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AN ARTIFICIAL NEURAL NETWORK MODEL SUPPORTED WITH HYBRID MULTI-CRITERIA DECISION-MAKING APPROACHES TO RANK LEAN TOOLS FOR A FOUNDRY INDUSTRY

Summary

The primary objective of this study is to optimise operating efficiency and minimise waste within a core foundry shop through the application of lean manufacturing techniques. The research emphasises the significance of Artificial Neural Networks (ANNs) in aligning an expert assessment matrix with lean tool rankings, particularly in addressing the challenges associated with fuzzy logic-based leanness computation. The expert assessment matrix was constructed with the entropy approach for generating weights and the TOPSIS ranking algorithm for evaluating lean tools. The use of the TOPSIS technique resulted in a notable level of agreement, with a percentage of 73.42%, and a corresponding level of disagreement of 26.57%, when compared to the expert evaluation matrix developed for the assessment of lean tools. The expert assessment matrix that was produced was utilised in the analysis of the efficacy of several lean tools inside a foundry core manufacturing line. The research suggests the implementation of an automated conveyor system for the transportation of several cores, which would lead to the optimisation of floor space, enhanced safety measures, and more schedule flexibility. The findings of this study reveal a significant decrease of 79.6% in non-value-added activities (NVA), a notable improvement of 62.66% in process efficiency, a substantial reduction of 66.66% in waiting times, a considerable decrease of 35% in personnel requirements, and a significant cost reduction of 45%. A three-month accident-free workplace demonstrated the efficacy of the safety strategy.

Key words: *lean manufacturing, MCDM, process time, cost, safety, defect, productivity, neural network, core station, foundry*

1. Introduction

In the 1950s, Taiichi Ohno introduced the Toyota Production System (TPS), a revolutionary manufacturing approach. Subsequently, in the late 1980s, the concept of lean manufacturing emerged as a derivative of TPS, tailored to better suit Western manufacturing companies [1]. Recent research has expanded the scope of waste reduction beyond the traditional areas and now encompasses issues such as the underutilisation of skills and infrastructure [2,3]. Among the methodologies explored, value stream mapping (VSM) has emerged as a highly effective technique for identifying waste within an organisation's processes [4]. The adoption of lean principles, coupled with appropriate training, has shown promising results in enhancing the performance of manufacturing industries. While numerous lean tools (LTs) have been identified by researchers, organisations often face challenges in selecting the most suitable LTs for implementation [5]. The integration of all these lean tools and techniques can be a lengthy and costly process for manufacturing organisations. Consequently, there is a growing need for a systematic approach to selecting and implementing lean concepts [6]. Recent studies have proposed frameworks that incorporate industrial engineering and optimisation methods, offering a variety of lean tools to choose from [7,8]. These frameworks provide a structured and data-driven approach to help organisations make informed decisions about which lean tools to employ, streamlining the implementation process and maximising the benefits of lean manufacturing principles.

This study offers a methodology that leverages value stream mapping and plant planning to meet specific requirements. It involves the prioritisation and evaluation of lean tools using two Multi-Criteria Decision-Making (MCDM) techniques: TOPSIS and entropy. Decision-making inherently involves selecting the most appropriate course of action from a range of options. Decision-makers are primarily tasked with harmonising competing objectives while working within system constraints. In recent times, there has been growing interest in the application of artificial neural networks (ANNs) to aid decision-making processes. Neural networks excel at modelling complex input-output relationships. The primary focus of this paper is to present a strategy-based decision model founded on MCDM principles, while also validating the data using neural networks. While the study acknowledges the potential of neural networks, it does not delve into the intricacies of designing these networks. The proposed model is outlined in a comprehensive manner and is elucidated through a case study, offering a practical illustration of its application.

The approach involves the evaluation of lean tools based on input parameters. In this methodology, future rankings were generated using the proposed strategic model without requiring direct input from decision-makers. It is worth noting that conventional decision-making methods follow a similar process. Figure 1 illustrates the distinction between these models and traditional decision-making approaches. Typically, multi-criteria decision-making (MCDM) methods have been employed for the manual ranking of lean tools. However, in this study, lean tools were ranked based on their ability to capture and handle complex, non-linear relationships using artificial neural networks. In the case of ANNs, the correct conclusions were drawn by combining reasoning based on historical data and a well-structured neural network model. The MATLAB NN toolbox was utilised for training the neural network. This innovative method for ranking lean tools takes the results of MCDM models and uses them as the input for ANNs. Moreover, the evaluation and modelling phases consider the past performance of objects, enhancing the overall robustness of the approach.

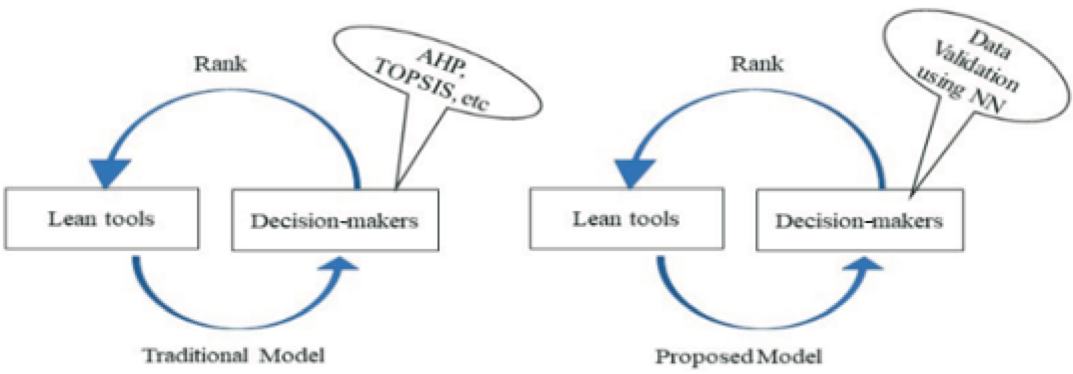


Fig. 1 The conceptual contrast between the proposed model and conventional procedures

In the assessment of an organisation's leanness, various methods were employed to evaluate the criteria that influence its leanness. In this study, a significant approach involves the utilisation of an artificial neural network in a hybrid multi-criteria decision-making (MCDM) framework. This approach is particularly valuable due to the presence of uncertainty, imprecision, and ambiguity in scoring methods, necessitating a robust MCDM-based model [9-11]. To assess leanness effectively, decision-makers play a crucial role by contributing performance measures and ratings for different criteria. These criteria are essential for evaluating the effectiveness of lean processes, and decision-makers often express their assessments using linguistic factors [12-14]. In this study, an exploratory approach was taken to understand the relationships between criteria, facilitators, and performance scores. This was achieved by constructing a network that incorporates historical data and employs a neural network for analysis. The Euclidean distance method was subsequently applied to assess the organisation's level of leanness. Decision numbers provided by decision-makers were transformed into decision variables and compared to linguistic categories. Furthermore, this study goes beyond assessment by providing recommendations for enhancing areas with identified potential for improvement. It examines key lean performance metrics, including process time, cost, a work-in-progress (WIP) inventory, and defect rates, both before and after implementing the leanness assessment method, to analyse production developments [15].

To investigate the effectiveness of lean management practices within an organisation, the following research objectives were addressed: (1) present a hybrid MCDM TOPSIS and entropy framework for choosing and ranking lean tools; (2) assess the order of lean tools produced by the hybrid TOPSIS and entropy approaches; and (3) show the value of efficacy of the projected case study by applying it to the foundry manufacturing industry. The following sections present the literature review, methodology, and case study implementation. The improvements are then illustrated by making comparisons between the current and future state of VSM, after which conclusions and proposals for further study are presented.

2. Review of literature

Previous studies have primarily examined production within organisations and have explored critical factors related to lean implementation from a manufacturing perspective. These studies have paved the way for the research opportunity addressed in this study.

By methodically identifying and eliminating waste (any activity that consumes resources without providing consumer value), the lean concept intends to provide manufacturers with a new competitive edge [16–18]. Therefore, unlike mass production, which takes advantage of economies of scale, lean production is customer-centric. In order to maximise profits, companies should follow the lead of Hu et al., 2015 [19] and create a company culture that prioritises the needs of customers [20]. Since this is the case, many businesses of varying sizes and scopes are attempting to adopt lean manufacturing practices, which aim to change labour-intensive production with systems that are more valued, adaptable, and productive [21].

Lean manufacturing has demonstrated success in many organisations which has made it more appealing to small and medium enterprises (SME) worldwide. Consequently, numerous organisations have adopted lean manufacturing techniques to enhance their production and efficiency [22]. The use of JIT, Kanban, Hoshin, and 5S among other lean tools has been shown to boost productivity and quality in numerous cases of lean deployment in small and medium business units (SMB) [23]. Based on a series of case studies conducted by Panizzolo et al. (2012), it has been found that using lean methodologies in Indian small and medium enterprises (SMEs) can greatly improve their manufacturing performance. This is particularly relevant for SMEs in developing countries. [23]. Upadhye et al. (2010) described the significant steps in an Indian SME to implement lean philosophy in order to increase its efficiency and effectiveness [24]. The company recognised that the implementation of lean tools, such as 5S and SMED, would lead to improvements as a result of adhering to the lean philosophy. Similarly, numerous analyses have revealed the advantages enjoyed by small enterprises employing lean methods and equipment. Grewal (2008) observed a 33.18% decrease in cycle time, an 81.5% decrease in switch time, an 81.4% decrease in lead time, and a 1.41% decrease in value added time in a small company located near Ludhiana that implemented VSM [25]. In addition, Matt and Rauch (2013) implemented a study to aid small businesses in northern Italy in implementing lean production [26]. Dora et al. (2013) found that the implementation of lean practices in European SME food processors is low and still evolving [27]. The study revealed a staggering productivity increase of over 25% across all products. Various additional studies demonstrate the unexplored capacity of small businesses and the efficacy of lean methodology in small and medium-sized enterprises (SMEs). Minimisation of cycle time, set-up time, lead time, and delivery time can reduce the amount of space used, product quality, and cost [28]. Consequently, the importance of lean implementation in SMBs is now widely recognised. Multiple international studies have found surprisingly low success rates for lean initiatives in SMBs. In addition, Thomas et al. (2014) claimed that lean and Six Sigma edges in the United Kingdom are advancing slowly [29]. In reality, only 4% to 6% of small businesses transition to lean organisations. The LM concept tools promote job safety and reduce the causes of accidents in the workplace at various levels [30]. J. Furman et al. (2021) suggest that the use of proper LM tools to control waste in one place can reduce waste in other places as well [31]. The study found that previous research had commonly utilised selection methods for lean tools by examining the associations between either lean tools and performance metrics, lean tools and waste reduction, or all together [32-33].

