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MODELO FUZZY PARA AVALIAR O NÍVEL DO LEAN MANUFACTURING EM UMA INDÚSTRIA METALÚRGICA DE PEQUENO PORTE

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Resumo: As pequenas empresas têm dificuldade em implementar sistemas de gestão da produção. Isso causa problemas de superprodução, alto estoque e altas taxas de produtos defeituosos. A Manufatura Enxuta (Lean Manufacturing) atua como uma metodologia para alcançar a eliminação de desperdícios. É importante que as empresas identifiquem seu nível atual de Lean para melhorar suas operações. Portanto, este trabalho tem como objetivo apresentar um modelo utilizando lógica fuzzy, aplicado em uma pequena indústria metalúrgica. Um modelo de inferência Fuzzy foi especificado e modelado no software fuzzy toolbox MATLAB R2013a®. A simulação realizada no modelo levou em consideração a realidade atual da empresa, pois foi observado que não há métricas Lean em seus processos. Uma grande vantagem do modelo é a possibilidade de ajustes para qualquer tipo de organização, uma vez que as variáveis de entrada e saída podem receber outros valores linguísticos.

Palavras-chave: Lógica fuzzy. Manufatura enxuta. Indústria metalúrgica.

Abstract: Small companies find it difficult to implement production management systems. This causes problems of overproduction, high inventory and high rates of defective products. Lean Manufacturing acts as a methodology to achieve waste elimination. It is important that companies identify their current level of Lean to improve their operations. This work aims to present a model using fuzzy logic, applied in a small metallurgical industry. A Fuzzy inference model was specified and modeled on the software fuzzy toolbox MATLAB R2013a®. The simulation performed on the model took into account the current reality of the company, noting that there are no Lean metrics in its processes. A great advantage of the model is the possibility of adjustments for any type of organization since the input and output variables can receive other linguistic values.

Keywords: Fuzzy logic. Lean manufacturing. Metallurgical industry.

1 Introduction

Lean Manufacturing (LM) is a management approach that originated in Japan shortly after World War II at the Toyota car plant, which created a new management method known as the Toyota Production System (Womack & Jones, 1960).

Lean Manufacturing or Lean Production (PE) is a philosophy which together with tools and techniques focus on the identification and elimination of waste present in operations because Lean acts as a methodology to achieve the elimination of waste (Uhlmann, 2015).

The main objective of lean manufacturing is to reduce waste continually in human effort, inventory, time to market and manufacturing space, in order to respond to customer demand while maintaining product quality (Susilawati & Sarwar, 2015).

Lean manufacturing is a production strategy with a focus on continuous improvement of production processes by eliminating activities that do not add value to the final customer (Silva et al., 2019).

The first step adopted by all implementation models of Lean Manufacturing is the evaluation of lean production. It is necessary for the organization to identify its current Lean level to improve its lean operations. The literature presents an index that represents the level of implementation of lean production in a company. This index is called Leanness. The Leanness of a system can be quantified and measured by comparing the current state with the best and worst cases (Alcantara, 2017).

A systematic measurement can help managers and other interested parties since Lean Manufacturing is a set of practices designed to achieve perfection in the identification and elimination of waste (Oleghe; Salonitis, 2016).

Small-scale companies have difficulties to measure their level of Lean Manufacturing because they do not know how to identify their problems. According to Walter and Tubino (2013), even though Lean Manufacturing assessment methods cover several critical aspects in relation to its implementation, it is difficult to find what fits perfectly in all companies and in all production systems.

To measure the organizational performance as the result set that the organization achieved while executes its activities is paramount. The indicators created from the Lean assessment allow constant monitoring of results of individual processes and the organization's overall results (Predoso; Muller, 2017).

Therefore, this research presents a Fuzzy inference model for measuring the level of Lean Manufacturing applied in a small metallurgical industry.



2 Literature revision

Lean Manufacturing since its creation and dissemination has undergone adaptations to serve the various industries. Many managers use Lean tools to eliminate waste and ensure better efficiency in companies (Deveras, 2019).

Lean manufacturing is defined as a production strategy, its purpose is to improve the production system by removing stages / activities of processes that do not benefit the product and do not add value (Tubino, 2015).

According with Rodrigues (2014), Taiichi Ohno is considered the father of the Toyota Production System. On his trip to the United States, Taiichi Ohno noted the effectiveness of the Piggly Wiggly supermarket in terms of the movement of materials and goods. The “method” adopted in this supermarket served as a basis for Ohno that, years later, would create the basis for the Just-in-time philosophy.

The Just-in-time (JIT) is a disciplined approach, which aims to improve global productivity and extinguish waste. This philosophy enables cost-effective production since its principle is to supply only the right quantity at the right time and place, using the minimum of facilities. JIT aims to meet demand instantly, with extreme quality and without waste (Slack et al., 2009).

Waste is any activity that does not add value to customers. In order to understand and identify waste it is necessary to understand customers and what they value. To please them it is necessary to eliminate or, at least, reduce activities classified as waste and that they do not wish to pay (Ohno, 1997; Hu et al., 2015).

