Intelligent Prediction Model: Optimized Neural Network for Lean Manufacturing Technology

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Jobin M V
Assistant Professor
Mets School of Engineering Mala
jobinmv9@gmail.com

Abstract: Lean manufacturing (LM) is a method, which focuses on reducing wastes and increasing the productivity within manufacturing firms. Several analyses were performed on LM technology depending on minimal lead times, enhanced quality and reduced operating costs. However, limitation exists in understanding its role to develop managing commitment, worker involvement and in turn its organizational performance. This paper intends to propose a new Neural Network (NN) based intelligent prediction framework. The initial process is manual labeling or response validation, which is carried out by utilizing the responses attained for each questions under each factors including lean awareness, employee involvement, management commitment, lean technology, Organizational Performance (OP) and Organizational Support (OS). Subsequently, NN is exploited for prediction process, where the features (received responses) are given as input and the labeling values attained are set as target. Further, in order to improve the prediction performance, the NN training is performed by a new Hybrid Particle Swarm and Pigeon Optimization (HPS-PO) algorithm via tuning the optimal weights. In fact, the proposed algorithm is the combination of Particle Swarm Optimization (PSO) and Pigeon Optimization Algorithm (POA), respectively. Finally, the performance of the proposed model is examined over conventional methods in terms of prediction analysis and error analysis.

Keywords: Lean manufacturing;Neural Network; PSO algorithm; Pigeon Optimization; HPS-PO model.

1. Introduction

Over the past decade, LMS was attaining a rising consideration as it serves as one of the method for productivity improvement and cost minimization in manufacturing (Xiong, et al., 2019; Möldner, et al., 2020). LMS mainly focuses on eliminating the wastes in the production process as initiated by Henry Ford. On the other hand, the lean drive in production has been quite passive for several decades (Antonio, et al., 2017; Susilawati, et al., 2015) . Lean is generally attained by exploiting the tools, which comprises of Value Stream Mapping (VSM), mistake proving, pull-production and visual management that are world-class techniques and tools effectively deployed in various sectors. This theory of enhancement through waste minimization is termed as lean approach (Silva, et al., 2013; Schonberger, 2019).

In a machine production firm, targeted wastes for elimination or reduction take account of unnecessary in-process inventory, unwanted transport of materials faulty processed part and so on (Marodin, et al., 2018; Munteanu & Ştefănigă, 2018; Abu, et al., 2019) . These wastes should be eliminated or reduced for improved performance of the firm. More profits are foreseen from lean practice in the manufacturing industries *(Li & Dawood, 2016)*. They are; improved quality, flexibility, reduced inventory; minimal production times, communication, and consumer satisfaction (Ghobadian, et al., 2018; Gandhi, et al., 2018) .

Unfortunately, equipment or labour failure could pave the way for major irregularities within lean and it can make the whole process to drop back (Botti, et al., 2017; Cai, et al., 2019). Machine learning techniques such as Artificial Neural Networks (ANNs) are deployed for handling numerous phases of software testing (Büyüközkan, et al., 2015; Banga, et al., 2020*; Sai Ambati, et al., 2020; Khorasani & Zeyun 2014; Srinivas & Ch, 2020; Chithra & Jagatheeswari, 2019)* Experimentations were conducted to assess the efficiency of the system and in addition, methods like Principle Components Analysis (PCA) were adopted to discover faults in the system. However, wide-ranging investigations to use lean approaches on machine manufacturing firms are still not satisfactory (Jordon, et al., 2019; Nassereddine & Wehbe, 2018*; Prasanalakshmi & Farouk, 2019; Potamias et al., 2019; Rupapara, et al., 2021)*

The major contributions of this research work are:

- Determining the manual labeling framework, where the response validation is done manually for individual factors.
- Introduces an optimized NN model for prediction purpose, where the weights are fine-tuned by a new hybrid algorithm.
- Proposing a new hybrid algorithm termed as HPS-PO, which combines the concept of PSO and POA algorithms.

The rest of the paper is organized as: Section 2 portrays the reviews done under this topic. Section 3 depicts about the architecture of proposed prediction model for LMS technology. Further, Section 4 addresses the proposed manual labeling. Optimization assisted NN for prediction: hybrid particle swarm and pigeon optimization algorithm is depicted in Section 5 and Section 6 describes the resultants and conclusion is elucidated in Section 7.

2. Literature review

2.1 Related works

In Prasad, et al., (2020) have analysed the risks that aroused in the execution of LMS in textile companies situated in southern India. The risks were recognized by exploiting the groups of mapping schemes namely, VSM, poka-yoke, kanban, 5S, kaizen, and visual controls. In addition, probable levels of achievement before and after the adoption of LMS were revealed by means of radar illustrations. At last, analysis was made with respect to time for validating the outcomes of the presented model.

In Jayanth, et al., (2020) have highlighted the performance of Lean as a method for constant enhancement in productivity and quality in electronics sector. The major plan was to demonstrate the electronic sector that LMS could raise the production by improving quality and minimizing errors. The foremost optimization constraints for manufacturing line were selected and examined with reference to the information on electronic manufactures. From the analysis, the quality and productivity level using LMS has been enhanced over the existing systems.

