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Improvement of lean manufacturing approach based on MCDM techniques for sustainable manufacturing

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Abstract: The purpose of this paper is to propose an improved lean manufacturing approach to enhance the sustainability performances of manufacturing processes. To do that, three phases are proposed. The first phase aims to propose an extended value stream mapping method to quantify the sustainability indicators and assess the manufacturing process. In the second phase, entropy method is used to determine the weights of indicators. In the final phase, the weights obtained from entropy method are used in fuzzy evaluation based on distance from average solution (EDAS) and fuzzy technique for order preference by similarity to the ideal solution (TOPSIS) to rank a set of kaizen events according to their ability to improve the sustainable indicators. The novelty and the main contributions of the proposed approach are proved by the development of an extended VSM method. Also, the proposed approach contributes by a new methodology for enhancing the application process of the conventional lean manufacturing approach.

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Keywords: value stream mapping; VSM; lean manufacturing tools; entropy; fuzzy logic; evaluation based on distance from average solution; EDAS; TOPSIS; sustainable manufacturing.

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1 Introduction

Sustainable manufacturing, it is a term that extracted from the adaptation of sustainable development principle to manufacturing field due to some disruptions facing the global industry such as the lack of natural resources, the increased number of manufacturing enterprise followed by an increase in the environmental impacts (Faulkner and Badurdeen, 2014; Vinodh et al., 2016). For this reason, sustainable manufacturing must be strategically planned to deal with these obstacles effectively and permanently using advanced improvement approaches. Moreover, it is necessary to open a new competitive field under the name competitiveness level towards sustainability, which ensures the existence of companies in the industrial world. To achieve this goal, many methods and philosophies have been used.

The lean manufacturing approach is an improvement strategy that was developed by Toyota. Lean manufacturing has been defined as a set of concepts, principles, methods, procedures and tools geared towards the improvement of the production flow by reducing waste throughout the value chain while continuing to improve product and process performance (Eatock et al., 2009). In addition, lean manufacturing approach leads to improve quality, reduce costs and increased productivity (Taylor et al., 2015). This is given the set of effective tools such as kanban, value stream mapping (VSM), total productive maintenance (TPM) and single minute exchange of die (SMED).

Formerly, lean manufacturing approach is oriented to deal with a limited number of criteria or indicators such as process variation, customer satisfaction, cycle time and inventory (Soltani et al., 2019). But recently with the emergence of the sustainable manufacturing concept, the improvement scope is broadened and currently covers environmental, economic and social indicators, which make the implementation of lean manufacturing approach more difficult.

In this regard, it is necessary to improve the lean manufacturing approach by using other methods such as multi-criterion decision-making (MCDM) methods in order solve some complexities that are related to lean manufacturing application process.

The problem investigated in this framework is related to product creation using processes under environmental, economic and social constraints. Therefore, the main contribution of this paper is to propose an integrated approach that enhances and extend the lean manufacturing approach by using multi-criteria decision-making techniques. In addition, the proposed approach aims to orient the benefits of lean manufacturing approach toward the sustainable manufacturing field in order to improve manufacturing processes from environmental, economic and social viewpoints.

The organisation of this paper is as follows. In Section 2, presents the literature and review. Section 3 depicts the structure of the proposed approach. We highlight in Section 4 the validation of the proposed approach. Section 5 discusses the obtained results. Section 6 provides the conclusions of the working paper.

Table 1 Related works

	Author	*Contribution*	*Limitations*
	Al-Odeh et al. (2015)	Proposed an application of VSM method to reduce cycle time, non-value added time and cost.	The proposed study is limited to the economic side of manufacturing processes.
Extended lean manufacturing approach	Verma and Sharma (2016)	Developed an energy value stream mapping to reduce the waste of energy.	The proposed work deals with environmental indicators.
	Chiarini (2014)	Claimed the benefits of lean manufacturing tools on environmental management.	The framework treated an environmental problem by using lean manufacturing tools.
	Cherrafi et al. (2016)	Presented the first integrated framework based on lean green and Six Sigma using five stages and sixteen steps.	The presented framework has a large number of steps and tools, which are time-consuming to be applied.
	Faulkner and Badurdeen (2014)	Developed a sustainable VSM to visualise a manufacturing process from sustainability perspectives.	Despite the diversity of indicators, the application process of VSM method was investigated with a conventional manner.
	Vinodh et al. (2016)	Proposed an integrated framework based on VSM and LCA to improve the sustainability of production.	The proposed framework focused much more on environmental side of manufacturing process.
Improved lean manufacturing approach	Soltani et al. (2019)	Integrated VSM with AHP and TOPSIS method to improve the sustainability of the manufacturing process.	Investigated the improvement priority of operations. The application priority of improvement opportunities has not been investigated.
	Anvari et al. (2014)	Proposed a modified VIKOR method to select suitable lean tool in complex manufacturing systems.	Investigated the lean manufacturing selection tool problem.
	Behnam et al. (2018)	Proposed an integrated approach using the VSM method and ANP methods to identify and prioritise the defined wastes.	The proposed approach is limited to prioritise the different kinds of wastes.
	Ratlalan et al. (2018)	Integrated VSM method with analytic hierarchy process (AHP) to identify the wastes and determine the weight of each one.	The proposed approach just investigated the rank of different kinds of wastes.

2 Literature and review

The concept 'lean' was first coined in Đwomack et al. (1990) book, *The Machine that Changed the World*. Lean manufacturing focuses on meeting the needs of the customer and reducing time, decreasing waste and improving productivity (Bader et al., 2020). Lean is a modern strategy for production management and a philosophy based on three purposes: to eliminate wasted time, effort and material; to provide customers with made-to-order products; to reduce costs while improving quality (Mazzola et al., 2007). These purposes can be achieved through using a set of effective tools and methods as VSM, TPM, SMED and 5S.

The VSM method, it is one of the best and well know lean manufacturing tools. VSM provides a graphical presentation which is used as a technique for analysing both material and information flows (Đwomack et al., 1990). Traditionally, the application of lean manufacturing approach is based on five consistent steps: data collection, create a current VSM, analyse and identify the root causes of waste, create a future state, and implement the final plan (Abdus et al., 2013).

Currently, the complexity of manufacturing processes and the multiplicity of objectives, have a negative impact on the implementation of conventional lean manufacturing, which obliged many practitioners to extend its application area. Therefore, Table 1 presents a set of the most relevant research that aims to broaden and enhance the classical lean manufacturing approach.

