	• Good process condition • High reliability	Requires concern on online plasma monitoring system
Alberto et al. [5]	k-NN algorithm	• Predicts failure patterns • Offers new stable update	Need consideration on reliability
Zhou et al. [6]	TIO model	• Determines optimal clustering • Low set up cost	Speed limitations are not considered
Alessio et al. [7]	Markov process	• Evaluates repair probability • Minimal time duration	Continuous degradations have to be focused more
Joeri et al. [8]	Weibull distribution	• Reduced maintenance cost • Minimal downtime of machine	Misspecification errors require more concern

model was implemented in [6] that provides low set up cost along and it determines optimal clustering. Nevertheless, speed limitations are not concerned. In addition, Markov process was suggested in [7] which evaluate repair probability with minimal time duration. However, continuous degradations have to be focused more. Weibull distribution was introduced in [8] which minimizes the maintenance cost with minimal downtime of machine. However, misspecification errors require more concern.

2. Data collection from class II machines on condition-based maintenance

In prior to this prediction model, a study is attempted to quantify the influence of machine vibrations in class II machines (defined as per ISO 10816) with respect to availability and reliability of a chemical process plant for condition-based maintenance programs. The results obtained have revealed the unique pattern of variation of both the system availability and reliability values when the state changes from the failure initiation state to potential failure state. The data collected in the case study is presented in a recent study by Lasithan L. et al.[1], based on the manually collected data, an automatic system model using machine learning is mandatory.

3. Proposed prediction model for condition-based maintenance of class II machines

The implemented prediction approach on CBM of class II machines encompasses 2 most important phases such as: “Feature extraction and Classification”. At first, the input pa-

[1]Lasithan L., Shouri P., Rajesh V. An availability and reliability centered approach for condition based maintenance programs — A case study for class-II machines, in communication.

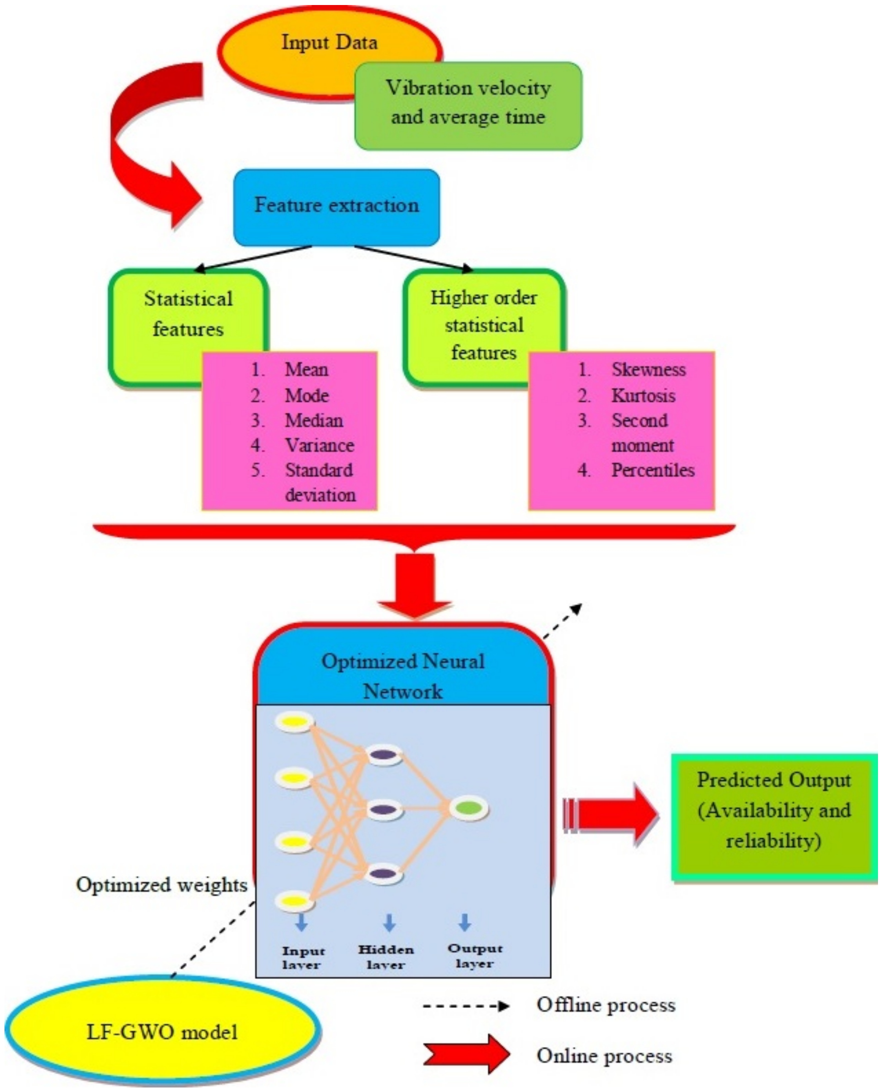

Fig. 1. Block diagram of adopted prediction framework

rameters namely, Vibration velocity and average time is subjected to feature extraction, wherein the statistical features (Fe_{st}) and higher order statistical features (Fe_{hst}) are derived. These features are then given as the input to a prediction model, wherein, NN is used. The outputs attained from NN determine the availability and reliability of chemical process plants for CBM programs, as the system is already trained with the information. For optimization purpose, this work exploits LF-GWO model that aids in attaining enhanced prediction results by optimal selection of weights in NN in a precise way. Fig. 1 shows the illustrative demonstration of developed LF-GWO prediction framework.