In Yadav, et al., (2020) presented an approach for improving the approval of LMS in manufacturing companies. The Decision Making Trial And Evaluation Laboratory (DEMATEL) and hybrid Fuzzy Analytical Hierarchy Process (FAHP) tools were deployed for quantifying and identifying the relationships amongst the drivers for LM execution. This hybridized model assisted in documenting the comparative priority and importance of the 31 drivers of lean manufacturing. Further, the outcomes exposed that enhanced quality management, shop-floor management, and manufacturing strategy drivers were the most significant drivers that enhanced the LM adoption.

In Oleghe & Salonitis, (2016) have focused on the lean index variations that revealed the LM features of the system. Varied lean index models have been proposed so far, however, they do not focused on the variations in lean index. Therefore, in this work, the variations in lean index were formulated using fuzzy logic oriented model. Finally, the simulation outcomes have proved the superiority of the adopted model in terms of robustness.

In Deshkar, et al., (2018) have adopted the theory of 'lean', in a plastic bag company by exploiting "VSM" framework. It mapped the present processes of the firm and evaluated it, and thus the wastes were found and accordingly, the bottlenecks were rectified. Also, the solutions were suggested for eradicating the identified wastes on the basis of 7 kinds of LM wastes. Moreover, a future state map was formed and consequently, both future and current state maps were examined with respect to processing time and lead time for computing the gain using VSM.

In Alhuraish, et al., (2016) have developed an AHP framework on the basis of 3 criterions, which determined the most effectual and optimal techniques of LM and "six sigma" in diverse firms. The criterions were "innovation performance, fiscal performance, and functioning performance". The outcomes have established the consequence of three criterions, for which certain methodologies were adopted. The revealed outcomes have shown that the firms, which implemented both six sigma and LM, were much proficient than firms that implemented either six-sigma or LM system.

In Velmurugan, et al., (2020) have developed a framework for waste management and productivity enrichment via lean theory in Indian firms. In this context, VSM was deployed for ignoring non-value-added steps and identifying value-added steps. Here, the non-value activities were recognized in every step and among every step by observing their waste of resources and time. Thus, by minimizing the amount of non value actions, the time consumption gets minimized and the throughput speed gets raised. This formulated the developed process more effectual.

In Sutharsan, et al., (2020) have presented a Lean Manufacturing System (LMS) approach for modelling an enhanced order handling procedure and it also examined the improvements attained using this model. Here, the foremost accomplishments have formed a win-win scenario for the non-manufacturing firms across value chain. Furthermore, the enhancement of the adopted model was achieved by eradicating the wastes from non-manufacturing units throughout whole value chain. In the same way, the adopted LMS model aided the case companies in accomplishing higher effectiveness. Table 1 demonstrates the reviews on conventional LMS models.

Table 1: Features and Challenges of Traditional LMS models

Author [citation]	Methodology	Features	Challenges
Prasad, et al., (2020)	VSM	❖ Higher lean speed ❖ Improved worker efficiency	❖ Textile machinery costs high.
Jayanth, et al., (2020)	VSM	❖ Enhanced quality level ❖ High productivity	❖ No consideration on floor layout. ❖ Congestion problems are not focused
Yadav, et al., (2020)	FAHP model	❖ Offers unique balance ❖ Raises the economy	❖ No contemplation on structural comparisons. ❖ Relation among drivers is not considered
Oleghe & Salonitis, (2016)	Fuzzy logic	❖ Robust model ❖ Higher lean performance	❖ No validation in real life case study. ❖ Limitations exist on variation analysis
Deshkar, et al., (2018)	VSM	❖ Eliminates wastes ❖ Reduced cycle time	❖ No validation of future state map before implementation on shop floor.
Alhuraish, et al., (2016)	AHP	❖ Increased profit ❖ High productivity	❖ No significant operational performance in electronic firms.
Velmurugan, et al., (2020)	VSM model	❖ Less expensive ❖ High throughput speed	❖ Layout of the plant is not optimized. ❖ Distance travelled by WIP is not collected.
Sutharsan, et al.,	Lean	❖ Eliminates wastes	❖ Expanding to diverse perceptions was not

(2020)	approach	❖ Achieve win-win scenario	explored sufficiently.

3. Architecture of Proposed Prediction Model for LMS technology

3.1 Proposed Architecture

In this paper, a novel prediction model is introduced for LMS technology that comprises of two major phases viz. Proposed Manual labelling and Classification which is illustrated in Fig. 1. Initially, manual labelling or response validation is done manuallyby utilizing the responses attained for each questions under each factors. The responses are attained for individual factors such as lean awareness, employee involvement, management commitment, lean technology, OP and OS. As the next process, the features (received responses) are set as input and the labelling values are set as target for training NN.This work deploys optimized NN for prediction process, where the weights are optimally chosen by exploiting a new HPS-PO algorithm. The output of factor analysis is shown in Table 2.

