A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience

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ABSTRACT:

The on-going offshore outsourcing processes have resulted in complex, global and more vulnerable supply chain to disruptions. However, a good supplier choice would preserve or even improve supply chain resilience. Despite this critical potential effect, this topic remains relatively underdeveloped in the literature. Accordingly, this study proposes a coupled method based on FCM and AHP. The final model shows the impact of locational decision in offshore outsourcing process on supply chain resilience. Moreover, it allows simulating locations scenarios over time through an inference process. The simulations foresee the impacts of three alternative locations on capabilities required in a resilient supply chain. The sensitivity analysis of the findings reveals that one location would improve supply chain resilience meanwhile the others would damage it. This FCM-AHP analysis enhances the understanding of academics and practitioners about the importance of locations criteria and their influence in the supply chain resilience capabilities.

Keywords: Location criteria; Supply Chain resilience capabilities; offshore outsourcing decisions; FCM; AHP.

1. Introduction

Offshore outsourcing process is one of the most adopted strategy in the current and globalized business world. It allows firms to focus on core competencies, to improve their productivity, to gain in efficiency, effectiveness and flexibility, to share risk, to access to specialized resources, to enter into new markets and to a large extent, achieve cost savings. Although promising, this technique is not a panacea to handle all enterprise today-concerns. In fact, outsourcing can add new threats, often unrecognized hazards to the client firms (Johnson, 2006; Kishore & Herath, 2010; Nakatsu & Iacovou, 2009), and by extension, in their supply chains (SC).

Offshore outsourcing implies to transfer ownership business activities and/or processes to low-cost providers outside of the client company country of origin (Hätönen, 2009; Lahiri & Kedia, 2011). The central following question is “where to outsource”. In fact, the provider selected will be a new player in the ever increasing integrated SC. According to Rice & Caniato (2003), ‘the supply network is inherently vulnerable to disruptions and the failure of any one element in it could cause the whole network to fail’. Therefore, an incorrect choice would lead to a very negative repercussion on the entire network.

Offshore outsourcing location decisions would affect the business profitability of client firms, as well as their market position (Gylling, Heikkilä, Jussila, & Saarinen, 2015). However, in many cases, executives have scarce information and limited time to make decisions. In addition, a great variety of criteria should be considered to assess the available alternatives, which largely exceed the humans’ cognitive ability. Multi-criteria decision making approaches have been widely used to assess available alternatives (Lin, Wang, & Qin, 2007; Liu, Berger, Zeng, & Gerstenfeld, 2008). However, each alternative entails hidden risks (Hätönen, 2009), which have not been considered in previous researches.

Nowadays the adoption of lean and agile thinking, globalization and offshore outsourcing processes have contributed to make SC more vulnerable (Carvalho, Barroso, Machado, Azevedo, & Cruz-Machado, 2012; Kamalahmadi & Parast, 2016; Ponomarov & Holcomb, 2009). Most of client firms have already offshored core competencies to suppliers globally dispersed, focusing their efforts on selected key value creating competences. This trend has resulted in a growing SC complexity and interdependency between their entities, which explains the rise of SC vulnerability leading to more frequent disruptions (Rezapour, Farahani, & Pourakbar, 2016; Zeng & Yen, 2016).

A recent study exposes the effects of the Tohoku earthquake (happened in Japan 2011) in Toyota and most of their suppliers (Matsuo, 2015). It stresses the importance of collaborating between SC players to recover to the normal activity. Therefore, certain capabilities can improve SC resilience against unexpected disruptions. More specifically, a resilient SC is capable of anticipating and minimizing negative effects of disruptions, as well as significantly reducing the recovery time needed to return to the normal activity or even to a better state (Blackhurst, Dunn, & Craighead, 2011; Christopher & Peck, 2004; Pettit, Fiksel, & Croxton, 2010; Rice & Caniato, 2003). It is argued that a resilient firm may improve its competitive position and the responsive capability of its SC (Sheffi & Rice Jr, 2005). Hence, SC resilience has been considered an important issue in the location decision making process (Bailey & De Propris, 2014). In spite of this, literature has made little efforts in examining the links between locational decision in offshore outsourcing process and SC resilience.

By focusing on preserving or improving SC resilience from offshore outsourcing location decision-making, this study proposes a combined approach based on Fuzzy Cognitive Maps (FCM) and Analytic Hierarchy Process (AHP). FCM is capable of representing all possible causal connections between criteria considered to assess alternative location, together with capabilities identified in resilient SCs. It has also the ability to deal with uncertain and imprecise data by using fuzzy weights. Likewise, FCM can foresee the impact of alternative locations on SC resilience by simulating scenarios over time.

FCM has also disadvantages. The main difficulty is to assign the weight to the casual links. Some researchers have used a linguistic evaluation (Mourhir et al., 2015; Obiedat & Samarasinghe, 2016). However, the difficulty is only shifted because the question remains on how to translate a linguistic evaluation into a quantitative evaluation. In this paper, we propose to overcome this transformation disadvantage with a new method based on AHP (Ishizaka & Labib, 2011; Saaty, 1980).

The rest of the paper sets the background of the study in section 2. The methodology is described in section 3. Section 4 presents a real case study and Section 5 concludes the paper.

2. Background

2.1 Locational decision in offshore outsourcing process

Location selection has a strategic importance for companies searching to increase their competitiveness, performances and efficiency. However, an erroneous location may cause drawbacks as for example higher transportation costs, loss of qualified labour and difficult administrative processes. Therefore, choosing a suitable location for outsourcing activities is a complex issue that requires a careful and combined analysis of numerous criteria. Vestring, Rouse, & Reinert (2005) claim that each location has its own strengths and weaknesses, therefore a portfolio of locations should be selected to spread the risk. They identify several factors to consider that include operating costs, regulatory environment, domestic markets, engineering talent, political stability, currency fluctuations, facility costs, infrastructure, and language skills.

Due to the plurality of criteria, multi-criteria decision analysis methods have been largely used to solve location selection problems. Gupta, Mehlawat, & Grover (2016) combined VIKOR and trapezoidal intuitionistic fuzzy numbers for selecting a plant location. Decision Making Trial and Evaluation Laboratory (DEMATEL), the Analytic Network Process (ANP) and Multi-Attributive Border Approximation area Comparison (MABAC) have been combined to selecting wind farm locations (Gigović, Pamučar, Božanić, & Ljubojević, 2017). A 2-tuple hybrid ordered weighted averaging (THOWA) has been used for the location selection of city logistics centres (Rao, Goh, Zhao, & Zheng, 2015).

Fuzzy AHP-TOPSIS has been adopted for the selection of thermal power plant location (Choudhary & Shankar, 2012). AHP and ELECTRE have been combined for selecting the location of a dry port location (Ka, 2011). Fuzzy AHP-TOPSIS has been applied for location selection for landfill of industrial wastes. PROMETHEE, TOPSIS and MAUT have been used to select the location of a new casino (Ishizaka, Nemery, & Lidouh, 2013). AHP was used for selecting a plant location (Gothwal & Saha, 2015). As it can be seen, there are a high number of studies on location selection. However, only few have tackled outsourcing location selection. Liu, Berger, Zeng, & Gerstenfeld (2008) have used AHP to select an outsourcing location. Lin, Wang, & Qin (2007) combine AHP and PROMETHEE.

