Stream processing data decision model for higher environmental performance and resilience in sustainable logistics infrastructure

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STREAM PROCESSING DATA DECISION MODEL FOR HIGHER ENVIRONMENTAL PERFORMANCE AND RESILIENCE IN SUSTAINABLE LOGISTICS INFRASTRUCTURE

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STREAM PROCESSING DATA DECISION MODEL FOR HIGHER ENVIRONMENTAL PERFORMANCE AND RESILIENCE IN SUSTAINABLE LOGISTICS INFRASTRUCTURE

Abstract

Purpose: As the global freight transport network has experienced high vulnerability and threats from both natural and man-made disasters. As a result, a huge amount of data is generated in freight transport system in form of continuous streams; it is becoming increasingly important to develop sustainable and resilient transport system to recover from any unforeseen circumstances quickly and efficiently. The aim of this paper is to develop a stream processing data driven decision-making model for higher environmental performance and resilience in sustainable logistics infrastructure by using fifteen dimensions with three interrelated domains.

Design/methodology/approach: A causal and hierarchical stream processing data driven decision-making model to evaluate the impact of different attributes and their interrelationships and to measure the level of environmental performance and resilience capacity of sustainable logistics infrastructure is proposed. This work uses Fuzzy Cognitive Maps and Fuzzy Analytic Hierarchy Process techniques. A real-life case under a disruptive event scenario is further conducted.

Findings: The result shows that which attributes have a greater impact on the level of environmental performance and resilience capacity in sustainable logistics infrastructure.

Originality/value: In this paper, causal and hierarchical stream processing data decision and control system model was proposed by identified three domains and fifteen dimensions to assess the level of environmental performance and resilience in sustainable logistics infrastructure. The proposed model gives researchers and practitioners insights about sustainability trade-offs for a resilient and sustainable global transport supply chain system by enabling to model interdependencies among the decision attributes under a fuzzy environment and streaming data.

Keywords: Resilience, Streaming data, Logistics infrastructure, Environmental performance, Fuzzy cognitive maps, Fuzzy analytic hierarchy process, Sustainability

1. Introduction

Logistics sector has gained a significant impact on the supply chains due to increasing trend in the transportation of freight goods worldwide. The freight logistics system implies a connected network, in which a number of transport links and nodes in supply chain are engaged for providing reliable and transparent end-to-end logistics services. Currently, it is a word of big data. In contrast to traditional data, big data gave its own characteristics such as with three basic Vs: volume, variety and velocity (Wang et al., 2018; Raut et al., 2019) and with four additional Vs: variability (Milne & Watling, 2019), value (Addo-Tenkorang & Helo, 2016), veracity (Raut et al., 2019) and visualisation (Milne & Watling, 2019). However, big data is not noticeable by reason of its size, but because of its relation to other data. This huge amount of data also offers several challenges for dynamic environmental management in logistics network design. In this system, the transport links usually consist of a set of transport modes such as road, rail, sea, air or inland waterways to connect the respective nodes in freight logistics corridors, whereas transport nodes mainly consist of numerous logistics infrastructures such as seaports, hinterland terminals, multimodal terminals, freight logistics hubs, logistics centers, logistics clusters, freight villages and logistics platforms. Logistics infrastructures have been designed to formalize the interaction and interconnection of different resources (Bychkov et al., 2016) and provide intermediate locations where logistics value is added to the movement of containers and trailers to and from port facilities and to and from rail multimodal yards. Efficient, sustainable and competitive processes in logistics infrastructures require close cooperation and data exchange between all parties in supply chain. This would generate huge amount of data from different sources. In line with current sustainability targets in freight transport, the need to strike a balance between achieving economic efficiency and viability, safe and secure logistics infrastructures and services as well as environmentally friendly systems aimed at minimizing energy resource depletion, environmental degradation etc. (UNCTAD, 2014). Transport planners need new knowledge about the impact of any future adverse events or disruptions on the environmental performance and resilience of critical logistics infrastructures (Fonseca et al., 2017). Since there is growing awareness of susceptibility in the international supply chains, the productivity of freight logistics communities increasingly relies on the undisturbed functioning of these logistics infrastructures. In this respect, building resilience in a higher environmental performance transport system entails ensuring system integrity, service reliability and functionality, as well as rapid recovery after disruption (UNCTAD, 2014). Hence, an environmentally friendly and resilient logistics infrastructure is a key component for a resilient global supply chain and ensuring this infrastructure as resilient as practicable is an important environmental and economic priority for the stakeholders (O'Rourke, 2007; Ponomarov & Holcomb, 2009).

One of the key challenges in developing a sustainable and resilient freight transport network is to decide the indicators to assess the resilience of logistics infrastructures under huge amount of stream data. There is a growing need to assess environmental performance and resilience and develop appropriate and diverse indicators to quantify the readiness of a sustainable logistics infrastructure to respond and recover from any encountered adverse event or disruption. Despite the critical potential effect, this topic appears to be relatively less covered in the literature. Resilience in the broader sense, is the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions (IPCC, 2012).

Many everyday disruptions, which happened during the logistics operations, have less severe impacts: the freezing rain and sleet damaged ship dock, electric power outages caused delays in customs clearance, some goods trains had to stop, cargo-handling equipment is broken and so on. Such events will result in delay in delivery or cancelled shipments. In particular, increasing instances of environmental disruptions, partly caused by climate change such as massive snow, rainstorm or flood, has been upsetting freight logistics system and consequently international supply chains. Potential environmental interruptions to these logistics activities would therefore have explicit implications and incur significant losses and economic costs. In the context of logistics infrastructure, the concept of resilience comprises the capacity to withstand unanticipated disruption, to detect the occurrence of disruption, to absorb disturbance and to act effectively in a crisis in order to minimize the negative consequences of the disruption and to adapt changing conditions (Sheffi & Rice, 2005; Haimes, 2009; Hughes & Healy, 2014; Sheffi, 2015). Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents (Alderson, et al. 2015). Since some of disruptive events cannot be prevented completely, logistics infrastructures should be prepared for the occurrence of them. In this sense, continuous monitoring using big data and predictive analytics with streaming data enables the study of new kinds of variation (time-of-day, day-to-day, time-of-year, scenario-specific) to correlate with data on events/weather or incidents, data with system behavior, etc. to monitor unforeseen disruptions (Milne & Watling, 2019) and to prepare/warn and even to change system conditions before event or disaster occurs. This would help in improving both the sustainability as well as competitiveness in logistics infrastructure using streaming data approach. Therefore, this study focuses on the below key question: *How to develop a higher environmental performance and resilience focused logistics infrastructure under streaming data?* Further, considering the characteristics of streaming data, it is different from traditional static data (Zhu et al., 2018; Song et al., 2017). Thus, it is important for decision makers to make use of stream data applications for better managing environment and resilience capacity in logistics infrastructure.

In this research, a data stream based human decision and control system based on hybrid causal and hierarchical MADM method combining Fuzzy Cognitive Maps (FCM) and Fuzzy Analytic Hierarchy Process (FAHP) is proposed for modeling and solving environmental and resilience assessment problem of a selected logistics infrastructure under complex, poorly defined and uncertain environments. The paper is organized as follows: Section 2 discusses past literature to determine the environmental performance and resilience domains and dimensions in logistics infrastructure, Section 3 presents the proposed two-stage FCM and FAHP based causal and hierarchical stream processing data driven decision model and Section 4 discusses the empirical study. Last section provides the discussion and future research direction in this field.

2. Literature review: Domains and dimensions of environmental performance and resilience in logistics infrastructure

In the context of a logistics network and transport management, the concept of resilience is defined as follows; Rice & Caniato (2003) considered that resilience is the *ability to react* to an unexpected disruption and *restore normal supply network operations*. Christopher and Peck (2004) pointed out that resilience is the ability of a system to return to *its original state or move to a new, more desirable state* after being disturbed. Sheffi (2005) described resilience as *containment of disruption* and *recovery* from it. Fiksel (2006) defined that resilience is the capacity of an organization to *survive, adapt and grow* in the face of turbulent change. Hollnagel (2004) emphasized that resilience is an intrinsic ability of an organization (system) to maintain and regain stable state, which allows it to continue operations after a major mishap and/or in the presence of a continuous stress. Holling (2001) deemed that resilience is the capacity of a system to survive, adapt and grow in the face of unforeseen changes, even catastrophic incidents. Thus, it could be highlighted that resilience emphasizes the ability to quickly recover from a shock or disaster. This also includes the terms such as "elasticity" and "flexibility" which mean adaptability and anti-disruption. Network's topological and operational attributes are important in order to evaluate a network's potential performance in case of possible future disruptions (Miller-Hooks et al. 2012). The importance of a robust and reliable transport system has led to considerable research in order to understand the mechanisms and interrelationships, which create vulnerability, and further to find ways to mitigate the consequences of incidents (Mattsson & Jenelius, 2015).

Several scholar have studied on characteristics of the development of successful infrastructures for multimodal terminals and logistics hubs. Sheffi (2012) made significant contributions in this field and argued that the most direct and effective way to improve resilience is to enhance the infrastructures. Their study suggested the following attributes of successful logistics facilities: (i) Favorable geography because of transport economics with origins and destinations that follow very specific geographical patterns. (ii) Supporting infrastructure because the cluster is as good as its transport network infrastructure. (iii) Supportive, efficient government because they are the main providers of public infrastructure such as roads, railways, ports and airports. (iv) Education, research and innovation because all economic clusters depend on qualified and competent people to do the work efficiently and effectively. (v) Collaboration and unity of purpose amongst all stakeholders, and (vi) Value-added services that extend beyond moving and storage functions to include transformation or modification of goods.