4. Extraction of statistical and higher order statistical features

4.1. Extraction of statistical features

Initially, the statistical features are determined from the parameters. Here, the statistical metrics namely; mean, mode, median, variance and SD are determined. The extracted statistical features are denoted by Fe_{st} .

4.2. Extraction of higher order statistical features

Skewness [35]: "It is a symmetry measure or the lack of symmetry exactly. A data set or distribution is symmetric only if it is similar to the left and right of the centre point". The mathematical expression of skewness SF_1 is given in Eq. (1).

$$SF_1 = \frac{\sum_{i=1}^{k} \frac{(Y_i - \mu)^3}{K}}{L^3}. \tag{1}$$

In Eq. (1), $Y_i = Y_1, Y_2, \ldots, Y_k$, μ indicates the mean value, L denotes the SD, and k refers to the count of data points. Moreover, L is calculated with k presents in the denominator rather than $k - 1$ while computing the skewness. Further, the skewness value is near zero for any symmetric data, and zero for the skewness for a normal distribution.

Kurtosis [35]: "It is a measure that identifies whether the data are light-tailed or heavy-tailed and related to the normal distribution". Data with less kurtosis [35] trends to provide the lack of outliers, or lower tails. Moreover, the datasets with larger kurtosis tends to provide outliers, or heavy tails. The mathematical formula of kurtosis SF_2 for univariate data such as Y_1, Y_2, ..., Y_k, is expressed in Eq. (2).

$$SF_2 = \frac{\sum_{i=1}^{k} \frac{(Y_i - \overline{\mathrm{Y}})^4}{K}}{L^4}. \tag{2}$$

The SD is calculated by k value presents in the denominator rather than $k - 1$ while computing the kurtosis.

Second Moment [36]: "It is a measure of the uniformity of an input data" and it is computed as in Eq. (3).

$$SF_3 = SM = \sum_u \sum_v \{g(u, v)\}^2. \tag{3}$$

Percentile [37]: It provides an idea of "how the data values are spread over the interval from the smallest value to the largest value". About Q percentage of data values comes under Q^{th} percentile, and around $100 - Q$ percentage of data values exceeds P^{th} percentile. The percentile features are denoted by SF_4.

The higher order statistical features are indicated as Fe_{hst}, and it is given in Eq. (4).

$$Fe_{hst} = SF_1 + SF_2 + SF_3 + SF_4. \tag{4}$$

Accordingly, the extracted statistical and higher order statistical features are summed up as Fe ($Fe = Fe_{st} + Fe_{hst}$). These features are given as input to optimized NN for predicting the availability and reliability.

5. Optimized NN model for prediction via LF-GWO algorithm

5.1. NN model

In fact, two major predictions are carried out by the optimized NN. They are predicting the availability and reliability as well. NN [38] considers the extracted feature Fe as input, which is represented in Eq. (5), wherein, signifies the entire count of features.

$$Fe = \{Fe_1, Fe_2, \ldots, Fe_m\}. \tag{5}$$

The NN model [28] includes output, hidden and input layers. The hidden layer output $z^{(H)}$ is defined by Eq. (6), where AF points out the activation function, $\widehat{i}$ and j points out neurons of hidden and input layers in that order, $We^{(H)}_{(Bi)}$ points out the bias weight to $\widehat{i}^{\text{th}}$ hidden neuron, n_i represents count of input neurons and $We^{(H)}_{(ji)}$ points out the weight from j^{th} input neuron to $\widehat{i}^{\text{th}}$ hidden neuron. The network output $\widehat{Q}_o$ is defined by Eq. (7), where, $\widehat{o}$ indicates the output neurons, n_h specifies hidden neuron count, $We^{(Q)}_{(B\hat{o})}$ signifies the output bias weight to $\widehat{o}^{\text{th}}$ output layer, and ,$We^{(Q)}_{(\widehat{i}\widehat{o})}$ denotes the weight from $\widehat{i}^{\text{th}}$ hidden layer to $\widehat{o}^{\text{th}}$ output layer. Further, the error between actual and predicted values is evaluated as in Eq. (8), which has to be lessened. In Eq. (8), n_x signifies the count of output neuron, $\widehat{Q}_{\widehat{o}}$ and signifies the predicted and actual output in that order.

$$Z^{(H)} = AF\left(We^{(h)}_{(B\hat{i})} + \sum_{j=1}^{n_i} We^{(h)}_{(j\hat{i})} Fe\right), \tag{6}$$

$$\hat{Q}^{Availability}\hat{o} = AF\left(We^{(Q)}_{(B\hat{o})} + \sum_{i=1}^{n_h} We^{(Q)}_{(\hat{i}\hat{o})} z^{(H)}\right) //NN1, \tag{7}$$

$$Er^* = \underset{\left\{We^{(H)}_{(B\hat{i})}, We^{(H)}_{(j\hat{i})}, We^{(Q)}_{(B\hat{o})}, We^{(Q)}_{(\hat{i}\hat{o})}\right\}=1}{\arg\min} \sum^{n_G} |Q_{\hat{o}} - \hat{Q}_{\hat{o}}|. \tag{8}$$

