Transactions on Data Analysis in Social Science 3(3) (2021) 150–158

ISSN Online: 2821-1936

Transactions on Data Analysis in Social Science

Journal Homepage: https://transoscience.ir

Modeling the Assessment of Supply Chain Agility in Urban Search and Rescue Organizations: A Case Study of Tehran Fire Department

H. Amin Tahmasbi[1,*], S. J. Razavi Nasab[2], R. Narimani Nasab[3]

[1] Assistant Professor, Department of Industrial Engineering, Faculty of Engineering, Shahrekord University, Iran
[2] Ph.D. Student in Industrial Management - Production and Operations, Islamic Azad University, Bandar Anzali International Branch, Iran
[3] Ph.D. Student, Islamic Azad University, Bandar Anzali International Branch, Iran

ARTICLE INFO

Article History:
Received 5 June 2021
Received in revised form 19 August 2021
Accepted 1 September 2021
Available online 7 September 2021

Keywords:
Supply Chain, Agility, Hybrid Modeling.

ABSTRACT

Agility refers to the ability to respond to unforeseen changes for proactive decision-making based on adaptability. Organizational agility consists of responsiveness, competence, flexibility, and speed components. Today, the quality of providing urban search and rescue services depends on their agility in unforeseen circumstances, requiring attention to these capabilities and capacities. In recent years, minimal efforts have been made to manage and design agile supply chain operations in crisis-oriented organizations, especially firefighting departments in the country. This article focuses on the agility of the supply chain in the fire department, utilizing a novel approach based on Adaptive Neuro-Fuzzy Inference System (ANFIS) in two dimensions: agility capabilities (flexibility, competence, cost, responsiveness, and speed) and agility enablers (collaborative relationships, process integration, information integration, stakeholder sensitivity). Ambiguity and complexity in the characteristics of agility, especially qualitative indicators, and the use of variables derived from experts' experiential knowledge highlight the necessity of using fuzzy logic to analyze the model's component information. By comparing the values obtained from the designed ANFIS in two dimensions of agility with the agility factor matrix, the agility position in the studied organization is located in the B region (potential agility). This assessment informs managers about the gap analysis between the current and desirable levels of agility, indicating that the organization is relatively well-equipped in terms of agility infrastructure, and in the near future, a higher level of agility can be predicted for its supply chain. Additionally, this research designs a dynamic model based on state-space equations and transformation functions to observe and investigate the dynamic behavior of supply chain agility over time. This model allows the organization to predict agility levels for future periods. In the presence of a gap between the current and desirable states, investments can be made to increase agility levels.

* Corresponding Author: Amintahmasbi@guilan.ac.ir
Assistant Professor, Department of Industrial Engineering, Faculty of Engineering, Shahrekord University, Iran

http://dx.doi.org/10.47176/TDASS.2021.150

1. INTRODUCTION

In recent decades, the growing complexity and dynamism of urban environments have highlighted the need for rethinking crisis management approaches and the role of emergency response organizations. One of the key concepts in this area is supply chain agility, which refers to an organization's ability to respond rapidly, flexibly, and effectively under uncertainty and turbulent conditions [1]. Although initially developed in the context of manufacturing industries, the concept has been extended to the public sector and humanitarian operations, including emergency response [2].

In urban crisis management, particularly in urban search and rescue (USAR) operations, the supply chain plays a crucial role in ensuring access to resources, equipment, and information within the shortest possible time [3]. Emergency response organizations operate in high-risk, uncertain environments, where the agility of their supply chains can determine the success or failure of missions [4].

Research indicates that supply chain agility in emergency and disaster contexts encompasses factors such as flexibility in procurement, speed of resource allocation, inter-organizational coordination, and the use of advanced information technologies [5-6]. Moreover, megacities such as Tehran face unique challenges including population density, vulnerable infrastructure, and frequent exposure to natural and man-made hazards, all of which intensify the necessity of modeling and assessing supply chain agility within their emergency response systems [7-8].

Specifically, the Tehran Fire Department, as one of the city's most vital USAR organizations, plays a critical role in responding to emergencies such as fires, earthquakes, and urban accidents. Developing a framework for modeling the assessment of supply chain agility in this organization could provide a pathway to improving operational performance, strengthening responsiveness, and enhancing urban resilience in times of crisis [9].