2.1 Review of literature on artificial neural networks

A neural network is an effective tool for making predictions using nonlinear models, but it can be challenging to determine the optimal network layout. The best network structure has been sought using an evolutionary algorithms technique. Au et al. (2008) observed basic connected neural network models and other estimating models [34]. Chambers and Campbell (2002) proposed a method for modelling system components using ANNs [35]. A comprehensive system was constructed by linking artificial neural network (ANN) meta models, and simulation was employed to instruct the ANN to function as a unified and versatile processing unit. Golmohammadi (2011) introduced a model for multi-criteria decision-making using a feed-forward neural network and fuzzy logic [36]. A correlation between input and output was established by training the model using neural networks and assigning weights to various criteria, enabling the model to make judgments.

The ranking of the options is dependent on the weights assigned by the decision-makers.

Ciurana et al. (2008) proposed a method for the selection of machine tools within a manufacturing company [37]. The selection of appropriate questionnaires will have an effect on both the process and the expansion of the organisation. In order to find the best tool for the organisation, neural networks have been deployed and, for the purpose of forecasting lumpy demand, In their study, Gutierrez et al. (2008) created a neural network model to compare its results with those obtained using the usual time sequence approach. The researchers found that the neural network model outperformed traditional methods, as stated in their conclusion [38]. In order to estimate manufacturing costs for a novel single disc brake design, Cavalieri et al. (2003) evaluated parametric and artificial neural network (ANN) approaches [39]. The outcome suggests that ANNs appear to strike a better balance between accuracy and development cost than other methods [40].

Numerous articles outline the application of integrated frameworks for the prioritising of lean tools, which are considered an MCDM issue. The frameworks employ MCDM techniques, including FAHP, fuzzy TOPSIS (FTOPSIS), and a fuzzy decision-making trial and evaluation laboratory (FDEMATEL) [5], [41-43]. Due to their ease of calculation, triangular fuzzy numbers (TFNs) are often employed in research [44].

2.2 Literature-identified knowledge gaps

In literature, the results of AHP and FAHP are compared with FTOPSIS, VIKOR and, PROMETHEE or other combinations of these techniques for industry. Researchers have utilised TOPSIS and COPRAS methodologies to optimise LT decision problems using a single-phased approach without any validation. The assessment of different frameworks for a lean tool for this problem was innovative in this study that used entropy TOPSIS and which was validated using an ANN approach. ANNs can capture non-linear relationships in data. In this investigation, the complexity was idealised as more of a cause-and-effect type for the multiple factors considered. The study focuses on the ranking of lean tools that can be effectively used for enhancing the process outcomes. Thus, the research outcome will be achieved by mapping the appropriate lean tools for improving the desired outcome of the factors investigated.

Artificial neural networks (ANNs) excel at capturing non-linear relationships within data. In this study, the complexity of the relationships was conceptualised as predominantly cause-and-effect for the multiple factors under consideration. The primary objective of this research was to prioritise and rank lean tools that can be effectively employed to enhance process outcomes. Consequently, the research aims to provide valuable insights by identifying the most suitable lean tools for improving the desired outcomes associated with the investigated factors.

The novelty of our work lies in the validation of the lean tools ranked by TOPSIS using artificial neural networks (ANNs), which are then mapped for the purpose of process improvement.

3. Methodology

The methodology was implemented after reviewing the research literature, interviewing experts, and surveying the managers in a foundry at the core shop and moulding division. Decision-making criteria were identified through the brainstorming method. The steps are illustrated in Figure 2 and are explained as follows.

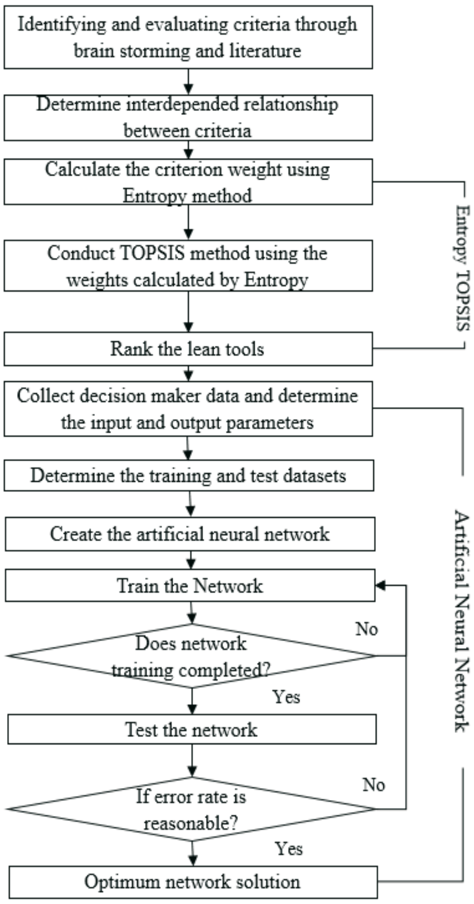


Fig. 2 The research methodology

Step 1: Identifying and evaluating criteria through brainstorming and literature

Determining the criteria is one of the most crucial aspects of decision-making models. Important aspects and characteristics of ranking lean tools include the selection of criteria, the design, and the lean tools as inputs to the decision-making model that has a direct impact on the efficiency of the model.

The selection of criteria and lean tools for ranking processes vary based on their objectives. In our case study, the foundry organisation utilised brainstorming as a method to determine the criteria that align with its strategic objectives. Therefore, decision-makers in the core shop and moulding division met and recorded the decision values which influence the process and the selection of an appropriate lean tool. The following criteria were identified: process time [C1], cost [C2], defects [C3], safety [C4] and quality [C5].

Step 2: Determining the interdependence of the criteria

Next, to account for the interdependence among the criteria, it became essential to establish a precise network structure that reflects these relationships. This network structure was constructed through a second round of brainstorming, primarily based on the following relationships: process time, cost, and defect rates may be influenced by factors such as productivity and safety considerations. Figure 3 visually represents the mapping of the interdependent structure of the criteria and lean tools. For the purpose of this study and implementation in the core shop, a selection of lean tools (LT) was identified. These lean tools include 5S (LT1), Value Stream Mapping (LT2), Just-in-Time (LT3), Kanban (LT4), Kaizen (LT5), Continuous Flow (LT6), Poka-yoke (LT7), Pull System (LT8), Setup Reduction (LT9), Standardised Work (LT10), Total Productive Maintenance (LT11), Cellular Manufacturing (LT12), and Jidoka (LT13).

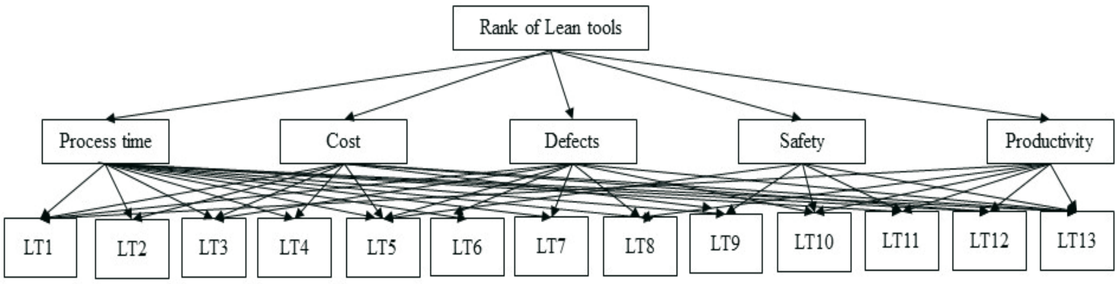


Fig. 3 Interdependent structure of criteria and lean tools

Step 3: Determining the weights of the criteria by the entropy technique

In contrast, Shannon's entropy emerges as a highly recommended method for determining criterion weights due to its efficiency in enhancing the reliability and precision of decision-making, all without the need for intricate modelling. This is unlike objective weighting techniques such as surveys, Delphi, or AHP, which can introduce subjective biases into index weights. The use of Shannon's entropy offers a more objective approach. As pointed out by Li et al., objective fixed weight methods like entropy have the advantage of mitigating human-induced disturbances. This is because they rely on information inherent in the indexes themselves, establishing index weights based on existing data [45]. Consequently, the application of entropy, in combination with the TOPSIS method, contributes to a substantial improvement in the reliability and accuracy of lean tool ranking, aligning the results more closely with factual information [46].

Step 4: Entropy weight calculation

The entropy weight method is a good way to work out the importance of the different criteria for TOPSIS computation. This method was originally derived from thermodynamics and later applied to information systems. Information entropy encompasses the unpredictability of communication signals. Similar to the objective of fixed weight methods, the entropy weight method calculates the index's weight based on the information volume. The normalising of the available decision matrix

$$m_{ij} = \frac{xij}{\sum_{1=n}^{k} xij} \tag{1}$$

The entropy of each index is calculated using equation (2).

$$E_j = \frac{1}{Ln} m \sum_{i=}^{n} P_ij \, ln \, P_{ij} j = 1 \ldots n \tag{2}$$

The assessment of the degree of deviation of essential information for each criterion

$$Dj = 1 - E_{ij} \quad j = 1 \ldots n \tag{3}$$

where *Dj* measures the grade of deviance of critical data for the *j*th criteria.

The calculation of the criteria's entropy weight

$$wj = \frac{Dj}{\sum_{i=1}^{n} Dj} \tag{4}$$

where *wj* is the importance weight of the *j*th criteria.

Step 5: TOPSIS (Technique for Order Performance by Similarity to Ideal Solution)

1. Yoon and Hwang created TOPSIS in 1981. The chosen option should be closest to the ideal solution and farthest from the negative-perfect solution [47].
2. Chen's fuzzy TOPSIS process is similar to the standard one and can be stated as a series of steps [48].
3. Rank alternatives in descending order of preference - c_1^*.

