A Predictive Performance Measurement System for Decision Making in the Supply Chain

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Abstract. Increasing business competitiveness forces companies to develop strategies in search of operational excellence. The supply chain aims to increase its efficiency by reducing costs without neglecting quality and service levels. The implementation of predictive performance evaluation systems as a management practice has increased in recent years because in addition to measuring the efficiency and effectiveness of processes under certain scenarios, it includes artificial intelligence techniques that anticipate future events and allow taking advantage of behavioral patterns of historical data and current information to identify risks and opportunities. This paper proposes a fuzzy logic-based performance measurement system to help predict purchasing behavior through the impact of attributes of the SCOR supply chain operations reference model. The SCOR level 1 indicators are used as a standard for benchmarking against other supply chains. The proposed model is applied through an illustrative case and, according to the results obtained, it facilitates performance prediction and allows scenario analysis. In addition, it is adaptive to any industry and cyclical in search of the desired result, therefore, it helps decision makers to anticipate situations under uncertainty parameters and conditions by determining through simulations the performance attributes with the greatest impact on purchasing and facilitating decision making.

Keywords: Supply chain · Predictive performance measurement · Models · Fuzzy logic techniques · Logistics KPIs

1 Introduction

The most important challenge of a supply chain has is to be able to fulfill a perfect delivery in time and form adding value to the consumer. The complexity of supply chain management has been increasing over the years as many companies compete in the marketplace trying to meet customer requirements. The supply chain considers the integration of repetitive functional activities along the network that include business processes, people, technology and infrastructure for

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the transformation of raw materials into finished products and services [1]. The planning, execution and inspection of the management of goods, services and information from point of origin to point of consumption is handled by logistics [2].

The complexity of supply chain management has increased due to business competitiveness, its administration has focused on maintaining an efficient organization of activities by seeking ways to eliminate challenges through innovative strategies included in performance measurement systems. Good management practices provide competitive advantages aimed at increasing service levels, reducing inventory and improving resource utilization [3,4].

Performance measurement systems contribute to the achievement of business objectives [4]. Its structure is based on the inclusion of key indicators and metrics that evaluate the efficiency and effectiveness of the supply chain processes [5]. There are different steps to develop a performance system: identification of achievements, recording of service level, optimization of processes, objective decision making, monitoring progress and identification of areas of opportunity, control and measurement of information, evaluation and elaboration of improvement plans [6]. However, it present deficiencies in their structure when there is no connection between the strategic objectives and the metrics used, they do not do a good job when there is a biased centralization in finance or when they include conflicting measures [7], the excess of metrics and the lack of manuals for their development hinder the measurement process [8], the use of benchmarking unambiguously by comparing their performance with leading companies or companies that are not logistically similar [9]. In addition, the design, development and implementation of the performance measurement system is not a one-time practice, but must be continuously inspected and monitored to adapt to the variability of the competitive environment [10,11].

Traditional measurement systems are based on historical, independent and static information, and are less efficient in results [12]; it perform corrective actions, however, they are not ideal for measuring the variability of supply chain processes. Consequently, many researches propose the implementation of predictive performance systems that foresee future problems or needs by anticipating performance [13]. Therefore, it is essential for a supply chain to have a system that is adaptable to its needs and customized to its line of business. Performance measurement is defined as the process of quantitative and/or qualitative evaluation of the effectiveness and efficiency of an activity or business process [14].

In recent years authors have developed several supply chain performance measurement frameworks for different problems or business models [15]; based on several criteria [6]: Balanced Scorecard (BSC); components of performance measures (resources, products and flexibility); location of measures in supply chain links (plan, source, manufacture and deliver); decision levels (strategic, tactical and operational); nature of measures (financial and non-financial); basis of measures (quantitative and non-quantitative) and traditional or modern measures (function-based or value-based).

Measurements aimed at assessing cost, agility, responsiveness, flexibility, sustainability, customer and internal processes are the most popular in research [5].

The purpose of this research is to propose a predictive model to measure supply chain performance through a hybrid approach. This paper is structured in five sections: in Sect. 2, a literature review is presented for the identification of suitable tools to perform feedback to the measurement systems used by companies. Section 3 explains the proposed model, Sect. 4 presents the results obtained through the application of the illustrative case and finally Sect. 5 presents the conclusions of the study.

This article makes three contributions to the literature; first, it determines the metrics of levels 1, 2 and 3 of the SCOR model that can be implemented in the purchasing area of the supply chain. Secondly, through a benchmarking between the indicators commonly used by companies and their association with SCOR metrics, the structure of the measurement systems is evaluated, i.e., it can be determined whether the measurements performed project good results. Finally, it provides a cyclic and adaptive system for any supply chain based on a hybrid model composed of SCOR metrics and attributes, a fuzzy analytical hierarchy process for the analysis of criteria priorities and a fuzzy inference system that performs the predictive evaluation in search of identifying the performance attributes with the greatest impact in the area of study, contributing to the improvement of decision making and the formulation of action plans.

2 Literature Review

This section reviews the literature on tools used for performance measurement and provides a current analysis of the applications.

