ANALYZING DISTRIBUTION QUALITY MANAGEMENT PERFORMANCE USING SIMULATION AND DESIGN OF EXPERIMENTS

Juan M. Cogollo-Flórez
Instituto Tecnológico Metropolitano
050034, Medellín, Colombia
E-mail:juancogollo@itm.edu.co

Alexander A. Correa-Espinal
Universidad Nacional de Colombia
050034, Medellín, Colombia
E-mail: alcorrea@unal.edu.co

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ABSTRACT

Distribution quality management performance in supply chains is a key issue for overall performance and competitiveness. This paper proposes a methodology for analyzing distribution quality management performance using simulation and design of experiments (DOE). This methodology has four steps: (i) Selection of variables, (ii) Determination of factors and levels, (iii) Performing the experimental simulation and (iv) Analysis of the results. The joint application of simulation and DOE allowed analyzing the effects of the independent variables on the distribution quality management performance. It was also possible to sort the independent variables according to the degree of impact on the response variable.

INTRODUCTION

A supply chain is a network of companies involved in different processes and activities to add value to products and services from suppliers to the end customer (Slack and Lewis 2017). It involves all the parties involved in customer satisfaction and includes the functions involved in receiving and satisfying customer requirements within each organization (Chopra 2018). Thus, Supply Chain Management is planning, designing, and controlling the flow of materials, information, and money throughout the supply chain to offer the end customer superior value effectively and efficiently (Sanders 2018).

Quality Management has expanded its principles to the entire supply chain to coordinate and integrate processes involving business activities and business structure (Robinson and Malhotra 2005; Akyuz 2011; Yoo and Cheong 2018). Supply Chain Quality Management implies a set of integrated systems that improve the performance of the links between the upstream supply chain with suppliers and the downstream supply chain with distributors and customers (Foster 2008; Batson and Mcgough 2007).

Supply chain quality management is the coordination and integration of the processes of all members of the supply chain in order to improve performance and achieve customer satisfaction, emphasizing cooperative learning (Parast 2013). The efficient operation of a supply chain to align separate entities and improve overall performance in quality management requires collaborative, coordinated, and integrated activities and making decisions based on performance measurement (Moharana et al. 2012; Bautista-Santos et al. 2015).

According to Das and Lashkari (2015), distribution plans are important for optimal business performance and for the interrelationship between distribution modes, perfect deliveries and product quality. They also state that improved responsiveness depends on the conditions of flexibility in facility location and size, customer density, and delivery requirements. Similarly, in distribution models for perishable products, it is necessary to consider the relationship between product quality deterioration and delivery distances (Chen et al. 2021).

Park (2005) establishes the need to jointly analyze and plan production and distribution systems as a successful strategy to maximize total net profit. Pettersson and Segerstedt (2013) state that quantification and disaggregation of logistics costs at the manufacturing and distribution stages is essential for making appropriate decisions to improve overall supply chain performance. Chiadamrong and Wajcharapornjinda (2012) consider quality costs as one of the main categories of supply chain costs and highlight the need to quantify them at all stages.

On the other hand, the design of experiments has been applied as a validation tool for computational simulation models, making it possible to determine the important factors with the least number of simulation runs (Duman 2007; Kleijnen 2005; Law 2017; Montevechi et al. 2010). The use of the design of experiments has advantages over the sensitivity analysis carried out by varying one parameter and leaving the rest fixed since the latter is statistically inefficient and does not take into account the interactions between factors (Law 2015). The validation of research based on simulation by using the design of experiments allows increasing the transparency of the simulation models behavior and the effectiveness of the results report (Lorscheid et al. 2012; Tarashioon et al. 2014).

Moreover, the fractional factorial design has been used for validating simulation and optimization studies applied in hybrid renewable energy systems with a large

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number of factors and uncertainty in resources and demand, and complex interaction between factors (Chang and Lin 2015). Also, it has been used to validate simulation models of factors that influence response capacity in fire safety studies (Suard et al. 2013). Hence, it is possible to use a fractional factorial design jointly with a simulation tool to analyze the variables behavior of the system studied in this work.