In NN, the weights, $We^{(H)}_{(B\widehat{i}}$), $We^{(H)}_{(j\widehat{i})}$, $We^{(Q)}_{(B\widehat{o})}$, $We^{(Q)}_{(i\widehat{o})}$ are optimally tuned via LF-GWO model. Here, the analysis to predict the availability and reliability of class-II machines is carried out by deploying two datasets namely,"Failure data of Primary blower and Failure data of ID fan". Eq. (7) determines the predicted output of availability, whereas the second NN determines the prediction of reliability, thereby the reliability from output layer of NN 2 is defined as per Eq. (9).

$$\hat{Q}^{Reliability}\hat{o} = AF\left(We^{(Q)}_{(B\hat{o})} + \sum_{i=1}^{n_h} We^{(Q)}_{(\hat{i}\hat{o})} z^{(h)}\right) //NN1. \tag{9}$$

5.2. Proposed LF-GWO algorithm

Though the conventional GWO [26] model encompasses a variety of enhancements, it suffers from specific limitations like, local optima, slower convergence etc [34, 45, 46]. Hence, certain modifications are needed and a new algorithm is developed. Generally, self-improvement is established to be capable in conventional optimization schemes [27–34]. The steps followed in the proposed LF-GWO are as follows.

The wolves α, β and γ are the most important wolves, which concern on hunting process. Amongst these, α is the leader that takes decisions on hunting procedure, sleeping place, time for awakening, etc, while, β and γ takes the 2nd and 3rd level and they aid α in decision making. Accordingly, the last set of wolves is ζ that focuses on eating. The encircling feature of wolves are formulated as in Eq. (11), where U signify coefficient vectors, J_p point out position vector of prey, J point out wolves' position vector and it point out present iteration and Z refers to the distance. In Eq. (10), V denotes the random vector that lies among 0 and 1 and it is computed as per Eq. (14). Conventionally, constraint $\widehat{b}$ in Eq. (12) lies between 2 to 0. As per the developed scheme, constraint $\widehat{b}$ is evaluated as shown in

Eq. (13), wherein, φ is computed as in Eq. (14). Here, ra_2 and ra_1 points out arbitrary vectors amongst $[0,1]$ and $it_{\max}$ point out the maximal iteration.

$$Z = |V.J_p(it) - J(it)|, \tag{10}$$
$$J(it+1) = J_p(it) - U.Z, \tag{11}$$
$$U = 2\hat{b}.ra_1 - \hat{b}, \tag{12}$$
$$\hat{b} = 2 - 2 * \sin^2\left(\frac{\varphi}{2}\right), \tag{13}$$
$$\varphi = \frac{1}{2}\arctan(it), \tag{14}$$
$$V = 2ra_2. \tag{15}$$

The numerical method for depicting the hunting nature of wolves is shown in Eq. (16). Conventionally, the last position of the wolf is updated by evaluating J_1, J_2 and J_3. As per the presented work, the final position of the wolf is computed based on levy flight distribution ($Levy(\beta)$) as revealed in Eq. (17).

$$Z_\alpha = |V_1 J_\alpha - J|, \quad Z_\beta = |V_2 J_\beta - J|, \quad Z_\gamma = |V_3 J_\gamma - J|, \tag{16}$$
$$J_{new}(it) = 0.5[J_\alpha - U_1.(Z_\alpha) + J_\beta - U_2.(Z_\beta) + J_\gamma - U_3.(Z\gamma)] + \alpha \oplus Levy(\beta). \tag{17}$$

Algorithm 1 Developed LF-GWO model

1: Initializing population
2: Compute the fitness
3: Assign J_α as best searching agent
4: Assign J_β as 2nd best searching agents
5: Assign J_γ as 3rd best searching agents
6: While ($it < it_{\max}$)
7: For every wolf
8: Update position based on proposed levy update as per Eq. (17)
9: End for
10: Determine $\hat{b}$ as per proposed computation in Eq. (13)
11: Update $\hat{b}$, U and V $it = it + 1$
12: Calculate the fitness
13: End while
14: Return J_α

6. Results and discussion

6.1. Simulation setup

The developed prediction approach on the CBM model using LF-GWO+NN was executed in MATLAB. The analysis was done via two datasets namely, "Failure data of Primary blower and Failure data of ID fan", which were represented as dataset 1 and dataset 2, respectively in a recent study by Lasithan L. et al.[2]. Vibration severity levels (critical values) based on the chart of ISO-10816 for class II machines are shown in Table 2. The availability and reliability

[2]See footnote on p. 73.