2.1 Tools to Evaluate Performance

Supply chain metrics drive performance. Erroneous assessments directly affect the key operations of any company and result in lost revenue, which in turn leads to lower long-term growth. Therefore, it is vital to use tools to measure supply chain performance. Measurement systems, frameworks, models, and techniques can be found in the literature [17,18].

The researchers [17] have followed a systematic literature review procedure on this topic, identifying the main trends in the field of supply chain performance measurement and classifying the information into approaches and techniques, also, they include the tools with the highest usage according to the search criteria contemplated: Delphi, techniques that deal with uncertainty, DEA, AHP, simulation and ANP. An update of the previous study modifies these results and includes the use of BSC, SCOR, AHP, simulation and DEA models [5]. However, a more recent article mentions AHP, DEA and fuzzy logic as the most commonly used [16].

2.2 Current Analysis of the Use of Tools

Taking into account the diagnosis presented in Sect. 2.1, a new information search is carried out. The literature review focuses on the tools used to measure some aspect or strategy of the supply chain in order to conform the hybrid model. The analysis includes 23 articles classified by author, techniques, models and artificial intelligence techniques listed in Table 1. Numbers 1 to 12 correspond to: 1: AHP, 2: ANP, 3: DEA, 4: DELPHI, 5: DEMATEL, 6: Simulation,7: SEM, 8: BSC, 9: SCOR, 10: FUZZY, 11: Neural networks and, 12: ANFIS.

Table 1. Literature review

N	Autor	Techniques							Models		AI		
		1	2	3	4	5	6	7	8	9	10	11	12
1	Lima-Junior and Carpinetti (2020)									x			x
2	Jollembeck Lopes and I. Pires (2020)		x								x		
3	Jiang et al. (2020)	x									x		
4	Lima-Junior and Carpinetti (2019)									x		x	
5	Akkawuttiwanich and Yenradee (2018)									x	x		
6	Bukhori et al. (2015)	x								x			
7	Sellitto et al. (2015)	x								x			
8	Tavana et al. (2016)			x									
9	Wibowo and Sholeh (2016)	x								x			
10	Chand et al. (2020)				x	x							
11	Govindan et al. (2017)	x									x		
12	Rasolofo-Distler and Distler (2018)								x				
13	Thanki and Thakkar (2018)		x			x			x		x		
14	Ramezankhani et al. (2018)			x		x							
15	Haghighi et al. (2016)			x					x				
16	Tajbakhsh and Hassini (2015)			x									
17	Yu et al. (2016)			x									
18	Zanon et al. (2020)									x	x		
19	Dissanayake and Cross (2018)	x		x				x		x			
20	Tavana et al. (2016)	x											x
21	Miranda et al. (2019)						x						
22	Brandenburg (2017)	x					x						
23	Singh et al. (2018)	x							x		x		
Total		**9**	**2**	**6**	**1**	**3**	**2**	**1**	**4**	**8**	**7**	**1**	**2**

The studies were conducted in manufacturing, environmental, agricultural, construction, service and transportation companies, and the strategies implemented focused mainly on measuring sustainability in the supply chain, customer perceived value and, in other cases, supplier selection and evaluation.

Figure 1 presents the summary of the review. It can be seen that AHP, SCOR and Fuzzy Logic represent the highest utilization in supply chain measurements. However, a comparative analysis of the application of the tools in each of the categories is performed.

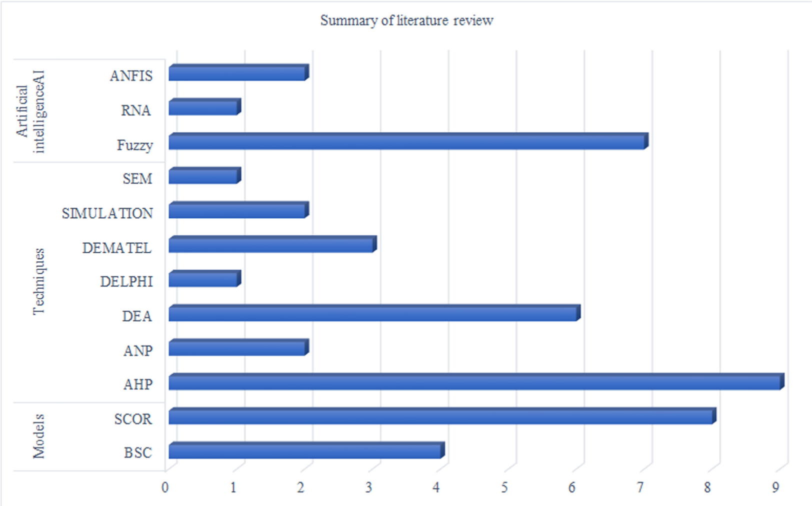

Fig. 1. Summary of literature review

The Supply Chain Operations Reference Model has a proven track record of case studies and literature research in a variety of industries. This model easily adapts to changing user requirements, effectively includes optimal metrics for assessing performance, and its criteria are compatible in a variety of supply chain contexts. As a standard model, it enables effective evaluation of supply chain performance [19]. The balanced scorecard has a history of use mainly in the financial area, however, this model has limitations because it includes fewer measures and it is complicated to measure the integrated supply chain using this approach [20]. According to this information, the model that meets the desired criteria of this study is the SCOR model.