Therefore, this paper proposes a methodology for analyzing distribution quality management performance using simulation and design of experiments. The experimental simulation approach is used to analyze the initial selection of variables and the interactions that influence distribution quality management performance. The joint application of simulation and design of experiments to study supply chain management is a current research trend.

FRACTIONAL FACTORIAL DESIGN

DOE consists of planning and performing a set of trials to obtain data and analyzing them statistically to answer questions about the studied system. In each experiment, changes are made to the input variables to identify the reasons for the changes observed in the output variable (Montgomery 2020). Factors are the variables studied in the experiment regarding how they influence or affect the response variable(s). The different values assigned to each factor in a DOE are called levels.

There are some DOEs, and selecting the right one depends on the experiment objective, the number of factors, the number of levels per factor, the studied effects, the experiment cost, and the desired precision. In general terms, it is possible to use experiments with a single factor, block designs, factorial designs, and robust designs (Jones and Montgomery 2020). The fractional factorial design is selected to perform the experiments in this work, so its basics are briefly explained below.

A fractional factorial design is a part or fraction of a full factorial design, in which the number of experimental runs is reduced without reducing the quality of relevant information about significant effects. The theory of fractional factorial designs is based on the hierarchy of effects: the main effects are more important, followed by double interactions, then triples, quadruples, etc. (Montgomery 2020). Fractional factorial designs are recommended in exploratory experiments where information on main effects and low-order interactions of multiple factors is required.

In full factorial designs with less than five factors ($k < 5$), the potentially important effects outnumber the a priori ignorable effects, so relevant information may be lost if they are fractionated. On the other hand, when $k \geq 5$, the number of ignorable effects exceeds the number of potentially important ones, indicating that these designs can be fractionated many times without losing valuable information. The larger the value of k, the greater the allowed degree of fractionation in the design (Antony 2023).

The resolution is a characteristic of a fractional factorial design and is related to the role exerted by the potentially relevant effects. The most common resolutions are III, IV, and V. In the resolution III design, the main effects are not aliases of each other, but there are main effects that are aliases of double interactions. In the resolution IV design, the main effects are not aliases of each other or with double interactions, but some double interactions are aliases of each other. In the resolution V design, the main effects and the double interactions are aliased with triple or higher-order interactions (Gutiérrez and De La Vara 2012). Thus, the higher the resolution, the better to study the relevant effects of the design.

Factorial designs are versatile as they can be adapted to different experimental conditions, such as simple replicates, factorial replicates, and experiments in exploratory phases. Using fractional factorial design is based on the fact that a small fraction of the factor effects are significant for a process, while the rest of the effects are inert for practical purposes, associating much of the variation with only a few factors.

SIMULATION USING FUZZY COGNITIVE MAPS

Fuzzy Cognitive Maps (FCMs) are soft computing tools for modeling complex systems using human knowledge or knowledge extracted from databases in the form of rules (León et al. 2010). An FCM consists of variables representing the system under study and weighted arcs representing the causal relationships between the concepts. Each arc has a value in the interval [-1, +1] according to the strength of the relationship between the variables. The weights of each pair of variables result from an adjacency or correlation matrix (Dickerson and Kosko 1994).

FCMs can be used to represent a specific behavior of the system, and the evaluation at run-time is fast to meet the requirements of real-time simulations (Buche et al. 2010). Using FCMs as a simulation tool makes it possible to model uncertain conditions of systems through a macroscopic level-based method, based on historical data and predicting the future states (Amini et al. 2021). As simulation step, the value of a variable is calculated by computing the influence of the interconnected variables by following a specific rule (Kang et al. 2016).

FCMs are adequate for modeling complex systems with limited and small data or when data are inaccessible because the collection is costly (Yousefi et al. 2020). FCMs can be used for simulating multiple scenarios since they reduce the dissimilarity between the current state vector and the expected response (Felix et al.

