Chapter 12
A Decision Making Approach Using Fuzzy Logic and ANFIS: A Retail Study Case

Tomas E. Salais-Fierro, Jania Astrid Saucedo Martínez, and Blanca I. Pérez-Pérez

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12.1 Introduction

In the current economy, an adequate supply chain management is mandatory to guarantee the survival of the industries, allowing them to increase their competitiveness.

The management and control of the companies resources is vitally important to achieve competitiveness in these companies. This implies that organizations must have a control inventory which allows to fulfill with the customer demand, keeping the control stock handling costs at an affordable level for the company [1].

The potential improvement of the inventory management collaborates to the income increasing, costs reduction, and a significant increment in the customer satisfaction. Hence, the utilization of inventory policies is significantly useful and is a study motivation for the logistic specialists [2]. In this way, the development of the management policies has kept the attention of the engineering researchers and the logistics chains. The main objective of an adequate inventory policy is to acquire a desired inventory level, avoiding complex purchasing orders and the stock variability [3].

T. E. Salais-Fierro (✉) · J. A. Saucedo Martínez · B. I. Pérez-Pérez
Universidad Autónoma de Nuevo León, San Nicolás de los Garza, Mexico
e-mail: tomas.salaisfr@uanl.edu.mx; jania.saucedomrt@uanl.edu.mx; blanca.perezprz@uanl.edu.mx

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This paper is divided into five sections. The following section refers to the literature revision prepared to describe some cases where interesting situations are exposed of the enterprises related to the supply chain and how have been resolved, approaching points like the inventory classification ABC, the forecasting analysis, and the fuzzy logic. Then in the next section, the study case is shown and the main problem is described. In the third part of the paper, the selected methodology is presented in which the solution of the case is based and the ANFIS tool is described, the one used to solve the main issue. In the fourth section, its describes the method in which the experiment was performed describing the obtained results based on the study case, going by some of the most representative products belonging to the inventory type A classification and with a high rotation index. Finally, the conclusions of the current project are presented and the recommendations for future research are highlighted.

12.2 Literature Review

In literature, a great interest is seen in this area, because it is a significant part of the performance of a company. As an example of the mentioned above, in this section a short review of different works is executed, related with this topic and the utility of the proposed solution tools.

A supplying policy consists on the decisions respecting on when and how much to reorder. These policies may adopt a variety of forms. Then, two types are mentioned by Chopra and Meindl [4]:

Continuous review: The stock is revised continuously. The time between the orders may fluctuate, considering the variable demand.

Periodic review: The status of inventory is inspected to regular ranges, then an order is requested to increase the stock level until to a specified one.

ABC Method

When it is required to manage a wide number of products, it is suggested the aggrupation and the elaboration of stock policies corresponding to each one of the resulting groups [5]. The ABC method is useful to get a better follow up of the stock, taking reference on the sales and the products volume [6]. The classification with the ABC inventory methodology is often applied in the industry [7, 8], which was created by GE [8] in 1950. Based on ideas of Pareto [9], it is concluded approximately the 20% of the stock contributes to the company the 80% of the total sales and incomes of the organization; or well-known as the 80–20 rule. The stock is classified into three main groups which are A, B, and C. The 20% of the items represents the A group, the next 30% to the group B, and the lasting 50% to the group C [7]. This allows us to focus our attention, firstly on the products that contribute to higher earnings (products type A) and to serve to the rest of the classification based on the company chances, taking better decisions with respect to the stock management.

EOQ: Economic Order Quantity

The economic order quantity (EOQ) was introduced by Ford W. Harris in 1915. This concept calculates the request quantity which reduces to the minimum the inventory cost of the organization [10].

Considering an annual demand D, a cost of the order S, unity cost C, warehousing cost h, where the objective is to estimate the Q lot size, which minimizes the total of the annual cost. The EOQ [8, 11] equation is the following:

$$Q = \sqrt{\frac{2DS}{hC}} \tag{12.1}$$

The EOQ model is one of the most antique stock model into the operations field and inventory management. This model has been the main angle for many other models in these fields, partially due to the fact of its simplification to execute [12]. On the other hand, the EOQ has been criticized for the lacking response to the difficulties of the current business world [13].