2.1 Research gap

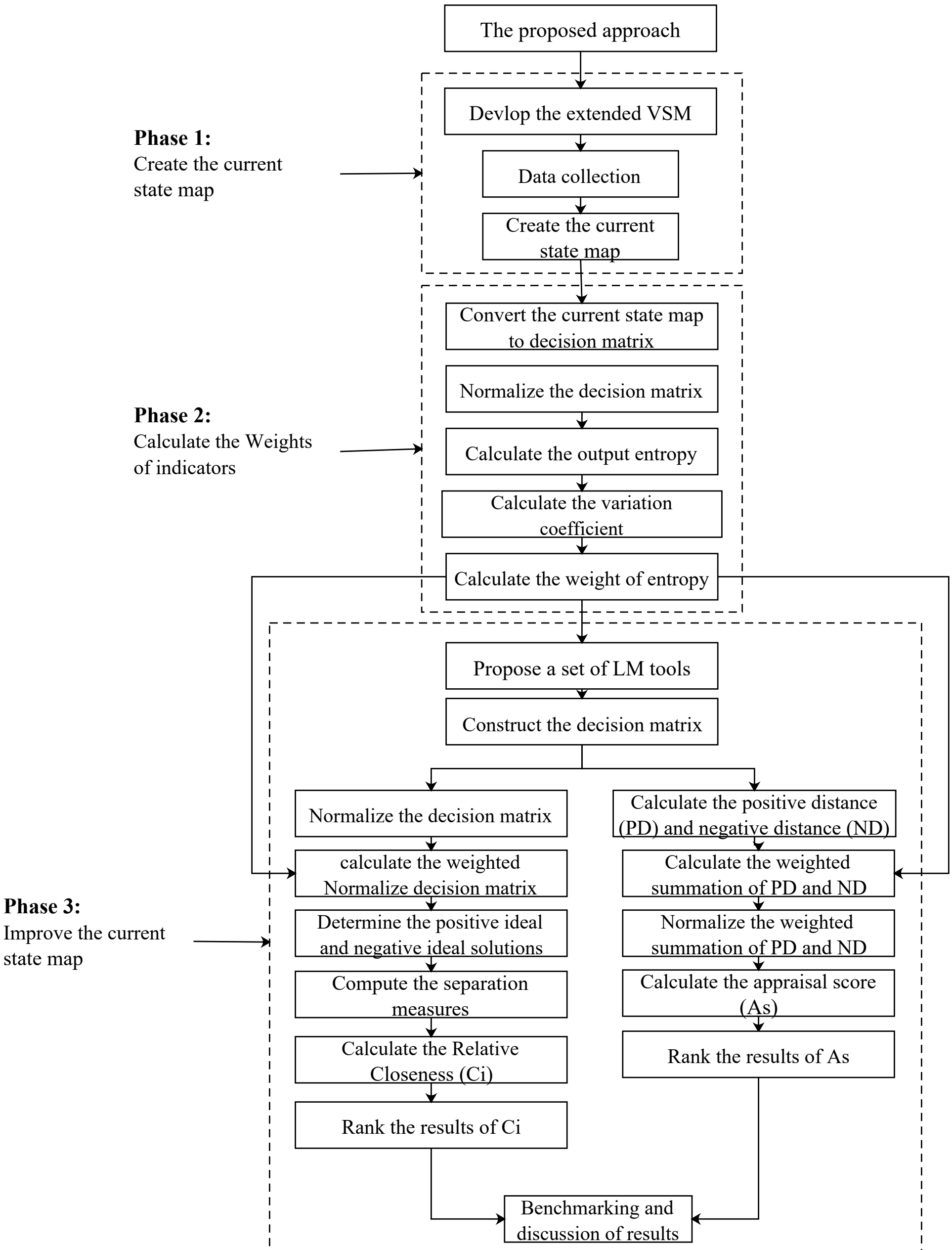
From the literature review, it can be claimed that VSM is the most widely lean manufacturing used approach for improving the sustainability of production. However, regarding the extended VSM approach, despite the average or a large number of indicators, the analysis and the improvement phases were performed conventionally. In addition, most of research that investigated the improvement of lean manufacturing approaches have limited to indicators weighting and wastes prioritising problems, and the problem related to rank the application of lean manufacturing tools and organise the improvement phase of VSM method has rarely investigated.

3 The proposed approach

A three phases methodology has been used in this study to integrate the lean manufacturing approach with MCDM methods for sustainable manufacturing improvement. In the first phase, we develop an extended VSM for data collection and sustainable manufacturing assessment. In the second phase, we applied the entropy method to determine the weight or the impact degree for each indicator. The selection of entropy method is based on its simplicity that used quantitative data with more consistent results. The third phase starts by selecting a set of lean manufacturing tools. These latter are defined as the appropriate lean manufacturing tools to improve the manufacturing processes. Then, we introduce fuzzy evaluation based on distance from average solution (EDAS) and fuzzy technique for order preference by similarity to the ideal solution (TOPSIS) approaches to rank the selected lean manufacturing tools according to their ability to improve the investigated indicators.

The flow diagram of the proposed approach is given in Figure 1.

Figure 1 The proposed approach



3.1 Phase 1: develop the extended VSM method

VSM, it is a lean manufacturing technique, it has emerged as the preferred way to implement the lean manufacturing approach (Singh et al., 2011). The conventional VSM does not explicitly consider sustainable performance, which may or may not be enhanced by lean tools implementation (Norton and Fearne, 2009). Therefore, the purpose of this phase is to extend the application area of the conventional VSM method by adding new button lines, based on the following steps.

3.1.1 Step 1: data collection

This step aims to identify and quantify the most influential sustainable indicators on the performance of the manufacturing process. Generally, the performance indicators are varied from industrial kind to another. For this reason, in this study, the sustainable indicators will be determined and quantified based on resource consumed, the kind of the manufacturing process, the available data and mathematical estimations.

3.1.2 Step 2: current state map development

After the collection and quantification of sustainable indicators, the values obtained are integrated into the conventional VSM method and presented by new button lines, each line includes a specific kind of indicators (economic or environmental or social).

The developed VSM is converted into a decision matrix and used as the main input in the next phase.

3.2 Phase 2: calculate the weight of each indicator using Shannon's entropy method

The entropy concept was first used in the thermodynamics field, after which Shannon introduced it into information theory (Shannon, 1948; Fedajev et al., 2019) and become a well-known MADM method used for obtaining the weights of criteria. In this study, the entropy method is used to compute the weights of indicators presented in the current state map. The consistent procedure of Shannon's entropy can be expressed in four steps (Fedajev et al., 2019):

Step 1 Normalise the decision matrix.

$$ind_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}, \quad i = 1, \ldots, m, \quad j = 1, \ldots, n \tag{1}$$

Step 2 Calculate the output entropy e_j of the j the indicator.

$$e_j = -k \sum_{j=1}^{m} ind_{ij} \times \ln\left(ind_{ij}\right), \quad i = 1, \ldots, m, \quad j = 1, \ldots, n \tag{2}$$

$$K = \frac{1}{(\ln m)} \tag{3}$$

Step 3 Calculate the variation coefficient.

$$g_i = \left(1 - e_j\right), \quad j = 1, \ldots, n \tag{4}$$

Step 4 Calculate the weight of entropy W_i related to each indicator.

$$W_i = \frac{g_i}{\sum_i^m g_i}. \tag{5}$$

3.3 Phase 3: improve the current state map

The main purpose of this phase is to investigate a new methodology to improve the current state map, to do these three consistent steps are proposed:

Step 1 Generally, the improvement of manufacturing processes is based on the implementation of kaizen events. Therefore, in the first step, we select the appropriate lean manufacturing tools for the actual state of the studied manufacturing process.

