Decision-making through Fuzzy TOPSIS and COPRAS approaches for lean tools selection: A case study of automotive accessories manufacturing industry

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Abstract

Similarity in prioritization of lean tools (LTs) by different frameworks on the same problem is a point of contention. The goal of the present research is to address LTs selection problem through two commonly used multi-criteria decision making approaches, namely the technique for order preference by similarity to ideal solution (TOPSIS) and complex proportional assessment (COPRAS). A framework involving value stream mapping and plant layout through TOPSIS and COPRAS approaches to find the best possible LTs for an automotive accessories manufacturing plant is developed and assessed in this research. The obtained similarity of rankings between TOPSIS and COPRAS is 71.42% and the difference is 28.58%. Based on the assessment, systematic layout planning (SLP) is selected as the most suitable LT and its implementation is elaborated in detail. Significant reductions were obtained in lead time (16.44%), non-value added time (61.03%), transportation distances (40.42%), and waiting time (86%). Additionally, lean implementation resulted in reduced inventory, reduced internal traffic, improved productivity, and improved customer service.

The LTs selection framework presented in this research work addresses the computational complexity associated with the existing models and allows the segregation of most preferable and least preferable criterion which eliminates the criteria weight generation methods.

Keywords: value stream mapping; lean manufacturing; TOPSIS; COPRAS; systematic layout planning; automobile industry.

1. Introduction

After World War II, the problems faced by Japanese manufacturers were different from other western countries such as financial, massive shortages of material, and human resources. The Toyota Production System (TPS) was introduced by Taiichi Ohno in the 1950s. In the late 1980s, the Lean Production System was developed from the TPS to make it more suited to the need of western manufacturing companies (Womack, Jones, & Roos, 1990). Seven basic wastes were identified in the TPS and recent studies have explored additional wastes such as under-utilization of people and under-utilization of facilities (Bhuvanesh Kumar & Parameshwaran, 2018). Most implementation practices revealed value stream mapping (VSM) as the best tool to identify wastes from an organization (Rohani & Zahraee, 2015). VSM has been practiced more frequently over recent decades and it is very effective in reducing the lead time for manufacturing organizations (Zahraee, Esrafilian, Kardan, Shiwakoti, & Stasinopoulos, 2021; Zahraee, Tolooie, Abrishami, Shiwakoti, & Stasinopoulos, 2020). Adapting lean principles greatly reduces non-value added (NVA) activities and yields cost savings in all operations of the manufacturing environment (Alefari, Almanei, & Salonitis, 2020).

Practicing lean principles with appropriate training may create favorable impact in the manufacturing industries in terms of their performance. There are many lean tools (LTs) reported by researchers; however, organizations often have difficulty in choosing the appropriate LT for implementation (Vinodh, Shivraman, & Viswesh, 2011).

Implementation of all the tools is a time consuming and costly process for SMEs; hence, a systematic selection methodology is needed for the organizations (M Bhuvanesh Kumar & Parameshwaran, 2019). To select the most appropriate LTs from the plethora of tools, recent studies have proposed frameworks that combine industrial engineering and optimization techniques (Devnath, Islam, Rashid, & Islam, 2020; M Bhuvanesh Kumar & Parameshwaran, 2020; Rezaei, Rahiminezhad Galankashi, Mansoorzadeh, & Mokhatab Rafiei, 2020). However, mathematical approaches used by these frameworks require analytical skills, which are lacking in many SMEs. With respect to the efforts to be made by the industrial practitioners, it is essential to assess different frameworks for a single problem. The novelty of the present study lies in the assessment over different frameworks for the LTs selection problem which is not available in the literature.

To address these needs, this research proposes a framework that employs VSM and plant layout to identify and eliminate waste. Further, the LTs are prioritized and assessed through two different multi criteria decision making (MCDM) approaches, namely technique for order of preference by similarity to ideal solution (TOPSIS) and complex proportional assessment of alternatives (COPRAS). To explore the ability of LM practices in the organization, the research addresses the following objectives: (1) To propose an LT selection framework using VSM, plant layout, TOPSIS, and COPRAS, (2) To assess the sequence of LTs resulting from both fuzzy integrated TOPSIS and COPRAS approaches, and (3) To corroborate the effectiveness of the proposed framework by implementing it in the manufacturing industry.

By achieving the objectives through the application of proposed framework in a case industry, the present work will contribute to the theory and practice of lean implementation in SMEs. Compared to the similar frameworks on this topic, the present research work minimizes the computational stages and more attention is given to the implementation practices. Also, the present study is substantiated through case study which is not explored by many of the similar studies. The subsequent sections present the literature review, methodology, and implementation through a case study. Finally, the present and future state maps are compared to visualize the improvements, followed by conclusion and future research directions.

2. Literature review

2.1 Review on lean implementation frameworks

The prioritization of LTs is considered as an MCDM problem and many articles have demonstrated the application of integrated frameworks. The frameworks use MCDM approaches such as fuzzy analytic hierarchy process (FAHP) (Susilawati, 2021), fuzzy failure mode and effects analysis (FFMEA) (M Bhuvanesh Kumar & Parameshwaran, 2019), fuzzy TOPSIS (FTOPSIS) (Baskaran & Lakshmanan, 2019), fuzzy decision making trial and evaluation laboratory (DEMATEL) (Seleem, Attia, Karam, & El-Assal, 2020), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Jing, Niu, & Chang, 2019) and fuzzy COPRAS (FCOPRAS) (M. B. Kumar, Parameshwaran, Antony, & Cudney, 2021), among others. Fuzzy enabled frameworks are arguably better due to several advantages, while handling linguistic judgments with ambiguity (Babaeinesami, Tohidi, & Seyedaliakbar, 2021). A large number of research articles use triangular fuzzy numbers (TFNs) due to its computation simplicity (Susilawati, 2021; Wang, 2021). The frameworks adapted by previous researchers are given in Table 1.

Table 1. Frameworks developed with respect to LTs selection and implementation

Research articles	**Integrated frameworks**	**Major LTs/ solutions selected**	**Limitations/ disadvantages**
Aouag, Soltani, and Mouss (2021)	Fuzzy DEMATEL-FQFD	Kaizen, Kanban, TPM	• A small number of indicators were considered.
M. B. Kumar et al. (2021)	FAHP-COPRAS	Plan-do-check-act (PDCA), TPM, 5S, Kaizen	• Dependent on the knowledge of expert team.