2019). So, after the simulation runs, it is possible to infer some behavioral properties of the variables and reach some conclusions about the system under study (Christoforou and Andreou 2017).

The dynamic behavior of the simulation with FCMs depends on the values of the weights of the variables interrelationships and the inference mechanism of the state transition. Thus, three different outcomes can be expected: (a) The state vector settles to a stationary value after a finite number of steps, reaching a so-called fixed attractor, (b) The state vector periodically settles to the same value after a finite number of steps, or, (c) The state vector changes chaotically (Papageorgiou 2014). Due to the characteristics and requirements of the DOE, the desired stopping criterion of the simulation in this work is to reach a fixed attractor.

METHODOLOGY

This work analyzes the interrelationships of the variables that determine quality performance in distribution through simulation and the design of experiments. The methodology consists of four steps: (i) Selection of variables, (ii) Determination of factors and levels, (iii) Performing the experimental simulation, and (iv) Analysis of the results (Figure 1).

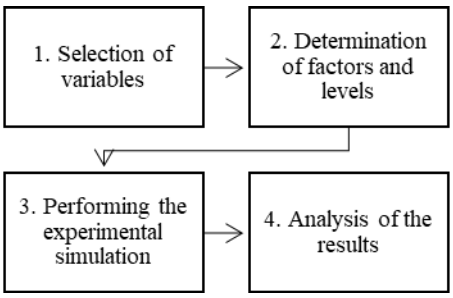

Figure 1: Methodology Steps

The definition of the experiment objective is the basis for selecting the variables of the simulation model. Thus, the selection of variables is made considering the characteristics of the experimental unit and the literature on supply chain quality performance. The experimental unit is a food products company with a production plant and distribution center in a city in Colombia. From there, distribution to the rest of the country is carried out. Overall distribution quality performance indicator data for the last twelve months were analyzed.

Factors are the independent variables tested in the experiment. The study of a factor requires testing it on at least two levels. There would be selected the factors previously known as influencing the response variable. In this paper, the factors are the variable interrelationships, and the levels are the limits of the correlation coefficient confidence intervals.

Performing the experimental simulation starts with the selection of the appropriate DOE by considering the factors, levels, and the resolution. The simulation runs are performed using the software FCM Expert. In each of them, the initial values correspond to the levels of the factors established in the experimental plan.

The analysis of results is based on the data obtained from the values of the fixed attractors of the response variables in each simulation run. The experimental results are sample observations of the studied system, so statistical methods are used to verify if the effects are significant. Statistical analysis consists of estimation of effects and the ANOVA test.

RESULTS

Selection of variables

The selection of the independent and dependent variables -which represent distribution quality performance- was made considering the performance measurement system of the case study. Table 1 shows the variables and their coding and definition. These three independent variables are currently in use in the company under study. More additional variables will be considered in the following research phases.

Table 1: Variables of the Distribution Quality Performance

Type	Variable	Definition
Response	C3: Distribution Performance	Quality performance of the distribution stage, as a result of the influence and interaction of the independent variables (Kleijnen and Smits 2003).
Independent	C3,1: Customer perfect deliveries (%)	Percentage of orders that the company delivers on time, complete, in good condition and without documentation problems (Jacobs and Chase 2018; Slack et al. 2016).
	C3,2: Customer rejections and returns (%)	Percentage of items rejected at the delivery or after receipt by the customer, due to non-compliance with one or more quality requirements (Flynn and Zhao 2015; Yao and Zhang 2009).
	C3,3: Distribution unit cost ($/item)	The unit cost of distributing the orders from the production facilities to the final consumer (Kleijnen and Smits 2003).

Determination of Factors and Levels

Correlation analysis of historical data was performed as starting point to analyze the interrelationships of the studied variables by simulation. The obtained correlation coefficient intervals at 95% confidence are in Table 2. The exclusion threshold interval for the correlation coefficient is (-0.4, 0.4). Therefore, the blank cells correspond to low correlation coefficient intervals (in the exclusion interval), which are not considered in this work.