However, as the challenges to freight transport network constantly evolves, the dynamic understanding of the vulnerability and risk factors is crucial to develop an environmentally resilient system. The approaches to address and assess resilience of the network also need to be evolved according to the new emerging challenges. Due to this, vast degree of turbulence and complexity in the global logistics network, collaboration at the network level is desired to allocate the required resources and to respond to these unpredicted disturbances (Pettit et al. 2010). Resilience is used in decision-making, where it is implemented as a response to interruption in many cases, although much of resilience remains rooted in preparedness (Marchese et al., 2018). Miller-Hooks et al. (2012) presented an exact methodology to address the problem of measuring maximum resilience level of an intermodal freight transport network and simultaneously deciding the optimal set of preparedness and recovery actions necessary to achieve it under certain constraints. Furthermore, freight transport network shares close relationships between the environmental performance and logistics infrastructure, as it trends to shape models of demand and resource availability. The role that freight transport network holds on the environmental performance of critical logistics infrastructures has been highlighted in relation to the effect on the global greenhouse gas emissions due to energy consumption (Futcher et al., 2013; Ellram & Golicic, 2016; Rüdiger et al., 2016) and environmental, noise and congestion concerns resulting from various transportation modes in logistics infrastructures (Buldeo Rai et al., 2018; Salomons & Berghauser Pont, 2012). García-Onetti et al. (2018). Fonseca et al. (2017) deemed to establish bridges between the environmental performance and resilience for the logistics infrastructures. In addition, Cutter, et al. (2008) also suggested considering environmental performance as a component of resilience for the logistics infrastructures. As the review of literature on environmental performance and resilience as well as indicators has demonstrated that definitions and explanations are varying in the literature and the best way to assess this is to identify the challenges presented by the fuzziness of those many interpretations and the problems embedded in the assessment of qualitative information through indicators.

Different trends towards the Internet of Things (IoT), Industry 4.0 and 5G networks can improve logistics efficiency. Especially, sensors and sensor networks are embedded in the physical logistics infrastructure (Psyllidis, 2016; Qin et al., 2019) and they generate streams of data through i.e. measurements and observations and deliver them directly to the system in a reliable, easy and quick manner. The data can report information in-real time about transport flows, trip generation, distribution and travel mode, environmental conditions, air quality, electricity usage, weather, temperature and humidity, sound levels etc. In the continuous processing of data streams across transport supply chain for transport planning purposes, processing situation may vary over the time (Anda et al., 2016; Qin et al., 2019): while, dynamic characteristics of data streams needs to be handled effectively. During processing, the volume or velocity of data streams can change significantly. For instance, transport flows and behaviors at a logistics port can differ depending on how many supply chains have used the port as a hub during the period of time, this could lead to changes of the stream characteristics. On the other hand, the data processing environment can also vary unexpectedly. For instance, massive flood and storm hit the main logistics hub and caused extensive damage or lead to a sudden reduction of available processing resources or network fluctuations. To cope with such varying processing situations, the need of adapting decision making on the behavior of environmental performance and resilience processing becomes critical. All those above-mentioned concerns can be considered as a research gap for this study to develop a stream processing data model for environmental performance and resilience.

After elucidating the importance of assessment of environmental performance and resilience, in this research, fifteen dimensions (sub-attributes, A_i) with three interrelated domains (main attributes, MA_i) are identified to assess environmental performance and resilience in logistics infrastructure. Note that this classification of environmental performance and resilience may differ depending on researcher's perspective (Tierney & Bruneau, 2007). A variety of definitions of environmental performance and resilience is provided according to the three aforementioned groups: (1) Technical domain refers to the ability of physical systems (including all interconnected components) to perform to acceptable/desired levels (e.g. added redundancy/ backups, geographical isolation, etc.) when subject to a hazard event (Bruneau et al., 2003). (2) Organizational domain represents the capacity of organizations to make decisions and take actions to plan, manage and respond to a hazard event in order to achieve the desired resilient outcome (Bruneau et al., 2003). (3) Operational domain includes development of well-orchestrated and collaborative operations, with shared awareness, capable of reaching self-synchronization, increasing the tempo of operations, flexible for inclusion of all organizations. These three domains depend on each other, as the communities invest in strengthening the infrastructure environmentally, technically and operationally, but this will not make the system any more resilient unless the organizations responding to an event are skilled, prepared and trained towards it. Various key domains and dimensions of environmental performance and resilience assessment in logistics infrastructure are given in Table 1.

Table 1
Domains and dimensions of environmental performance and resilience assessment in logistics infrastructure.

3. Proposed Methodology

This work is based on stream data application-based decision support and control model for environmental performance and resilience of logistics infrastrucuture. Here, the decision making is done for process control and generally driven by stream processing data. Stream processing enables users to evaluate high volume of data in real time. However, human involvement is also desirable in such cases for improved results. Managers and practitioners may apply several techniques in regard to process control such as decision tree, quality control tools (statistical process), test equipment for failures, decision support models etc. These approaches allow process manager to optimize and decide for their processes for higher sustainability. In this research, logistics infrastructure involves real time data analysis of data being generated from different nodes and points in logistics system. Further, some rules are needed to make decisions, and hence, an expert based data approach is used in this work.

The current literature recognized that fuzzy-based approaches are very effective to deal with imprecision and vagueness in multi-attribute decision-making (MADM) problems (Chan & Kumar 2007; Chan et al. 2008). A number of literatures such as Amindoust et al. (2012) and Govindan et al. (2013) highlighted the strategic importance of fuzzy models in different settings of MADM problems and applications, and explained the contribution of fuzzy sets in reaching at an effective solution. In the past, cognitive maps have been used for evaluating and assisting decision-making by examining the causal links among relevant domain concepts. A fuzzy cognitive map (FCM) is "*an extension of a cognitive map with the additional capability of representing feedback through weighted causal links*" (Khan & Quaddus 2004). Rodriguez-Repiso et al. (2007) discussed that the past methodologies and approaches used for categorizing and assessing the evaluation criteria have several limitations, which could be addressed by the FCM based approaches.

In addition, Ahmadi et al. (2015) presented an integrated approach based on FCM and FAHP to manage interrelated activities during the implementation of the new enterprise resource planning (ERP) system. Yang et al. (2011) proposed a hybrid approach combining fuzzy inference system (FIS) and FAHP to prioritize environmental issues in offshore oil and gas operations. A five-level hierarchy is developed. López & Ishizaka (2017) also proposed a hybrid method based on FCM and AHP to understand the impact of locations decisions in offshore outsourcing process on the supply chain resilience capabilities. The sensitivity analysis of the findings of this study also revealed that one location would improve supply chain resilience meanwhile the others would damage it. Irani et al. (2002) used an approach based on FCM to model the inter-relationships between key dimensions identified in a conceptual model for investment evaluation. They argued that FCM is an effective tool to model each evaluation factor and their interdependencies. Olazabal & Pascual (2016) used FCM for studying urban resilience ad transformation. Khan & Quaddus (2004) further argued that FCM could be an effective tool for both static and dynamic analysis of scenarios evolving with time. They discussed that an FCM provides relatively easy integration of an expert's domain knowledge into a collective knowledge base for a group involved in a decision process.

Moreover, Baykasoğlu & Gölcük (2015) developed a fuzzy MADM approach by integrating Fuzzy TOPSIS and FCMs to model complex decision-making problems. They argued that the integrated approach had the ability to effectively model interdependencies among the attributes along with addressing the uncertainties. Hajek & Froelich (2019) developed a group decision making model by integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps (IVIFCM) for the supplier selection task. Biloslavo & Dolinsek (2010) also proposed a hybrid approach for scenario planning for climate strategies by integrating group Delphi method, AHP and dynamic FCM and found superior results. López & Ishizaka (2018) also presented an innovative hybrid technique based on FCM and AHP to assess the performance of enterprise content management in the IT infrastructure. The proposed approach helped managers to reduce the malfunctions and misuses of enterprise content management. Furthermore, Nachazel (2018) presented an approach to transform an FCM model into an FCM-AHP model to analyze the strengths and weaknesses of the approaches in the artificial life model. They found that FCM-AHP provides a model with significantly lower computational time while keeping nearly the same level of proficiency as compared to the original FCM model.

In this study, a two-stage FCM and FAHP based causal and hierarchical interrelationship stream processing data driven fuzzy decision framework is proposed to evaluate the impact of different attributes and their interrelationships in measuring the resilience of a logistics infrastructure. The reasons for the selection of this research methodology are explained as follows (Kayikci & Stix, 2014; Baykasoğlu & Gölcük, 2015; Ahmadi et al., 2015; López & Ishizaka, 2018):

– Clear and easy to understand for experts/evaluators
– A high level of integration among attributes both causally and hierarchically
– It can be performed within relatively short time periods
– It gives a solid system description and
– Also useful for extension activities to train decision makers, if there are any misperceptions.

The methodology is well suited for causal and hierarchical structures. A hybrid approach combining FCM and FAHP incorporates fuzziness and criteria interactions into analysis in order to evaluate causally and hierarchically structured decision problem. The proposed causal and hierarchical interrelationship stream processing data driven decision approach comprises two parts as seen in Fig. 1. The first part consists of obtaining the overall attribute weights with understanding the causality among attributes by implementing FCM in the horizontal direction, whereas the second part is dedicated to implementing FAHP in order to rank the alternatives hierarchically in the vertical direction.

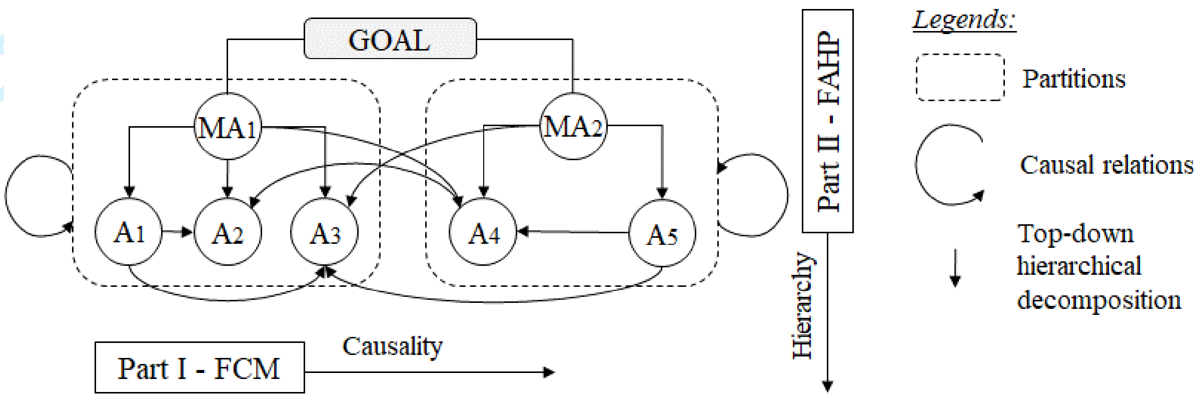
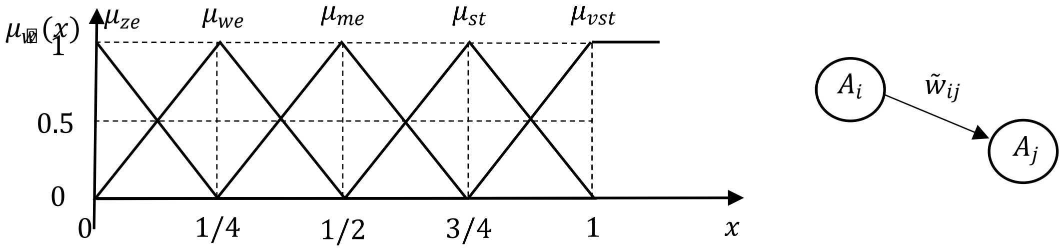


Fig. 1 A causal and hierarchical interrelationship stream processing data driven decision model based on FCM and FAHP.