M Bhuvanesh Kumar and Parameshwaran (2020)	FFMEA, AHP, and QFD	5S, Kaizen, Layout modification	• Not a generic application. • Cost-wise benefits are not emphasized.
Devnath et al. (2020)	QFD-TOPSIS	Kanban, Cellular manufacturing, Kaizen	• Vagueness associated with expert opinion was not addressed • No validation.
Seleem et al. (2020)	Fuzzy DEMATEL	Kaizen, 5S, Standardization	• Impact of the approach was subjective.
Prasad, Dhiyaneswari, Jamaan, Mythreyan, and Sutharsan (2020)	VSM and root cause analysis	5S, Kanban, Kaizen	• Not a generic approach.
Baskaran and Lakshmanan (2019)	FTOPSIS	Just-in-time manufacturing, One piece flow	• Results were subject to change with an increasing number of participants.
Jing et al. (2019)	Improved VIKOR method	Group technology, Mixed flow production	• Only one method was used to evaluate the criteria.
Yadav, Seth, and Desai (2018)	AHP-PROMETHEE	LSS project tracking and review, Organization culture, Quality check systems	• Increased complexity • Elimination of risk factor.
Belhadi, Touriki, and El fezazi (2017)	AHP-TOPSIS	Management participation, Organizational culture, Key performance indicators (KPIs)	• Not included the interrelationship between barriers and solutions,

2.2 Choice of MCDM approaches

Most of the frameworks developed were two-phased and have a common attribute with their methodologies. The first phase is to prioritize the wastes/barriers through relative weights while the second phase prioritizes the solutions or LTs. Combined frameworks integrating multiple MCDM techniques can create computational complications to practitioners. Hence the methodology for the problem of LTs selection should be simplified. The TOPSIS and COPRAS approaches classify attributes into two categories such as most preferable/positive ideal solutions and least preferable/negative ideal solutions (Varatharajulu, Duraiselvam, Kumar, Jayaprakash, & Baskar, 2021). Using these tools, the relative weights can be directly applied which can eliminate the requirement of the first phase from the two-phased computation procedure.

2.3 Gaps identified from the literature

The results of lean implementation frameworks for the same problem are questionable when the similarity is brought into consideration. The result of one framework is not compared with the other framework for the same problem. For example, the results of FAHP-TOPSIS for a particular case organization may be compared with the result of FQFD, FFMEA, PROMETHEE, or other combinations of these techniques. By doing so, the interdependency between the wastes and LTs/solutions can be considered generic and can give a better understanding. None of the papers have addressed this concern. After a careful review of the literature, the research gaps identified are:

(1) Though TOPSIS and COPRAS approaches can simplify the LTs selection problem as a single-phased approach, no research work has adapted these methods independently to reduce computational complexity.
(2) None of the published research works have compared the results of different MCDM approaches to the same case organization.

These research gaps created a scope for a novel approach to evaluate TOPSIS and COPRAS approaches for the prioritization of LTs to the same problem.

3. Methodology

The three-phase methodology adapted in the present study is shown in Figure 1. Recognition of wastes and LTs is carried out in phase I. Assessment of the MCDM approaches is carried out in phase II. The implementation of LTs and the comparison of current and future states are performed in phase III.

3.1 Phase I

Phase-I is associated with the development of the current state VSM. To better observe the different forms of wastes, the plant layout is drawn along with the VSM. An expert team consisting of a plant head and two industrial engineering professionals are selected for the team to appraise the existing state appropriately. Upon conducting several brainstorming sessions and observations, the wastes are identified. Suitable LTs are selected from the literature and verified with industrial engineering professionals.

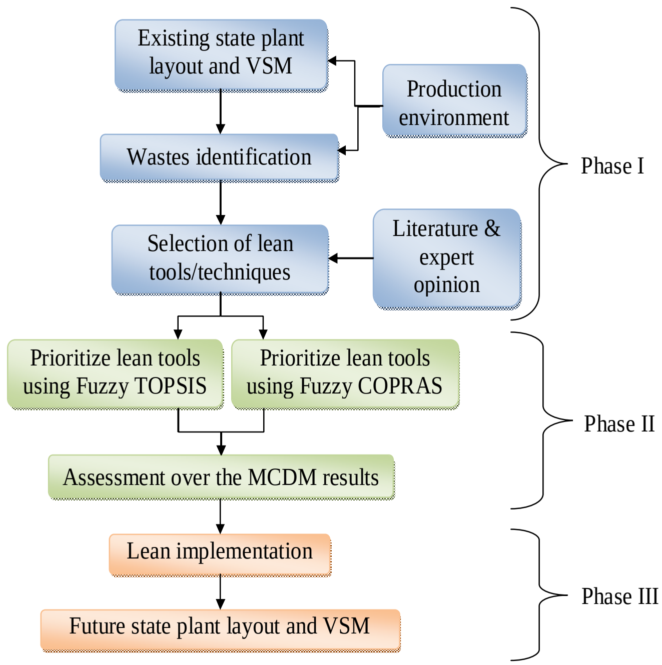

Figure 1. Methodology adapted

The experts are asked to input their opinion in a decision matrix to show the significance level of a particular LT to eliminate a particular waste. In order to avoid vagueness present in linguistic opinions, fuzzy logic with TFNs shown in Table 2 is used (M. B. Kumar et al., 2021). The decision matrix from each expert are averaged to form an all-inclusive synthetic dependency matrix 'D', as shown in Eq (1).

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \quad (1)$$

Where, 'n' is the number of identified wastes and 'm' is the number of identified LTs. Hence, 'd_{mn}' is the combined dependency value among the LT, 'm', and waste, 'n'. Further, these TFNs are defuzzified into a crisp numbers using the best non-fuzzy performance (BNP) using Eq (2) (M. B. Kumar et al., 2021).

$$BNP_i = [(U_{A_i} - L_{A_i}) + (M_{A_i} - L_{A_i})]/3 + L_{A_i} \quad (2)$$

Where, ‘ A_i’ is the averaged value of TFN for the i^{th} waste. L_{A_i}, M_{A_i}, and U_{A_i} are the lower, middle, and upper values of averaged TFN for the i^{th} waste. The newly formed dependency/decision matrix is expressed as ‘ $\widetilde{D}$ ’ in the subsequent sections.