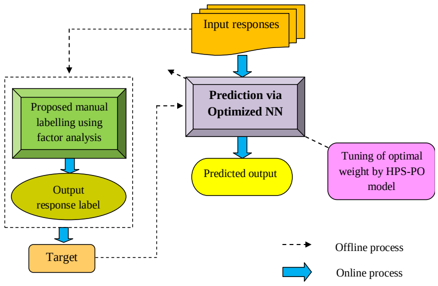


Fig. 1. Block diagram of Proposed prediction model for LMS Framework

Table 2: Factor analysis

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.127	29.786	29.786	10.127	29.786	29.786	8.064	23.719	23.719
2	5.730	16.853	46.639	5.730	16.853	46.639	4.739	13.940	37.658
3	3.814	11.219	57.857	3.814	11.219	57.857	4.588	13.493	51.151
4	3.484	10.247	68.104	3.484	10.247	68.104	4.011	11.798	62.950
5	2.502	7.360	75.464	2.502	7.360	75.464	3.614	10.630	73.579
6	1.653	4.861	80.326	1.653	4.861	80.326	2.294	6.746	80.326
Extraction Method: Principal Component Analysis									

4. Proposed Manual labelling

The output response label for each individual factors (lean awareness, employee involvement, management commitment, lean technology, OP and OS) is computed as per Eq. (1)-Eq. (6), where E_L and C_L denotes the Exploratory Factor Analysis (EFA) loadings and Confirmatory Factor Analysis (CFA) loading respectively. In addition, composite reliability denoted by CR and the Cronbach's α (C_α) are considered as the reliability scores of the response. In the below equations, N indicates the number of questions in each respective individual factors, O denotes the output of responses, q denotes the question and N^R denotes the normalized response. The values attained for EFA loading, CFA loading and reliability measures (C_R and C_α) is given in Table 3.

$$O(LA)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(LA)+C_{L1}(LA)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(LA)+C_{L2}(LA)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(LA)+C_{LN_{LA}}(LA)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(LA)+C_{\alpha}(LA)}{2}\right) \tag{1}$$

$$O(EI)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(EI)+C_{L1}(EI)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(EI)+C_{L2}(EI)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(EI)+C_{LN_{LA}}(EI)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(EI)+C_{\alpha}(EI)}{2}\right) \tag{2}$$

$$O(OP)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(OP)+C_{L1}(OP)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(OP)+C_{L2}(OP)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(OP)+C_{LN_{LA}}(OP)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(OP)+C_{\alpha}(OP)}{2}\right) \tag{3}$$

$$O(LT)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(LT)+C_{L1}(LT)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(LT)+C_{L2}(LT)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(LT)+C_{LN_{LA}}(LT)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(LT)+C_{\alpha}(LT)}{2}\right) \tag{4}$$

$$O(LT)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(LT)+C_{L1}(LT)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(LT)+C_{L2}(LT)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(LT)+C_{LN_{LA}}(LT)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(LT)+C_{\alpha}(LT)}{2}\right) \tag{5}$$

$$O(OS)=\left\{\begin{array}{l} N^{R}\ of\ q_{1}\left(\frac{E_{L1}(OS)+C_{L1}(OS)}{2}\right)+ \\ N^{R} of\ q_{2}\left(\frac{E_{L2}(OS)+C_{L2}(OS)}{2}\right)+ \\ \ldots N^{R}\ of\ q_{N_{LA}}\left(\frac{E_{LN_{LA}}(OS)+C_{LN_{LA}}(OS)}{2}\right) \end{array}\right\} * \left(\frac{C_{R}(OS)+C_{\alpha}(OS)}{2}\right) \tag{6}$$