3.1 Part I - FCM calculation

The FCM, first introduced by Kosko (1986), are the combination of Neural Networks and Fuzzy Logic that allow predicting the change of the attributes (concepts) represented in Causal Maps. They are fuzzy directed graphs with feedback, consisting of *various nodes* (representing the change in attributes like robustness or restoring) and *directed arcs* that connect and represent the causal relation between those nodes. Each attribute has a fuzzy value ranging from $[-1,1]$ and each arc is associated to a fuzzy weight with range $[-1,1]$. A positive weight represents a causal increase whereas a negative weight represents a causal decrease (opposite effect) (Carvalho, 2013). In this research, no negative value is used, as all attributes have a positive impact to improve the resilience in a logistics infrastructure and the causal fuzzy attribute weight $\tilde{w}_{ij}$are ranging between $w_{ij} = E \in [0,1]$. The weights of the attributes with respect to the goal are elicited from the decision makers of resilience assessment team by discussing questions with using if-then rules as follows (Kayikci & Stix, 2014):

– *"Do you think that the attribute i (A_i) affects any other attributes by any change or is affected by other attributes?" if yes, then*
– *"How do you assign the causal fuzzy weight between attribute i (A_i) and attribute j (A_j) according to linguistic terms?".*



TFM Functions	Linguistic Terms	Explanation
$\mu_{ze} = 0, 0, \frac{1}{4}$	zero	If A_i doesn't affects $A_j \rightarrow$ the fuzzy set for *an influence close to 0%* with membership functions (μ_{ze}), $\tilde{w}_{ij} = 0$ (neutral)
$\mu_{we} = 0, \frac{1}{4}, \frac{1}{2}$	weak	If A_i promotes $A_j \rightarrow$ the fuzzy set for *an influence close to 25%* with membership functions (μ_{we}), $\tilde{w}_{ij} > 0$ (positive)
$\mu_{me} = \frac{1}{4}, \frac{1}{2}, \frac{3}{4}$	medium	If A_i promotes $A_j \rightarrow$ the fuzzy set for *an influence close to 50%* with membership functions (μ_{me}), $\tilde{w}_{ij} > 0$ (positive)
$\mu_{st} = \frac{1}{2}, \frac{3}{4}, 1$	strong	If A_i promotes $A_j \rightarrow$ the fuzzy set for *an influence close to 75%* with membership functions (μ_{st}), $\tilde{w}_{ij} > 0$ (positive)
$\mu_{vst} = \frac{3}{4}, 1, 1$	very strong	If A_i promotes $A_j \rightarrow$ the fuzzy set for *an influence close to 100%* with membership functions (μ_{vst}), $\tilde{w}_{ij} > 0$ (positive)

Fig. 2 The five-TFM functions with corresponding five-linguistic terms.

The influence of attribute A_i on A_j can be one particular causal link associated with the qualitative term set $\mu_{\tilde{w}}(x)$ for example: {"zero" $\mu_{ze}(x)$, "weak" $\mu_{we}(x)$, "medium" $\mu_{me}(x)$, "strong" $\mu_{st}(x)$, "very strong" $\mu_{vst}(x)$} respectively; x represents the influence degree of a given linguistic term measured in the interval [0,1]. Each element of the fuzzy set represents the specified Triangular Fuzzy Memberships (TFM) function $\mu_{\tilde{w}}(x)$ by a triplet (l_{ij}, m_{ij},u_{ij}) of two attributes (A_i,A_j), to integrate the multiple decision maker opinions. The triplet includes three parameters, l, m and u and they respectively denote the smallest possible value, the most promising value and the largest possible value that describes a fuzzy event. Fig. 2 denotes a five-TFM functions corresponding to each one of the five-linguistic terms and their explanations. Each kth decision maker uses the aforementioned linguistic terms to infer the causal fuzzy weight ($\tilde{w}_{ij}^k$) for every pair of dimensions. Each causal fuzzy weight is represented with associated TFM: $\tilde{w}_{ij}^k = \tilde{\mu}(\mathrm{x}) = \{l_{ij}, m_{ij}, u_{ij}\}$, $i,j = 1 \ldots n$. After having all decision makers' perception, the results are discussed in a round table. This process is continued until a consensus among decision makers is reached. FCM steps are as follows:

(i) *Set up the aggregated group decision opinion:* For group decision making, an *arithmetic mean method* is used to aggregate the decision makers' opinions (Ishikawa et al., 1993). The triplet of l_{ij}, m_{ij}, u_{ij} for the group decision opinion are calculated according to Eq. (1). K represents the number of decision maker.

$$l_{ij} = \frac{1}{k}\sum_{i=1}^{n} l_{ij}^{k};\ m_{ij} = \frac{1}{k}\sum_{i=1}^{n} m_{ij}^{k};\ u_{ij} = \frac{1}{k}\sum_{i=1}^{n} u_{ij}^{k}\ \forall k = 1,2,\ldots,K \tag{1}$$

(ii) *Defuzzification:* Center of Gravity (CoG) method is employed. It has been previously examined as an efficient approach to achieve the quantification of linguistic terms with high efficiency (Glykas, 2010; Runkler, 1996). This approach aims to defuzzify the fuzzy weight ($\tilde{w}_{ij}$) of each interconnection to definite value (i.e., defuzzy value) representing the edge weight (w_{ij}) of each interconnection for A_i and A_j. This method determines the center of area of the combined membership function. The Eq. (2) is used to calculate the geometric center of this area under the combined membership function $\tilde{\mu}(x)$ (Runkler, 1996) which gives the final edge weight of each tow attributes.

$$w_{ij} = CoG = \frac{\int_{X_{min}}^{X_{max}} \tilde{\mu}(x).xdx}{\int_{X_{min}}^{X_{max}} \tilde{\mu}(x)dx} \tag{2}$$

(iii) *Generate the edge matrix:* The final weights for the causal interference are stored in an edge matrix $E = (w_{ij}),\ w_{ij} \in E,\ i,j = 1,2,\ldots n$ as seen in Eq. (3). It lists all one-edge paths on the cognitive maps. The edge matrix E is a square $n\ x\ n$ fuzzy matrix and the diagonal entries are $w_{ii} = 0$. n is the total number of attributes, w_{ij} is the edge weight from A_i to A_j.

$$E = [w_{ij}] = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \ldots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \ldots & 0 \end{bmatrix}_{nxn} \end{array},\ \forall w_{ij} \in [-1,1] \tag{3}$$

(iv) *Calculate the causal inference:* Attribute values are calculated according to Eq. (4).

$$A_i^{t+1} = f\Big(A_i^t + \sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^t.\, w_{ji}\Big),\ \forall i,j \in \{1,\ldots,n\}; t = 0,1,2,\ldots,T \tag{4}$$

where A_i^{t+1}, is the attribute value of the ith attribute at iteration time $t+1$, $f(x)$: threshold function is calculated $f(x) = 1/(1 + e^{-\lambda x})$, $0 \leq \lambda \leq 1$.

The attribute values are normalized as in Eq. (5); hence, final weights of the attributes are obtained:

$$w_i = A_i / \sum_{i=1}^{n} A_i \tag{5}$$

In Eq. (6), the final crisp weights are shown in matrix I by:

$$I = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}_{nx1}, \text{ where } \sum_{i=1}^{n} w_i = 1 \tag{6}$$

(v): *Calculate the indices:* Every attribute is defined by its out-degree $od(A_i)$, in-degree $in(A_i)$ and centrality $cen(A_i)$. Out-degree (out-arrows) $od(A_i)$ is the absolute row sum of edge weights (w_{ki}) in the edge matrix and represents the number of attributes, attribute A_i causally interacts seen in Eq. (7). In-degree (in-arrows) $id(A_i)$ is the absolute column sum of edge weights. (w_{ik}) in the edge matrix and represents the number of attributes causally interacting on attribute A_i seen in Eq. (8). The immediate domain or total degree of an attribute is the sum of its in-degree and out-degree, called centrality $cen(A_i)$ seen in Eq. (9). The centrality represents the dominance of attribute A_i to the causal flow on the cognitive map. The more central the attribute in the FCM, the more important the attribute is in the decision maker's perception.

$$od(A_i) = \sum_{k=1}^{n} |w_{ki}| \tag{7}$$

$$id(A_i) = \sum_{k=1}^{n} |w_{ik}| \tag{8}$$

$$cen(A_i) = od(A_i) + id(A_i) \tag{9}$$

The contribution of an attribute in an FCM can be interpreted by computation of its centrality; whether it is a transmitter, receiver or ordinary attribute. Transmitter (forcing functions, givens and tails) represents an attribute whose $od(A_i)$ is positive and $id(A_i)$ is zero. Receiver (utility variables, ends and heads) represents an attribute whose $od(A_i)$ is zero and $id(A_i)$ is positive. The total number of receivers in an FCM can be considered an index of its complexity (Vasantha & Smarandache, 2003). The rest of the attributes, both non-zero $od(A_i)$ and $id(A_i)$, are ordinary attributes (means).

3.2 Part II - FAHP calculation

When the attribute weights are determined, FAHP calculations are made to reach the final ranking of the alternatives. The AHP, first suggested by Saaty (1980), is one of the most widely used multi-attribute (criteria) decision-making methods. AHP can effectively handle both qualitative and quantitative data in order to decompose the problem hierarchically, such that, the problem is broken down thoroughly and its related sub criteria, with regards to hierarchical level, are listed in relation to the overall goal/objective to the sub-criteria (Mangla et al., 2016; Gandhi et al., 2016). However, the conventional AHP method may not reflect the human judgment accurately. Hence, AHP with its fuzzy extension, namely FAHP approaches which use the concept of fuzzy set theory and hierarchical structure analysis are proposed in order to solve MADM problems (Mangla et al., 2015). In this phase, Chang's (1996) extend analysis method was applied. FAHP steps are as follows:

(i) *Calculate the total of all importance scores* in the comparison matrix ($\tilde{M}$), as the final attribute weights by using Eq. (6) was obtained, only a fuzzy decision matrix is constructed is this phase. A group of experts provides the fuzzy rating values of each alternative, seen in Eq. (10).