Mihalache & Mihalache (2015) underline that the current research largely considers offshore location decisions from a static perspective. However, they indicate the need to incorporate changing conditions in the foreign locations, including wage levels and skills. This raises the question of whether firms are able to sense and respond to these changing conditions. In order to answer this question, our study uses a FCM coupled with AHP.

2.2 Capabilities in a resilient Supply Chain

SC disruptions are increasingly more frequent. These may lead to an excessive rise in costs, stock-out, delays, inability to serve clients demand, in addition to loss of market position of the firm (Blackhurst, Craighead, Elkins, & Handfield, 2005; Norrman & Jansson, 2004; Yosef Sheffi, 2005; Tang, 2006). These negative effects would be reduced with the presence of resilience capabilities among network members (Craighead, Blackhurst, Rungtusanatham, & Handfiel, 2007). Hence, in the last decades, it had raised among practitioners and academics a growing interest in building more resilient SC and preserving it.

Initially, Christopher & Peck (2004) formulated principles for creating resilient SC based upon a SC (re)engineering, risk management culture, agility and collaboration between entities. With this in mind, Tang (2006) describes robust strategies addressed at improving enterprises capabilities to preserve their operations when an unexpected disruption happens. The dynamic nature of these capabilities strengthens firms and support its readiness, response and faster recovery to the normal activities or even to reach a better standing.

Earlier studies pointed out the capabilities required to make SC more resilient (Chopra & Sodhi, 2004; Pettit, Croxton, & Fiksel, 2013; Ponomarov & Holcomb, 2009; Tukamuhabwa, Stevenson, Busby, & Zorzini, 2015). These are mainly flexibility, redundancy, collaboration, visibility and multiple sourcing (Zailani, Subaramaniam, Iranmanesh, & Shaharudin, 2015). Other works provide comprehensive frameworks on how these capabilities support the disaster management process (Ponomarov & Holcomb, 2009; Scholten, Scott, & Fynes, 2014). Wieland & Wallenburg (2013) focus their attention on how relational capabilities (communication, co-operation and integration) may impact SC resilience. Soni, Jain, & Kumar (2014) go one step further by modelling interdependences between them.

The review of the literature shows that the capabilities required to achieve a resilient SC have been extensively studied. However, these may be affected by other SC management decisions. This is the case for offshore outsourcing process (Bailey & De Propris, 2014; Juttner, Peck, & Christopher, 2003). A recent study describes synergies between driving factors for re-shoring decisions and resilience SC (Soroka, Naim, Purvis, & Hopkins, 2015). From the offshoring process perspective, we provide a hybrid FCM-AHP model for forecasting impacts of alternative locations on SC resilience. Next section explains this new method in detail.

3. Methodology

3.1 Theoretical foundations of FCM

FCM were firstly introduced by Kosko (1986). This artificial intelligence technique is an extension of Cognitive Maps (CM) that integrates characteristics of fuzzy sets and neural networks. Axerold (1976) provided the idea of CM for supporting decision-making. In addition to the important points (called nodes), he added causal connections between them (called edges). CM have been thereafter useful in problem solving when many decisional variables are causally interrelated (Jetter & Kok, 2014) because it can help decision-makers to highlight and analyse hidden relationships that contribute most to reaching relevant and significant solutions.

CM are signed digraphs where only the direction of the change between two nodes is modeled. A positive edge (noted with a positive sign +) indicates that the causal node casually increases or decreases the effect node in its same direction. A negative edge means that the causal node increases or decreases the effect node in its opposite direction.

In contrast to CM, FCM with fuzzy weights has the ability to deal with uncertain and imprecise data. This was introduced to model the intensity of the change when event occurs only to some degree (Kosko, 1986). More specifically, a FCM model is a graph-based knowledge representation (Dickerson & Kosko, 1993) which models a static or dynamic system using causal dependencies between a set of *n* nodes $V = (v_1, v_2, \dots, v_n)$. The intensity of causal connection between pair of nodes $< v_i, v_j >$ is evaluated by assigning fuzzy weights ($w_{i\rightarrow j} \in [-1, 1]$), where v_i is the pre-synaptic (causal) node and v_j is the post-synaptic (effect) node. The entire relationships can be represented in an adjacency matrix (W) with their sign and intensity (1). Three possible types of causal relationships among concepts can be entered in W:

- $w_{i\rightarrow j} > 0$ denotes positive causality, which implies that a change in v_i provokes a modification in v_j in the same direction.

- $w_{i \to j} < 0$ denotes negative causality, which implies that a change in v_i provokes a modification in v_j in the opposite direction.
- $w_{i \to j} = 0$ denotes there is no relationship between v_i and v_j.

$$W = \begin{pmatrix} \cdots & \cdots & \cdots & w_{1\to n} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & w_{i\to j} & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & w_{n\to n} \end{pmatrix} \quad (1)$$

3.2 Building an augmented FCM-AHP model

Different methods can be used to build FCMs. These are normally constructed through a multi-step process, where experts in the domain develop their mental models. In doing so, we propose to combine augmented FCM with AHP.

FCM has already been previously hybridized with diverse techniques for supporting decision-making methods. The driving forces for developing hybrid approaches lies in: A. Avoiding the weaknesses of individual techniques and integrating their strengths; or B. Getting multiplicity of application tasks when a single technique cannot deal with different sub-problems of the given task (Li, Davies, Edwards, Kinman, & Duan, 2002). Table 1 provides a comparison list of hybrid approaches based on FCM and their reason.

Concerning the driving force B, FCM allows to calculate local and/or global weights to be used in TOPSIS, AHP and ANP to assess alternatives (Baykasoğlu & Gölcük, 2015; Nachazel, 2015; Yu & Tzeng, 2006). FCM thus overcomes the problem of interdependence among criteria, as well as the problem of hard questions derived from pairwise comparison. On the other side, AHP allows to determine the initial state vector simulated in the FCM inference process by considering multiple criteria (Biloslavo & Dolinsek, 2010). Primitive Cognitive Network Process (PCNP) measures the initial values of experts to be further process in FCM (Zhou & Yuen, 2014). However, the question of tranforming linguistic evaluations of feedback between FCM variables into quantative evaluations has not been yet tackled.