Table 2. The scale to show linguistic opinions along with equivalent TFNs

Linguistic opinion	**Equivalent TFN**	**Reciprocal of TFN**
Enormously high significance (EHS)	(8, 9, 9)	(1/9, 1/9, 1/8)
Very high significance (VHS)	(7, 8, 9)	(1/9, 1/8, 1/7)
High significance (HS)	(6, 7, 8)	(1/8, 1/7, 1/6)
Fairly high significance (FHS)	(5, 6, 7)	(1/7, 1/6, 1/5)
Fair significance (FS)	(4, 5, 6)	(1/6, 1/5, 1/4)
Fairly low significance (FLS)	(3, 4, 5)	(1/5, 1/4, 1/3)
Low significance (LS)	(2, 3, 4)	(1/4, 1/3, 1/2)
Very low significance (VLS)	(1, 2, 3)	(1/3, 1/2, 1)
Enormously low significance (ELS)	(1, 1, 1)	(1, 1, 1)

3.2 Phase II

3.2.1. TOPSIS

In the TOPSIS method, the agreeable result can be observed as preferring the response with the closest distance from the positive ideal boundary and longest distance from the adverse ideal boundary (Ghosh, Mandal, & Ray, 2021). The TOPSIS methodology uses the following steps.

Step 1: The first step is the identification of dependent and independent attributes (wastes). The dependent attributes that require maximization function are referred to as the most preferable attributes. The independent attributes are those required by the minimization function and referred to as the least preferable attributes.

Step 2: The information related to the attributes is expressed in the form of a matrix, which is often referred to as the dependency matrix $D_{ij} = [x_{ij}]_{m \times n}$, which has i rows (m - LT) and j columns (n - attributes). The decision matrix, ‘ D_{ij}’,for the present work is given in Eq (3).

$$D_{ij} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} \tag{3}$$

Step 3: The elements of the decision matrix are normalized using Eq (4). The normalized matrix is expressed as ' N_{ij}'.

$$N_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad j = 1, 2, \dots, n \tag{4}$$

Step 4: A weighted normalized decision matrix is determined by multiplying the elements of the normalized decision matrix by its corresponding weights (W_j) obtained from the experts as shown in Eq (5). The elements of the resulted matrix forms a weighted normalized matrix, ' W_{ij}', using Eq (6) in which $\tilde{x}_{ij}$' is the weighted elements..

$$W_{ij} = N_{ij} \times W_j \tag{5}$$

$$W_{ij} = \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{pmatrix} \tag{6}$$

Step 5: The positive ideal solutions, A**, and negative ideal, A*, solutions are calculated using Eqs (7) and (8).

$$A^{**} = \{(\max W_{ij} | j \epsilon J), (\min W_{ij} | j \epsilon J')\} ; i = 1, 2, \dots, m ; J = 1, 2, \dots, n ; \tag{7}$$

$$A^{*} = \{(\min W_{ij} | j \epsilon J), (\max W_{ij} | j \epsilon J')\} ; i = 1, 2, \dots, m; J' = 1, 2, \dots, n \tag{8}$$

Where, ' J ' is related to the most preferable attributes and ' J' ' is related to the least preferable attributes.

Step 6: The separation measure is determined for each LT from the most preferable ideal solution using Eq (9). In the same way, the least preferable ideal solution is given by Eq (10).

$$S_i^{**} = \sqrt{\sum_{i=1}^{m}\left(W_{ij} - A_j^{**}\right)^2}, \text{ where } i = 1, 2, \dots, m \tag{9}$$

$$S_i^{*} = \sqrt{\sum_{j=1}^{n}\left(W_{ij} - A_j^{*}\right)^2}, \text{ where } i = 1, 2, \dots, m \tag{10}$$

Step 7: Further, the relative distance is estimated to be the ideal solution using Eq (11). A higher Ci* value represents better performance of the attributes corresponding to the LTs.

$$C_i^{*} = \frac{S_i^{*}}{S_i^{**} + S_i^{*}} \tag{11}$$

Step 8: Finally, ranking of the LTs is made based on the relative closeness value.

3.2.2. COPRAS

On the other hand, the COPRAS approach is also applied to prioritize the identified LTs in association with the identified wastes. The detailed computation procedure of COPRAS approach follows a five step procedure.

Step1: Constructing a defuzzified dependency matrix between m - LTs and n - attributes (wastes) as shown in Eq (12).

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \tag{12}$$

Step2: The elements of ‘ D ’ are normalized using Eq (13) to get a normalized dependency matrix ‘ $\widetilde{D}$ ’ in which ‘ $\widetilde{d_{ij}}$ ’ is an averaged element of ‘ $\widetilde{D}$ ’,. The resulting normalized matrix is represented by Eq (14).

$$\widetilde{d_{ij}} = \frac{d_{ij}}{\sum_{j=1}^{n} d_{ij}} \; ; i = 1\ to m;\ j = 1\ to\ n; \tag{13}$$

$$\widetilde{D} = \begin{bmatrix} \widetilde{d_{11}} & \widetilde{d_{12}} & \cdots & \widetilde{d_{1n}} \\ \widetilde{d_{21}} & \widetilde{d_{22}} & & \widetilde{d_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{d_{m1}} & \widetilde{d_{m2}} & \cdots & \widetilde{d_{mn}} \end{bmatrix} \tag{14}$$

Step 3: The elements are multiplied by relative weights (w_j) obtained from the expert members to form a weighted normalized dependency matrix, ‘ $\overline{\overline{D}}$ ’, as shown in Eq (15). The resultant matrix is in the form of Eq (16).

$$\overline{\overline{d_{ij}}} = \widetilde{d_{ij}} \times w_j \; ; i = 1 \text{ to } n, \text{ and } j = 1 \text{ to } m \tag{15}$$

$$\overline{\overline{D}} = \begin{bmatrix} \overline{\overline{d_{11}}} & \overline{\overline{d_{12}}} & \cdots & \overline{\overline{d_{1n}}} \\ \overline{\overline{d_{21}}} & \overline{\overline{d_{22}}} & & \overline{\overline{d_{2n}}} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{\overline{d_{m1}}} & \overline{\overline{d_{m2}}} & \cdots & \overline{\overline{d_{mn}}} \end{bmatrix} \tag{16}$$

