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Causal mechanism in transport collaboration

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ABSTRACT

The changing climate in supply chain management, driven by technological trends, increased competition, demand pressure, globalization and outsourcing has led companies to be more receptive to forming coalitions while taking a broader strategic view of the marketplace. The structure of a transport coalition is an important issue influencing the life cycle of such relationships. This structure is a set of consensual relationships that connect key operating criteria for the coalition. The structure can change over time. This structural change is causal and its extreme situation might cause deterioration of the coalition. This work proposes a systematic way of analyzing the causal inference mechanism between the operating collaborative criteria and their categories in transport collaboration using a fuzzy cognitive map based approach. The findings address the decision making on the level of collaborative integration of coalition by the detection thresholds according to "go", "go with conditions" and "no-go" signals. This approach is supported with the application to a "real world" case of a multi-echelon heterarchical transport network through a series of simulation experiments.

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1. Introduction

Transport management is a highly leveraged function for value creation meaning that even small improvements in business processes can drive large increases in profitability and cost reduction (Stank & Goldsby, 2000). Therefore the transport industry has seen a recent emergence of strategic collaborative initiatives (Cruijssen, Dullaert, & Fleuren, 2007; Fugate, Davis-Sramek, & Goldsby, 2009). Studies have shown that there is a notable realization of collaborative actions in the business of freight transport with particular increases in the use of intermodal shipments and the improvement of carrier tracking and shipment consolidation (Graham, 2011). Transport collaboration can be considered to be a strategic asset for optimizing the supply chain and improving the competitiveness of companies (Kayikci & Zsifkovits, 2012). Therefore, transport users, transport service providers and/or technology providers establish *coalition communities* in order to reap benefits from joint operational processes. Since every coalition has unique aspects, there is no "*one size fits all approach*" for building a transport collaboration. That being said, the *structure* of a collaboration should contain the combination of automated and adaptive *technologies*, business *processes* and proactive *human collaboration* in socio-technical systems (Gaurav, 2004; Ritter, Lyons, & Swindler, 2007). Success for a transport coalition is achieved when the above-mentioned combination is strategically aligned for every coalition partner. The structure of transport collaboration can change over time. This change in the structure is causal (Dickerson & Kosko, 1998). The analysis of *causal mechanisms* among critical criteria is crucial as it might provide early signals about the level of collaborative integration of a coalition. These signals are mainly used for decision making and prediction. In previous work, we investigated thirty-seven operating criteria within five main categories for transport collaboration structures. This work utilizes those criteria and is aimed at answering the following research question: *How would a given pair of criteria in transport collaboration structure be causally interrelated. In other word, how would every change in the pair of criteria affect the transport collaboration structure under a set of scenario conditions?* To address these concerns, a Fuzzy Cognitive Map (FCM) based model is proposed, which can give early signals for the possible future condition of coalition by detecting "go", "go with conditions" and "no-go". These signals can be interpreted as the level of collaborative integration respectively as "full-integration", "partly integration" and "no integration". The FCM approach is especially useful for solving unstructured problems in soft knowledge-based issues (e.g. organizational theory, intra-organizational relations, and transport network), where different decision criteria are causally interrelated and fundamentally "fuzzy" (Kosko, 1986). FCM can be seen as descriptive models which can explain the ways coalition partners actually do derive explanations of the past, make predictions of the future, and choose policies in the present (Schwenk, 1988), from those aspects FCM is also applicable for the scenario development (Glykas, 2010; Jetter & Schweinfort, 2011; Van Vilet, Kok, & Veldkamp, 2010). In an FCM-based model, we utilized a pair-wise

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scenario matrix in the FCM iterative process to compare every pair of given criteria using simulation experiments. The form of extended FCM gives fuzzily intersected zones to observe the causal mechanism among a system set. These zones can infer the intensity of change in the structure. This research is based on the empirical findings of transport collaboration practices in a "real-world" coalition and the required data for the approach was collected in advance from a questionnaire. The findings of this research show how the change among two criteria can affect the transport collaboration structure and the result can be divided into smaller fuzzy sets or sub-domains in order to observe the change in the structure. This paper assumed that the coalition has a high level of collaborative integration. The result of this study provides a structured understanding of the system perceptions for the coalition partners. Therefore, it contributes to the simplification of the decision making process for a coalition by scenario development based on the FCM-based model.

2. Criteria and categories in transport collaboration structure

Today, the most frequently identified underlying inefficiencies encountered by transport managers are poor capacity utilization, empty backhaul, high transport costs, low profit margins and the sometimes harsh environmental impact of transport logistics. Transport collaboration has grown in popularity as a sustainable strategy over the last few years to cope with such industry consequences. Transport collaboration refers to innovative approaches with socio-technical systems applied to collaborative transport planning and execution encompassing platform-based, automated, adaptive technologies, supporting business processes and proactive human collaboration (Gaurav, 2004; Ritter et al., 2007). Coalition communities in transport collaboration occur across a variety of levels and business functions between two organizations (bi-lateral) or in a network of multiple organizations (multi-lateral) that is driven in three planes: vertically, horizontally, and laterally. These can vary with the level of collaborative integration from a very superficial transactional relationship to a highly integrated relationship among coalition partners (Kayikci & Zsifkovits, 2012). This may not only involve exploiting synergies between participants, but also conducts the allocation of benefits fairly among them. Transport collaboration typically requires a consolidation of capacities across different business units where the centralization of transport management allows the allocation of the resources more efficiently. Transport collaboration models are powered by advanced software systems and the Internet which allow companies to expand collaborative transport networks on a large scale. In effect companies are forming web-based and more traditional partnerships to reduce the transportation and inventory costs while raising the bar on customer service. Transport users and transport service providers enter into relationships to fill perceived needs; one of which is for scarce resources. Each partner contributes necessary resources with the expectation of receiving valued returns (Fugate et al., 2009). A coalition's partners must decide together on the selection of the proper collaborative infrastructure and systems. Bringing together the right partners and selecting the right process and technology for collaboration are as critical as defining the supporting structure at the right time. Close collaboration is always desirable to align the involved parties and then enhance the value of the transport network's combined activities (Kayikci & Zsifkovits, 2012). However, many collaborative transport initiatives fail to deliver the value expected from them (Kampstra, Ashayeri, & Gattorna, 2006; Lambert & Knemeyer, 2004) and come to an end with separation and failure (Graham, 2011). This results in a misalignment of transport collaboration structure and results in poor decision making and wrong actions being taken.

Structure is an important issue influencing the level of collaborative integration of coalition; it can be seen as a collection of criteria and the set of interactive relationships that connects these criteria. After elucidating the importance of transport collaboration structure, in previous work we investigated thirty-seven criteria with five main categories based on their attributes (as seen in Table 1). These criteria and categories are used as fuzzy logic toolkit in this research. These categories were: (1) *Technical perspective*: contains Information and Communication Technology (ICT) capabilities which facilitate data integration and exchange across supply chain. (2) *Risk perspective:* refers to the possible risk areas in management of transport collaboration associated with strategic restructuring activities like transport chain, skill set, control risk and so on., (3) *Financial perspective:* gives a reflection of financial performance ensuring financial integrity within distinct organizations are in place for reducing costs and increasing overall efficiency. (4) *Organizational perspective:* indicates the organizational alignment that involves readiness of integration, co-ordination and collaboration across organizations (5) *Operational perspective:* comprise the effective resource (asset) utilization and customer service, efficient transport costs and environmental sustainability.

3. Research methodology

Causal inference is a central aim of both experimental as well as observational studies in the social sciences. It is a big challenge to infer counterfactual conditions from observed data by accounting for what would have happened versus what actually happened. The term of causal mechanism is the causal process through which the effect of a treatment on an outcome comes about (Imai, Dustin, & Teppei, 2013). This causal process draws the connection between different criteria. Causal effect is the findings that change in one criterion leads to change in another criterion. FCM is a powerful technique for representing models of causal inference among pairs of criteria. This paper formally analyzes the causal mechanism of transport collaboration by proposing a FCM-based model. Intuitively, FCM is a fuzzy digraph with feedback (Kosko, 1986) that represents a causal system with uncertain and incomplete causal information. The human experience and knowledge on the complex systems is embedded in the structure of FCMs and the corresponding causal inference processes. FCM combines simple actions to model human knowledge and dynamic behavior for decision making process (Dickerson & Kosko, 1994; Jetter & Schweinfort, 2011). FCM is developed by the number of decision makers who know the system and its behavior under different circumstances in such a way that the accumulated experience and knowledge are integrated in a causal relationship among the system components (Kosko, 1992). FCM analyzes the causal interference (i.e. positive, negative or zero) between given criteria and the degree of influence (x) of this interference expressed in linguistic terms. However, there are other semi-quantitative and qualitative modeling methods available besides FCM; Ozesmi and Ozesmi (2004) and Van Vilet et al. (2010) mentioned that FCM addresses the following characteristics. These are our reasons for choosing FCM instead of other methods:

- It is easy to understand (as all decision makers should be able to understand the basics)
- Has a high level of integration (needed for the complex issues related to transport)
- Can be performed over a relatively short time
- Gives a system description.
- It is also useful for extension activities to educate decision makers, if there are any misperceptions.

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Table 1
Criteria and categories of transport collaboration structure.

Category	Criterion	Abbr. code	C_i	Definition
Technical perspective	Reliability	RELI	C_1	Track and traceability, reliability of technical systems
	Standardization	STD	C_2	Acceptable data standards in order to facilitate information exchange
	Technological capabilities	TECHCAP	C_3	Support multiple technologies, multiple collaborative models and scalability of collaborative solutions
	Integration level	INTL	C_4	Operation, coordination or strategic; which are ad-hoc or formal basis.
	Information quality	INFQ	C_5	Quality of data transactions
	System performance	SPER	C_6	Capability for operating, network and application level
	Flexibility in toolset	FLEXT	C_7	Maximum scalability and flexibility in functions
Risk perspective	Skill set	SKILL	C_8	Lack of skilled staff, organizational incompatibility
	Feasibility	FEA	C_9	Investability of the strategy
	Technology usage	TECHUS	C_{10}	Lack of technological investment and integration
	Safety and security	SASE	C_{11}	Confidentiality
	Transport chain	TRCHAIN	C_{12}	Risk in the structure of the transport chain i.e. risk in intermodal transport
	Profitability	PROF	C_{13}	Capability risk to make more profit, low cost saving potential
	Control risk	CONT	C_{14}	Loss of managerial control
	Infrastructure	INF	C_{15}	Risk in basic facilities
Financial perspective	Overall efficiency	OVEFF	C_{16}	All associated costs in transport collaboration process
	Transport cost	COST	C_{17}	The economic cost of transportation
	Level of orientation	ORIENT	C_{18}	Long-, mid- or short-term direction
	Accelerated ROI	ROI	C_{19}	Faster return on investment
	Cost sharing	COSTSHAR	C_{20}	Ability to share and allocate cost
	Financial performance	FINANS	C_{21}	Resulting with high financial ratios
Organizational perspective	Organizational fit	ORGFIT	C_{22}	Organizational readiness for collaboration. The ability to work formally or informally with external partners
	Management involvement	MNG	C_{23}	Support and acceptance from managerial level
	Openness of communication	OPENCOM	C_{24}	Agreement on open dialogues; open to partnership and collaboration.
	Information sharing	INFSHAR	C_{25}	Willingness to share information
	Transparency	TRANS	C_{26}	Enhancing full of cross-organizational visibility for data exchange
	Leadership	LEAD	C_{27}	Readiness for leadership in the coalition
	Trusting relationship	TRUST	C_{28}	The level of trust and commitment to collaborate for a long term.
Operational perspective	Asset optimization	ASSET	C_{29}	The performance of the asset utilization
	Capacity	CAPA	C_{30}	Total operating capacity
	Replenishment length	REPLEN	C_{31}	Process length
	Lead time	LEADT	C_{32}	Process time
	Flexibility in processes	FLEXP	C_{33}	Ability to change processes according to unexpected conditions
	Carbon footprint	SUST	C_{34}	Sustainability – Reduction of CO2 emissions
	Predictability	PREDIC	C_{35}	Predictability of demand
	Variability	VAR	C_{36}	Variability of demand
	Service level	SERV	C_{37}	High, medium or low effectiveness