In terms of techniques, the most widely used is the analytical hierarchical process - AHP due to its simplicity, ease of use and great flexibility. AHP consists of three main operations: hierarchy construction, priority analysis and consistency checking. It is one of the most widely used multi-criteria decision making tools and is used in selection, evaluation, cost-benefit analysis, allocations, planning and development, prioritization and ranking [21]. Data Envelopment Analysis - DEA is applied to identify sources of inefficiency, classify decision making units (DMU), evaluate management, assess the effectiveness of programs or policies, create a quantitative basis for reallocating resources, etc. [22].

On the other hand, the combination of one or more techniques is called hybrid approaches. Techniques compatible with the SCOR model are AHP, simulation and Topsis [23]. Therefore, the aggregation of AHP to the model can be considered. However, faced with the need for correct and automated decision making, the implementation of statistical or artificial intelligence (AI) techniques has increased in case investigations and illustrative tests, being employed to estimate supply chain performance based on multiple measures, to predict or check results. Adopting or combining these techniques adds new intelligent capabilities to measurement. Fuzzy logic is an approach that deals with imprecise data and knowledge, so it is ideal when historical data is not available or when decisions must be made under circumstances of uncertainty, in such cases Fuzzy AHP can be used.

The advantages of using artificial intelligence techniques transcend in the adoption of guiding metrics and related to different factors of supply chain management [24]; the ability to work with qualitative data and decision making under uncertainty [25]; adaptation to the environment [7]; and the compatibility of metrics for benchmarking [24].

To finalize the inclusion of techniques in the model, we add the application of fuzzy set theory to deal with uncertainty in the evaluation process [26]. In this regard, fuzzy inference system (FIS) has been mainly used in supply chain management problem to overcome the interior imprecision in criteria evaluation [27].

In conclusion, the hybrid model is made up of the attributes and metrics SCOR, FAHP and the fuzzy inference system with which it is intended to evaluate and provide feedback to the current measurement systems used in companies.

3 Proposed Methodology

The methodology to carry out the model is a modification of the model [28], consisting of three elements: literature review, model development and application. The modifications made are established in the configuration of the supply chain in the purchasing area based on assumptions about the SCOR performance attributes focused on the same area and the inclusion of a fuzzy AHP as a consensus technique to increase the robustness of the FIS rule design. Figure 2 illustrates the main elements of the method:

The first step is a literature review of four main theoretical concepts: performance measurement of the object of study, in this case, the purchasing area, information on the SCOR model focused on procurement attributes and indicators, the FAHP technique as a method of priority analysis and, finally, the fuzzy inference system and its applicability for supply chain performance measurement.

Secondly, the predictive performance measurement system model is developed based on the inclusion of the FAHP results as input data for the mathematical formulation of the FIS in the cause and effect relationship of the metrics.

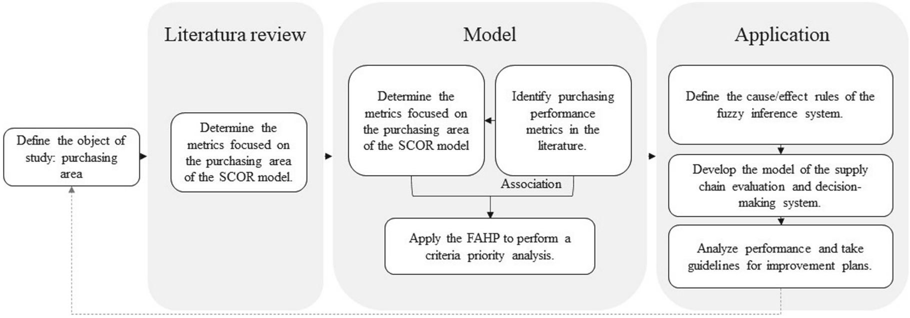

Fig. 2. Methodology

Finally, the application of the model is executed in order to demonstrate its applicability, for this, performance indicator indices and the collaboration of experts are needed to associate the SCOR model metrics with those found in the literature, subsequently measuring performance and analyzing results.

For data collection, two inputs are required in the model: current performance of the SCOR indicators focused on sourcing (information collected from literature from financial databases and articles and reports) and the second input comes from expert knowledge, which substantiates the particularities and specifics of the procurement process environment; data calculated by means of experience and linguistic scores. These data are used to form the FIS rule base.

The outputs are twofold: the current performance of the purchasing area and guidelines for improvement plans. The proposed model is cyclical in order to continuously measure different categories of the supply chain.

3.1 Theoretical Concepts

Purchasing: this area enables the company to acquire the inputs it requires with the necessary quality, in the right quantity, at the right time and at the right price. Nowadays, managers have emphasized the performance evaluation of this link; they measure and evaluate its contribution and the result is usually positive due to its ability to maximize value and minimize waste by acting proactively; improving efficiency and effectiveness in the chain [29].

The proposed methodology seeks to examine operational activities (quantitative data) and tactical and strategic activities (qualitative and less tangible data). Measurement leads to recognition of function; it establishes objectives and ground rules from which policies can be developed. In addition, benchmarking aims to discover best practices, customize them and implement them.