2. LITERATURE REVIEW

The increasing frequency of urban disasters has necessitated the development of agile supply chain frameworks, particularly in humanitarian contexts such as urban search and rescue (USAR) operations. The Tehran Fire Department serves as a pertinent case study, given its critical role in emergency management. This literature review synthesizes existing research on supply chain agility, particularly in the context of USAR, while identifying knowledge gaps and suggesting future research directions.

Agility in supply chains refers to the ability to respond swiftly and effectively to changing conditions. Singh et al. (2018) explored the interaction of factors impacting resilience in humanitarian supply chains, highlighting the need for flexibility and rapid decision-making in disaster scenarios. Their findings indicate that a resilient supply chain can significantly enhance the effectiveness of humanitarian operations, but the specific mechanisms through which agility is cultivated remain under-researched [10].

Similarly, Patel and Sambasivan (2021) provided a systematic review of supply chain agility literature, emphasizing the importance of agility in managing disruptions. They noted that while theoretical frameworks exist, empirical studies focusing on specific sectors like USAR are limited. This gap underscores the necessity for tailored research that addresses the unique challenges faced by urban rescue organizations [11].

Various methodologies have been proposed for assessing supply chain agility. Vinodh et al. (2013) presented an agile supply chain assessment model applied in the automotive components sector, illustrating a structured approach to evaluating agility. The adaptability of such models to the context of USAR remains unexplored, indicating a potential avenue for future research [12].

Alimardani et al. (2013) introduced a hybrid SWARA and VIKOR methodology for supplier selection in agile environments. Their approach highlights the integration of qualitative and quantitative criteria, which could inform similar frameworks in USAR settings. However, the application of these methodologies in emergency management contexts requires further investigation to confirm their efficacy [13].

The integration of technology, particularly in Supply Chain 4.0, has been identified as a critical factor in enhancing agility. Sobb et al. (2020) surveyed cybersecurity challenges within Supply Chain 4.0, suggesting that technological advancements can facilitate quicker responses to emergencies. The potential for technology to bolster USAR operations is an area ripe for research, especially concerning the operational realities faced by organizations like the Tehran Fire Department [14].

Kruijff et al. (2014) explored human-robot collaboration in urban search and rescue, demonstrating how technology can be leveraged to enhance operational efficiency. Their findings suggest that integrating advanced technologies into traditional supply chain models can significantly improve agility. However, empirical studies that assess the impact of such integrations specifically within USAR contexts remain sparse [15].

Effective risk management is crucial for maintaining supply chain resilience. Kumar and Anbanandam (2020) investigated the impact of risk management culture on supply chain resilience in the Indian manufacturing sector, revealing that a robust risk management framework can significantly mitigate disruptions. The application of similar risk management principles in the context of USAR operations is an open question, as existing literature primarily focuses on commercial sectors rather than humanitarian responses [16].

Dasaklis et al. (2017) highlighted the importance of emergency supply chain management during public health crises, such as smallpox outbreaks. Their findings suggest that adaptability and preparedness are essential for effective emergency responses. However, the intersection of these principles with urban rescue operations has not been sufficiently explored [17].

The literature on supply chain agility in humanitarian operations, particularly in urban search and rescue organizations, highlights several critical insights while revealing significant gaps. As urban disasters continue to pose challenges globally, future research must focus on developing tailored models and frameworks that enhance the agility and effectiveness of organizations like the Tehran Fire Department. Addressing these gaps will not only contribute to academic discourse but also improve practical outcomes in emergency management.

3. RESEARCH METHODOLOGY

The effort has been made to extract agility indicators in the supply chain by studying relatively comprehensive literature in two domains: capabilities and enablers. These indicators are then presented as a conceptual model based on a logical pattern. Generally, three types of questionnaires have been used in this research. The first questionnaire, designed as a fuzzy Delphi technique, is used to extract the components of agility. The second questionnaire is designed for the validation of the conceptual model and consists of 12 questions, a combination of open and closed-ended questions. The final questionnaire is designed to measure agility components (inputs to ANFIS) in the studied organization and includes 16 closed-ended questions for design, distribution, and collection. The questionnaires include an introduction to explain the research objectives and attempt to gain the cooperation of respondents. Operational definitions of each concept are also provided in the relevant questions.

In this research, considering the characteristics mentioned for members of the expert group, the following steps were taken in the statistical population.

1.3 Linguistic Variable Definition:

Experts were asked to express their agreement through linguistic variables. Since individuals' different characteristics affect their mental interpretations of qualitative variables, by defining the range of qualitative variables, experts with the same mindset responded to the questions. Fuzzy numbers corresponding to the linguistic variables used are shown in Table 1.