Step 2 This step investigates the correlation between the performance indicators and the lean manufacturing tools in order to construct the decision matrix. To do this, three decision-makers were selected, each one assign weights that indicate the relationship between indicators and lean manufacturing tools. The assigned weights are given by fuzzy triangular numbers, as shown in Table 2.

The aggregated fuzzy weights for each element of the decision matrix are given as (Tsao and Chu 2002):

$$a_{ij} = \left(x_{ij}, y_{ij}, z_{ij}\right)$$

where

$$\begin{gathered} x_{ij} = \min\left\{x_{ijk}\right\}, y_{ij} = \frac{1}{k}\sum_{k=1}^{k} y_{ijk}, z_{ij} = \max\left\{z_{ijk}\right\} \\ i = 1, 2, 3, \ldots, m, \ j = 1, 2, 3, \ldots, n, \ k = 1, 2, 3, \ldots, K \end{gathered} \tag{5}$$

Step 3 Once the decision matrix is constructed, this step aims to determine the rank or the application priority of the proposed lean manufacturing tools by using fuzzy EDAS and fuzzy TOPSIS approaches.

Table 2 Linguistic variable for lean manufacturing tools prioritising

Weights	*Fuzzy numbers*
None	(0, 0, 0.1)
Very low	(0.1, 0.2, 0.3)
Low	(0.3, 0.4, 0.5)
Medium	(0.5, 0.6, 0.7)
High	(0.7, 0.8, 0.9)
Very high	(0.9, 1, 1)

3.3.1 Prioritising the lean manufacturing tools by using fuzzy EDAS approach

The EDAS method it is MCDM method introduced by Ghorabaee et al. (2015). This method is based on the principle of computing the distance of each alternative from the average solution with respect to each criterion (Ghorabaee et al., 2017). The fuzzy EDAS method, it is an extension of the classical EDAS that used to deals with the multi-criteria decision-making problems with fuzzy information. The application process of fuzzy EDAS is based on the following steps (Ghorabaee et al., 2016):

Step 1 Compute the average solution according to each criterion, as follows:

$$AV = \left[\check{av}_j\right]_{1\times m}$$

where

$$\check{av}_j = \frac{1}{n} \oplus_{i=1}^{n} x_{ij} \tag{6}$$

and $\check{av}_j$ presents the average solution with respect to each criterion.

Step 2 Calculate the positive distance (PD) and ND from the average solution, as follows:

$$PD = \left[\widetilde{pd}_{ij}\right]_{n\times m}$$

$$ND = \left[\widetilde{nd}_{ij}\right]_{n\times m}$$

where

$$\widetilde{pd}_{ij} = \begin{cases} \dfrac{\max\left(0, x_{ij} \ominus \check{av}_j\right)}{\check{av}_j} & \text{if } j \in BC \\ \dfrac{\max\left(0, \check{av}_j \ominus x_{ij}\right)}{\check{av}_j} & \text{if } j \in NC \end{cases} \tag{7}$$

$$\widetilde{nd}_{ij} = \begin{cases} \dfrac{\max\left(0, \check{av}_j \ominus x_{ij}\right)}{\check{av}_j} & \text{if } j \in BC \\ \dfrac{\max\left(0, x_{ij} \ominus \check{av}_j\right)}{\check{av}_j} & \text{if } j \in NC \end{cases} \tag{8}$$

BC and *NC* are the sets of beneficial and non-beneficial criteria, respectively.

Step 3 Calculate the weighted sum of positive and NDs for all criteria, using equations (9) and (10):

$$sp_i = \oplus_{j=1}^{m} w_i\, pd_{ij} \tag{9}$$

$$sn_i = \oplus_{j=1}^{m} w_i nd_{ij} \tag{10}$$

Step 4 Normalise the values of sp_i and sn_i as follows:

$$sp_i^{(n)} = \frac{sp_i}{sp_{\max}} \tag{11}$$

$$sn_i^{(n)} = 1 - \frac{sn_i}{sn_{\max}} \tag{12}$$

Step 5 Calculated the appraisal score (As_i) for all criteria using equation (13).

$$As_i = \frac{1}{2}\left(sp_i^{(n)} + sn_i^{(n)}\right) \tag{13}$$

Step 6 Rank the results of As_i in descending order.

3.3.2 Technique for order preference by similarity to the ideal solution

TOPSIS is an MCDM method developed by Hwang and Yoon (1981), it is used for extracting the best rank of a set of criteria. The fuzzy TOPSIS approach was proposed by Chen (2000). It represents an extension of the conventional TOPSIS. In the fuzzy TOPSIS approach, the weighting and rating process is performed by using fuzzy numbers. The application process of fuzzy TOPSIS is based on the following steps as follows (Chen, 2000):

Step 1 Based on the fuzzy decision matrix: the normalised fuzzy decision matrix can be represented as (Tsao and Chu 2002):

$$\bar{R} = [\bar{r}_{ij}]_{m \times n}$$

where $\bar{r}_{ij}$ is the normalised value of $\bar{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}),$ which calculated by using equations (14) or (15).

$$\bar{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), j \in C \tag{14}$$

$$\bar{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), j \in B \tag{15}$$

where B and C are the sets of benefit criteria and cost criteria, respectively.

Step 2 Compute the weighted normalised decision matrix by multiplying the normalised fuzzy decision matrix by the vector weights of indicators, using equation (16):

$$\bar{V} = [\bar{v}_{ij}]_{m \times n}, i = 1, 2, 3, \ldots\ldots, m \quad j = 1, 2, 3, \ldots, n$$

where

$$\bar{v}_{ij} = \bar{r}_{ij_{ij}} \otimes w_j \tag{16}$$

The weights used in this phase are carried out from the entropy method.