Table 3: EFA, CFA Loadings and Reliability Measures

Items	EFA loadings	CFA loadings	CR	Cronbach's α
Lean Awareness				
I have an idea about the various tools used in lean manufacturing	.67	0.793	.871	.870
I can adapt to the new tools and systems of lean manufacturing.	.78	0.736		
I am able to identify the non -value-added activities in a process and correct them.	.71	0.65		
I am aware of the merits and demerits of lean manufacturing	.76	0.693		
I know the steps involved in the implementation process of lean manufacturing	.74	0.711		
Employee Involvement				
I participate in problem-solving discussions conducted by the Lean team	.71	0.728	.892	.891
I take initiatives to give suggestions on programmers for continuous improvement in different processes	.68	0.631		
I am aware of the qualities which the customers expect from the products of my organization	.77	0.809		
I always focus on improving the 5S of my workstation	.67	0.785		
I feel that lean implementation will help to improve the performance of employees	.68	0.734		
I am involved in product/process development programmers	.78	0.71		
I feel that the ease of work increased after the implementation of lean	.66	0.742		
Management Commitment				
Our management takes initiatives for involving customers in process /product design modification	.78	0.773	.905	.900
Our management selects suppliers who can help in the easy implementation of lean manufacturing.	.71	0.747		
Our management helps in improving the level of employee satisfaction and employee modification	.76	0.792		
The department heads in our organization play an important role in encouraging lean manufacturing	.66	0.746		
Our top management encourages collaborative decision making	.71	0.702		
The management rewards employees for learning new skills	.73	0.726		
The top management has good control and coordination over the lean activities	.72	0.729		
The management takes steps to improve the health and safety conditions of the employees	.71	0.684		
Lean Technology				
The implementation of lean technology helps in eliminating wastes in a process	.66	0.684	.871	.870
The lean technology adaptation brings continuous improvement	.65	0.781		
The organization can move to zero defects by implementing lean technology	.67	0.734		
The implementation of lean technology has helped in reducing inventory	.64	0.777		
The lean technology adaption has improved total quality management	.67	0.754		
The implementation of lean technology has helped in increasing the flexibility of the production process.	.64	0.61		
Lean technology helps in the decentralization of work	.65	0.733		
OP				
The goals of our organization reflect the needs of the customers	.71	0.637	.896	.895
The performance of the organization after lean implementation has helped in meeting goals.	.76	0.644		
There is rapid development in product and process technology after implementing lean	.69	0.694		
The return on investment of the organization is good.	.68	0.794		
The customer satisfaction has improved after implementing lean	.63	0.711		
Our stakeholders are happy with the present condition of the firm	.64	0.64		
Our products have good brand recognition	.66	0.663		
OS				
A well-maintained policy for lean manufacturing is adapted by the organization	.65	0.76	.881	.880
The organization adapts rules and regulations for every employee	.67	0.63		
The organization works with a process of structured decision making	.68	0.729		
The organization communicates through good channels	.69	0.60		
The organization maintains good coordination among all departments	.70	0.688		
The organization adapts a good control mechanism over lean production	.71	0.727		
The organization has got a good functional relationship management	.78	0.662		
I understand the overall policy of the organization to lean manufacturing.	.80	0.657		

5. Optimization Assisted Neural Network for Prediction: Hybrid Particle Swarm and Pigeon Optimization Algorithm

5.1 Optimized Neural Network

A neural network is a network or circuit of neurons, or in a modern sense, an artificial neural network, composed of artificial neurons or nodes (Mohan, et al., 2016).The input given to NN is specified by Eq. (7), where F denotes the features (received responses)and nu signifies the total count of features.

$$F = \{F_1, F_2, ... F_{nu}\} \tag{7}$$

The model includes input, output, and hidden layers. The output of the hidden layer $e^{(H)}$ is defined as in Eq. (8), where A refers to the "activation function", $\hat{i}$ and j refers to the neurons of hidden and input layers correspondingly, $W^{(H)}_{(B\hat{i})}$ denotes bias weight to $\hat{i}^{th}$ hidden neuron, $n_{\hat{i}}$ symbolizes count of input neurons and $W^{(H)}_{(j\hat{i})}$ denotes the weight from j^{th} input neuron to $\hat{i}^{th}$ hidden neuron. The output of the network $\hat{G}_o$ is determined as in Eq. (9), where $\hat{o}$ refers to the output neurons, n_h indicates the number of hidden neurons, $W^{(G)}_{(B\hat{o})}$ denotes output bias weight to the $\hat{o}^{th}$ output layer, and $W^{(G)}_{(\hat{i}\hat{o})}$ specifies the weight from $\hat{i}^{th}$ hidden layer to $\hat{o}^{th}$ output layer. Consequently, the error amongst the predicted and actual values is computed as per Eq. (10) that should be reduced. In Eq. (10), n_G symbolizes the output neuron count, $G_{\hat{o}}$ and $\hat{G}_{\hat{o}}$ refers to the actual and predicted output respectively. Here, the features (received responses) are set as input and the labelling values are set as target for training NN.

$$e^{(H)} = A\left(W^{(H)}_{(B\hat{i})} + \sum_{j=1}^{n_{\hat{i}}} W^{(H)}_{(j\hat{i})} F \right) \tag{8}$$

$$\hat{G}_{\hat{o}} = A\left(W^{(G)}_{(B\hat{o})} + \sum_{\hat{i}=1}^{n_h} W^{(G)}_{(\hat{i}\hat{o})} e^{(H)} \right) \tag{9}$$

$$Er^* = \underset{\left\{W^{(H)}_{(B\hat{i})}, W^{(H)}_{(j\hat{i})}, W^{(G)}_{(B\hat{o})}, W^{(G)}_{(\hat{i}\hat{o})}\right\}}{\arg\min} \sum_{=1}^{n_G} \left| G_{\hat{o}} - \hat{G}_{\hat{o}} \right| \tag{10}$$

Accordingly, the training of NN model is carried out using a new HPS-PO algorithm via optimizing the weights $W = W^{(H)}_{(B\hat{i})}, W^{(H)}_{(j\hat{i})}$, $W^{(G)}_{(B\hat{o})}$ and $W^{(G)}_{(\hat{i}\hat{o})}$.