The linear scale transformation is: $\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), c_j^* = \max_i c_{ij}$ (5)

To avoid the effect of the index dimension and its range of change on the assessment results, the original matrix must be normalised to ensure that all the characteristics are in the same format and have the same value. In this way, normalised numbers can be calculated.

The Jahanshahloo et al. formula [49] is:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{\sqrt{\sum_{i=1}^{n}\left(\left(a_{ij}\right)^2 + \left(c_{ij}\right)^2\right)}}, \frac{b_{ij}}{\sqrt{\sum_{i=1}^{n} 2b_{ij}}}, \frac{c_{ij}}{\sqrt{\sum_{i=1}^{n}\left(\left(a_{ij}\right)^2 + \left(c_{ij}\right)^2\right)}}\right), \tag{6}$$

where $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$ are the elements of the decision matrix.

Construct the weighted normalised decision matrix.

In this section, a set of weights of *n* indicators *wj*= $\{v_{ij} = 1, 2, \ldots, n\}$, where $wj > 0$ is applied to compute the weighted normalised decision matrix

$$\tilde{v}_{ij} = \tilde{w}_j \times \tilde{r}_{ij}, j = 1,2, \ldots m; i = 1,2,3 \ldots \ldots n \tag{7}$$

Determine the fuzzy ideal and fuzzy negative-ideal solutions.

The positive ideal solution contains the optimal values of every characteristic from the weighted normalised choice matrix, whereas the negative ideal solution has the worst values determined as follows:

$$A^{+} = \{\tilde{v}_1^{+}, \tilde{v}_2^{+}, \ldots\ldots \tilde{v}_m^{+}\} \tag{8}$$

$$A^{-} = \{\tilde{v}_1^{-}, \tilde{v}_2^{-}, \ldots\ldots \tilde{v}_m^{-}\} \tag{9}$$

where, $\tilde{v}_j^{+} = (1,1,1)$ and $\tilde{v}_j^{-} = (0,0,0), j = 1,2,3, \ldots\ldots\ldots. m$

Calculate the separation measure.

After computing the distance between each option and the positive and negative ideal solutions, the separation value is calculated.

Ideal Separation: $$S_i^{+} = \sum_{j=1}^{m} s(\tilde{v}_{ij}, \tilde{v}_j^{+}) \qquad i = 1,2, \ldots\ldots\ldots.. n \tag{10}$$

Negative –ideal Separation: $$S_i^{-} = \sum_{j=1}^{m} s(\tilde{v}_{ij}, \tilde{v}_j^{-}) \quad i = 1,2, \ldots n \tag{11}$$

where $s(\tilde{v}_{ij}, \tilde{v}_j^{+})$ and $s(\tilde{v}_{ij}, \tilde{v}_j^{-})$ are distance measurements calculated with the vertex method:

$$d(\tilde{x}_{ij}, \tilde{y}_{ij}) = \sqrt{\frac{1}{3}\left[\left(x_{ij}^1 - y_{ij}^1\right)^2 + \left(x_{ij}^2 - y_{ij}^2\right)^2 + \left(x_{ij}^3 - y_{ij}^3\right)^2\right]} \tag{12}$$

$$\tilde{x}_{ij} = \left(x_{ij,}^1 x_{ij}^2, x_{ij}^3\right), \ \tilde{y}_{ij} = \left(y_{ij,}^1 y_{ij}^2, y_{ij}^3\right)$$

Calculate the relative closeness to the ideal solution.

The closeness coefficients of each alternative are calculated by

$$c_i^{*} = \frac{S_i^{-}}{(S_i^{+} + S_i^{-})}, \ 0 < c_i^{*} < 1, \ \ i = 1,2,3 \ldots. n, \tag{13}$$

$$c_i^{*} = 1 \text{ if } \ A_i = A^{+} \quad c_i^{*} = 0 \text{ if } A_i = A^{-}.$$

Finally, the alternatives can be ranked based on the closeness coefficients, in which the best alternative is the one with the highest value.

Step 6: Neural network structure

Traditionally, multi-criteria decision-making (MCDM) has been a manual process for ranking lean tools. However, this research departs from the conventional approach by assessing the ranking based on how effectively artificial neural networks (ANNs) can capture and retain complex information. In the case of artificial neural networks, achieving the correct results involves the fusion of logical reasoning, historical data, and a well-designed neural network model. The MATLAB Neural Network toolbox was utilised for simulating the network in this research. Several strategic factors come into play, including the selection of input variables, the network architecture, and the volume of training data, all of which significantly impact the accuracy of neural leanness assessment network forecasts. Key considerations in neural network modelling encompass the size of input nodes, the presence of hidden layers, hidden neurons, training rules, training rates, and stop criteria for training. For most scenarios, a single hidden layer sufficed, although increasing the number of hidden layer units proved advantageous [50]. Selecting the optimal architecture was the first step in building the neural network model. Backpropagation emerged as the most prominent neural network architecture for pattern recognition [51]. Figure 4 illustrates the overall architecture of backpropagation, comprising three parallel layers. To advance a backpropagation model, a training set of input and output data patterns was essential. The first layer included input variables, while the second layer(s) housed processing units known as hidden nodes, and the third layer contained output variables. Weighted connections linked these layers, and these weights were estimated through training or manual initialisation. The correct outcome was attained by manually initialising the weights and iteratively adjusting them towards the target.

Neural network training consisted of two stages. In the first stage of backpropagation training, the network received an input sequence, and the resulting activity propagated to the output nodes. The programme compared the actual output with the expected output from the training dataset. This comparison generated an error signal for each neuron in the output layer. During the subsequent reverse phase, these error signals were propagated back through the network to adjust the layer weights. This process was repeated until the difference between the actual and expected outputs fell within an acceptable range [52]. The objective of this approach was to identify fault value systems for all network weights using gradient descent. We used a well-liked activation function called the rectified linear unit (ReLU). For negative inputs, it returns zero; for positive inputs, it returns the input value.

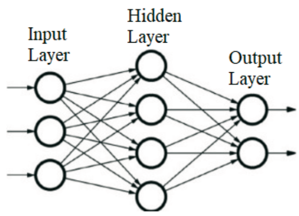


Fig. 4 The structure of the neural network

Step 7: Application of the neural network for the ranking of lean tools

The application stages are presented in the following sections. Figure 5 shows the detailed structure of the neural network:

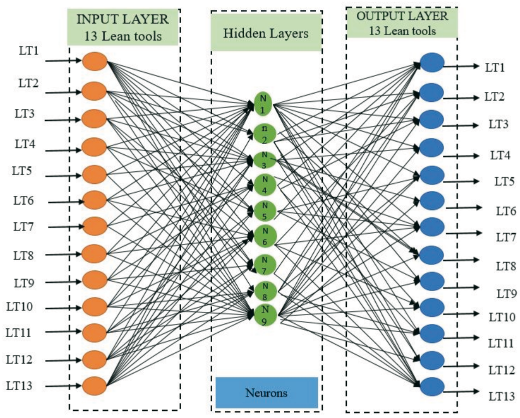
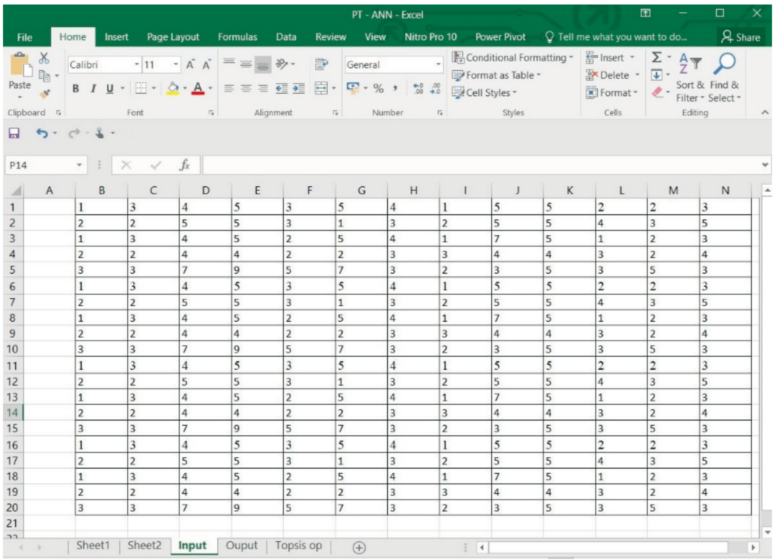


Fig. 5 Proposed network architecture

Input variable

The decision-makers' chosen data were combined to create the input data for ranking the lean tools. In order to prepare these data for future ranking, logic was used to merge them. The data collected cannot be combined using any predefined logic. Through experimenting or repetitions, the ideal combination was found. The data used affect both the training time and precision. In this study, the data collected utilised to calculate the organisation's level of leanness was created by integrating the five most recent evaluation results. Since the data set was small, to improve output, a larger data set was used which can help the model generalise better because it provides more diverse examples for training. In this investigation, the data set was repeatedly used three times for better accuracy in prediction. The training time and accuracy depend on the input data. Figure 6.a shows the input dataset:

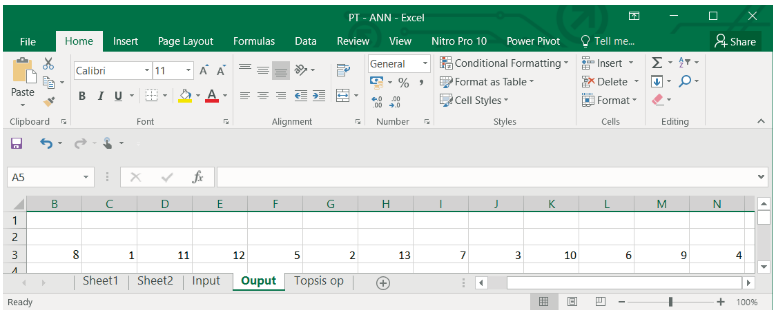


	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		1	3	4	5	3	5	4	1	5	5	2	2	3
2		2	2	5	5	3	1	3	2	5	5	4	3	5
3		1	3	4	5	2	5	4	1	7	5	1	2	3
4		2	2	4	4	2	2	3	3	4	4	3	2	4
5		3	3	7	9	5	7	3	2	3	5	3	5	3
6		1	3	4	5	3	5	4	1	5	5	2	2	3
7		2	2	5	5	3	1	3	2	5	5	4	3	5
8		1	3	4	5	2	5	4	1	7	5	1	2	3
9		2	2	4	4	2	2	3	3	4	4	3	2	4
10		3	3	7	9	5	7	3	2	3	5	3	5	3
11		1	3	4	5	3	5	4	1	5	5	2	2	3
12		2	2	5	5	3	1	3	2	5	5	4	3	5
13		1	3	4	5	2	5	4	1	7	5	1	2	3
14		2	2	4	4	2	2	3	3	4	4	3	2	4
15		3	3	7	9	5	7	3	2	3	5	3	5	3
16		1	3	4	5	3	5	4	1	5	5	2	2	3
17		2	2	5	5	3	1	3	2	5	5	4	3	5
18		1	3	4	5	2	5	4	1	7	5	1	2	3
19		2	2	4	4	2	2	3	3	4	4	3	2	4
20		3	3	7	9	5	7	3	2	3	5	3	5	3