SCOR model: the supply chain operations reference model was introduced as a standard format that links processes, people, performance, best practices and a roadmap for supply chain excellence to meet customer demand. The performance section focuses on understanding supply chain results and constitutes two types of components: attributes; which group metrics and express specific strategies to reach a goal and, metrics; which are standard to quantify the performance of a process, i.e. measure the ability to achieve those strategic directions [19]. SCOR recognizes five performance attributes: reliability, agility, responsiveness, cost and asset management. Associated with the attributes are Level 1 strategic metrics that calculate whether an organization is successful in achieving its positioning. According to the literature review, the attributes and metrics that include source-related issues as part of their rationale are presented in Table 2.

Table 2. Performance attributes and level 1 indicators

Attribute	SCOR level 1 indicator
Realibility	Perfect order fulfilment
Agility	Upside supply chain adaptability
Asset management	Cash-to-cash cycle time
	Return on working capital
Costs	Total supply chain management costs
Responsiveness	Order fulfillment cycle time

FUZZY AHP: In seeking to understand the fuzzy nature of human reasoning, an extended version of AHP combined with fuzzy sets is proposed. This technique, known as fuzzy AHP, evaluates and classifies alternatives and has the advantage of allowing the use of appropriate linguistic values to cope with the imprecision and subjectivity of risk when making decisions [30]. The FAHP methodology is composed of several steps presented below:

– Representation for pairwise comparison: fuzzy numbers are used to model the vagueness of judgments by indicating the relative importance that one aspect has over another by means of linguistic terms and thus construct comparative matrices. Triangular fuzzy numbers (TFN's) are represented as a triplet (l,m,u) where l and u are the lower and upper values, respectively, and m is the mean value. Table 3 includes this information.

Table 3. Fuzzy AHP Saaty's scale [31]

Classic Saaty's scale	Linguistic terms	Fuzzy scale
1	Equally important	(1, 1, 1)
3	Weakly important	(2, 3, 4)
5	Fairly important	(4, 5, 6)
7	Strongly importnat	(6, 7, 8)
9	Absolutely important	(9, 9, 9)
2	Values designed for evaluation of so called interphase	(1, 2, 3)
4		(3, 4, 5)
6		(5, 6, 7)
8		(7, 8, 9)

– Synthesize the judgments: if there is more than one decision maker, it is necessary to group their preferences using the geometric mean and obtain a final result.

$$\widetilde{A}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \left(\prod_{t=1}^{q} \tilde{A}_{ij}^{(t)}\right)^{\frac{1}{q}} = (\tilde{a}_{ij}^{(1)} \otimes \tilde{a}_{ij}^{(2)} \otimes \cdots \otimes \tilde{a}_{ij}^{(q)})^{\frac{1}{q}} \tag{1}$$

$$= \left(\left(\prod_{t=1}^{q} l_{ij}^{(t)}\right)^{\frac{1}{q}}, \left(\prod_{t=1}^{q} m_{ij}^{(t)}\right)^{\frac{1}{q}}, \left(\prod_{t=1}^{q} u_{ij}^{(t)}\right)^{\frac{1}{q}}\right)$$

– Calculate fuzzy weights: in this step multiple fuzzy sets of the matrix are aggregated into one by means of Eq. (2), the value of the "mean" by means of the geometric operation is then normalized to generate the fuzzy weight of a criterion, by means of Eq. (3).

$$\tilde{r_i} = [\tilde{a}_{ij} \otimes ... \tilde{a}_{in}]^{1/n} \tag{2}$$

$$\tilde{W_i} = \tilde{r_i} \otimes (\tilde{r_1} \oplus \tilde{r_2} \cdots \oplus \tilde{r_n})^{-1} \tag{3}$$

– Defuzzification of fuzzy weights: converts the fuzzy results into crisp values that are more intuitive and easier for final comparison by means of the center of area (Eq. 4), then Eq. (5) is used to normalize the weights:

$$M_i = \left(l_i^W + 2m_i^W + u_i^W\right)/4, \; i = 1, 2..., n. \tag{4}$$

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{5}$$

– Consistency check: this step ensures that there are few contradictions between the pairwise comparison of the matrix, it is performed by means of the following equations:

$$CI = \frac{\lambda Max - n}{n - 1} \tag{6}$$

$$CR = \frac{CI}{RI} \tag{7}$$

Fuzzy inference system - FIS: is a systematic reasoning process that exposes input/output mappings using fuzzy logic to produce numerical values from linguistic values associated with membership functions [32]. It has been widely implemented in supply chain context on issues of supplier selection, supplier performance evaluation, risk, sustainability, green supply chain management, among others [33]. It has five main elements:

– A rule base composed of "IF-THEN" scenarios.
– A database of membership functions of the fuzzy sets used in the fuzzy rules.
– Decision making is an inference operation on the rules.
– A fuzzification for the transformation of crisp inputs based on linguistic values.
– A defuzzification, an operation that converts the output of the fuzzy logic into a crisp output.

3.2 Model

Figure 3 shows the proposed model that seeks to understand the impact of supply chain performance dimensions. It establishes a cyclical structure composed of three steps: determining indicators focused on the area of study, categorizing performance attributes and applying the fuzzy inference system and, finally, modeling simulation scenarios.