Table 2: Correlation Coefficients Intervals between Variables

	C3	**C3,1**	**C3,2**	**C3,3**
C3				
C3,1	[0.8, 1.0]		[-1.0, -0.8]	[-0.8, -0.6]
C3,2	[-1.0, -0.8]			[0.7, 0.9]
C3,3	[-0.9, -0.7]	[-0.7, -0.5]	[0.4, 0.6]	

Thus, the experimental factors are the interactions of the variables with significant correlation coefficient intervals shown in Table 2. Table 3 shows the experimental factors and their levels. The *Low* and *High* levels correspond to the lower and upper limits of the correlation coefficient confidence intervals, respectively.

Table 3: Factors and levels of the Experiment

Factor	***Low***	***High***
A (C3,1→C3)	0.8	1.0
B (C3,2→C3)	-1.0	-0.8
C (C3,3→C3)	-0.9	-0.7
D (C3,1→C3,2)	-1.0	-0.8
E (C3,1→C3,3)	-0.8	-0.6
F (C3,2→C3,3)	0.7	0.9
G (C3,3→C3,1)	-0.7	-0.5
H (C3,3→C3,2)	0.4	0.6
Response variable	C3 (Distribution performance)	

Performing the Experimental Simulation

The selection of the appropriate fractional factorial design was made considering the number of experimental factors (eight) and getting a high resolution (IV or V). The latter avoided confounding main effects with double or triple interactions, with an acceptable number of runs. Then, a 2^{8-2} design with resolution V and 64 simulation runs was selected.

The system studied using the selected fractional factorial design has variables and degrees of causality between them (factors and levels) and it is necessary to evaluate the impact of their interactions on the response variable. Accordingly, FCMs were selected as the simulation technique to obtain the value of the response variable from the factor levels in each simulation run (Papageorgiou 2014). Figure 2 shows an example of a simulation run result.

The 64 experimental simulation runs were performed using the Kosko activation rule with self-memory (Christoforou and Andreou 2017):

$$A_i(k+1) = f\left(A_i(k) + \sum_{j=1}^{n} A_j(k) * w_{ji}\right) \quad (1)$$

where the value A_i (response variable) at time k+1 is calculated as the sum of the previous value of A_i at the previous time k with the product of the value A_j of node C_j at time k and the value of the weight of the cause-effect relationship w_{ji} (levels of the experiment). The stopping criterion selected for each simulation run was to obtain a fixed attractor, as shown in Figure 2.

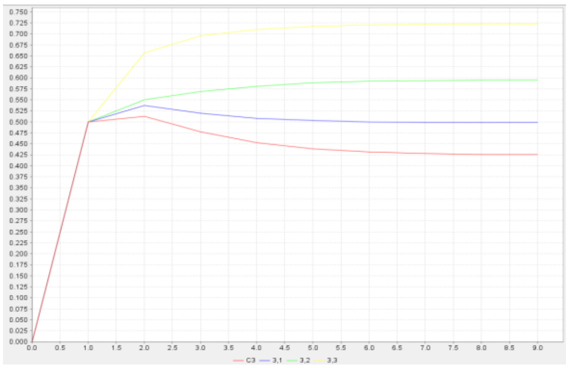

Figure 2: An Example of a Simulation Run Result

Analysis of the Results

The analysis of the experimental simulation results was carried out using a sequential phased approach, excluding and transferring to error the non-significant effects until the final model with significant sources of variation was obtained (Rigdon et al. 2022). The results of the final regression model obtained make it possible to identify that the variable with the highest impact on distribution quality management performance is the distribution unit cost (correlation coefficient = 0.58), followed by customer rejections and returns (0.54) and customer perfect deliveries (0.42).

The ANOVA test of the simulation results (Table 4) shows that all main effects are statistically significant, confirming the initial selection of the variables that influence the distribution quality management performance. This is also noted in the behavior of the standardized Pareto diagram of effects (Figure 3) and the main effects plot (Figure 4).