In the vision of Ohno (1997) and Slack et al. (2009) waste is classified in seven groups: overproduction, waiting time, transport, inventory, defects in products, over processing and movement.

I. Overproduction: To produce more than necessary for the next production process and is the greatest source of waste, according to Toyota.

II. Waiting: Machine efficiency and labor efficiency are two common measures, which are widely used to assess machine and labor waiting times, respectively. Less obvious is the amount of material waiting time, which is hidden by operators busy with producing in-process stock, which is not needed at the time.

III. Transport: The moving of materials within the factory, as well as double or triple moving of stock in process, which does not add value. Changes in the physical arrangement that makes more accessible the steps of the process, improvement of transportation methods and in the organization of the workplace, can reduce waste.

IV. Over processing: There may be sources of waste in the process itself. Some operations exist only because of bad component design or bad maintenance and can be eliminated.

V. Inventory: It happens when the company has storage of finished or semi-finished products greater than the minimum required.

VI. Movement: An operator may seem busy, but sometimes no value is being added by the activity. Simplifying activities is a good handling waste reduction source.

VII. Defects in products: It occurs when an item in the production process or even the finished product does not meet the required quality characteristics. As a result, this waste materializes in the form of refuse or rework.

Occurring waste in the production process of a factory indicates that actions linked to lean production are flawed or non-existent. The elimination of waste is directly correlated to the success of the Lean philosophy since waste increases production costs considerably (Mussolini et al., 2019; Azadeh et al., 2015).

2.1 The logic fuzzy

The term fuzzy and the formalization of fuzzy sets were coined by Lotfi A. Zadeh, in 1965, when he worked with problems of classifying sets that did not have well-defined borders or a non-classical logical system. Zadeh aimed to provide a mathematical tool for handling inaccurate or vague information. Ranking fuzzy numbers has an important role in a fuzzy decision making process (Malaman et al., 2017; Tsai, 2011).

The theory of fuzzy sets has been widely used, highlighting their use in modeling systems whose variables are qualitative and with subjective properties or imprecise values. Fuzzy logic works with the scoring of the alternatives and the weight of the criteria represented by linguistic variables (Lima Junior et al., 2018).

In a set that is defined in a universe of elements through a membership function, in which values are included in the inclusive range of [0.1]. The membership function expresses the compatibility of the term that denominates the set with its meaning (Zadeh, 1965).

Fuzzy logic is considered a set of mathematical principles for the outline of knowledge based on the degree of relevance of the terms $\mu(x)$ (Lima, 2017). According to Equation 1.

$$\mu(x) = \begin{cases} 1 & \text{if, and only if, } x \in A \\ 0 & \text{if, and only if, } x \notin A \\ 0 \leq \mu(x) \leq 1 & \text{if } x \text{ belong to } A \end{cases} \quad (1)$$



The membership range corresponds to [0,1], where 0 means that an element does not belong to a particular set, 1 means complete membership to the set, and values between 0 and 1 represent partial degrees of membership (Dragovic, 2015). Fuzzy sets are defined by ordered pairs and these pairs indicate each element with its degree of relevance to the set (Medeiros et al., 2015).

To illustrate a set of fuzzy logic, where a is the diffuse set, $\mu_a(x)$ is the membership function $x \in X$ universe or universe of discourse, we use the Equation 2.

$$a = \{(x, \mu_a(x)) \mid x \in X\} \tag{2}$$

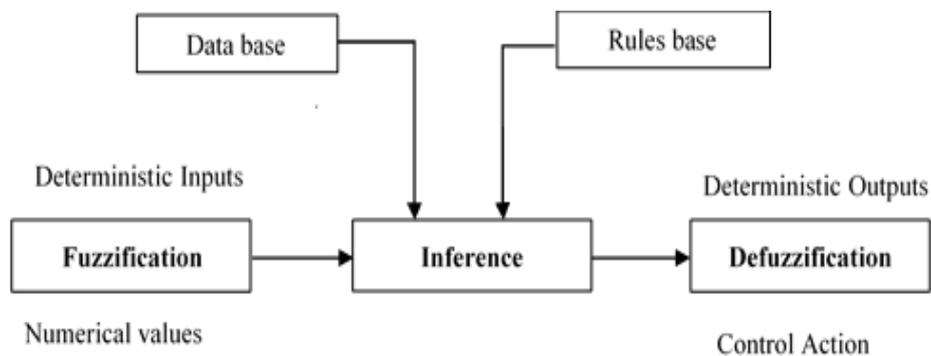
The fuzzy sets have the pertinence functions that are classified as: triangular, trapezoidal, Gaussian and sigmoid (Simões & Shaw, 1999). The fuzzy inference method consists of an input evaluation process and its main objective is to draw conclusions using the theory of fuzzy sets. This methodology is defined through inference models, which consider the type of problem that will be analyzed. Inference models can be classified into: Mamdani and Sugeno (Medeiros et al., 2015; Simões & Shaw, 1999).