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{M}_{A_iA_j} = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}l_{A_iA_j}, \sum_{i=1}^{n}\sum_{j=1}^{n}m_{A_iA_j}, \sum_{i=1}^{n}\sum_{j=1}^{n}u_{A_iA_j}\right) \tag{10}$$

where $\tilde{M}_{A_iA_j}$ is the importance score comparing the importance of activity A_i (row) against activity A_j (column).

(ii) *Calculate the fuzzy synthetic extent* S_{A_i} for each row in the comparison matrix, seen in Eq. (11) and Eq. (12).

$$S_{A_i} = \left(\sum_{j=1}^{n}\tilde{M}_{A_iA_j}\right) \mathrm{x} \left[\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{M}_{A_iA_j}\right]^{-1} i,j = 1,2,\ldots n \tag{11}$$

Where,

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{M}_{A_iA_j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n}u_{A_iA_j}}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n}m_{A_iA_j}}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n}l_{A_iA_j}}\right) \tag{12}$$

(iii) *Calculate the local contribution weight of activities:* The fuzzy synthetic extent of each activity $A_i(S_{A_i})$ is first compared with the fuzzy synthetic extents of all other activities. The degree of possibility for each triangular fuzzy synthetic extent $S_{A_i}, i = 1,2,...,n$ to be greater than all other fuzzy synthetic extents $S_{A_j}, j = 1,2,...,n$ is the given by Eq. (13) and Eq. (14):

$$V(S_{A_i} \geq S_{A_1}, S_{A_2},...,S_{A_n}) = \min V(S_{A_i} \geq S_{A_j})\ i,j = 1,2,....,n; i \neq j \quad (13)$$

Assume that $S_{A_1} = (l_{A_1}, m_{A_1}, u_{A_1})$ and $S_{A_2} = (l_{A_2}, m_{A_2}, u_{A_2})$ then

$$V(S_{A_2} \geq S_{A_1}) = \sup_{y \geq x} \left[\min (\mu_{S_{A_1}}(x), \mu_{S_{A_2}}(y))\right]$$

$$V(S_{A_2} \geq S_{A_1}) = \{1, if\ m_{A_2} \geq m_{A_1};\ 0, if\ l_{A_1} \geq u_{A_2}; \quad (14)$$

$$\frac{l_{A_1} - u_{A_2}}{(m_{A_2} - u_{A_2}) - (m_{A_1} - l_{A_1})}, \text{otherwise } \}$$

The non-fuzzy local contribution weight, *defuzzified weights* (W_{A_i}) of each activity A_1 is then obtained by using minimum of $V(S_{A_i} \geq S_{A_1}),..., V(S_{A_i} \geq S_{A_n})$. Afterwards, the local contribution weights of all activities are normalized (the sum of the weights is 1.0) and are then used in the model.

(iv): *Calculate the normalized contribution weight of activities* in Eq. (15)

$$NW_{A_i} = W_{A_i}/\sum_{i=1}^{n} W_{A_i} \quad (15)$$

(v) *Set up the aggregated group decision opinion:* For group decision making, *a geometric mean prioritization method* is used (Davies, 1994; Dong et al., 2010) seen in Eq. (16). A group TFN, $\tilde{M}$ can be display in a triplet(l_{ij}, m_{ij}, u_{ij}). Assume that a decision group has K decision makers.

$$l_{ij} = (\prod_{k=1}^{K} l_{ij}^{k})^{1/K};\ m_{ij} = (\prod_{k=1}^{K} m_{ij}^{k})^{1/K};\ u_{ij} = (\prod_{k=1}^{K} u_{ij}^{k})^{1/K} \quad (16)$$

In which $(l_{ij}^1, m_{ij}^1, u_{ij}^1), (l_{ij}^2, m_{ij}^2, u_{ij}^2),..., (l_{ij}^k, m_{ij}^k, u_{ij}^k)$ represents different judgments of k, $k = 1,2,...,$ K decision makers of the group. This algorithm is then applied at every hierarchical level. The selection of a geometric mean could retain more consistency with the synergistic behavior of group judgment technique (Davies, 1994) instead of using an eigenvalue method (Saaty, 1980).

4. Empirical Study: Assessment of Environmental Performance and Resilience in Sustainable Logistics Infrastructure

As a real-life logistics infrastructure, an integrated multimodal logistics hub (freight village) was chosen to assess environmental performance and resilience under a disruptive event scenario. A group decision-making setting involving three experts/evaluators (DM1, DM2 and DM3) was established for this purpose. Decision makers were selected according to their qualifications including professional experience, activities and in-depth knowledge related to logistics and sustainability and also their availability and locations. Experts participated in this study are working in Istanbul for big logistics companies and they are highly experienced logistics manager, logistics hub infrastructure manager and project manager with average 15 years of work experience in logistics industry. One of them obtained master degree in logistics and two of them obtained bachelor degree in industrial engineering with the focus of logistics and supply chain management. This study was pursued between 01. January - 30. April 2019. The selected integrated multimodal logistics hub is located in Ambarli, Istanbul, Turkey and it provides road, rail and sea transport links. Table 2 demonstrates the proposed causal and hierarchical stream processing data driven decision model which consists of the following steps.

4.1 Step 1: Identify the resilience assessment attributes, alternatives and linguistic scales

As mentioned in Section 2, according to literature review, three main attributes: technical domain (MA1), organizational domain (MA2) and operational domain (MA3) and fifteen sub-attributes: robustness (A1), redundancy (A2), resourcefulness (A3), maintenance (A4), safe-to-fail (A5), preparedness (A6), collaboration (A7), leadership and culture (A8), skilled labor and management (A9), lessons learned (A10), repositioning (A11), mode flexibility (A12), rapidity (A13), restoring (A14) and resource allocation (A15) were selected for assessment of environmental performance and resilience in logistics infrastructure in this study. Additionally, four alternatives were identified according to expert opinions in order to demonstrate the level of environmental performance and resilience capacity of logistics infrastructure, namely: *Low level* (L): poor environmental performance and resilience improvements should be done. *Moderate level* (M): less than desirable environmental performance and specific resilience improvements should be prioritized. *High level* (H): optimal environmental performance in relation to measures, some resilience improvements could be made. *Very high level* (V): meets all requirements in terms of achieving higher environmental performance and resilience.

Table 2
The proposed causal and hierarchical stream processing data driven decision model.

The main attributes, sub-attributes and alternatives are shown in a causal and hierarchical evaluation framework in Fig. 3. First, the linguistic scales are determined by using expert opinions. As mentioned in previous section, no negative value is used in this research, as the *parameters have a positive impact to improve the sustainability*. A linguistic scale in Table 3, is constructed for the relative importance of the attribute weights by using TFM within the range [0,1]. Another linguistic scale is formed, as shown in Table 4, is formed in order to assess the causal relationship among attributes by using TFM within the range [0,1]. In Table 5, A linguistic scale is used to rate the alternatives with respect to attributes by using TFM within the range [0,10]. All linguistics scales contain no negative value.

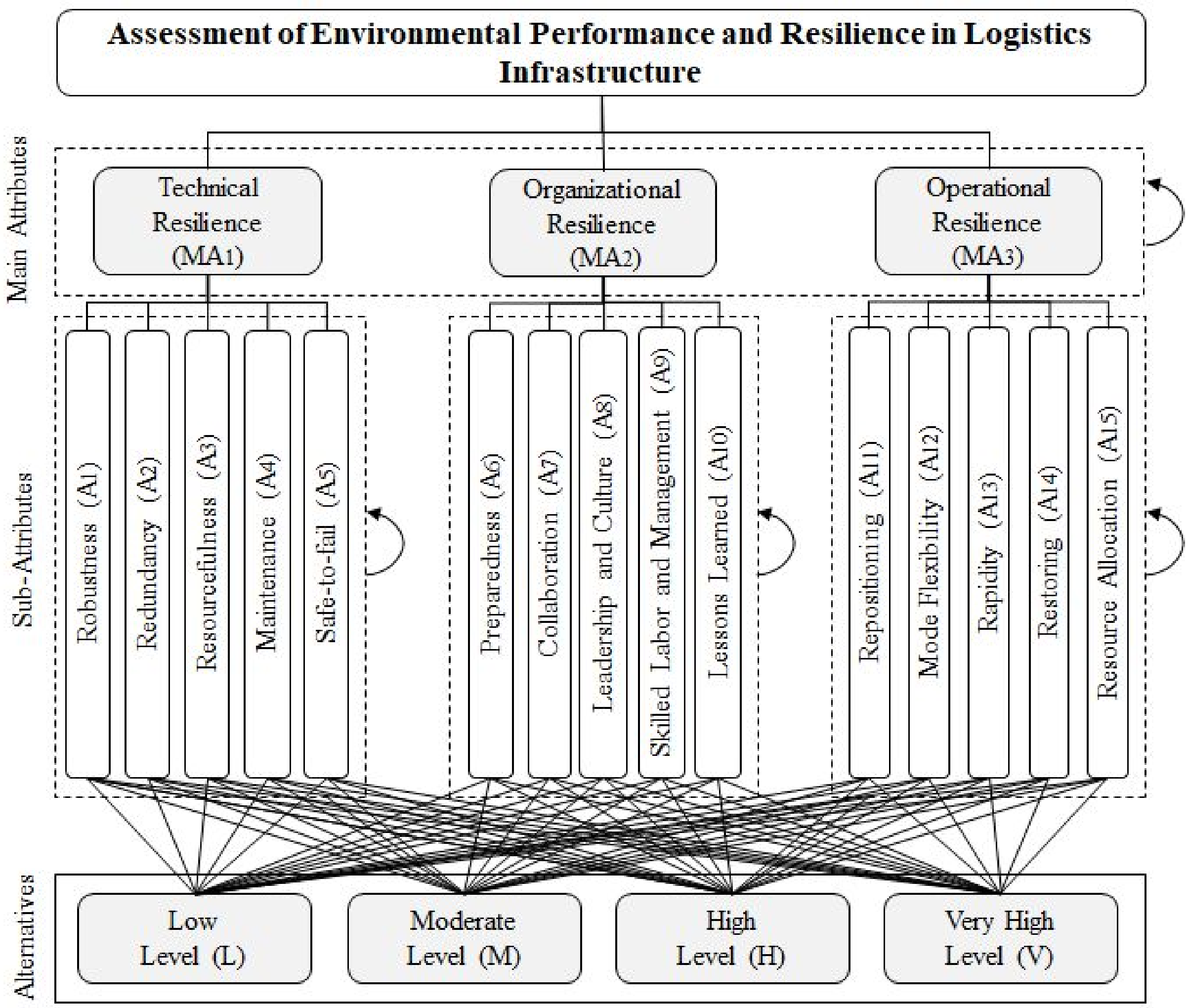


Fig. 3 Causal and hierarchical stream processing data evaluation framework.