Safety Stock

Generally, the organizations take decisions respect to their stocks based to their historical registers. These data are compiled through the time and are analyzed to determine possible inventory parameters, such as the safety stock. However, there is a possibility that data might own significant imprecision [14]. This type of situations puts in doubt the statistical traditional approach and is chosen for using the Cagan Safety Inventory [15]. Chopra defines the inventory as the stock that keeps in case the demand exceeds the expectations, it is useful to balance the uncertainty. The adequate safety stock level is based on three main factors: the demand, supply uncertainty, and the desirable product availability. As the demand or supply uncertainty increases, the required safety stock levels also expand [4].

Bayesians Networks

The Bayesians networks are probabilistic models used for the prediction and decision taking under uncertainty. The quantity required, the number of products

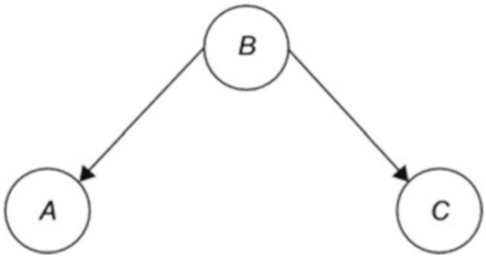


Fig. 12.1 Example of simple Bayesian network

to manufacture and the inventory have variations due to unexpected events. The Bayesian networks have been employed to estimate the probability of the offer and demand distribution, letting to make adjustments in the production and inventory plans [16]. A simple Bayesian network (Fig. 12.1) has random variables A, B, and C, which are the graph nodes. The artists represent the causal relations between them. The A and C variables have a causal dependency with variable B [17].

The Bayesians networks are adequate for the settlement of neuronal interactions due to their graphic nature and a rigorous subjacent theory. The edges of a Bayesian network are directional, for the trajectory neuronal signals proper modeling [16].

Fuzzy Logic

The fuzzy logic pretends to qualify imprecise information or with a certain vagueness grade, doing emphasis just in the fuzzy variables which represent this information and not the model as one [18, 19].

Uncertainty

Comes up from the lack of information (lexicon impression, something incomplete), particularly the inaccuracy of measurements [20].

Vagueness

The natural language vagueness is another aspect which limits the intention of being precise in an employed language to describe or sharing knowledge, communication, among others. The basic meanings of the words can be understood and have the capacity of communicate them in an acceptable rank, but generally, getting on the same level of understanding is not always possible [20].

The fuzzy logic allows to manage human subjectivities and system vagueness, perception, and reasoning. It is known that classic models define any systems or scenario mathematically and their results are rough values (crisp). In the other hand, the fuzzy logic handles variables that affect in the system's behavior obtaining more flexible outcomes. Therefore, with fuzzy logic, the variables are expressed in linguistic terms, for example: "large, medium and small," the relations are defined in rules based in If-Then terms, and the results are fuzzy subgroups, which can then be converted in rough values (crisp) using defuzzification techniques. The entry rough values are transformed and expressed in linguistic terms. In this step, the grade of membership of a variable is determined within a particular fuzzy class. This is specified across the evaluation of the membership function of the fuzzy group value [21]. A membership function defines the belonging point of a fuzzy group element mathematically. Then, the membership function defines the fuzzy subgroup A, where X is the domain of the variable in which A is sharped. In this approach, into the domain belonging to A, each element is defined with x values defining by steps for each X. Even though both are subsets, classic and fuzzy, are defined by the membership functions, the grade an element belongs to the classic subset is limited to be only zero or one. On the other hand, the value that each element takes is between the zero and one range, the above to define the fuzzy classification to which each element belongs [22]. This can be shown graphically in Fig. 12.2.

The helpfulness of the fuzzy sets lay in the capacity of modeling something uncertain or ambiguous. Some of the reasons why the fuzzy logic is employed to control processes are the next ones: when the process is too non-lineal or too complex to use conventional control designs. Another situation is because the fuzzy logic is less expensive, so they can obtain optimal results with data with a level of vagueness, considering the accuracy implies a cost on time, money, and resources, contributing to the expected utility just to a certain point, raising the costs of the model. By other hand, it is important to note that sometimes the organization is not able to provide information due to the lack of time or the risk of spread confidential information. In graphic of Fig. 12.3, it can be observed the precision cost of the information [23].

