Uncertainty Modeling of Sourcing Performance in Supply Chain Quality Management

Juan M. Cogollo-Flórez

***Abstract*—Sourcing performance measurement in Supply Chain Quality Management is carried out under uncertain and changing conditions. This paper proposes a methodology for uncertainty modeling of Sourcing Performance using Fuzzy Grey Cognitive Maps and Design of Experiments. This methodology has four steps: (i) Selection of model variables, (ii) Determination of causal relationships, (iii) Construction of the model, and (iv) Dynamic performance of the model with Design of Experiments. The application of the fractional factorial design validated the adequate dynamic functioning of the model and allowed identifying the factors that have a significant effect on the response variable.**

***Index Terms*—Design of experiments, fuzzy grey cognitive maps, sourcing performance, supply chain quality management.**

I. Introduction

Supply Chain Management (SCM) is the coordination of production, inventory, location, and transportation to achieve the best possible performance in responsiveness and efficiency in a supply chain [1]. SCM involves planning, design, and control of the flow of materials, information, and money throughout the supply chain to deliver superior value to the end customer effectively and efficiently [2]. SCM is based on collaboration between companies to achieve common strategic positioning and improved operational efficiency [3]. SCM involves logistics management and other processes such as Quality Management [4].

On the other hand, the focus of Quality Management (QM) has shifted from the traditional company-centric scenario to complete supply chain systems. This shift in focus has caused a change in the competitive priorities of many companies, from product quality to the overall quality of the supply chain [5]. Thus, Supply Chain Quality Management (SCQM) is the result of the integration of SCM and QM and their evolution from an operational approach to a strategic approach.

SCQM is the coordination and integration of business processes in the supply chain to measure, analyze and improve products, services, and processes, to create value and achieve the satisfaction of all customers [6]. SCQM refers to the QM practices aimed to improve supply chain overall performance and develop a single approach to synchronously manage issues related to QM in every supply chain stage [7].

The uncertainty in Supply Chain Quality Management refers to issues in which the decision maker does not know what to decide and is confused about the objectives, lacks information about the supply chain and its environment, lacks information about process capabilities and is unable to predict the impact of possible control actions on the behavior of the supply chain [8]. The supply chain uncertainty involves some limitations when implementing performance measurement systems under deterministic methods approach, since they require knowing the data inputs value of the system.

Therefore, this paper proposes a methodology for uncertainty modeling of Sourcing Performance using Fuzzy Grey Cognitive Maps and Design of Experiments (DOE). The modeling approach used in this work focuses on the analysis of the variables' interaction strength regarding the Sourcing Performance in Supply Chain Quality Management. The results allow establishing possible degrees of impacts of the changes made in a variable with respect to other state or response variables through a multiple linear regression model.

II. Literature Review

Fuzzy Cognitive Maps (FCMs) are a combination of fuzzy set theory with heuristic learning of neural networks [9]. FCMs consists of variables or concepts (C) that represent the studied system and directed arcs that represent the causal relationships between the concepts. The concepts are denoted with the subscripts i (cause node) and j (effect node). Each directed arc has a weight w_{ij} in the interval [-1, +1], which represents the strength of the relationship between i and j.

Besides, Fuzzy Grey Cognitive Maps (FGCMs) are an extension of FCMs and constitute a flexible modeling approach based on Grey Systems Theory [10]. FGCMs allow modeling uncertainty in the weight values of the relationships between variables, assigning them grey numbers instead of the exact values of the FCM (Fig. 1).

A grey number ($\otimes$g) is one whose exact value is unknown, but the range within which this value is included is known. A grey number is an interval that can have only a lower limit, only an upper limit, or both a lower limit and an upper limit.

When the grey number has a lower limit ($\underline{g}$) and an upper limit ($\bar{g}$), it is known as the interval grey number. Consequently, in a FGCM the weights of the causal relationships between concepts i and j are measured in terms of their grey intensity and are expressed as:

$$\otimes w_{ij} \in [\underline{w}_{ij}, \overline{w}_{ij}] \;\Big|\; \underline{w}_{ij} \leq \overline{w}_{ij}, \{\underline{w}_{ij}, \overline{w}_{ij}\} \in [-1, +1] \qquad (1)$$

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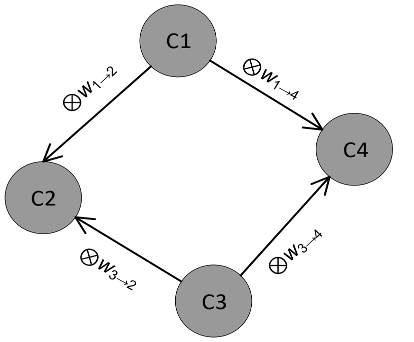

Fig. 1. Example of a FGCM with four concepts.

The study of the FGCM convergence is a topic of growing interest since the incorporation of grey values in the interrelations affects the inference process. In some cases, a simplification approach is used, taking as the white value the midpoint of the grey weight range, reducing the FGCM to an FCM, which can lead to erroneous conclusions. On the other hand, running the inference process with all possible combinations of the interrelations could lead to non-feasible solutions [11].