Fig. 6.a Input data

Target value

The output was a set of data combined in the same fashion as the input data. Both input and output are fed during back propagation training. Error was generated and neuronal weights were derived based on these data. It is a 13 by 1 matrix, representing static data of 1 and samples of 13 elements of input data that have been clubbed. Figure 6.b shows the target values:



	B	C	D	E	F	G	H	I	J	K	L	M	N
1													
2													
3	8	1	11	12	5	2	13	7	3	10	6	9	4

Fig. 6.b Target value

Step 8: Neural network architecture

The network is constructed after determining the input values and target variables and specifying their requirements.

The number of levels and network type are the key factors in this case. Here, two layers are used. Finding the ideal weight combination requires a significant amount of calculation when there are more factors and multifaceted networks present.

Figure 6.c illustrates the network layers, including the input and neuron quantities used for training the dataset. The output dataset consisted of the ranking of lean tools.

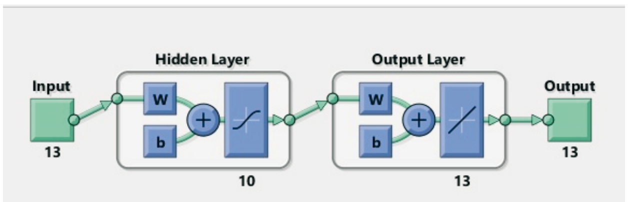


Fig. 6.c Network layers

In this situation, feed forward backpropagation is the most common learning technique that can deal with these problems. Consequently, this model uses feed-forward backpropagation learning. TRANSLIM was chosen as the training function. Two layers were chosen as the number of layers. Figure 6 illustrates the multi-layered network with the TRANSIG transfer function as the first layer and the PURELIN transfer function as the second layer. The second layer will be used to converge towards the intended output since the first layer will be used to determine the pattern of the model. The network architecture parameters are shown in Figure 7. A two-layer feed-forward network can effectively address multidimensional mapping problems when provided with continuous input and a sufficient number of neurons in the hidden layer. In this model, 10 neurons were suitable for small data sets, but this depends on the complexity of the task and the nature of the data. Using a small number of neurons (e.g., 10) can lead to a simpler model. Simpler models are less prone to overfitting, which is a common concern when dealing with small data sets.

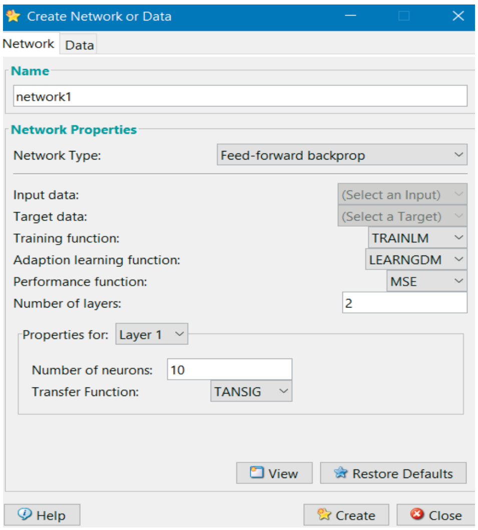


Fig. 7 Parameters to train the network

Step 9: Training and testing

The challenge in emerging neural networks is identifying the optimal training point at which the neural network produces optimal results. Usually, a neural network that has been trained to give the lowest number of errors when faced with the training data set is not generalisable. The required information must be divided into two separate groups for this function to work. The training set is the collection of data used to train the neural network. The second group is the test set, which is periodically examined to determine the error rate. The network producing the fewest errors on the test set is preserved. After the network is structured, training can occur. The linguistic factors provided by the decision-makers make up the training data. Seventy percent of the available data is used to train the model as shown in Figure 8. In the test phase, the effectiveness of the network is assessed by contrasting the outcomes of cases from the non-training set with the actual assessments of scores given by the decision-makers. After the data have been validated, they are used to determine the leanness of the organisation.

Step 10: Validation

In order to evaluate the lean tools for the criteria, the model was evaluated by simulating the network for the entire database. The data used to evaluate and test the criteria are shown in Figure 8. Here 13 samples taken randomly from 15 data sets and 80% of the data set are used for training and the remaining 20% of the data set is used for validation and testing with each 10% respectively.

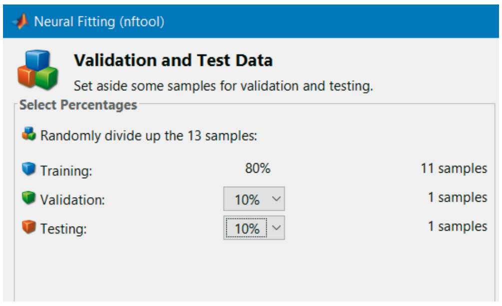


Fig. 8 Validate and test data

4. Case study

The research study was conducted at a core shop division of a foundry in the southern portion of Tamil Nadu, India. It produces a wide variety of castings for the Indian and international market, including pump housings, valves, engine heads for automobiles, gear box housing, and pressure plates. Product quality and demand in India help it maintain market leadership.

Phase I: Development of current state mapping and existing plant layout

Preliminary visits included direct remarks and interviews with case workers. Due to needless conveyance and movement, the shop floor of the company lacked an efficient process flow. In addition, unplanned continuous production regardless of demand may result in the overproduction of products that become obsolete. Figure 9 depicts the layout of the core shop, which is an integral part of the foundry. Depending on needs, a wide range of cores ranging from 1 kg to 4.5 kg are manufactured here. Mixing sand, filling a shooter with sand, shooting the shooter, core cleaning, pasting, painting, baking, and finally storing the core are the sequence of operations required. Material flow, layout details, and operating times are recorded by engaging with the management, managers, and workers. Local inspection gathers cycle time (CT), shifts, and operators.

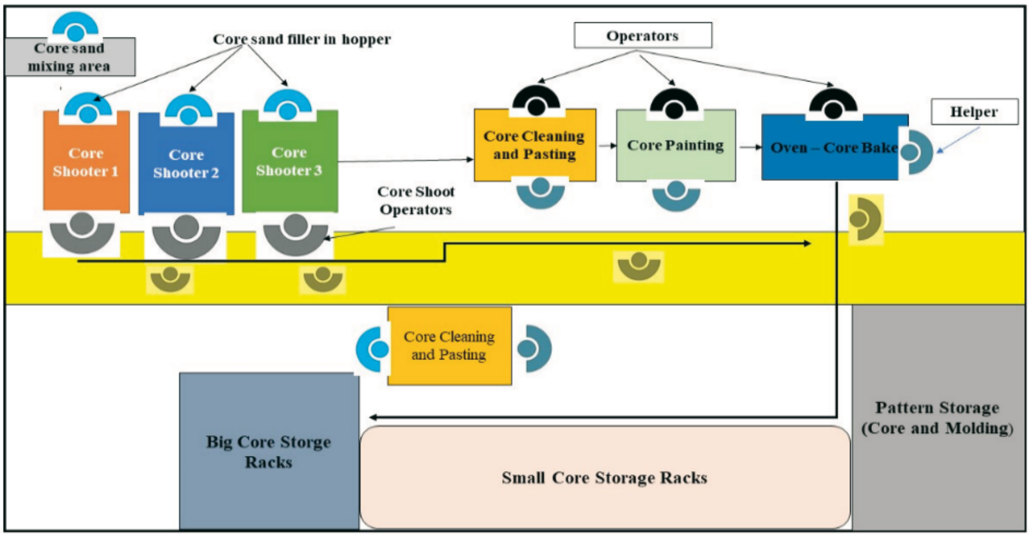


Fig. 9 Existing layout of core shop

Figure10 shows the current stream mapping of the current layout where process time and NVA time are derived. The discovered waste is excess work in the process inventory, according to the plant layout, current state mapping, and observations, the underutilisation of people, unnecessary motion, waiting for the core to arrive at the respective station, core defects due to poor handling, and a longer lead time.

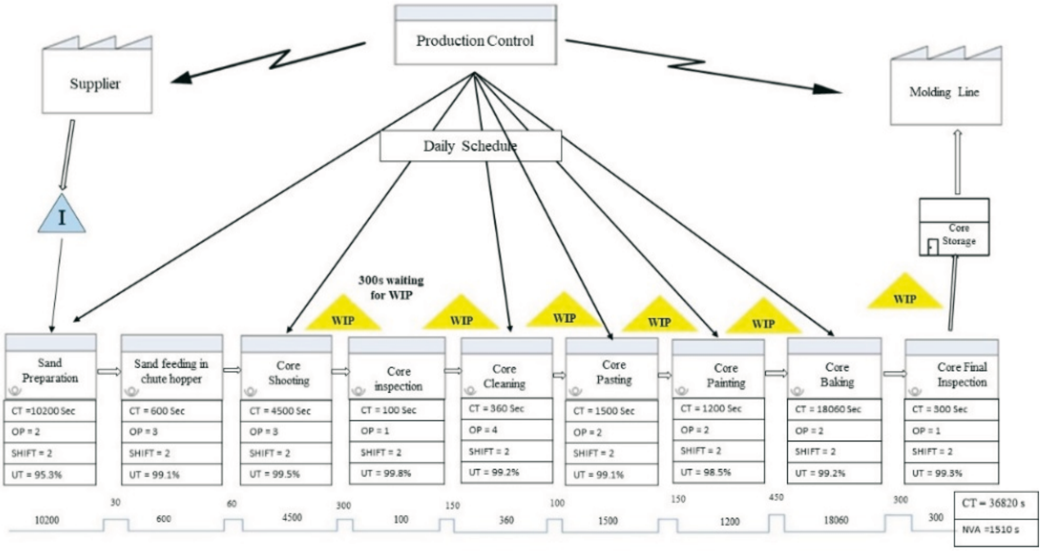


Fig. 10 Current stream mapping of core station

Cost calculation before implementing lean tools

Manpower utilised in each shop is shown in Table 1.