Exist two types of inference fuzzy systems: Mamdani and Sugeno. When the output of the membership functions are fuzzy groups, the inference fuzzy system Mamdani is the most common used [24]. The main idea of the Mamdani system is to describe the process between linguistic variables and to use the same ones as

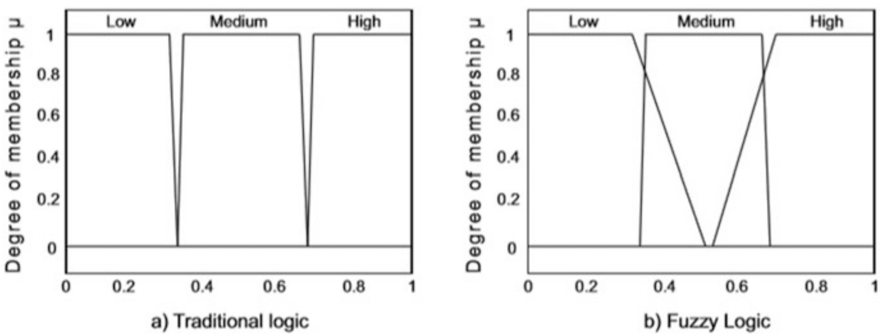
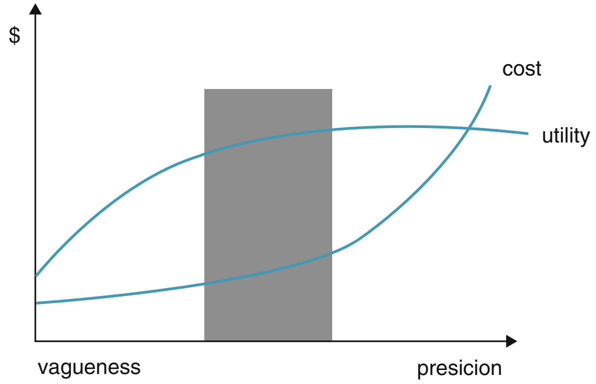


Fig. 12.2 Example of groups of (**a**) classical logic and (**b**) fuzzy logic

Fig. 12.3 Graphical cost benefit of accuracy of information



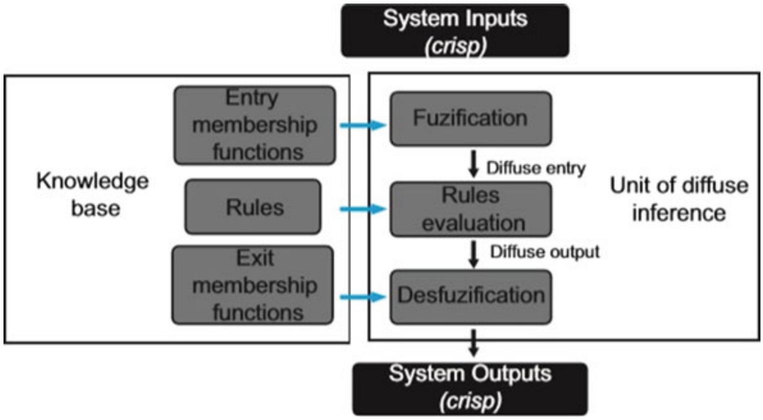


Fig. 12.4 Diffuse inferential system block diagram

entry data of the fuzzy control rules [25]. The Mamdani fuzzy inference system owns a knowledge basis, from where the entry membership functions are obtained, as the fuzzy rules and the output membership functions too. On the other side, also has a fuzzy inference unit, composed by the fuzzification system, the fuzzy rules evaluation, and the defuzzification process [26]. This can be shown in Fig. 12.4.

ANFIS

A Subsection Sample

The fuzzy logic and the fuzzy inference systems (FIS) were proposed by Zadeh [18], providing an option for the decision taking based on ambiguous, imprecise, or incomplete information. The fuzzy logic represents the used knowledge utilizing "If-Then" rules. FIS is mainly composed of fuzzy rules, membership functions, and defuzzification and fuzzification operations. Through the fuzzy inference, the tough entry data produce an ordinary output which is easy to understand and perform. There are three categories of fuzzy inference systems: Mamdani, Takagi-Sugeno (TS), and the Takagi-Sugeno Evolution (ETS). The identification of the basic rules is the key for a fuzzy inference system, presenting two main issues: (1) There are no standard methods for the human knowledge transformation or a basic rule experience. (2) Adjustments are required to the membership functions, to minimize the output mistakes, maximizing the performance. In the current project, ANFIS is used to achieve the FIS identification and its refinement.

Some ANFIS Uses

- The prediction of the daily precipitation using a variety of meteorological parameters of surface [27].
- In the econometric field, it is used to predict the performance of the stock market [28, 29].
- Breast cancer detection [30].

