Intelligent Prediction Model: Optimized Neural Network for Lean Manufacturing Technology

Jobin M V * and Aiswarya Menon **

**Professor, Mets School of Engineering Mala, Jobin027@gmail.com*

***Aiswarya Menon, Assistant Professor , Mets School of Engineering Mala, aiswaryamenonm@gmail.com*

**Corresponding Author: jobinmv9@gmail.com*

Submitted **:** 06-01-2021

Revised **:** 15-10-2021

Accepted **:** 26-10-2021

ABSTRACT

Lean manufacturing (LM) is a method, which focuses on reducing wastes and increasing productivity within the manufacturing firms. Several analyses on LM technology were performed previously, depending on minimal lead times, to enhance the quality and reduce the operating costs. However, limitation exists in understanding its role in developing the managing commitment, worker involvement, and in turn, its organizational performance. This paper intends to propose a new Neural Network (NN) based on the intelligent prediction framework. The initial process is manual labeling or response validation, which is carried out by utilizing the responses attained for each question under each factor, including lean awareness, employee involvement, management commitment, lean technology, Organizational Performance (OP), and Organizational Support (OS). Subsequently, NN is exploited for the prediction process, where the features (received responses) are given as the inputs and the labeling values attained are set as the targets. Further, 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. The proposed algorithm is a combination of Particle Swarm Optimization (PSO) and Pigeon Optimization Algorithm (POA). Finally, the performance of the proposed model is examined over conventional methods, in terms of prediction analysis and error analysis.

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

INTRODUCTION

Over the past decade, LMS has been attaining a rising consideration, as it serves as one of the methods 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 world-class techniques and tools, which comprise of Value Stream Mapping (VSM), mistake proving, pull-production and visual management, which are effectively deployed in various sectors. This theory of enhancement through waste minimization is termed as the lean approach (Silva, et al., 2013; Schonberger, 2019).

In a machine production firm, the targeted wastes for elimination or reduction take into account the unnecessary in-process inventory, unwanted transport of materials faulty processed parts, and so on (Marodin, et al., 2018; Munteanu & Ştefănigă, 2018; Abu, et al., 2019). These wastes should be eliminated or reduced for attaining improved performance of the firm. More profits are foreseen from lean practices 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 drop back (Botti, et al., 2017; Cai, et al., 2019).Machine learning techniques such as Artificial Neural Networks (ANNs)are usually 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 to assess the efficiency of the system and in addition, methods likePrinciple Components Analysis (PCA) are adopted to discover faults in the system. However, wide-ranging investigations to use the 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.
- Introducing an optimized NN model for prediction purposes, where the weights are fine-tuned by a new hybrid algorithm.
- Proposing a new hybrid algorithm, termed 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 based on this topic. Section 3 depicts the architecture of the proposed prediction model for the LMS technology. Further, Section 4 addresses the proposed manual labeling. The Optimization- assisted NN for prediction: hybrid Particle Swarm and the Pigeon Optimization algorithm is depicted in Section 5. Subsequently, the Section 6 describes the resultants and the conclusion is elucidated in Section 7.

LITERATURE REVIEW

Related works

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, the probable levels of achievement before and after the adoption of LMS were revealed using radar illustrations. At last, the analysis was made with concern to time for validating the outcomes of the presented model.

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

Yadav, et al., (2020) have presented an approach for improving the approval of LMS in the manufacturing companies. The Decision Making Trial and Evaluation Laboratory (DEMATEL) and the hybrid Fuzzy Analytical Hierarchy Process (FAHP) tools were deployed for quantifying and identifying the relationships among the drivers for LM execution. This hybridized model assisted in documenting the comparative priority and the 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.

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 focus on the variations in lean index. Therefore, in this work, the variations in lean index were formulated using a fuzzy logic- oriented model. Finally, the simulation outcomes proved the superiority of the adopted model, in terms of robustness.

Deshkar et al. (2018) have adopted the theory of 'lean' in a plastic bag company by exploiting the VSM framework. It mapped and evaluated the present processes of the firm and at the end, the bottlenecks were rectified. Also, solutions were suggested for eradicating the identified wastes based on 7 kinds of LM wastes. Moreover, a future state map was formed. Consequently, both the future and the current state maps were examined to process the time and the lead time for computing the gain using VSM.