5.2. Solution encoding

As mentioned above, the weights of optimized NN are optimally tuned that helps in improving the prediction performance of NN. Here, the features (received responses) is fed as an input and the labeling values attained are set as target. To improve the prediction performance, the training of NN is carried out using HPS-PO algorithm.

5.3 Proposed HPS-PO Algorithm

Even though, the existing PSO model (Jordon, et al., 2019) results with precise estimations; it also involves few drawbacks like"slow convergence and reduced internal memory". Therefore, to prevail over the drawbacks of existing PSO, the concept of POA (Goel, 2014) is merged with it to introduce a new model termed as HPS-PO scheme. Hybrid optimization algorithms have been reported to be promising for certain search problems (Beno, et al., 2014). The procedure of HPS-PO model is as follows: PSO was introduced by Eberhart andKennedy in 1995 based on the inspiration they attained from the dynamic movement as well as the social behaviorof flock of birds. This model is better in resolving the optimization issues and is appropriate for continuous variable problems. Every solution is regarded as a bird called particle and every particles have their own fitness function that is evaluated based on the objective function. Every particle has a position vector, the memory vector and the velocity vector. The position of k^{th} particle at the time stamp t is denoted by $X_k(t)$ and the memory vector is signified by X_k^{best}. On adding the velocity vector $V_k(t)$, the position of the particle gets varied and the present position of the particle is mathematically expressed as per Eq. (11). The proposed contribution is given as follows: As per the proposed model, if the current fitness $\left(f^c\right)$ is better than the previous fitness $\left(f^p\right)$, the velocity gets updated as per Eq. (12), in which r_1 and r_2 denotes the uniformly distributed arbitrary variables, c_1 and c_2 symbolizes the accelerating constants. The inertia weight w_{ki} of the particle and the best position found by the neighborhood of particle k at dimension i is represented using the term X_{ki}^{best}.

$$X_k(t+1) = X_k(t) + V_k(t+1) \tag{11}$$

$$\begin{aligned} V_{ki}(t+1) = {} & x_{ki}V_{ki}(t) + c_1 r_{1i}(X_{ki}^{best}(t) - X_{ki}(t)) \\ & + c_2 r_{2,i}(X_{ki}^{best}(t) - X_k(t)) \end{aligned} \tag{12}$$

On the other hand, if the previous fitness is better than the current fitness, i.e. if $\left(f^p > f^c\right)$, the velocity gets updated based on the PIO algorithm as shown in Eq. (13), where X_k denotes the position, V_i denotes the velocity, ra indicates the random integer, R denotes the map, X_g denotes the global best position and t indicates the iteration. The pseudo code of proposed HPS-PO model is given in algorithm 1.

$$V_i(t) = V_i(t-1).e^{-Rt} + ra.(X_g - X_k(t-1)) \tag{13}$$

Algorithm 1 : HPS-PO algorithm

Initialization
For the entire particle in the swarm
Calculate the fitness value
If the current fitness $\left(f^c\right)$ is better than the previous fitness $\left(f^p\right)$
Compute the velocity as per Eq. (12)
Update the position of the particle using Eq. (11)
Else
Update velocity using PIO algorithm as per Eq. (13)
End if
End for

6. Results and discussions

6.1 Experimental Setup

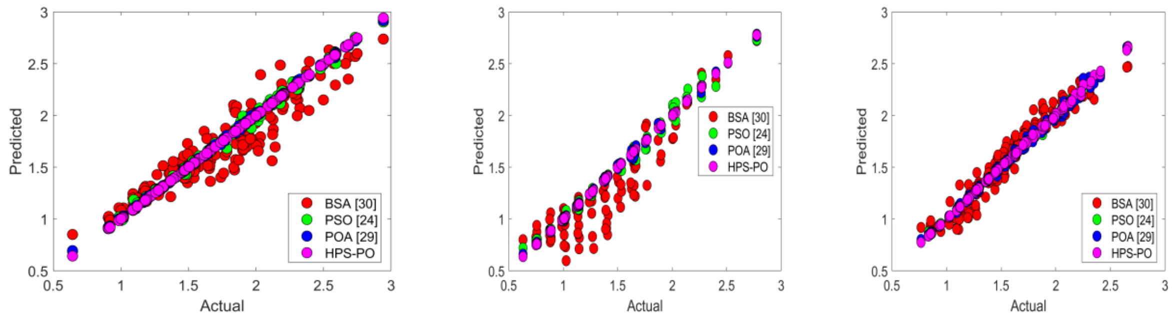
The proposed prediction model for LMS technology was implemented in MATLAB and the results were observed. Here, evaluation was done using the responses collected under different factors including lean awareness, employee involvement, management commitment, lean technology, OP and OS. Further, the betterment of the proposed HPS-PO model was compared over other traditional optimization models like Backtracking Search Algorithm (BSA; Hassan & Rashid, 2020), PSO (Jordon, et al., 2019) and POA (Goel, 2014). Moreover, the presented scheme is validated over the existing classifiers such as Bayesian Network (BN; Bos, et al., 2020), RF (Li, et al., 2020) and SVM (Gu, et al., 2019) for each considered factors. In addition, error analysis was done with respect to varied metrics namely Mean Absolute Percentage Error (MAPE), Root-Mean-Square Error (RMSE) and mean correlation. The parameters fixed for NN is summarized in Table 4.