Table 2. List of hybrid approaches based on FCM

Article	Objectif	Combined techniques	Driving forces	Explanation
(Yu & Tzeng, 2006)	Numerical examples	ANP and FCM	A	FCM estimates global weight vector of ANP
(Biloslavo & Dolinsek, 2010)	Impact of organizational and technological changes on climate-related issues	Delphi, AHP and FCM	A	Delphi tehcinques identify factors, AHP computes the initial state vector then simulated in the FCM inference process
(Shiau & Liu, 2013)	Evaluate transport sustainability strategies	AHP and FCM	B	AHP ranks key sustainable indicators. The 10 first are used in the FCM to build causal-relationships between them
(Asadi, Soltani, Gasevic, Hatala, & Bagheri, 2014)	Determine automated feature model configuration	AHP, FCM and HTN	B	AHP calculates local weights; meanwhile FCM estimates global weights. HTN finds the optimal feature model configuration.
(Zhou & Yuen, 2014)	Measure the factors on box office sales	PCNP and FCM	A	PCNP quantifies the weights of factors to construct a concept in FCM. FCM simulates the influences on each others.
(Ahmadi, Yeh, Papageorgiou, & Martin, 2015)	Managing readiness relevant activities in implementing an ERP system	FAHP, FCM and DEMATEL	B	FAHP computes the readiness contribution weight of activities. FCM determines how these activities interact on each other. The multiplication of both FAHP and FCM inference's results determines the overall ERP readiness. DEMATEL analyses the results of the ERP readiness assessment by using static FCM model.
(Azadeh, Zarrin, Abdollahi, Noury, & Farahmand, 2015)	Evaluating and optimizing the leanness degree of organizations	FDEA, FCM, DEMATEL and AHP	B	FCM and FDEA separately quantify firms leanness and rank them. DEMATEL evaluates impact degree of the leanness factors on each other, and subsequently AHP and DEA ranks them.
(Baykasoğlu & Gölcük, 2015)	Prioritize strategies for transforming higher education systems.	Fuzzy TOPSIS and FCM	A	FCM calculates the attribute weights To be used in TOPSIS to rank alternatives
(Nachazel, 2015)	Decision-making in artificial life	AHP and FCM	A	FCM estimates the weights of criteria used to determine which activity should individual choose with AHP
(Kang, Zhang, & Bai, 2016)	Evaluation of the oil-spill emergency response capability	AHP and FCM	B	FCM and AHP determine the weights in first and second levels of the distribution model, respectively.

The defuzzification is often carried out by using the centroid method, the max aggregation method or the mamdani inference mechanism (Mago, Mehta, Woolrych, & Papageorgiou, 2012). In our paper, AHP generates quantitative evaluations from the linguistic evaluation of the experts (Ishizaka & Nguyen, 2013, Meesariganda & Ishizaka, 2017). Furthermore, this method incorporates a consistency measure, which strengthens the robustness of the final FCM model. Hence, we propose a new combination of FCM and AHP. The main steps in the process are as follows:

Step 1. Experts identify key variables (nodes) that describe a targeted system (or real problem).

Step 2. Experts identify causal connections between nodes ($w_{i \to j}$). This requires to define the type of relationship (positive or negative) between v_i and v_j, as well as the intensity. It can be expressed in form of IF-THEN rules, where the sender or influencing node follows a binary code (ON or OFF) and the receiver or influenced node increases (+) or decreases (-) by a level evaluated using linguistic terms. Thus, one graphical FCM model is obtained for each expert (E_i). This also is formally called adjacency matrix (W^{E_i}).

Step 3. All fuzzy evaluations are mapped into a range [-1,1], where negative number represents negative causalities. Hence, linguistic evaluations need to be translated into this quantitative range. This is a difficult task that has been overlooked in the literature. In this paper, we propose to use AHP (Ishizaka & Labib, 2011; Saaty, 1980) for this transformation. The *n* linguistic terms are pairwise compared in a square matrix A (2) on a 1-9 evaluation scale, where 1 indicates the equal importance and 9 the extreme importance.

$$\mathbf{A} = \begin{bmatrix} 1 & a_{12} & & a_{1n} \\ a_{21} & \dots & a_{ij} & \dots \\ \dots & a_{ji} = 1/a_{ij} & \dots & \dots \\ a_{n1} & \dots & \dots & 1 \end{bmatrix} \quad (2)$$

where a_{ij} is the comparison between the linguistic term *I* and *j*

The matrix is reciprocal $a_{ij} = 1/a_{ji}$ with the diagonal being equal at the unity because the linguistic term is compared with itself. Therefore, only the upper part of the matrix is required from the experts (Ishizaka, 2012). If a matrix is sufficiently consistent, weights are calculated as shown in formula (3) (Ishizaka & Lusti, 2006):

$$AW=\lambda_{max}W \tag{3}$$

where A is the comparison matrix,

λ_{max} is the principal eigenvalue

W is the vector of the weights.

As A has a redundancy of information, the consistency of the entered judgments by the experts can be tested with the consistency ratio (CR):

$$CR=CI/RI \tag{4}$$

where $CI=(\lambda_{max}-n)/(n-1)$ is the consistency index

n is the dimension of the comparison matrix

λ_{max} is the principal eigenvalue

RI is the ratio index.

The ratio index (RI) is the average of the consistency index of numerous randomly filled matrices. Saaty (1977) considers that a consistency ratio exceeding 10% may indicate a set of judgments too inconsistent to be reliable and therefore recommends to revise the evaluations.

Step 4. As experts' models are normally quite different, it may be necessary to use other methodologies to reach a consensus between them such as the Delphi method (Jetter & Kok, 2014; Nalchigar, Nasserzadeh, & Akhgar, 2011) or the augmented method(Ahmadi et al., 2015; Lopez & Salmeron, 2014).

In the augmented FCM method, the adjacency matrices provided by all experts are added to obtain the final diagraph-based FCM model (Dickerson & Kosko, 1993). This approach does not need that experts change their former opinions to obtain a consensus as in the Delphi methodology (Salmeron, 2009). In addition, experts' models are not constrained by a closed list of concepts in such a way to ensure that the final FCM represents all the insights. For these reasons, we propose to use the augmented approach to build the FCM.

The ultimate the aim of the augmented FCM method is to generate the augmented adjacency matrix (W^{AUG}) from the outputs achieved in the previous steps. For this purpose, the W^{E_i} of each expert are added. When more than one participant assign non-zero $w_{i\to j}$ value, then $w_{i\to j}^{Aug} = \sum_{k=1}^{n} w_{i\to j}^{P_k}/n$ where k is the identifier of each participant and n is the number of experts. FCM model also incorporates connections indicated by one expert without the need of any additional transformation. Finally, the augmented graph-based model is drawn in line with the adjacency matrix obtained (W^{AUG}).

3.3 FCM inferences

FCM is not only used to represent a causal reasoning of the phenomenon. It allows also predicting future implications through dynamic simulations of scenarios. For this purpose, FCM incorporates the concept of neurons in the sense that it can be “on” (+1) or “off” (-1) but also states in-between which are fuzzy states. When a node changes its state, it affects all other connected nodes. If the threshold level of the effect node is reached, it will also change state and by consequence may also change further nodes within the network. Already activated nodes may be even altered again due to a feedback loop. By consequence, the activation spreads in a non-linear manner until the system reaches its stability or a chaotic behaviour.

The inference process begins by assigning an input value [0, 1] to each FCM node, which corresponds to the initial state vector:

$$V_{S_i}^0 = (v_1^0 \quad v_2^0 \quad \dots \quad v_{n-1}^0 \quad v_n^0) \tag{5}$$

where v_n^0 points out the value of the node at the instant 0.