T a b l e 2. ISO-10816 vibration severity standards for class II machines

Condition of class-II machines	Vibration Velocity (rms value), mm/sec
Good operating condition	0.28 to 1.12
Satisfactory	1.80 to 2.80
Unsatisfactory	4.50 to 7.10
Unacceptable	11.2 to 45.9

T a b l e 3. Failure datas for the components (due to reasons other than vibration in white section

SI. No	Component	Frequently happening failure mode	Mean time between failures (MTBF), hours	Mean time to repair (MTTR), hours	Availability
1	Feed screw (FS)	Melting of water jacket	5760	504	0.91954
2	Oil pump (OP)	Decrease in pump pressure due to bearing wear	1608	2	0.99876
3	Screw compressor (SC)	Temperature rise due to oil shortage	4250	2	0.99953
4	Electrostatic Precipitator (ESP)	Electrode failure	144	24	0.857144
5	Pendulum Mill (PM)	Pendulum failure	1800	336	0.8427
6	Drum Filter (DF)	Corrosion in drum	1440	72	0.95238

T a b l e 4. Power requirement, speed and load on the primary blower and ID fan

Vibration affected machine	Power requirement, HP	Speed requirement, RPM	Load, kg
Primary blower	6.3	1555.2	6.6
ID fan	29.2	1296	20.5

T a b l e 5. Failure data for primary blower and id fan other than vibration

Component	Frequently happening failure mode	MTBF, hours	MTTR, hours	Availability
Primary blower	Electrical problem of motor	3654	336	0.91579
ID fan	Corrosion in leaf	15 330	168	0.98915

vary with respect to vibration velocity and time. This has been illustrated in Fig. 2 and 3 (Lasithan et al.[3].). The failure data for Feed screw (FS), Furnace oil pump (OP), Screw Compressor (SC), Electrostatic precipitator (ESP), Pendulum mill (PM), and drum filter (DF) are shown in Table 3. Using Fan laws, the power requirement, speed and load on the primary blower and ID fan are shown in Table 4. Table 5 gives the failure data for the primary blower and ID fan other than vibration. Here, the performance of developed scheme was measured over extant schemes like DBN [39], LA+NN [40], EHO+NN [41], MFO+NN [42], PSO+NN [43], WOA+NN [44] and GWO+NN [26]. Moreover, the performance of the developed model was measured over extant models regarding varied learning rates such as 50, 55, 60, 65, 70, 75 and 80. Moreover, the superiority of the presented model was validated with respect to error analysis in terms of MAE, MAPE, MARE, MSE, MSPE, MSRE, RMSE, RMSPE and RMSRE.

[3]See footnote on p. 73

6.2. Error analysis: Proposed vs. conventional models for dataset 1

The error among the actual target and predicted outcomes for the implemented CBM approach using LF-GWO+NN over traditional models are described in this section for varied error factors namely, MAE, MAPE, MARE, MSE, MSPE, MSRE, RMSE, RMSPE and RMSRE. The analysis using dataset 1 for MAE, MAPE, MARE metrics are given in Fig. 4, MSE, MSPE, MSRE metrics are given in Fig. 2 and RMSE, RMSPE and RMSRE metrics are given in Fig. 3. The outcomes are taken by varying the learning rates such as 50, 55, 60, 65, 70, 75 and 80. From the analysis, the error output for the presented approach has accomplished minimal values for all learning rates. More predominantly, the adopted scheme has achieved the least MAE value of 10 while the learning rate is 50. That is, the developed approach is 88.24, 60, 50, 79.17, 85.29 and 60 % enhanced than extant DBN, LA+NN, EHO+NN, MFO+NN, PSO+NN and GWO+NN models when the learning rates is 50. In addition, the analysis on MSE attained by the presented model over extant approaches for varied learning rates is shown in Fig. 2. The minimized error measures prove how accu-

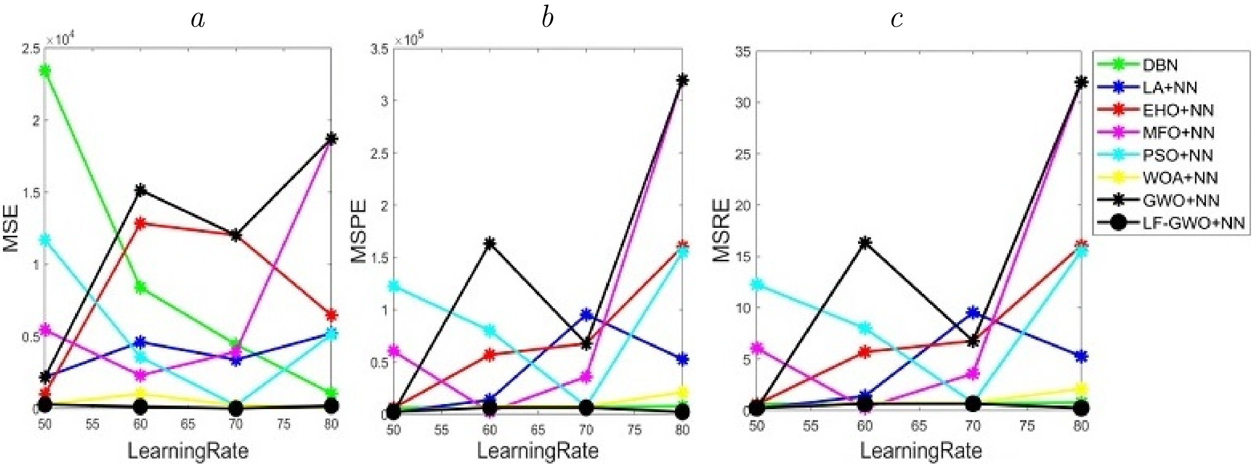

Fig. 2. Error analysis of developed scheme over existing schemes regarding MSE (a), MSPE (b) and MSRE (c) for dataset 1