Step 4: The attributes required to be maximized are the most preferable and given higher weights. The attributes required to be minimized are the less preferable and are given lesser weights. Using Eqs (17) and (18), the summation of normalized values of more preferable attributes, ‘ P_i ’, and least preferable attributes, ‘ R_i’, are computed.

$$P_i = \sum_{j=1}^{k} \overline{\overline{d_{ij}}} \tag{17}$$

Here, ‘ k ’ is the number of more preferable attributes. The number of less preferable attributes can be derived as ‘ $(n - k)$ ’.

$$R_i = \sum_{j=k+1}^{n} \overline{\overline{d_{ij}}} \tag{18}$$

Step 5: The final weights of the LTs are computed using Eq (19).

$$Q_i = P_i + \frac{R_{min} \sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{R_{min}}{R_i}} \tag{19}$$

Step 6: Efficacy degree of each LT denoted as ‘ N_i ’ is calculated using Eq (20).

$$N_i = \frac{Q_i}{Q_{max}} \times 100\% \tag{20}$$

3.2.3. Assessment of MCDM approaches

The prioritized lists of LTs from both the TOPSIS and COPRAS approaches are compared for their percentage of similarity of sequence.

3.3 Phase III

This is the implementation and realization phase where the selected tools from the top order of prioritized list are implemented in the organization. According to the changes made in the existing state, the future state plant layout and VSM are developed.

4. Case Study

The case study was conducted in automotive accessories manufacturing company located in the southern part of India. They manufacture bumpers, footsteps, and luggage carriers for the Indian automobile industry. The product quality and demand from the Indian market enables them to stay at the top of the market.

4.1 Phase I: Development of current state VSM and plant layout

During the initial visits, direct observations and discussions with people from the case organization were performed. The organization's shop floor lacked an efficient process flow due to unnecessary transportation and movement. Also, unplanned continuous production irrespective of demand leads to overproduction of products that may become obsolete. The current state plant layout is shown in Figure 2, and the current state VSM is shown in Figure 3. The sequence of operations to make a steel car bumper are, bending process, plate cutting operation, plate drilling process, plate leveling operation, welding process, grinding process, 7-tank process, polishing and buffing processes, sub-assembly of components, and packing. The material flow distance, layout details, and operation times are noted by interaction with the manager, supervisors, and staff. A close inspection is made to gather the data such as operating time (OT), changeover (C/O), available time (AT), cycle time (CT), and number of operators. Following the data collection, the plant layout was measured for its total area, relative position of resources, and distances between different functional cells.

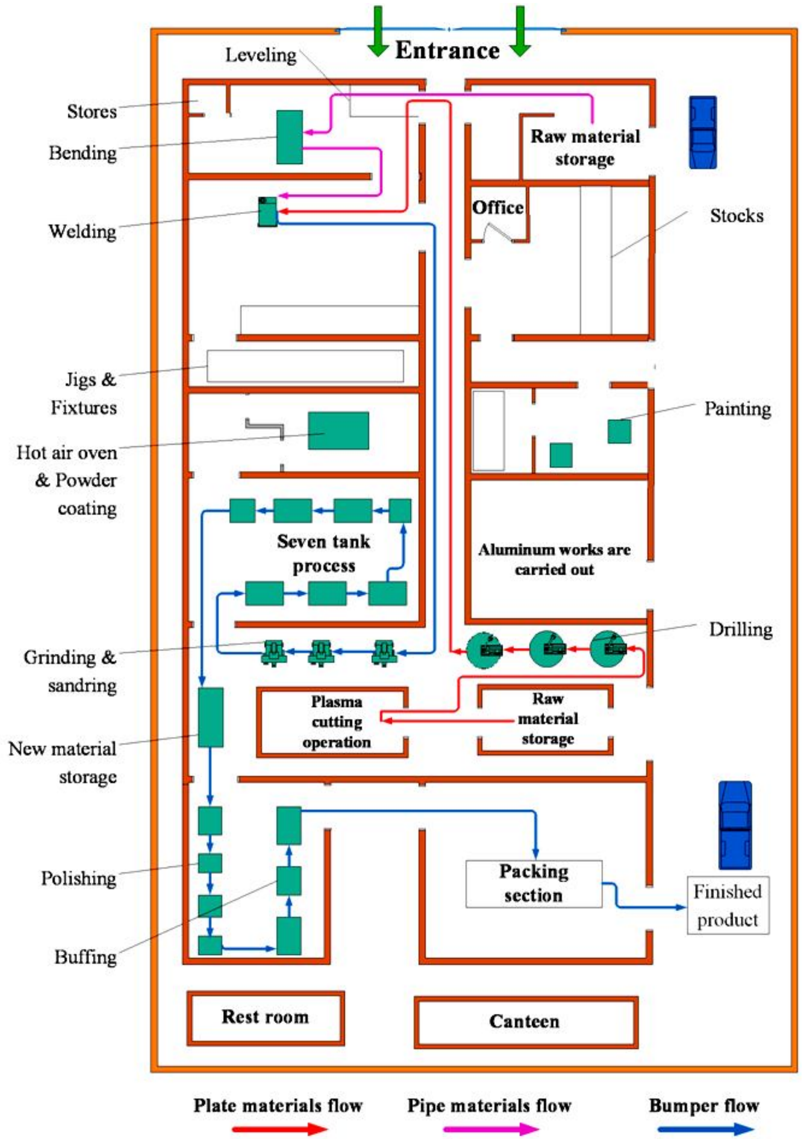

Figure 2. Existing plant layout

The VSM of the current state shown in Figure 3 illustrates the flow of materials transported to successive operations, mode of communication from the manager, and quantitative information related to each process. Various measures such as lead time and NVA time are derived. Based on a complete study made from the plant layout, current state VSM, and observations, the wastes identified are: excess inventory (W1), unnecessary transportation (W2), material wastes (W3), underutilization of people (W41), unnecessary motion (W5), waiting (W6), and long lead time (W7). Also, during the transportation of work-in-process (WIP), internal traffic was high. With the help of the experts' opinion and the literature, the LTs identified for the case organization are cross functional training (LT1), layout planning (LT2), one-piece flow (LT3), standardization (LT4), 5S (LT5), kaizen (LT6), and workforce monitoring (LT7).