An FCM F can be defined through a graph, i.e. $M = (V, E)$, that models the map structure. Formally, an FCM F is a 4-tuple $F = (M, w, v, T)$ and it consists of a map structure $M = (V, E)$, where V is a set of concepts $V = \{C_i | i = 1, \ldots, n\}$ and edge $E = \{(C_i, C_j) \mid C_i, C_j \in V\}$; edge weight $w_{i,j} = E \in [-1, 1]$, the vector value of each concept $v = V \in [0, 1]$ and real time value $T \in \mathbb{R}$ modeling the iteration length in cognitive inference. A *concept* C_i in FCM represents a criterion. Interconnections among concepts are characterized by an *edge* with an arrow that indicates the causal interference and the direction of influence for an ordered pair of concepts (C_i, C_j); the degree of causal increase or decrease among these two concepts are determined by *edge weight* w_{ij}. Human knowledge and experience are reflected in the selection of concepts and edge weights for the interconnections between concepts of the FCM. The causal relationship among two concepts can be bi-directed (as seen between C_1 and C_3 in Fig. 1) and their edge weights do not necessarily have to be at the same value, they can be positive (+) as well as negative ($-$) ($w_{ij}, w_{ji}, w_{ij} \neq w_{ji}$). There are three possible types of causal relationships among concepts: $w_{ij} > 0$, positive causality between C_i and C_j; $w_{ij} = 0$, no relationship between C_i and C_j; $w_{ij} < 0$, negative causality between C_i and C_j. The independencies between concepts can be visualized through a causal diagram of the kind shown in Fig. 1. This diagram represents the graphical illustration of six concepts that are causally linked to each other. This causal linkage among concepts is represented with nine edge weights. We assume that the concepts which influence the problem were identified in advance.

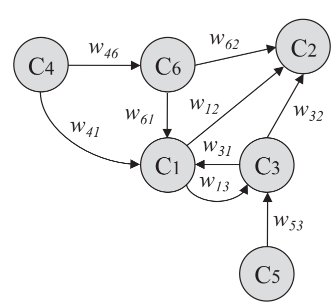

Fig. 1. Causal diagram.

Primarily there are four steps involved in the proposed FCM-based model: (1) generation of the edge matrix, (2) causal inference and computation of the indices, (3) calculation of

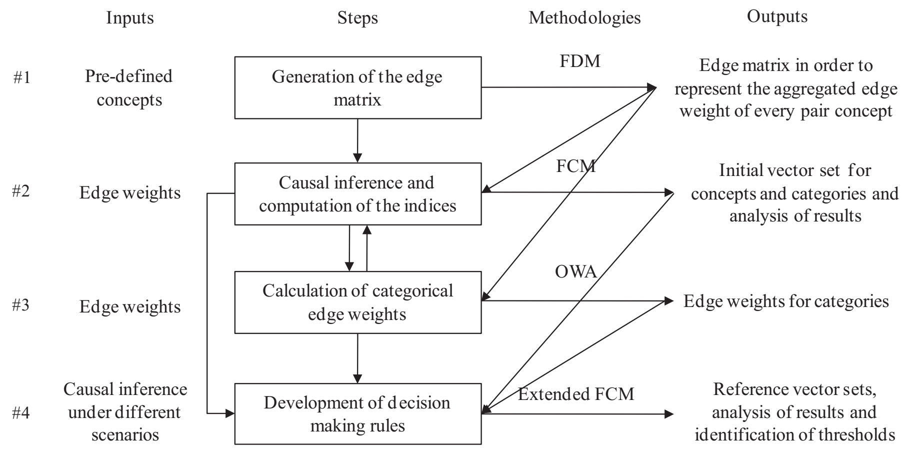

Fig. 2. Framework of the proposed FCM-based model.

categorical edge weights, (4) development of decision making rules. The detail of the proposed model is given in Fig. 2, and the procedures are presented in-depth in the following subsections.

3.1. Step 1: generation of the edge matrix

The first step is the data collection phase in order to generate the edge matrix for FCM. Various methodologies in FCM could be used in order to reach a group consensus among the decision makers. Delphi is a well-known methodology used to structure the decision makers' communication process to reach a consensus regarding a complex problem. One of the main features of the Delhi study is that the experts have the opportunity to change their opinions regarding to feedback reports. Here, the Fuzzy Delphi Method (FDM) is utilized and integrated into the FCM to assign the causal weight (w_{ij}) between two concepts (C_i, C_j) by group decision-making. FDM was first proposed by Ishikawa et al. (1993). It is based on the combination of the traditional Delphi technique and fuzzy set theory. Noorderhaben (1995) indicated that applying the FDM to group decision can solve the fuziness of common understanding of decision maker opinions. Moreover, FDM supports the FCM-based model using an interactive procedure of knowledge acquisition and it helps to prevent the model from the possible inconsistencies and cycles. In fuzzy set theory, membership functions assign to each object a degree of membership ranging on a given scale (Saaty, 1980). Different fuzzy membership functions used by other were considered including a triangular membership function, Gaussian membership function and a trapezoidal membership function (Passino & Yurkovich, 1998). We adopted triangular membership functions since they are the most commonly used ones fort this study. A tilde ($\sim$) will be replaced above the weight symbol to represent the causal fuzzy weight ($\tilde{w}_{i,j}$). The FDM steps are as follows:

i. *Set up the Triangular Fuzzy Memberships (TFM):* The equation of triangular includes three parameters, i.e. l, m and u, as shown in Fig. 3. The parameters l, m and u, respectively, denote the smallest possible value, the most promising value and the largest possible value that describes a fuzzy event. Each number in the pair-wise comparison matrix represents the subjective opinion of decision makers and is an ambiguous concept; fuzzy numbers work best to consolidate fragmented decision maker opinions.

$\tilde{w}_{i,j}$ represents the specified TFM function $\mu_{\tilde{w}}(x)$ by a triplet (l_{ij}, m_{ij}, u_{ij}) of two concepts (C_i, C_j), to integrate the multiple decision maker opinions, the following formulas are applied (Ishikawa et al., 1993).

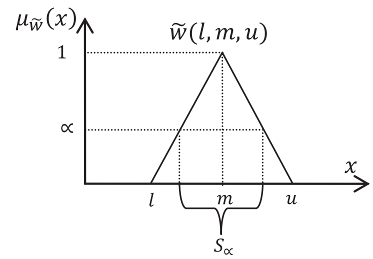

Fig. 3. A triangular fuzzy membership function, $\widetilde{W}$.

$$l_{ij} = min\{l_{ij}^k\} \qquad \forall k = 1,2,\ldots,K \tag{1}$$

$$m_{ij} = \frac{1}{k}\sum_{k=1}^{k} m_{ij}^k \qquad \forall k = 1,2,\ldots,K \tag{2}$$

$$u_{ij} = max\{u_{ij}^k\} \qquad \forall k = 1,2,\ldots,K \tag{3}$$

where $l_{ij}^k, m_{ij}^k, u_{ij}^k$, respectively represent the lower value (Min), average (Mean) and upper value (Max) of the corresponding TFM function $\mu(x)$ measured by a given kth decision maker, where $l_{ij} \leqslant m_{ij} \leqslant u_{ij}$, and K is the total number of decision makers. Accordingly, the TFM function with $l_{ij} \leqslant m_{ij} \leqslant u_{ij}$ is given below:

$$\mu\tilde{w}(x) = \begin{cases} (x - l_{ij})/(m_{ij} - l_{ij}) & l_{ij} \le x \le m_{ij} \\ (x - u_{ij})/(u_{ij} - m_{ij}) & m_{ij} \le x \le u_{ij} \\ 0 & x < l_{ij} \ or \ x > u_{ij} \end{cases} \tag{4}$$

In this step, we specified nine TFM functions associate the nine linguistic terms which are used to assign causal fuzzy weights between two concepts. They represent the overall suggestion of all decision makers for this particular causal links associated with the qualitative term set $T(x)$: {"negative very strong"–$\mu_{vs}(x)$, "negative strong"–$\mu_s(x)$, "negative medium"–$\mu_m(x)$, "negative weak"–$\mu_w(x)$, "zero"–$\mu_z(x)$, "positive weak" $\mu_w(x)$, "positive medium" $\mu_m(x)$, "positive strong" $\mu_s(x)$, "positive very strong" $\mu_{vs}(x)$} respectively; x represents the influence degree of a given linguistic term measured in the interval $[-1, 1]$. Each element of the fuzzy set corresponds to a TFM function as shown in Fig. 4. It can be seen that these have a finer distinction between grades in the lowest and highest ends of the influence scale. Table 2 shows the definition of TFM functions.

ii. *Determination of interconnections among the concepts and assigning causal fuzzy weights to the interconnections by group decision-making:* After specifying fuzzy membership functions,

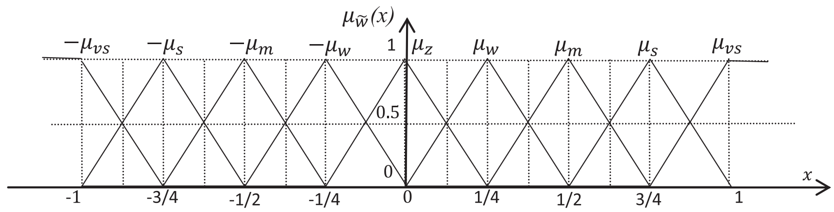

Fig. 4. The nine TFM functions corresponding to each one of the nine-linguistic terms.

Table 2
The definition of TFM functions.