Table 1. Triangular fuzzy numbers and verbal variables

Fuzzy Number	Linguistic Variable	Triangular Fuzzy Number
1	No effect	(0, 0, 0.25)
2	Very low impact (VL)	(0, 0.25, 0.5)
3	Low impact (L)	(0.25, 0.5, 0.75)
4	High impact (H)	(0.5, 0.75, 1)
5	Very high impact (VH)	(0.75, 1, 1)

To convert fuzzy numbers from Table 1 into crisp numbers, the Mamdani's formula according to Equation (1) is used [14]. In this equation, X represents the crisp value of the fuzzy number, m is the centroid triangular value, β is the right domain, and α is the left domain.

$$X = m + \frac{\beta-\alpha}{4} \quad (1)$$

1.3. First-stage Survey

In this stage, the selected components were sent to the expert group members, and their level of agreement with each component was obtained. Their suggested and corrective opinions were summarized. Considering the proposed options and linguistic variables defined in the questionnaire, the fuzzy average for each component was calculated based on the following relationships [18].

$$A_1 = (a_1^{(i)}, a_2^{(i)}, a_3^{(i)}), i = 1,2,3,\dots n \quad (2)$$

$$A_{ave} = (m_1, m_2, m_3) = (\frac{1}{n}\sum_{i=1}^{n} a_1^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a_2^{(i)}, \rightleftarrows \frac{1}{n}\sum_{i=1}^{n} a_3^{(i)}) \quad (3)$$

In Equation (2), Ai represents the viewpoint of expert i, and A_{ave} represents the average viewpoints of the experts. a_1, a_2, a_3 are fuzzy triangular numbers.

1.4. Second-stage Survey

In this stage, while making necessary changes to the agility components, a second questionnaire was prepared. It was sent again to the expert group members along with their previous opinions and the degree of difference from the average opinions of others. The threshold is calculated using the following formula:

$$A_{m2} \rightleftarrows, A_{m1}) = \left|\frac{1}{3}[(a_{m21} + a_{m22} + a_{m23}) - (a_{m11} + a_{m12} + a_{m13})]\right| \quad (4)$$

Equation (4) represents the expert opinions in the second stage, where (a_{m21},a_{m22},a_{m23}) indicate the opinions of experts in the second stage, and (am11, am12, am13) represent the opinions of experts in the first stage. The difference in opinions between the two stages is denoted by S (A_{m2}, A_{m1}).

1.5. Neural-Adaptive Learning Techniques

These techniques prepare a method for fuzzy modeling to train information, finding membership function parameters in a way that the fuzzy inference system leads to the best mapping from the input space to the output space. The parameters of membership functions in this system are adjusted using the backpropagation method alone or in conjunction with the least squares method. This allows us to train the system based on the information that models an object. The inference system has four inputs representing collaborative relationships (e1), process integration (e2), information integration (e3), and sensitivity to stakeholders (e4). Its output is the level of supply chain agility enablers [19].

To consider the time dimension in the model and observe changes in enablers and capabilities and their impact on agility, dynamic system modeling can be performed. The changes resulting from the interaction of variables and the identification of their future behaviors are examined in different time periods. The variables of influence level, time of influence, decay time, and influence frequency are obtained based on expert opinions and in fuzzy values using linguistic variables. If x exists and y exists, the effect of component i on J is considered linearly [19,20].
If there is an influence frequency (f) and y exists, the effect is considered quadratic. In a group opinion, some experts express their views on the transformation function G(s). The transformation function G(s) models the Laplace transform relationship between the input and output of each component. Since the number of experts is more than one, group decision-making techniques, including averaging membership functions, are used to aggregate their opinions to determine the final values of the G(s) function. Since the number of experts (n) has expressed opinions about the parameters of the transformation function, the information must be unified for use in modeling and having the transformation function. Suppose m experts have expressed fuzzy numerical opinions about one of the G(s) parameters.

For modeling, the total opinions of these m experts about each of the parameters are summarized and calculated in the form of a single opinion. To calculate the final membership function values for each element of the reference set U, the following relationship is used for experts:

$$\mu_{FJ} = \frac{1}{m}\sum_{i=1}^{m} \mu_{ij} \quad (5)$$

The final value of the desired parameter can be determined using the following relationship :

$$V_F = \left\{ \frac{\mu_{F1}}{x_1}, \frac{\mu_{F2}}{x_2}, \ldots . \frac{\mu_{Fn}}{x_n} \right\} \quad (6)$$

Equation (6) is used to determine the final fuzzy value of the desired parameter, where V_f is the fuzzification of the parameter in relation to two elements, and μ_{Fj} is the final aggregated fuzzy value of experts' opinions about the membership of element X_j in the universal set.

