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Fuzzy logic applied to the decision support measures of the plastic packaging production management system

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Abstract — *Currently the automation through decision support systems, plays a key role within the production chain, from small to large companies, this study proposes a fuzzy inference model, in the support in decision making measures of the production management system of a given plastic packaging plant. Analyzing the distinctions in a forceful way of each step that end up influencing the process, and aiming to adapt to customer requests. Using as principle for the proposed system the adequacy of work shifts using the maximum production that the plant has. The MatLab software was used to treat the data, thus adjusting the variables, which were selected due to their degree of influence on the cycle because they are variables that determine the order of the product's manufacture, are they: delivery time, quantity required, manufacturing process and the quantity of shifts that will be needed to produce a particular product, observing with the use of this tool an improvement in shift management, which reduced unnecessary costs, and a good understanding in the production cycle in relation to the characteristics of orders.*

***Keywords*— Fuzzy logic, production cycle and shift adaptation.**

I. INTRODUCTION

In a company that does not define a means of managing the production system, makes the development of numerous tasks occur in a complicated way slowing down the process, experts in the area often follow by processing a continuous end of many variants opposite, among them, the implementation of certain times, reception of priority buyers, preservation of reduced collections, supervision of the repeated seasonal of actors in the production cycle.

In this configuration, determining a schedule in production acts as a strategic contractor, since planners need to evaluate numerous variables that may compromise the process both in the procurement part and in production itself.

With all the requirements given to the work in an accurate operation are commonly put by a predetermined collectivity of rules, in which the cases of a certain degree of complexity (SLACK *et al*., 2018).

Based on this base system is proposed to develop a fuzzy inference model, as a new means of approach to act in order to sequence the production in a plastic packaging plant. That is, adopt a condition that is linked to the margin of subsidies of the entire collection of this arrangement, varying the existing procedure to produce and making it simpler to manage.

To which it refers, the sequencing and data when decisions involving certain activities need to be taken on the order in which the tasks should be performed, regardless of whether they are finite or infinite loading (PENOF *et al*., 2017).

Diffuse or cloudy logic or as initially spoken fuzzy, is a technique that aggregates the field of artificial intelligence, employing qualitative thoughts for classification of variables and approximate, unfinished or uncertain information to make decisions.

The composition of the model is obtained by a base of linguistic precepts, demarcation of the maximum and minimum perimeters of fuzzy sets, meaning the interfaces of inputs and outputs and the mechanism created of inference. Note that it is a logical principle that seeks to help formalize the approximation of reasoning, reproducing through techniques the human capacity to deal with imprecise understanding (ZADEH, 1988).

Diffuse reasoning, or the so-called approximation of reasoning, refers to the technique of inference as a summarized set of known rules and facts. Where these rules make up a characterization of knowledge of the fuzzy system and are employed to present the interdependence of the model in the input and output.

We human beings are able to reason with these circumstances, using the experiences lived in the day-to-day of our common sense and point of view. Now solving problems with high degrees of complexity for a computerized system is much more problematic, since they are more exposed to risks of failure (SANTOS, 2003).

II. LITERATURE REVIEW

2.1 Fuzzy Systems

Nebulous logic is based on fuzzy sets, first published in 1965 where it was named by Lofti Asker Zadeh (NOGUEIRA E NASCIMENTO, 2017), professor at Berkeley, University of California, using the treatment of dubious information, such as imprecise data, ambiguity, uncertainty, which are attributions of the way of thinking, thus implementing the vague concepts that had already had its first steps with the Polish Jan Lukasiewicz (1878-1956).

As fuzzy logic is momentarily applied in modeling systems that exhibit a high complexity index, human thought is simulated and replicated through linguistic variables and can use comparative, qualitative or quantitative techniques among others in the measures for each decision to be made. (MUÑOS E MIRANDA, 2016).

Diffuse logic differs from existing ones in that its focus is on the phenomenon of improbability. In this case the fuzzy conceptualization operates in a way that can be perceived as a circumstance in which it is not admissible to easily contest "yes" or "no". Where to articulate something between "right" and "wrong," such as "maybe" or "almost," becomes substantially more appropriate.