During the simulation process, inputs are computed through a finite number of interactions in chain according to the following formula (Stylios & Groumpos, 2004)

$$v_i^{t+1} = f\left(v_i^t + \sum_{i\neq j}^{n} v_j^t \cdot \omega_{j\to i}\right) \tag{6}$$

where v_i^{t+1} is the value of node v_i at the instant $t+1$, $\omega_{i\to j}$ is the fuzzy weight expressing the intensity of causal relationship between nodes v_j and v_i, and $f(x)$ is the transformation function. Researches should assess the existing transformation functions in order to select the one that is most suitable to the requirements of the study.The most commonly applied transformation functions are (Nápoles, Papageorgiou, Bello, & Vanhoof, 2016; Tsadiras, 2008) :

The binary (7) is a discrete function where nodes can be either activated or not. This is capable of representing an increase of a node or a stable behaviour. However, it is not capable of representing a decrease of a node. In this case, chaotic attractor will not be reached in the inference process. Therefore, the binary transformation function should be applied in highly qualitative problems in which only increases and/or stability of nodes are modelled.

$$f(x)=\begin{cases}1, & if\ x<0\\ 0, & if\ x\geq 0\end{cases} \tag{7}$$

The trivalent (8) is another discrete function which can represent an increase, decrease or stable behaviour of a node. It will also not produce a chaotic attractor. This should be thus applied in qualitative problem in where changes in any direction or stability are possible but the degree of change is irrelevant.

$$f(x)=\begin{cases}0 & if\ x<0\\ 1 & if\ x=0\\ -1 & if\ x>0\end{cases} \tag{8}$$

Both the sigmoid unipolar function (9) and the hyperbolic tangent function (10) are continuous transformation functions which can represent any degree of change. Hence, these can be used in qualitative and quantitative problems where the degree of change is relevant. According to (Feyzioglu, Buyukozkan, & Ersoy, 2007), the hyperbolic tangent function is more suitable when fuzzy weights fall within the range [-1, 1].

$$f(x)=\frac{1}{1+e^{-\lambda\cdot x}} \tag{9}$$

$$f(x) = \tanh(x) = \frac{e^{\lambda \cdot x} - e^{-\lambda \cdot x}}{e^{\lambda \cdot x} + e^{-\lambda \cdot x}} \tag{10}$$

The continuous transformation functions use lambda (λ) as a constant for the function slope. Although $\lambda = 5$ has shown to get a good degree of normalization with the sigmoid function (Bueno & Salmeron, 2009), it might tend to approximate outputs to extreme values , i.e. to one or zero, with the hyperbolic tangent function. On the contrary, for smaller values of λ, the hyperbolic function approximates a linear function. Earlier studies (Mago et al., 2012; Miao & Liu, 2000) researched the best λ and suggested $\lambda = 1$.

A new value is calculated with (6) for each node at each time step. FCM inference finishes when the limit vector is reached. This happens when either $V^t = V^{t+1}$ or $V^{t+1} - V^t \leq \varepsilon$; where ε is a residua (Espinosa-Paredes, Nuñez-Carrera, Laureano-Cruces, Vázquez-Rodríguez, & Espinosa-Martinez, 2008). The inference process can also result in a limit cycle. This implies that the vector state continues changing around several fixed states. When continuous transformation function is used [(9) or (10)], a chaotic behaviour is possible (Papageorgiou, 2011). This happens when the inference process finds different outputs for each time step, and therefore, the FCM does not reach stability. In this study, dynamic simulations of scenarios are used to foresee the impact of outsourcing off-shored location decisions on SC resilience.

4. Case study

This section describes a real study of the augmented FCM-AHP method for supporting outsourcing offshore location decision-making considering SC resilience. Unlike empirical studies which pursue generalized findings, case studies have proved to be an excellent vehicle to examine real-life situations in the SCM (Seuring, 2008). In this study, we have been tasked to measure the resilience capacity as regards to the effects of outsourcing location by applying a single and explanatory case study (Yin, 2013).

A single case study research strategy has been sometimes criticized due to questionable generalizability of the results. However, this provide convincing findings especially when the real case selected to provide deep insights that alternative cases may not reveal (Siggelkow, 2007). Our chosen setting is of particular value since it assesses a global SC of spirit drinks with geographically remote locations worldwide. This SC is also characterized by high complexity, where only one SC entity, the focal producer, has more than 30 production facilities worldwide and multiple tiers of both suppliers and customers. In the past, that focal producer made several outsourcing and offshoring decisions. This firm has also implemented practices to improve its resilience capacity.

4.1 A FCM model for supporting offshore outsourcing location decision-making

With the purpose of building the augmented FCM model in mind, we followed the process step-by-step described in Section 3.2. Two participants (experts) took part in the study. They currently occupy the business analyst position and the supply chain manager position in the firm. Through personal interviews of the experts by the authors of this paper, we constructed their diagraph. Our role was to extract their cognitive mapping. This task was quite easy as they worked since a long time on outsourcing and resilience strategies. The identified nodes are given in the Table 2 and Table 3.

Table 3. Criteria considered in the offshore decisions

ID	Criterion
Off1	Quality of the final product
Off2	Transport infrastructure
Off3	Government regulation
Off4	Cultural distance
Off5	Delivery time
Off6	Political risks
Off7	Facility security
Off8	Management cost
Off9	Tax rates
Off10	Transport cost
Off11	Monitoring cost
Off12	Technological infrastructure
Off13	Exchange rates
Off14	Labour cost
Off15	Technical and language skills of employees
Off16	Origin denomination regulatory compliance

Table 4: Capabilities detected in resilient SC

ID	Capability
Res1	Flexibility
Res2	Visibility
Res3	Anticipation
Res4	Recovery
Res5	Security
Res6	Adaptability
Res7	Financial strength
Res8	Market position
Res9	Collaboration

In the second step, they identified the sign, direction and intensity of causal connections between nodes (arcs). In order to define the intensity, we established six linguistic terms {None, Very Weak, Weak, Moderate, Strong, Very Strong}. Experts used them to reflect the influence or strength of the causality ($w_{i \to j}$) between pair of nodes $< v_i, v_j >$.

In the third step, experts carried out a pairwise comparison between linguistic terms using 9 point scale proposed in (Saaty, 1977). Appendix A includes the questionnaire. From the pairwise comparisons, quantitative intensities are obtained with AHP (3). Table 4 shows the derived intensities. The consistency ratio remained below 0.1 for all comparisons matrices. All the experts have the same weights, and therefore the aggregate intensities is simply given by an average of each intensities. We thus reached an adjacency matrix provided by experts (W^{E_i}) which consist of real numbers in the range [-1,1].

Table 5. Linguistics variables and their associated quantitative intensities.

Code	Fuzzy weights	Intensities (Participant 1)	Intensities (Participant 2)	Intensities (Global)
N	None	0	0	0
VW	Very Weak	0.032	0.042	0.037
W	Weak	0.058	0.075	0.066
M	Moderate	0.113	0.141	0.127
S	Strong	0.229	0.266	0.248
VS	Very strong	0.568	0.477	0.522
Inconsistency ratio		0.07	0.007	*0.03*

Finally, we applied step 4 to compute the final adjacency matrix (W^{Aug}). This is given in Table 6. In addition, we drew a graph-based model in line with W^{Aug}. Figure 1 shows the complete FCM, which will be used to forecast the impacts of outsourcing offshore location decisions on SC resilience. Please note that neither of the two experts detected interactions between Off4 and the rest of nodes. Hence, it was not represented in the final FCM model. The graphical representation of the augmented FCM shows the following results:

- The FCM model includes causal connections between outsourcing offshore location criteria (nodes). Managers should pay special attention at the trigger nodes. These are transport infrastructure (Off2), political risks (Off6), tax rates (Off9), technological infrastructure (Off12) and exchange rates (Off13). Their impacts can generate a cascading effect on the rest of the criteria, and therefore their consequences in SC resilience are hard to predict. The dynamic behavior of the FCM may shed light on this matter.
- Outsourcing offshore location decisions may improve or harm the SC resilience. From Figure 1, we can observe that the criteria with the highest number of causal connection are transport cost (Off10) and technological infrastructure (Off12). They impact directly on 4 and 5 capabilities respectively. However, their effects are on an opposite direction. While Off10 exerts a negative effect, Off12 improves SC resilience. Therefore if a company aims to a higher resilience, the selected location should have a high-quality technological infrastructure, and generate low transport costs.
- The capabilities receiving the highest number of causal connections are Res1

(Flexibility) and Res4 (Recovery). As they are both positively and negatively affected by offshoring criteria, the static analysis of the FCM do not provide enough evidence about improvement or harm.