After determining the aggregated fuzzy values from the experts' perspectives, the obtained values can be defuzzified using one of the de-fuzzy/fuzzy elimination techniques. In this research, the center of gravity method is used for fuzzy elimination, and the center of gravity formula is as follows:

$$Z^* = \frac{\sum_{j=1}^{n} \mu_A(xj).xj}{\sum_{j=1}^{n} \mu_A(xj)} \quad (7)$$

This relationship is considered one of the most effective methods for fuzzy defuzzification [10 and 16]. To assess the validity of the designed dynamic model, statistical tests can also be employed. In this method, selected experts are asked to express their opinions on the output (agility) by considering various inputs (capabilities and agile enablers) in specified time periods. Subsequently, the available opinions are compared with the actual outputs of the designed system. For this purpose, the sign test can be used to compare the first community (expected results from the experts' perspective) and the second community (output of the designed dynamic system). The first community represents the expected results from the experts, and the second community represents the output of the designed dynamic system. The statistical hypotheses in this test are described as follows.

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2$$

If the P-value is greater than the significance level (α), the null hypothesis is not rejected, indicating that there is no significant difference between the knowledge of the experts (55 individuals) in the supply chain agility domain and the output of the designed system.

To determine the relationships between the system components and form Laplace transform functions, we need to specify three parameters: the effectiveness (K), the time of impact (T), and the decay time (Θ).

To define the transfer functions between two components, the organization's experts were asked to answer the following three questions:

1. What is the impact of enablers on agility capabilities?
2. Over what time frame do enablers affect agility capabilities?
3. In the absence of investment and the lack of agile enablers, how long does it take for agility capabilities to decay?

To answer these questions, respondents were asked to determine the mutual effects of components using the provided five-option linguistic model presented in Table 1. To calculate the final membership function values for each element of the reference set U, experts used the relationship (8). Additionally, for defuzzification, to determine crisp values for K, T, and Θ, the center of gravity relationship was applied. By placing the values of K, T, and Θ in the corresponding Laplace transform functions, the formulated dynamic model can be executed. The modeling and execution of the dynamic model were performed in J2ME.

$$\mu_{Fj} = \frac{1}{m} \sum_{j=1}^{m} \mu_{ij} \quad (8)$$

The membership function of the elements of a fuzzy set A, denoted as A, is called the membership function of the set A. The membership function of a fuzzy set is a mapping of the elements of set A to the interval [1 and 0] in a way that [1 and 0] → y: A. In general, any function that implements such a mapping can be used as the membership function of a fuzzy set. The reason for using Gaussian functions is their differentiability, which is a requirement for ANFIS systems [14]. Additionally, this category of functions, due to the variation in the parameter σ or the standard deviation, can open and close the capability, covering most values. A Gaussian membership function is defined as follows:

$$gussian(x,\sigma,c) = e \times p(-(\frac{x-c}{\sigma})^2) \quad (9)$$

In the above equation, c represents the center of symmetry and Ϭ determines the degree of openness of the function. The Gaussian function has a smooth curve, and its parameters can be adjusted based on linguistic variable features. The range of variations for input and output variables is defined between 0 and 1.

The training data consists of input/output data pairs used to model the target through the hybrid training technique. Error Tolerance is utilized to set a goal for stopping the training process, directly related to the error size. When the error of the training data falls within this error range, the training process stops. The training error is the difference between the output value of the training data and the fuzzy inference system output corresponding to that training data (inputs related to the outputs of the training data). The training error stores the root mean square error (RMSE) for each training cycle related to the training dataset.

$$RMSE = \sqrt{\frac{1}{n}(\sum \quad (x - x_d)^2} \quad (10)$$

In the current research, the Mean Magnitude of Relative Error (MMRE) is employed for validating the target model. MMRE is used to control the model's adaptability to data during and after a certain stage of training. After a specific training stage, the model begins to adapt during the ongoing training. Typically, the model's error for the validation dataset increases as training continues after the stage where adaptation begins. This serves as a straightforward solution for detecting the overfitting phenomenon in the designed model (ensuring that the changes in training and validation data are synchronized to witness the absence of overfitting in the system).