In fuzzy we work with linguistic and non-numerical variables like the previous one, that means that the numerical variables have to be transformed by the developer or program into linguistic variables and make the calculations from there.

Figure 1 presents the Implementation of steps in Fuzzy Logic (JUNGES, 2006).

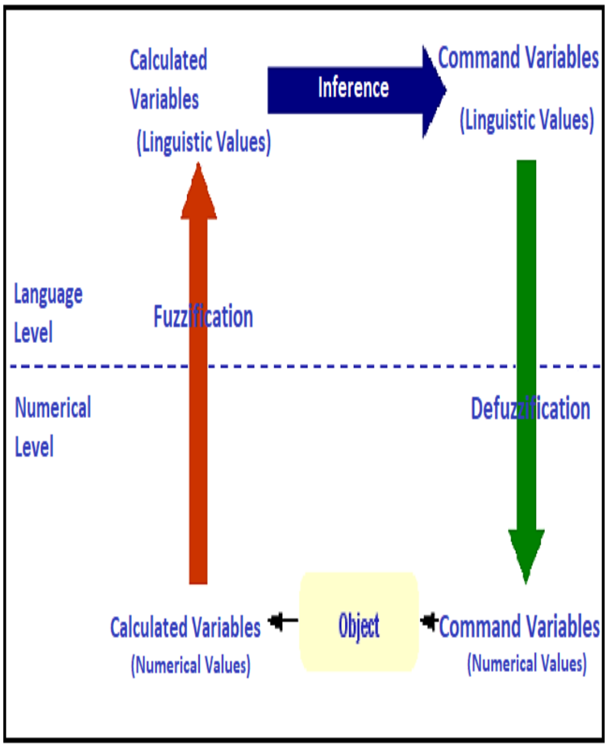

Fig. 1: Implementation of steps in Fuzzy logic

Fuzzy logic allows computers to understand in an orderly way the diffuse variables of human understanding, transforming them into values that can be read more easily by machines, due to their great ability with verbal expressions (DAMBROSIO, 2017).

2.2 Production Planning and Control

Production Planning and Control, commonly known as PCP, is a process applied to the management of production exercises and is an essential component in the administrative composition of a manufacturing system, as a definitive element of manufacturing integration.

PCP is a key element in the company's strategy to meet the needs of consumers with quality and reliability (PAN *et al.*, 2014).

By combining the data from the company's production resource management system that works with the planning, scheduling and control functions, in addition to defining the quantities that will be used to produce, along with the factory sketch to efficiently use the input process flow, and recognizing each production process and workforce determination, whether man or machine for the processing of raw materials, a production map will be created, called PMP - Master Production Plan. Currently, there are agencies focused on the PCP, dedicated to greater operational activity in daily production. In Figure 2 is

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shown the schematic representation of the planning and control of production (QUITÉRIO, 2010).

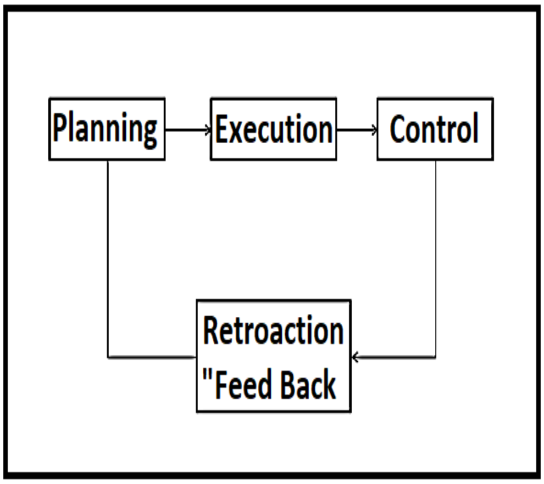

Fig. 2: Schematic Representation of Production Planning and Control.

According to OLIVEIRA *et al*. (2015), a better decision that brings benefits in quality, even if it causes an increase in costs, is still admissible.

Those who do not plan, program and control what they produce may have problems to achieve the productivity rates and quality ratings required by the market, thus being condemned to consequent extinction.