Sun et al. [31] studied the variable behavior of the demand of automobiles, how to forecast it and mention the tools to measure it. They compared and carried out the demand forecast of cars by analyzing the results of two models: Auto-regressive integrated moving average (ARIMA) combined with (TSDM) compared to a hybrid model of partial least square (PLS) regression and the adaptive network based on ANFIS giving the latter better results.

Candan et al. [32] focused on the study of the demand of products of the pharmaceutical industry, taking into account its complexity to be based on human factors such as seasonal and epidemic diseases and market shares of competing products among others. To make forecasts, they based on artificial neural network (ANN) topology with an ANFIS approach.

12.3 Methodology

Taking in consideration what was said in the previous sections, the next steps are established to describe the proposed tools for the problem solution.

First, it analyzes all the products of the company that make the inventory based on the information of the products that the organization provides, where the inventory is ordered using the ABC methodology. Subsequently, this methodology indicates a focus on the products within the classification type A. A product was selected from the best sellers and with high inventory turnover.

Then, the variables are modeled using fuzzy logic and experiments were carried out with the help of the ANFIS method using the Matlab tool. With this we can propose the necessary policies to support the decision maker. This can be seen in Fig. 12.5.

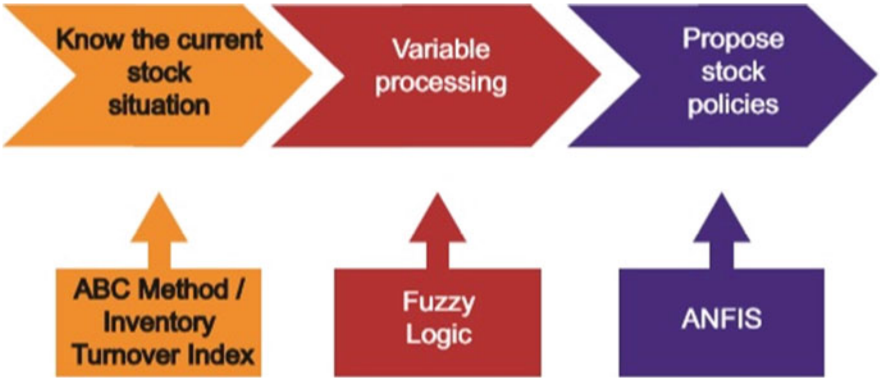


Fig. 12.5 Methodology

Applying ABC Method

The ABC method helps us to have a better inventory tracking, based on the sales and the volume of the products [6]. Approximately, the 20% of inventory provides to the economy the 80% of sales and incomes within the company, this is well-known as the "80–20" Rule. Stock is classified into three known groups as A, B, and C. The 20% of the articles represents to the A Group, the next 30% are articles from the B Group, and the last 50% is part of the C Group [7]. This allows us to focus our attention firstly in the products which contribute with higher income (A Group), taking care of the remaining classification based on the company possibilities, enabling a better decision take respecting to the inventory management.

Variable Processing

The human knowledge is represented generally by imprecision, vagueness, and approximates. In the real life, some definitions are handled with vagueness through words like: tall, medium, and short [33].

Fuzzy Logic

In literature, the theory provides a mechanism to represent linguistics constructions such as "many," "down", "medium," "often," "few." In general, the fuzzy logic offers an inference structure which allows proper capacities of human reasoning [20].

A fuzzy system is characterized due to the permission on using the experts' knowledge in an area they dominate, which works as a basis in the process automatization in such a way that, the knowledge is formalized, being ambiguous as a feasible algorithm formed by calculations like additions and comparisons [34].

Fuzzy Sets

Per its name, it is a group without a sharped outline, i.e., the transition since "belonging to the group" to "not belonging to the group" is gradual, being a soft transition, a characteristic of the membership functions which provide fuzzy and flexible sets along the modeling, where commonly linguistic expressions are used, e.g. "water is hot," or "the temperature is high" [8, 35].