Table 4: The ANOVA Test Results

Source	**Sum of squares**	**DF**	**Mean squares**	**F-Value**	**P-Value**
A:A	0.019082	1	0.019082	5659.91	0.0000
B:B	0.026402	1	0.026402	7831.16	0.0000
C:C	0.033001	1	0.033001	9788.51	0.0000
D:D	0.002494	1	0.002494	739.67	0.0000
E:E	0.002236	1	0.002236	663.25	0.0000
F:F	0.003090	1	0.003090	916.52	0.0000
G:G	0.007693	1	0.007693	2281.96	0.0000
H:H	0.004288	1	0.004288	1272.05	0.0000
Error	0.00018543	55	0.00000337		
Total	0.0984728	63			

All the interactions between the variables studied were significant for distribution quality management performance. Therefore, it is important to consider minimal variations in the value of the interactions in the analysis of their effects on distribution performance.

The risks of physical distribution make the interactions between distribution unit cost, perfect customer deliveries, and customer rejections and returns very uncertain and have a significant impact on performance (Jaqueta et al. 2020).

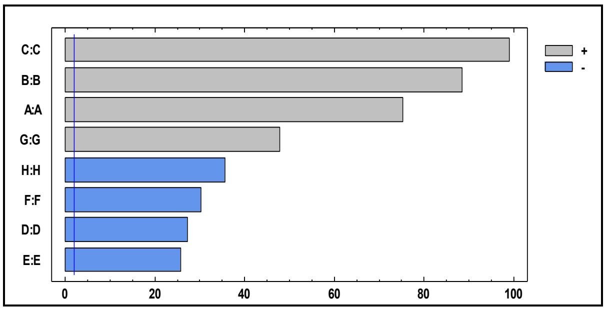

Figure 3: Standardized Pareto Diagram of Effects for Distribution Performance

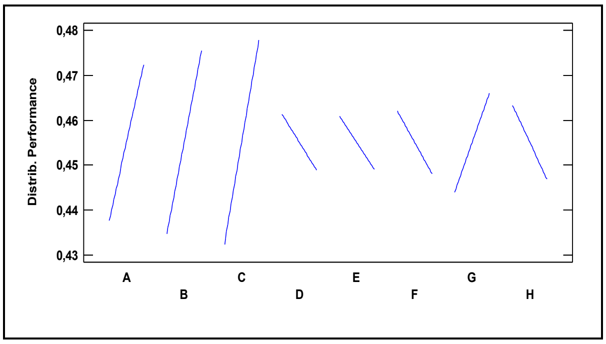

Figure 4: Main Effects Plot for Distribution Performance

CONCLUSIONS

The study of distribution quality management performance in supply chains must go beyond the descriptive approach characteristic of most traditional models. The joint application of simulation and the design of experiments makes it possible to analyze complex or little-studied systems from the perspective of analyzing the impacts of the relationships between variables.

Because the purpose of this work is to analyze the impact of the relationships between factors and that there is a relatively high number of them ($k \geq 5$), the foundations of experimental design recommend using a fractional factorial design. Selecting this type of DOE allowed for obtaining sufficient information to research the effects of the independent variables on the response variable with a reasonable number of runs.

The methodology developed in this research is adaptable to the particular conditions of performance measurement in other supply chains or specific sectors. For its application in a given business sector, it is essential to have historical information that makes it possible to extract knowledge of the variables interrelationship strength by using multivariate descriptive statistical analysis.

The simulation approach of this research focuses on analyzing the variables interrelationship strength as evidence of the quality management performance in the supply chain. Therefore, it is not possible to obtain a mathematical model for predicting the value of the response variable. However, it allows establishing possible degrees of impact of the changes made in one variable with respect to other ones.

This article is a product of ongoing research whose main objective is the application of analytical modeling techniques in Supply Chain Quality Management. Future work is developing predictive models of quality performance in the supply chain from data collected online on the behavior of state variables of the different supply chain stages.