III. MODELING SYSTEM

The possibility of creating automatic rules for the input variables, together with the generation of probable combinations by means of the pertinence functions and the variables, enable the usefulness of this model. To develop the model, Matlab was used as a tool through the Fuzzy Logic Toolbox - (2016a). It is important to emphasize that in this environment you can not create rules automatically, on the other hand you can with your help, legitimize the results offered by the model and check the performance.

Taking into account all the factors mentioned in the literature review, numerous data are mapped within the plant, as well as others with a degree of relevance to better define a new approach in the production cycle adapting to customer orders. Collecting the information from the experts in the areas implicit in this process, certain criteria were established where each one is part of the combinatorial analysis of indicators, which are developed in such a way as to arrive at the measures to be taken by the experts for the specific purposes. Based on this line of reasoning, it was defined which variables will be part of the model composition taking into account its numerical range and linguistic value, making it clear that there are other variables that influence the production, but for the model presented only three were chosen due to their degree of importance in the process, the remaining variables were considered as met, in Table 1 linguistic variables of input and output, you can see where it will originate from the functions of relevance to the model that follows:

Table 1: Input and output language variables

Variables	Number Range	Linguistic Value
Entries:		
Deadline for Delivery	[0 100]	(short, medium, long,)
Required Quantity	[0 100]	(small, medium, large)
Production Process	[0 100]	(low, medium, high)
Outputs:		
Number of shifts required	[0 100]	(1 Shift, 2 Shifts, 3 Shifits)

In Figure 3 necessary shifts, a help system is implemented in the Graphic User Interface area.

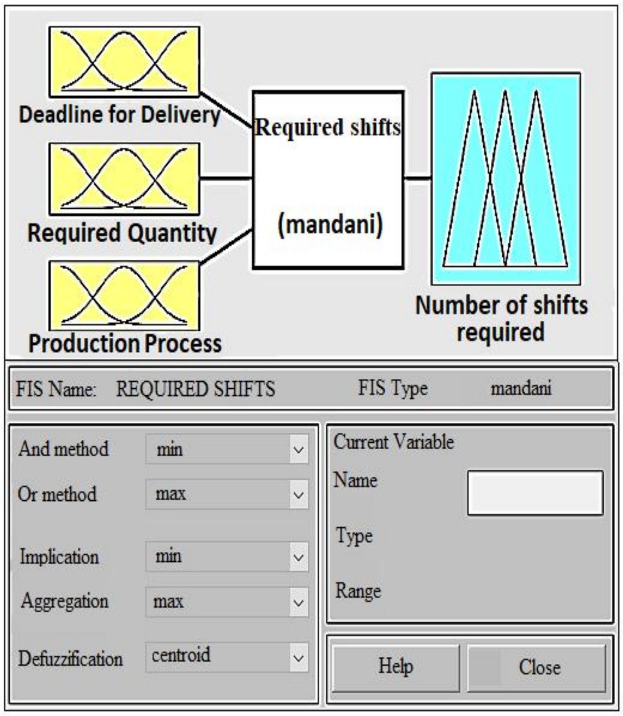

Fig. 3: Required shifts

3.1 Input and Output Variables

Regarding the description of the variables, they represent the knowledge of the specialist in fuzzy inference, being denominated as input and output variables of the system, corresponding in linguistic terms that represent mode of inaccuracy. Thus, the variables of the proposed system are:

a) **Delivery Time** – This linguistic variable respects the delivery time of the finished product, agreed between the company and a particular customer.

This estimate of the delivery time is continuously updated by the professionals of the commercial area and production planning, a measure considered to be suitable, because it is necessary at the time of negotiation to know if what is being proposed will in fact be able to be done in a timely manner. Its linguistic values are:

Short - Corresponds to the period of 1 to 30 days. **Medium** - Corresponds to the period of 35 to 65 days.

Long - Corresponds to the term of 70 to 100 days.

The fuzzification of this variable is trapezoidal at the ends and triangular in the central part of the chart as Figure 4 delivery time.