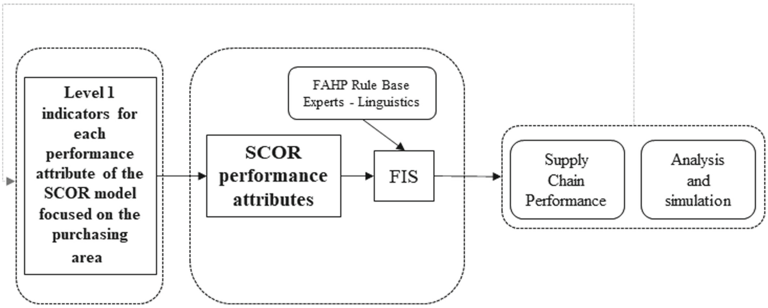

Fig. 3. Proposed model [28]

The model is configured according to the inputs, i.e., depending on the category or strategy of the supply chain to be evaluated, the applicable SCOR indicators and, therefore, the attributes are identified. The number of indicators per attribute determines the number of FIS to be performed.

4 Results

4.1 Association of Indicators

The application of the model is performed in a hypothetical case. The indicators of the purchasing area are searched in the literature and by means of the frequency in the articles contemplated 12 related in Fig. 4 are included. In the case of performing this procedure in a company, the current indicators are used.

To achieve a successful association of indicators, it is recommended to review the metrics of levels 1, 2 and 3 of the SCOR model and the description of the indicators found in the literature. After grouping these two sources, the information is simplified in such a way that it is possible to have one indicator per attribute, taking only the most relevant indicators from the literature that measure aspects of cost, inventory, delivery and quality.

Table 4 shows the final association of indicators and the conversion of figures, the current performance indexes and reference figures (taken as objective figures) are obtained from reports on the evolution of the logistics performance of supply

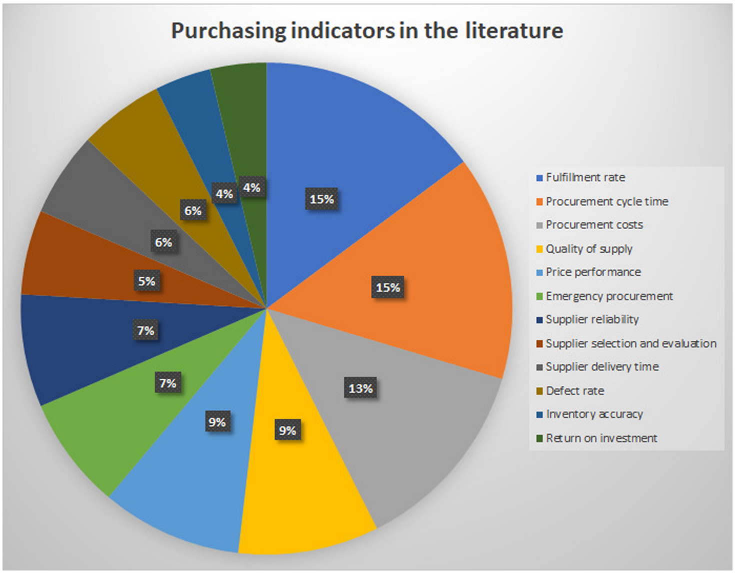

Fig. 4. Purchasing indicators in the literature

chains. In the case of applying this model in a company, these figures can be taken from the enterprise resource planning system or from the indexes of the measurement system used by the company.

Table 4. Final association of indicators and conversion of figures

SCOR level 1 indicator	Literature Indicator	Unit	Current number	Reference Figure	Proportional relationship	Converted figure (range 0–10)
Perfect order fulfillment	Compliance rate	Percentage	88	96	Direct	9
Upside supply chain adaptability	Emergency procurement	Percentage	5	3	Inverse	6
Cash-to-Cash cycle time	Return on investment	Time	6	4	Inverse	7
Return on working capital	Inventory accuracy	Percentage	80	97	Direct	8
Total supply chain managment costs	Procurement costs	Percentage	50	40	Inverse	8
Order fulfilment cycle time	Procurement cycle time	Time	6.5	4	Inverse	6

The figures are converted into a uniform range from zero to ten in order to make future internal and external benchmarking feasible. The calculation of the converted figures is carried out using the proportional relationship of the indicator with respect to performance, i.e. in the case of a direct ratio the higher the value the better the performance [28], e.g. in perfect order fulfillment and return on working capital. On the other hand, an inverse ratio refers to high figures that affect or worsen performance, as in the case of order fulfillment cycle time and the others. The following equations are used to find the values:

$$Direct\ proportional\ relationship = actual\, number/reference\, figure \quad (8)$$

$$Inverse\ proportional\ relationship = reference\, figure/actual\, number \quad (9)$$

According to the final association, the model to be implemented in this study is represented by Fig. 5.