Table 3
Linguistic variables for relative importance weight of attributes.

4.2 Step 2: Formulate the relationships between attributes

After identifying linguistic scales, FCM methodology is applied in order to determine the overall attribute weights. First, the attribute weights (gw_{ij}) for main attributes (domains) are calculated. The relative importance weight of each of MA1, MA2 and MA3 are obtained from three decision makers: DM1, DM2 and DM3 as shown in Table 6. Afterwards, the degrees of dependency among each of main attributes are acquired according to Eqs. (1-2). Aggregated fuzzy influence matrices are obtained. The resulting aggregated dependency degrees among main attributes are given in Table 7.

Table 4
Linguistic variables for causal relationships among attributes.

Table 5
Linguistic variables for rating of alternatives.

Table 6
The relative importance weights of the main attributes.

Employing Eqs. (3-4), aggregated dependency degrees among main attributes are defuzzified to be used in the FCM model given in Eq. (17). The aggregated decision makers' respond list of causal weights for domains is given in Appendix A. Final main attribute weights in accordance with Eq. (5-6) are depicted seen in Eq. (18) after obtaining 20 times iterations ($t = 20$) to converge the results. The *organizational domain* (MA_2) holds the highest weight, this means that organizational domain has highest impact on the assessment of resilience in integrated multimodal logistics hub than the operational and technical domains.

$$E_{MA} = \begin{bmatrix} 0 & 0.27 & 0.45 \\ 0.22 & 0 & 0 \\ 0 & 0.50 & 0 \end{bmatrix} \tag{17}$$

$$I_{MA} = \begin{array}{c} MA_1 \\ MA_2 \\ MA_3 \end{array} \begin{bmatrix} 0.31 \\ 0.36 \\ 0.33 \end{bmatrix} \tag{18}$$

Table 7
Aggregated dependency degrees among main attributes.

Table 8
The relative importance weights of the attributes.

Similarly, sub-attribute weights (w_{ij}) for each partition (dimensions) are calculated by using an FCM simulation. Every decision maker gives its opinion for fifteen attributes seen in Table 8. All opinions are aggregated according to Eq. (1-2) is employed seen in Table 9 and the initial values for sub-attributes (A_i^0) before simulation ($t = 0$) are derived.

Table 9
Aggregated dependency degrees among attributes.

The aggregated decision makers' respond list of causal weights for dimensions is given in Appendix B. Afterwards, using Eqs. (3-4), aggregated dependency degrees among sub-attributes are defuzzified. Final weight values (w_i) for resilience sub-attributes (A_i^{20}) per Eqs. (5-6) are depicted after obtaining simulation with 20 iterations ($t = 20$) to merge the results. Then the results are normalized, where the sum of sub-attributes values is 1. Table 10 depicts the overall priorities of resilience attributes. Fig. 4 shows the dynamic behaviour of environmental performance and resilience dimensions according to 20 iterations, where the change in sub-attributes weights even after 5th iteration remains constant. The dimensions of *Rapidity* (A_{13}), *Preparedness* (A_6) and *Maintenance* (A_4) obtained the highest weight values. FCM indices for $od(A_i)$, $id(A_i)$ and $cen(A_i)$ are denoted in Appendix C. Causal flows among sub-attributes are demonstrated with three layers from the lower level to the upper level which consist of a number of transmitter, receiver or ordinary attributes.

The findings appear to show that two transmitters, dimensions for *Safe-to-fail* (A_5) and *Mode Flexibility* (A_{12}) and one receiver, dimension for *Collaboration* (A_7) are determined, whereas twelve ordinaries are identified. Collaboration (A_7) is the only receiver in the map which is the most influenced sub-attribute in the map and its out-degree value is zero. The dimensions for *Safe-to-fail* (A_5) and *Mode Flexibility* (A_{12}) are the transmitters, which influence other attributes, therefore their in-degree values are zero. According to results, especially three sub-attribute weights obtain highest value respectively, *Rapidity* (A_{13}), *Preparedness* (A_6) and *Maintenance* (A_4), this implies that these are the initiators and drivers of sustaining environmental performance and resilience in the selected integrated multimodal logistics hub.

Table 10
Overall priorities of environmental performance and resilience attributes.

Main attributes (MA_i^{20})	Main attributes weights (gw_i)	Sub-attributes (A_i^{20})	Sub-attributes weights (final values, $t = 20$)	Overall sub-attributes normalized weights (w_i)
MA_1	0.31	A_1	0.74	0.067
		A_2	0.76	0.069
		A_3	0.66	0.061
		$\boldsymbol{A_4}$	**0.82**	**0.075**
		A_5	0.78	0.071
MA_2	0.36	$\boldsymbol{A_6}$	**0.74**	**0.077**
		A_7	0.50	0.052
		A_8	0.61	0.063
		A_9	0.65	0.067
		A_{10}	0.61	0.064
MA_3	0.33	A_{11}	0.69	0.067
		A_{12}	0.63	0.061
		$\boldsymbol{A_{13}}$	**0.81**	**0.078**
		A_{14}	0.71	0.069
		A_{15}	0.60	0.058

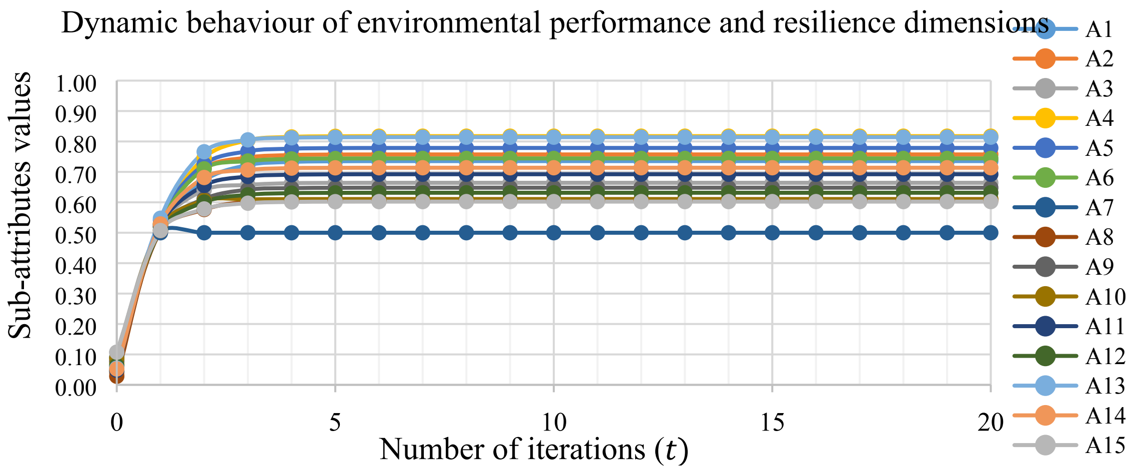


Fig. 4 Dynamic behaviour of environmental performance and resilience dimensions.

4.3 Step 3: Asses fuzzy rating values of alternatives

After calculating all attribute weights, the next step is to prioritize alternatives. Accordingly, the fuzzy rating values of alternatives are elicited from decision makers and fuzzy decision tables are constructed according to each attribute. Table 11 shows the fuzzy rating value of alternatives for sub-attribute A_1, where three DMs used linguistic variables for rating of alternatives in Table 4 and compared four alternatives pair-wise for each attribute. FAHP calculations are carried out by employing Eqs. (10-15). Afterwards, the consistency ratio (CR) is employed to examine the consistency of DMs' judgements (Saaty, 1980). This ratio also enabled DMs to evaluate the reliability of questionnaire used. All CR values should not be greater than 0.10, otherwise, DM should reenter the judgments. First of all, the consistency index (CI) should be calculated with Eq. (19), where λ_{max} is eigenvalue of comparison matrix, and n represents the level alternative number. Then, the same procedure is applied to calculate the fuzzy rating values for other attributes.

Table 11
Fuzzy rating values of alternatives for A_1.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{19}$$

CR is calculated by using Eq. (20), where RI presents the random consistency index acquired from the list: n:RI {1: 0, 2: 0, 3: 0.58, 4: 0.90, 5: 1.12, 6: 1.24, 7: 1.32, 8: 1.41, 9: 1.45}. There were four alternatives ($n = 4$), therefore, RI was chosen as RI = 0.90.

$$CR = CI/RI \tag{20}$$

In this study, CR was ranked between $0.0029 - 0.0949$. As a result, all findings were deemed to be consistent. After gathering evaluations from DMs, these are aggregated according to Eq. (16) and the list of aggregated normalized contribution weights (NW_{ij}) for attributes according to a disruptive event scenario are constituted seen in Table 12.

Table 12
Aggregated normalized contribution weights of attributes.

Table 13
Final weights value of alternatives.

4.4 Step 4: Ranking of result

Subsequently, obtaining two matrices, sub attributes weights (w_i) for Table 10 and normalized contribution weights (NW_{ij}) for Table 12, are multiplied and the final weights of alternatives, the level of environmental performance and resilience capacity in the selected integrated multimodal logistics hub, are calculated. So that, the final results of FAHP analysis are summarized in Table 13. Based on the normalized weights values, the ranking of alternatives from most to least according to level of environmental performance and resilience capacity is as follows:

M = 0.2880 > H = 0.2487 > L = 0.2351 > V = 0.2282.

In respect of ranking, the result can be concluded that M is assessed as current level of environmental performance and resilience capacity in the given logistics infrastructure according to highest normalized weight value among others. The obtained result according to given research question means that the selected logistics center in the context of a disruptive event scenario performs *moderate level* (M). It acquires less than desirable performance and specific improvements should be prioritized in order to improve the resilience performance.

