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A conceptual model for intermodal freight logistics centre location decisions

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Abstract

The persistent growth of freight traffic congestion and air pollution in urban areas and the increase of imbalance and inefficiency in land use development drive public authorities and users to find alternative logistics solutions to ease the freight traffic problem. Intermodal freight logistics centres play an important role in achieving socio-economic and environmental sustainability by enhancing an optimal integration of different modes to provide an efficient and cost-effective use of the transport system through customer-oriented, door-to-door services while favouring competition among transport operators. An efficient logistics centre structure may lead to a significant profit and return on investment as well as a significantly increased competitive advantage in the market place by meeting strategic commercial objectives, where determination of the location is a key factor in enhancing the efficiency of urban freight transport systems and initializing relative sufficient supply chain activities. Hence, public authorities should consider the importance of this topic by any given decision in terms of strong economical, social and environmental implications before announcing an area as a logistics centre. The objective of this study is to explore the applicability of the way for the development of a conceptual model based on a combination of the fuzzy-analytical hierarchy process (AHP) and artificial neural networks (ANN) methods in the process of decision-making in order to select the most appropriate location. A numerical example is provided to demonstrate the concept of proposed model.

Keywords: Location problem; intermodal freight logistics centre; selection; decision-making; fuzzy-AHP; ANN

1. Introduction

Intermodal freight logistics and passenger transport in today's highly competitive environment are gaining a remarkable profile in the planning of Europe's city regions. Their roles in shaping cities driven by congestion and environmental concerns, the changing requirements of global supply chain systems and the rapid advancement of information and communication technologies (Zografos and Regan, 2004) are also being examined more closely by investors, city planners and environmental lobbyists.

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The European traffic predictions show a significant growth of traffic levels by 2020 which is expected to be 30% in freight logistics and 20% in passenger transport. However rapid growth in transport is deteriorating cities (like pollution, traffic congestion, accidents, environmental emissions, dependence on fossil fuels etc.), freight transport is a key support system has become a more and more central issue to resolving conflicts between economic development, sustainability and social equality. Moreover, environmental problems concerned with transport could be ameliorated through the improvement of transport efficiency and carefully located logistics centres.

One of the main objectives of the sustainable long term transport development program is to develop a framework for an optimal integration of different modes of transport in the regional logistics centres so as to enable efficient and cost-effective use of the transport system through seamless, customer-oriented door-to-door services, favouring competition among transport operators (Babkock and German, 1989). In the scope of the European Union (EU) transport policies, in order to enhance intermodality and interoperability, many logistics centres are formed. These centres play a critical role in optimizing and intensifying logistic services along supply chains, presenting a practical means to solve urban traffic congestion while increasing the efficiency of the freight transport, thus encouraging innovation and lowering of the transportation cost that focus on intermodal operations, and logistics activities.

An intermodal freight logistics centre is a cluster of quality industrial/intermodal /distribution/logistics buildings located within a secure perimeter where a range of support services are provided by every user. It enables a high degree of accessibility and transfers freight from one mode to another with generating less negative environmental impacts (McCalla, 2001; Weisbrod et al., 2002).

The location of the logistics centres is a key element in enhancing the efficiency of urban freight transport systems and initializing relative supply chain activities sufficiently; thus, the location of a intermodal freight logistics centre should be selected carefully; otherwise it may cause irreversible consequences in the city planning and also it may create bottlenecks that lead to rapid increase in cost in providing transport solutions. All influencing factors for the determination of a location should be considered and well planned. Hence, public authorities should consider the importance of this topic by any given decision in terms of strong economical, social and environmental implications before announcing an area as a logistics centre.

Facility location and capacity planning problems have been solved using different operational research techniques for years where the selection of logistics location has been long considered one of the most important complex decision-making problems to analyze. In real-world systems, selecting the “most appropriate” location should be considered and evaluated in terms of many different influence factors resulting in a vast amount of information which are most of uncertain and imprecise. Furthermore, the determination of dependent and independent relationship between selection criteria for location problem is very difficult to classify. Most of the conventional decision-making models like linear programming (LM), mixed integer programming (MIP) and goal programming (GP) etc. have limitations to enlighten the interrelations among the sub-criteria of the given context by the validity of the additivity and independence assumptions and moreover the application costs are very high in terms of limited data handling capabilities of the approaches, therefore they can only be applied in solving the medium-sized simple problems.