TFM Functions	Linguistic Terms	Explanation
$-\mu_{vs} = (-1, -1, -\frac{3}{4})$	Negative very strong	If C_x inhibits C_y → the fuzzy set for “an influence close to -100%” with membership functions $\{-\mu_{vs}\}$ (negative numbers) $(\tilde{w}_{ij} < 0)$
$-\mu_s = (-1, -\frac{3}{4}, -\frac{1}{2})$	Negative strong	If C_x inhibits C_y → the fuzzy set for “an influence close to -75%” with membership functions $\{-\mu_s\}$ (negative numbers) $(\tilde{w}_{ij} < 0)$
$-\mu_m = (-\frac{3}{4}, -\frac{1}{2}, -\frac{1}{4})$	Negative medium	If C_x inhibits C_y → the fuzzy set for “an influence close to -50%” with membership functions $\{-\mu_m\}$ (negative numbers) $(\tilde{w}_{ij} < 0)$
$-\mu_w = (-\frac{1}{2}, -\frac{1}{4}, 0)$	Negative weak	If C_x inhibits C_y → the fuzzy set for “an influence close to -25%” with membership functions $\{-\mu_w\}$ (negative numbers) $(\tilde{w}_{ij} < 0)$
$\mu_z = (-\frac{1}{4}, 0, \frac{1}{4})$	Zero	If C_x doesn’t affect C_y → the fuzzy set for “an influence close to 0%” with membership functions $\{\mu_z\}$ (neutral) $\tilde{w}_{ij} = 0$
$\mu_w = (0, \frac{1}{4}, -\frac{1}{2})$	Positive weak	If C_x promotes C_y → the fuzzy set for “an influence close to 25%” with membership functions $\{\mu_w\}$ (positive numbers) $\tilde{w}_{ij} > 0$
$\mu_m = (\frac{1}{4}, -\frac{1}{2}, \frac{3}{4})$	Positive medium	If C_x promotes C_y → the fuzzy set for “an influence close to 50%” with membership functions $\{\mu_m\}$ (positive numbers) $\tilde{w}_{ij} > 0$
$\mu_s = (\frac{1}{2}, -\frac{3}{4}, 1)$	Positive strong	If C_x promotes C_y → the fuzzy set for “an influence close to 75%” with membership functions $\{\mu_s\}$ (positive numbers) $\tilde{w}_{ij} > 0$
$\mu_{vs} = (\frac{3}{4}, 1, 1)$	Positive very strong	If C_x promotes C_y → the fuzzy set for “an influence close to 100%” with membership functions $\{\mu_{vs}\}$ (positive numbers) $\tilde{w}_{ij} > 0$

decision makers are asked separately to determine causal links and to assign causal fuzzy weights $(\tilde{w}_{ij})$ for every pair of concepts using if-then rules in questionnaires. Below, questions for every pair of concepts are listed in the questionnaire in order to understand their perceptions:

– “Do you think that the concept x (C_x) affects any other concepts or is affected by other concepts?” *if* yes, *then*
– “How do you assign the causal fuzzy weight between concept x (C_x) and concept y (C_y) according to linguistic terms?”

Here, every kth decision maker uses the aforementioned linguistic terms to infer the causal fuzzy weight $(\tilde{w}^k_{ij})$ for every pair of concepts. Every causal fuzzy weight is represented with associated TFM $\tilde{w}^k_{ij} = \mu(x) = \{l_{ij}, m_{ij}, u_{ij}\}$. 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. Three rounds of sessions in FDM were implemented in this study as recommended in Mullen (2003). Afterwards, the combined fuzzy weight $(\tilde{w}_{ij})$ for every pair of concepts is calculated according to Eqs. (1)–(3). $(\tilde{w}_{ij})$ is now represented by a combined fuzzy membership function $\tilde{\mu}(x)$ within the range $[-1, 1]$. $\tilde{\mu}(x)$ has three parameters according to computation of $\tilde{w}_{ij} = \mu(x) = \{\tilde{l}_{ij}, \tilde{m}_{ij}, \tilde{u}_{ij}\}$.

iii. *Defuzzification:* Subsequently, the process of defuzzification can then be conducted. Here, the Center of the Gravity (CoG) method is employed, as it has been investigated previously as an efficient method to accomplish 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. This method determines the center of area of the combined membership function. The following Eq. (5) 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 interconnection.

$$W_{ij} = CoG = \frac{\int_{x_{min}}^{x_{max}} \tilde{\mu}(x) \cdot x dx}{\int_{x_{min}}^{x_{max}} \tilde{\mu}(x) dx} \tag{5}$$

iv. *Screen evaluation indexes:* After defuzzification process, the proper weights can be screened out from the numerous criteria by setting a suitable threshold of $S = \alpha$ by decision makers consensus, eliminate w_{ij}’s having “S'' less than α. Schematic diagram of FDM threshold is seen on Fig. 3. The principle of screening is as (6):

$$\begin{aligned} &S \geq \alpha, \text{then it is accepted, which is in the evaluation index.} \\ &S < \alpha, \text{then it is rejected, delete.} \end{aligned} \tag{6}$$

v. *Generation of the edge matrix:* Finally, for the sake of simlicity, the all final edge 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. (1). 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 concepts, w_{ii} is the edge weight from C_i to C_j.

$$E = [w_{ij}] = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} & \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \ldots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \ldots & 0 \end{bmatrix}_{nxn} \end{array}, \forall w_{ij} \in [-1,1] \tag{7}$$

The FCM structure is isomorphic to the n x n edge matrix E of causal edge strength values. The ith row of E lists the causal strength of the edges from concept C_i to all other concepts. The jth column lists the causal strength of the edges from all concepts that impinge on C_j.

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3.2. Step 2: causal inference and computation of the indices

This step is the computation phase of the indices for every concept. A causal mechanism takes place in order to calculate the reference vector set $V_{REF} = \{ v^T_{ref_i} \mid i = 1, \ldots, n; t \in \mathbb{R}$, where v associates the real value of each concept and T is used to model the iteration length in cognitive inference. The detailed inference mechanism of the FCMs was introduced in many publications. Basically, the following steps are as follows:

i. *Calculate the causal inference:* the iteration process is carried out along discrete steps, from $t = 0$,= 1, $t = 2$…to $t = T$ based on a calculated edge matrix E. The value of each concept (v_i) is calculated, computing the influence of other concepts to the specific concept, by applying the Eq. (8) (Kosko, 1986). V^t_i is the state value of concept C_i at iteration time t. v^{t-1}_j is the value of interconnected concept C_j at iteration time $t-1.w_{ji}$ represents the weight of the interconnection from concept C_j to concept C_i which are set to a specific value based on the expert's perception. All concept values (v^t_i) at iteration time t are stored in reference state vector set (V^t_{REF}), whereas the edge matrix remains fixed.

$$\begin{cases} V^t_{REF} = (v^t_i)_{1\times n} \\ v^t_i = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} v^{t-1}_j \cdot w_{ji} \right) i,j = 1,2,\ldots,n;\; t = 0,1,2,\ldots,T \end{cases} \tag{8}$$

$f(v_i)$ is the threshold (transformation) function and it is applied to v^t_i in order to transform the final values to continuous values with the interval [0, 1] through Eq. (9), where concepts can take values. This transformation obtains for obtaining a better understanding and representation of activation levels of concepts. λ is a *parameter* in determining the degree of fuzzification of the function and $0 \leqslant \lambda \leqslant 1$ is used to adjust its inclination. In this study it has been set as $\lambda = 1$.

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

The initial vector values (v^t_{in}) for each concept might be ϵ [0, 1] and they are listed in the initial state vector set ($V^t_{IN} = \{ v^t_{in_i} \mid i = 1, \ldots, n;\; t = 0\}$) for iteration process might be ϵ [0, 1]. In this study, v^t_{in} for each concept at iteration time $t = 0$ are taken as 0.5 in order to avoid the marginal parameters in the reference state vector set and the numerical weights are set to a specific value based on the expert's perception. The initial vector set representation is $V^0_{IN} = \{0.5, 0.5, \ldots, 0.5 \mid \forall v^0_{in} = 0.5\}$ Thereafter, the system is free to interact. After Tth iteration time step, the new reference state vector set are computed as $V^t_{REF} = \{ v^t_{ref_i} \mid i = 1,2,\ldots,n;\; t = 1,2,\ldots,T\}$. This reference state vector set represents the reference vector values of all concepts. In this study, the total iteration time step is set as $T = 20$. This interaction continues until the following requirements on convergence are satisfied:

- A fixed point equilibrium is reached: $V^{t+1}_{REF} = V^t_{REF}(t \in T)$, where V^t_{REF} is the final state.
- A limited cycle is reached: $V^{t+\Delta T}_{REF} = V^t_{REF}(t \in T)$, where V^t_{REF} is the final state and the system falls in a loop of a specific period, and after a certain number of inference steps, ΔT, it reaches the same state V^t_{REF}.
- Chaotic behavior is exhibited.

After T'th iteration, the calculated reference vector set V^T_{REF} is stored in a E^T_{REF} matrix, where $E^T_{REF} = [V^T_{REF}]_{nxn}; n = 11$.

ii. *Calculate the indices:* Every concept is defined by its out-degree $od(C_i)$, in-degree $id(C_i)$ and centrality $cen(C_i)$. Out-degree (out-arrows) $od(C_i)$ is the absolute row sum of edge weights (w_{ki}) in the edge matrix and represents the number of concepts, concept C_i causally interacts on (Eq. (10)). In-degree (in-arrows) $id(C_i)$ is the absolute column sum of edge weights. (w_{ik}) in the edge matrix and represents the number of concepts causaly interacting on concept C_i (Eq. (11)). The immediate domain or total degree of a concept is the sum of its in-degree and out-degree (Eq. (12)), called *centrality* $cen(C_i)$. The centrality represents the dominance of concept C_i to the causal flow on the cognitive map. The more central the concept in the FCM, the more important the concept is in the decision maker's perception.

$$od(C_i) = \sum_{k=1}^{n} \mid w_{ki} \mid \tag{10}$$

$$id(C_i) = \sum_{k=1}^{n} \mid w_{ik} \mid \tag{11}$$

$$cen(C_i) = od(C_i) + id(C_i) \tag{12}$$

The contribution of a concept in a FCM can be interpreted by computation of its centrality; whether it is a *transmitter*, *receiver* or *ordinary* concept. *Transmitter* (forcing functions, givens and tails) represents a concept whose $od(C_i)$ is positive and $id(C_i)$ is zero. *Receiver* (utility variables, ends and heads) represents a concept whose $od(C_i)$ is zero and $id(C_i)$ is positive. The total number of receiver in a FCM can be considered an index of its complexity (Vasantha & Smarandache, 2003). The rest of the concepts, both non-zero $od(C_i)$ and $id(C_i)$, are *ordinary* concepts (means). In Fig. 1, from above mentioned reasons C_4 and C_5 represent the transmitter, whereas C_2 is the receiver, the rest of the concepts are called as ordinary concepts. The hierarchy index (h) is calculated in order to measure the structure of a complex FCM as seen in Eq. (13) (Ozesmi & Ozesmi, 2004).

$$h = \frac{12}{(n-1)n(n+1)} \sum \left[\frac{od(C_i) - (\sum od(C_i))}{n} \right]^2 \mid i = 1,2,\ldots,n. \tag{13}$$

If h is equal to 1, then the FCM is full-hierarchical; and if h is equal to zero, then the system is full-democratic. Democratic FCM maps are much more adaptable for heterarchical transport network because of their high level of integration and dependence. The coalition partners with more democratic maps are more likely to perceive that the system can be changed and thus these partners can be starting point for achieving coalition objectives.