4.5 Step 5: Measuring sensitivity

Sensitivity analysis is used to examine the impact of using different thresholds such as different decision makers and/or different sub-attributes on the result. This exploration is useful in conditions where uncertainties exist in the definition of the importance of different factors and situations (Govindan et al., 2013). In this study, nine different conditions are employed for the sensitivity analysis. Table 14 depicts the details of nine different conditions and a graphical illustration of the result is displayed in Fig. 5. For instance, condition #7 considers all environmental performance and resilience dimensions only with DM1, whereas condition #5 considers only technical and operational domains with DM1, DM2, and DM3. The result of a sensitivity analysis is used to validate the proposed model. According to different conditions, the sequence of alternatives changes. However, the ranks of alternatives are altered respecting weights, M performs as the level of environmental performance and resilience in every condition. This result proves that the decision-making process is sensitive to the type of attributes and the number of decision makers involved and their expertise with the subject. Their perception to decide on the level of environmental performance and resilience capacity for the selected integrated multimodal logistics hub was precisely given.

Table 14
Result of sensitivity analysis of causal and hierarchical stream processing data driven decision model for level of environmental performance and resilience assessments.

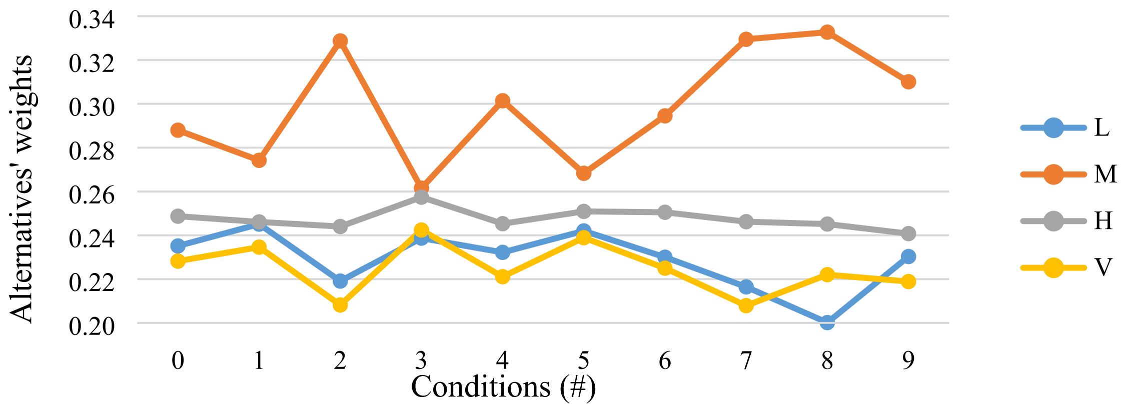


Fig. 5 The result of sensitivity analysis of causal and hierarchical stream processing data driven decision model.

5. Discussion

Since the emerging trends driven by Industry 4.0 and IoT are transforming logistics as well as logistics infrastructures, the massive data can be generated through sensors and sensor networks to analyze and compare event conditions per scenario. The real-time stream processing data needs to be processed to predict the future conditions of possible events and take actions against them before they can occur. Therefore, the development of the stream processing data decision model is necessary to assess the level of environmental performance and resilience in logistics infrastructure. The higher the level of environmental performance and resilience capacity in logistics infrastructure, the more sustainable is the transport supply chain system. In this study, key attributes responsible for affecting the environmental performance and resilience capacity of logistics infrastructures are identified and subsequently analyzed. Further, due to involvement of data streaming, there is a huge amount of data is generated in logistics network system. As these attributes are interrelated, experts' knowledge is extracted and combined in the new stream data based proposed decision system.

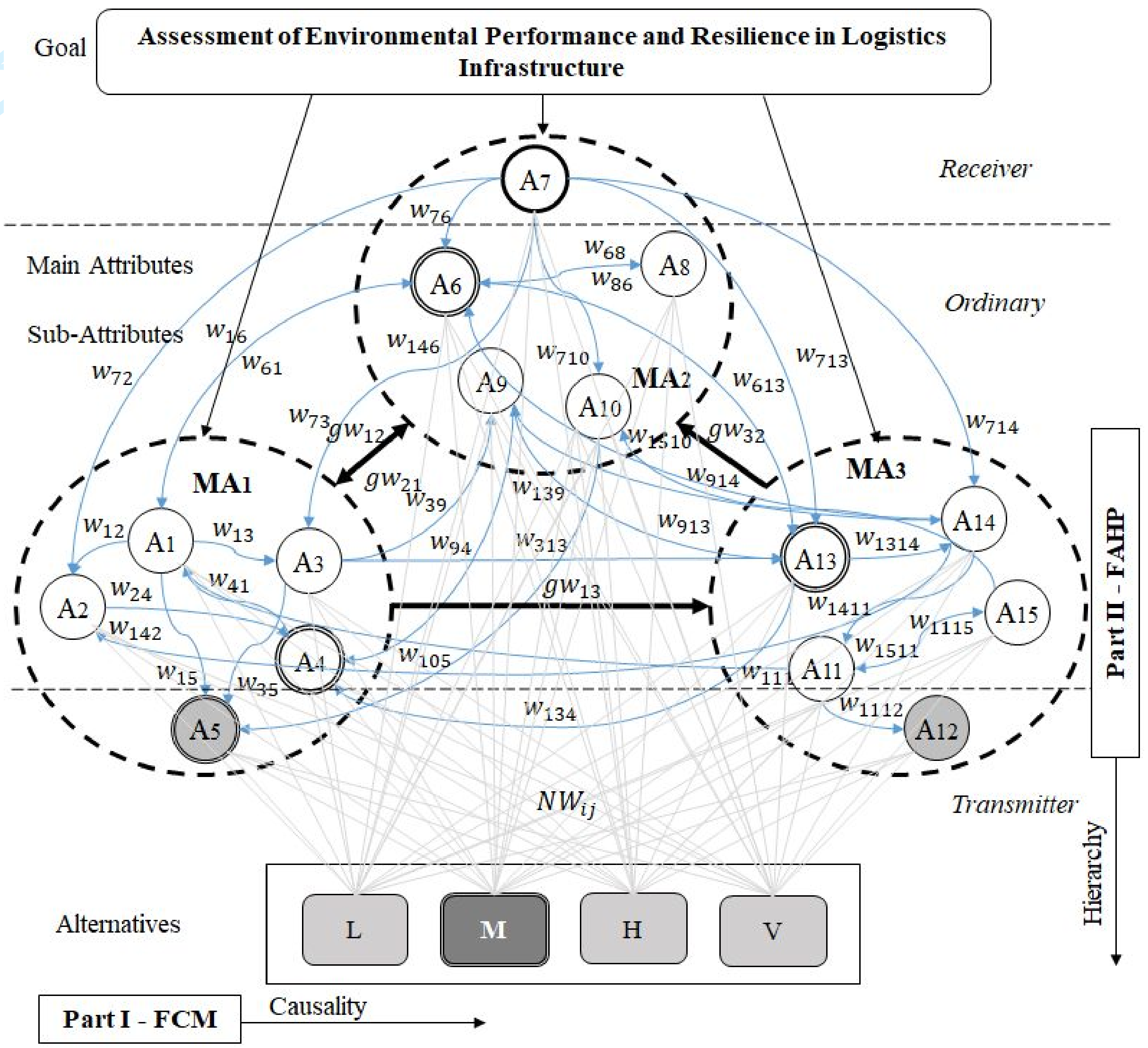


Fig. 6 The causal relations and top-down hierarchical decomposition with stream processing data decision model.

Fig. 6 infers the causal relations and top-down hierarchical decomposition of the selected multimodal modal logistics terminal with employing causal and hierarchical interrelationship stream processing data driven decision method combining FCM and FAHP approaches. The first stage employs FCM in order to derive the causal relationships among attributes (resilience domains/dimensions), then second stage uses FAHP to determine the relative weights of alternatives and present the level of environmental performance and resilience capacity of the given logistics infrastructure. The causal relationships among attributes can directly affect the relative weights of alternatives. If one attribute deteriorates itself, this can affect the whole relations of other attributes and ultimately the resilience level of the logistics infrastructure. Furthermore, this model shows which attributes need to be improved to enhance a sustainable and resilient freight transport network. According to findings, the domain for *Organizational* (MA_2) has the greatest impact on the assessment of environmental performance and resilience, respectively followed by *Operational* (MA_3) and *Technical* (MA_1). This can be interpreted that organizational preparedness has much more impact on environmental performance and resilience than other domains. Furthermore, the dimensions of *Rapidity* (A_{13}), *Preparedness* (A_6) and *Maintenance* (A_4) possess the highest weight values, whereas *Collaboration* (A_7) and *Resource Allocation* (A_{15}) have the lowest weight values to affect environmental performance and resilience, as seen their values in Table 10. The highest contribution weights of attributes are respectively *Preparedness* (NW_{62}), *Collaboration* (NW_{72}) and *Lessons Learned* (NW_{102}) and all contribute to *Moderate Level* of environmental performance and resilience, as seen their values in Table 12. At the end, the result of the study reveals that the level of environmental performance and resilience capacity of this selected integrated multimodal logistics hub performs at moderate level. Although, the logistics hub has been resilient against any disrupted event, some specific improvements need to be prioritized; such as the logistics hub needs to be further prepared against any unforeseen disruptions; connection and collaboration between logistics network partners need to intensify in the future and to ensure an effective and efficient logistics network process that reflects all members; the organization needs to learn from past experience, not to repeat the failures of the past, and to build on successes against the threat of any disruption. Beyond this, the result of sensitivity analysis shows also that the model is validated for all possible conditions and the data driven expert knowledge is accurate to assess the environmental performance and resilience.

The drawing the FCM maps and FAHP would be complicated, if more attributes are employed in the model. Hence, the aid of visualization software can simplify the illustration of causal relations and top-down hierarchical decomposition (De Nooy et al., 2018). In this study, all calculations were done by using MS Excel and R software (https://www.r-project.org/). In addition, Pajek software (http://mrvar.fdv.uni-lj.si/pajek/) was utilized to analyze and visualize the result of causal and hierarchical interrelationship stream processing data driven decision model.

6. Conclusion and future research

Proper planning for developing logistics infrastructures has become essential for ensuring coherent and integrated development that will support and enable efficient supply chains.

Logistics infrastructures and related transport elements (trains, ships, planes and trucks) comprise a crucial lifeline in whole supply chain, where any disruptions can cause unavoidable delays and economic losses. Therefore, ensuring these infrastructures as resilient as practicable is an important environmental and economic priority for the stakeholders. In addition, huge amount of data is also generated in freight transport system in form of continuous streams.