Step 3 Determine the positive ideal (A^+) and negative ideal (A^-) solutions using equations (7) and (8), respectively.

$$\begin{gathered} A_i^+ = \left\{ \left(\max \overline{v}_{ij} \mid j \in J \right), \left(\min \overline{v}_{ij} \mid j \in J' \right) \right\} = \left\{ \overline{v}_1^+, \overline{v}_2^+, \overline{v}_3^+, \ldots, \overline{v}_n^+ \right\} \\ i = 1, 2, 3, \ldots, m, \ j = 1, 2, 3, \ldots, n \end{gathered} \tag{17}$$

$$\begin{gathered} A_i^- = \left\{ \left(\min \overline{v}_{ij} \mid j \in J \right), \left(\max \overline{v}_{ij} \mid j \in J' \right) \right\} = \left\{ \overline{v}_1^-, \overline{v}_2^-, \overline{v}_3^-, \ldots, \overline{v}_n^+ \right\} \\ i = 1, 2, 3, \ldots, m, \ j = 1, 2, 3, \ldots, n \end{gathered} \tag{18}$$

where J and J' denote the sets of beneficial criteria and non-beneficial criteria, respectively.

Step 4 Compute the separation measures of each alternative from the positive ideal and the negative ideal solutions based on the Euclidean distances using equations (19) and (20).

$$S_i^+ = \sqrt{\tfrac{1}{3} \sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \quad j = 1, 2, 3, \ldots, n; i = 1, 2, 3, \ldots, m \tag{19}$$

$$S_i^- = \sqrt{\tfrac{1}{3} \sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \quad j = 1, 2, 3, \ldots, n; i = 1, 2, 3, \ldots, m \tag{20}$$

Step 5 Calculate the relative closeness to the ideal solution using equation (21)

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{21}$$

Step 6 Rank the results of C_i in descending order.

Finally, a comparative study is proposed to assess the rank obtained from fuzzy EDAS and fuzzy TOPSIS approaches through using several weighting approaches.

4 Application of the proposed approach

The validity and the applicability of the proposed approach were investigated in a small and medium-sized company that produces photovoltaic panels located in Algeria. The choice of this company is based on the high automatisation degree and the complexity of its manufacturing process that composed of eight operations, as shown in Figure 2.

4.1 Application of VSM

This phase was performed based on a detailed study of the works of Faulkner and Badurdeen (2014) and Vinodh et al. (2016). However, the purpose of this phase is to broaden the application area of VSM method in order to improve the sustainability of the manufacturing process. To achieve this goal, several buttons lines were added to the conventional VSM method based on the following steps.

Figure 2 The studied manufacturing process (see online version for colours)

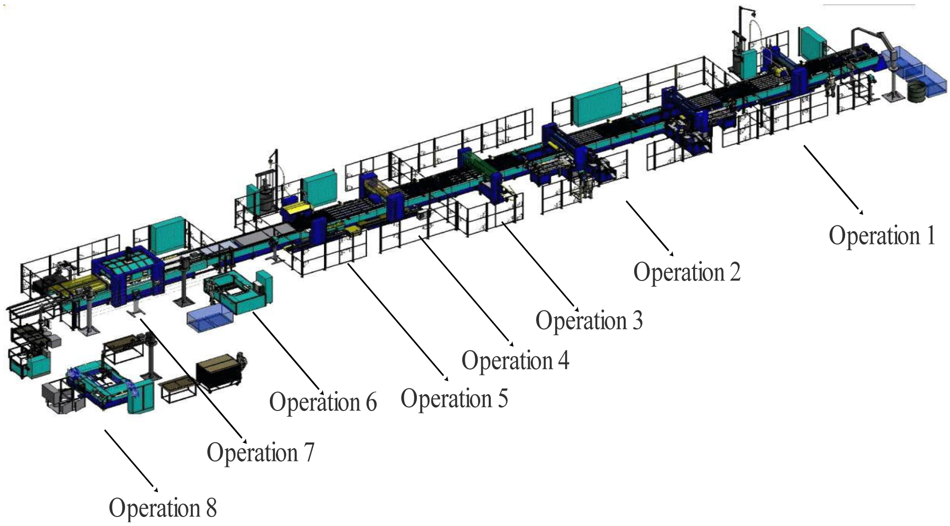
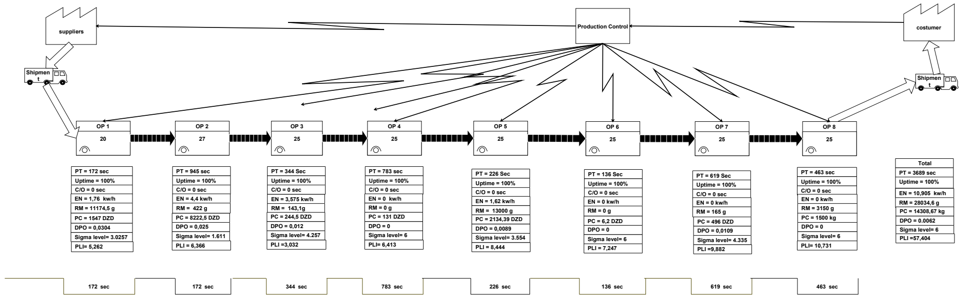


Table 3 The sustainable indicators

Pillars	*Indicators*	*Description*
Environmental indicators	Raw material (RM)	Several raw materials are used to manufacture the photovoltaic panel, such as cellule, copper wire, glass, aluminium frame. The quantities of raw materials consumed in each operation were obtained from the process and product datasheet.
	Electricity consumption (EC)	In this manufacturing process, electricity consumption is the main source of energy used to manufacture the photovoltaic model. The quantity of electricity consumed in each operation is obtained according to the power of the machines.
Economic Indicators	Production costs (PC)	This indicator presents the costs provided for each operation including raw material costs, energy costs, labour costs, which are obtained from the computability service.
	Production time (PT)	It is the amount of time required to execute each operation, which measured by using a chronometer device.
	Defect per opportunities (DPO)	Indicates the number of defects in a process per opportunity. Which calculated by using the following equation: $DPO = Nb.deffect / (production \times Nb.opportunuities)$.
	Sigma level (SL)	It is an index that used to assess the quality level and the competitiveness of a manufacturing process.
Social indicators	Physical load index (PLI)	It Is an index developed by Hollmann et al. (1999) to assess the physical work the ergonomic conditions. The PLI is calculated based on questionnaire responses which measure the frequency of occurrence (from never to very often) for different body positions (Faulkner and Badurdeen, 2014). The questionnaire and computational equation are presented in Appendix A.

Figure 3 The current state map



4.1.1 Data collection and quantification

Data collection and quantification is the most important process to develop the extended VSM method. Therefore, the data collection process began by reviewing the most sustainability indicators used in Faulkner and Badurdeen (2014), Vinodh et al. (2016) and Cherrafi et al. (2016). The obtained indicators were compared with the performance of the studied manufacturing process as well as investigated with the selected decision-makers. As a result, the final list of indicators treated in this study is presented in Table 3.

4.1.2 Develop the current state map

The current state map of the manufacturing process is organised into eight operations, which encompass the values of all the presented indicators, as shown in Figure 3.

4.2 Compute the weight of each indicator using entropy method

The diversity of indicators is one of the main factors that reflect the difference between the traditional and the extended lean manufacturing approach.