REFERENCES

Akyuz, G. 2011. "Collaborative Quality Management". In *Supply Chain Management - Pathways for Research and Practice*, D. Önkal and E. Aktas (Eds.), Rijeka, InTech 43–56.

Amini, M.; M. Hatwagner; G. Mikulai; and L.T. Koczy. 2021. "Developing a Macroscopic Model Based on Fuzzy Cognitive Map for Road Traffic Flow Simulation." *Infocommunications Journal* 13, No. 3, 14–23. https://doi.org/10.36244/ICJ.2021.3.2.

Antony, J. 2023. *Design of Experiments for Engineers and Scientists*. 3rd ed. Elsevier, London, UK.

Batson, R.G. and K.D. Mcgough. 2007. "New Direction in Quality Engineering: Supply Chain Quality Modelling." *International Journal of Production Research* 45, No. 23, 5455–5464. https://doi.org/10.1080/00207540701325140.

Bautista-Santos, H.; L. Martínez-Flores; G. Fernández-Lambert; M. Bernabé-Loranca; F. Sánchez-Galván; and N. Sablón-Cossío. 2015. "Integration Model of Collaborative Supply Chain." *Dyna* 82, No. 193, 145–154. https://doi.org/10.15446/dyna.v82n193.47370.

Buche, C.; P. Chevaillier; A. Nédélec; M. Parenthoen; and J. Tisseau. 2010. "Fuzzy Cognitive Maps for the Simulation of Individual Adaptive Behaviors." *Computer Animation And Virtual Worlds* 21, 573–587. https://doi.org/10.1002/cav.363.

Chang, K. and L. Grace. 2015. "Optimal Design of Hybrid Renewable Energy Systems Using Simulation Optimization." *Simulation Modelling Practice and Theory* 52, 40–51. https://doi.org/10.1016/j.simpat.2014.12.002.

Chen, J.; F. Tijun; and F. Pan. 2021. "Urban Delivery of Fresh Products with Total Deterioration Value." *International Journal of Production Research* 59, No.7, 2218–2228. https://doi.org/10.1080/00207543.2020.1828638.

Chiadamrong, N., and P. Wajcharapornjinda. 2012. "Developing an Economic Cost Model for Quantifying Supply Chain Costs." *International Journal of Logistics Systems and Management* 13, No. 4, 540–571. https://doi.org/10.1504/IJLSM.2012.050171.

Chopra, S. 2018. *Supply Chain Management: Strategy, Planning, and Operation*. 7th ed. Pearson, New York, NY.

Christoforou, A. and A. Andreou. 2017. "A Framework for Static and Dynamic Analysis of Multi-Layer Fuzzy

Cognitive Maps." *Neurocomputing* 232, 133–145. https://doi.org/10.1016/j.neucom.2016.09.115.

Das, K. and R.S. Lashkari. 2015. "A Supply Chain Product Delivery and Distribution Planning Model." *Operations and Supply Chain Management: An International Journal* 8, No. 1, 22–27. https://doi.org/10.31387/oscm0190129.

Dickerson, J. and B. Kosko. 1994. "Virtual Worlds as Fuzzy Cognitive Maps." *Presence: Teleoperators and Virtual Environments* 3, No. 2, 173–189. https://doi.org/10.1109/VRAIS.1993.380742.

Duman, E. 2007. "Decision Making by Simulation in a Parcel Transportation Company." *Journal of The Franklin Institute* 344, No. 5, 672–683. https://doi.org/10.1016/j.jfranklin.2006.02.030.

Felix, G.; G. Nápoles; R. Falcon; W. Froelich; K. Vanhoof; and R. Bello. 2019. "A Review on Methods and Software for Fuzzy Cognitive Maps." *Artificial Intelligence Review* 52, 1707–1737. https://doi.org/10.1007/s10462-017-9575-1.

Flynn, B. and X. Zhao. 2015. *Global Supply Chain Quality Management: Product Recalls and Their Impact*. CRC Press, Boca Raton, FL.