Fuzzy Interface

It is known as the process of the mapping formulation, starting from an entry data to an exit using fuzzy logic. Mapping provides a basis from where the decisions can be taken, being judgment basis. The fuzzy inference process involves a variety of concepts such as membership functions, logic operations, and "if-then" rules. The main objective of the fuzzy inference process is to be formulated within expressions of natural [33] e.g.:

```
begin
{{antecedent} THEN conclusion {consequent}}
end
```

According to Chakraborty et al. [33], the different steps in the fuzzy inference process are as follows:

- Fuzzification of entry values: When the premise value is provided, such as an entry, this must correspond to one or more linguistic groups with some membership values, see Fig. 12.6.
- Strength calculation: After the entries are fuzzified, the grade for each part of the antecedents is satisfied for every known rule.
- The level of a rule is the strength rule of the correspondent one. i.e., if there is more than one antecedent, then the rule is calculated by the minimal standard operation.

There are different forms or graphics of the membership functions, such as triangular, trapezoidal, Gaussian, or with variations, presented in Fig. 12.7.

There are two types of fuzzy inference: Mamdani and Takagui-Sugeno, which differ in the output membership function, the one determined.

According to Jang and Sun [8, 35], the nature of the fuzzy models is similar to the "divide and conquer" meaning. The "if" (condition) "then" (action) rule divides the input space into many local fuzzy regions, while the consequent describes the behavior of a region through its constitution [36].

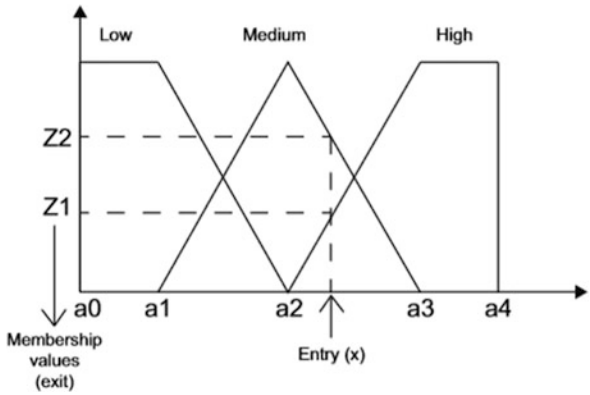


Fig. 12.6 Fuzzification

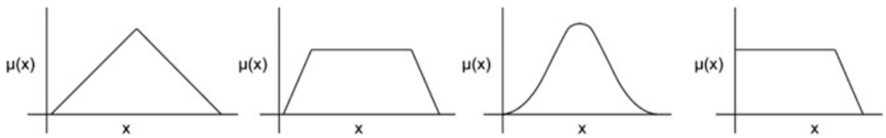


Fig. 12.7 Different forms of graphs corresponding to the membership functions

Defuzzification

Defuzzification means to convert a fuzzy value in a crisp one. This comes up due to the fuzzy results cannot be used as well in the applications. Therefore, it is mandatory to transform fuzzy quantities in crisp quantities or scalar ones to be processed in the future, through the defuzzification process. Defuzzification reduces the membership functions collections values in one quantity [37]. In the fuzzy control systems, the steps for the defuzzification involve the selection of one single value for the controller output. According to Rouhparvar and Panahi [38] we have many strategies.

Mamdani Model

To begin, we have the input of real data to the fuzzy logic system, whose values are numerical (crisp). The fuzzificator function or blurry convertor is to take the numeric values coming from the exterior, turning them in fuzzy values that can be processed by the inference mechanism. The fuzzy values are the input values membership levels to the different fuzzy conjuncts, on which the universe has been divided among the input variables. The objective of the inference system is to take the belonging levels supported by the rules, generating the output of the fuzzy system. The rules form the knowledge basis in which the fuzzy system keeps the linguistic system, allowing to solve the issue for which has been designed. A rule has two parts: the IF (antecedent) and the conclusion (Then). For example, if the output (inventory) is low, then the input (order size) is high. In a Mamdani system,

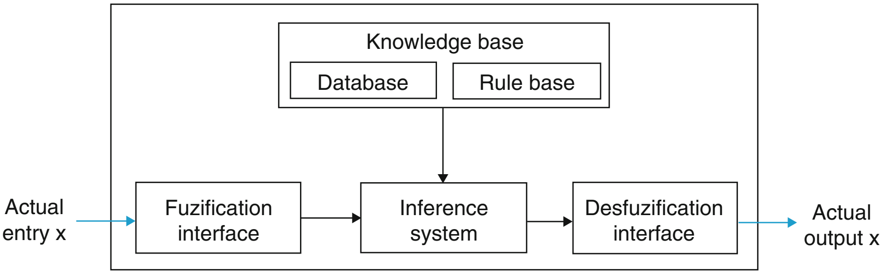
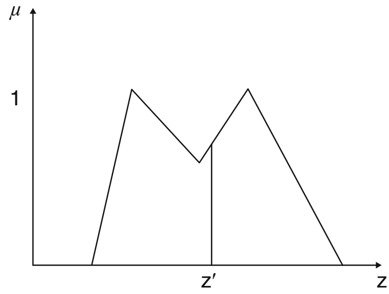