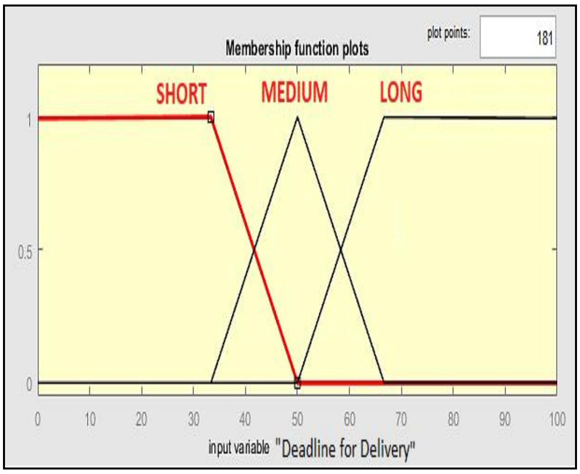

Fig. 4: Delivery time

b) **Quantity Required** - Briefly, nothing more is than the quantity that the customer requested of too much product, this variable is responsible for directing the process, so that it is determined what will be necessary of inputs the factory have, to be able to meet the request of customers. Its linguistic values are:

Small - It corresponds to a quantity of 1 to 300 units.

Medium - Corresponds to a quantity of 350 to 650 units.

Large - It corresponds to the quantity of 700 to 1000 units.

The relevance of this variable is also considered high in the aid of the shifts with the fuzzification also according to the parameters of the first variable described as Figure 5 required quantity.

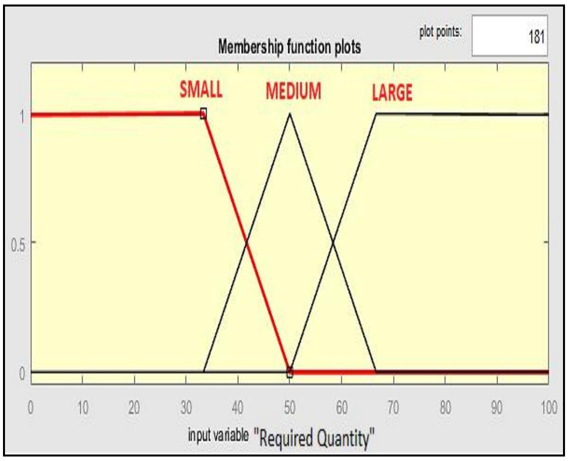

Fig. 5: Required quantity

c) **Production Process -** is a linguistic variable that in the developed model, corresponds to the period for the execution of a certain product, that is, it is the time that it takes for a given part to be manufactured.

This product processing time will always be mapped together with those who know the processes and the data that will be obtained to define this parameter should be based on the model in Table 3.2 percentage of inference of the manufacturing steps, which defines the phases of the manufacturing process with its certain percentage of inference in the process, which in other words originates the margin that each step adds labor in the service that follows.

Table 2: Inference percentages of production steps

Process Steps	**% Percentage of Inference**
Raw Material Addition	20%
Extrusion	20%
Treatment	10%
Winding 01	15%
Cutting and Welding	10%
Winding 02	15%

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Printing	10%
Total Cycle	**100%**

Its linguistic values are:

Low - Corresponds to the time from 1 to 720 hours. **Medium** - Corresponds to the time from 840 to 1560 hours.

High - Corresponds to the time from 1680 to 2400 hours.

Figure 4.4 shows the trapezoidal membership function representing the production process.

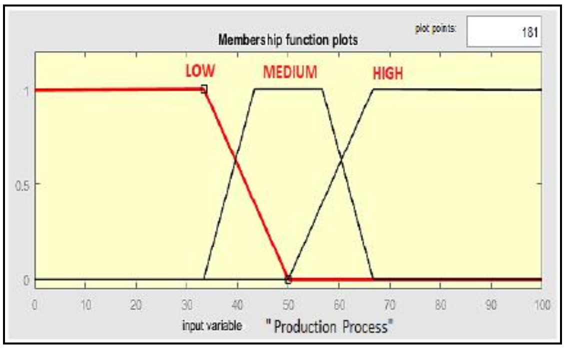

Fig. 6: Production process

d) **Number of Required Shifts -** This linguistic variable of exit of the proposed model, will be responsible for defining the amount of labor, that is, based on this exit will be generated a sequencing in the manufacture that caused with the use of up to one or more shifts always using the maximum production. In this new scenario we will have a new concept of sequencing.