Table 1 Details of manpower utilised in core shop [Before Implementation]

S. No.	Station	No. of manpower
1	Sand Mixing	1
2	Sand filling	3
3	Core shooter	3
4	Carrying core from shooter to other station	4
5	Cleaning and pasting	4
6	Painting	2
7	Oven	2
8	Moving to core from oven to storage	1

Cost of manpower per day was Rs 800/-
No. of manpower was 20 per day
Total cost = cost of manpower × No. of manpower × month × year
Total cost = 800 × 20 × 30 × 12 = Rs 5,760,000/-

5. Result and discussion

The hierarchical structure of four criteria used to rank 13 lean tools is represented in Figure 3. The lean tools (LT1 to LT13) are located at the base of the hierarchy, while the criteria used to rank the lean tools are located in the middle. On a scale from 1 to 9, the criteria and alternatives are assessed. Table 2 shows the details of the decision-makers. Table 3 displays the linguistic factors and ratings for the alternatives and criterion. The calculated normalised, weighted normalised matrix and ideal solutions using TOPSIS is shown in Tables 4, 5, and 6.

Table 2 Details of decision-makers

Decision-makers	Designation	Area of expertise	Years of experience
DM1	VP	Manufacturing	20
DM2	Director	Manufacturing	18
DM3	Sr Manager	Manufacturing and Design	15
DM4	Professor	Industrial engineering	22
DM5	Professor	Manufacturing engineering	20

The pairwise comparison of criteria to assess the leanness was analysed by Saaty's method shown in Table 3 [53].

Table 3 Linguistic factors and ratings for the alternatives and criteria by Saaty

Description	Values
Equal importance	1
Less importance	3
Essential or strong importance	5
Important	7
Very important	9
Intermediate values	2, 4, 6, 8

5.1 Calculate the normalised decision matrix

Table 4 Entropy weights and normalised matrix with reference to process time

Entropy weights	0.22754	0.12577	0.34273	0.09471	0.20924
Lean tools	**DM1**	**DM2**	**DM3**	**DM4**	**DM5**
5S	0.076923	0.14548	0.07352	0.17747	0.16984
VSM	0.23077	0.14548	0.22056	0.17747	0.16984
JIT	0.30769	0.3637	0.29409	0.35494	0.3963
Kanban	0.38462	0.3637	0.36761	0.35494	0.50952
Kaizen	0.23077	0.21822	0.14704	0.17747	0.28307
Continuous flow	0.38462	0.21822	0.36761	0.17747	0.3963
Poka-yoke	0.30769	0.21822	0.29409	0.26621	0.16984
Pull system	0.07692	0.14548	0.07352	0.26621	0.11323
Set up reduction	0.38462	0.3637	0.51465	0.35494	0.16984
Standard works	0.38462	0.3637	0.36761	0.35494	0.28307
TPM	0.15385	0.29096	0.07352	0.26621	0.16984
Cellular manufacturing	0.15385	0.21822	0.14704	0.17747	0.28307
Jidoka	0.23077	0.3637	0.22056	0.35494	0.16984

5.2 Calculate the weighted normalised decision matrix

Table 5 Weighted normalised matrix with reference to process time

Lean tools	DM1	DM2	DM3	DM4	DM5
5S	0.017503	0.0183	0.0252	0.01681	0.035537
VSM	0.05251	0.0183	0.0756	0.01681	0.035537
JIT	0.070013	0.04574	0.10079	0.03362	0.08292
Kanban	0.087516	0.04574	0.12599	0.03362	0.10661
Kaizen	0.05251	0.02745	0.0504	0.01681	0.059229
Continuous flow	0.087516	0.02745	0.12599	0.01681	0.08292
Poka-yoke	0.070013	0.02745	0.10079	0.02521	0.035537
Pull system	0.017503	0.0183	0.0252	0.02521	0.023691
Set up reduction	0.087516	0.04574	0.17639	0.03362	0.035537
Standard works	0.087516	0.04574	0.12599	0.03362	0.059229
TPM	0.035006	0.0366	0.0252	0.02521	0.035537
Cellular manufacturing	0.035006	0.02745	0.0504	0.01681	0.059229
Jidoka	0.05251	0.04574	0.0756	0.03362	0.035537

Table 6 Ideal solution

Decision-makers	DM1	DM2	DM3	DM4	DM5
Positive ideal solution	0.087516	0.04574	0.17639	0.03362	0.10661
Negative ideal solution	0.017503	0.0183	0.0252	0.01681	0.023691

The ranking of lean tools of the process time criteria is listed in Table 7 based on the performance score.

Table 7 Performance score and rank of lean tools with reference to process time

Lean tools [LT]	Performance score	Rank
5S	0.060492	2
VSM	0.32102	6
JIT	0.58441	9
Kanban	0.75047	13
Kaizen	0.28613	5
Continuous flow	0.69133	11
Poka-yoke	0.46636	8
Pull system	0.042724	1
Set up reduction	0.70531	12
Standard works	0.65573	10
TPM	0.14257	3
Cellular manufacturing	0.246	4
Jidoka	0.35413	7

5.3 Assessment over MCDM approaches

With reference to the calculated results, the ranking of lean tools obtained from the entropy - TOPSIS methodology for the process time is LT8 >LT1 >LT11>LT12 >LT5 >LT2 >LT13 >LT7 >LT3 >LT10 >LT6 >LT9 >LT4. TOPSIS ranks the pull system (LT8) highest with a closeness value of 0.042 and Kanban (LT4) last with 0.75. Table 8 shows the ranking of lean tools on other criteria. The objective of the pull system is to manufacture goods only in response to consumer demand. This particular methodology effectively mitigates the issue of overproduction and significantly curtails the building of surplus inventory. Kanban serves as a tool for effectively managing and controlling the flow of work-in-progress.

Table 8 Ranking of lean tools based on criteria

Cost	LT12 > LT8 > LT11 > LT3 > LT5 > LT2 > LT6 > LT7 > LT10 > LT1 > LT9 > LT13 > LT4
Defects	LT10 > LT3 > LT6 > LT12 > LT9 > LT4 > LT5 > LT11 > LT13 > LT7 > LT2 > LT1 > LT8
Safety	LT8 > LT12 > LT11 > LT1 > LT5 > LT3 > LT2 > LT13 > LT10 > LT9 > LT7 > LT6 > LT4
Quality	LT6 > LT12 > LT3 > LT7 > LT4 > LT2 > LT13 > LT10 > LT5 > LT1 > LT11 > LT9 > LT8

5.4 Improving the designed input and output

The neural network's inputs and outputs are unique, but there are hidden issues. These errors might affect training and test performance.

After modifying the inputs and outputs of the model, the mean squared error (MSE) values for both the training and test results decreased after eight samples.

5.5 Under fitting

A training and validation loss that keeps declining at the end of the plot is another sign of an underfit model. This shows that the model can still learn more and that the training process was stopped too soon. Figure 11.a shows the gap between training and validation which indicates the curve is underfit.

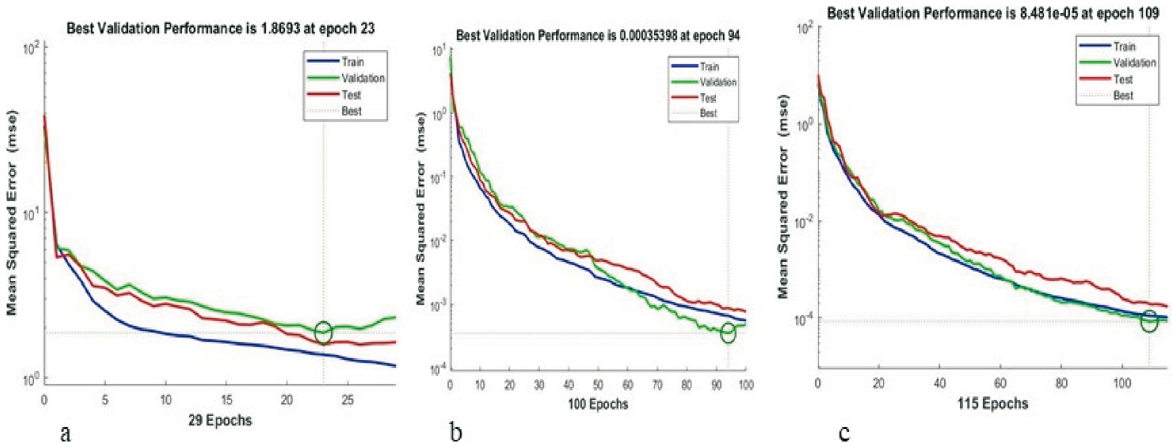


Fig. 11.a Performance and validation curve a. epoch 29. b. epoch 100 c. epoch 115

5.6 Over fitting

Overfitting is when a model learns the training data set, including statistical noise, too well. To fit a model that is more flexible, we must estimate a greater quantity of parameters. "Overfitting the data" means these advanced models follow mistakes or noise too closely. Figure 11.a illustrates the overfit curve. The more sensitive a model is to the training data, the less well it generalises to new data, increasing generalisation error. Overfitting is evident when:

1. The training loss keeps going down, but the validation loss has reached its lowest point and is now going up.
2. Nonetheless, an overfitting model is not always undesirable. In effect, it signifies that the model has derived every possible learning signal.

5.7 Optimal fit

The learning algorithm sought the best match. Generally, the model's training loss is less than its validation loss. Training and validation loss learning curves should differ. The optimum fit is when training loss stabilises. Figure 11.c shows the optimal fit curve.

1. The validation loss plot approaches a point of stability.
2. The generalisation gap is negligible (nearly zero in an ideal situation).