Fig. 12.8 General structure of a rule system based on the diffuse Mamdani type

Fig. 12.9 Centroid method



either the background and the rule conclusion is given by linguistic expressions. The output that is generated by the inference system is a fuzzy output that cannot be read by an external element. In order to read the output as a crisp value, the fuzzy output before must be processed by a defuzzification process, which gives the numeric output data. All this can be observed in Fig. 12.8.

- *Centroid Method*—This is the most used method. Also, named gravity center or area center [20]. It is determined by the area center of the belonging function [38]. Graphically it is perceived as in Fig. 12.9, where the result of the figure center from the operation is presented.

- *COS: Center of Sums*—The overlap zone is counted twice. This method compounds the consequential membership function, taking the algebraic sum of the outputs for each one of the fuzzy conjuncts that constitutes $\tilde{A}_1$, $\tilde{A}_2$, ... etc. The defuzzified value $x*$ is given by the Eq. (12.2). This method can be easily implemented by the user, being directed to the quick inference cycles. This method can be easily implemented by the user, being directed to the quick inference cycles.

$$x^* = \frac{\sum_{i=1}^{N} xi \sum_{k=1}^{N} \mu_{\tilde{A}k}\ x_i}{\sum_{i=1}^{N} \sum_{k=1}^{N} \mu_{\tilde{A}k}\ x_i} \tag{12.2}$$

- *MOM: Mean of Maximums: Center of Sums*—The rule mode consists on choosing the support value in which the membership function reaches the highest

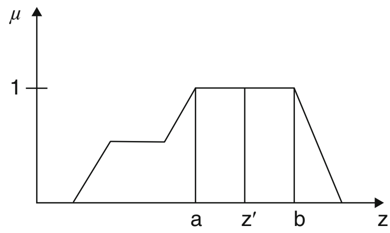


Fig. 12.10 MOM example

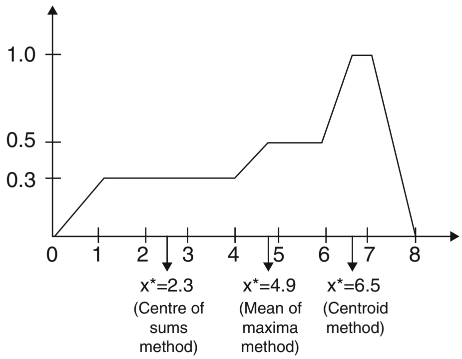


Fig. 12.11 Defined outputs of the three methods: Centroid, MOM, COS

peak. The mean maximum method takes a maximum affiliation [38]. The Eq. (12.3) shows that

$$x^* = \frac{\sum_{i=0}^{N}\sum_{i=0}^{N}\binom{n}{k} x x_{y^2} x_{y^2 1}{}^{n} Y \mu_{Ak^2}{}^{i} - x_i}{\sum_{i=1}^{N}\sum_{i=0}^{N}\binom{n}{k} x^k a^{n-k}} \tag{12.3}$$

The graphic remains as is shown in Fig. 12.10.

We can see graphically an example where the results can be appraised of each one of the methods previously mentioned. See Fig. 12.11.

Takagi-Sugeno Model

The Takagi and Sugeno model is based in the fuzzy logic system [18], a non-lineal system which assigns an input vector in a scalar output. A non-lineal Takagi-Sugeno forecaster uses a small window of past measurements to predict the next value in a time series [36].

In the Sugeno fuzzy system, the fuzzification mechanism and the fuzzy inference work in the same form as denominated Mamdani, but the based rules of the Sugeno knowledge are different, due to they have as output numeric values, hence does not require defuzzification. The Sugeno model employs the rules to produce an output in each rule. The output rules consist in a lineal combination of input variables and a constant terminus. The final output is the weighted weight of each output rule [39].