This phase aims to determine the weight of each indicator presented in the current state by using entropy method. Therefore, to simplify the application of entropy method, the first step we transform the current state map to a decision matrix, as shown in Table 4.

Table 4 Decision matrix for entropy method

Operations	*RM*	*EC*	*PT*	*PC*	*DPO*	*SL*	*PLI*
Op 1	11,174.5000	1.7600	172	1574	0.0304	3.0257	5.262
Op 2	402.0000	4.4000	946	8,222.5000	0.0256	1.6114	6.366
Op 3	143.1000	3.1250	344	244.5000	0.0122	4.2575	3.032
Op 4	0.0000	0.0000	783	131.0800	0.0000	6.0000	6.413
Op 5	13000	1.6200	226	2,134.3900	0.0089	3.5549	8.444
Op 6	0.0000	0.0000	136	6.2000	0.0000	6.0000	7.274
Op7	165.0000	0.0000	619	496	0.0110	4.3358	9.882
Op 8	3,150.0000	0.0000	463	1500	0.0000	6.0000	10.731

Table 5 The normalised decision matrix

Operations	*RM*	*EC*	*PT*	*PC*	*DPO*	*SL*	*PLI*
Op 1	0.8596	0.4000	0.0444	0.1908	1.0000	0.6777	0.2896
Op 2	0.0309	1.0000	1.0000	1.0000	0.8414	1.0000	0.4330
Op 3	0.0110	0.7102	0.2568	0.0290	0.4005	0.3971	0.0000
Op 4	0.0000	0.0000	0.7988	0.0152	0.0000	0.0000	0.4391
Op 5	1.0000	0.3682	0.1111	0.2590	0.2932	0.5571	0.7029
Op 6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5510
Op7	0.0127	0.0000	0.5963	0.0596	0.3615	0.3792	0.8897
Op 8	0.2423	0.0000	0.4037	0.1818	0.0000	0.0000	1.0000

Secondly, the normalisation of the decision matrix is performed by using equation (1), and the results obtained are presented in Table 5.

The rest of the entropy steps, such as: calculate the entropy value, compute the coefficient of variation and calculate the entropy weight, are applied successively, and the results obtained are presented in Table 6.

Table 6 The results of entropy method

Operations	*RM*	*EC*	*PT*	*PC*	*DPO*	*SL*	*PLI*
Op 1	–0.3666	–0.2944	–0.1429	–0.2428	–0.3672	–0.2124	–0.2190
Op 2	–0.0609	–0.3662	–0.3490	–0.3184	–0.3591	–0.1423	–0.2439
Op 3	–0.0269	–0.3581	–0.2212	–0.0695	–0.2736	–0.2571	–0.1553
Op 4	0.0000	0.0000	–0.3290	–0.0430	0.0000	–0.3031	–0.2449
Op 5	–0.3564	–0.2833	–0.1711	–0.2838	–0.2318	–0.2331	–0.2819
Op 6	0.0000	0.0000	–0.1217	–0.0034	0.0000	–0.3031	–0.2618
Op7	–0.0302	0.0000	–0.2995	–0.1165	–0.2597	–0.2595	–0.3029
Op 8	–0.2456	0.0000	–0.2605	–0.2364	0.0000	–0.3031	–0.3135
$e_i = -h \times \sum_i^n ind_{ij} \times \ln(ind_{ij})$	0.5226	0.6261	0.9112	0.6318	0.7172	0.9685	0.9730
$1 - e_i$	0.4774	0.3739	0.0888	0.3682	0.2828	0.0315	0.0270
$W_i = 1 - e_i \Big/ \sum_i^n 1 - e_i$	0.2894	0.2266	0.0538	0.2232	0.1714	0.0191	0.0164

4.3 Improve the current state map

This phase investigates the improvement of the current state map. Firstly, we propose a set of lean manufacturing tools, namely kanban, 5S, visual management, TPM, SMED, takt time and pokayoké. These latter were selected based on their capability for improving the sustainable indicators and on the current state of the manufacturing process.

Table 7 The decision matrix for EDAS and TOPSIS methods

Lean manufacturing tools	*RM*			*EC*			*PT*			*PC*			*DPO*			*SL*			*PLI*		
	D1	*D2*	*D3*	*D1*	*D2*	*D3*	*D1*	*D2*	*D3*	*D1*	*D2*	*D3*	*D1*	*D2*	*D3*	*D1*	*D2*	*D3*	*D1*	*D2*	*D3*
Kanban	m	l	l	h	vh	vh	vh	vh	vh	h	m	vh	l	m	h	l	m	m	h	h	m
5s	n	n	n	l	m	l	h	vh	vh	l	vl	m	h	m	m	h	l	l	vh	vh	vh
Visual management	vl	l	l	h	m	h	vh	h	h	h	m	m	m	h	l	h	m	h	h	h	h
TPM	vl	n	n	h	m	m	m	m	h	h	m	l	vl	l	l	l	vl	n	m	l	vl
SMED	n	n	n	h	m	m	vh	h	m	l	m	h	l	l	l	l	vl	m	h	m	l
Takt time	n	n	n	h	h	h	vh	vh	vh	vh	vh	h	l	m	m	l	l	m	m	h	l
Pokayoké	h	h	h	l	m	m	h	h	m	h	m	vh	vh	vh	vh	vh	vh	vh	h	h	h

Table 8 The aggregated decision matrix

Lean manufacturing tools	*RM*	*EC*	*PT*	*PC*
Kanban	(0.3000, 0.4667, 0.7000)	(0.7000, 0.8333, 0.9000)	(0.9000, 1.0000, 1.0000)	(0.5000, 0.8000, 1.0000)
5s	(0.0000, 0.0000, 0.1000)	(0.3000, 0.4667, 0.7000)	(0.7000, 0.9333, 1.0000)	(0.1000, 0.4000, 0.7000)
Visual management	(0.1000, 0.3333, 0.5000)	(0.5000, 0.7333, 0.9000)	(0.7000, 0.8667, 1.0000)	(0.5000, 0.6667, 0.9000)
TPM	(0.0000, 0.0667, 0.3000)	(0.5000, 0.6667, 0.9000)	(0.5000, 0.6667, 0.9000)	(0.3000, 0.6000, 0.9000)
SMED	(0.0000, 0.0000, 0.1000)	(0.5000, 0.6667, 0.9000)	(0.5000, 0.8000, 1.0000)	(0.3000, 0.6000, 0.9000)
Takt time	(0.0000, 0.0000, 0.1000)	(0.7000, 0.8000, 0.9000)	(0.9000, 1.0000, 1.0000)	(0.7000, 0.9333, 1.0000)
pokayoké	(0.7000, 0.8000, 0.9000)	(0.3000, 0.5333, 0.7000)	(0.5000, 0.7333, 0.9000)	(0.5000, 0.8000, 1.0000)
Lean manufacturing tools	*DPO*	*SL*	*PLI*	
Kanban	(0.3000, 0.6000, 0.5000)	(0.3000, 0.5333, 0.7000)	(0.5000, 0.7333, 0.9000)	
5s	(0.3000, 0.6000, 0.9000)	(0.3000, 0.5333, 0.9000)	(0.9000, 1.0000, 1.0000)	
Visual management	(0.3000, 0.6000, 0.9000)	(0.5000, 0.7333, 0.9000)	(0.7000, 0.8000, 0.9000)	
TPM	(0.1000, 0.3333, 0.5000)	(0.0000, 0.2000, 0.5000)	(0.1000, 0.4000, 0.7000)	
SMED	(0.3000, 0.4000, 0.5000)	(0.1000, 0.4000, 0.7000)	(0.3000, 0.6000, 0.9000)	
Takt time	(0.3000, 0.5333, 0.7000)	(0.3000, 0.4667, 0.7000)	(0.3000, 0.6000, 0.9000)	
Pokayoké	(0.9000, 1.0000, 1.0000)	(0.9000, 1.0000, 1.0000)	(0.7000, 0.8000, 0.9000)	