The objective of this output is to be established in a dynamic way, a model that can warn the orderly priorities of new shifts that will be needed to not compromise the delivery time.

Figure 7 shows the number of necessary shifts, representing the trapezoidal pertinence function.

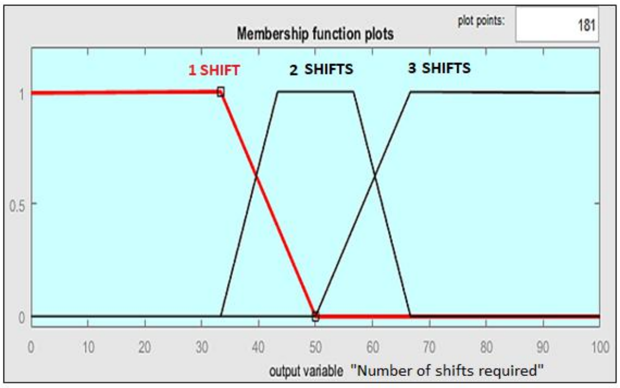

Fig. 7: Number of shifts required

3.2 Rules Basis

To build the knowledge base of the model and its rules of inference, many analyses were needed with the experts of the organization. In this way, one can add information to the system so that it can respond to all possible situations.

It was adopted in the system the inference machine using the Mamdani method and the logical operation "and" (intersection).

In the defuzzifier stage, the most commonly used method was the area center or centroid, which is based on the calculation of the center of gravity of the association function, responsible for calculating the area of the curve of the output linguistic variable, determined by the inference machine, and finding the matching indicator that divides this area in half.

Then the 3 input variables of the suggested model are defined, where the first input variable Delivery Time has 3 pertinences, the second variable Quantity Required also contains 3 pertinences, and the third variable Production Process, has 3 pertinences, consequently generating the mathematical formulation $3^3 = 27$, according to Figure 8 combinatorial analysis.

Deadline for Delivery	Required Quantity	PRODUCTION Process	Number of shifts required
short	small	low	1
short	small	medium	1
short	small	high	2
medium	small	low	1
medium	small	medium	1
medium	small	high	2
long	small	low	1
long	small	medium	1
long	small	high	1
9 combinações			
Deadline for Delivery	Required Quantity	PRODUCTION Process	Number of shifts required
short	medium	low	1
short	medium	medium	2
short	medium	high	3
medium	medium	low	1
medium	medium	medium	2
medium	medium	high	3
long	medium	low	1
long	medium	medium	1
long	medium	high	2
9 combinações			
Deadline for Delivery	Required Quantity	PRODUCTION Process	Number of shifts required
short	large	low	2
short	large	medium	3
short	large	high	3
medium	large	low	2
medium	large	medium	3
medium	large	high	3
long	large	low	1
long	large	medium	1
long	large	high	2
9 combinações			

$3^3=27$

Fig. 8: Combinatorial analysis

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The demonstration of the main Inference Rules Base of linguistic variables resulted in 27 combinations as previously discussed, where part of it can be observed in Figure 9 rules of inference of linguistic variables.

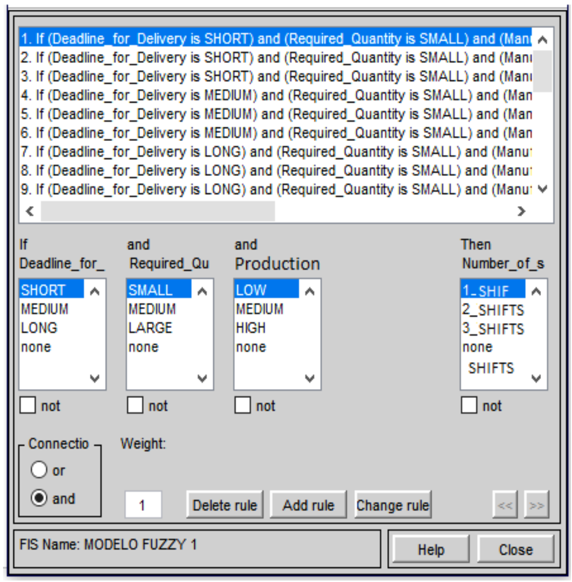

Fig. 9: Rules for inference of linguistic variables

The rule viewer allows all diffuse inference processes to be interpreted simultaneously, and also shows how adherence to some functions affects the overall outcome, showing how each rule and its results work.