Foster, S. T. 2008. "Towards an Understanding of Supply Chain Quality Management." *Journal of Operations Management* 26, No. 4, 461–467. https://doi.org/10.1016/j.jom.2007.06.003.

Gutiérrez, H. and R. De La Vara. 2012. *Analysis and Design of Experiments.* 3rd ed. McGrawHill, México.

Jacobs, F., and R. Chase. 2018. *Operations and Supply Chain Management*. 15th ed. McGrawHill, New York, NY.

Jaqueta, S.; E. Mashilo; K. Mocke; and A. Agigi. 2020. "Physical Distribution Challenges and Adaptations: A Qualitative Study of South Africa-Based Organisations Operating in Emerging African Markets." *Journal of Transport and Supply Chain Management* 14, No. 1, 1–16. https://doi.org/10.4102/jtscm.v14i0.475.

Jones, B. and D.C. Montgomery. 2020. *Design of Experiments: A Modern Approach.* John Wiley & Sons, Hoboken, NJ.

Kang, B.; H. Mo; R. Sadiq; and Y. Deng. 2016. "Generalized Fuzzy Cognitive Maps: A New Extension of Fuzzy Cognitive Maps." *International Journal of Systems Assurance Engineering and Management* 7, No. 2, 156–166. https://doi.org/10.1007/s13198-016-0444-0.

Kleijnen, J. and M. T. Smits. 2003. "Performance Metrics in Supply Chain Management." *Journal of the Operational Research Society* 54, No. 5, 507–514. https://doi.org/10.1057/palgrave.jors.2601539.

Kleijnen, J. 2005. "An Overview of the Design and Analysis of Simulation Experiments for Sensitivity Analysis." *European Journal of Operational Research* 164, No. 2, 287–300. https://doi.org/10.1016/j.ejor.2004.02.005.

Law, A. 2015. *Simulation Modeling and Analysis*. 5th ed. McGrawHill, New York, NY.

Law, A. 2017. "A Tutorial on Design of Experiments for Simulation Modeling." In *Proceedings of the 2017 Winter Simulation Conference*, 550–564. Las Vegas, NV, USA.

León, M.; C. Rodriguez; M. García; R. Bello; and K. Vanhoof. 2010. "Fuzzy Cognitive Maps for Modeling Complex Systems." In *Proceedings of 9th Mexican International Conference on Artificial Intelligence - MICAI 2010.* Springer, Berlin, 166–174. https://doi.org/10.1007/978-3-642-16761-4_15.

Lorscheid, I.; B. Heine; and M. Meyer. 2012. "Opening the 'Black Box' of Simulations: Increased Transparency and Effective Communication Through the Systematic Design of Experiments." *Computational and Mathematical Organization Theory* 18, No. 1, 22–62. https://doi.org/10.1007/s10588-011-9097-3.

Moharana, H.; J.S. Murty; S.K. Senapati; and K. Khuntia. 2012. "Coordination, Collaboration and Integration for Supply Chain Management." *International Journal of Interscience Management Review (IMR)* 2, No. 2, 46–50.

Montevechi, J.; R. De Almeida; A. Paiva; R. Costa; and A. Medeiros. 2010. "Sensitivity Analysis in Discrete-Event Simulation Using Fractional Factorial Designs." *Journal of Simulation* 4, No. 2, 128–142. https://doi.org/10.1057/jos.2009.23.

Montgomery, D. 2020. *Design and Analysis of Experiments*. 10th ed. John Wiley & Sons, Hoboken, NJ.

Papageorgiou, E. 2014. *Fuzzy Cognitive Maps for Applied Sciences and Engineering: From Fundamentals to Extensions and Learning Algorithms*. Springer, Berlin. https://doi.org/10.1007/978-3-642-39739-4.

Parast, M. 2013. "Supply Chain Quality Management: An Inter-Organizational Learning Perspective." *International Journal of Quality & Reliability Management* 30, No. 5, 511–529. https://doi.org/10.1108/09574090910954864.