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

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

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

Table 1: Features and Challenges of the Traditional LMS models

Author [citation]	**Methodology**	**Features**	**Challenges**
Prasad, *etal*., (2020)	VSM	❖ Higher lean speed ❖ Improved worker efficiency	❖ Textile machinery costs were high.
Jayanth, *et al.*, (2020)	VSM	❖ Enhanced quality level ❖ High productivity	❖ No consideration on floor layout. ❖ Congestion problems were not focused
Yadav, *et al.,*(2020)	FAHP model	❖ Offered unique balance ❖ Raised the economy	❖ No contemplation on structural comparisons. ❖ Relation among drivers were not considered
Oleghe & Salonitis, (2016)	Fuzzy logic	❖ Robust model ❖ Higher lean performance	❖ No validation on real-life case study. ❖ Limitations existed in the variation analysis
Deshkar, *et al.,*(2018)	VSM	❖ Eliminated wastes ❖ Reduced cycle time	❖ No validation on future state map, before the 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 was not optimized. ❖ Distance travelled by WIP was not collected.
Sutharsan, *et al.,*(2020)	Lean approach	❖ Eliminated wastes ❖ Achieve daw in-win scenario	❖ Expansion to diverse perceptions was not explored sufficiently.

ARCHITECTURE OF THE PROPOSED PREDICTION MODEL FOR LMS TECHNOLOGY

Proposed Architecture

In this paper, a novel prediction model is introduced for LMS technology and it comprises of two major phases viz. Proposed Manual labelling and Classification, which are illustrated in Fig.1. Initially, the manual labelling or response validation is done manuallyby utilizing the responses attained for each question, under each factor. 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 the input and the labelling values are set as the 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.

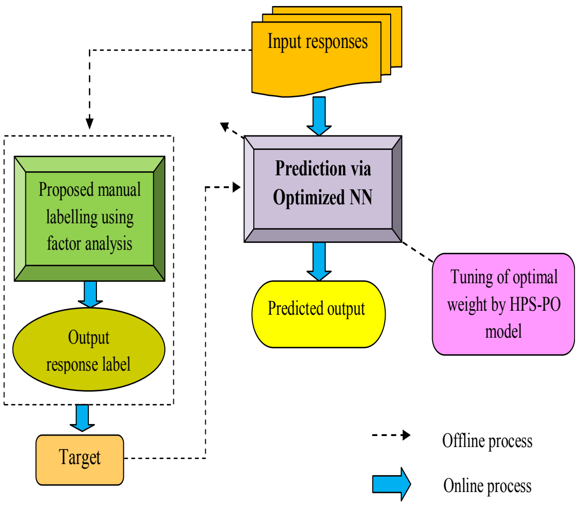


Fig. 1. Block diagram of the proposed prediction model for LMS Framework

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									

PROPOSED MANUAL LABELLING

The output response label for each factor (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, the composite reliability denoted by CR and the Cronbach's α $\left(C_\alpha\right)$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 denote the normalized response. The values attained for EFA loading, CFA loading and reliability measures (C_R and C_α) are given in Table 3.

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

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

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

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

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

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

Table 3: EFALoadings, 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 to the 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 wastes	.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		

OPTIMIZATION-ASSISTED NEURAL NETWORK FOR PREDICTION: HYBRID PARTICLE SWARM AND PIGEON OPTIMIZATION ALGORITHM

Optimized Neural Network

A neural network is a network or circuit of neurons, called as an Artificial Neural Network that is composed of artificial neurons or nodes (Mohan, et al., 2016)The input given to NN is specified in 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 in Eq. (8), where A refers to the activation function", $\hat{i}$ and j refers to the neurons ofhidden and input layers, respectively, $W^{(H)}_{(B\hat{i})}$ denotesthe bias weight to the $\hat{i}^{th}$ hidden neuron, $n_{\hat{i}}$ symbolizes the count of input neurons and $W^{(H)}_{(j\hat{i})}$ denotes the weight from the j^{th} input neuron to the $\hat{i}^{th}$ 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 indicatesthe number of hidden neurons, $W^{(G)}_{(B\hat{o})}$ denotes the output bias weight to the $\hat{o}^{th}$ output layer and $W^{(G)}_{(\hat{i}\hat{o})}$ specifies the weight fromthe $\hat{i}^{th}$ hidden layer tothe $\hat{o}^{th}$ output layer. Consequently, the error between the predicted and the actual values is computed as per Eq. (10) and it should be reduced. In Eq. (10), n_G symbolizes the output neuron count, while $G_{\hat{o}}$ and $\hat{G}_{\hat{o}}$ refers to the actual andthe predicted outputs, respectively.Here, the features (received responses) are set asthe inputs and the labelling values are set asthe targets for training NN.