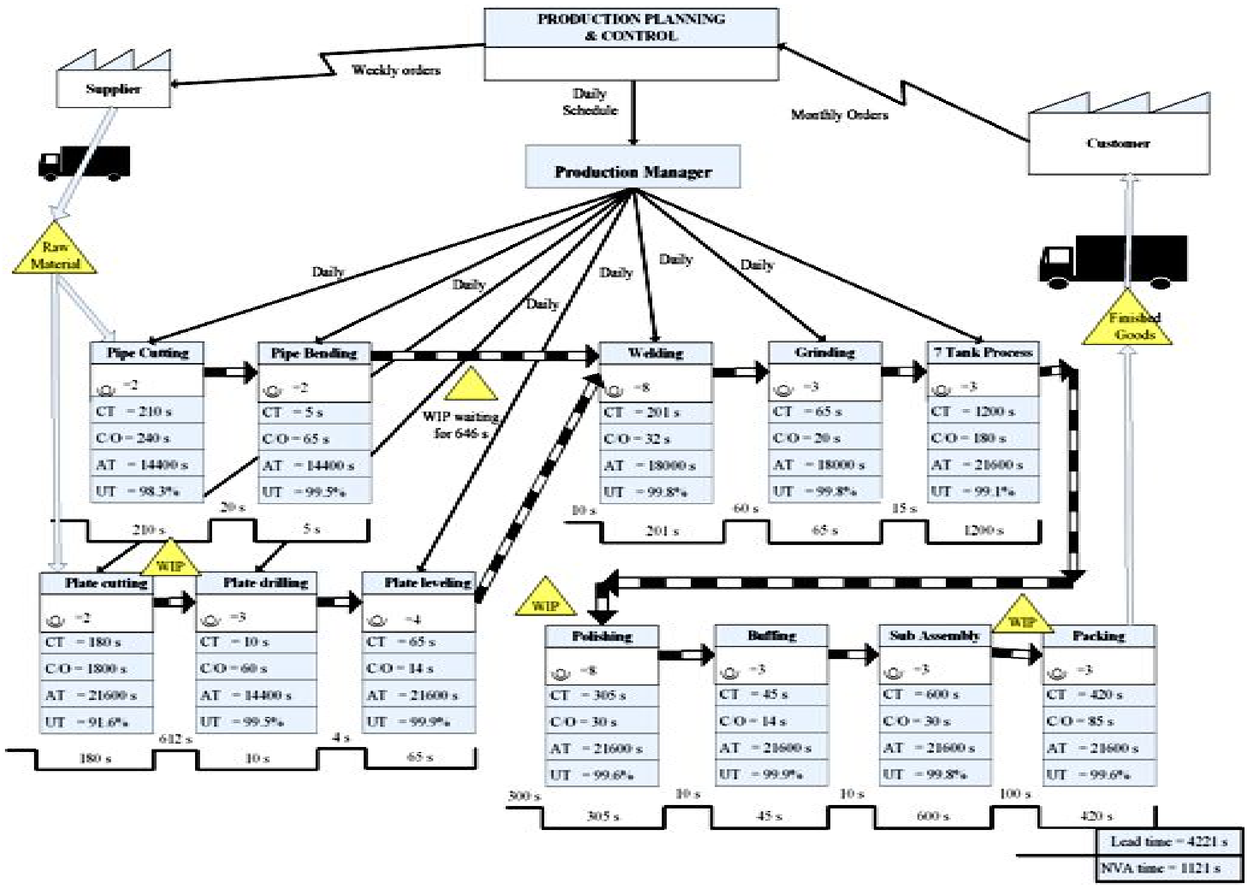

Figure 3. Current state VSM

4.2 Phase II: TOPSIS and COPRAS methods

The averaged experts' opinions on the dependency between the wastes and LTs are defuzzified using Eq (2). The obtained BNP values drawn from Eq (2) forms a synthetic dependency matrix of 7 × 7 as shown in Table 3.

Table 3. Dependency matrix between wastes and LTs

LP/W	W1	W2	W3	W4	W5	W6	W7
LT1	1.333	2.333	1.667	1.000	4.000	3.333	1.667
LT2	6.000	5.667	5.000	2.000	6.333	8.222	7.333
LT3	1.333	2.333	8.222	8.222	5.667	1.000	3.000
LT4	2.333	8.444	1.667	1.333	6.667	6.333	5.667
LT5	5.333	4.667	5.333	1.000	3.333	5.333	8.667
LT6	7.667	5.667	6.667	1.333	1.667	3.667	2.333
LT7	8.222	5.000	3.667	1.000	1.667	4.667	1.000

4.2.1Ranking of LTs using TOPSIS

The TOPSIS approach is further applied to rank the identified LTs.

Step 1: Waste reduction is the most preferable attribute; therefore, it requires maximization function. Underutilization of people is the least preferable and needs the minimization function. With experts' help, the most preferable attributes are given with a relative weight of 0.15 and least preferable attributes are given with a relative weight of 0.1; therefore, the cumulative weight for all of the attributes is 1.

Step 2 : The dependency matrix of the present work is expressed as Eq (21).

$$[D_{7\times7}] = \begin{pmatrix} 1.333 & 2.333 & \dots & 1.667 \\ 6.000 & 5.667 & . & 7.333 \\ \vdots & \vdots & . & \vdots \\ 8.222 & 5.000 & \dots & 1.000 \end{pmatrix} \quad (21)$$

Step 3: The dependency matrix is then normalized using Eq (4) to obtain the normalized dependency matrix as shown in Eq (22).

$$[N_{7\times7}] = \begin{pmatrix} 0.094 & 0.167 & \dots & 0.124 \\ 0.424 & 0.407 & . & 0.547 \\ \vdots & \vdots & . & \vdots \\ 0.581 & 0.359 & \dots & 0.074 \end{pmatrix} \quad (22)$$

Step 4: Based on the relative weights assigned to the attributes, a weighted normalized decision matrix using Eq (5) is developed as shown in Eq (23).

$$[\widetilde{D}_{7\times7}] = \begin{pmatrix} 1.333 & 2.333 & \dots & 1.667 \\ 6.000 & 5.667 & . & 7.333 \\ \vdots & \vdots & . & \vdots \\ 8.222 & 5.000 & \dots & 1.000 \end{pmatrix} \quad (23)$$

Step 5: Using Eqs (7) and (8), the positive ideal solutions, A** and negative ideal solutions, A*, are computed as shown in Eq (24).

$$\begin{pmatrix} A^{**} \\ A^{*} \end{pmatrix} = \begin{pmatrix} 0.087 & 0.091 & 0.091 & 0.093 & 0.082 & 0.091 & 0.097 \\ 0.014 & 0.025 & 0.018 & 0.011 & 0.020 & 0.011 & 0.011 \end{pmatrix} \tag{24}$$

Step 6 & 7: Similarly, the separations measures and the relative distances are calculated using Eqs (9)-(11) as shown in Table 4. Finally, the ranking of LTs is performed based on the highest value of Ci*.