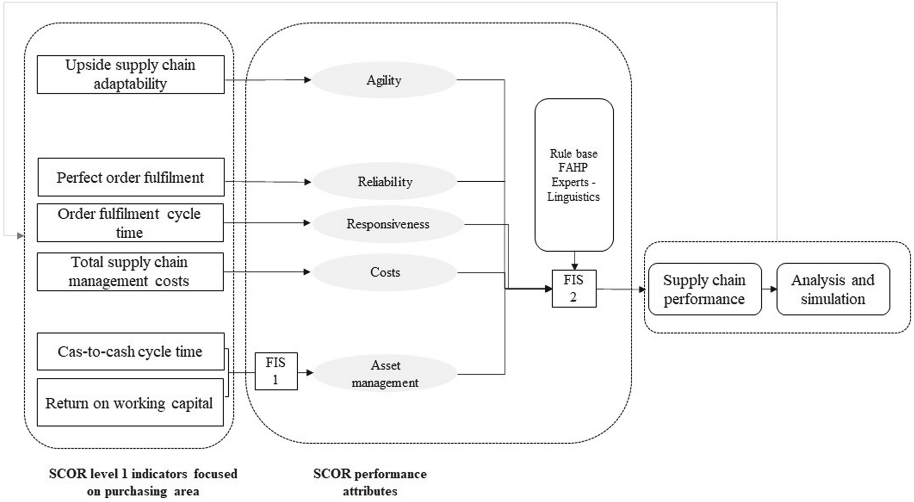

Fig. 5. Configured model

4.2 FAHP Application

In the previous section, the possible indicators used in the companies in the purchasing process were identified and associated with those of SCOR qualitatively and quantitatively. The FAHP technique is intended to determine the degree of importance of each performance attribute with respect to the area of study. These two data sources will feed the FIS rule base.

Judgments were collected by applying a survey to eleven experts in the area: people with knowledge and work experience in the field. Table 5 includes the grouping of these preferences. The acronyms correspond to RL: reliability, AG: agility, RS: responsiveness, CO: cost and AM: asset management.

The consistency ratio of this matrix is 0.016, a value suitable for the methodology. This means that there are few contradictions between the different managers considered.

Table 5. Comparison matrix for criteria

Attribute	RL			AG			RS			CO			AM		
RL	1.00	1.00	1.00	1.69	2.06	2.44	1.53	1.78	2.02	0.53	0.68	0.88	1.27	1.53	1.85
AG	0.41	0.49	0.59	1.00	1.00	1.00	0.51	0.58	0.69	0.24	0.29	0.36	0.66	0.78	0.94
RS	0.49	0.56	0.65	1.46	1.71	1.97	1.00	1.00	1.00	0.22	0.27	0.35	0.90	1.03	1.18
CO	1.13	1.48	1.90	2.77	3.43	4.13	2.84	3.70	4.52	1.00	1.00	1.00	2.73	3.22	3.74
AM	0.54	0.66	0.79	1.07	1.28	1.51	0.85	0.97	1.11	0.27	0.31	0.37	1.00	1.00	1.00

Table 6 lists the geometric means of the fuzzy comparison values of all attributes, the fuzzy weights, the total and inverse values, as well as the normalized relative weights.

Table 6. FAHP results

Attribute	**ri**			**Wi**			Mi	Ni
RL	1.116	1.305	1.518	0.169	0.230	0.312	0.235	0.230
AG	0.506	0.578	0.672	0.077	0.102	0.138	0.105	0.102
RS	0.679	0.769	0.882	0.103	0.135	0.181	0.139	0.136
CO	1.894	2.271	2.657	0.287	0.400	0.547	0.408	0.399
AM	0.666	0.759	0.865	0.101	0.134	0.178	0.137	0.133
Total	**4.861**	**5.682**	**6.593**				1.02	
Reverse (Power of -1)	0.206	0.176	0.152					
Increase order	0.152	0.176	0.206					

With the results obtained, it can be observed that the cost attribute with a relative weight of approximately 40% has the greatest relevance according to the experts' judgment in the area of supply chain purchasing, followed by reliability with 23%, while responsiveness and asset management obtain 14% and 13%, respectively. Finally, according to the results obtained, the attribute that has the least impact on the area of study is agility with 10%.

4.3 FIS Application

Two FIS are established in the model:

- FIS 1 calculates asset management from its concerning indicators. The rule base and membership functions of this first FIS are parameterized according to the experts' perception of the supply chain and the process performed by the fuzzy AHP;
- FIS 2 calculates the value of sourcing on five inputs: asset management; the consequent of FIS 1. Superior supply chain adaptability, perfect order fulfillment, order execution cycle time and total cost of supply chain management,

the level 1 indicators of agility, reliability, responsiveness and cost, respectively. It is significant to note that, in the second FIS, the rule base should be parameterized considering the purchasing value perspective.

For the two FIS defined, linguistic qualification variables are applied (Table 7).

Table 7. Linguistic terms to evaluate the antecedents and consequent [28]

Linguistic terms	**TFN'S**
Under	(0, 0, 5)
Medium	(0, 5, 10)
High	(5, 10, 10)

Linguistic terms	**TFN'S**
Very low	(0, 0, 2.5)
Low	(0, 2.5, 5)
Medium	(2.5, 5, 7.5)
High	(5, 7.5, 10)
Very high	(7.5, 10, 10)

Fuzzy "IF-THEN" rules are generated as a function of the antecedent linguistic variables and the number of entries. An FIS has an equal rule base ax^n, where x is the number of antecedent linguistic variables and n is the number of inputs to an FIS. The number of rules increases significantly as the number of entries increases. Therefore, 9 rules for the first FIS and 243 for the second FIS should be included in the model.