3.3. Step 3: calculation of categorical edge weights

In this step, the edge weights among the categories are calculated. Concepts on FCM are presented as either decomposed or integrated into certain categories. In order to compute the causal inference among these categories we used the one of fuzzy subset aggregation methods. In the literature, some useful fuzzy subset aggregation methods are presented (Kelman & Yager, 1998; Kosko, 1986): t-norms (triangular-norm) and t-conorms, Ordered Weighted Averaging (OWA) operators or priority and second order criteria. In this study we used OWA operator, as this method was used formerly by Zhang, Liu, and Zhou (2003) to compute the quotient FCM weights. OWA was introduced first by Yager (1988) as an aggregation technique. The aggregated categorical edge weights between the pair of groups are associated with a particular position in the ordering, rather than being associated with a specific argument (Yager & Filev, 1999). Nevertheless in this study, assignments are processed on a system of "first in first assigned" as a rule of thumb. Let the categorical directed edge weight ($gw_{ij}; -1 \leq gw_{ij} \leq 1$) between the pair of groups (G_i and G_j; G_i, $G_j \rightarrow gw_{ij}$) and there are l edge weights. $\{w_{i_1 j_1}, \ldots, w_{i_l j_l}\}$ among these groups. The categorical edge weights can be computed separately according to every direction of the number of edge weights and also their causal increase and decrease. That means the categorical edge weights between G_i and G_j can be positive (+) as well as negative (−) and bi-directed (gw_{ij}, gw_{ji}, $gw_{ij} \neq gw_{ji}$).

As seen Eq. (14), an OWA operator (gw_{ij}) of dimension l is a mapping $f_{gw}: \mathbb{R}^l \to \mathbb{R}$, that has an associated weight vector W_k of dimension l having the properties. b_k is the kth largest element of the multi-set. $\{w_{i_1j_1},\ldots,w_{i_lj_l}\}$

$$\begin{cases} gw_{ij} = f_{gw}(w_{i_1j_1},\ldots,w_{i_1j_1}) & \\ gw_{ij} = \sum_{k=1}^{l} W_1 b_1 = W_1 b_1 + \cdots + W_l b_l & \\ W_k = \frac{w_{i_kj_k}}{\sum_{k=1}^{l} w_{i_kj_k}} & i,j=1,2,\ldots,n;\ W_k \in [0,1]; 1 \le k \le l. \\ \sum_{k=1}^{l} W_k = (W_1 + \cdots + W_l) = 1 & \end{cases} \tag{14}$$

This part can be illustrated by Fig. 5 which shows the categorical representation of concepts in Fig. 1. Suppose that there are two categories (G_1 and G_2) and three edges from G_1 to G_2 with edge weights: $w_{1_12_1}(w_{62}) = 0.4, w_{1_22_2}(w_{61}) = 1.0, w_{1_32_3}(w_{41}) = 0.6$

Then, we obtain Eq. (14):

$$W_1 = \frac{0.4}{2} = 0.2; \quad W_2 = \frac{1.0}{2} = 0.5; \quad W_3 = \frac{0.6}{2} = 0.3;$$
$$\sum_{k=1}^{l} W_k = W_1 + W_2 + W_3 = 1$$

Thus, we have:

$$gw_{12} = f_{gw}(0.4, 1.0, 0.6) = \sum_{k=1}^{l} W_k b_k$$
$$= 0.2 \times 1.0 + 0.5 \times 0.6 + 0.3 \times 0.4 = 0.62$$

3.4. Step 4: development of decision making rules

In the last step, decision-making thresholds are identified by using the extended FCM approach. This step examines the changes in transport collaboration structure. In the extended FCM approach, a (11 × 11) pair-wise scenario matrix is inserted into the FCM's iteration process. This pair-wise scenario matrix can provide straightforward to causal *what-if* questions. This process enables one to run different scenario conditions of two selected concepts or categories. FCM is already used as a scenario development in some research (Glykas, 2010; Jetter & Schweinfort, 2011; Van Vilet et al., 2010). The matrix consists of 121 squares and each square is called as a scenario condition. Therefore, 121 different scenario conditions are displayed on the matrix. A scenario condition based on knowledge and insight into the future possible conditions will

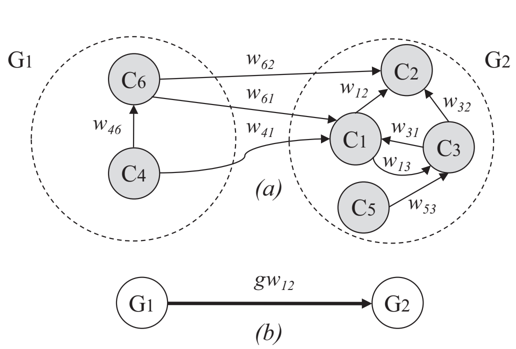

Fig. 5. (a) Categorical disposition of FCM and residual network. (b) Causal inference of an edge in the categorical FCM.

be more likely to succeed. It is not a prediction, rather an illumination of drivers of change; and to understand them gives managers a better control over their situations.

The association of the pair of concepts under different scenario conditions might result with the variations in the reference state vector set (V^T_{REF}). These variations are displayed with the fuzzily intersected zones on a graph. The fuzzily intersected zones can be interpreted for the causal link analysis to estimate the influence degree of pair concepts on reference state vector set. If there is no association between two concepts, there will be established no fuzzily intersected zones on graph. That means that there cannot be a causal relationship between these criteria. In another word, that their association cannot change the reference state vector set.

In the extended FCM, the initial vector values (v^t_{in}) of two selected concepts (C_x, C_y) are varied asynchronously on the pair-wise scenario matrix, when one goes up (or down), the other goes up (or down) at the same time. Their initial vector values ($v^t_{in_x}, v^t_{in_y}$) at iteration time $t = 0$ range between ∈ [0, 1] by 0.1 interval, this interval states the scenario conditions on the matrix; whereas other initial input state vector values ($v^t_{in_i}$) remain the same for the all scenario conditions as 0.5. Below some scenario samples of initial input state vector sets can be seen:

$$V^t_{IN} = \{v^t_{in_i}\} i = 1,2,\ldots,n; t = 0; \forall v^0_{in_i} \in [0.5]; v^0_{in_x}, v^0_{in_y}$$
$$\in \{0, 0.10, 0.20, \ldots, 0.90, 1.00\}$$

$$V^0_{IN}(0.50, 0.50) = \{0.50, 0.50, \ldots, 0.50, \ldots, 0.50, \ldots, 0.50\};$$
$$v^0_{in_x} = 0.50; v^0_{in_y} = 0.50$$

$$V^0_{IN}(0.10, 0.10) = \{0.50, 0.50, \ldots, 0.10, \ldots, 0.10, \ldots, 0.50\};$$
$$v^0_{in_x} = 0.10; v^0_{in_y} = 0.10$$

$$V^0_{IN}(0.30, 0.70) = \{0.50, 0.50, \ldots, 0.30, \ldots, 0.70, \ldots, 0.50\};$$
$$v^0_{in_x} = 0.30; v^0_{in_y} = 0.70$$

$$V^0_{IN}(0.80, 0.20) = \{0.50, 0.50, \ldots, 0.80, \ldots, 0.20, \ldots, 0.50\};$$
$$v^0_{in_x} = 0.80; v^0_{in_y} = 0.20 \ldots \text{etc.}.$$

The output vector sets (V^T_{OUT}) at iteration time $t = T$ is calculated for every initial vector value condition ($v^t_{in_x}, v^t_{in_y}$) of selected two criteria (C_x, C_y), where the initial vector values for $v^t_{in_x}, v^t_{in_y}$ remain same until end of iteration process therefore; the output vector values for $v^t_{in_x}, v^t_{in_y}$ should be equal the initial vector values for $v^t_{in_x}, v^t_{in_y}$:

$$V^t_{OUT} = \{v^t_{out_i}\}, i = 1,2,\ldots,n; t = 1,2,\ldots,T; v^0_{out_x} \in v^0_{in_x}; v^0_{out_y} \in v^0_{in_y}$$

$$V^T_{OUT}(0.50, 0.50) = \{0.57, 0.50, \ldots, 0.50, \ldots, 0.50, \ldots, 0.98\};$$
$$v^0_{out_x} = 0.50; v^0_{out_y} = 0.50$$

$$V^T_{OUT}(0.10, 0.10) = \{0.56, 0.51, \ldots, 0.10, \ldots, 0.10, \ldots, 0.98\};$$
$$v^0_{out_x} = 0.10; v^0_{out_y} = 0.10$$

$$V^T_{OUT}(0.30, 0.70) = \{0.57, 0.50, \ldots, 0.30, \ldots, 0.70, \ldots, 0.98\};$$
$$v^0_{out_x} = 0.30; v^0_{out_y} = 0.70$$

$$V^T_{OUT}(0.80, 0.20) = \{0.57, 0.50, \ldots, 0.80, \ldots, 0.20, \ldots, 0.99\};$$
$$v^0_{out_x} = 0.80; v^0_{out_y} = 0.20$$

After *Tth* iteration all computed output vector sets for the selected vector values v^T_x, v^T_y are summed up in an 11 × 11 scenario matrix (E^T_{OUT}) (raw input, Fig. 6a).

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$$E_{OUT}^{T} = [V_{REF}^{T}(v_{in_x}^{0}, v_{in_y}^{0})]_{nxn}; \forall v_{in_x}^{0}, v_{in_y}^{0} \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}; \mathrm{n} = 11$$

The reference vector set $V_{REF}^{T} = \{v_{ref_i}^{T} \mid i = 1, \ldots, n; T \in \mathbb{R}\}$, which is calculated in Step 2 according to initial vector set $V_{IN}^{t} = \{v_{in_i}^{t} | i = 1, \ldots, n; \forall 0.5; t = 0\}$,demonstrates the optimal situation of transport coalition. Let $V_{OUT}^{T}[v_{in_x}^{0}, v_{in_y}^{0}] \mid v_{in_x}^{0}, v_{in_y}^{0} \in [0, 1]$ the output vector set for each scenario condition. The difference between two n-dimensional vectors set for V_{OUT}^{T} and $V_{REF}^{T}$is calculated simply by using Euclidean distance formulation in Eq. (15):

$$d(V_{OUT}^{T}[v_{in_x}^{0}, v_{in_y}^{0}], V_{REF}^{T}) = \sqrt{\sum_{i=1}^{n} (v_{out_i}^{T}[v_{in_x}^{0}, v_{in_y}^{0}] - v_{ref_i}^{T})^2} \tag{15}$$

The Euclidean distance is a direct measure of similarity between the outputs vectors set (V_{OUT}^{T}) that is closest to a reference vector set (V_{REF}^{T}). The least distant one from the reference vector set is the most similar to the reference vector. The minimum of this distance suggests the nearest match. Therefore Euclidean distance is useful in classification algorithms such as vector quantization and neighbor classification (Collins, Brown, & Marshall, 1995). Finally, all calculated distances are listed in $d(E_{OUT}^{T}, E_{REF}^{T})$ matrix (Fig. 6b), where $E_{REF}^{T} = [V_{REF}^{T}]_{nxn}$; n = 11. This comparison matrix is illustrated as a graphical representation with colors, where every distance from the reference vector sets is represented in a different color. The matrix consists of 121 squares (11 × 11 matrix). Each element of the matrix is being the percentage of the corresponding pixel's area. The gray-scale representation of such a matrix is shown in Fig. 6c, mapping 0% coverage of a pixel's area to black, which means there is a big difference between V_{REF}^{T} and V_{OUT}^{T}, and 100% coverage of area to white which means V_{REF}^{T} and V_{OUT}^{T} are identical or there is a little difference among their vector series.