4. THEORY AND CALCULATIONS

The statistical assumptions to test whether there is a significant difference between the system output (community one) and the expert opinions (community two) are as follows.

$$H_0: \mu_1 = \mu_1$$
$$H_1: \mu_1 \neq \mu_2$$

Considering α = 0.05 and utilizing the SPSS software, the P-Value was calculated as 0.071, which is greater than the α level. Consequently, the null hypothesis P_{value} (H0) is not rejected, indicating that there is no significant difference between the output of the designed ANFIS and the knowledge of experts. Therefore, after conducting the second-stage survey and comparing the opinions presented in the first stage with the results of this stage, as the difference between the two stages is less than the threshold (1.0 and 0), the survey process is halted [19]. To form the decision-making group, experts ranked 13th and 14th were utilized, with 55 of them participating, and fuzzy group decision-making techniques were used to integrate the obtained information. All 35 questionnaires used in this stage were returned and of the interval type. Therefore, the geometric mean method was employed for aggregating expert opinions for each of the questions.

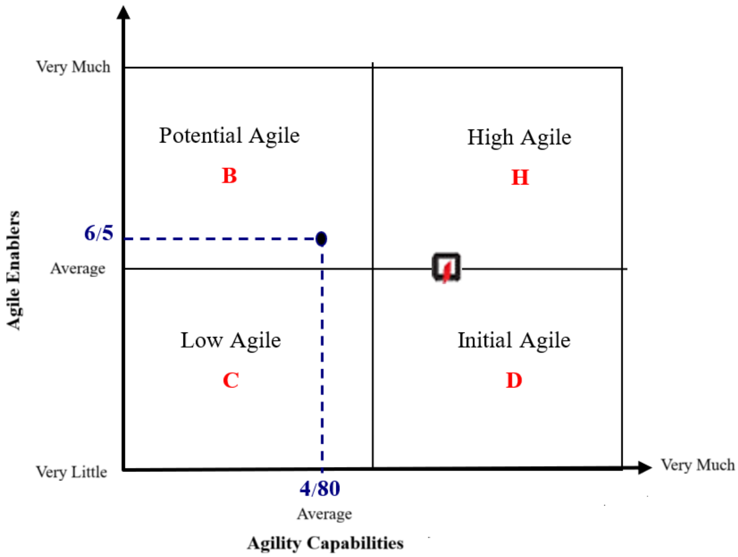

Fig. 1. Alignment of Tehran Fire Department's supply chain in the agility factors matrix.

The input values for the execution of the designed ANFIS models are determined. By comparing the calculated values for the two dimensions of agility with the agility factors matrix (Figure 1), we conclude that, in terms of location, the supply chain agility of the Tehran Fire Department is in region B.

5. CONCLUSION

In the case study, the agility position of the supply chain is in region B or Potential Agile. This indicates that the organization, in terms of agile infrastructure or capabilities, is relatively well-positioned, and in the near future, a higher level of agility can be predicted for the organization's supply chain. The designed dynamic model, based on state-space equations and transformation functions in the Laplace domain, provides organizations and their managers with the ability to predict the level of agility for future periods by considering current capabilities and structures of their organizations. If there is a gap between the current status and the desired status, they can invest and focus on enhancing capabilities to increase agility. It is worth mentioning that to determine the desirable level of agility, one must consider agility drivers, including six important categories: social and legal factors, business networks, competitive environment, stakeholders' needs, technology, and internal performance drivers. Therefore, leveraging organizational strengths based on environmental opportunities will progressively elevate the Tehran Fire Department's organizational agility, measurable according to the parameters of the research model.

6. RECOMMENDATIONS

As a suggestion for future research, investigating the conditions of uncertainty in the implementation of the educational improvement budget and the system's effects on the agility of the supply chain and support in the Tehran Fire Department can be considered.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

Acknowledgments

We would like to express our gratitude to all individuals who contributed to this project.