The Mamdani inference style was created by Professor Ebrahim Mamdani from the University of London (United Kingdom) in 1975. The Mamdani model of fuzzy inference requires four elements that are called fuzzifier and defuzzifier, rule base and fuzzy inference (Nogueira & Nascimento, 2017).

The Mamdani fuzzy inference process consists of defining the value of each consequent of the fuzzy rules. Once the rules are described, the fuzzy inference system is used. This can be divided into three phases: fuzzification, inference and defuzzification (Bueno, 2017; Vergara et al, 2016). Figure 1 shows the fuzzy inference system.

Figure 1

Mamdani's fuzzy inference system



Source: Bueno, (2016).



In fuzzification, the degree of membership is determined by a membership function in which the fuzzifier converts the actual input values into a degree of membership in Fuzzy sets, to be treated by the inference machine (Medeiros et al., 2016).

In the inference phase the linguistic values, resulting of fuzzification, are combined to generate linguistic output values according to the Fuzzy inference rules chosen at the start (Coelho et al., 2018).

Defuzzification is the step where the resulting regions are converted into numeric values by the system output variable. There are several methods of defuzzification, one of them is the centroid method where the geometric center of the final set is chosen, and it consists of the average of centroid points weighted by the areas (Monteiro et al., 2018).

3 Research methodology

The case study took place during the first half of 2019 where on-site visits were made at the metallurgical company for interviews with the main managers and employees to collect information relevant to the research, such as the company's product mix and operations flowchart.

To assess the Lean level, a Fuzzy inference model was specified, modeled on the MATLAB R2013a® software fuzzy toolbox, allowing the management of fuzzy variables and operators and adapting them to any use without restrictions.

The implementation of the system included the following steps: Description of the input sets; Description of fuzzy output sets; Inference rules of the fuzzy model; Conceptual model of the fuzzy inference system; Analysis of the output behavior. For the creation of the model, three of the seven major production wastes were selected, which according to the Lean philosophy are harmful to organizations. The selected variables were overproduction, inventory in process and transport.

Input variables were selected through the expert knowledge of the main factors that contribute to organizations implementing and maintaining the Lean Manufacturing philosophy.

Fuzzy sets of triangular relevance were created for the three input variables and the output variable. The pertinence functions developed for this system were; the numerical range and the linguistic value, according to Table 1.



Table 1

System functions

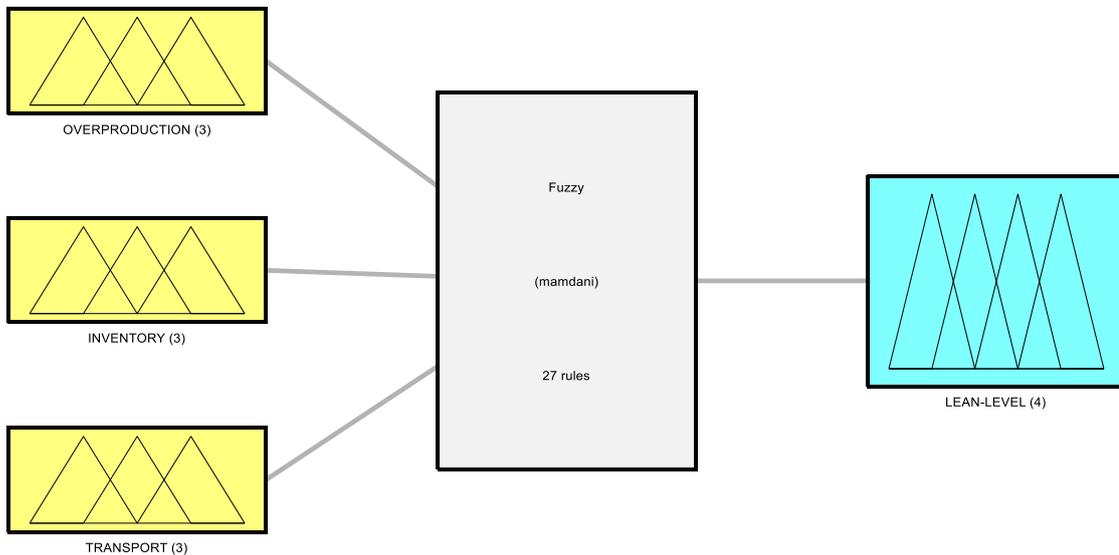
Variables	Numeric Range	Linguistic Value
INPUTS	[0 - 100]	(LOW, MEDIUM, HIGH)
OVERPRODUCTION		
INVENTORY		
TRANSPORT		
OUTPUTS	[0 - 100]	EXTREMELY LEAN
LEAN LEVEL		LEAN
		LESS LEAN
		NOT LEAN

Source: The authors (2020).

Figure 2, shows the Mamdani fuzzy model with the input and output variables, in the Graphical User Interface area in the Matlab software.