If there is no association between the criteria, graph will be drawn with one color. Fig. 6c displays eleven different zones. Each zone is drawn by a unique color. In the graphical illustration, the dark colored zones denote the strong changes (more probable) in the vector series whereas the light colored zones represent the weak changes (less probable); in other word, that the dark colored zones give the most affected situation, the very light colored zones the less affected situation in the vector series. Every little change in criterion C_x and criterion C_y may affect the reference output vector set (V_{OUT}^{T}) strong (dark colored) and or weak (light colored). This can drive the tactical outputs in the transport coalition to make a decision for the level of collaborative integration. That means that the probable changes in transport collaboration structure can be used to predict the future condition (V_{OUT}^{T}) of the system being modeled by the FCM for a particular initial condition (V_{REF}^{T}). The used set of scenario conditions provides a stimulus to the FCM, which may cause structural changes in the future conditions of a coalition. These zones can be clustered as fuzzily intersected zones with a coloring scheme. The fuzzily intersected zones in the graphical illustration can be determined by using three thresholds: "go", "go with conditions" and "no-go" as seen in Fig. 6d. These thresholds are determined according to change of V_{OUT}^{T} from V_{REF}^{T}. If there is no change between V_{REF}^{T} and V_{OUT}^{T}, then the distance $d(V_{OUT}^{T}, V_{REF}^{T})$ should be zero. The distance values for each scenario conditions are compared and counted into the corresponding thresholds by using Eq. (16):

$$\text{Thresholds}(d) = \begin{cases} go & 0.3 \le d(V_{OUT}^{T}, V_{REF}^{T}) \le 0 \\ go(w/condition) & 0.6 \le d(V_{OUT}^{T}, V_{REF}^{T}) \le 0.3 \\ no-go & d(V_{OUT}^{T}, V_{REF}^{T}) > 0.6 \end{cases} \tag{16}$$

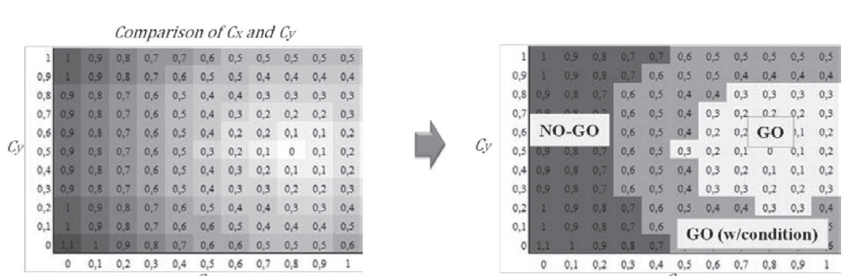
These thresholds are used to analyze the dynamic behavior of transport collaboration structure. Threshold "go" represents the light colored and less affected zones; the changes in the pair of criteria up to 30% are acceptable. The coalition has a "full-integration" which refers to strategic partnering at an intensive level of integration. Each partner considers the other as an extension of itself with a long-term engagement and no ending date for the respective partnerships (Kayikci & Zsifkovits, 2012). This integration includes

$$E_{OUT}^{T} = \begin{bmatrix} V_{OUT}^{T}(0.00,1.00) & V_{OUT}^{T}(0.10,1.00) & \cdots & V_{OUT}^{T}(0.90,1.00) & V_{OUT}^{T}(1.00,1.00) \\ V_{OUT}^{T}(0.00,0.90) & V_{OUT}^{T}(0.10,0.90) & \cdots & V_{OUT}^{T}(0.90,0.90) & V_{OUT}^{T}(1.00,0.90) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ V_{OUT}^{T}(0.00,0.10) & V_{OUT}^{T}(0.10,0.10) & \cdots & V_{OUT}^{T}(0.90,0.10) & V_{OUT}^{T}(1.00,0.10) \\ V_{OUT}^{T}(0.00,0.00) & V_{OUT}^{T}(0.10,0.00) & \cdots & V_{OUT}^{T}(0.90,0.00) & V_{OUT}^{T}(1.00,0.00) \end{bmatrix}_{11\times 11}$$

(a)

$$d(E_{OUT}^{T}, E_{REF}^{T}) = \begin{bmatrix} d(0.00,1.00) & d(0.10,1.00) & \cdots & d(0.90,1.00) & d(1.00,1.00) \\ d(0.00,0.90) & d(0.10,0.90) & \cdots & d(0.90,0.90) & d(1.00,0.90) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d(0.00,0.10) & d(0.10,0.10) & \cdots & d(0.90,0.10) & d(1.00,0.10) \\ d(0.00,0.00) & d(0.10,0.00) & \cdots & d(0.90,0.00) & d(1.00,0.00) \end{bmatrix}_{11\times 11} \quad \forall C_x, C_y$$

(b)



(c) (d)

Fig. 6. (a) Raw vector data, (b) matrix representation of vector set differences, (c) gray scale representation of pair-wise scenario matrix, and (d) representation with three thresholds.

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a convergence of cost, process and technology. Threshold "no-go" represents the dark colored (black) zones and most affected zones; the changes in the pair of criteria bigger than 60% are not acceptable as these may change the transport collaboration structure. It refers to an arm's length relationship at the lower integration level; coalition partners cooperate only on ad-hoc matters involving a limited number of exchanges. This kind of collaboration is not considered to be actual collaboration since there is no stable joint commitment; therefore the coalition has "no integration". No-go threshold shows the extreme situation which would cause the resolution of the coalition. Transport coalition could not continue beyond the "no-go" threshold. The "go with conditions" represents the in-between and middle-affected zones that. The changes in the pair of criteria bigger than 30% and lesser than 60% may not be harmful for the collaboration and they enable system components to continue under certain circumstances. The coalition has "partly integration", which refers integrated collaboration as well as limited collaboration in which a long term partnership is not the goal. It involves the overlapping of functional areas between coalition partners. A transport coalition could perform over the "go" and "go with conditions". These aforementioned thresholds related with future possible scenarios may give coalition partners the perspective of collaborative integration.

4. Case study: causal mechanism in transport collaboration

This research paper is based on sets of scenarios which are determined in a 11*x*11 pair wise scenario matrix and their subsequent usage as input to coalition building process. In this research, a real-world transport coalition is selected to examine the applicability of the proposed method and to explain the practical implications. The coalition was composed of three medium-sized companies from the Fast Moving Consumer Goods (FMCG) industry and two carriers. Five companies decided to form a coalition and act conjointly on their outbound transport operations. Their outbound shipments were staged and handled in the common market area. In previous research, we investigated 37 criteria and 5 categories to support the transport collaboration structure which were extracted from intensive literature reviews and numerous surveys in freight transport industry. We used these criteria and categories as a FCM toolkit in this research. According to proposed model, firstly a FDM was conducted using surveys in three rounds to determine the causal inference and the influence degree of corresponding concepts with the group consensus. The coalition partners were assigned five decision makers to participate in the Delphi study. Decision makers were pooled together and informed about the procedures of FCM-based model in advance. Each decision maker had equal voting rights (unweighted case). They agreed as to which criteria were crucial and representative for the modeling of the FCM. Subsequently, they were asked separately to justify the cause-effect relationship among concepts and infer causal fuzzy weights ($\tilde{w}_{ij}$) for every interconnection using *if-then* rules in questionnaires. They were asked to qualitatively assess causal inference among concepts using the pre-specified nine linguistic terms, i.e. "negative very strong", "negative strong", "negative medium", "negative weak", "zero", "positive weak", "positive medium", "positive strong", "positive very strong". After receiving the first round questionnaires, inconsistency and cycles in database were detected, as those produce any feedback, therefore they need to be eliminated from the database. In the responses, no cycles were detected. In this research, decision makers reached a consensus in advance on the causality direction of the compared pair of concepts in order to avoid cycles and inconsistency on FCM matrix. The questionnaires were performed in three rounds until reach the consensus. Subsequently, the opinions of decision makers in FDM questionnaires were converted to triangular fuzzy numbers according to Eq. (1)–(3) and defuzzified weights were figured out after calculation according to Eq. (5). These give the final edge weights (w_{ij}). Afterwards all weights were sorted in a list and screened. The weights should run between $-1 \leqslant w_{ij} \leqslant 1$. The weights with threshold $\propto$ equal or above 0.2 were adopted as important key items whereas the other weights with threshold $\propto$ below 0.2 were deleted because those were not relevant for the study. All selected edge weights after defuzzification and FDM screening are listed in the decision makers' respond list shown in Appendix A. The data collected in the first section were employed to generate the edge matrix. Consequently all defuzzied edge weights extracted from the decision makers opinions were summed up in an 37*x*37 FCM edge matrix.

Due to computational complexity, an R-Package[1] is used for the simulation experiment, as the maximum number of comparisons is $37 * 36/2 = 666$ and there were $666 * 121 = 80.586$ different scenarios. Every weight had either negative or positive or no causality. As seen in Appendix A, only 116 pair concepts out of 666 were assigned with the assigned fuzzy weights. This shows that the number of interconnections among 37 concepts is 116. 30 out of 116 were evaluated with the negative causality ($w_{ij} < 0$) and 86 had positive causality ($w_{ij} > 0$). The rest of concept pairs had no relationship ($w_{ij} = 0$), therefore they were taken out of the respond list. For the iteration process, the initial vector values v_i^t at iteration $t = 0$ are set as 0.5. For the iteration process, the initial vector values v_i^t at iteration $t = 0$ are set as 0.5. The initial vector set is $V_{IN}^0 = \{0.5, 0.5, \ldots, 0.5\}$; By using R-Package 20 iterations were performed to calculate the value of each concept (v_i) according to Eq. (8) and subsequently its indices (out-degree $od(C_i)$, in-degree $id(C_i)$ and centrality $cen(C_i)$) according to Eq. (10)–(12) which are listed in Appendix B. After 20*th* iteration the reference vector set is calculated as $V_{REF}^{20} = \{v_1^{20}, v_2^{20}, \ldots, v_x^{20}, \ldots, v_y^{20}, \ldots, v_i^{20}\}, i = 1, 2, \ldots, m; t = 1, 2, \ldots, 20$. Afterwards the fuzzy cognitive maps were drawn with the aid of visualization software of Pajek[2] (Fig. 7) where every perspective (sub-category) is shown with different shape and gray color on the map. The strength of the causality between two concepts is shown in different gray colors and the sizes of lines. Negative causality is drawn with dashed lines, whereas positive causality is drawn with straight lines.