- Furthermore, the indirect connections and hidden patters among nodes should be taken into account to foresee the impact of outsourcing offshore location decision on SC resilience. This issue can be clarified by analyzing the dynamic behavior of the FCM.

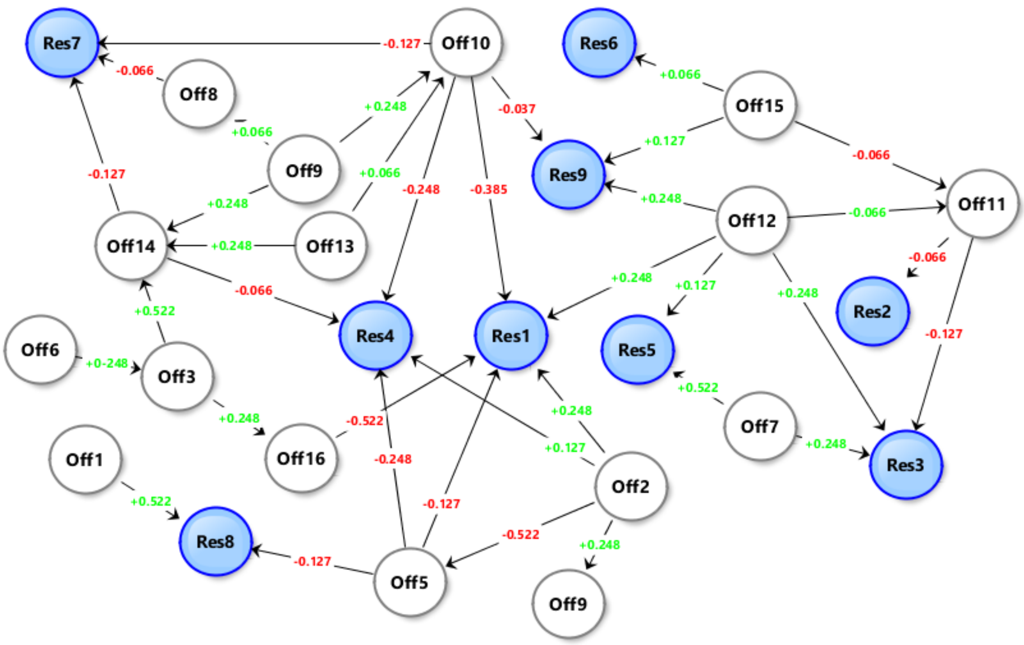


Figure 1. FCM for supporting offshore outsourcing location decision-making

Table 6. Adjacency matrix

ID	off1	off2	off3	off4	off5	off6	off7	off8	off9	off10	off11	off12	off13	off14	off15	off16	Res1	Res2	Res3	Res4	Res5	Res6	Res7	Res8	Res9
off1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,522	0
off2	0	0	0	0	-0,522	0	0	0	0,248	0	0	0	0	0	0	0	0,248	0	0	0,127	0	0	0	0	0
off3	0	0	0	0	0	0	0	0	0	0	0	0	0	0,522	0	0,25	0	0	0	0	0	0	0	0	0
off4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
off5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,127	0	0	-0,248	0	0	0	-0,127	0
off6	0	0	0,248	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
off7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,248	0	0,522	0	0	0	0
off8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,066	0	0
off9	0	0	0	0	0	0	0	0,066	0	0,248	0	0	0	0,248	0	0	0	0	0	0	0	0	0	0	0
off10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,385	0	0	-0,248	0	0	-0,127	0	-0,037
off11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,066	-0,127	0	0	0	0	0	0
off12	0	0	0	0	0	0	0	0	0	0	-0,066	0	0	0	0	0	0,248	0,248	0,248	0	0,127	0	0	0	0,248
off13	0	0	0	0	0	0	0	0	0	0,066	0	0	0	0,248	0	0	0	0	0	0	0	0	0	0	0
off14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,066	0	0	-0,127	0	0
off15	0	0	0	0	0	0	0	0	0	0	-0,066	0	0	0	0	0	0	0	0	0	0	0,07	0	0	0,127
off16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,522	0	0	0	0	0	0	0	0
Res1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Res9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

4.2 Simulating alternative location scenarios

The static analysis of FCM allows only identifying the direct relationships between nodes. We can also evaluate the dynamic behaviour of the model over time by applying an inference process as described in Section 3.3. These results will help managers to foresee the effect of offshoring location decision-making in the resilience of their SC.

The inference process begins by defining the scenarios to be simulated. With this goal in mind, the same experts were consulted. They explain us that the firm can offshore the entire production process of one of their products in either of three different partner facilities. We identify them as location 1, location 2 and location 3. We carried out a moderated group discussion in which experts assessed them. In this way, they assigned a score belonging to the range [0,1] to each outsourcing offshore location criterion included in the final FCM model (Figure1). Each score represents how much a location fulfils a criterion, where 1 means a full fulfilment and 0 no fulfilment. In order to simplify this task, a five-point scale was developed (Table 7). Table 8 shows the location scores given as regards to each criterion.

Table 7. Five-point scale

Score	Expression
0	Standard/Very low
0.25	Fair/Low
0.5	Good/High
0.75	Very good/ Very high
1	Excellent/Extremelly high

Table 8. Location scenarios

	Location 1		Location 2		Location 3	
Node	Score	Description	Score	Description	Score	Description
Off1	0	-	0	-	0	-
Off2	1	Excellent transport infrastructure	0	-	0	-
Off3	0	-	0	-	0	-
Off4	0	-	0	-	0	-
Off5	0	-	0	-	0.75	Very high delivery time
Off6	0	-	1	Extremely high political risks	0.5	High political risk
Off7	1	Excellent facility security	0.25	Fair facility security	0.5	Good facility security
Off8	0.75	Very high management cost	0	-	0	-
Off9	1	Extremely high tax rates	0	-	0	-
Off10	0	-	0.5	High transportation costs	1	Extremely high transportation cost
Off11	0	-	0.5	High monitoring costs	0.5	High monitoring cost
Off12	0.5	Good technological infrastructure	0	-	0	-
Off13	1	Extremely high exchange rates	0	-	0	-
Off14	1	Extremely high labour cost	0.25	Low labour cost	0	-
Off15	1	Employees with excellent technical and language skills	0	-	0.5	Employees with good technical and language skills
Off16	0	-	0	-	0	-

Subsequently, we define the three scenarios, one for each location, at the instant 0, with (5). Each scenario is simulated by computing (5) and W^{Aug} through (6). Given that fuzzy weights are within the range [-1, 1], we applied the hyperbolic tangent function (10) (Feyzioglu et al., 2007; Stylios & Groumpos, 2000) with $\lambda = 1$. Section 3.3 gives a more detailed explanation about the selection of the transformation function. Scenarios 1, 2 and 3 reached stability after 121, 123 and 185 time steps respectively, with $\varepsilon \leq 0.0001$. Table 9 presents the results obtained in the inference process.