Figure 2

Input and output variables of the Mamdani system



System Fuzzy: 3 inputs, 1 outputs, 27 rules

Source: The authors (2020).

The behavior of the fuzzy input sets was described numerically where the variables overproduction, inventory and transport can assume the linguistic values "Low", "Medium" and "High".

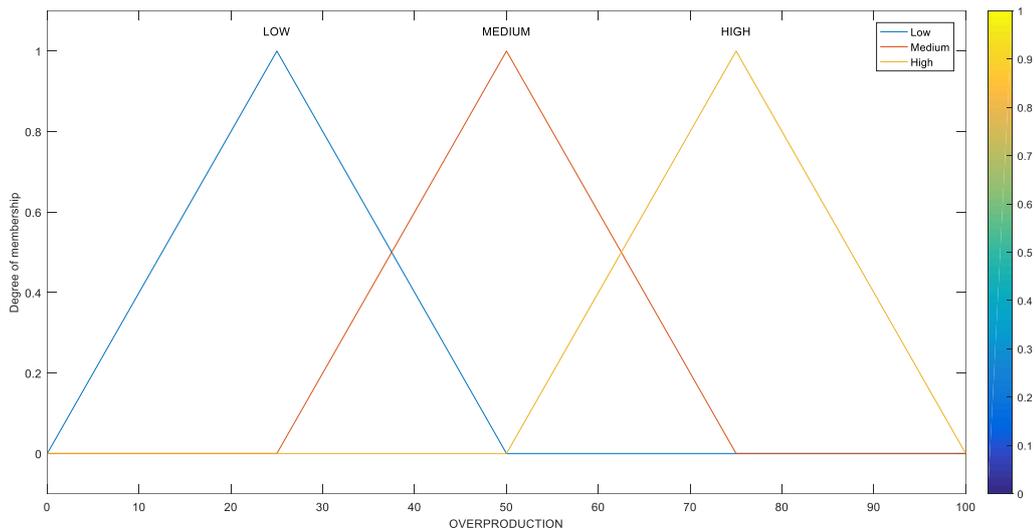
The categories of the parameter ranges were obtained through the specialist in the area of Lean Manufacturing, were: Low with parameters (0,25,50); Medium with parameters (25,50,75); High with parameters (50,75,100).

The scores described in the Table above represent the existence of regions where the entries can be considered belonging to the category (low, medium and high). The first value of the interval represents the beginning of the belonging range.

The second value represents the peak region, and the third value determines the end of the range for that category. Figure 3 outlines the association graph for the overproduction input variable. The Figure 4 outlines the association graph for the input variable inventory in process. Figure 5 outlines the association graph for the transport input variable.

Figure 3

Overproduction variable

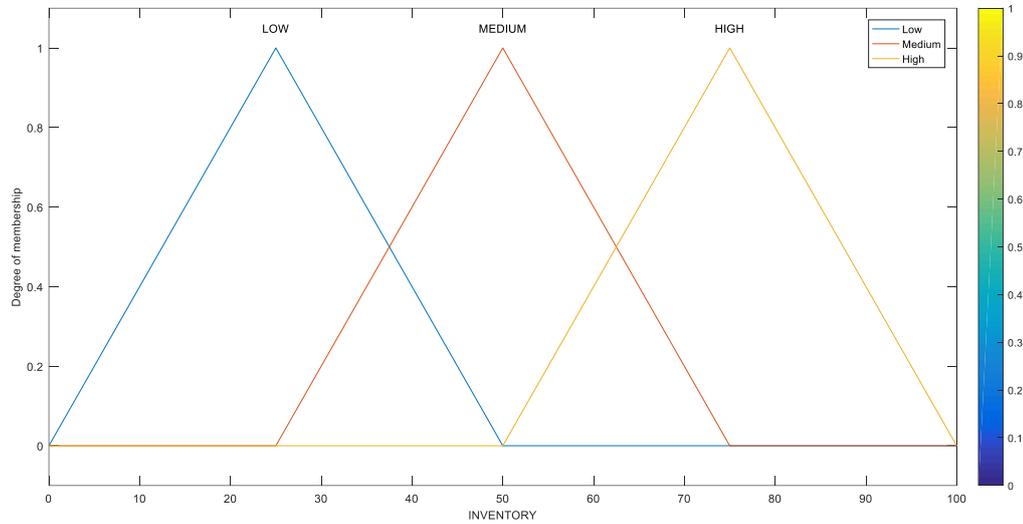


Source: The authors (2020).