Overfitness is likely with continued optimal training. The example plot below illustrates the case of an optimal fit, presuming that a global minimum of the loss function has been identified. In the majority of instances, the neural network prediction closely matches the actual value. A few values were not as near as others due to the decision-makers' lean tool selections. Given that the learning rate of the artificial neural network is between 99.5% and 99.3%, these errors may be disregarded. The ANN estimates were more accurate, according to this study. Calculating the projected MAPE and correlation coefficient shows the prediction models' accuracy (R). RMSE is the fit and regression standard errors. RMSE implies fit. Figure 12.a and Fig. 12.b display the ANN model's regression analysis.

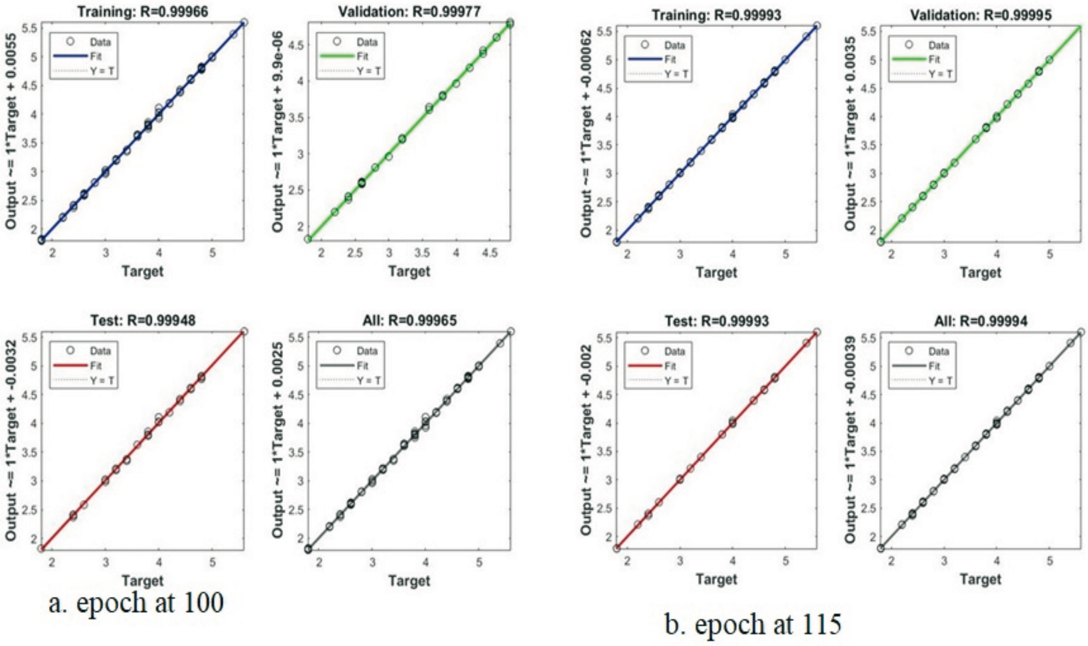


Fig. 12 Correlation between ANN prediction and the actual ranking of lean tools:

The 0.99 correlation coefficient indicates great agreement between the experiment and the model. RMSE and MAPE were satisfactory and consistent with the ANN's learning and testing stages. The model's correctness is supported by reasonable agreement between the anticipated and the experimental results.

The assessment of the rankings of lean tools based on the entropy TOPSIS approaches reveal 73.42% concurrency and 26.57% non-concurrency in the results.

Table 9 Testing and validation error

S. No.	Epoch	R		MSE	
		Training	Validation	Training	Validation
1	100	0.99966	0.99977	2.06512e-3	7.31176e-4
2	115	0.99993	0.99995	3.53979e-4	8.79101e-4

5.8 Performance of the model

Using MATLAB, the training, validation, and testing data sets were predicted. The training data-set metrics are superior to the validation data-set metrics, which are superior to the test data-set metrics. These variations reflect the impact of these sets of data on the model's training. The training data set was used to modify the network's weights and bias, the validation data set was used to halt training before overfitting occurs, and the test data set had no impact whatsoever on the training procedure. As expected, the metrics of the cross-validation experiment are comparable to the metrics of the validation data set. They achieved an impressive R^2 value of 0.9997 and RMSE of 0.0008 for the best architecture on their validation data set as shown in Table 9. Back-propagation learning constructed the feed-forward single hidden layer network. The network was provided with input and output vectors for supervised learning. During network training and testing, back-propagation learning with the decision-makers' value of lean tools was applied. According to the results, the model can rate lean tools successfully.

5.9 Comparison of ranks obtained from ET and ANN

Figure 13 shows a comparison of the ranks obtained from ET and ANN, where a small difference was observed.

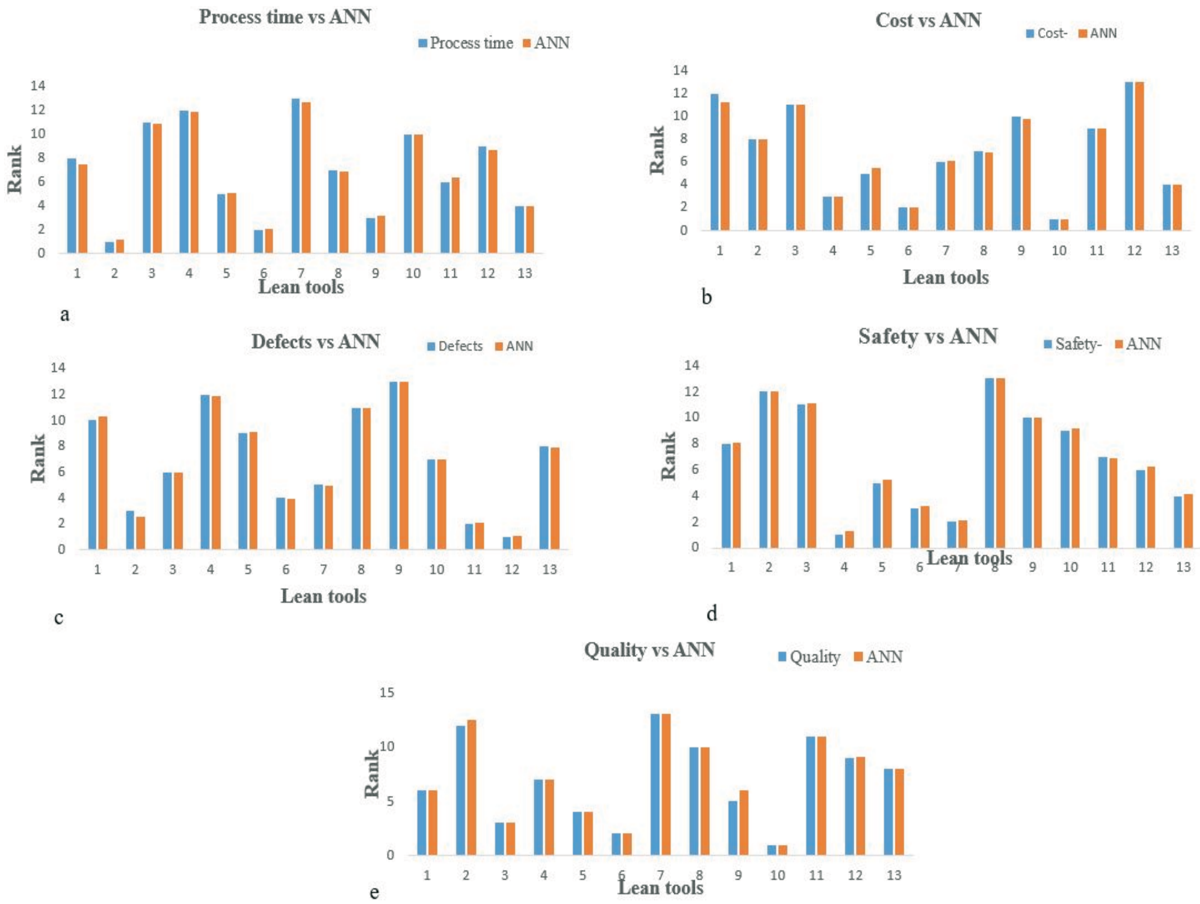


Fig. 13 Comparison of ranks obtained from ET and ANN.
a. Process time, b. Cost, c. Defects, d. Safety, e. Quality

6. Phase II: Proposed layout and future state VSM

When examining lean tools such as continuous flow (L6), the pull system (L8), standard work (L10), and cellular manufacturing (L12), it is crucial to acknowledge that their efficacy is contingent upon the particular manufacturing environment and objectives. An instance of a proficient production technique is the implementation of a conveyor system which enables the seamless and efficient execution of uninterrupted, large-scale manufacturing processes. On the other hand, alternative methodologies such as the pull system, cellular manufacturing, and work standards place higher emphasis on minimising waste and improving efficiency. As a result, these techniques are considered highly suitable for many production scenarios and are particularly relevant to the present investigation. The use of a conveyor system within the central station serves to mitigate the superfluous transportation of materials, personnel, and machinery. The implementation of a conveyor system at all stations results in a decrease in the number of operators required as well as their movements and work-in-progress inventory. The modified layout is shown in Figure 14.