Table 9. Results of the simulation of Location 1, 2 and 3

	Location 1		Location 2		Location 3	
Nodes	Input	Output	Input	Output	Input	Output
Off1	0	0.000	0	0.000	0	0.000
Off2	1	0.154	0	0.000	0	0.000
Off3	0	0.000	0	0.468	0	0.436
Off5	0	-0.580	0	0.000	0.75	0.125
Off6	0	0.000	1	0.153	0.5	0.123
Off7	1	0.154	0.25	0.132	0.5	0.123
Off8	0.75	0.436	0	0.000	0	0.000
Off9	1	0.469	0	0.000	0	0.000
Off10	0	0.653	0.5	0.148	1	0.126
Off11	0	-0.387	0.5	0.148	0.5	-0.291
Off12	0.5	0.149	0	0.000	0	0.000
Off13	1	0.154	0	0.000	0	0.000
Off14	1	0.688	0.25	0.766	0	0.754
Off15	1	0.154	0	0.000	0.5	0.123
Off16	0	0.000	0	0.638	0	0.626
Res1	0	-0.613	0	-0.844	0	-0.844
Res2	0	0.539	0	-0.311	0	0.376
Res3	0	0.651	0	0.341	0	0.549
Res4	0	-0.477	0	-0.591	0	-0.632
Res5	0	0.614	0	0.554	0	0.543
Res6	0	0.316	0	0.000	0	0.291
Res7	0	-0.731	0	-0.638	0	-0.631
Res8	0	0.563	0	0.000	0	-0.358
Res9	0	0.450	0	-0.258	0	0.319

4.2.1 Results of simulation of scenario 1

The simulation of the scenario 1 shows how the outsourcing of the production process in location 1 may affect SC resilience of the firm studied. In order to a better understand about it, the appendix B shows a detailed analysis how this simulation may impact on other location criteria. Focusing our attention on resilience capabilities, Figure 2 shows the effects of this simulation over time. Capacities reach stability in the range of -0.731 to 0.651. This scenario alters all resilience capabilities with both positive and negative influences. More specifically, the anticipation (Res3) reached the highest positive value (0.651). This is due to the negative impact of the monitoring cost required (Off11) that is smaller than the positive influences of an excellence facility security (Off7) and a good technological infrastructure (Off12). The SC security (Res5) receives a very similar impact (0.614) due to the positive effects of Off7 and Off12. In addition, market position (Res8) also obtains a positive slightly higher influence (0.563), which might be caused by the decrease in delivery time (Off5). The other side of the coin is the financial strength. Outsourcing the production process in location 1 may highly damage the SC financial strength (Res7 = -0.731). The effect of extremely high taxes (Off9) and exchange rates (Off13) may trigger a cascade of effects on the transport cost (Off10) and the labour cost (Off14). All this taken together, the very high rise of management cost (Off8) explains the negative repercussion of location 1 on the financial strength. However, this does not mean that outsourcing offshore the production in location 1 generates economic loss, even if it requires very high economic efforts.

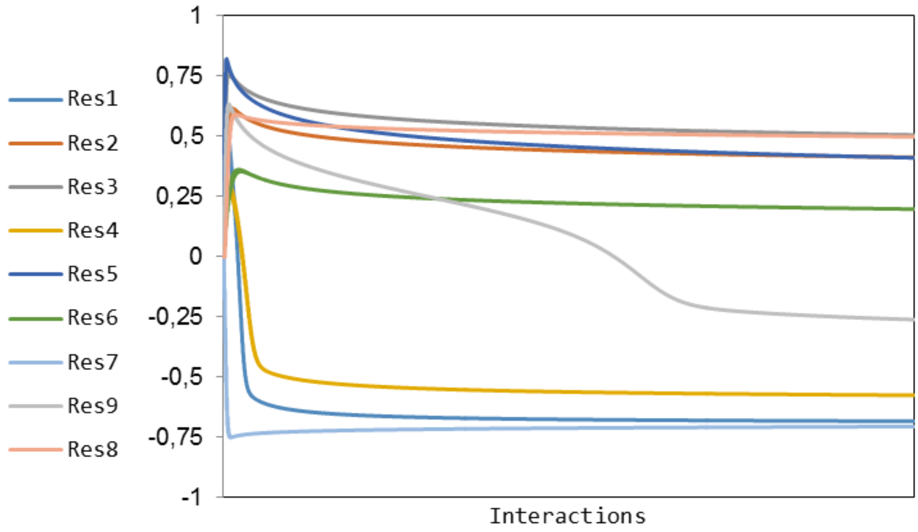


Figure 2. Results of simulating location 1 on resilience capabilities.

4.2.2 Results of simulation of scenario 2

The simulation of the scenario 2 displays how outsourcing the production process in location 2 may influence SC resilience. A more detailed about effects in no activated location criteria is presented in Appendix B.Figure 3 represents the impacts of that location on resilience capacities.The simulation of scenario 2 did not have any impact on the adaptability (Res6) and the market position (Res8). The other resilience capabilities reaches values in the range of -0.844 to 0.554. Results reveal that location 2 leads to moderate improvement in security (0.554) and a slightly moderate improvement in anticipation (Res3 = 0.341). The other effects on the resilience capabilities were negatives. The flexibility (Res1) received the highest negative impact (-0.844). The high transportation cost (0ff10) and the ripple effect caused by the high political risks (Off6) would explain this high loss of SC flexibility. Moreover, as in scenario 1, we can observe a negative impact on financial strength in a lower magnitude (-0.638). This happens because the lower taxes, exchange rates and labour costs offset the increase in transportation costs.

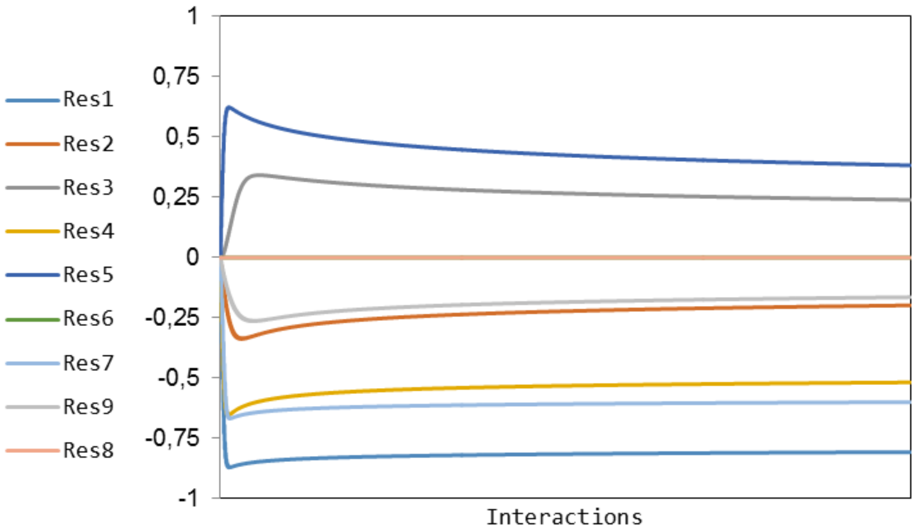


Figure 3. Results of simulating location 2 on resilience capabilities.