Figure 4

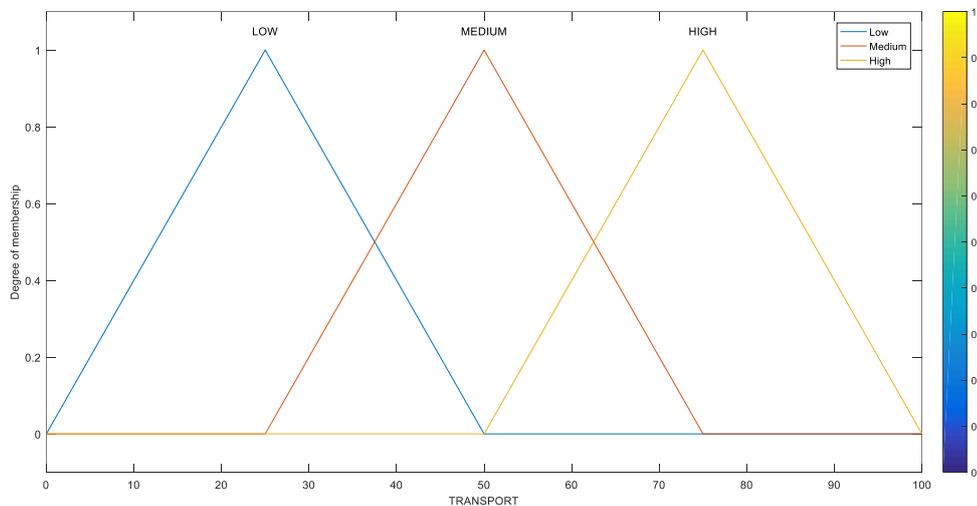
Variable Inventory in process



Source: The authors (2020).

Figure 5

Transport variable



Source: The authors (2020).

The output of the fuzzy inference system describes the probabilities of the final evaluation belonging to one of the entry categories created when the result varies between the defined values. The categories of the parameter ranges were obtained through the specialist in the area of Lean Manufacturing were: Extremely lean with parameters (60,80,100); Lean with parameters (40, 60, 80); Less lean with parameters (20,40,60) and Not lean with parameters (0,20,40). With all input and output variables mapped and defined the rule base for linguistic variables was developed. The composition of the base of inference rules for the linguistic variables, used in the construction of the fuzzy model to

determine the Lean level, resulted in 27 combinations. The inference rules are of the “if-then” type generating a combination of the input and output variables established by the specialist. Example in the Figure 6:

Figure 6

Example the composition of the base of inference rules for the linguistic variables used

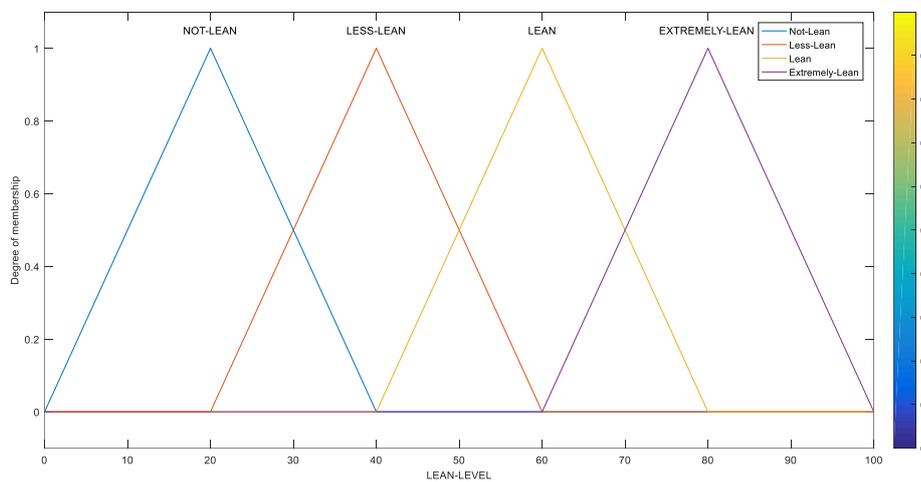
1. If (OVERPRODUCTION is LOW) and (INVENTORY is LOW) and (TRANSPORT is LOW) then (LEAN-LEVEL is EXTREMELY-LEAN) (1)
2. If (OVERPRODUCTION is LOW) and (INVENTORY is LOW) and (TRANSPORT is MEDIUM) then (LEAN-LEVEL is LEAN) (1)
- ...

Source: The authors (2020).

The Figure 7 outlines the graph of association of the input and output variables. The Lean level is characterized by diffuse sets associated with a triangular belonging function.

Figure 7

Lean level output variable



Source: The authors (2020).

The fuzzy inference procedure assesses the input variables and their linguistic values by observing each rule, activating some of them and providing a degree of relevance for each set inserted.



4 Study results

Taking as example the metallurgical company that presents high levels of overproduction, stock in process and transport as input variables through the created fuzzy inference model, it was possible to determine the organization's Lean level. The Figure 8 shows the production process of the small metallurgical company. Figure 9 shows the behavior of the diffuse diagram in its simulation process, which considers the current state of the company.