The hierarchy index of FCM is calculated as 0,03615 according to Eq. (13). This result indicates that the system is democratic that means the system is based on heterarchical transport collaboration networks and the coalition partners have same decision right. This result also shows that a high level of collaborative integration exists in the coalition.

Causal flows among criteria are demonstrated with three layers from the lower level to the upper level which consist of a number of *transmitter*, *receiver* or *ordinary* concepts. The findings appear to show that there are five transmitters and one receiver on FCM according to their in-degree and out-degree values (Fig. 7). The concepts of *standardization* (C_2), *technology usage* (C_{10}), *infrastructure* (C_{15}), *management involvement* (C_{23}) and *variability* (C_{36}) are the transmitters of FCM, therefore their in-degree values are zero, whereas *service level* (C_{37}) is the only receiver which is the most influenced concept in the map and its out-degree value is zero. The rest of the concepts are the ordinary of the map where both in-degree and out-degree are non-zero. The results show that the concept of service level is the most affected concept by the others. Moreover the performance of service level may be affected heavily by the changes respectively in *technological integration level* (C_4), *information sharing* (C_{25}), *technological capabilities* (C_3), *flexibility in processes* (C_{33}), *trusting relationship* (C_{28}), *reliability* (C_1),

1 http://www.r-project.org/
2 http://pajek.imfm.si/doku.php

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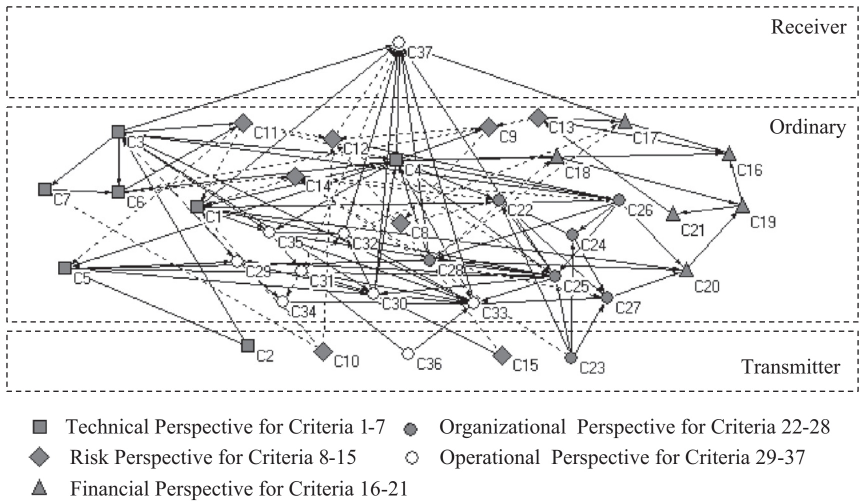

Fig. 7. The causal flows from the lower level to the upper level.

transparency (C_{26}), *capacity* (C_{30}) and which occupy the highest centrality values as seen in Appendix B.

High centrality value of a concept shows its importance in the entire cognitive model (Kosko, 1986). Those concepts with the highest centrality values are considered as the most important concepts on the FCM which may affect the other concepts potentially than others and those should be properly taken into consideration in order to obtain a successful coalition. Since there are a high number of concepts in this model, we have a complex causal relationship structure. Therefore, we could only show below some of causal relationship paths from the FCM which are drawn from the lesser to higher effected concepts. The beginning of the path shows the transmitter and the end of the path shows the receiver like it is determined in Fig. 7.

$C_2 \to C_3 \to C_4 \to C_5 \to C_{25} \to C_{37}(++)$causality
$C_2 \to C_3 \to C_{26} \to C_{28} \to C_4 \to C_1 \to C_{25} \to C_{29} \to C_{34} \to C_{33} \to C_{37}(++)$causality
$C_{36} \to C_{31} \to C_{33} \to C_{37}(++)$causality
$C_{10} \to C_{12} \to C_{37}(--)$causality
$C_{15} \to C_{30} \to C_{32} \to C_{37}(++)$causality
$C_{23} \to C_{24} \to C_{22} \to C_{27} \to C_{20} \to C_{19} \to C_{21} \to C_{13} \to C_{17} \to C_{37}(++)$causality
$C_{23} \to C_{22} \to C_{25} \to C_{35} \to C_{31} \to C_{37}(+-)$causality

The chain of causal relations related to concept C_{37}, reveals that the *service level* (C_{37}) is influenced by *information sharing* (C_{25}), *flexibility in processes* (C_{33}), *lead time* (C_{32}), *transport cost* (C_{17}), *transport chain* (C_{12}) and *replenishment length* (C_{31}). Also the concept of *flexibility in processes* C_{33} is influenced by *replenishment length* (C_{31}) and *carbon footprint* (C_{34}). Consequently, the interrelation of these influence criteria should be carefully interpreted to reach the group consensus, before agreeing on the structure of transport collaboration in a coalition. In our "real world" case study the extracted concepts, as above mentioned have more influences to reach the better *service level* in a coalition and also they affect the life cycle of the coalition.

R-Package computed the edge weights among categories according to Eq. (14) in Step 3. These are listed in Table 3. Then the indices were calculated according to Eqs. (8). (10)–(12). The results were listed in Table 4. They show that *technical perspective* in terms of its centrality value has strong influence on other categories in this coalition. There are only ordinary categories, that means, all categories are interrelated to each other. The other categories are listed according to their centrality values respectively: financial, organizational, risk and operational (see in Table 4). Afterwards, the causal flow among categories were drawn, it is demonstrated in Fig. 8.

Table 3
Categorical weights of five categories.

Category$_i$	gw_{ij}	Category$_j$	Category$_i$	gw_{ij}	Category$_j$
Technical	0.66	Risk	Financial	0.8	Risk
Technical	−0.59	Risk	Financial	−0.65	Organizational
Technical	0.78	Financial	Financial	0.58	Operational
Technical	0.80	Organizational	Organizational	0.81	Technical
Technical	0.66	Operational	Organizational	0.50	Risk
Risk	−0.55	Technical	Organizational	−0.68	Risk
Risk	0.63	Financial	Organizational	0.61	Financial
Risk	−0.77	Organizational	Organizational	−0.65	Financial
Risk	−0.80	Operational	Organizational	0.67	Operational
Risk	0.52	Operational	Operational	0.65	Technical
Financial	0.92	Technical	Operational	−0.48	Financial

Table 4
Indices for Categories.

Category	$od(C_i)$	$id(C_i)$	$cen(C_i)$	Category value(v_i)
Technical	2.92	2.86	5.78	0.93
Risk	2.01	2.61	4.62	0.86
Financial	2.53	2.95	5.48	0.91
Organizational	2.21	2.70	4.92	0.88
Operational	2.57	1.13	3.70	0.91

In last step, a (11×11) pair-wise comparison matrix was inserted into the iteration process. Here, every comparison of the pair of concepts is drawn with a set of scenarios which consists of 121 sub-scenarios. Every scenario indicates a vector set and the difference of this vector set from reference vector set is represented with a unique gray color on the gray scale representation. During the iteration process, every concept C_x is compared with the other concept C_y by taking initial values between {0, 1} with 0.1 intervals whereas the other concepts initial values remain same as 0.5 and the new output vector set (V_{OUT}^{20}) at iteration time $t = 20$ was calculated. If V_{OUT}^{20} differs from V_{REF}^{20}, then the difference between V_{OUT}^{20} and V_{REF}^{20} is represented with a different color on the graph, as this process was explained in Step 4. The 666 comparisons lead to 15 discrete distance values. That means 15 different colors were used to demonstrate these vector sets visually on a gray scale graph.

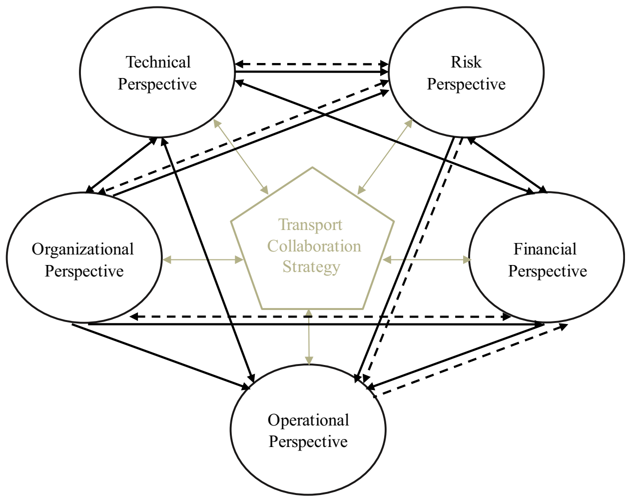

Fig. 8. Causal inference among categories.

We could only show some limited results of this study by producing some scenarios which are represented in Fig. 9. In this respect, we use the following key considerations to address when establishing the FCM-based model:

- How would the changes in information sharing and trust affect the system components of transport collaboration? (Fig. 9a)
- How would the changes in integration level and technical reliability (track and tracing) affect the system components of transport collaboration? ((Fig. 9b)
- How would the changes in the technology usage and technical reliability (track and tracing) affect the system components of transport collaboration? (Fig. 9c)
- How would the changes in management support and information quality affect the system components of transport collaboration? (Fig. 9d)
- How would the changes in information sharing and transportation cost affect the system components of transport collaboration? (Fig. 9e)
- How would the changes in technical integration level and service level affect the system components of transport collaboration? (Fig. 9f)

No partnership can exist without trust. Trust is a frequently mentioned construct in many models of long-term business