Table 9 The weighted normalised decision matrix

Lean manufacturing tools	*RM*	*EC*	*PT*	*PC*
Kanban	(0.0965, 0.1501, 0.2251)	(0.1762, 0.2098, 0.2266)	(0.0484, 0.0538, 0.0538)	(0.1116, 0.1786, 0.2232)
5s	(0.0000, 0.0000, 0.0322)	(0.0755, 0.1175, 0.1762)	(0.0377, 0.0502, 0.0538)	(0.0223, 0.0893, 0.1562)
Visual management	(0.0322, 0.1072, 0.1608)	(0.1259, 0.1846, 0.2266)	(0.0377, 0.0466, 0.0538)	(0.1116, 0.1488, 0.2009)
TPM	(0.0000, 0.0214, 0.0965)	(0.1259, 0.1679, 0.2266)	(0.0269, 0.0359, 0.0484)	(0.0670, 0.1339, 0.2009)
SMED	(0.0000, 0.0000, 0.0322)	(0.1259, 0.1679, 0.2266)	(0.0269, 0.0430, 0.0538)	(0.0670, 0.1339, 0.2009)
Takt time	(0.0000, 0.0000, 0.0322)	(0.1762, 0.2014, 0.2266)	(0.0484, 0.0538, 0.0538)	(0.1562, 0.2083, 0.2232)
Pokayoké	(0.2251, 0.2572, 0.2894)	(0.0755, 0.1343, 0.1762)	(0.0269, 0.0395, 0.0484)	(0.1116, 0.1786, 0.2232)
Lean manufacturing tools	*DPO*	*SL*	*PLI*	
Kanban	(0.0514, 0.1028, 0.0857)	(0.0057, 0.0102, 0.0134)	(0.0082, 0.0120, 0.0148)	
5s	(0.0514, 0.1028, 0.1543)	(0.0057, 0.0102, 0.0172)	(0.0148, 0.0164, 0.0164)	
Visual management	(0.0514, 0.1028, 0.1543)	(0.0096, 0.0140, 0.0172)	(0.0115, 0.0131, 0.0148)	
TPM	(0.0171, 0.0571, 0.0857)	(0.0000, 0.0038, 0.0096)	(0.0016, 0.0066, 0.0115)	
SMED	(0.0514, 0.0686, 0.0857)	(0.0019, 0.0076, 0.0134)	(0.0049, 0.0098, 0.0148)	
Takt time	(0.0514, 0.0914, 0.1200)	(0.0057, 0.0089, 0.0134)	(0.0049, 0.0098, 0.0148)	
Pokayoké	(0.1543, 0.1714, 0.1714)	(0.0172, 0.0191, 0.0191)	(0.0115, 0.0131, 0.0148)	

4.3.1 Construct the decision matrix

In this study, the decision matrix presents the relationship matrix that describes the correlation between the proposed lean manufacturing tools and sustainable indicators. The decision matrix was constructed based on experts' opinion. Therefore, we form a decision group of three experts consisting of production manager, quality manager and information technology manager. The experts are chosen based on the experience in their respective fields. However, each expert was asked to make a weight describe the influence degree of each lean manufacturing tool on sustainable indicators using the fuzzy triangular numbers (Table 3). The obtained decision matrix is presented in Table 7.

To obtain the aggregated fuzzy decision matrix, we use the average operator base on equation (5). The results obtained are presented in Table 8.

The aggregated decision matrix is the main input in fuzzy TOPSIS and fuzzy EDAS approaches.

4.3.2 Ranking the lean manufacturing tools by using fuzzy TOPSIS approach

In this step, the rank of lean manufacturing tools is investigated by using fuzzy TOPSIS approach based on the steps presented previously. Firstly, the aggregated decision matrix (Table 8) was normalised using equation (14), the results obtained were multiplied by the compromised weights obtained from entropy method. The weighted and normalised decision matrix is given in Table 9.

Secondly, the distance from the positive ideal (S^+), negative ideal solutions (S^-) and the relative closeness to the ideal solution (C_i) are computed using equations (19), (20) and (21), respectively. The results are presented in Table 10.

Table 10 The results of the fuzzy TOPSIS approach

Lean manufacturing tools	S^+	S^-	C_i	*Rank*
Kanban	0.2350	0.3784	0.6169	2
5s	0.5285	0.0788	0.1298	7
Visual management	0.3246	0.2992	0.4796	3
TPM	0.4799	0.1341	0.2184	5
SMED	0.4829	0.1276	0.2090	6
Takt time	0.3490	0.2505	0.4178	4
Pokayoké	0.1273	0.4770	0.7893	1

Finally, the application of lean manufacturing tools should be prioritised based on the rank presented in Table 8. This means that pokayoké has the application priority followed by kanban, visual management, takt time, TMP, SMED and 5S, respectively.

4.3.3 Ranking the lean manufacturing tools by using fuzzy EDAS approach

In this step, we present another manner to prioritise the application of lean manufacturing tools by using fuzzy EDAS approach. Therefore, based on the aggregated decision matrix (Table 8), we apply equations (7) and (8) to calculate the PD and ND from the average solution. The results obtained are presented in Tables 11 and 12.