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

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

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

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 $W^{(G)}_{(\hat{i}\hat{o})}$.

Solution encoding

As mentioned above, the weights of the optimized NN are optimally-tuned to help in improving the prediction performance of NN. Here, the features (received responses) are fed as the inputs and the attained labelling values are set as the targets. To improve the prediction performance, the training of NN is carried out using the HPS-PO algorithm.

Proposed HPS-PO Algorithm

Even though the existing PSO model (Jordon, et al., 2019) has resulted in precise estimations, afew drawbacks like, slow convergence and reduced internal memory still exists. Therefore, to eliminate the drawbacks of existing PSO, the concept of POA [14](Goel, 2014) is merged with it to introduce a new model, termed as the HPS-PO scheme. The hybrid optimization algorithms have been reported to be promising for certain search problems[5](Beno, et al., 2014).PSO was introduced by Eberhart and Kennedy in 1995 based on the inspiration they attained from the dynamic movement as well as the social behaviorof a flock of birds. This model is better at resolving theoptimization issues and it is appropriate for continuous variable problems. The procedure of the HPS-PO model is as follows: Every solution is regarded as a bird (called particle) and every particle has its own fitness function, which is evaluated based on the objective function. Every particle has a position vector, the memory vector and the velocity vector. The position of the k^{th} particle at the time stamp t is denoted by $X_k(t)$ andthe memory vector is signifiedby 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). Here, r_1 and r_2 denote the uniformlydistributed arbitrary variables, while 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 the 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-POalgorithm

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

RESULTS AND DISCUSSIONS

Experimental Setup

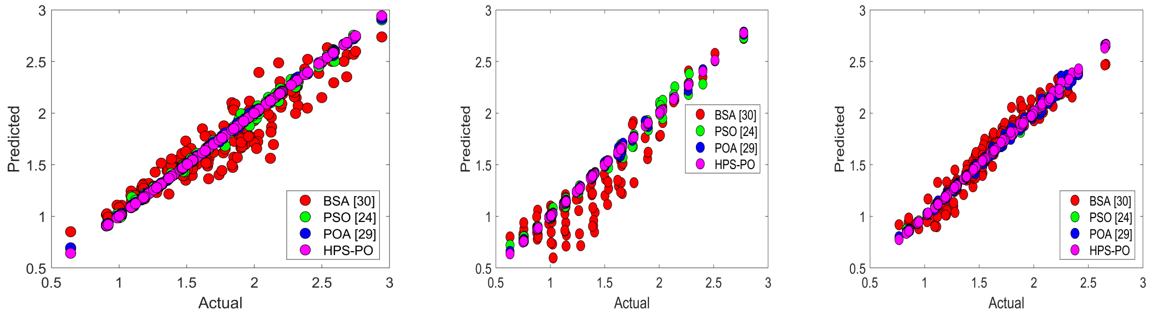
The proposed prediction model for LMS technology has been implemented in MATLAB and the results have been observed. Here, the evaluation was done using the responses collected under different factors, including lean awareness, employee involvement, management commitment, lean technology, OP and OS. Further, the betterment of the proposed HPS-PO model has been compared over the 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 has been 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 of the considered factors. In addition, the error analysis has been 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