In this research, a causal and hierarchical stream processing data driven fuzzy decision-making model combining with FCM and FAHP approaches is proposed. The model is used to understand the assessment of environmental performance and resilience in logistics infrastructure to sustain a resilient and sustainable global transport supply chain system by enabling to model interdependencies among the decision attributes under a fuzzy environment and streaming data. This proposed approach can help researchers and practitioners (managers, planners, designers) of logistics infrastructure to understand how the selected attributes affect each other and at the end, how all attributes affect the overall environmental performance and resilience of infrastructure. In addition, this study also helps practitioners in understanding under what conditions the environmental performance and resilience perform undesirable and what attributes should be improved immediately per disruptive event scenarios. This study has several limitations. First, the study considers only limited number of identified attributes. Furthermore, the study focuses only one scenario, which demonstrates a general disruptive event and does not specify a special disruptive event, also the study does not provide to examine the proposed framework under different disruptive event scenarios. Next, the proposed model uses experts' knowledge and perceptions to solve environmental and resilience assessment problem, the result of this study might differ what experts involved in the study, therefore the generalizability of the findings for the selected logistics infrastructure is low. In addition, the proposed model can be tested under different scenarios to determine which environmental and resilience attributes perform best against which disruptive events over a certain time frame. As a future research, the methodology could be extended and developed by employing intuitionistic fuzzy sets and other decision-making tools such as ANP, TOPSIS, DEMATEL etc. Finally, the proposed model can be potentially applied in the other research areas e.g. smart infrastructures (smart cities, digital economy), agriculture, environment protection, risk management and all.

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Appendix A. Decision makers' respond list for causal weights in domains

gw_{ij}	G_i	G_j	Min (l_{ij})	Mean (m_{ij})	Max (u_{ij})	De-fuzzy (gw_{ij})	gw_{ij}	G_i	G_j	Min (l_{ij})	Mean (m_{ij})	Max (u_{ij})	De-fuzzy (gw_{ij})
gw_{12}	G_1	G_2	0.15	0.27	0.40	0.27	gw_{21}	G_2	G_1	0.10	0.22	0.35	0.22
gw_{13}	G_1	G_3	0.30	0.45	0.60	0.45	gw_{32}	G_3	G_2	0.35	0.50	0.65	0.50

Appendix B. Decision makers' respond list for causal weights in dimensions

w_{ij}	A_i	A_j	Min (l_{ij})	Mean (m_{ij})	Max (u_{ij})	De-fuzzy (w_{ij})	w_{ij}	A_i	A_j	Min (l_{ij})	Mean (m_{ij})	Max (u_{ij})	De-fuzzy (w_{ij})
w_{12}	A_1	A_2	0.38	0.50	0.62	0.50	w_{714}	A_7	A_{14}	0.45	0.60	0.73	0.59
w_{13}	A_1	A_3	0.37	0.48	0.62	0.49	w_{86}	A_8	A_6	0.35	0.50	0.65	0.50
w_{15}	A_1	A_5	0.50	0.65	0.78	0.64	w_{94}	A_9	A_4	0.55	0.70	0.83	0.69
w_{16}	A_1	A_6	0.17	0.30	0.45	0.31	w_{913}	A_9	A_{13}	0.45	0.60	0.75	0.60
w_{24}	A_2	A_4	0.50	0.65	0.77	0.64	w_{914}	A_9	A_{14}	0.45	0.60	0.73	0.59
w_{35}	A_3	A_5	0.65	0.77	0.88	0.77	w_{105}	A_{10}	A_5	0.30	0.45	0.60	0.45
w_{39}	A_3	A_9	0.40	0.55	0.68	0.54	w_{111}	A_{11}	A_1	0.30	0.45	0.60	0.45
w_{313}	A_3	A_{13}	0.60	0.75	0.87	0.74	w_{1112}	A_{11}	A_{12}	0.65	0.78	0.90	0.78
w_{41}	A_4	A_1	0.37	0.50	0.63	0.50	w_{1115}	A_{11}	A_{15}	0.45	0.60	0.75	0.60
w_{61}	A_6	A_1	0.27	0.40	0.55	0.41	w_{134}	A_{13}	A_4	0.55	0.70	0.83	0.69
w_{68}	A_6	A_8	0.45	0.58	0.72	0.58	w_{139}	A_{13}	A_9	0.17	0.30	0.45	0.31

w_{613}	A_6	A_{13}	0.35	0.50	0.65	0.50	w_{1314}	A_{13}	A_{14}	0.18	0.28	0.38	0.28
w_{72}	A_7	A_2	0.40	0.55	0.70	0.55	w_{142}	A_{14}	A_2	0.55	0.70	0.83	0.69
w_{73}	A_7	A_3	0.50	0.65	0.78	0.64	w_{146}	A_{14}	A_6	0.17	0.30	0.45	0.31
w_{76}	A_7	A_6	0.50	0.65	0.78	0.64	w_{1411}	A_{14}	A_{11}	0.40	0.55	0.70	0.55
w_{710}	A_7	A_{10}	0.50	0.63	0.77	0.63	w_{1510}	A_{15}	A_{10}	0.10	0.22	0.35	0.22
w_{713}	A_7	A_{13}	0.30	0.45	0.60	0.45	w_{1511}	A_{15}	A_{11}	0.55	0.70	0.83	0.69

Appendix C. FCM Criteria and Indices

Domains	Dimensions	A_i	$od(A_i)$	$id(A_i)$	$cen(A_i)$	T	R	O	A_i^T
Technical	Robustness	A_1	1.94	1.36	3.29			1	0.74
Technical	Redundancy	A_2	0.64	1.74	2.38			1	0.76
Technical	Resourcefulness	A_3	2.05	1.13	3.18			1	0.66
Technical	Maintenance	A_4	0.50	2.03	2.53			1	0.82
Technical	Safe-to-fail	A_5	0.00	1.86	1.86	1			0.78
Organizational	Preparedness	A_6	1.49	1.76	3.24			1	0.74
Organizational	Collaboration	A_7	3.52	0.00	3.52		1		0.50
Organizational	Leadership and Culture	A_8	0.50	0.58	1.08			1	0.61
Organizational	Skilled Labor and Management	A_9	1.89	0.85	2.74			1	0.65
Organizational	Lessons Learned	A_{10}	0.45	0.86	1.31			1	0.61
Operational	Repositioning	A_{11}	1.83	1.24	3.07			1	0.69
Operational	Mode Flexibility	A_{12}	0.00	0.78	0.78	1			0.63
Operational	Rapidity	A_{13}	1.28	2.29	3.57			1	0.81
Operational	Restoring	A_{14}	1.55	1.47	3.02			1	0.71
Operational	Resource Allocation	A_{15}	0.92	0.60	1.52			1	0.60

T: Transmitter, R: Receiver, O: Ordinary

TABLES

Table 1
Domains and dimensions of environmental performance and resilience assessment in logistics infrastructure.

Environmental Performance and Resilience Domains (MA_i)	Environmental Performance and Resilience Dimensions (A_i)	Definition and Main References
Technical Domain (MA_1)	Robustness (A_1)	The ability of elements, systems and other units of analysis to withstand a given level of stress or demand without suffering degradation or loss of function (Tierney & Bruneau, 2007; Haimes, 2009). Having backup power generators or infrastructure protection (e.g., storm surge, fire and barge channel) can stimulate environment and resilience capacity to maintain continuity of logistics infrastructure operations (Nair et al., 2009).
	Redundancy (A_2)	The extent to which system elements or other infrastructure units of analysis exist that are substitutable, in the event of disruption, degradation, or loss of functionality (Godschalk, 2003; Tierney & Bruneau, 2007; Haimes, 2009). For example, having redundant cargo handling facilities including cranes and reach stackers can reduce the environmental impact of disruptions. A number of similar routes are available with spare capacity.
	Resourcefulness (A_3)	The ability to diagnose and prioritize problems and to initiate solutions by identifying and mobilizing material, monetary, informational, technological, and human resources (Tierney & Bruneau, 2007).
	Maintenance (A_4)	Maintenance activities for logistics infrastructure, including on-time repair scheduling of cargo handling machines/equipment and availability of spare equipment, strengthen a logistics infrastructure ability to withstand disruptions (Hosseini, 2016). The reliability of a logistics infrastructure, defined as the probability that logistics infrastructure continues its normal operations for a given time interval under normal operating conditions, is a measure of the effectiveness of environmental performance and logistics infrastructure (Hosseini et al., 2016).
	Safe-to-fail (A_5)	The extent to which innovative design approaches are developed, recognizing that the possibility of failure can never be eliminated (Hughes & Healy, 2014). Infrastructure does not harm its users or expose them, unduly to hazards (Murray-Tuite, 2006).
Organizational Domain (MA_2)	Preparedness (A_6)	The ability to sense and anticipate hazards, identify problems and failures, and to develop a forewarning of disruption threats and their effects and environment (Hughes & Healy, 2014).
	Collaboration (A_7)	The ability to establish relationships, mutual aid arrangements and regulatory partnerships, understand interconnectedness and vulnerabilities across all aspects of supply chains and distribution networks (Godschalk 2003; Resilient Organisations 2012). For example, establishment a seamless flow of information and coordination among owners, operators, system users, and overseers (e.g., logistics infrastructure staff, multimodal transport operators, freight operators, utility operators, freight forwarders, shipping agents, regulatory agencies and emergency agencies) can reduce the operational as well as environmental impact of disruptions.
	Leadership and Culture (A_8)	The ability to develop an organizational mind-set/culture of enthusiasm for challenges and opportunity (Resilient Organisations 2012).

	Skilled Labor and Management (A_9)	Training operators and managers is important action to react and control a disruption and to maintain environmental continuity. In addition, the use of skilled labor reduces the time of loading and unloading tasks by fully utilizing equipment such as container cranes, reach stackers and straddle carrier (Nair et al., 2009).
	Lessons Learned (A_{10})	Contingency plan be tested and revised after disruptive events to reflect lessons learned (Imran et al., 2014).
Operational Domain (MA_3)	Repositioning (A_{11})	Shipping containers are generally stacked at dry dock locations; however, repositioning transport units (e.g. containers, semi-trailers) and large items on the ground in the case of natural disasters can be useful (Madhusudan & Ganapathy, 2011)
	Mode Flexibility (A_{12})	In the case of a logistics infrastructure disruption, shipping at logistics centers (port, terminal) for a specific transport mode can be congested and delayed. Under this condition, mode flexibility enables cargo to be rerouted and transported through an alternative transport mode (e.g., road, rail, waterway) with charging extra shipping costs in order to avoid supply disruptions and favor environmental performance (Godschalk 2003; Morlok & Chang, 2004; MacKenzie et al., 2012).
	Rapidity (A_{13})	The capacity to restore functionality in a timely way, containing losses and avoiding disruptions. (Tierney & Bruneau, 2007).
	Restoring (A_{14})	Restorative capacity refers to the ability of a system to repair or restore damages and save resources from a disruption (Murray-Tuite, 2006, Vugrin et al., 2011). It is considered to be a permanent feature of system resilience. In the context of logistics infrastructure recovery, the damaged equipment (e.g., crane, power generator) can be repaired or restored depending on the severity of disruption but also on budget availability and it also includes the availability of human-based resources (e.g., skilled labors, technical engineers), and non-human-based resources (e.g., repair equipment) (Haimes, 2009).
	Resource Allocation and Management (A_{15})	It refers to the manner in which resources are distributed in order to recover and conserve environment from disruptive events. Effective resource allocation requires the use of resources such as the physical capacity of the network, the equipment that facilitates the rerouting or redirection of the network flow and personnel in a timely manner. It also requires an accurate processing of the kind and quantity of resources needed so that the expected value delivery level of the infrastructure system is maintained (Mayada, 2013).