Figure 8

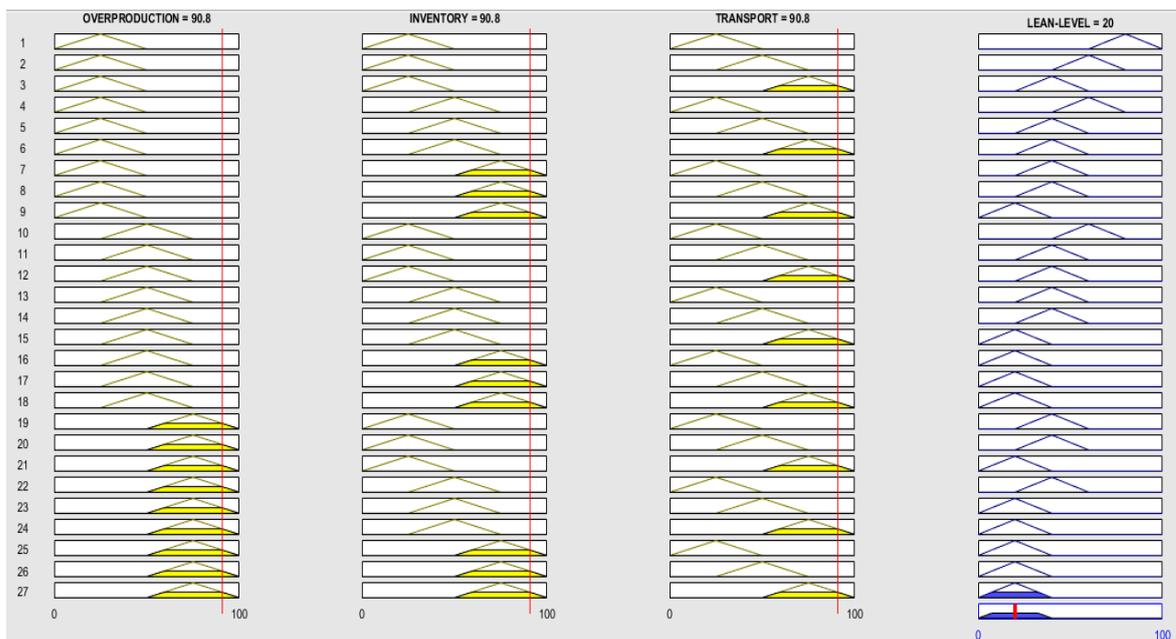
The overproduction and high stock in process of the metallurgical company



Source: The authors (2020).

Figure 9

Behavior of the diffuse diagram for the current scenario of the company



Source: The authors (2020).

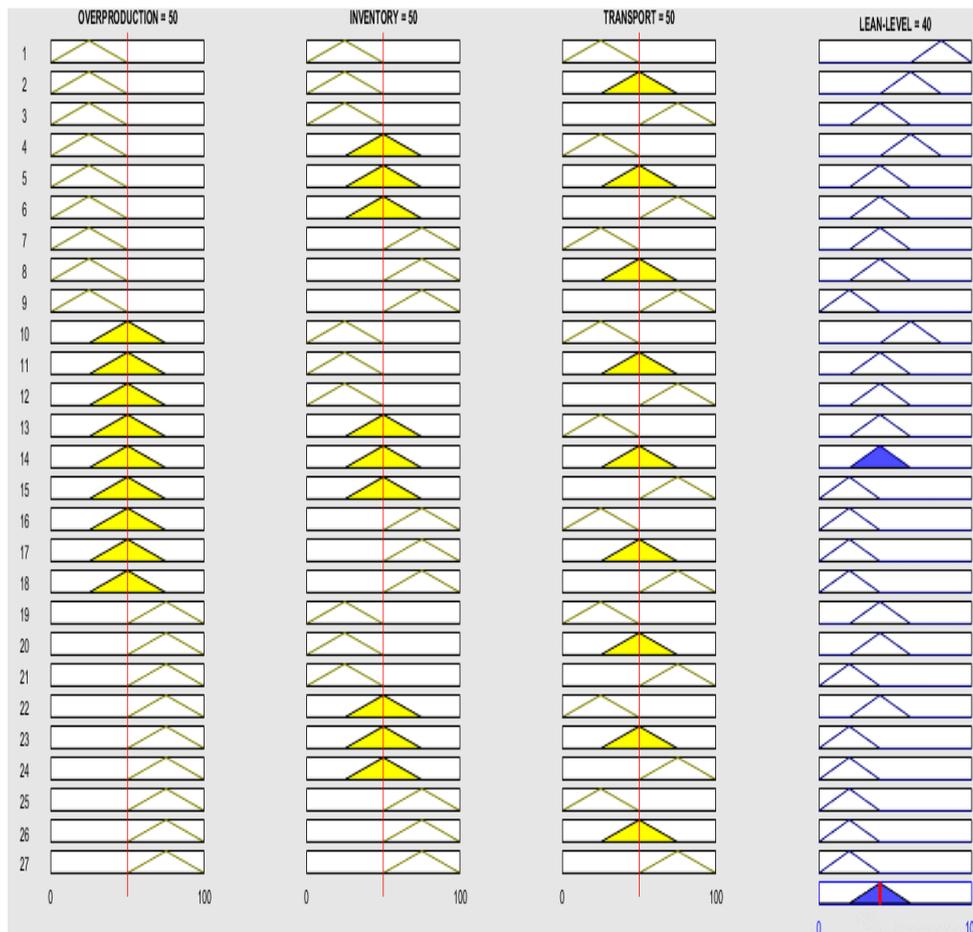
The output variable shows the Lean level that the company appears to have with the resulting value 20. This value belongs in the Non-Lean region and indicates that the company does not practice Lean philosophy.