4.2.3 Results of simulation of scenario 3

The simulation of the scenario 3 indicates how outsourcing the production process in location 3 may affect SC resilience of the firm studied. Appendix B presents impacts on no activated location criteria.On the resilience capacities side, figure 4 shows that all nodes were altered. Their values are within the interval [-0.844, 0.549]. As in scenario 1, the anticipation (Res3) was the most strongly affected, although its intensity was moderate in scenario 3 (0.549). This can be explained by the indirect and positive effect of employees with good technical and language skills (Off15) from location 3. The simulation of scenario 3 also exerted a moderate positive influence in Res5 (0.543). This might be the consequence of a good facility security from location 3 (Off7). As in scenario 2, the flexibility suffered the highest negative impact (-0.844). Moreover, financial strength (Res7) was again negative and slightly more affected (-0.631). A very different result is reached by the market position capability (Res8). Results point out that when the production process is offshored in location 3, Res8 is negative and slightly moderately damaged (-0.358). This is due to in the very high delivery time (Off5) of location 3.

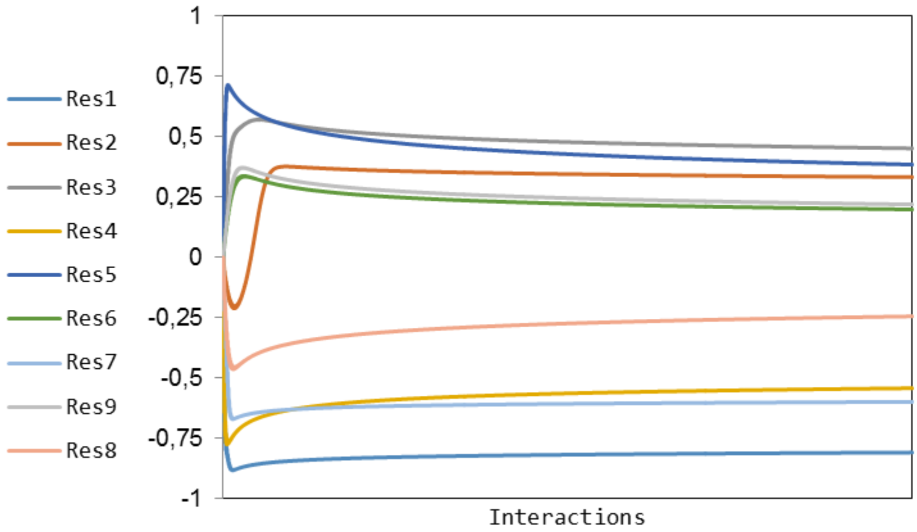


Figure 4. Results of simulating location 3 on resilience capabilities.

4.2.4 Sensitivity analysis of location impacts on SC resilience capacities

The comparison between the impacts of three location on the SC resilience highlights relevant issues. Figure 5 depicts how the scenarios influence each resilience capability. Depending on the scenario simulated, these are improved, preserved or damaged.

The three locations may impact negatively on **Flexibility**. It is interesting to note that location 2 and 3 have exactly the same influence (-0.844), while location 1 generates a lower effect (-0.613). This is due to the positive effect of Transport infrastructure and Technological infrastructure only activated in location 1. However, it is not enough to compensate the high cost caused by Tax rates and Exchange rates in location 1. Hence, if managers seek to preserve or improve the Flexibility, the location should provide a good Tax rates and Exchange rates, as well as reduced transport cost and delivery time.

Regarding the **Visibility**, location 1 has a positive moderate influence with (0.539), whereas location 3 causes a slightly lower impact (0.376). Location 2 presents a negative effect (-0.311). The positive impacts implied by location 1 and 3 are found despite the unfavourable and direct effect of the Monitoring cost. This is probably due to the activation of the Technological infrastructure and the Technical and language skills of employees, which are at a good and excellent levels in scenario 1, respectively. Hence, if managers aim to improve or preserve a high Visibility, they should choose location 1. Location 3 ranks at the second position because it provides a good level of Technical and language skills of employees and a standard Technological infrastructure, as well as a high Monitoring cost. If we just consider the Visibility, location 2 should be discarded, since the effect of their high Monitoring cost is not compensated by the standards of the Technological Infrastructure and the Exchange rates.

The three locations may have a positive impact on the **Anticipation**. Location 1 is again ranked at the first position with a slightly high improvement (0.651). In fact, scenario 1 presents an excellent Facility security, whereas scenario 3 and 2 show a good and fair Facility security respectively. Hence, location 3 reaches the second position and location 2 the last one.

The three locations may damage the **Recovery**. Scenario 1 affects moderately negatively the Recovery (-0.477). Although location 1 relies on an excellent Transport infrastructure, their extremely high labour cost makes the Recovery difficult. Scenario 2 exerts a negative high influence on the Recovery (-0.591). This is due to a high Transport cost and low Labour cost. The highest damage on the Recovery is observed in Scenario 3. The effect of a very high Delivery time and extremely high Transport cost explains its negative high influence (-0.632). Therefore, if the aim of the firm is to improve or preserve the Recovery, it should rule out all the three locations. With that goal in mind, managers should select a location with low level of Delivery time, Transport cost and Exchange rates and a good Transport infrastructure.

Concerning the **Security**, all the three locations may have a positive impact. The Facility security and the Technological infrastructure can directly cause improvements on the Security. From this standpoint, location 1 is also ranked at the first position with a slightly high improvement (0.614). This is due to an excellent Facility security and good Technological infrastructure. Location 2 and 3 generates almost identical impact, respectively 0.554 and 0.543. Hence, location 2 reaches the second position and location 3 the last one.

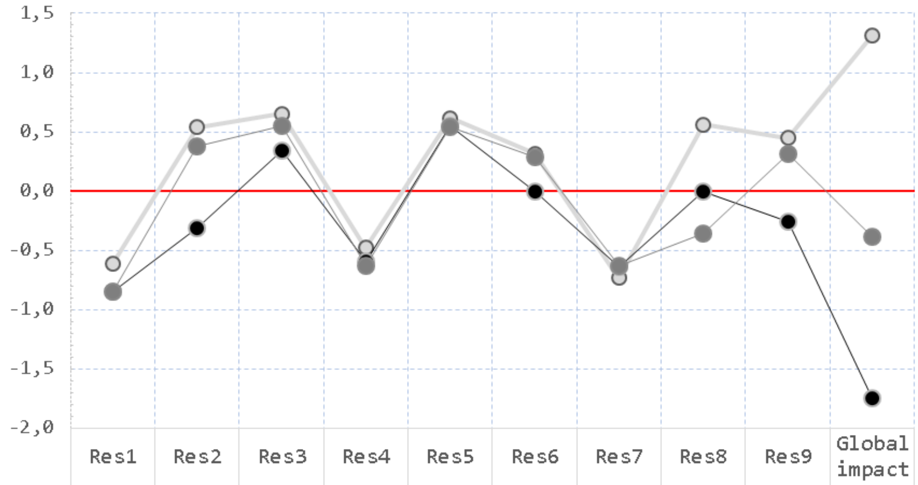
Adaptability may be only improved with a slightly moderate intensity by the scenario 1 (0.316) and 3 (0.291). Scenario 2 does not impact the Adaptability. This is explained by the direct effect of Technical and language skills of employees. Locations 1 and 3 have respectively an excellent and good Technical and language skills of employees. Therefore, they are ranked at the first two positions.