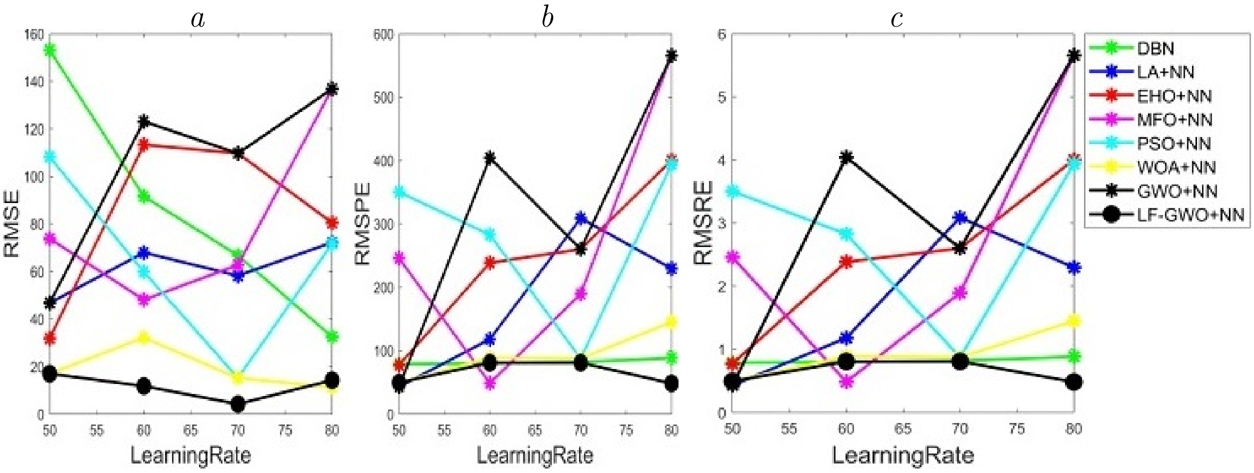

Fig. 3. Error analysis of developed scheme over existing schemes regarding RMSE (a), RMSPE (b) and RMSRE (c) for dataset 1

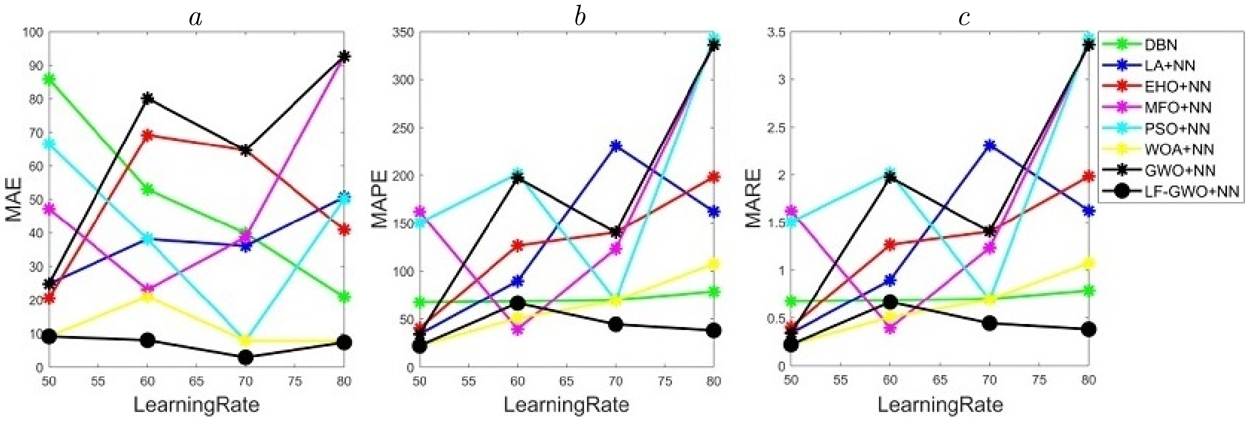

Fig. 4. Error analysis of developed prediction scheme over existing schemes regarding MAE (*a*), MAPE (*b*) and MARE (*c*) for dataset 1

rate the prediction is by the proposed work. The MSE has to be minimal for the improved prediction results. On noticing Fig. 2, the adopted LF-GWO+NN scheme has attained a minimal MSE value (0.001) when the learning rate is 50. That is, the adopted scheme is 99.96, 99.5, 99, 99.8, 99.92 and 99.5 % superior to traditional DBN, LA+NN, EHO+NN, MFO+NN, PSO+NN and GWO+NN models. Likewise, when the learning rate is 80, the developed scheme has attained a minimal MAPE value of 48 that is lesser than the extant approaches, thus making sure about the prediction of the introduced model. Consequently, the assessment proves the betterment of suggested LF-GWO+NN scheme in predicting both availability and reliability.