Table 4: NN parameters

Parameters	Count
Input weight	Number of hidden neuron× Number of input neuron
Hidden layer weight	Number of hidden neuron
Bias weight	Number of hidden neuron+ Number of output neuron
$n_{\hat{i}}$	Number of questions in each individual factor
n_h	10
n_G	1

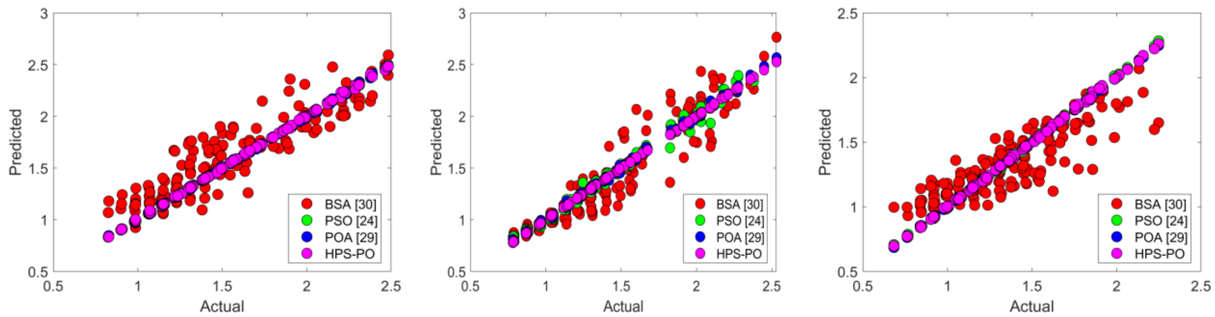
6.2 Impact of Proposed Optimization inPrediction: Proposed versus Conventional Algorithm

This section explains the impact of proposed optimization algorithm in prediction purpose. Fig. 2 and Fig. 3 depict the analysis of presented modelover traditional optimization schemes, whereas Fig. 4 and Fig. 5 depict the prediction analysis for presented model over traditional classifiers. From the attained graphs, the deviation between the actual target and predicted results is minimal with the implemented HPS-PO algorithm, while the traditional optimization schemes as well as the traditional classifiers show a higher deviation between the actual target and predicted results. More specifically, from Fig. 2(a), the predicted output under HPS-PO approach has accomplished better performance, as its prediction rate is much nearer to the actual value for all response. Here, when the actual data is at 1, the predicted output data also holds a value of 1. In addition, From Fig. 2(b), when the actual output is at 3, the predicted output for traditional BSA, PSO and PIO models are 2.5, 2.3 and 2.8 respectively.



(a) (b) (c)

Fig. 2. Prediction Analysis of Proposed model over and traditional optimization models for individual factors such as (a) employee involvement (b) lean awareness and (c) lean technology

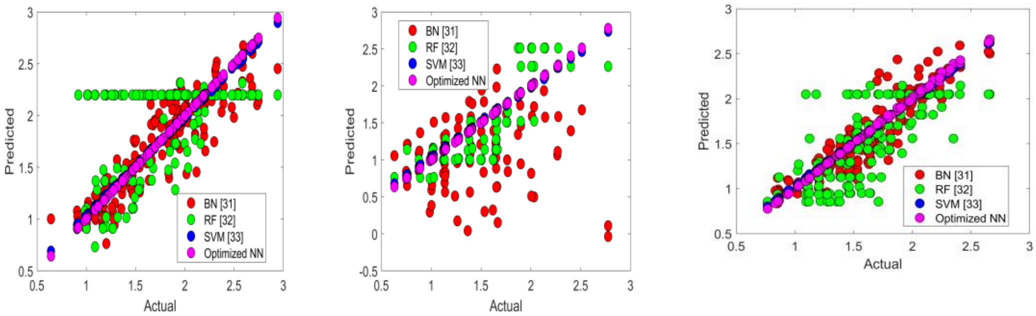


(a) (b) (c)

Fig. 3. Prediction performance of Proposed model over and traditional optimization models for individual factors such as (a) Management commitment(b) OP and (c) OS