The input parameters are derived from a common analysis by researchers and experts in the organization to test the decision model. The values are evaluated based on the actions expected in the production environment, including previous process data.

Once we know the delivery time, the quantity required and the manufacturing process, we will determine the amount of labor to be applied in the process.

The model parameters are shown below:

[System]

Name=' NECESSARY_SHIFTS01'

Type='mamdani'

Version=2.0

NumInputs=3

NumOutputs=1

NumRules=27

AndMethod='min'

OrMethod='max'

ImpMethod='min'

AggMethod='max'

DefuzzMethod='centroid'

[Input1]

Name=' DELIVERY PERIOD'

Range=[0 100]

NumMFs=3

MF1=' SHORT':'trapmf',[-6667 33.33 33.33 50]

MF2='MEDIUM':'trimf',[33.33 50 66.67]

MF3='LONG':'trapmf',[50 66.67 66.67 6667]

[Input2]

Name='QUANTITY-REQUIRED'

Range=[0 100]

NumMFs=3

MF1='SMALL':'trapmf',[-6667 33.33 33.33 50]

MF2='MEDIUM':'trimf',[33.33 50 66.67]

MF3='BIG':'trapmf',[50 66.67 66.67 6667]

[Input3]

Name=' PRODUCTION PROCESS'

Range=[0 100]

NumMFs=3

MF1='LOW':'trapmf',[-6667 33.33 33.33 50]

MF2='MEDIUM':'trapmf',[33.33 43.33 56.67 66.67]

MF3=' HIGH':'trapmf',[50 66.67 66.67 6667]

[Output1]

Name=THE AMOUNT OF SHIFT-NEEDED '

Range=[0 100]

NumMFs=3

MF1='1Â SHIFT':'trapmf',[-6667 33.33 33.33 50]

MF2='2Â SHIFTS':'trapmf',[33.33 43.33 56.67 66.67]

MF3='3Â SHIFTS':'trapmf',[50 66.67 66.67 6667]

[Rules]

1 1 1, 1 (1) : 1

1 1 2, 1 (1) : 1

1 1 3, 2 (1) : 1

2 1 1, 1 (1) : 1

2 1 2, 1 (1) : 1

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2 1 3, 2 (1) : 1

3 1 1, 1 (1) : 1

3 1 2, 1 (1) : 1

3 1 3, 1 (1) : 1

1 2 1, 1 (1) : 1

1 2 2, 2 (1) : 1

1 2 3, 3 (1) : 1

2 2 1, 1 (1) : 1

2 2 2, 2 (1) : 1

2 2 3, 3 (1) : 1

3 2 1, 1 (1) : 1

3 2 2, 1 (1) : 1

3 2 3, 2 (1) : 1

1 3 1, 2 (1) : 1

1 3 2, 3 (1) : 1

1 3 3, 3 (1) : 1

2 3 1, 2 (1) : 1

2 3 2, 3 (1) : 1

2 3 3, 3 (1) : 1

3 3 1, 1 (1) : 1

3 3 2, 1 (1) : 1

3 3 3, 2 (1) : 1

In Figure 10 three-dimensional surface viewer, it is possible to see graphically changing the angles the results found.

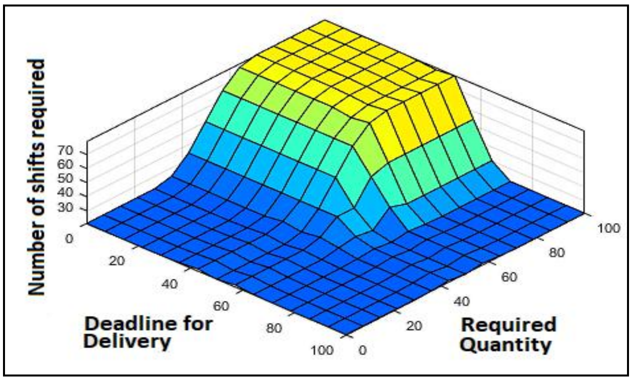

Fig. 10: Three-dimensional surface viewer

The data displayed in the rule viewer facilitates the interpretation of the fuzzy inference process, where it is also possible to demonstrate functions that reflect on the overall result of the system. By varying the input values, it is possible to evaluate the outputs of the proposed system, obtaining a value that allows a correct analysis of the efficiency of the method adopted to aid in decisions. In Figure 11 viewer of rules of number of shifts, it is shown the results that refer to the production order, where the decision model is visualized using Matlab, which represents the output.