If the company partially adopts some Lean tools and improves its rates of overproduction, in-process inventory and transportation, the Lean level will assume a new value.

Figure 10 shows another simulation scenario where the input variables receives the average degree of relevance. The simulation demonstrates that if the company starts to adopt Lean tools and reduce its rates of overproduction, in-process inventory, and transportation the Lean index will undergo a change. The industry under these conditions will be considered Less Lean.

Figure 10

The result from inferences for a scenario of improvement in the indices of the input variables



Source: The authors (2020).

Another simulation considers that the company maintains Lean tools such as the 5S program for organization and visual management, Kanban and Just-in-time for inventory control, Poka-Yoke to prevent defects, total productive maintenance (TPM) for the management of machines and equipment,



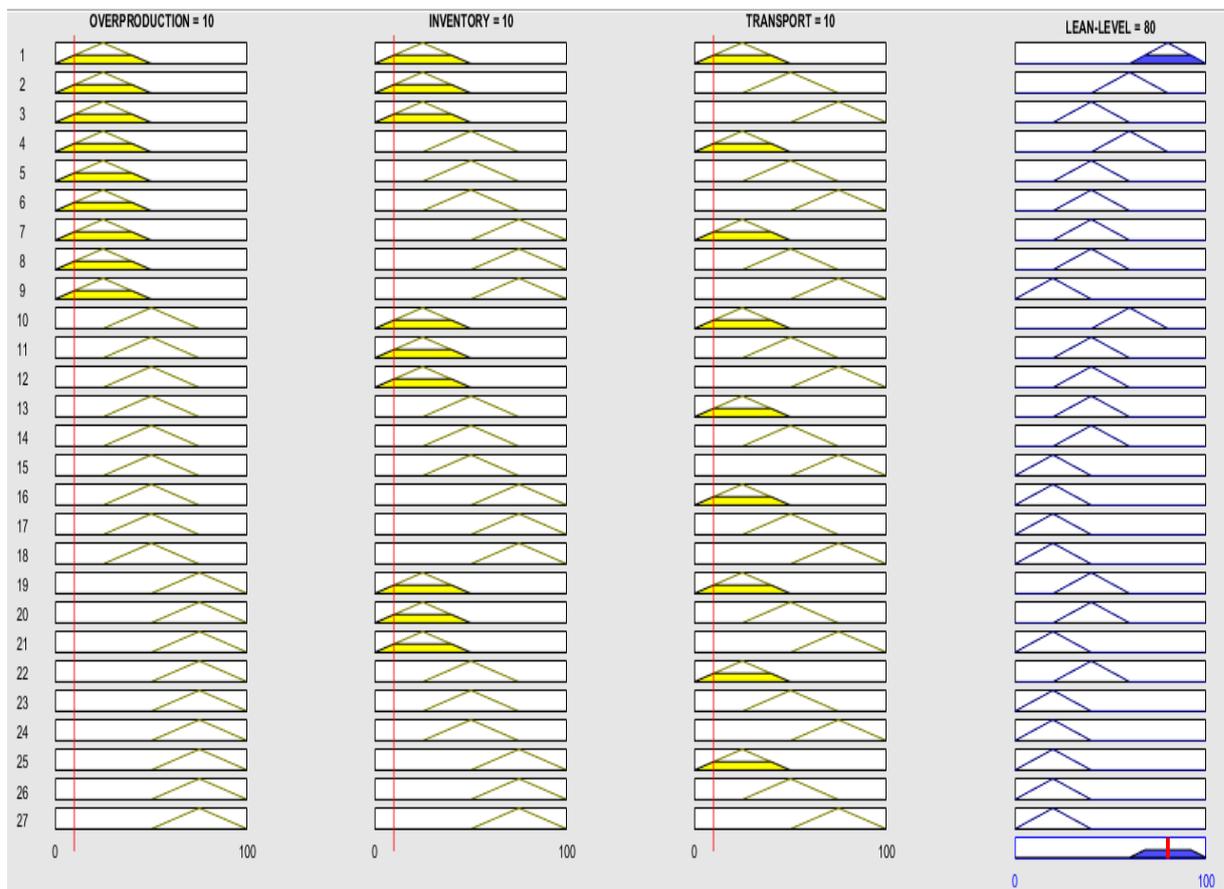
value flow mapping to expose waste in current processes and track operations that do not add value to the product and other tools applicable to the process.

The adoption of Lean tools contributes to eliminate/reduce waste from overproduction, in-process inventory and transportation.

Figure 11 shows the simulation whose input variables assume low degree of relevance, that is, a scenario of low overproduction, low stock in process and low transport and for these conditions the result is Extremely Lean.