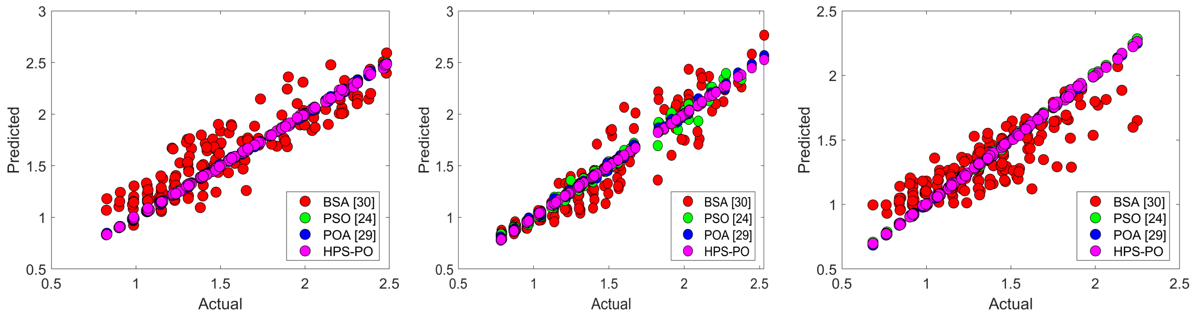
Impact of the proposed optimization inPrediction: Proposed versus Conventional Algorithm

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



(a) (b) (c)

Fig. 2. Prediction analysis of the proposed model over thetraditional optimization models for individual factors such as: (a) employee involvement, (b) lean awareness and (c) lean technology

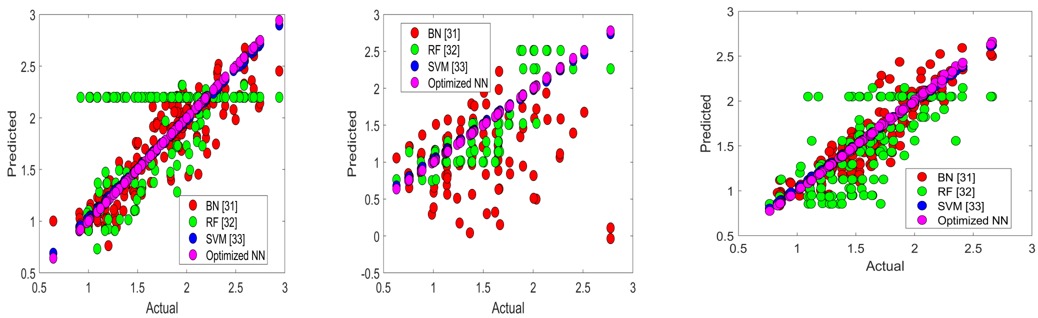


(a) (b) (c)

Fig. 3. Prediction performance of the proposed model over thetraditional optimization models for individual factors such as:(a) Management commitment, (b) OP and (c) OS

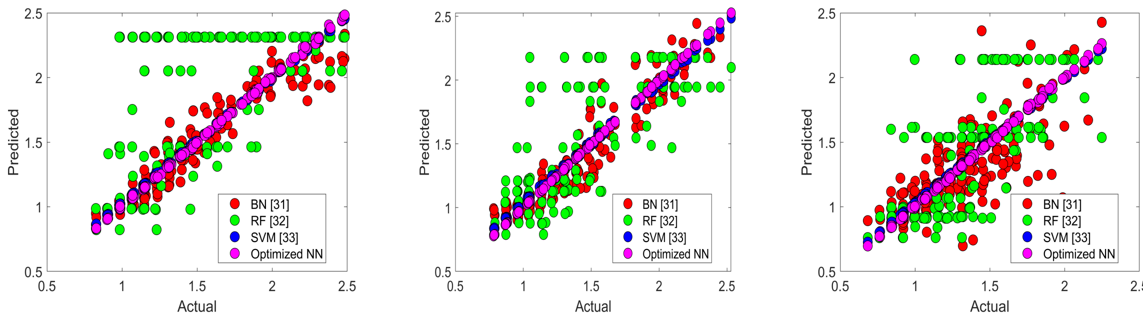
Prediction Analysis: Proposed Classifier over Traditional Classifier

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 the predicted results using the 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 2In contrast, the existing traditional BN and Random Forest(RF)models have produced the predicted outputs as 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 oftheproposed classifier over thetraditional classifiersfor individual factors such as: (a) employee involvement, (b) lean awareness and (c) lean technology