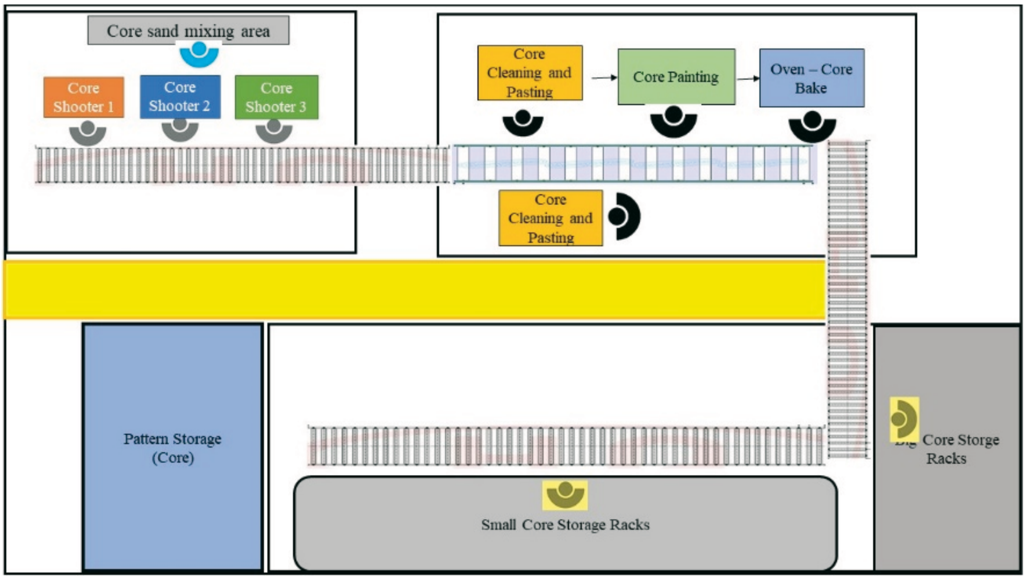


Fig. 14 Modified layout with material handling system

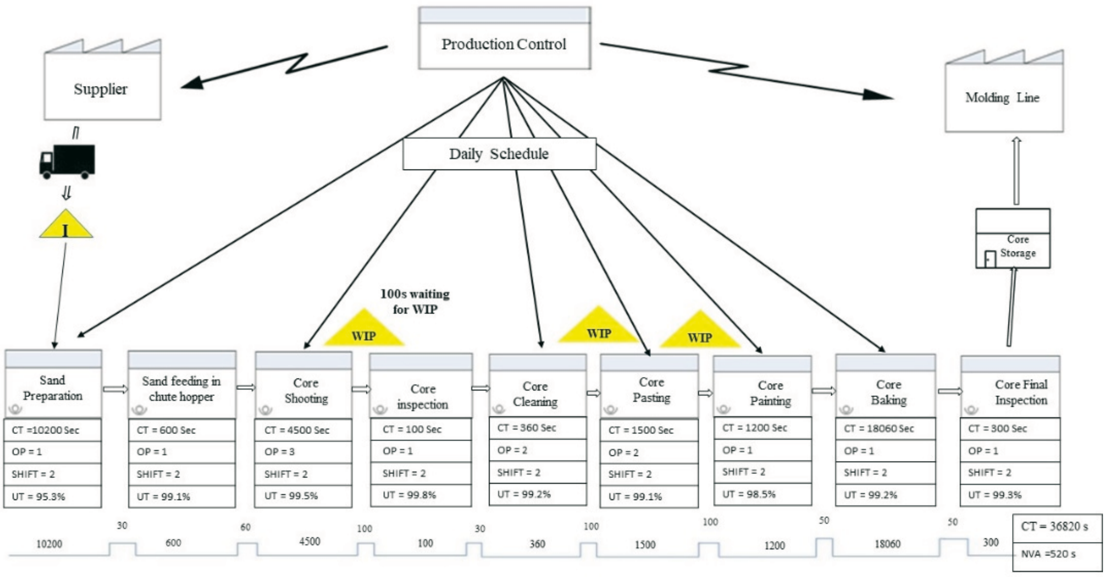


Fig. 15 Future state VSM of the modified layout

Manpower utilised in each shop after installation of the conveyor is shown in Table 10

Table 10 Details of manpower utilized in core shop [After Implementation]

S. No.	Station	No. of manpower
1	Sand mixing	1
2	Sand filling	1
3	Core shooter	3
4	Carrying core from shooter to other station	0
5	Cleaning and pasting	2
6	Painting	1
7	Oven	1
8	Moving to core from oven to storage	2

Cost calculation of post implementation

Cost of manpower per day is Rs 800/-

No. of manpower is 11

Total cost = cost of manpower × No. of manpower × month × year

Total cost = 800 × 11 × 30 × 12 = Rs. 3,168,000/-

Cost Savings = (5,760,000 – 3,168,000) = Rs. 2,592,000/-

Percentage of Cost saving = 45%

Following the adjusted layout, a future state value stream map (VSM) was formulated, as illustrated in Figure 15. These modifications were made based on an analysis of the newly established state. In this envisioned future state, notable improvements are evident. Specifically, there was a substantial reduction in lead time, decreasing from 99,418 seconds to 36,820 seconds (equivalent to a 62.66% reduction), and a significant decrease in non-value-added (NVA) time, which declined from 2,510 seconds to 510 seconds (representing a remarkable 79.6% reduction).

The results from post-implementation of lean practices have been meticulously documented within the VSM of the future state. A comparative analysis between the current and future states demonstrates substantial improvements:

- Non-value-added time process time decreased from 25.33 minutes to 8.66 minutes, marking a 65.56% reduction.
- Process time fell from 18.63 minutes to 7.26 minutes, reflecting a 61.03% decrease.
- Work-in-progress (WIP) waiting time decreased from 300 seconds to 100 seconds, a 66.66% reduction.

Furthermore, there was a commendable reduction in manpower, decreasing from 20 to 13 employees (a 35% reduction), resulting in annual cost savings of Rs. 3,168,000/-. These outcomes underscore the enhanced performance of the core shop. Notably, the defect rate witnessed a decrease, and the post-implementation of the roller conveyor system resulted in zero accidents over the past three months, signifying a positive safety record and approach.

In summary, conveyor systems and pull systems work together in lean manufacturing by optimising material flow, reducing waste, minimising WIP, and aligning production with customer demand. While conveyor systems facilitate the physical movement of materials, pull systems provide the logic and control to ensure that production remains efficient and responsive to changes in demand. Together, they contribute to a more agile and efficient manufacturing environment.

7. Conclusion

This research study shows two distinct multi-criteria decision-making (MCDM) techniques, namely entropy and TOPSIS, to assist a foundry core division within a manufacturing organisation in the selection of lean tools. The results of post-lean implementation have demonstrated remarkable enhancements, including a substantial reduction in non-value-added activities (NVA) by 79.6%, a notable improvement in process efficiency by 61.03%, a significant reduction in waiting times by 62.66%, a 35% decrease in workforce requirements, and a commendable cost reduction of 45%. In addition to these positive findings, the study proposes additional recommendations. (a) the incorporation of material handling equipment designed to simultaneously transport multiple cores; (b) the optimisation of floor space to enhance safety measures; and (c) the replacement of obsolete machinery with modern alternatives. The adaptability of this framework is contingent upon the expertise and knowledge of the experts involved, as their insights contribute significantly to its effectiveness. The study also highlights the utility of artificial neural networks (ANNs), particularly when aligning data from decision-makers with the ranking of lean tools. ANNs serve as a potent analytical tool in this context, given their effectiveness in addressing the repetitiveness associated with fuzzy logic leanness computation. Future research can explore the applicability of various MCDM techniques across diverse sectors to validate the generalisability of the findings. Furthermore, prospective studies may leverage simulation and cost-benefit analyses to corroborate the obtained results. To handle uncertainty within the decision-making environment and assign appropriate weights to each criterion, further research could explore the integration of hybrid neuro-MCDM models.

REFERENCES

[1] Womack, J. P., Jones, D. T., Roos, D. & Carpenter, D. S. (1990). The Machine That Changed the World: The Story of Lean Production-- Toyota's Secret Weapon in the Global Car Wars That Is Now Revolutionizing World Industry. New York: Simon and Schuster.

[2] M. Bhuvanesh Kumar & R. Parameshwaran (2018): Fuzzy integrated QFD, FMEA framework for the selection of lean tools in a manufacturing organization, Production Planning & Control. https://doi.org/10.1080/09537287.2018.1434253

[3] Vinoth Kumar, H. & Sivakumar, A. (2022). Integrating Ergonomic Factors with Waste Identification Diagram to Enhance Operator Performance and Productivity in the Textile Industry. Transactions of FAMENA, 46 (1), 1-21. https://doi.org/10.21278/TOF.461032621

[4] Rohani, J. M., & Zahraee, S. M. (2015). Production Line Analysis via Value Stream Mapping: A Lean Manufacturing Process of Color Industry. Procedia Manufacturing, 2, 6-10. https://doi.org/10.1016/j.promfg.2015.07.002

[5] Vinodh, S. et al. (2011) "Ahp-Based Lean Concept Selection in A Manufacturing Organization." Journal of Manufacturing Technology Management 23: 124-136. https://doi.org/10.1108/17410381211196320

[6] Kumar, M. B., & Parameshwaran, R. (2019). Fuzzy weighted geometric mean approach-based FMEA to prioritise lean failure modes in manufacturing industries. International Journal of Manufacturing Technology and Management,33(6), 398. https://doi.org/10.1504/IJMTM.2019.104550

[7] Devnath, A., Islam, M. S., Rashid, S., Islam, E. An integrated QFD-TOPSIS method for prioritization of major lean tools: a case study. International Journal of Research in Industrial Engineering, 2020; 9(1): 65-76. https://doi.org/10.22105/riej.2020.213445.1110

[8] M. Bhuvanesh Kumar & R. Parameshwaran, 2020. "A comprehensive model to prioritize lean tools for manufacturing industries: a fuzzy FMEA, AHP and QFD-based approach," International Journal of Services and Operations Management, Inderscience Enterprises Ltd, vol. 37(2), pages 170-196. https://doi.org/10.1504/IJSOM.2020.10032455

[9] Vinodh, S., Gautham, S.G., Ramiya, R.A. and Rajanayagam, D. (2010b), "Application of fuzzy analytic network process for agile concept selection in a manufacturing organization", International Journal of Production Research, Vol. 48 Nos 23/24, pp. 7243-64. https://doi.org/10.1080/00207540903434963

[10] Baguley, P., Page, T., Koliza, V. and Maropoulos, P. (2006), "Time to market prediction using type-2 fuzzy sets", Journal of Manufacturing Technology Management, Vol. 17 No. 4, pp. 513-20. https://doi.org/10.1108/17410380610662924

[11] Ullah, A.M.M.S. (2005), "A fuzzy decision model for conceptual design", Systems Engineering, Vol. 8 No. 4, pp. 296-308. https://doi.org/10.1002/sys.20038

[12] Shamsuzzaman, M., Ullah, A.M.M.S. and Bohez, E.L.J. (2003), "Applying linguistic criteria in FMS selection: fuzzy-set-AHP approach", Journal of Integrated Manufacturing Systems, Vol. 14 No. 3, pp. 247-54. https://doi.org/10.1108/09576060310463190

[13] Wang, R.C. and Chuu, S.J. (2004), "Group decision-making using a fuzzy linguistic approach for evaluating the flexibility in a manufacturing system", European Journal of Operational Research, Vol. 154 No. 3, pp. 563-72. https://doi.org/10.1016/S0377-2217(02)00729-4

[14] Ullah, A.M.M.S. and Harib, K.H. (2008), "An intelligent method for selecting optimal materials and its application", Advanced Engineering Informatics, Vol. 22 No. 4, pp. 473-83. https://doi.org/10.1016/j.aei.2008.05.006

[15] Vinodh, S., Arvind, K. R., & Somanaathan, M. (2010). Application of value stream mapping in an Indian camshaft manufacturing organization. Journal of Manufacturing Technology Management, 21(7), 888-900. https://doi.org/10.1108/17410381011077973

[16] Womack, J. P., Jones, D. T., Roos, D. & Carpenter, D. S., 1990. The Machine That Changed the World: The Story of Lean Production-- Toyota's Secret Weapon in the Global Car Wars That Is Now Revolutionizing World Industry. New York: Simon and Schuster.