Figure 11

The result from inferences for the third situation

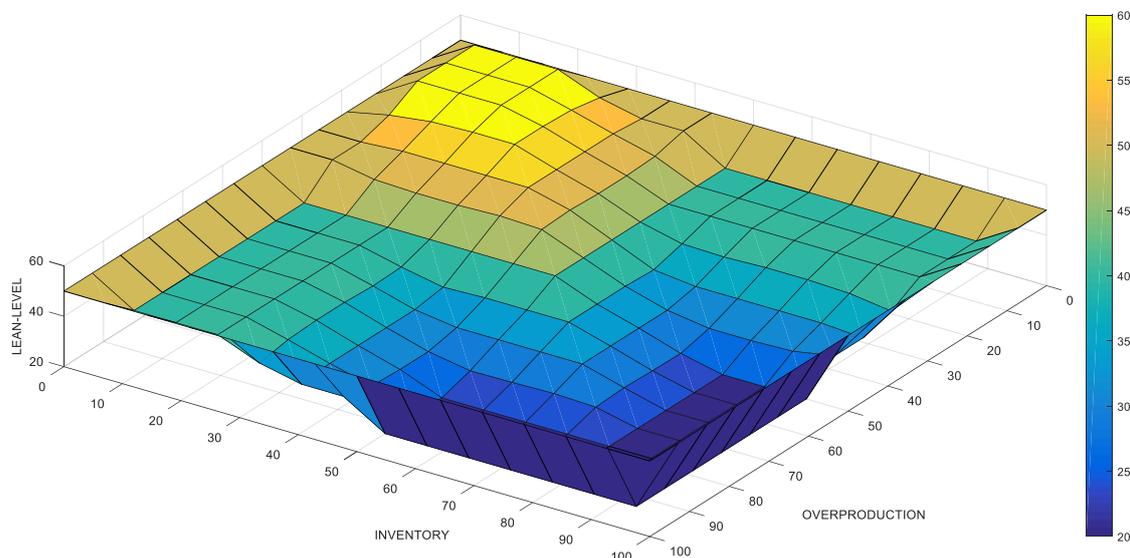


Source: The authors (2020).

Figure 12 shows the 3D surface graph addressing the correlation between the input, in-process and overproduction variables with the output Lean level.

Figure 12

The 3D graphic for combining overproduction and inventory input variables



Source: The authors (2020).

The graph above allows the analysis of the relationship between the inputs and output. In general, when the inputs have a low degree of relevance, the Lean level is high, which can be seen in the yellow hue of the graph judged as an optimal region.

5 Discussion of results

Lean manufacturing systems provide organizations with several benefits (Van der Steen, MP and Tillema, 2018). Lean Manufacturing and its tools are widespread in several companies, for example, automobile industries, textile industries, electronics industries and are even applicable to the service sector (Nawanir et al., 2018).

However, the manufacturing sector faces several ambiguities about how to identify, classify, manage and eliminate waste to improve production performance (Patidar et al., 2017).

With this, this work sought to classify the level of Lean Manufacturing of a small company that operates in the metallurgy branch using the fuzzy logic. The results obtained with the application of fuzzy logic shows that the company is not Lean.

The small metallurgical company has a high stock in process, a high overproduction and high internal transport. The simulations demonstrate that the adoption of traditional Lean tools and also other management tools raise the company Lean level. The model can be used in small and medium-sized companies in different fields. As the Lean Manufacturing program is being implemented, the



model proposed in this article can be used to assess whether the actions are valid, following the levels of Non-Lean, Less-Lean, and Lean until reaching the extremely Lean level.

Therefore, in the search for the elimination of waste, commitment from the top management to the operational level of the organization is fundamental. In addition, setting up a Lean Manufacturing implementation program is paramount, this program must be highly planned with constant training offers and monitoring of the metrics used so that resources are allocated efficiently (Tortorella et al., 2018).

6 Conclusions

The specified fuzzy inference model used a qualitative approach, supported by the diffuse logic, allowing to determine the Lean level that the organization is. The results obtained in the model are consistent with the reality of the company, showing the lack of adoption of Lean tools, and the need to reduce or eliminate waste.

The specified model proved to be suitable for analyzing the input variables that determine the organization Lean level.

From this analysis it was possible to identify the main methods of implementing Lean Manufacturing, which were the most suitable tools, principles and approaches of Lean for the company.

In the industrial universe, several companies seek continuous improvements for their production processes. The application of the Lean philosophy brings several benefits from the reduction of setup up to the reduction of work related accidents.

However, small companies have difficulties to implement the Lean philosophy in their manufacturing processes. They often do not have metrics to determine their level of Lean Manufacturing.

A great advantage of the model is the possibility of being adjusted for any type of organization because the input and output variables can receive other linguistic values.

A point to be observed when using fuzzy logic as a support tool is the evaluator perception that must be an expert in the area and have experience to judge and analyse the company domain.

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