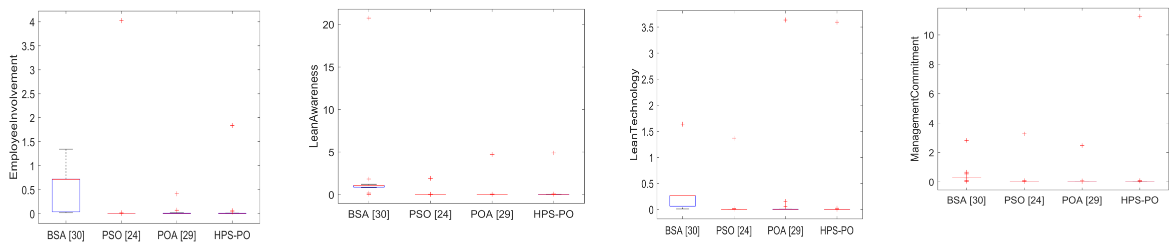


(a) (b) (c)

Fig. 5. Prediction performance of the proposed classifier over thetraditional classifiersfor individual factors such as: (a) Management commitment, (b) OP and (c) OS

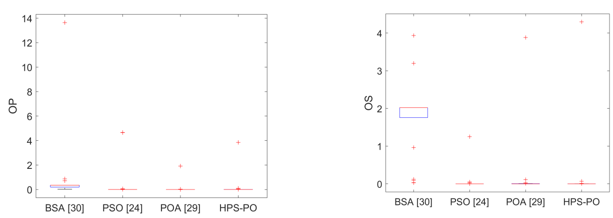
Box plot Analysis

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 has been carried out by plotting the convergence (deviation between the actual and the target outputs) attained by the proposed as well as the existing optimization models for each factor being considered. 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. Fig. 6 (a) reveals that the proposed model for employee involvement has provided a minimal deviation of0.001, whereas BSA, PSO and POA have shown 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 the proposed model over thetraditional optimization models for individual factors such as: (a) employee involvement, (b) lean awareness,(c) lean technology and (d) management commitment



(a) (b)

Fig. 7. Box plot analysis of the proposed model over thetraditional optimization models for individual factors such as: (a) OP (b) OS

Error Analysis

Table 5 and Table 6 summarises the error analysis of the presented scheme over the traditional optimization models as well as the 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 been found to obtain a minimal error for all the measures, when compared to the other methods. More specifically, from Table 5, the MAPE of the adopted scheme has attained a minimal value for lean awareness and it is 98.69%, 92.08%and 78.63% better than the traditional optimization models like, 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 the 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 to the traditional optimization models.Table6 reveals the enhanced performance of the optimized NN over the existing classification models like, BN, RF, and SVM. The attained RMSE measure for OP also has a minimal value of 0.00332 which is 97.57%, 98.99% and 88.65% better than the traditional classifiers namely, BN, RF, and SVM models. Thus, the enhanced performance of the adopted model has been validated in terms of error analysis.

Table 5: Error analysis of the proposed modelover the traditional optimization models for variedfactors

Lean awareness				**Employee involvement**			
Methods	**MAPE**	**RMSE**	**Mean correlation**	**Measures**	**MAPE**	**RMSE**	**Mean correlation**
BSA (Hassan, B. A., Rashid, T. A, 2020)	12.275	0.21068	175.39	BSA (Hassan, B. A., Rashid, T. A, 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, B. A., Rashid, T. A, 2020)	10.555	0.18903	242.8	BSA (Hassan, B. A., Rashid, T. A, 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, B. A., Rashid, T. A, 2020	8.8098	0.18578	199.86	(Hassan, B. A., Rashid, T. A, 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

CONCLUSION

This paper has introduced a new NN-based intelligent prediction framework. Initially, the manual labeling or response validation has been done for individual factors by utilizing the responses attained for each question and by deploying the factor analysis. The individual factors included lean awareness, employee involvement, management commitment, lean technology, OP and OS. Further, the optimized NN has been deployed to enhance the prediction performance, in which the weights have been fine-tuned by exploiting a new HPS-PO algorithm. Finally, a precise analysis has been made for validating the enhancement of the presented model over the traditional schemes. Particularly, on considering the MAPE measure, the suggested scheme for lean awareness has provided99.54%, 98.6%, and 92.45% better results than the 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 have comparatively accomplished 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.

References

Abu, F., Gholami, H., Saman, M. Z. M., Zakuan, N., Streimikiene, D. 2019. The implementation of lean manufacturing in the furniture industry: A review and analysis on the motives, barriers, challenges, and the applications, *Journal of Cleaner Production*, 234: 660-680.