6.3. Error analysis: Proposed vs. conventional models for dataset 2

The performances of the adopted scheme (LF-GWO+NN) over extant schemes for varied error metrics such as MAE, MAPE, MARE, MSE, MSPE, MSRE, RMSE, RMSPE and RMSRE are described in this section. Accordingly, error analysis was performed for learning rates such as 50, 55, 60, 65, 70, 75 and 80 that are revealed in Fig. 5, 6 as well as Fig. 7. On noticing the examination resultants, the adopted LF-GWO+NN model has obtained minimal error (for all metrics) while evaluated over prevailing schemes. In particular, reduced error values guarantee the enhanced performance of the developed model. More particularly, on considering MAPE from Fig. 5, *b*, the adopted model for dataset 2 has attained less value, and it is 66.67, 82.76, 86.49, 87.5, 86.49, 28.57 and 86.49 % better than traditional DBN, LA+NN, EHO+NN, and MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively. Similarly, on considering the RMSE metric from Fig. 7, *a*, the implemented LF-GWO+NN model seems to attain minimal values than the developed model for all learning rates. That is, the adopted approach for learning rate 70 is 80.77, 87.18, 87.18, 50, 72.22 and 87.18 % better than conventional DBN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively with less error rate. While focusing the RMSRE measure from Fig. 7, *c*, the presented scheme has accomplished minimal error for all learning rates. Therefore the analysis proved the supremacy of the proposed LF-GWO+NN work in attaining minimal error rates. This analysis results prove the impact of optimization in predicting both the availability and reliability by proposed work.

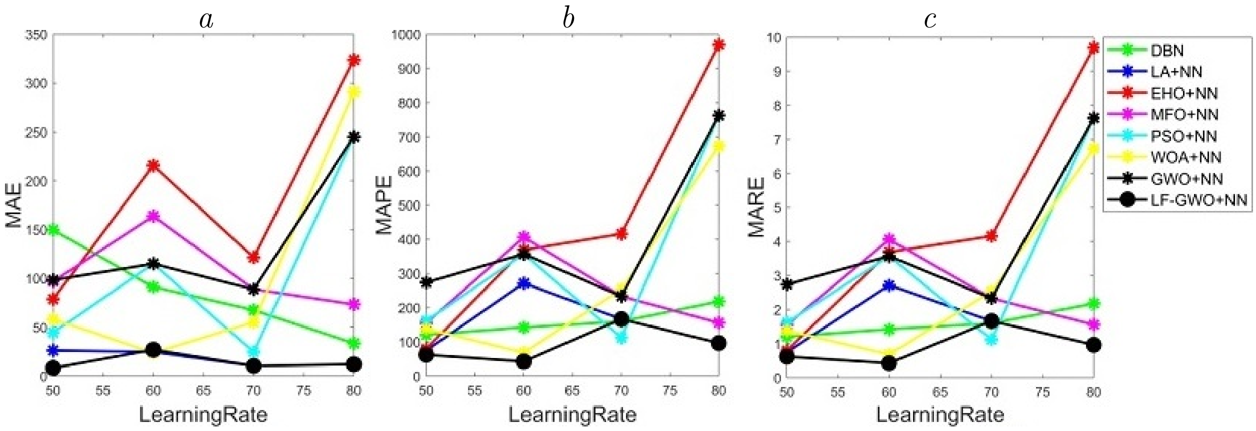

Fig. 5. Error analysis of developed scheme over existing schemes regarding MAE (a), MAPE (b) and MARE (c) for dataset 2

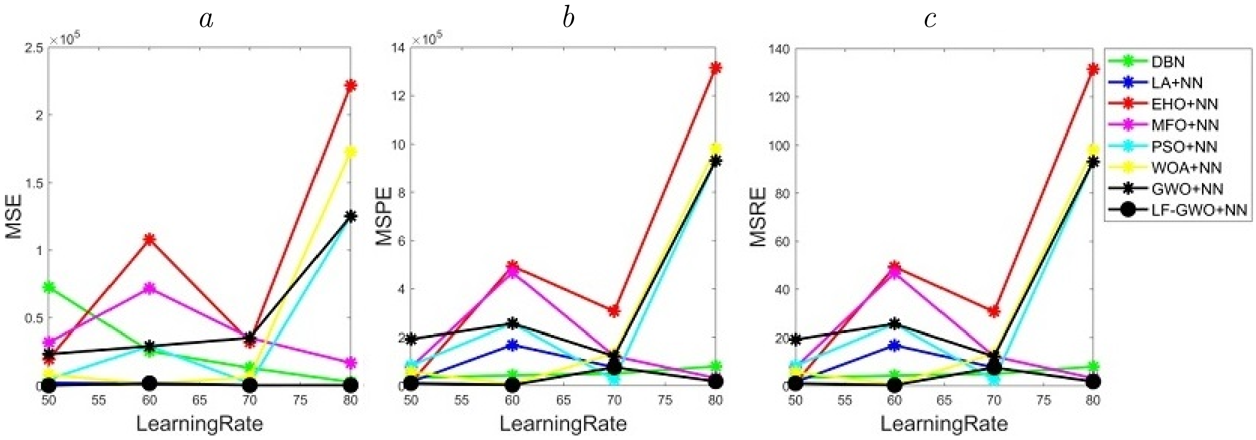

Fig. 6. Error analysis of developed scheme over existing schemes regarding MSE (a), MSPE (b) and MSRE (c) for dataset 2