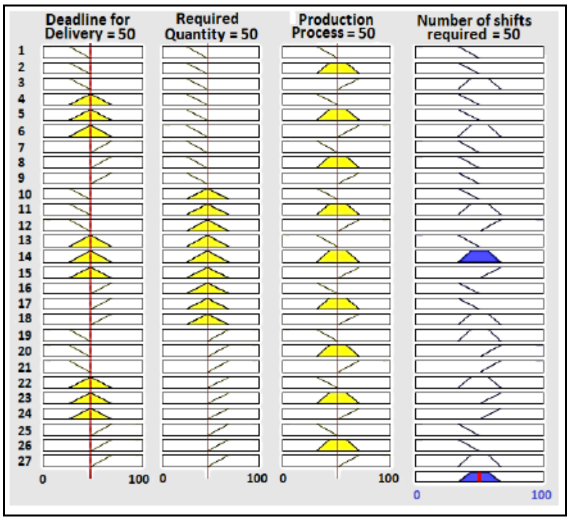

Fig. 11: Shift quantity rules viewer

In Figure 12, when adopting hypothetical values to the input values, considering them in percentages, in which the value adopted for the input variable delivery time represents 50%, for the required quantity 50% and for the production process 50%, resulting in a shift forecast corresponding to 50%, that is, two shifts of work will be necessary using all the lines, considering their maximum production to perform the subsequent task, so that the third shift will continue working ahead of the production of other orders.

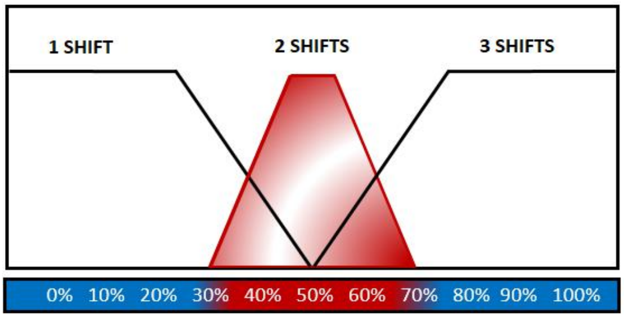

Fig. 12: Selected shift output

IV. CONCLUSION

From the observation of the analyzed aspects it was concluded when describing the production model, a better conduction in the development of the proposed support model because it encompasses the processes as a whole

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that helped to segment the operations performed in the production of plastic packaging, in view of the arguments cited it can be observed that improving the shift management actually reduces unnecessary costs, which entails the definition of a new approach in the production cycle that organizes it by the characteristics of orders. We concluded that the use of fuzzy logic as support in decision making is undoubtedly a differential within the production of plastic packaging, since it is plausible to indicate a specific procedure within the company, as occurred in the sequencing of activities. The return that was obtained by the system proceeded in an acceptable manner, demonstrating in a short way that the decision making based on inaccuracies and indeterminacy is able to be supported by the proposed fuzzy inference system. However, it is necessary to highlight the consideration of the expert's understanding for the modeling of the system, adding estimates and disseminating the teaching applied in the manipulation of data, and especially in the preparation of the rule base.

In relation to the implementation of inference, the support in the decision-making measures of the production management system of a given plastic packaging plant, adapting to the customer's request, with the purpose of improving the sequencing of production, consecutively seeking to reconcile effectively the amount of labor to the requested request, regardless of the scenario required by the customer. In situations of rapidly changing scenarios, where companies are submitted, imply that within the enterprises the automated systems can elaborate a new dynamic, building concise routines, not remaining conditioned to people's decisions, because in decision making there will always be differences.

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