To calculate the fuzzy system output, the different consequences are weighted, keeping in mind the value in which the antecedent was activated for each one of the rules. The equation would be $w_1y_1 + w_2y_2 + \ldots w_ny_n\ w_1 + w_2 + \ldots w_n$

$$Y = \frac{w1y1 + w2y2 + \ldots wn\ yn}{wnyn\ w1 + w2 + \ldots wn} \tag{12.4}$$

Model Mamdani Vs. Takagi-Sugeno (TS)

The main difference between the methods Mamdani and Sugeno is found in the rules consequences. Mamdani utilizes fuzzy conjuncts as rules consequences while Sugeno employs lineal functions of the input variables as a rule consequence.

Some of the TS advantages are the following:

- Is computationally efficient.
- Works optimally with the lineal techniques (e.g. the PID control).
- Works great with the optimization and adaptation techniques.
- The output surface for the continuity has been guaranteed.
- Is adequate for the mathematical analysis.

The advantages of Mamdani are listed below:

- Is intuitive
- Has a wide acceptation
- Is adequate to handle human input sources

12.4 Inventory Policies Development

Rules

Based on the decision takers experience, a combination of different scenarios is created, specifying the expected result being observed through history. These fuzzy variables combination, from forecast, inventory, delivery time, and projects, provide us a total of 63 fuzzy rules that suggest us a result regarding the order tons to require to the foreign supplier. The generated rules from the process are exposed below (Table 12.1).

The following is an example of the "If-Then rules", where the use of the conditions (IF-AND) arises, which when they are met, give us a "THEN" response that affects our fuzzy output variable: "Order".

Rule 1: If {Forecast is Low} and {Inventory is Low}, Then {Order = Low}
Rule 2: If {Forecast is Low} and {Inventory is Medium}, Then {Order = Low}

Table 12.1 Fuzzy rules generated

Rules	Forecast	Inventory	Lead time	Project	Order
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Medium	Low
3	Low	Low	Low	High	Low
4	Low	Low	Medium	Low	Low
5	Low	Low	High	Low	Medium
6	Low	Medium	Low	Low	Low
7	Low	High	Low	Low	Low
8	Low	Low	Medium	Medium	Low
9	Low	Medium	Medium	Low	Low
10	Low	Medium	Low	Medium	Low

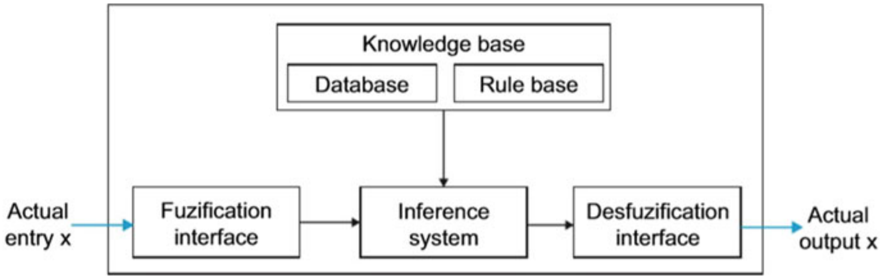


Fig. 12.12 Architecture of the proposed fuzzy inference model

The fuzzy model finally remains in the following way, as is shown on Fig. 12.12 where we can identify clearly the fuzzy variables involved in the case: forecast, inventory, delivery time, and projects; which are processed through the preset rules based on the Mamdani model, providing us in the order output variable result.

Output Defuzzification

Within the defuzzification process, it is required to pick the technique to implement this action. In this case, the centroid method was utilized, which is used commonly. The equation for discreet variables is listed in the Eq. (12.5).

$$\text{Centroid} = \frac{\sum_x \mu A(X)x}{\sum_x \mu A(X)} \tag{12.5}$$

This defuzzification method is also known as gravity center in literature. Consists in obtaining the area center under a formed curve by the fuzzy output function (see Fig. 12.13).