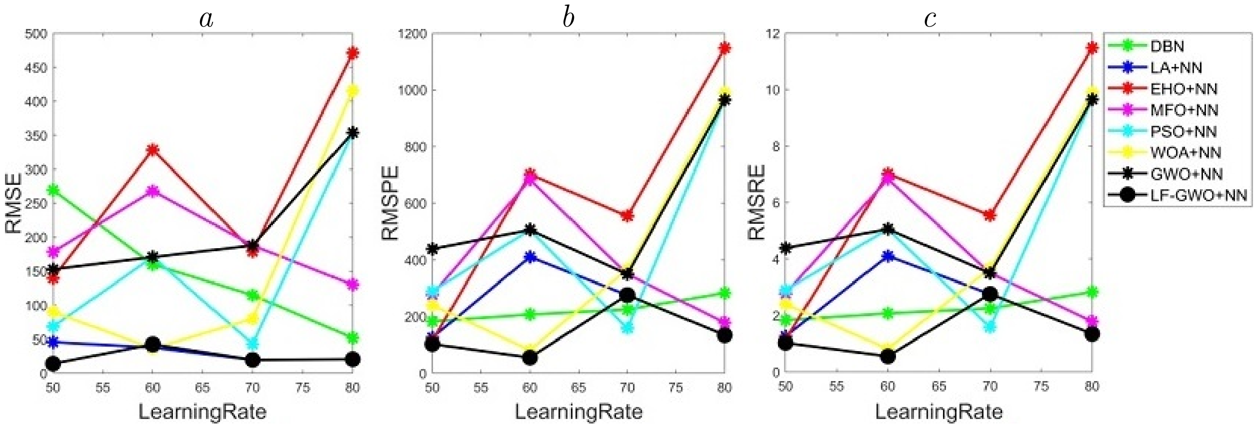

Fig. 7. Error analysis of developed scheme over existing schemes regarding RMSE (a), RMSPE (b) and RMSRE (c) for dataset 2

6.4. Overall error analysis

Tables 6, 7 describe the overall error analysis of the adopted LF-GWO+NN model over traditional schemes. Accordingly, error analysis was performed for metrics like MAE, MAPE, MARE, MSE, MSPE, MSRE, RMSE, RMSPE and RMSRE for dataset 1 and dataset 2. On examining the graphs, the adopted LF-GWO+NN model has attained minimal error (for all metrics) while evaluated over prevailing schemes. Predominantly, on considering RMSE from Table 6, the developed model for dataset 1 has attained less value, and it is 93.66, 92.74, 96.14, 93.26, 72.21, 72.21 and 96.14 % better than DBN, LA+NN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively. Similarly, on considering dataset 2, the MSE of implemented model is 84.47, 91.35, 88.18, 57.18, 80.96 and 88.18 % better than DBN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively with less error rate. While considering the RMSRE measure from Table 6, the presented LF-GWO+NN model scheme has accomplished minimal error for the presented approach. Specifically, for dataset 1, the suggested model is 1.07, 73.76, 68.83, 57.26, 68.83, 7.28 and 7.28 % better than conventional DBN, LA+NN, EHO+NN, MFO+NN, GWO+NN, WOA+NN and PSO+NN models respectively. On analyzing the RMSE measure from Table 7, the presented model for dataset 2 has achieved a minimal value of 19.874, while the compared models like DBN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and

Table 6. Overall error analysis: Proposed vs. conventional models in terms of varied metrics for dataset 1

Metrics	LF-GWO+NN	GWO+NN	WOA+NN	PSO+NN	MFO+NN	EHO+NN	LA+NN	DBN
MAE	2.93	64.63	7.86	7.86	38.72	64.63	36.11	39.86
MSE	17.88	12 032.00	231.49	231.49	3940.40	12 032.00	3392.30	4454.20
RMSE	4.23	109.69	15.22	15.22	62.77	109.69	58.24	66.74
MSPE	6573.70	67 666.00	7646.40	7646.40	35 978.00	67 666.00	95 451.00	6717.20
RMSPE	81.08	260.13	87.44	87.44	189.68	260.13	308.95	81.96
MAPE	44.53	140.47	69.32	69.32	123.52	140.47	230.91	69.97
MARE	0.45	1.40	0.69	0.69	1.24	1.40	2.31	0.70
MSRE	0.66	6.77	0.76	0.76	3.60	6.77	9.55	0.67
RMSRE	0.81	2.60	0.87	0.87	1.90	2.60	3.09	0.82

Table 7. Overall error analysis: Proposed vs. conventional models in terms of varied metrics for dataset 2