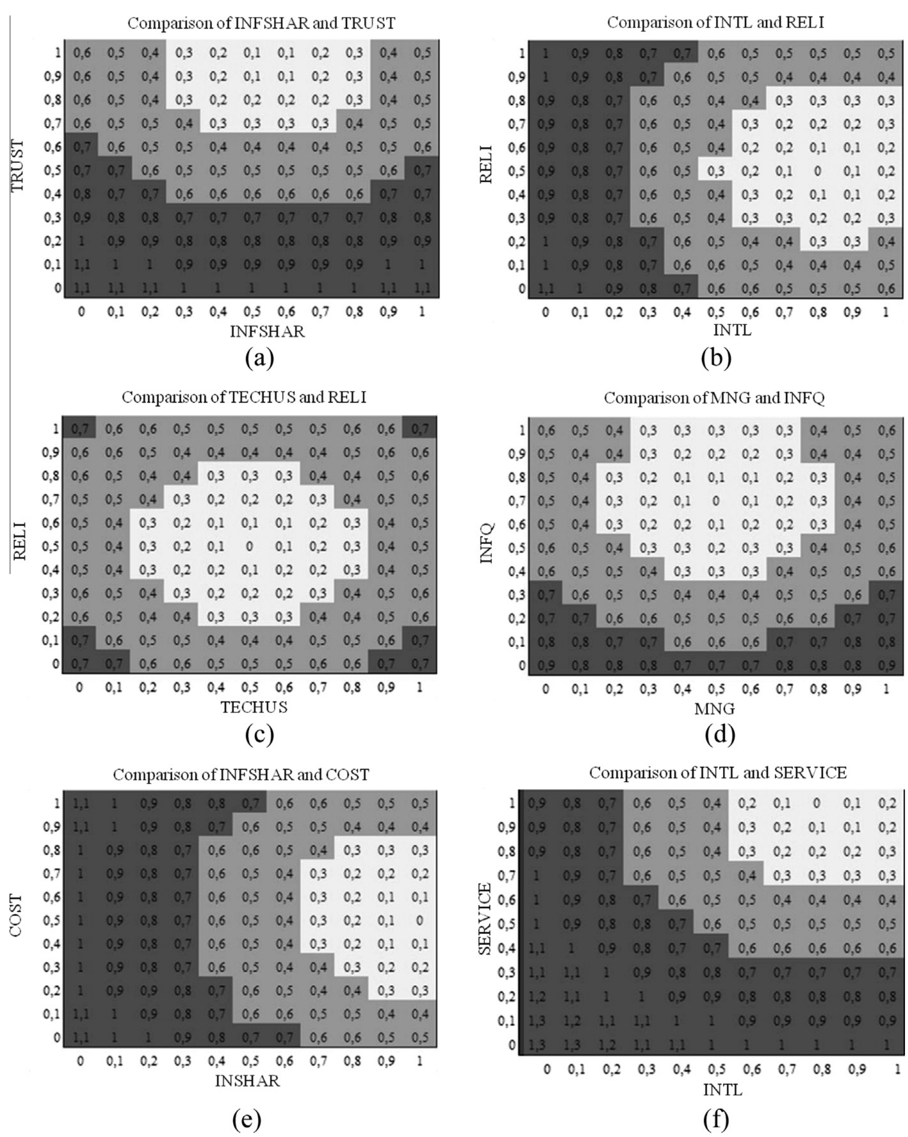

Fig. 9. Gray scale representation of the reference output vectors used for classifying digits according to the pair of selected concepts.

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relationships and appears to be the major inhibitor of successful logistics outsourcing relationships. In this study, we found that in terms of decision maker's perception, coalition partners are more willing to share information when the level of trust is high. The loss of trust might therefore cause less information sharing in the coalition. In Fig. 9a the dark colored zones represent the most affected situations for the criteria trust (C_{28}) and information sharing (C_{25}), there will be no integration if the changes in this pair of concepts are high. Fig. 9b shows that the high technical reliability (C_1) (track and tracing) can be possible with the high level of technical integration (C_4). The low level of technical integration will affect the components of transport collaboration structure. In this transport collaboration the high reliability and high technical integration level are wanted for full-integration. Technical integration enables an entire shipment to be completed electronically and initiated, managed, executed and delivered across multiple supply chains without repeated manual intervention. Fig. 9c demonstrates the relationship between reliability (C_1) and technical usage (C_{10}). It is interpreted that the extreme scenarios in both technical usage and reliability will affect the system components. The transport industry is moving from one-to-one Electronic Data Interchange (EDI) to collaboration technologies to achieve the high level of system reliability, where it is important to enlarge technical usage. The average level of reliability and technical usage is desired for full-integration.

Fig. 9d shows that the average level of management involvement (C_{23}) and high level of information quality (C_5) will support full-integration of coalition. Management involvement is also a key consideration for coalition partners to pursue long lasting relationships. Top management should understand and communicate to organizational members that cooperation and competition can be applied simultaneously, and that both can contribute to achieving organizational goals. Fig. 9e shows that the fuzzily intersected zones for the low level of information sharing (C_{25}) vs. the high transport cost (C_{17}) and the high level of information sharing vs. the low transport cost are desired conditions so that coalition will have full-integration. This means that coalition partners cannot obtain high capacity utilization with the less information sharing. The sharing of transport information is important from a costs perspective because it can replace unnecessary costs for transport or storage of goods. Fig. 9f denotes that the high level of technical integration (C_4) and the high level of customer service (C_{37}) will perform very well in this transport coalition in order to obtain the high level of collaborative integration. The low level of technical integration as well as customer service will affect the components of the system structure and that will result in the dissolution of the coalition.

For the categorical modeling, the system is run according to categorical edge weight results. The below scenarios were conducted which are represented in Fig. 10.

- How would the changes of categories in technical and operational perspectives affect the components of transport collaboration? (Fig. 10a)
- How would the changes of categories in financial and risk perspectives affect the system categories of transport collaboration? (Fig. 10b)

In Fig. 10a, the low changes in operational perspective and the low changes in technical perspectives may affect the system components of transport collaboration. This would show that the high operational flexibility can be executed in this type of a coalition. High technical integrity would result in a high level of operational perspective. Fig. 10b, the resulting configuration with the low changes in financial situation and risk perspective would cause the strong cross effect in system components.

5. Conclusions and perspectives

Research on building transport coalitions is relatively scarce, and also there is a lack of sufficient analysis of causal mechanisms for such structural conditions. As a whole, this paper elaborates an FCM-based model to analyze the causal inference mechanism for transport collaboration by using a set of scenarios. Using key operating criteria were previously identified by the authors. The proposed FCM-based model is applied in a case study of a medium-sized transport coalition. This research assumed a high level of collaborative integration for coalition partners. In other words, that there is a good alignment among the number of operating criteria in the transport collaboration. This paper elucidates how the change in criteria interacts with each other and how this change affects the structure of transport collaboration. The findings of case study were implemented as a predictable input in a coalition to understand under what scenario conditions the change of the pair of criteria would affect the transport collaboration structure. By this way, FCM-based model gives a cognitive perspective on strategic decision making in a coalition. This perspective refers early signals to fledgling coalition partners in the process of building a coalition by using three threshold values: "no-go", "go" and "go with conditions". We have limited the scope of our investigation by focusing on operating criteria like trust, information sharing, management involvement, integration level, transport cost, service level, system reliability, data standardization and so on. An important finding of this study is that generally speaking, the transport collaboration structure might be heavily affected by some of the operating criteria that this paper investigated. By using an FCM-based model we can determine the intensity level of the criteria so that coalition partners can implement the exact conditions in order to enable long lasting relationships. However, the findings of the study would not be

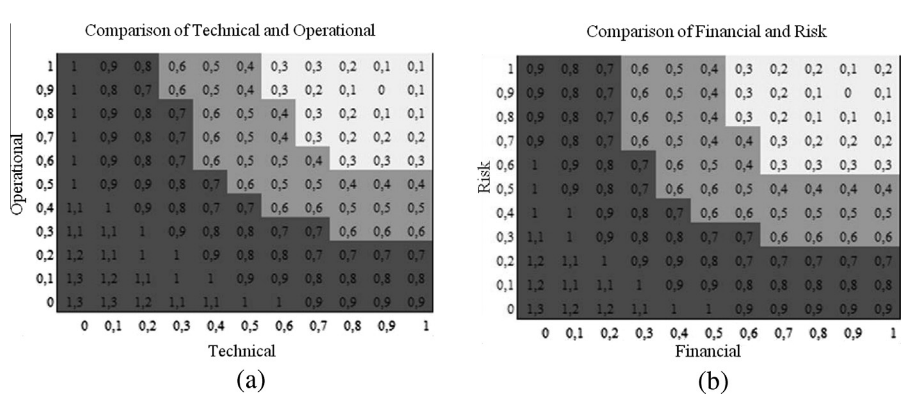

Fig. 10. Gray scale representation of the reference output vectors used for classifying digits according to the pair of selected categories.

satisfactory in all cases since the sample studied is restricted considerably with respect to the size of coalition and industry sector. Therefore the results of this study would have to be carefully generalized if applied to other applications or scenarios. Nonetheless, this study offers a unique perspective to use the FCM-based model in order to answer the research question: *how would every change in the pair of criteria affect the transport collaboration structure under a set of scenario conditions?*. This approach can be implemented into different research problems to find out the causal mechanism between the criteria. Additionally, our results provide evidence in terms of the pair-wise scenario comparisons of criteria that transport collaboration in heterarchical transport networks are superior for transport users and service providers rather than those who work alone. The appropriate use of proposed FCM-based model not only provides greatly needed insight into decision making, but also helps elevate the importance of coalition structures. Further research is required to develop a tool for transport collaboration metrics in order to create a collaboration profile for coalition partners. Knowledge of such relationships would help practitioners in a coalition whether they have suitable technological as well as organizational capacity to invest in developing their resources and collaboration.