Table 11 The PD from average solution

Lean manufacturing tools	*RM*	*EC*	*PT*	*PC*
Kanban	(0.0000, 0.9600, 3.4545)	(0.0000, 0.2411, 0.8000)	(0.0000, 0.1667, 0.4894)	(0.0000, 0.1667, 1.4138)
5s	(0.0000, 0.0000, 0.0000)	(0.0000, 0.0000, 0.4000)	(0.0000, 0.0889, 0.4894)	(0.0000, 0.0000, 0.6897)
Visual management	(0.0000, 0.4000, 2.1818)	(0.0000, 0.0922, 0.8000)	(0.0000, 0.0111, 0.4894)	(0.0000, 0.0000, 1.1724)
TPM	(0.0000, 0.0000, 0.9091)	(0.0000, 0.0000, 0.8000)	(0.0000, 0.0000, 0.3404)	(0.0000, 0.0000, 1.1724)
SMED	(0.0000, 0.0000, 0.0000)	(0.0000, 0.0000, 0.8000)	(0.0000, 0.0000, 0.4894)	(0.0000, 0.0000, 1.1724)
Takt time	(0.0000, 0.0000, 0.0000)	(0.0000, 0.1915, 0.8000)	(0.0000, 0.1667, 0.4894)	(0.0000, 0.3611, 1.4138)
Pokayoké	(0.8148, 2.3600, 4.7273)	(0.0000, 0.0000, 0.4000)	(0.0000, 0.0000, 0.3404)	(0.0000, 0.1667, 1.4138)
Lean manufacturing tools	*DPO*	*SL*	*PLI*	
Kanban	(0.0000, 0.0328, 0.4000)	(0.0000, 0.0000, 1.0417)	(0.0000, 0.0405, 0.8000)	
5s	(0.0000, 0.0328, 1.5200)	(0.0000, 0.0000, 1.6250)	(0.0161, 0.4189, 1.0000)	
Visual management	(0.0000, 0.0328, 1.5200)	(0.0000, 0.3276, 1.6250)	(0.0000, 0.1351, 0.8000)	
TPM	(0.0000, 0.0000, 0.4000)	(0.0000, 0.0000, 0.4583)	(0.0000, 0.0000, 0.4000)	
SMED	(0.0000, 0.0000, 0.4000)	(0.0000, 0.0000, 1.0417)	(0.0000, 0.0000, 0.8000)	
Takt time	(0.0000, 0.0000, 0.9600)	(0.0000, 0.0000, 1.0417)	(0.0000, 0.0000, 0.8000)	
Pokayoké	(0.2600, 0.7213, 1.8000)	(0.1667, 0.8103, 1.9167)	(0.0000, 0.1351, 0.8000)	

Table 12 The ND from average solution

Lean manufacturing tools	*RM*	*EC*	*PT*	*PC*
Kanban	(0.0000, 0.0000, 0.2222)	(0.0000, 0.0000, 0.1695)	(0.0000, 0.0000, 0.0735)	(0.0000, 0.0000, 0.4531)
5s	(0.3636, 1.0000, 1.0000)	(0.0000, 0.3050, 0.6441)	(0.0000, 0.0000, 0.2794)	(0.0000, 0.4167, 0.8906)
Visual management	(0.0000, 0.0000, 0.7407)	(0.0000, 0.0000, 0.4068)	(0.0000, 0.0000, 0.2794)	(0.0000, 0.0278, 0.4531)
TPM	(0.0000, 0.7200, 1.0000)	(0.0000, 0.0071, 0.4068)	(0.0000, 0.2222, 0.4853)	(0.0000, 0.1250, 0.6719)
SMED	(0.3636, 1.0000, 1.0000)	(0.0000, 0.0071, 0.4068)	(0.0000, 0.0667, 0.4853)	(0.0000, 0.1250, 0.6719)
Takt time	(0.3636, 1.0000, 1.0000)	(0.0000, 0.0000, 0.1695)	(0.0000, 0.0000, 0.0735)	(0.0000, 0.0000, 0.2344)
Pokayoké	(0.0000, 0.0000, 0.0000)	(0.0000, 0.2057, 0.6441)	(0.0000, 0.1444, 0.4853)	(0.0000, 0.0000, 0.4531)
Lean manufacturing tools	*DPO*	*SL*	*PLI*	
Kanban	(0.0000, 0.0000, 0.5800)	(0.0000, 0.0345, 0.6111)	(0.0000, 0.0000, 0.4355)	
5s	(0.0000, 0.0000, 0.5800)	(0.0000, 0.0345, 0.6111)	(0.0000, 0.0000, 0.0000)	
Visual management	(0.0000, 0.0000, 0.5800)	(0.0000, 0.0000, 0.3519)	(0.0000, 0.0000, 0.2097)	
TPM	(0.0000, 0.4262, 0.8600)	(0.0000, 0.6379, 1.0000)	(0.0000, 0.4324, 0.8871)	
SMED	(0.0000, 0.3115, 0.5800)	(0.0000, 0.2759, 0.8704)	(0.0000, 0.1486, 0.6613)	
Takt time	(0.0000, 0.0820, 0.5800)	(0.0000, 0.1552, 0.6111)	(0.0000, 0.1486, 0.6613)	
Pokayoké	(0.0000, 0.0000, 0.0000)	(0.0000, 0.0000, 0.0000)	(0.0000, 0.0000, 0.2097)	

Based on the weights obtained from entropy method, we use equations (9) and (10) to compute the weighted summation of the positive and NDs (sp_i and np_i). The results obtained are presented in Table 13.

Then, the normalised values of sp_i and np_i ($sp_i^{(n)}$ and $np_i^{(n)}i$) and the appraisal score As_i of all lean manufacturing tools are calculated by using equations (11)–(12). These results are presented in Table 14.

The rank presented in Table 14, indicates that pokayoké method has the highest appraisal score, which means that this method has the priority of application with respect to the sustainable indicators. Moreover, the rank of the rest lean manufacturing tools is as follows: kanban, visual management, takt time, TMP, SMED and 5S, respectively.

Table 13 The weighted summation of the positive and NDs

Lean manufacturing tools	sp_i	np_i
Kanban	(0.0000, 0.3849, 1.6245)	(0.0000, 0.0007, 0.3260)
5s	(0.0003, 0.0173, 0.5789)	(0.1052, 0.4522, 0.7602)
Visual management	(0.0000, 0.1513, 1.4054)	(0.0000, 0.0062, 0.5323)
TPM	(0.0000, 0.0000, 0.8082)	(0.0000, 0.3422, 0.7387)
SMED	(0.0000, 0.0000, 0.5709)	(0.1052, 0.3836, 0.6845)
Takt time	(0.0000, 0.1330, 0.7207)	(0.1052, 0.3089, 0.5060)
Pokayoké	(0.2836, 0.8615, 2.1508)	(0.0000, 0.0544, 0.2766)