Regarding the application of FGCMs in SCQM, some works stand out. Haeri and Rezaei [12] developed a supplier selection model by incorporating sustainability criteria and FGCMs to analyze interdependences using grey values of relationship weights. In [13] was proposed a model to analyze the causal relationship between organizational culture and supply chain performance, using FGCMs, grey clustering and multiple fuzzy inference. In [14] used FGCMs for evaluating and modeling causal relations into a reliability analysis of an electric power system.

III. Methodology

The proposed methodology consists of four steps: (i) Selection of Model Variables, (ii) Determination of Causal Relationships, (iii) Construction of the Model, and (iv) Dynamic Performance of the Model with DOE. This section shows the development of the first two stages and the next section shows what corresponds to the three remaining stages.

A. Selection of Model Variables

The selection of the state variables and the response variable that represent Sourcing Performance in Supply Chain Quality Management was carried out considering the works of [7], [15]–[19]. Table I shows the model variables, specifying their type, description and assigned ID.

TABLE I: Model Variables

Type	Variable	Description	ID
Response/ Dependent	Sourcing Performance	Quality performance level of sourcing. Its result depends on the influence and interaction of the state variables.	C1
State/ Independent	Suppliers perfect orders (%)	It is used to evaluate and monitor suppliers regarding compliance with the agreed negotiation conditions of times, product quality, delivery conditions and complete information.	C1,1
	Rejections and returns to suppliers (%)	They are due to breaches of the specifications agreed in the negotiation by the suppliers and cause reprocessing and delays in operations because of the return of raw material to the supplier.	C1,2
	Sourcing Fill Rate (%)	It measures the fulfillment percentage regarding all the items ordered from the supplier and has a close relationship with the service level of the suppliers.	C1,3
	Ordering Cost ($)	The cost of issuing a purchase order. It includes administrative, communication, or related fixed costs.	C1,4

B. Determination of Causal Relationships

Table II shows the interrelationships of the variables, using the previous coding. Since it is necessary to validate the strength of these interrelationships, their weight (*w*) is not assigned an exact value, but a grey value that, additionally, incorporates the uncertainty of Supply Chain Quality Management.

TABLE II: Interrelationships of Variables

Cause node (*i*)	Effect node (*j*)	Weight notation	Interval $\otimes w_{ij}$
C1,1	C1	$\otimes w_{1,1\to 1}$	[0.8, 1.0]
C1,2	C1	$\otimes w_{1,2\to 1}$	[-1.0, -0.8]
C1,3	C1	$\otimes w_{1,3\to 1}$	[0.8, 1.0]
C1,4	C1	$\otimes w_{1,4\to 1}$	[-0.6, -0.4]
C1,1	C1,2	$\otimes w_{1,1\to 1,2}$	[-1.0, -0.8]
C1,1	C1,4	$\otimes w_{1,1\to 1,4}$	[-1.0, -0.9]
C1,2	C1,3	$\otimes w_{1,2\to 1,3}$	[-0.6, -0.4]
C1,2	C1,4	$\otimes w_{1,2\to 1,4}$	[-0.6, -0.4]
C1,3	C1,4	$\otimes w_{1,3\to 1,4}$	[-1.0, -0.9]

IV. Results

A. Construction of the Model

The construction of the Sourcing Performance model in Supply Chain Quality Management using fuzzy grey cognitive maps was carried out by combining the information from Tables I and II and configuring them in the structure shown in Fig. 2.

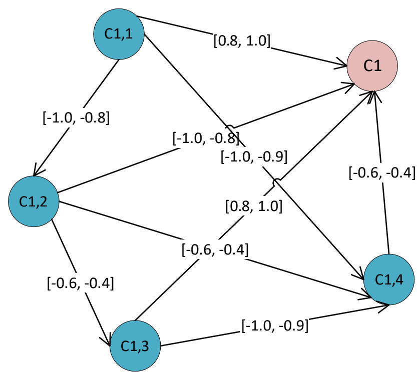

Fig. 2. FGCM Model for Sourcing Performance.

B. Dynamic Performance of the Model with DOE

Validation of the model dynamic performance was carried out using a fractional factorial design in the inference process [20]. The factors are the interrelationships between concepts and are defined based on Table I. The experiment objective is to determine the main factors and their effects on the response variable (sourcing performance) and to confirm the selection of concepts and their interrelationships, as well as the use of intervals or exact numbers for the interrelationships weights.

The low and high levels of the factors correspond to the minimum and maximum values of the respective grey number (Table III). Considering the number of factors (nine), a 2^{9-4} design with resolution IV and 32 simulation runs was selected.

The simulation experiment performance was carried out using the self-memory Kosko activation function [21]. The results analysis of the experiment showed that the effects of double and triple interactions are not significant. The analysis of variance (Table IV) and the standardized Pareto chart of effects (Fig. 3) show that the effects of the main factors are significant, except for factor I, which corresponds to the relationship C1,3 → C1,4 (from Sourcing Fill Rate to Ordering Cost).