4.2.2 Ranking of LTs using COPRAS

The ranking of the LTs using the COPRAS approach is made by the subsequent steps.

Step 1: The decision matrix given in Eq (21) is drawn here for computations.

Step 2: The framed decision matrix is further normalized using Eq (13). The resulted matrix is shown in Eq (25).

$$\tilde{\mathrm{D}} = \begin{pmatrix} 0.041 & 0.68 & \dots & 0.056 \\ 0.186 & 0.166 & . & 0.247 \\ \vdots & \vdots & . & \vdots \\ 0.255 & 0.147 & \dots & 0.034 \end{pmatrix} \tag{25}$$

Step 3: Similar to the TOPSIS approach, underutilization of people is given the least preference with a relative weight of 0.1 and other wastes are given the most preferences with a relative weight of 0.15. The weighted normalized decision matrix using Eq (15) is computed and presented in Eq (26).

$$\bar{\mathrm{D}} = \begin{pmatrix} 0.006 & 0.010 & \dots & 0.008 \\ 0.028 & 0.028 & . & 0.037 \\ \vdots & \vdots & . & \vdots \\ 0.038 & 0.022 & \dots & 0.005 \end{pmatrix} \tag{26}$$

Step 4: The summation of the most preferable, Pi, and least preferable, Ri, normalized values are calculated using Eqs (17) and (18).

$$\begin{pmatrix} P_i \\ R_i \end{pmatrix} = \begin{pmatrix} 0.068 & 0.183 & 0.103 & 0.148 & 0.156 & 0.129 & 0.112 \\ 0.006 & 0.013 & 0.052 & 0.008 & 0.006 & 0.008 & 0.006 \end{pmatrix} \tag{27}$$

Steps 5 & 6: Finally, the weight of each LT is calculated and ranked based on the efficacy degree of each project using Eqs (19) and (20) as presented in Table 4.

Table 4. Ranking of LTs using TOPSIS and COPRAS

LT	**S****	**S***	**C***	**TOPSIS ranking**	**Pi**	**Ri**	**Qi**	**Ni**	**COPRAS ranking**
Cross functional training (LT1)	0.160	0.039	0.194	7	0.068	0.006	0.072	38%	7
Layout planning (LT2)	0.088	0.122	0.582	1	0.183	0.013	0.190	100%	1
One piece flow (LT3)	0.127	0.120	0.484	2	0.103	0.052	0.130	68%	5
Standardization (LT4)	0.125	0.108	0.464	3	0.148	0.008	0.152	80%	3
5S (LT5)	0.114	0.082	0.420	5	0.156	0.006	0.159	84%	2
Kaizen (LT6)	0.117	0.099	0.458	4	0.129	0.008	0.133	70%	4
Workforce monitoring (LT7)	0.126	0.091	0.420	6	0.112	0.006	0.116	61%	6

4.2.3 Assessment over MCDM approaches

With reference to the computed results, the ranking of LTs obtained from the TOPSIS methodology is LT2 > LT3 > LT4 > LT6 > LT5 > LT7 > LT1 and LT2 > LT5 > LT4 > LT6 > LT3 > LT7 > LT1 by COPRAS. Layout planning (LT2) is ranked first with a relative closeness value of 0.58 and cross functional training (LT1) is ranked lowest with a relative closeness value of 0.19 in TOPSIS. Similarly, based on the COPRAS calculations, layout planning (LT2) is ranked first with an efficacy degree of 100%, and cross functional training (LT1) is ranked lowest with an efficacy degree of 38%. The ranking of LTs using COPRAS has a greater occurrence with TOPSIS calculations. The similarity between the rankings is 71.42% between both the MCDM approaches with the same input. The remaining 28.58% in ranking differentiate the approaches.

4.3 Phase III

4.3.1. Lean implementation

The first ranked LT, layout planning (LT2), is initially selected to implement within the organization. In order to modify the existing plant layout systematically, the SLP method is adopted as it is a proper and structured planning method for designing an effective plant layout (Ali Naqvi, Fahad, Atir, Zubair, & Shehzad, 2016). SLP is a tool used to position a workstation in a production floor by locating the two regions that are very close to one another with logical relationship and high frequency. For the present case study, the data table is created as an initial step to collect the information related to the distance in meters between the 12 consecutive operations as shown in Table 5. SLP uses the relationship chart (REL) in which the diamond shaped cells carry the values for the degree of closeness between workstations. A scale shown in Table 6 is used for this purpose (Qamar, Meanazel, Alalawin, & Almomani, 2020). The pair-wise ratings of closeness are inter-departmental and are used to compose an appropriate layout.

Table 5. Distance between the operations of workstations

Operations	Distance between operations (ft)											
	1	2	3	4	5	6	7	8	9	10	11	12
Cutting process		4.0										
Bending process			45.2									
Plate cutting process				5.0								
Drilling process					45.2							
Leveling process						4.5						
Welding process							28.0					
Grinding process								5.0				
7 Tank process									18.0			
Polishing process										3.0		
Buffing process											12.0	
Sub Assembling												4.0
Packing process												

Table 6. Alphabetical codes used for REL chart

S.No	Alphabetical codes	Description
1	A	Absolutely necessary
2	E	Especially important
3	I	Important
4	O	Ordinary
5	U	Unimportant
6	X	Undesirable

As part of the SLP procedure, a REL chart is developed with the help of number of trips times and the distance between locations as presented in Figure 4. According to the frequency and significance of the processes, the alphabetical codes from Table 6 are used. From the activity relationship, it is clear that the pairs within the existing sequence of operations has a strong relationship such as bending & plate cutting (A), drilling & leveling (A), welding & grinding (A), and 7-tank process & polishing (E). The pairs of other processes have a lesser important relationship (O). Shifting of departments within these pairs without disturbing the production sequence can be done. Hence, a number of alternative layouts were proposed by reallocating the processes based on the importance from most to least. Among the proposed layouts, the best layout is chosen considering the practical limitations.