Declaration of Interest

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

REFRENCESS

[1] Christopher, M. (2000). The agile supply chain: Competing in volatile markets. Industrial Marketing Management, 29(1), 37–44. https://doi.org/10.1016/S0019-8501(99)00110-8

[2] Sharifi, H., & Zhang, Z. (2001). Agile manufacturing in practice: Application of a methodology. International Journal of Operations & Production Management, 21(5/6), 772–794. https://doi.org/10.1108/01443570110390462

[3] van Wassenhove, L. N. (2006). Humanitarian aid logistics: Supply chain management in high gear. Journal of the Operational Research Society, 57(5), 475–489. https://doi.org/10.1057/palgrave.jors.2602125

[4] Oloruntoba, R., & Gray, R. (2006). Humanitarian aid: An agile supply chain? Supply Chain Management: An International Journal, 11(2), 115–120. https://doi.org/10.1108/13598540610652492

[5] Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. European Journal of Operational Research, 175(1), 475–493. https://doi.org/10.1016/j.ejor.2005.05.016

[6] Charles, A., Lauras, M., & van Wassenhove, L. (2010). A model to define and assess the agility of supply chains: Building on humanitarian experience. International Journal of Physical Distribution & Logistics Management, 40(8/9), 722–741. https://doi.org/10.1108/09600031011079355

[7] Kovács, G., & Spens, K. M. (2009). Identifying challenges in humanitarian logistics. International Journal of Physical Distribution & Logistics Management, 39(6), 506–528. https://doi.org/10.1108/09600030910985848

[8] Pettit, S. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development and implementation of an assessment tool. Journal of Business Logistics, 31(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

[9] Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W., & Whybark, D. C. (2012). Humanitarian and disaster relief supply chains: A matter of life and death. Journal of Supply Chain Management, 48(2), 21–36. https://doi.org/10.1111/j.1745-493X.2012.03267.x

[10] Singh, R., Gupta, A., & Gunasekaran, A. (2018). Analysing the interaction of factors for resilient humanitarian supply chain. International Journal of Production Research, 56(21), 6809–6827. https://doi.org/10.1080/00207543.2018.1424373

[11] Patel, B., & Sambasivan, M. (2021). A systematic review of the literature on supply chain agility. Management Research Review, 44(12), 1711–1736. https://doi.org/10.1108/mrr-09-2020-0574

[12] Vinodh, S., & Prasanna, M. (2011). Evaluation of agility in supply chains using multi-grade fuzzy approach. International Journal of Production Research, 49(15), 5263–5276. https://doi.org/10.1080/00207543.2010.524260

[13] Alimardani, M., Zolfani, S., Aghdaie, M. H., & Tamošaitienė, J. (2013). A novel hybrid SWARA and VIKOR methodology for supplier selection in an agile environment. Technological and Economic Development of Economy, 19(3), 533–548. https://doi.org/10.3846/20294913.2013.814606

[14] Sobb, T., Turnbull, B., & Moustafa, N. (2020). Supply Chain 4.0: A survey of cyber security challenges, solutions and future directions. Electronics, 9(11), 1864. https://doi.org/10.3390/electronics9111864

[15] Kruijff, G., Janíček, M., Keshavdas, S., Larochelle, B., Zender, H., Smets, N., Mioch, T., Neerincx, M. A., van Diggelen, J., Colas, F., Liu, M., Pomerleau, F., Siegwart, R., Hlaváč, V., Svoboda, T., Petříček, T., Reinstein, M., Zimmermann, K., Pirri, F., Gianni, M., … Sulk, M. (2014). Experience in system design for human-robot teaming in urban search & rescue. In N. Correll, M. A. Hsieh, & D. Rus (Eds.), Distributed autonomous robotic systems (pp. 111–125). Springer. https://doi.org/10.1007/978-3-642-40686-7_8

[16] Kumar, S., & Anbanandam, R. (2020). Impact of risk management culture on supply chain resilience: An empirical study from Indian manufacturing industry. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(2), 246–259. https://doi.org/10.1177/1748006X19886718

[17] Dasaklis, T. K., Rachaniotis, N., & Pappis, C. (2017). Emergency supply chain management for controlling a smallpox outbreak: The case for regional mass vaccination. International Journal of Systems Science: Operations & Logistics, 4(1), 27–40. https://doi.org/10.1080/23302674.2015.1126379

[18] Lin, C.-T., Chiu, H., & Tseng, Y.-H. (2006). Agility evaluation using fuzzy logic. International Journal of Production Economics, 101(2), 353-368.https://doi.org/10.1016/j.ijpe.2005.01.011

[19] White, A., Daniel, E. M., & Mohdzain, M. (2005). The role of emergent information technologies and systems in enabling supply chain agility. International journal of information management, 25(5), 396-410. https://doi.org/10.1016/j.ijinfomgt.2005.06.009

[20] Dove, R. (2002). Response ability: the language, structure, and culture of the agile enterprise: John Wiley & Sons.