Using the procedure performed by [34], the rules are constructed based on the weights of the criteria (results of the FAHP). The proportion of the linguistic terms is determined in an interval of [0, 1] of both antecedents and consequent and the output of the rule is tilted according to the weight defined for the five linguistic terms of the consequent.

Table 8 presents the fuzzy rules for FIS 1. The same procedure is performed for the FIS 2 rules taking into account all scenarios and combinations.

Table 8. Inference rules for FIS 1

IF			THEN
Cash-to-cash time	OP	Return on working capital	Asset management
Low	AND	Low	Very low
Low	AND	Medium	Very low
Low	AND	High	Low
Medium	AND	Low	Low
Medium	AND	Medium	Medium
Medium	AND	High	High
High	AND	Low	High
High	AND	Medium	Very high
High	AND	High	Very high

The fuzzy model is based on Mamdani's algorithm and runs in the Fuzzy Logic Toolbox of the MATLAB software that develops fuzzy logic programs. Figure 6 shows the design of FIS 1 with its two input variables and the output variable.

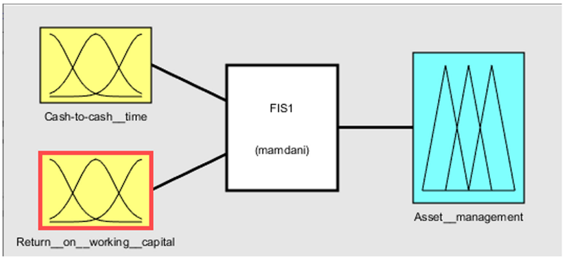

Fig. 6. FIS1 design

Figure 7 presents the rule viewer: a roadmap of the whole fuzzy inference process. The first two columns incorporate the antecedents (yellow graphs) and the third the consequent of each rule (blue graphs). Each rule is a row of graphs, and each column is a variable. The rule numbers are shown to the left of each row. The resulting graphs in the third column correspond to the aggregated weighted decision for the given inference system. This decision will depend on the input values. Finally, the result obtained in this first FIS is 6.67, a representative value of asset management from its corresponding indicators that translates to have a "medium" behavior according to the scale used. The value is determined according to the aggregation of active or executed rules (5, 6, 8 and 9, graphs with blue filling).

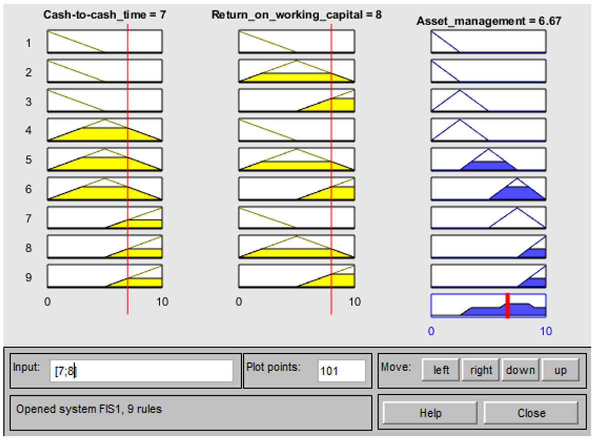

Fig. 7. Rule viewer: FIS 1 (Color figure online)

FIS 2 includes five input variables: reliability, agility, responsiveness, cost and asset management. Due to the high number of rules, Fig. 8 summarizes the output of the fuzzy system showing only the active rules, a total of 32 rules.