Alhuraish, I., Robledo, C., Kobi, A. 2016. Assessment of Lean Manufacturing and Six Sigma operation with Decision Making Based on the Analytic Hierarchy Process, *IFAC-PapersOnLine,* 49(12): 59-64.

Antonio, G. D., Bedolla, J. S., Chiabert, P. 2017.A Novel Methodology to Integrate Manufacturing Execution Systems with the Lean Manufacturing Approach, *Procedia Manufacturing*, 11: 2243-2251.

Banga, H. K., Kumar, R., Kumar, P., Purohit, A., Singh, K. 2020. Productivity improvement in manufacturing industry by lean tool, *Materials Today: Proceedings.*

Beno, M. M., Valarmathi, I. R., Swamy, S. M and Rajakumar,B. R. 2014. Threshold prediction for segmenting tumour from brain MRI scans, *International Journal of Imaging Systems and Technology,* 24(2): 129-137, DOI: https://doi.org/10.1002/ima.22087.

Bos, L. M. M., Sanderse, B., Bierbooms,W. A. A. M. 2020. Adaptive sampling-based quadrature rules for efficient Bayesian prediction, *Journal of Computational Physics*, 417:Article 109537.

Botti, L., Mora, C., Regattieri, A. 2017. Integrating ergonomics and lean manufacturing principles in a hybrid assembly line, *Computers & Industrial Engineering*, 111: 481-491.

Büyüközkan,G., Kayakutlu,G., Karakadılar,İ. S. 2015. Assessment of lean manufacturing effect on business performance using Bayesian Belief Networks, *Expert Systems with Applications,* 42(19): 6539-6551.

Cai, W., Lai, K., Liu, C., Wei, F., Lv, L. 2019. Promoting sustainability of manufacturing industry through the lean energy-saving and emission-reduction strategy, *Science of The Total Environment*, 665: 23-32.

Chithra, R. S and Jagatheeswari, P. 2019. Enhanced WOA and Modular Neural Network for Severity Analysis of Tuberculosis.*Multimedia Research*. 2(3): 43-55.

Deshkar, A., Kamle, S., Giri, J., Korde, V. 2018. Design and evaluation of a Lean Manufacturing framework using Value Stream Mapping (VSM) for a plastic bag manufacturing unit, *Materials Today: Proceedings*, 5(2), Part 2: 7668-7677.

Gandhi, N. S., Thanki, S. J., Thakkar, J. J. 2018. Ranking of drivers for integrated lean-green manufacturing for Indian manufacturing SMEs, *Journal of Cleaner Production*, 171: 675-689.

Ghobadian, A., Talavera, I., Bhattacharya, A., Kumar, V., O'Regan, N. 2018. Examining legitimatisation of additive manufacturing in the interplay between innovation, lean manufacturing and sustainability, *International Journal of Production Economics*.

Goel, S. 2014. Pigeon optimization algorithm: A novel approach for solving optimization problems, *International Conference on Data Mining and Intelligent Computing (ICDMIC),* New Delhi, 1-5, doi: 10.1109/ICDMIC.2014.6954259.

Gu, J., Wang, L., Wang, H., Wang, S. 2019. A novel approach to intrusion detection using SVM ensemble with feature augmentation,*Computers & Security*, 86: 53-62.

Hassan, B. A., Rashid, T. A. 2020. Operational framework for recent advances in backtracking search optimisation algorithm: A systematic review and performance evaluation, *Applied Mathematics and Computation*, 370, Article 124919.

Jayanth, B. V., Prathap, P., Sivaraman, P., Yogesh, S., Madhu, S. 2020. Implementation of lean manufacturing in electronics industry, *Materials Today: Proceedings*.

Jordon, K., Dossou, P.-E., Junior, J. C. 2019. Using lean manufacturing and machine learning for improving medicines procurement and dispatching in a hospital, *Procedia Manufacturing,* 38: 1034-1041.

Khorasani, G and Zeyun, L. 2014. Implementation of technology acceptance model (tam) in business research on web based learning system . *International Journal of Innovative Technology and Exploring Engineering*. 3(11): 112-116.

Li, K., Chen, W., Zhang, Q., Wu, L. 2020. Building Auto-Encoder Intrusion Detection System Based on Random Forest Feature Selection Computers & Security, In press, *journal* pre-proof Available online, 29:101851.