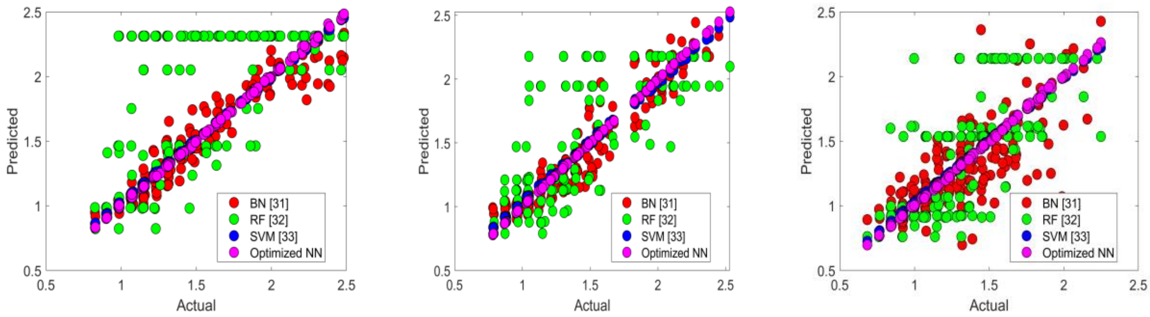
6.3 Prediction Analysis: Proposed Classifier over Traditional Classifier

The prediction performance using the proposed optimized NN over the conventional classifiers is described in this section. On examining Fig. 4 and Fig. 5, the deviation found between the actual target and predicted results using proposed optimized NN is negligible, whereas the traditional classifiers have shown a higher deviation. Particularly, from Fig. 4(b), when the actual output is at 2, the predicted output for the optimized NN model is at 2, while the existing traditional BN and Random Forest (RF) models are at 1.51 and 1.5 respectively. Thus the enhanced prediction capability offered by the optimized NN is revealed effectively.



(a) (b) (c)

Fig. 4. Prediction performance of Proposed Classifier over and traditional classifiersfor individual factors such as (a) employee involvement (b) lean awareness and (c) lean technology

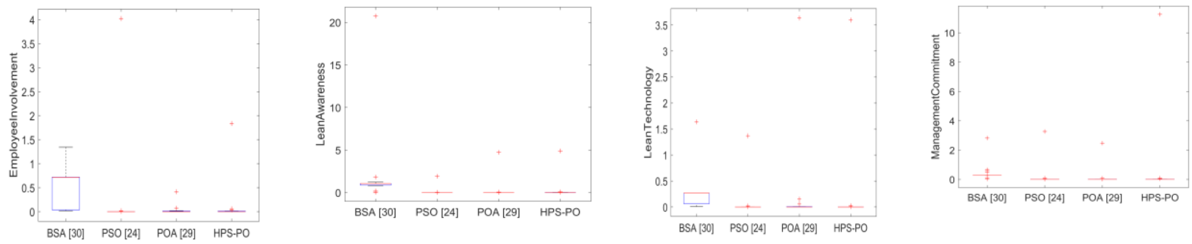


(a) (b) (c)

Fig. 5. Prediction performance of Proposed Classifier over and traditional Classifiersfor individual factors such as (a) Management commitment(b) OP and (c) OS

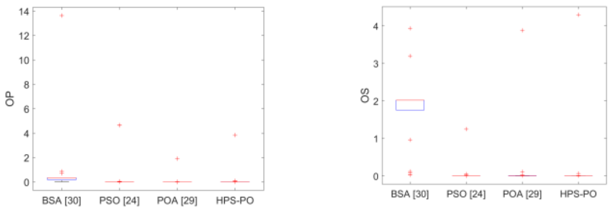
6.4 Box plot Analysis

Fig. 6 (a) and Fig. 6 (b) demonstrate the convergence analysis of the proposed model over the conventional optimization models using box plots. The box plots are usually exploited for revealing information regarding the characteristics of the performed analysis. Here, the analysis was carried out by plotting the convergence (deviation between actual and target output) attained by the proposed as well as existing optimization models for each individual factors. To establish the presented HPS-PO scheme as a sophisticated model, the deviation should be minimal. Here, the proposed model reveals a small deviation when compared over the other existing models such as BSA, PSO and POA. Thereby, from Fig. 6 (a), the proposed model for employee involvement reveals a minimal deviation of0.001, whereas BSA, PSO and POA show a deviation of 0.1, 0.1 and 0.2. This shows the betterment of the implemented model over the compared models.



(a) (b) (c) (d)

Fig. 6. Box plot Analysis of proposed model over and traditional optimization models for individual factors such as (a) employee involvement (b) lean awareness and (c) lean technology (d) Management commitment



(a) (b)

Fig. 7. Box plot Analysis of Proposed model over and traditional optimization models for individual factors such as (a) OP (b) OS

6.5 Error Analysis

Table 5 and Table 6 summarises the error analysis of the presented scheme over traditional optimization models as well as traditional classifiers respectively. Here, the adopted HPS-PO scheme is compared over the conventional models by considering the error measures such as RMSE, MAPE and mean correlation. On observing the attained outcomes, the implemented model has obtained minimal error for all measures when compared to other methods. More specifically, from Table 5, the MAPE of adopted scheme attains to be minimal for lean awareness is 98.69%, 92.08%and 78.63% better than traditional optimization models such as BSA, PSO and POA. In addition, the implemented scheme for employee involvement has revealed a minimal MAPE value of 0.0008, which is 99.89%, 99.29% and 98.48% superior to existing optimization models like BSA, PSO and POA. Similarly, the error values accomplished by the adopted scheme for OP and OS are lesser, when compared over the traditional optimization models.Table 6 reveals the enhanced performance of optimized NN over the existing classification models like BN, RF and SVM. The RMSE measure for OP also reveals a minimal value of 0.00332 that is 97.57%, 98.99% and 88.65% better than traditional classifiers namely, BN, RF and SVM models. Thus, the enhanced performance of the adopted model is validated in terms of error analysis.