Table 14 The results of fuzzy EDAS approach

Lean manufacturing tools	$sp_i^{(n)}$	$np_i^{(n)}$	
Kanban	(0.0000, 0.3703, 1.5630)	(0.2631, 0.9985, 1.0000)	
5s	(0.0003, 0.0166, 0.5569)	(–0.7183, –0.0219, 0.7622)	
Visual management	(0.0000, 0.1456, 1.3522)	(–0.2030, 0.9860, 1.0000)	
TPM	(0.0000, 0.0000, 0.7776)	(–0.6696, 0.2267, 1.0000)	
SMED	(0.0000, 0.0000, 0.5493)	(–0.5471, 0.1330, 0.7622)	
Takt time	(0.0000, 0.1279, 0.6934)	(–0.1436, 0.3020, 0.7622)	
Pokayoké	(0.2728, 0.8289, 2.0694)	(0.3748, 0.8771, 1.0000)	
Lean manufacturing tools	As_i	$def(As_i)$	*Rank*
Kanban	(0.1316, 0.6844, 1.2815)	0.6955	2
5s	(–0.3590, –0.0027, 0.6595)	0.0738	7
Visual management	(–0.1015, 0.5658, 1.1761)	0.5515	3
TPM	(–0.3348, 0.1133, 0.8888)	0.1952	5
SMED	(–0.2736, 0.0665, 0.6557)	0.1288	6
Takt time	(–0.0718, 0.2149, 0.7278)	0.2715	4
Pokayoké	(0.3238, 0.8530, 1.5347)	0.8911	1

Table 15 A comparative study

Lean manufacturing tools	*Quantitative weighting*				*Qualitative weighting*			
	Entropy weights		*CRITIC weights*		*AHP weights*		*BWM weights*	
	Fuzzy EDAS	*Fuzzy TOPSIS*	*Fuzzy EDAS*	*Fuzzy TOPSIS*	*Fuzzy EDAS*	*Fuzzy TOPSIS*	*Fuzzy EDAS*	*Fuzzy TOPSIS*
Kanban	2	2	2	2	2	2	2	2
5s	7	7	5	5	5	5	5	5
Visual management	3	3	3	3	3	3	3	3
TPM	5	5	7	7	7	7	7	7
SMED	6	6	6	6	6	6	6	6
Takt time	4	4	4	4	4	4	4	4
Pokayoké	1	1	1	1	1	1	1	1
					CI = 0.0822		KSI = 0.0399	

5 Results and discussion

In this paper, an integrated approach of three phases is proposed for enhancing the application process of the classical lean manufacturing approach. In the first phase, the assessment of the manufacturing process was indicated that *raw material (RM)*, *electricity consumption (EC)*, *production costs (PC)*, *production time (PT)*, *defect per opportunities (DPO)*, *sigma level (SL)* and *physical load index (PLI)* are the most influential indicators that should be taken into consideration to improve the sustainability of the manufacturing process. The mentioned indicators were quantified and integrated into VSM method in order to construct the current state map.

In the second phase, we transform the current state map to a decision matrix and introduce entropy method to calculate the weight of each indicator. The obtained weights are used as inputs in fuzzy EDAS and fuzzy TOPSIS to rank a set of proposed lean manufacturing tools.

Finally, a benchmarking is presented to assess the results carried out from fuzzy EDAS and fuzzy TOPSIS by using qualitative and quantitative weighting approaches. The results obtained are presented in Table 15.

According to Mousavi-Nasab and Sotoudeh-Anvari (2017), it is very difficult to select the best MCDM methods to resolve a studied problem.

Based on Table 15, we conclude that fuzzy EDAS and fuzzy TOPSIS are suitable approaches for the investigated problems. In addition, the results obtained indicate a very high correlation between fuzzy EDAS and fuzzy TOPSIS approaches whatever the kind of weighting approaches (qualitative or quantitative).

6 Conclusions

Improving the sustainability of manufacturing processes is one of the important tasks to achieve success for manufacturing firms. However, the implementation of advance manufacturing techniques helps the manufacturing organisations to produce more customised products of higher quality and lower cost (Raj et al., 2008).

In this study, we have proposed a new approach that integrates the lean manufacturing approach with MCDM methods to enhance the sustainability of manufacturing processes. The proposed approach is composed of three phases. Firstly, we have extended the classical VSM method to assess the sustainability of the manufacturing process. Then, the entropy method has been introduced to determine the weights of the indicators. Finally, the weights obtained are introduced into fuzzy EDAS and fuzzy TOPSIS to set out the application priority of a set of lean manufacturing tools. To illustrate the validity of the proposed approach, we applied it to a case study of a manufacturing process that produces photovoltaic modules. A benchmarking has also been performed using qualitative and quantitative weighting approaches to demonstrate the stability of the results. The performed benchmarking indicates that the proposed approach is efficient, and the ranking results are relatively stable.

The main contributions of this paper are that the proposed approach provides a comprehensive framework to analyse and improve the sustainability of manufacturing processes. In addition, the proposed approach enhances the application process of lean manufacturing approach and broadens its application area by addressing the environmental, social, and economic aspects of manufacturing processes.

The major limitations of this study are that the application of the proposed framework is based on one case study, this affects the generality of the proposed model. In addition, the proposed approach treats an average number of indicators. Therefore, these limitations provide the direction for our future works.

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Appendix

Table 16 Questionnaire for computing the PLI

Trunk		*Never*	*Seldom*	*Sometimes*	*Often*	*Very often*
T_1	Straight, upright					
T_2	Slightly inclined					
T_3	Strongly inclined					
T_4	Twisted					
T_5	Laterally bent					
Arms		*Never*	*Seldom*	*Sometimes*	*Often*	*Very often*
A_1	Both below shoulder					
A_2	One arm above shoulder					
A_3	Both arms above shoulder					
Legs		*Never*	*Seldom*	*Sometimes*	*Often*	*Very often*
L_1	Sitting					
L_2	Standing					
L_3	Squatting					
L_4	Kneeling with one or both					
L_5	Walking, moving					
Weight – upright		*Never*	*Seldom*	*Sometimes*	*Often*	*Very often*
W_{u1}	Light					
W_{u2}	Medium					
W_{u3}	Heavy					
Weight – inclined		*Never*	*Seldom*	*Sometimes*	*Often*	*Very often*
W_{i1}	Light					
W_{i2}	Medium					
W_{i3}	Heavy					
		Never	*Seldom*	*Sometimes*	*Often*	*Very often*
Scores assignable		0	1	2	3	4

Source: Hollmann et al. (1999)

PLI calculating equation:

$$\begin{aligned} PLI = {} & 0.974 \times T_2 score + 1.104 \times T_3 score + 0.068 \times T_4 score + 0.173 \times T_5 score \\ & + 0.157 \times A_2 score + 0.314 \times A_3 score + 0.405 \times L_2 score + 0.152 \times L_4 score \\ & + 0.152 \times L_5 score + 0.549 \times Wu_1 score + 1.098 \times Wu_2 score + 1.647 \times Wu_3 score \\ & + 1.777 \times Wi_1 score + 2.416 \times Wi_2 score + 3.056 \times Wi_3 score \end{aligned}$$