Table 2

The proposed causal and hierarchical stream processing data driven decision model.

#	Input	Step #	Methodology	Output
1	In section 2 demonstrated environmental performance and resilience attributes	Identify the resilience assessment attributes, alternatives and linguistic scales	Literature review and expert opinions	Determined domains, dimensions, alternatives and their TFM functions
2	Environmental performance and resilience domains	Formulate the relationships between attributes	FCM	Causal relationships for domains as well as dimensions and their

	and dimensions, TFM functions			analysis
3	The causal weights of environmental performance and resilience domains, attributes and alternatives, TFM functions	Asses fuzzy rating values of alternatives	FAHP	Assessment of the level of environmental performance and resilience capacity of logistics infrastructure
4	Final weights of alternatives	Ranking of result	Ranking analysis	Ranking the final weights from the highest to the lowest ones
5	Setting different thresholds	Measuring sensitivity	Sensitivity analysis	Proving the sensitiveness of decision-making process according to different conditions

Table 3
Linguistic variables for relative importance weight of attributes.

Linguistic variables	TFM functions
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1)
Very high (VH)	(0.9, 1, 1)

Table 4
Linguistic variables for causal relationships among attributes.

Linguistic variables	TFM functions
Very weak (VW)	(0, 0.1, 0.2)
Weak (W)	(0.1, 0.2, 0.35)
Medium weak (MW)	(0.2, 0.35, 0.5)
Fair (F)	(0.35, 0.5, 0.65)
Medium strong (MS)	(0.5, 0.65, 0.8)
Strong (S)	(0.65, 0.8, 0.9)
Very strong (VS)	(0.8, 0.9,1)

Table 5
Linguistic variables for rating of alternatives.

Linguistic variables	TFM functions

Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

Table 6
The relative importance weights of the main attributes.

	DM1	DM2	DM3
MA_1	H	H	H
MA_2	ML	L	M
MA_3	H	VH	MH

Table 7
Aggregated dependency degrees among main attributes.

	Aggregated weights	Defuzzified weights	Normalized weights
MA_1	(0.70, 0.90, 1)	0.87	0.43
MA_2	(0.13, 0.30, 0.50)	0.31	0.15
MA_3	(0.70, 0.87, 0.97)	0.84	0.42

Table 8
The relative importance weights of the attributes.

	DM1	DM2	DM3
A_1	H	VL	H
A_2	ML	L	M
A_3	H	VH	MH
A_4	MH	H	L
A_5	M	M	L
A_6	MH	L	ML
A_7	ML	VH	H
A_8	L	VL	M
A_9	H	L	H
A_{10}	M	H	MH
A_{11}	L	MH	ML
A_{12}	VL	VH	M
A_{13}	ML	H	L
A_{14}	M	VL	MH
A_{15}	MH	H	VH

Table 9
Aggregated dependency degrees among attributes.

(A_i^0)	Aggregated weights	Defuzzified weights	Normalized weights (initial values, $t = 0$)

A_1	(0.47, 0.60, 0,70)	0.59	0.07
A_2	(0.13, 0.30, 0.50)	0.31	0.04
A_3	(0.70, 0.87, 0.97)	0.84	0.11
A_4	(0.40, 0.57, 0.73)	0.57	0.07
A_5	(0.20, 0.37, 0.57)	0.38	0.05
A_6	(0.20, 0.37, 0.57)	0.38	0.05
A_7	(0.57, 0.73, 0.83)	0.71	0.09
A_8	(0.10, 0.20, 0.37)	0.22	0.03
A_9	(0.47, 0.63, 0.77)	0.62	0.08
A_{10}	(0.50, 0.70, 0.87)	0.69	0.09
A_{11}	(0.20, 0.37, 0.57)	0.38	0.05
A_{12}	(0.40, 0.50, 0.60)	0.50	0.06
A_{13}	(0.27, 0.43, 0.60)	0.43	0.06
A_{14}	(0.27, 0.40, 0.57)	0.41	0.05
A_{15}	(0.70, 0.87, 0.97)	0.84	0.11

Table 10
Overall priorities of environmental performance and resilience attributes.

Main attributes (MA_i^{20})	Main attributes weights (gw_i)	Sub-attributes (A_i^{20})	Sub-attributes weights (final values, $t = 20$)	Overall sub-attributes normalized weights (w_i)
MA_1	0.31	A_1	0.74	0.067
		A_2	0.76	0.069
		A_3	0.66	0.061
		$\boldsymbol{A_4}$	**0.82**	**0.075**
		A_5	0.78	0.071
MA_2	0.36	$\boldsymbol{A_6}$	**0.74**	**0.077**
		A_7	0.50	0.052
		A_8	0.61	0.063
		A_9	0.65	0.067
		A_{10}	0.61	0.064
MA_3	0.33	A_{11}	0.69	0.067
		A_{12}	0.63	0.061
		$\boldsymbol{A_{13}}$	**0.81**	**0.078**
		A_{14}	0.71	0.069
		A_{15}	0.60	0.058

Table 11
Fuzzy rating values of alternatives for A_1.

	DM1				DM2				DM3			
A_1	L	M	H	V	L	M	H	V	L	M	H	V
L	1,1,1	1/F	MP	1/MP	1,1,1	MP	1/VP	1/F	1,1,1	1/P	MP	1/P

M	F	1,1,1	1/VP	MG	1/MP	1,1,1	P	1/F	P	1,1,1	1/P	MG
H	1/MP	VP	1,1,1	P	VP	1/P	1,1,1	P	1/MP	P	1,1,1	VP
V	MP	1/MG	1/P	1,1,1	F	F	1/P	1,1,1	P	1/MG	1/VP	1,1,1

$V(S_L \geq S_M, S_H, S_V) = 0.283$; $V(S_M \geq S_L, S_H, S_V) = 1.00$; $V(S_H \geq S_L, S_M, S_V) = 0.131$; $V(S_V \geq S_L, S_M, S_H) = 0.308$; $\frac{CI}{RI} = 0.0687$

$V(S_L \geq S_M, S_H, S_V) = 0.491$; $V(S_M \geq S_L, S_H, S_V) = 0.223$; $V(S_H \geq S_L, S_M, S_V) = 0.329$; $V(S_V \geq S_L, S_M, S_H) = 1$; $\frac{CI}{RI} = 0.0454$

$V(S_L \geq S_M, S_H, S_V) = 0.670$; $V(S_M \geq S_L, S_H, S_V) = 1.00$; $V(S_H \geq S_L, S_M, S_V) = 0.416$; $V(S_V \geq S_L, S_M, S_H) = 0.402$; $\frac{CI}{RI} = 0.0758$

Table 12

Aggregated normalized contribution weights of attributes.

A_i	NW_{ij}	L	NW_{ij}	M	NW_{ij}	H	NW_{ij}	V
A_1	NW_{11}	0.224	NW_{12}	0.293	NW_{13}	0.190	NW_{14}	0.293
A_2	NW_{21}	0.264	NW_{22}	0.254	NW_{23}	0.272	NW_{24}	0.210
A_3	NW_{31}	0.285	NW_{32}	0.231	NW_{33}	0.280	NW_{34}	0.203
A_4	NW_{41}	0.218	NW_{42}	0.318	NW_{43}	0.210	NW_{44}	0.254
A_5	NW_{51}	0.237	NW_{52}	0.274	NW_{53}	0.274	NW_{54}	0.216
A_6	NW_{61}	0.207	NW_{62}	0.458	NW_{63}	0.209	NW_{64}	0.126
A_7	NW_{71}	0.189	NW_{72}	0.355	NW_{73}	0.247	NW_{74}	0.210
A_8	NW_{81}	0.251	NW_{82}	0.203	NW_{83}	0.273	NW_{84}	0.273
A_9	NW_{91}	0.224	NW_{92}	0.276	NW_{93}	0.292	NW_{94}	0.208
A_{10}	NW_{101}	0.222	NW_{102}	0.335	NW_{103}	0.209	NW_{104}	0.233
A_{11}	NW_{111}	0.215	NW_{112}	0.244	NW_{113}	0.287	NW_{114}	0.254
A_{12}	NW_{121}	0.209	NW_{122}	0.276	NW_{123}	0.257	NW_{124}	0.257
A_{13}	NW_{131}	0.265	NW_{132}	0.241	NW_{133}	0.265	NW_{134}	0.229
A_{14}	NW_{141}	0.244	NW_{142}	0.274	NW_{143}	0.232	NW_{144}	0.250
A_{15}	NW_{151}	0.271	NW_{152}	0.271	NW_{153}	0.240	NW_{154}	0.218

Table 13

Final weights value of alternatives.

Alternatives	Normalized weights
L	0,2351
M	**0.2880**
H	0.2487
V	0.2282

Table 14

Result of sensitivity analysis of causal and hierarchical stream processing data driven decision model for level of environmental performance and resilience assessments.

#	Main attribute/Sub-attribute	Decision maker	Result (ranking)
0	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM1, DM2, DM3	M>H>L>V

1	A_1, A_2, A_3, A_4, A_5	DM1, DM2, DM3	M>H>L>V
2	$A_6, A_7, A_8, A_9, A_{10}$	DM1, DM2, DM3	M>H>L>V
3	$A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM1, DM2, DM3	M>H>V>L
4	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}$	DM1, DM2, DM3	M>H>L>V
5	$A_1, A_2, A_3, A_4, A_5, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM1, DM2, DM3	M>H>L>V
6	$A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM1, DM2, DM3	M>H>V>L
7	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM1	M>H>L>V
8	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM2	M>H>V>L
9	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$	DM3	M>H>L>V