Appendix A. Decision makers' respond list after FDM screening

w_{ij}	C_i	C_j	Min (l_{ij})	Max (u_{ij})	Mean (m_{ij})	De-fuzzy (w_{ij})	w_{ij}	C_i	C_j	Min (l_{ij})	Max (u_{ij})	Mean (m_{ij})	De-fuzzy (w_{ij})
w_{120}	C_1	C_{20}	0.5	1	0.9	0.80	w_{1737}	C_{17}	C_{37}	0	1	0.75	0.58
w_{125}	C_1	C_{25}	0.75	1	1	0.92	w_{184}	C_{18}	C_4	0.75	1	1	0.92
w_{126}	C_1	C_{26}	0.5	1	0.95	0.82	w_{1819}	C_{18}	C_{19}	0.5	1	0.75	0.75
w_{135}	C_1	C_{35}	0.25	1	0.75	0.67	w_{1916}	C_{19}	C_{16}	0	0.75	0.3	0.35
w_{137}	C_1	C_{37}	0.25	1	0.6	0.62	w_{1921}	C_{19}	C_{21}	0.25	1	0.8	0.68
w_{23}	C_2	C_3	0	1	0.55	0.52	w_{2019}	C_{20}	C_{19}	0	0.75	0.3	0.35
w_{25}	C_2	C_5	0.25	1	0.75	0.67	w_{2113}	C_{21}	C_{13}	0.5	1	0.9	0.80
w_{34}	C_3	C_4	0.75	1	1	0.92	w_{2225}	C_{22}	C_{25}	0.5	1	0.85	0.78
w_{36}	C_3	C_6	0.25	1	0.75	0.67	w_{2227}	C_{22}	C_{27}	0.25	1	0.55	0.60
w_{37}	C_3	C_7	0	1	0.65	0.55	w_{2314}	C_{23}	C_{14}	−1	−0.5	−0.8	−0.77
w_{311}	C_3	C_{11}	0	1	0.6	0.53	w_{2322}	C_{23o}	C_{22}	0.25	1	0.75	0.67
w_{326}	C_3	C_{26}	0.75	1	1	0.92	w_{2324}	C_{23}	C_{24}	0.25	1	0.75	0.67
w_{329}	C_3	C_{29}	0.25	1	0.65	0.63	w_{2325}	C_{23}	C_{25}	0.25	1	0.65	0.63
w_{330}	C_3	C_{30}	0.25	1	0.85	0.70	w_{2327}	C_{23}	C_{27}	0	1	0.45	0.48
w_{333}	C_3	C_{33}	0.75	1	1	0.92	w_{2422}	C_{24}	C_{22}	0.25	1	0.65	0.63
w_{335}	C_3	C_{35}	0.25	1	0.65	0.63	w_{2427}	C_{24}	C_{27}	0	0.75	0.45	0.40
w_{337}	C_3	C_{37}	0.25	1	0.6	0.62	w_{2529}	C_{25}	C_{29}	0.25	1	0.85	0.70
w_{41}	C_4	C_1	0.75	1	1	0.92	w_{2530}	C_{25}	C_{30}	0.5	1	0.95	0.82
w_{45}	C_4	C_5	0.75	1	1	0.92	w_{2533}	C_{25}	C_{33}	0.25	1	0.75	0.67
w_{46}	C_4	C_6	0.75	1	1	0.92	w_{2535}	C_{25}	C_{35}	0.25	1	0.7	0.65
w_{49}	C_4	C_9	0.5	1	0.75	0.75	w_{2537}	C_{25}	C_{37}	0.75	1	1	0.92
w_{416}	C_4	C_{16}	0.5	1	0.8	0.77	w_{2612}	C_{26}	C_{12}	0	1	0.5	0.50
w_{422}	C_4	C_{22}	0.25	1	0.8	0.68	w_{2614}	C_{26}	C_{14}	−1	−0.25	−0.6	−0.62
w_{425}	C_4	C_{25}	0.75	1	1	0.92	w_{2620}	C_{26}	C_{20}	0.25	1	0.55	0.60
w_{426}	C_4	C_{26}	0	1	0.75	0.58	w_{2624}	C_{26}	C_{24}	0.25	1	0.65	0.63
w_{433}	C_4	C_{33}	0.25	1	0.65	0.63	w_{2625}	C_{26}	C_{25}	0.75	1	1	0.92
w_{435}	C_4	C_{35}	0	1	0.55	0.52	w_{2628}	C_{26}	C_{28}	0.25	1	0.7	0.65
w_{437}	C_4	C_{37}	0.75	1	1	0.92	w_{2720}	C_{27}	C_{20}	0.25	1	0.55	0.60
w_{525}	C_5	C_{25}	0.25	1	0.65	0.63	w_{2733}	C_{27}	C_{33}	0	0.5	0.25	0.25
w_{529}	C_5	C_{29}	0	1	0.5	0.50	w_{284}	C_{28}	C_4	0.75	1	1	0.92
w_{530}	C_5	C_{30}	0	1	0.5	0.50	w_{285}	C_{28}	C_5	0.25	1	0.75	0.67
w_{69}	C_6	C_9	−1	0	−0.6	−0.53	w_{2814}	C_{28}	C_{14}	−1	−0.25	−0.75	−0.67
w_{611}	C_6	C_{11}	0.25	1	0.85	0.70	w_{2818}	C_{28}	C_{18}	−1	−0.25	−0.7	−0.65
w_{614}	C_6	C_{14}	−1	−0.25	−0.65	−0.63	w_{2820}	C_{28}	C_{20}	0.25	1	0.6	0.62
w_{76}	C_7	C_6	0.5	1	0.9	0.80	w_{2825}	C_{28}	C_{25}	0.75	1	1	0.92
w_{814}	C_8	C_{14}	−1	−0.25	−0.6	−0.62	w_{2827}	C_{28}	C_{27}	−1	0	−0.55	−0.52
w_{822}	C_8	C_{22}	−1	−0.5	−0.9	−0.80	w_{2837}	C_{28}	C_{37}	0.25	1	0.7	0.65
w_{98}	C_9	C_8	−1	−0.5	−0.85	−0.78	w_{2934}	C_{29}	C_{34}	0.25	1	0.75	0.67
w_{912}	C_9	C_{12}	−1	−0.25	−0.7	−0.65	w_{304}	C_{30}	C_4	0.25	1	0.7	0.65
w_{101}	C_{10}	C_1	−1	−0.25	−0.6	−0.62	w_{3029}	C_{30}	C_{29}	0.5	1	0.9	0.80
w_{103}	C_{10}	C_3	−1	−0.25	−0.65	−0.63	w_{3031}	C_{30}	C_{31}	0	0.75	0.35	0.37
w_{107}	C_{10}	C_7	−1	0	−0.45	−0.48	w_{3032}	C_{30}	C_{32}	0	1	0.45	0.48
w_{1012}	C_{10}	C_{12}	−1	0	−0.5	−0.50	w_{3033}	C_{30}	C_{33}	0.25	1	0.7	0.65
w_{111}	C_{11}	C_1	−1	0	−0.4	−0.47	w_{3037}	C_{30}	C_{37}	0.25	1	0.7	0.65

(*continued on next page*)

Decision makers' respond list after FDM screening (*continued*)

w_{ij}	C_i	C_j	Min (l_{ij})	Max (u_{ij})	Mean (m_{ij})	De-fuzzy (w_{ij})	w_{ij}	C_i	C_j	Min (l_{ij})	Max (u_{ij})	Mean (m_{ij})	De-fuzzy (w_{ij})
w_{114}	C_{11}	C_4	−1	0	−0.55	−0.52	w_{3132}	C_{31}	C_{32}	−1	−0.25	−0.75	−0.67
w_{115}	C_{11}	C_5	−1	−0.25	−0.65	−0.63	w_{3133}	C_{31}	C_{33}	0.25	1	0.65	0.63
w_{1112}	C_{11}	C_{12}	−1	0	−0.5	−0.50	w_{3134}	C_{31}	C_{34}	−1	−0.25	−0.6	−0.62
w_{1225}	C_{12}	C_{25}	−1	−0.75	−1	−0.92	w_{3137}	C_{31}	C_{37}	−1	−0.25	−0.7	−0.65
w_{1237}	C_{12}	C_{37}	−1	−0.5	−0.9	−0.80	w_{3217}	C_{32}	C_{17}	−1	0	−0.45	−0.48
w_{139}	C_{13}	C_9	−1	−0.25	−0.7	−0.65	w_{3237}	C_{32}	C_{37}	0.5	1	0.9	0.80
w_{1317}	C_{13}	C_{17}	0.25	1	0.65	0.63	w_{3332}	C_{33}	C_{32}	0.5	1	0.8	0.77
w_{141}	C_{14}	C_1	−1	0	−0.45	−0.48	w_{3337}	C_{33}	C_{37}	0.75	1	1	0.92
w_{1422}	C_{14}	C_{22}	−1	−0.25	−0.6	−0.62	w_{3433}	C_{34}	C_{33}	0.25	1	0.6	0.62
w_{1512}	C_{15}	C_{12}	−1	−0.25	−0.7	−0.65	w_{3531}	C_{35}	C_{31}	0.25	1	0.6	0.62
w_{1530}	C_{15}	C_{30}	0	1	0.55	0.52	w_{3532}	C_{35}	C_{32}	0.25	1	0.7	0.65
w_{1613}	C_{16}	C_{13}	0.5	1	0.9	0.80	w_{3533}	C_{35}	C_{33}	0.25	1	0.7	0.65
w_{1716}	C_{17}	C_{16}	0.25	1	0.55	0.60	w_{3631}	C_{36}	C_{31}	0.25	1	0.6	0.62
w_{1728}	C_{17}	C_{28}	−1	−0.25	−0.7	−0.65	w_{3633}	C_{36}	C_{33}	0.25	1	0.65	0.63

Appendix B. FCM criteria and indices

Category	Criterion	Abbr. code	C_i	$od(C_i)$	$id(C_i)$	$cen(C_i)$	T	R	O	Concept value (v_i)
Technical	Reliability	RELI	C_1	3.82	2.48	6.30			1	0.52
Technical	Standardization	STD	C_2	1.18	0.00	1.18	1			0.50
Technical	Technological capability	TECHCAP	C_3	7.08	1.15	8.23			1	0.49
Technical	Integration level	INTL	C_4	8.52	3.92	12.43			1	0.82
Technical	Information quality	INFQ	C_5	1.63	2.88	4.52			1	0.73
Technical	System performance	SPER	C_6	1.87	2.38	4.25			1	0.81
Technical	Flexibility in toolset	FLEXT	C_7	0.80	1.03	1.83			1	0.51
Risk	Skill set	SKILL	C_8	1.42	0.78	2.20			1	0.42
Risk	Feasibility	FEA	C_9	1.43	1.93	3.37			1	0.42
Risk	Technology usage	TECHUS	C_{10}	2.23	0.00	2.23	1			0.50
Risk	Safety and security	SASE	C_{11}	2.12	1.23	3.35			1	0.70
Risk	Transport chain	TRCHAIN	C_{12}	1.72	2.80	4.52			1	0.31
Risk	Profitability	PROF	C_{13}	1.28	1.60	2.88			1	0.75
Risk	Control risk	CONT	C_{14}	1.10	3.30	4.40			1	0.12
Risk	Infrastructure	INF	C_{15}	1.17	0.00	1.17	1			0.50
Financial	Overall efficiency	OVEFF	C_{16}	0.80	1.72	2.52			1	0.76
Financial	Transport cost	COST	C_{17}	1.83	1.12	2.95			1	0.53
Financial	Level of orientation	ORIENT	C_{18}	1.67	0.65	2.32			1	0.41
Financial	Accelerated ROI	ROI	C_{19}	1.03	1.10	2.13			1	0.65
Financial	Cost sharing	COSTSHAR	C_{20}	0.35	2.62	2.97			1	0.83
Financial	Financial performance	FINANS	C_{21}	0.80	0.68	1.48			1	0.61
Organizational	Organizational fit	ORGFIT	C_{22}	1.38	3.40	4.78			1	0.72
Organizational	Management involvement	MNG	C_{23}	3.22	0.00	3.22	1			0.50
Organizational	Openness of communication	OPENCOM	C_{24}	1.03	1.30	2.33			1	0.70
Organizational	Information sharing	INFSHAR	C_{25}	3.75	6.63	10.38			1	0.97
Organizational	transparency	TRANS	C_{26}	3.92	2.32	6.23			1	0.79
Organizational	Leadership	LEAD	C_{27}	0.85	2.00	2.85			1	0.66
Organizational	Trusting relationship	TRUST	C_{28}	5.60	1.30	6.90			1	0.54
Operational	Asset optimization	ASSET	C_{29}	0.67	2.63	3.30			1	0.88
Operational	Capacity	CAPA	C_{30}	3.60	2.53	6.13			1	0.85
Operational	Replenishment length	REPLEN	C_{31}	2.57	1.60	4.17			1	0.76
Operational	Lead time	LEADT	C_{32}	1.28	2.57	3.85			1	0.77
Operational	Flexibility in processes	FLEXP	C_{33}	1.68	5.65	7.33			1	0.98
Operational	Carbon footprint	SUST	C_{34}	0.62	1.28	1.90			1	0.53
Operational	Predictability	PREDIC	C_{35}	1.92	2.47	4.38			1	0.85
Operational	Variability	VAR	C_{36}	1.25	0.00	1.25	1			0.50
Operational	Service level	SERV	C_{37}	0.00	8.12	8.12		1		0.99

T: Transmitter, R: Receiver, O: Ordinary.

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