Table 5: Error analysis of the Proposed work over Traditional optimization models for variedindividual factors

Lean awareness				**Employee involvement**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BSA (Hassan & Rashid, 2020)	12.275	0.21068	175.39	BSA (Hassan & Rashid, 2020)	7.471	0.16361	272.2
PSO (Jordon, et al., 2019)	2.0234	0.039413	191.02	PSO (Jordon, et al., 2019)	1.1301	0.02811	279.25
POA (Goel, 2014)	0.7493	0.014469	190.77	POA (Goel, 2014)	0.52761	0.011344	279.08

HPS-PO	0.16015	0.003461	190.59	HPS-PO	0.008041	0.000164	278.63
Management commitment				**Lean technology**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BSA (Hassan & Rashid, 2020)	10.555	0.18903	242.8	BSA (Hassan & Rashid, 2020)	5.3771	0.099476	231.69
PSO (Jordon, et al., 2019)	0.26492	0.005096	235.97	PSO (Jordon, et al., 2019)	0.51002	0.011991	228.55
POA (Goel, 2014)	0.53669	0.009924	235.79	POA (Goel, 2014)	1.0851	0.024074	228.6
HPS-PO	0.37934	0.008415	235.86	HPS-PO	0.3834	0.00956	228.91
OP				**OS**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BSA (Hassan & Rashid, 2020)	8.8098	0.18578	199.86	BSA (Hassan & Rashid, 2020)	10.622	0.17843	156.5
PSO (Jordon, et al., 2019)	2.2561	0.04892	206.51	PSO (Jordon, et al., 2019)	0.52768	0.009177	159.96
POA (Goel, 2014)	0.79453	0.016559	206.34	POA (Goel, 2014)	0.045512	0.000578	159.96
HPS-PO	0.15091	0.00332	205.65	HPS-PO	0.42748	0.007508	159.92

Table 6: Error analysis of the Proposed work over Traditional classification models for varied individual factors

Lean awareness				**Employee involvement**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BN (Bos, et al., 2020)	34.896	0.79772	137.21	BN (Bos, et al., 2020)	10.203	0.22156	269.16
RF (Li, et al., 2020)	11.465	0.27253	193.19	RF (Li, et al., 2020)	20.274	0.41736	289.48
SVM (Gu, et al., 2019)	2.1198	0.027668	192.16	SVM (Gu, et al., 2019)	1.1854	0.02198	278.48
Optimized NN	0.16015	0.003461	190.59	HPS-PO	0.008041	0.000164	278.63
Management commitment				**Lean technology**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BN (Bos, et al., 2020)	6.7466	0.15762	228.39	BN (Bos, et al., 2020)	8.5305	0.17481	224.68
RF (Li, et al., 2020)	30.659	0.57507	282.06	RF (Li, et al., 2020)	15.915	0.32362	217
SVM (Gu, et al., 2019)	1.3204	0.020464	237.11	SVM (Gu, et al., 2019)	1.0568	0.017328	229.43
Optimized NN	0.37934	0.008415	235.86	HPS-PO	0.3834	0.00956	228.91
OP				**OS**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BN (Bos, et al., 2020)	7.6789	0.13659	204.27	BN (Bos, et al., 2020)	12.953	0.25081	155.35
RF (Li, et al., 2020)	16.418	0.32739	213.96	RF (Li, et al., 2020)	18.93	0.32554	166.76
SVM (Gu, et al., 2019)	1.9754	0.029255	206.76	SVM (Gu, et al., 2019)	1.6083	0.020869	161.77
Optimized NN	0.15091	0.00332	205.65	HPS-PO	0.42748	0.007508	159.92

7. Conclusion

This paper had developed a new NN based intelligent prediction framework. Initially, the manual labeling or response validation was done for individual factors by utilizing the responses attained for each questions and by deploying the factor analysis. The individual factor included lean awareness, employee involvement, management commitment, lean technology, OP and OS. Further, in order to enhance the prediction performance, optimized NN was deployed, in which the weights were fine-tuned by exploiting a new HPS-PO algorithm. Finally, a precise analysis was made for validating the enhancement of presented model over traditional schemes. Particularly, on considering the MAPE measure, the suggested scheme for lean awareness was 99.54%, 98.6% and 92.45% better than traditional classifiers namely, BN, RF and SVM. The RMSE of the implemented model for employee involvement has accomplished a lower value of 0.000164, whereas, the traditional classification models namely, BN, RF and SVM has accomplished comparatively higher RMSE values of 0.22156, 0.41736 and 0.000164. Thus, the superiority of the developed model has been verified successfully. The future direction of this work focuses on investigating the lean technique for removing waste from the social manufacturing process.

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