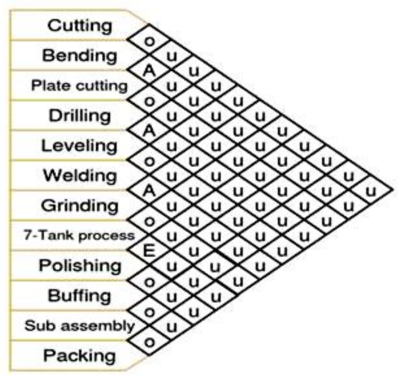

Figure 4. Activity relationship chart

4.3.2 Modified layout & future state VSM

A modified layout based on the selection from the SLP is constructed as shown in Figure 5. The major modification made on the existing plant layout is the relocation of the plasma cutting operation to unused space found near the stock storage. Therefore, the distance and transportation time from the welding booth were reduced to half. Relocation of plasma cutting operation left an empty space in which the polishing, buffing, and packing processes are accommodated. This enabled the packing process to complete faster compared to the former layout. Inventories and stock yards were also modified in the future state plant layout. The modified layout also leaves several empty spaces that can support the future expansion plans. The future state VSM is drawn according to the modified layout as shown in Figure 6. The modifications are made as per the analysis conducted on the new state. The values of CT, C/O time, and AT are updated in the future state VSM. The reduction of lead time and NVA time is observed in the future state. The uptime (UT) for the processes is calculated using Eq (28).

$$UT = \frac{AT - (C/O)}{AT} \tag{28}$$

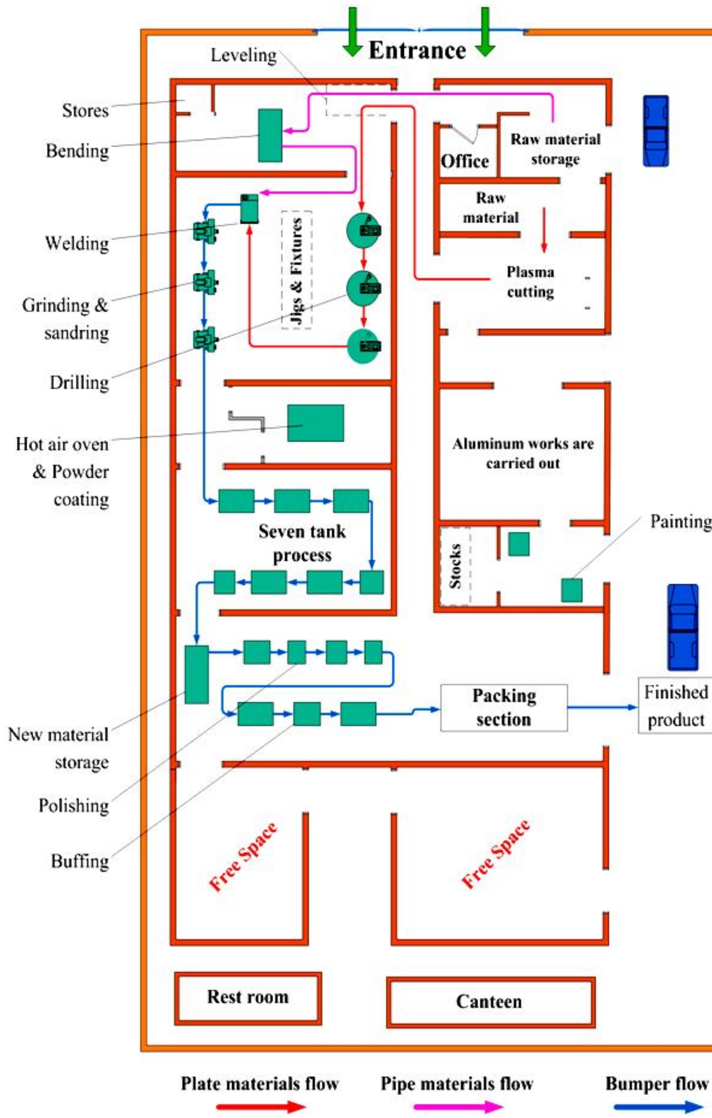

Figure 5. Modified plant layout

5. Sensitivity Analysis

The sensitivity analysis is carried out to compare and validate the MCDM approaches. It will also address the associated uncertainty issues (Hasheminezhad, Hadadi, & Shirmohammadi, 2021). It is conducted based on 3 cases as shown in Table 7 and Figure 7. In order to represent different cases, the weights for experts' opinion were changed. For instance, weight for first expert is given 0.4 compared to other two experts which is 0.3 for case 1. According to sensitivity analysis, the ranking remains unchanged for both the MCDM approaches for all the cases expect the case 1 of TOPSIS approach in which the ranking of LT5 and LT7 alone varied. Despite of an insignificant variation, the rankings from MCDM approaches were stable and reliable.