Metrics	LF-GWO+NN	GWO+NN	WOA+NN	PSO+NN	MFO+NN	EHO+NN	LA+NN	DBN
MAE	10.51	88.88	55.188	24.54	88.88	121.45	10.51	67.66
MSE	394.97	35 379	6434	1876.8	35 379	32 313	394.97	13 230
RRMSE	19.87	188.09	80.212	43.32	188.09	179.76	19.87	115.02
MSPE	76 395	$1.23 \cdot 10^5$	$1.34 \cdot 10^5$	25 258	$1.23 \cdot 10^5$	$3.07 \cdot 10^5$	76 395	50 774
RMSPE	276.4	350.04	366.46	158.93	350.04	554.18	276.4	225.33
MAPE	166.94	233.57	253.11	112.07	233.57	416.14	166.94	160.24
MARE	1.67	2.34	2.53	1.12	2.33	4.16	1.67	1.60
MSRE	7.64	12.25	13.42	2.52	12.25	30.71	7.64	5.08
RMSRE	2.76	3.50	3.66	1.59	3.50	5.541	2.76	2.25

GWO+NN has achieved relatively higher RMSE values of 115.02, 179.76, 188.09, 43.322, 80.212, 188.09. Therefore the analysis proved the supremacy of the proposed work in attaining minimal error rates.

6.5. Discussion

In this work, a novel prediction model on CBM in class II machines are proposed. To predict the availability and reliability, vibration velocity and average time are considered as input parameters. To show the effectiveness of the proposed method, the offered scheme was compared over the traditional methods with respect to various measures. For analysis, two datasets have been utilized, namely, "Failure data of Primary blower and Failure data of ID fan". The analysis is carried out based on error measures like MAE, MAPE, MARE, MSE, MSPE, MSRE, RMSE, RMSPE and RMSRE. On noticing the result, it can be observed that the proposed method attains minimal value, which is evident through Fig. 4 to 7 for both the dataset 1 and 2, respectively. The result reveals the improved prediction accuracy. This was attained by fine-tuning the weights of NN using Levy Flight Adopted Grey Wolf Optimization (LF-GWO).

Conclusion

This paper had developed a new CBM model using LF-GWO+NN algorithm. At first, the statistical and higher-order statistical features were derived. Subsequently, the features were offered as input to NN for prediction, where the weights of NN get fine-tuned via LF-GWO+NN model. At last, the superiority of offered scheme was established over the conventional schemes regarding various measures. Predominantly, the proposed LF-GWO+NN model has attained minimal error (for all metrics) when evaluated over prevailing schemes. More particularly, on considering RMSE, the adopted model for dataset 1 has attained less value, and it was 93.66, 92.74, 96.14, 93.26, 96.14, 72.21 and 72.21 %, better than DBN, LA+NN, EHO+NN, MFO+NN, GWO+NN, WOA+NN and PSO+NN models respectively. Similarly, on considering dataset 2, the MSE of implemented model was 84.47, 91.35, 88.18, 57.18, 80.96 and 88.18 % better than DBN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively with less error rate. While considering the RMSRE measure, the presented LF-GWO+NN model scheme has accomplished minimal error for the presented approach. Specifically, for dataset 1, the suggested model was 1.07, 73.76, 68.83, 57.26, 7.28, 7.28 and 68.83 % better than conventional DBN, LA+NN, EHO+NN, MFO+NN, PSO+NN, WOA+NN and GWO+NN models respectively. Therefore, the supremacy of the introduced LF-GWO+NN approach has been confirmed effectively.

Data availability statement. The data that support the findings of this study are "Failure data of Primary blower and Failure data of ID fan", available in Lasithan et al.[4].

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ИНФОРМАЦИОННЫЕ ТЕХНОЛОГИИ

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Новый подход к прогнозированию технического обслуживания по состоянию машин класса II с помощью оптимизированной нейронной сети

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Аннотация

Техническое обслуживание по состоянию (condition-based maintenance, CBM) использует реальные условия эксплуатации компонентов для принятия решения об их замене и/или обслуживании, таким образом увеличивая срок службы оборудования и сводя к минимуму помехи при обслуживании. Система CBM выявляет существенные изменения и колебания сигналов и переменных на основе информации датчика, чтобы избежать или предотвратить поломку машин. Таким образом, в данной работе разрабатывается новая модель прогнозирования на CBM в машинах класса II, в которой скорость вибрации и среднее время рассматриваются в качестве входных параметров и, соответственно, прогнозируются доступность и надежность машин. Предлагаемая схема состоит из двух основных этапов, таких как (1) выделение признаков и (2) предсказание. Сначала выполняется выделение статистических и статистических признаков более высокого порядка. Найденные признаки передаются классификатору нейронной сети (NN), который предсказывает конечный результат (доступность и надежность машин). Чтобы повысить точность прогноза классификатора, веса NN точно настраиваются с помощью оптимизации Levy Flight Adopted Gray Wolf (LF_GWO). Доказано преимущество представленного подхода по отношению к различным мерам.

Ключевые слова: CBM, машины класса II, нейронная сеть, доступность и надежность, алгоритм LF_GWO.

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