This implies that the weight of this relationship can be specified using a concrete number, generally the mean value of interval ($w_{1,3\rightarrow 1,4}$ = -0.95). When this effect is excluded from the analysis of variance, an adjusted coefficient of determination of 99.3% is obtained. The Durbin-Watson (DW) statistic for the residuals was 1.7408 (P = 0.2045), which indicates that there is no evidence of serial autocorrelation in the residuals, with a significance level α = 0.05.

TABLE III: FACTORS AND LEVELS OF THE EXPERIMENT

Factor	Relationship	Low	High
A	C1,1→C1	0.8	1.0
B	C1,2→C1	-1.0	-0.8
C	C1,3→C1	0.8	1.0
D	C1,4→C1	-0.6	-0.4
E	C1,1→C1,2	-1.0	-0.8
F	C1,1→C1,4	-1.0	-0.9
G	C1,2→C1,3	-0.6	-0.4
H	C1,2→C1,4	-0.6	-0.4
I	C1,3→C1,4	-1.0	-0.9

TABLE IV: THE ANOVA TABLE FOR THE EXPERIMENT

Source	Sum of squares	DF	Mean squares	F-Value	P-Value
A:Factor_A	0.005465	1	0.005465	2324.00	0.0000
B:Factor_B	0.001714	1	0.001714	728.85	0.0000
C:Factor_C	0.003172	1	0.003172	1348.83	0.0000
D:Factor_D	0.000417	1	0.000418	177.58	0.0000
E:Factor_E	0.000621	1	0.000622	264.18	0.0000
F:Factor_F	0.000014	1	0.000015	6.20	0.0208
G:Factor_G	0.000257	1	0.000258	109.56	0.0000
H:Factor_H	0.000019	1	0.000019	7.91	0.0101
I:Factor_I	0.000009	1	0.000009	3.66	0.0688
Error	0.000052	22	0.000002		
Total	0.011741	31			

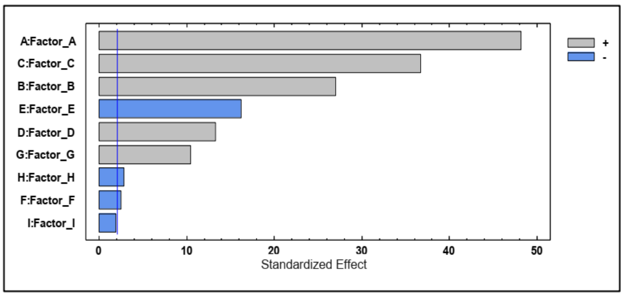

Fig. 3. Standardized Pareto Chart of Effects for Sourcing Performance.

This result is consistent with previous work where it was proven that in joint decision making in supply chains the target Fill Rate should be specified in advance in the contract and that the impact of its variation is not significant in reducing costs [22]. Also, it is not realistic or beneficial for supply chain partners to have low Fill Rate indicators or high variability. Generally, the determination of the target Fill Rate is a compromise solution with the total costs of the logistics system and the proper approach is to establish the best possible cycle count configuration given a set of items [23].

Finally, the experiment results allow obtaining a multiple regression model to predict the value of the response variable in the inference process using Fuzzy Grey Cognitive Map in the analysis of Sourcing Performance (SP):

$$SP = 0.8254 + 0.0131 \otimes w_{1,1\rightarrow 1} \in [0.8, 1] + 0.0074 \otimes w_{1,2\rightarrow 1} \in [-1, -0.8] + 0.00996 \otimes w_{1,3\rightarrow 1} \in [0.8, 1] + 0.00361 \otimes w_{1,4\rightarrow 1} \in [-0.6, -0.4] - 0.00441 \otimes w_{1,1\rightarrow 1,2} \in [-1, -0.8] - 0.00067 \otimes w_{1,1\rightarrow 1,4} \in [-1, -0.9] + 0.00284 \otimes w_{1,2\rightarrow 1,3} \in [-0.6, -0.4] - 0.00077 \otimes w_{1,2\rightarrow 1,4} \in [-0.6, -0.4] - 0.00052*(-0.95)$$

V. CONCLUSION

A Fuzzy Grey Cognitive Map model was developed to address uncertainty in the Sourcing Performance measurement. The model integrates design of experiments to evaluate the convergence and the significant effects of the main factors. Thus, the use of design of experiments provides a new alternative for analyzing Fuzzy Grey Cognitive models.

This modeling methodology allowed to quantify the capacity of the selected factors to explain the changes in the response variable. These results also validate the choice of concepts and weights of the interrelationships of the model. This makes it possible to adequately deal with the uncertainty inherent to these models without resorting to generalizations with concrete values of the relationships strength between concepts.

The modeling methodology of Sourcing Performance in Supply Chain Quality Management developed in this paper has a flexible scheme that is adaptable to the conditions of supply chains or specific sectors. For its application in each context, it is essential to have historical data that allow obtaining knowledge of the variables interrelationships strength using multivariate descriptive statistical analysis.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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