Li, Z and Dawood, S.R.S. 2016. World city network in China: a network analysis of air transportation network . *Modern Applied Science*. 10(10): 213.

Marodin, G., Frank, A. G., Tortorella, G. L., Netland, T. 2018. Lean product development and lean manufacturing: Testing moderation effects, *International Journal of Production Economics,* 203: 301-310.

Mohan, Y., Chee, S. S., Xin, D. K. P and Foong, L. P. 2016. Artificial Neural Network for Classification of Depressive and Normal in EEG, *2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)*.

Möldner, A. K., Garza-Reyes, J. A., Kumar, V. 2020. Exploring lean manufacturing practices' influence on process innovation performance, *Journal of Business Research*, 106: 233-249.

Munteanu, V., Ştefănigă,A. 2018. Lean Manufacturing in SMEs in Romania, *Procedia - Social and Behavioral Sciences*, 238:492-500.

Nassereddine, A., Wehbe, A. 2018. Competition and resilience: Lean manufacturing in the plastic industry in Lebanon, *Arab Economic and Business Journal*, 13(2): 179-189.

Oleghe, O., Salonitis, K. 2016. Variation Modeling of Lean Manufacturing Performance Using Fuzzy Logic Based Quantitative Lean Index, *Procedia CIRP*, 41, 608-613.

Potamias, Rolandos-Alexandros, Siolas, G and Stafylopatis, A. 2019. A robust deep ensemble classifier for figurative language detection. *In International Conference on Engineering Applications of Neural Networks*. 164-175. Springer. Cham.

Prasad, M. M., Dhiyaneswari, J. M., Jamaan, J. R., Mythreyan, S., Sutharsan, S. M. 2020. A framework for lean manufacturing implementation in Indian textile industry, *Materials Today: Proceedings*.

Prasanalakshmi, B and Farouk, A. 2019. Classification and Prediction of Student Academic Performance in King Khalid University-A Machine Learning Approach. *Indian Journal of Science and Technology*. 12: 14.

Rupapara, V., Rustam, F., Shahzad, H.F., Mehmood, A., Ashraf, I and Choi, G.S. 2021. Impact of SMOTE on Imbalanced Text Features for Toxic Comments Classification using RVVC Model . *IEEE Access*.

Sai Ambati, L., Narukonda, K., Bojja, G.R and Bishop, D. 2020. Factors Influencing the Adoption of Artificial Intelligence in Organizations-From an Employee's Perspective.

Schonberger, 2019. The disintegration of lean manufacturing and lean management, *Business Horizons*, 62(3): 359-371.

Silva, C., Vaz, P., Ferreira, L. M. 2013. The impact of Lean Manufacturing on environmental and social sustainability: a study using a concept mapping approach, *IFAC Proceedings,*46(24): 306-310.

Srinivas, V and Ch, S. 2020. Hybrid Particle Swarm Optimization-Deep Neural Network Model for Speaker Recognition. *Multimedia Research*. 3(1): 1-10.

Susilawati, A., Tan, J., Bell, D., Sarwar, M. 2015. Fuzzy logic based method to measure degree of lean activity in manufacturing industry, *Journal of Manufacturing Systems,* 34: 1-11.

Sutharsan, S. M., Prasad, M. M., Vijay, S. 2020. Productivity enhancement and waste management through lean philosophy in Indian manufacturing industry, *Materials Today: Proceedings*.

Tanweer, M.R., Suresh, S and Sundararajan, N. 2015. Self regulating particle swarm optimization algorithm, *Information Sciences*, 294: 182-202.

Velmurugan, V., Karthik, S., Thanikaikarasan, S. 2020. Investigation and implementation of new methods in machine tool production using lean manufacturing system, *Materials Today: Proceedings*.

Xiong, G., Shang, X., Xiong, G and Nyberg, T. R. 2019. A kind of lean approach for removing wastes from non-manufacturing process with various facilities, *IEEE/CAA Journal of Automatica Sinica*, 6(1): 307-315.

Yadav, G., Luthra, S., Huisingh, D. Mangla, S. K., Liu, Y. 2020. Development of a lean manufacturing framework to enhance its adoption within manufacturing companies in developing economies, Journal of Cleaner Production, 245, Article 118726.