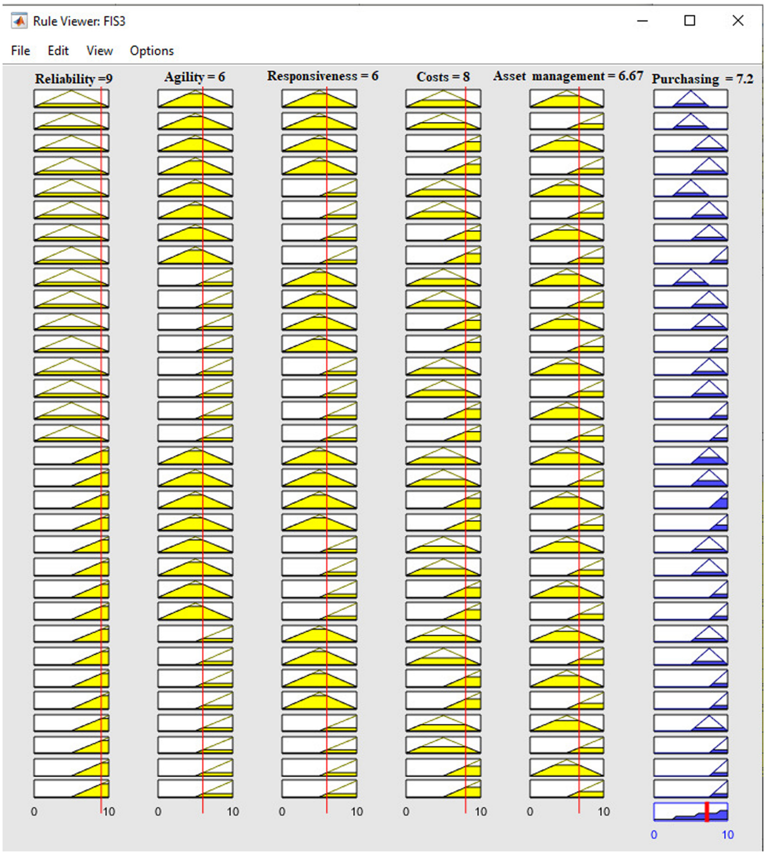

Fig. 8. Rule viewer: FIS 2

After the application of the second FIS and according to the result obtained, the purchasing performance presents a value of 7.2 determined as "medium" according to the scenarios taken into account and the evaluations entered in each of the variables of the model. It is worth mentioning that these indexes can be modified in search of a better performance or in order to obtain a desired value.

4.4 Simulation Scenarios

Following the output of FIS 2, ten comparison surfaces are generated between the attributes of the SCOR model. The plots show the three-dimensional relationship between various input and output variables. The variation of the output versus the input variables depends on the fuzzy inference rules developed. In this case, the plot of the purchasing performance as a function of the attributes is shown. This analysis helps to identify the shortest path to maximize the shopping value index. In addition, the FIS output surface provides researchers and experts with the opportunity to examine the effect of criteria on performance.

Due to the quantity, Fig. 9 presents only four cost comparison surfaces versus the other attributes because it obtained the highest contribution to purchases according to the scenario analysis.

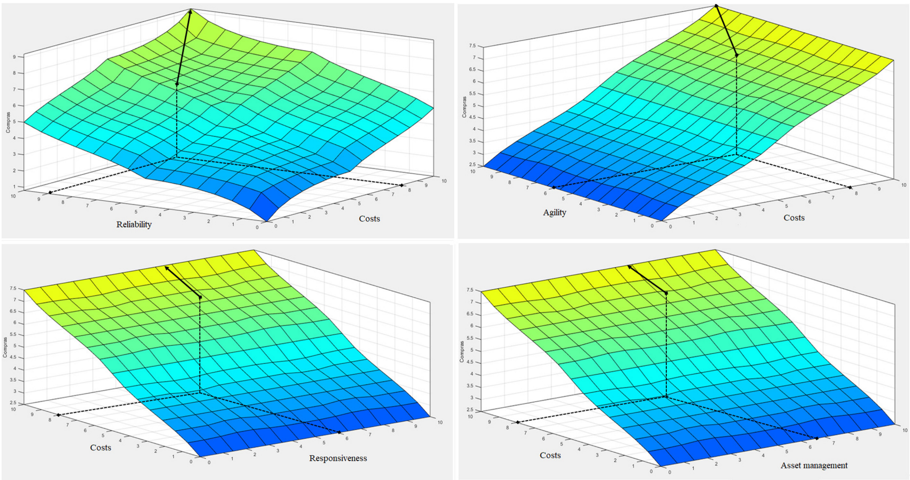

Fig. 9. Response surfaces

The behavior of very random fluctuations in the surface represents weakness and at the same time indicates an erroneous development of the generated fuzzy rules. In order to represent the sustainability and strength of the rules, the surfaces should show an approximate ascending and descending pattern. Therefore, according to the obtained behavior of few surface disturbances it can be deduced that the development of the rules was good.

In conclusion, through the analysis of all the surfaces, it is possible to deduce that the improvement mainly of costs should be essential in view of the fact that it has the greatest impact on the study area under the scenarios and parameters contemplated.

5 Conclusions

The findings reinforce the proposition that the adoption of a hybrid predictive model based on the metrics and attributes of the SCOR model with FAHP for prioritization of criteria and assignment of weights and, FIS for evaluation appears to be a viable technique to assist managers in the decision making process of supply chain performance management.

SCOR Level 1 indicators are applied as a means to evaluate the purchasing area by allowing benchmarking with other supply chains and to facilitate communication with stakeholders. The system provides the possibility of anticipation and prioritization. In addition, the model evaluates the number of indicators used in the companies and their purpose with corrective effects, also, it can take into account the variability of the processes, so it is a cyclical model in which simulations can be performed constantly varying the input data and the target goals.

It is important to mention that the basis of the fuzzy inference system is in the construction of the rules, the definition of linguistic terms and fuzzy numbers is ideal to accompany the knowledge and experience of the decision makers with a mathematical foundation through consensus techniques. The application of the FAHP for this part was successful, since it provided solidity and robustness to the rules, which was reflected in the behavior of the response surfaces.

Main contributions of this research:

– Predictive performance evaluation system for supply chain decision making.
– Hybrid model consisting of SCOR, FAHP and FIS that successfully combined and complemented each other and showed good performance measurement behavior.
– The opportunity to use the model to perform measurements in a cyclical and adaptable way for any category of the supply chain and under different parameters.
– The possibility of a corrective benchmarking for the structure (indicators) of the measurement system used by the company applying it.

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