The three locations may cause a loss on the **Financial strength**. If we see Figure 1, the Financial strength is directly affected by the location criteria related to offshore location costs. Hence, an economic effort is required by the location decision. Accordingly, managers should firstly choose location 3 (-0.631) followed by location 2 (-0.638) and location 1 (-0.731).

Regarding the **Market position**, the three locations may lead to widely disparate effects. Location 1 may cause a moderate improvement in the Market position (0.563), whereas location 2 does not have any influence. The positive effect of location 1 is explained by the indirect effect of good Technological infrastructure on the Market position. However, location 3 presents a slightly negative effect (-0.358). This is due to its very high Delivery time. Therefore, if managers pursue to improve the Market position, they should choose location 1.

The **collaboration** has a positive moderate improvement (0.45) in location 1, whereas location 3 causes slightly lower moderate impact (0.319). Location 2 has a negative effect (-0.258). This is explained by the direct negative action of a high Transport cost. The finding of location 3 are positive despite the unfavourable direct effect of the Transport cost. This may be compensated by the positive effect of the good Technical and language skills of employees in scenario 3. At the contrary, location 1 presents a good Technological infrastructure and excellent Technical and language skills of employees. Therefore, if managers pursue to improve or preserve the Collaboration, they should choose locations 1 and 3 in the first and second place, respectively.

By adding all effects caused by each location, we thus obtain their **global impact**. The findings highlight that when the firm offshore the production process in location 1, SC resilience may be improved. At the contrary, location 2 and 3 may damage it. Hence, from a resilient SC point of view, the firm studied should chose location 1.



	Res1	Res2	Res3	Res4	Res5	Res6	Res7	Res8	Res9	Global impact
Location 1	-0,613	0,539	0,651	-0,477	0,614	0,316	-0,731	0,563	0,450	1,312
Location 2	-0,844	-0,311	0,341	-0,591	0,554	0,000	-0,638	0,000	-0,258	-1,746
Location 3	-0,844	0,376	0,549	-0,632	0,543	0,291	-0,631	-0,358	0,319	-0,387

Figure 5. Results of sensitivity analysis of location effects in resilience capacity.

5. Conclusions

Outsourcing is a technique that has been used since a long time. However, today its usage has sharply increased and its associated risks too. In this paper, we have developed a new framework to assess the impact of outsourcing practices on the SC resilience capabilities. It is based on the hybridation of FCM and Analytic Hierarchy Process. The new hybrid method is capable of quantifying the uncertainty in causal connections in a precise way. The main methodological contribution is the precise transformation of linguistic evaluations into quantitative ones with AHP. It is to note that constructing the FCM is not an easy task. In our case study, this exercise has not been difficult because the experts worked a long time on the outsourcing problematic and resilience capabilities.

The proposed method can support practitioners while evaluating alternative outsourcing locations according to their impacts on the SC resilience. Experts perceived the main advantage of the proposed method in the ability to predict effects due to indirect implications, which are otherwise very difficult to predict, especially for large models. In fact, in our case, one location would improve resilient capabilities and two locations would rather damaged it. Such location behavior could not been predicted without our simulation.

The simulations also highlight that offshore outsourcing processes may damage Flexibility, Financial strengths, and Recovery capacity of SC. These damages are explained by the negative influences of the Delivery time, Tax rate, Exchange rate, Transport cost and Labor costs. Hence, if practitioners pursue to preserve those capabilities, they should choose the location, which significantly reduces the above-mentioned criteria. On the contrary, the results reveal that offshore outsourcing processes may reinforce Security and Anticipation capabilities. This happens when the location has a good Technological infrastructure and the Facility security. The above-mentioned criteria should thus have hight weights.

It would be very relevant for practitioners to know when the FCM predictions will happen (in the short, half or long term). However, the inference mechanism of FCM lacks a measure of time. To overcome this weakness, new hybrid methods would be developed in future studies.

For academics, this paper provides a groundwork for further studies because it is the first time that a research shows how offshore outsourcing location decision-making can improve, preserve or damage SC resilience. Looking to the future, empirical works would validate the influences detected. In addition, the developed hybrid method is generic, flexible and easily adaptable. Therefore, it could be applied easily to other sectors to represent messy problems with causalities and predict future outcomes.

Appendix A. Extract of the questionnaire

Circle one number per row below using the scale:
1 = Equal 3 = Moderate 5 = Strong 7 = Very strong 9 = Extreme
2, 4, 6, 8 are intermediate values

Compare the relative performance of one **linguistic term** with **all other linguistic terms** to determine the strength of relationship between FCM nodes.

None	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very Weak
None	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Weak
None	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Moderate
None	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Strong
None	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very strong
Very Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Weak
Very Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Moderate
Very Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Strong
Very Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very strong
Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Moderate
Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Strong
Weak	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very strong
Moderate	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Strong
Moderate	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very strong
Strong	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Very strong

Appendix B. Detailed analysis of the simulation effects in no location criteria activated

Node	Location 1		Location 2		Location 3	
	Output	Explanation	Output	Description	Output	Description
Off1	0.000	NA	0.000	NA	0.000	NA
Off2	0.154	CA	0.000	NA	0.000	NA
Off3	0.000	NA	0.468	The extremely high political risks might cause its moderate rise.	0.436	The extremely high political risks might cause its moderate rise.
Off5	-0.580	Moderately reduced, since location 1 is near to the main market of the product. Indeed, this does not regress the units produced to the client firm, but go straight to their channels of distribution.	0.000	NA	0.125	CA
Off6	0.000	NA	0.153	CA	0.123	CA
Off7	0.154	CA	0.132	CA	0.123	CA
Off8	0.436	CA	0.000	NA	0.000	NA
Off9	0.469	CA	0.000	NA	0.000	NA
Off10	0.653	Slightly higher by the extremely high taxes and exchange rates existing in location 1.	0.148	CA	0.126	CA
Off11	-0.387	These are driven down although with a moderate intensity. The technological infrastructure and high-qualified employees in location 1 make this task easier.	0.148	CA	-0.291	CA
Off12	0.149	CA	0.000	NA	0.000	NA
Off13	0.154	CA	0.000	NA	0.000	NA
Off14	0.688	CA	0.766	CA	0.754	High increase due to the indirect effect of high political risks.
Off15	0.154	CA	0.000	NA	0.123	CA
Off16	0.000	NA	0.638	Slightly high increase due to the indirect effect of extremely high political risks.	0.626	Slightly high increase due to the indirect effect of extremely high political risks.

Note: NA: Not Altered
CA: Criterion activated

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