[17] Shah, R. & Ward, P. T., 2007. Defining and developing measures of lean production. Journal of operations management, 25(4), pp. 785-805. https://doi.org/10.1016/j.jom.2007.01.019

[18] Panwar, A., Jain, R. & Rathore, A., 2015. Lean implementation in Indian process industries - some empirical evidence. Journal of Manufacturing Technology Management, 26(1), pp. 131- 160. https://doi.org/10.1108/JMTM-05-2013-0049

[19] Hu, Q., Mason, R., Williams, S. & Found, P., 2015. Lean implementation within SMEs: a literature review. Journal of Manufacturing Technology Management, 26(7). https://doi.org/10.1108/JMTM-02-2014-0013

[20] Karim, A. & Arif-Uz-Zaman, K., 2013. A methodology for effective implementation of lean strategies and its performance evaluation in manufacturing organizations. Business Process Management Journal, 19(1), pp. 169-196. https://doi.org/10.1108/14637151311294912

[21] Zhou, B., 2012. Lean principles, practices, and impacts: a study on small and medium sized enterprises (SMEs). Annals of Operations Research, 241(1), pp. 457-474. https://doi.org/10.1007/s10479-012-1177-3

[22] Gunasekaran, A., Forker, L. & Kobu., B., 2000. Improving operations performance in a small company: a case study. International Journal of Operations & Production Management, 20(3), pp. 316-336. https://doi.org/10.1108/01443570010308077

[23] Panizzolo, R., Garengo, P., Sharma, M. K. & Gore, A., 2012. Lean manufacturing in developing countries: evidence from Indian SMEs. Production Planning & Control: The Management of Operations, 23(10-11), pp.769-788. https://doi.org/10.1080/09537287.2011.642155

[24] Upadhye, N., Deshmukh, S. G. & Garg, S., 2010. Lean manufacturing system for medium size manufacturing enterprises: An Indian case. International Journal of Management Science and Engineering Management, 5(5), pp. 362-375. https://doi.org/10.1080/17509653.2010.10671127

[25] Grewal, C. (2008). An initiative to implement lean manufacturing using value stream mapping in a small company. International Journal of Manufacturing Technology and Management, 15(3/4), 404. https://doi.org/10.1504/IJMTM.2008.020176

[26] Matt, D. T. & Rauch, E., 2013. Implementation of Lean Production in small sized Enterprises. Procedia CIRP, Volume 12, p. 420-425. https://doi.org/10.1016/j.procir.2013.09.072

[27] Dora, M. et al., 2013a. Application of lean practices in small and medium-sized food enterprises. British Food Journal, 116(1), pp. 125-141. https://doi.org/10.1108/BFJ-05-2012-0107

[28] Ravikumar, M. M., Marimuthu, K. & Parthiban, P. (2015). Evaluating lean implementation performance in Indian MSMEs using ISM and AHP models. International Journal of Services and Operations Management, 22(1), pp. 21-39. https://doi.org/10.1504/IJSOM.2015.070881

[29] Thomas, A. J. et al. (2014). An empirical analysis of Lean Six Sigma implementation in SMEs - a migratory perspective. International Journal of Quality & Reliability Management, 31(8), pp. 888-905. https://doi.org/10.1108/IJQRM-04-2013-0070

[30] Małysa, T. & Furman, J. (2021). Application of selected lean manufacturing (LM) tools for the improvement of work safety in the steel industry. Metalurgija, 60 (3-4), 434-436. Retrieved from https://hrcak.srce.hr/256129

[31] Furman, J. & Małysa, T. (2021). The use of lean manufacturing (LM) tools in the field of production organization in the metallurgical industry. Metalurgija, 60 (3-4), 431-433. Retrieved from https://hrcak.srce.hr/256128

[32] Naeemah, A.J. and Wong, K.Y. (2023), "Selection methods of lean management tools: a review", International Journal of Productivity and Performance Management, Vol. 72 No. 4, pp. 1077-1110. https://doi.org/10.1108/IJPPM-04-2021-0198

[33] Sivakumar, A., Saravanakumar, S., Sathiamurthi, P. & KarthiVinith, K.S. (2022). Forecasting the Equipment Effectiveness in Total Productive Maintenance Using an Intelligent Hybrid Conceptual Model. Transactions of FAMENA, 46 (3), 29-40. https://doi.org/10.21278/TOF.463042822

[34] Au, K. F., Choi, T.M., & Yu, Y., (2008). Fashion retail forecasting by evolutionary neural networks. International Journal of Production Economics, 114, 615-630. https://doi.org/10.1016/j.ijpe.2007.06.013

[35] Chambers, M., & Mount-Campbell, C. A. (2002). Process optimization via neural network metamodeling. International Journal of Production Economics, 79(2), 93-100. https://doi.org/10.1016/S0925-5273(00)00188-2

[36] Golmohammadi, D. (2011). Neural network application for fuzzy multi-criteria decision-making problems. International Journal of Production Economics, 131(2), 490-504. https://doi.org/10.1016/j.ijpe.2011.01.015

[37] Ciurana, J., Garcia-Romeu, M. L., Ferrer, I., & Casadesús, M. (2008). A model for integrating process planning and production planning and control in machining processes. Robotics and Computer-Integrated Manufacturing, 24(4), 532-544. https://doi.org/10.1016/j.rcim.2007.07.013

[38] Gutierrez, R.S., Solis, A.O. and Mukhopadhyay, S. (2008), "Lumpy demand forecasting using neural networks", International Journal of Production Economics, Vol. 999 No. 2, pp. 409-20. https://doi.org/10.1016/j.ijpe.2007.01.007

[39] Cavalieri, S., Pinto, R. and Maccarrone, P. (2003), "Parametric vs neural network models for the estimation of production costs: a case study in the automotive industry", International Journal of Production Economics, Vol. 91 No. 2, pp. 165-77. https://doi.org/10.1016/j.ijpe.2003.08.005

[40] Vijayan, S. & Parameshwaran Pillai, T. (2022). Application of a Machine Learning Algorithm in a Multi Stage Production System. Transactions of FAMENA, 46 (1), 91-102. https://doi.org/10.21278/TOF. 461033121

[41] Susilawati, A. (2021). Productivity enhancement: lean manufacturing performance measurement based multiple indicators of decision making. Production Engineering,15(3-4), 343-359. https://doi.org/10.1007/s11740-021-01025-7

[42] S. M. Baskaran and A. Lakshmanan, (2019) "A framework model for lean tools selection for improving material flow using fuzzy TOPSIS," Int. J. Productiv. Qual. Manage., vol. 27, no. 2, pp. 196-228, https://doi.org/10.1504/IJPQM.2019.100144

[43] Seleem, Sameh N; El-Awady Attia; Karam, Ahmed; El-Assal, Ahmed. (2020) A lean manufacturing road map using fuzzy-DEMATEL with case-based analysis, International Journal of Lean Six Sigma; Bingley Vol. 11, Iss. 5, (2020): 917-942. https://doi.org/10.1108/IJLSS-12-2017-0147

[44] Feng Wang (2021), Preference degree of triangular fuzzy numbers and its application to multi-attribute group decision making, Expert Systems with Applications, Volume 178, 114982, ISSN 0957-4174. https://doi.org/10.1016/j.eswa.2021.114982

[45] Li X, Wang K, Liu L, Xin J, Yang H, Gao C. (2011) Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. Procedia Engineering.; 26:2085-91. https://doi.org/10.1016/j.proeng.2011.11.2410

[46] Jozi, S.A., Shafiee, M., MoradiMajd, N. et al. (2012). An integrated Shannon's Entropy-TOPSIS methodology for environmental risk assessment of Helleh protected area in Iran. Environ Monit Assess 184, 6913-6922. https://doi.org/10.1007/s10661-011-2468-x

[47] Hwang, C.L. and Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications. Springer-Verlag, New York. https://doi.org/10.1007/978-3-642-48318-9

[48] Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets and Systems, 114(1), 1-9. https://doi.org/10.1016/S0165-0114(97)00377-1

[49] Jahanshahloo, G. R., Hosseinzadeh Lotfi, F., & Davoodi, A. R. (2009). Extension of TOPSIS for decision-making problems with interval data: Interval efficiency. Mathematical and Computer Modelling, 49(5-6), 1137-1142. https://doi.org/10.1016/j.mcm.2008.07.009

[50] Golmohammadi, D., Creese, R., Valian, H. (2009). Neural network application for supplier selection. International Journal of Product Development, Inderscience Enterprises Ltd, vol. 8(3), pages 252-275.

[51] Luxhøj, J. T., Riis, J. O., & Stensballe, B. (1996). A hybrid econometric-neural network modelling approach for sales forecasting. International Journal of Production Economics, 43(2-3), 175-192. https://doi.org/10.1016/0925-5273(96)00039-4

[52] Vimal, K. E. K., & Vinodh, S. (2013). Application of artificial neural network for fuzzy logic based leanness assessment. Journal of Manufacturing Technology Management, 24(2), 274-292. https://doi.org/10.1108/17410381311292340

[53] Saaty, R. W. (1987). The analytic hierarchy process-what it is and how it is used. Mathematical Modelling, 9(3-5), 161-176. https://doi.org/10.1016/0270-0255(87)90473-8

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