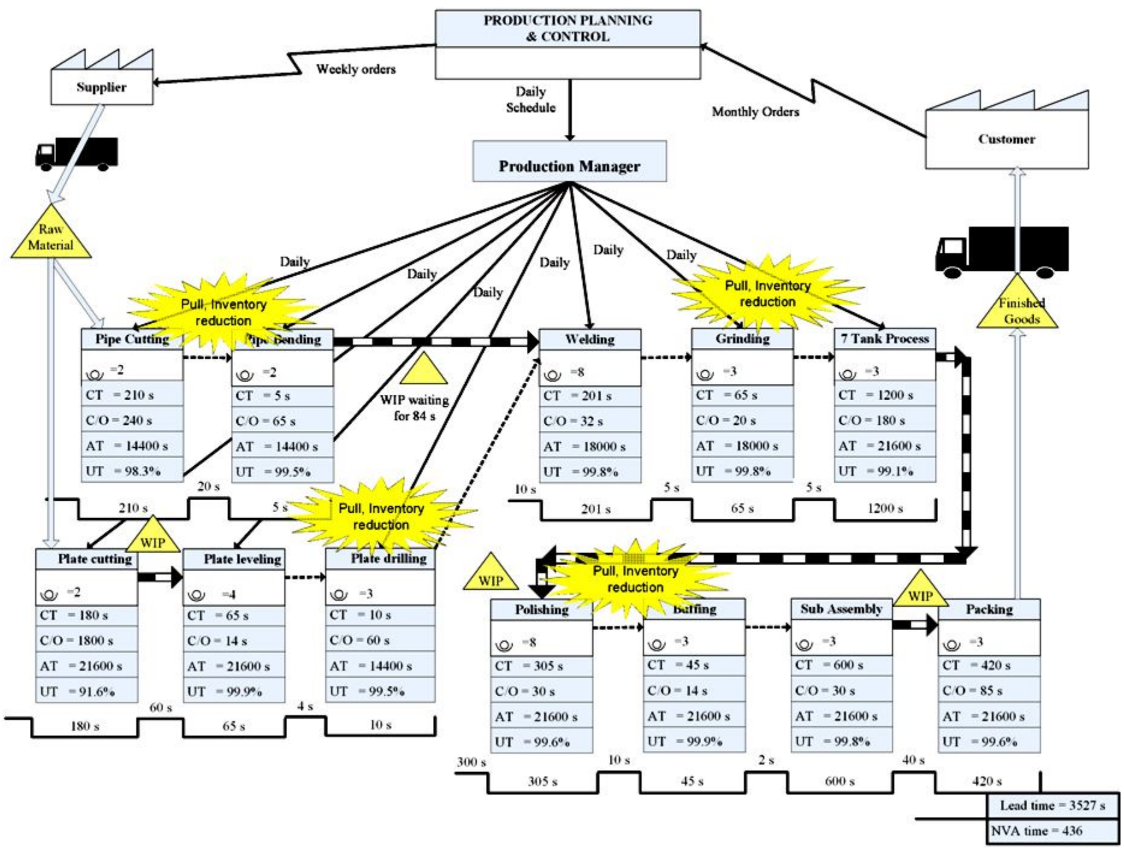

Figure 6. Future state VSM

Table 7. The cases for sensitivity analysis of proposed framework

Criteria	Expert 1	Expert 2	Expert 3
Original Weights	0.333	0.333	0.333
Case 1	0.4	0.3	0.3
Case 2	0.3	0.4	0.3
Case 3	0.3	0.3	0.4

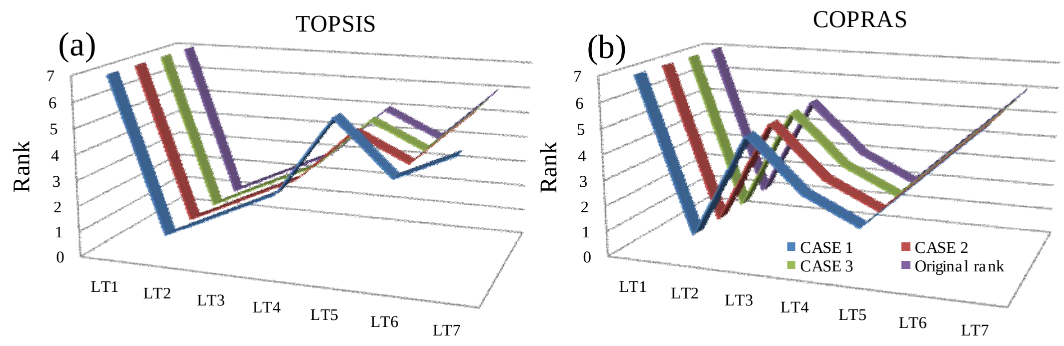

Figure 7. Sensitivity analysis of (a) TOPSIS approach, and (b) COPRAS approach

6. Discussion

The assessment among the rankings from TOPSIS and COPRAS approaches revealed 71.42% concurrency and 28.57% non-concurrency in the results. Most of the LTs are ranked similar except LT3 (one piece flow) and LT5 (5S). This show the ranking by these two methods is reliable; hence the top ranked LT (SLP) from both the approaches was selected as a generalized solution and implemented in the case industry. A few operations were relocated based on the importance in the relationship acquired from the REL chart. The results after the lean implementation have been recorded in VSM of future state. Comparison of the present and future state VSM showed great reductions in lead time from 70.35 min to 58.78 min (16.44%), NVA time from 18.63 min to 7.26 min (61.03%), total transportation distance from 188 m to 112 m (40.42%), and WIP waiting time from 646 s to 84 s (86%). Additionally, the enhanced layout reduced internal traffic and inventories considerably. This will also improve employee participation, efficiency and customer service.

Comparing with the similar studies in the topic, the framework developed in the present study minimized the computation stages and the ranking results were more reliable as validated through sensitivity analysis. Using the outcomes of this research, the practicing managers can understand that ineffective allocation of resources lead to the generation of wastes which can hinder the organizational performance. More importantly, project managers should realize that systematic layout planning during the design stage of production floor will reduce reallocation cost and minimize most of the operation oriented wastes. Apart from the theoretical and practical contribution, this study will also help to develop more number of lean implementation frameworks in future.

7. Conclusion

This research work applied two different MCDM approaches, namely TOPSIS and COPRAS, for a LT selection problem for an automotive accessories manufacturing organization. The ranking results had more concurrency among them. After implementing the selected LT from the ranking, the analysis was carried out by comparing the current and future state VSMs to calculate definite improvements. Future state map showed a significant reduction in lead time, NVA time, and transportation time & distance. There were also some tangible benefits such as reduced internal traffic, stagnation of parts, inventory, improved supervision, and saving of floor space obtained. Besides the favorable outcomes, a few more suggestions are given as, (a) addition of material handling equipment, (b) improve the packing section by providing tables, and (c) replace the obsolete machines with new machines. The effectiveness of the framework depends on the knowledge and experience of the experts; therefore, it is subject to change. Future research should compare the results of other MCDM approaches for different industries to confirm the generalization. Future studies can include simulation and cost benefit analysis to validate the results.

Declaration of interest

The authors declare that there is no competing interest to disclose.

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