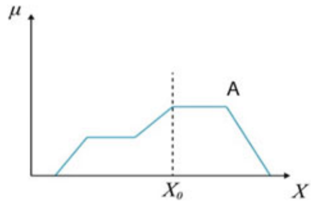


Fig. 12.13 Defuzzification method

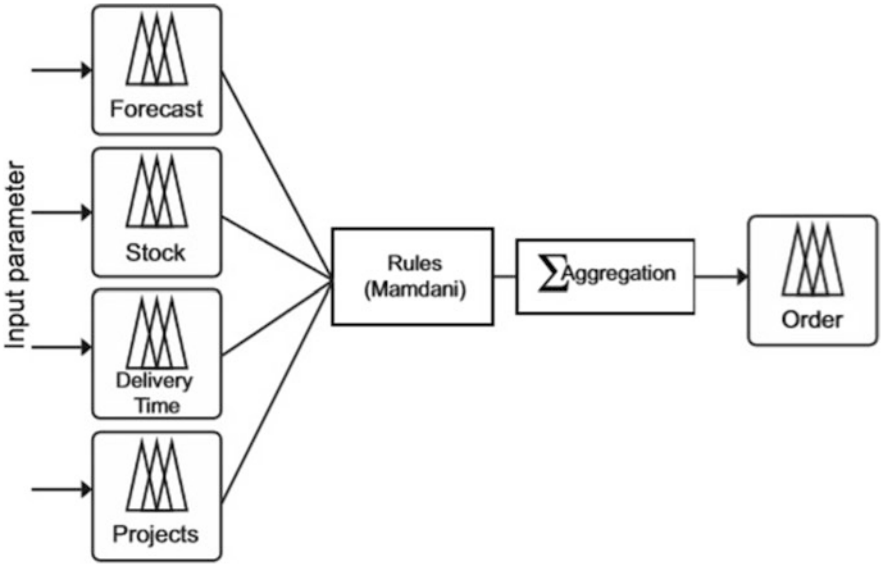


Fig. 12.14 ANFIS: Input variables with Mamdani rules

ANFIS

Keep in mind ANFIS is generated from a specific input or output, an inference system where the membership parameters are adjusted using the retro-propagation algorithm (artificial neuronal network), inducing the fuzzy system learns from the input or output data provided. The ANFIS model to employ is shown on Fig. 12.14, counting with.

- Input variables: They are 4: Forecast, inventory, delivery time, and projects.
- Belonging functions: We have three belonging groups in each one of the four variables: low, medium, and high.
- Rules: There are 63 fuzzy rules acquired from the experts experience combination.
- Input belonging function: One by each rule. Each value stills being fuzzified.
- Aggregation: Mamdani is used with the centroid method to defuzzify values.
- Output: Shows the process result: order variable, with a tons value to request (crisp).

12.5 Conclusion

In Table 12.2 it is shown the results that were obtained applying the proposed approach. It represents the six planning periods, where the company requires approximately 367.9 days in orders, which do not cover the demand completely, considering a 57 days of backlog. If the triangular ANFIS 1 process is utilized, after the six periods order there are 436.53 material days, which do not generate backlog, but a surplus of 11.67 days does. For the Gaussian ANFIS 2—an order of 452.4 days is shown, also without backlog, but also presenting a 27.49 days surplus.

The use of ANFIS in this case indicates that the result is better than the current procedure, avoiding backlog generated due to the growth in the market. In this case, we note situations where few information is possessed and is not exact, this type of methodology is effective and provides results. Also, when few information is required, it is not expensive for the company regarding on obtaining time, human, and economic resources for their procurement.

The case presents certain characteristics regarding to the required information. Some of the main features are: relatively little information, one-year sales record, one-year inventory, and 6-month item purchase process. Besides, part of the information is mandatory (Delivery time and part of stock) presenting an uncertainty and vagueness of this one. If only the safety stock is considered, we would require a huge stock number, considering the high uncertainty. On the other side, we do not count with enough information to modify the forecast. Some of the mentioned methodologies in the chapter handle the uncertainty, such as safety stock, Bayesian networks, forming part of the possibilities theory, among others. Nevertheless, these topics which handle the probability theory do not include the vagueness, resulting of subjective causes, as it would be "the delivery time is high,", or "the stock is low.". This class of situations is common in problems where the experts take their decisions based on non-quantitative situations, in where we can apply the ANFIS methodology, which embraces the fuzzy logic.

For future research, the following is suggested:

- A study to build a more robust multi-objective method, that is, in addition to considering sales, take into account the other factors that can be considered for the formation of each of the groups indicated by the ABC method.
- Include the remaining products of groups A and B, to improve customer achievement, with the aim of reducing delays.

Table 12.2 Results of proposed approach

Concept	1	2	3	4	5	6	Total	Difference
Business order	51.53	61.02	61.02	40.80	51.00	102.00	367.90	
Business-stock-out	14.00	0.00	10.00	18.00	15.00	0.00	57.00	424.90
Triangular ANFIS1	70.31	76.53	65.00	75.41	72.76	76.53	436.53	11.67
Gaussian ANFIS2	72.04	76.50	77.10	75.30	74.90	452.4	27.49	

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