Park, Y. B. 2005. "An Integrated Approach for Production and Distribution Planning in Supply Chain Management." *International Journal of Production Research* 43, No. 6, 1205–1224. https://doi.org/10.1080/00207540412331327718.

Pettersson, A. and A. Segerstedt. 2013. "Measuring Supply Chain Cost." *International Journal of Production Economics* 143, No. 2, 357–363. https://doi.org/10.1016/j.ijpe.2012.03.012.

Rigdon, S.; R. Pan; D. C. Montgomery; and L. Freeman. 2022. *Design of Experiments for Reliability Achievement*. John Wiley & Sons, Hoboken, NJ.

Robinson, C. and M. Malhotra. 2005. "Defining the Concept of Supply Chain Quality Management and Its Relevance to Academic and Industrial Practice." *International Journal of Production Economics* 96, No. 3, 315–337. https://doi.org/10.1016/j.ijpe.2004.06.055.

Sanders, N. 2018. *Supply Chain Management: A Global Perspective*. 2nd ed. John Wiley & Sons, Hoboken, NJ.

Slack, N.; A. Brandon-Jones; and R. Johnston. 2016. *Operations Management*. 8th ed. Pearson, Harlow, UK.

Slack, N. and M. Lewis. 2017. *Operations Strategy*. 5th ed. Pearson, Harlow, UK.

Suard, S.; S. Hostikka; and J. Baccou. 2013. "Sensitivity Analysis of Fire Models Using a Fractional Factorial Design." *Fire Safety Journal* 62, 115–124. https://doi.org/10.1016/j.firesaf.2013.01.031.

Tarashioon, S.; W. D. Van Driel; and G. Q. Zhang. 2014. "Multi-Physics Reliability Simulation for Solid State Lighting Drivers." *Microelectronics Reliability* 54, No. 6–7, 1212–1222. https://doi.org/10.1016/j.microrel.2014.02.019.

Yao, D-Q. and N. Zhang. 2009. "Contract Design for Supply Chain Quality Management." *International Journal of Value Chain Management* 3, No. 2, 129–145. https://doi.org/10.1504/IJVCM.2009.026954.

Yoo, S-H. and T. Cheong. 2018. "Quality Improvement Incentive Strategies in a Supply Chain." *Transportation Research Part E: Logistics and Transportation Review* 114, 331–342. https://doi.org/10.1016/j.tre.2018.01.005.

Yousefi, S.; Mustafa J.; and A. Moradi. 2020. "Causal effect analysis of logistics processes risks in manufacturing industries using sequential multi-stage fuzzy cognitive map: a case study." *International Journal of Computer Integrated Manufacturing* 33, No. 10–11, 1055–1075. https://doi.org/10.1080/0951192X.2020.1747641.

AUTHOR BIOGRAPHIES

JUAN M. COGOLLO-FLÓREZ received the PhD degree in Engineering – Industry and Organizations and the M.Eng. degree in Management Engineering, both from the Universidad Nacional de Colombia. Currently, he is a Full Professor in the Department of Quality and Production, Instituto Tecnológico Metropolitano – ITM, Medellín, Colombia. His research interests include Advanced Statistical Quality Control, Supply Chain Quality Management, Performance Measurement, Fuzzy Modeling, and Process Quality Modeling. His e-mail address is: `juancogollo@itm.edu.co`

ALEXANDER A. CORREA-ESPINAL received the PhD degree in Statistics and Operational Research in 2007 from the Universitat Politècnica de Catalunya (Spain) and the M.Eng. degree in Industrial Engineering in 1999 from the Universidad de los Andes (Colombia). Currently, he is Head of the Department of Organizational Engineering, Universidad Nacional de Colombia, Medellín, Colombia. His current research interests are Advanced Design of Experiments, Statistical Quality Control, and Total Quality Management. His e-mail address is: `alcorrea@unal.edu.co`