The objective of this study is to explore the applicability of the way for the development of a conceptual model based on a combination of the fuzzy-analytical hierarchy process (AHP) and artificial neural networks (ANN) methods in the process of selecting the location of an intermodal logistics centre. In this study, the relative dependence and interdependence influence factors based on well-organized literature review are identified. Here, the fuzzy extension of the AHP technique is used to derive the priorities (relative weights) of each selected criterion. ANN are used to alleviate the multi-criteria decision-making (MCDM) and to obtain the best model configuration for the location problem. Matlab v. 6.5 is used for the ANN application. The model presented helps practitioners (i.e. decision-makers - public, regional and municipal authorities) to make a decision with respect to the considered criteria and contributes city logistics relative issues. Furthermore, the results of the model can be used to develop a software solution for location-selection problems in complex decision-making environments. Finally, the proposed conceptual model is illustrated to demonstrate an empirical case study to show the best solution among given alternatives. Further, the results provide some critical evaluations on how to improve each sub-criterion to reduce the gap between real and desired performance values to determine the most appropriate intermodal freight logistics location in any urban area.

2. Literature Review

Many classical and heuristic methods have been proposed to solve location problem, like linear, non-linear programming, simplex algorithm, lagrangian relaxation, branch & cut methods, branch and bound (Mayer and Wagner, 2002), local beam search, tabu search (Glover, 1993), artificial neural network, fuzzy control, AHP (Janic and Reggiani, 2001), generic algorithms, expert systems, multi-agent systems and so on. But conventional location selection methods have limitations associated with their inadequacy to add all the indicators to location selection models. These models are usually composed of some basic elements, like; objective functions, potential locations, requirements, a distance or time array, and some rules for allocation (Chi and Kuo, 2001).

There are different studies associated with location selection decisions that have been commonly carried out by using MCDM techniques, such as distribution centre selection with weighted fuzzy factor rating system (Ou and Chou, 2009), selection of distribution centres with three-stage hierarchy of selection (Vinh Van and Devinder, 2005), distribution location problem with QFD (Chuang, 2002), location problem with fuzzy-AHP (Kaboli, et al., 2007), logistic centre selection with dynamic dual-diamond model (Wang et al., 2005), logistics distribution location based on genetic algorithms and fuzzy comprehensive evolution (Ren and Wang, 2006), intermodal freight hub location decision with multi-objective evaluation model (Sirikijpanichkul and Ferreira, 2005; 2006), location selection of logistics centre based on Fuzzy AHP and TOPSIS (Wang and Liu, 2007), selection of logistics centre location with fuzzy MCDM based on entropy weight (Chen and Lili, 2006), facility or plant location selection with multiple objective decision making (Farahani and Asgari, 2007), facility location selection with AHP (Yang and Lee, 1997), convenience store location with fuzzy-AHP (Kuo et al., 2001), port selection with AHP (Ugboma et al., 2006), reverse logistics location selection (Kannan et al., 2008), selecting a site for a logistical centre on factor and methods (Chen and Liu, 2006), logistic centre selection with fuzzy-AHP and Electre Method (Ghoseiri and Lessan, 2008) and multi-modal hub location (Ashayeri and Kampstra, 2002).

In this study, a combination of fuzzy AHP & ANN methods is used, as these methods can provide a better outcome in using complex, multi-dimensional data to solve decision making problems for selecting location. Though as a computational intelligence enhancement, both fuzzy logic and ANN have some drawbacks, the proposed hybrid model with the persistence of these two methods provides some advantages for improving the results.

3. Methodology

The proposed model as shown in Figure 1, consists of two main phases and four attached components: (I) Fuzzy-AHP phase; (1) hierarchical structure development with fuzzy extension, namely fuzzy AHP, (2) weights determination, (3) data collection and (II) ANN phase; (4) decision-making based on ANN. The evaluation criteria and sub-criteria for fuzzy AHP hierarchical structure were selected according to the interview with decision makers (experts) and literature review. The respective data in these criteria were collected from a survey. The weights that are calculated from fuzzy-AHP are applied in the ANN to select the "most appropriate alternative" in freight logistics location selection. A detailed discussion about model is presented in the following sub-sections.

3.1. Fuzzy analytic hierarchy process

The Analytic Hierarchy Process (AHP), first suggested by Saaty (1980) more than two decades ago, is one of the widely used multi-criteria-decision-making methods (Saaty, 1980). AHP can effectively handle both qualitative and quantitative data to decompose the problem hierarchically where the problem is broken down thoroughly and its related sub-elements with regards to the hierarchical level are listed in relation from the overall objective (e.g. selecting the appropriate distribution methodology) to the sub-objectives (e.g. minimize cost, maximize process capability). AHP is composed of three main phases which are shown in Figure 2; (1) hierarchical problem decomposition: Identifying the decision problem and overall goal/objective – the problem is decomposed into sub-elements hierarchically (which are structured at different levels in the form of a hierarchy, from the top through the intermediate to the lower-level, which usually contains a finite number of decision elements) (2) evaluation phase: the relative importance of each element at a particular level is measured by a procedure of pair-wise comparison. Decision makers provide numerical values for the priority of each element using a rating scale. (3) synthesis of alternatives (ranking): the priority weights of elements at each level are computed using an eigenvector or least square analysis. The process is repeated for each level of the hierarchy until a decision is finally reached by overall composite weights (Saaty, 1980).

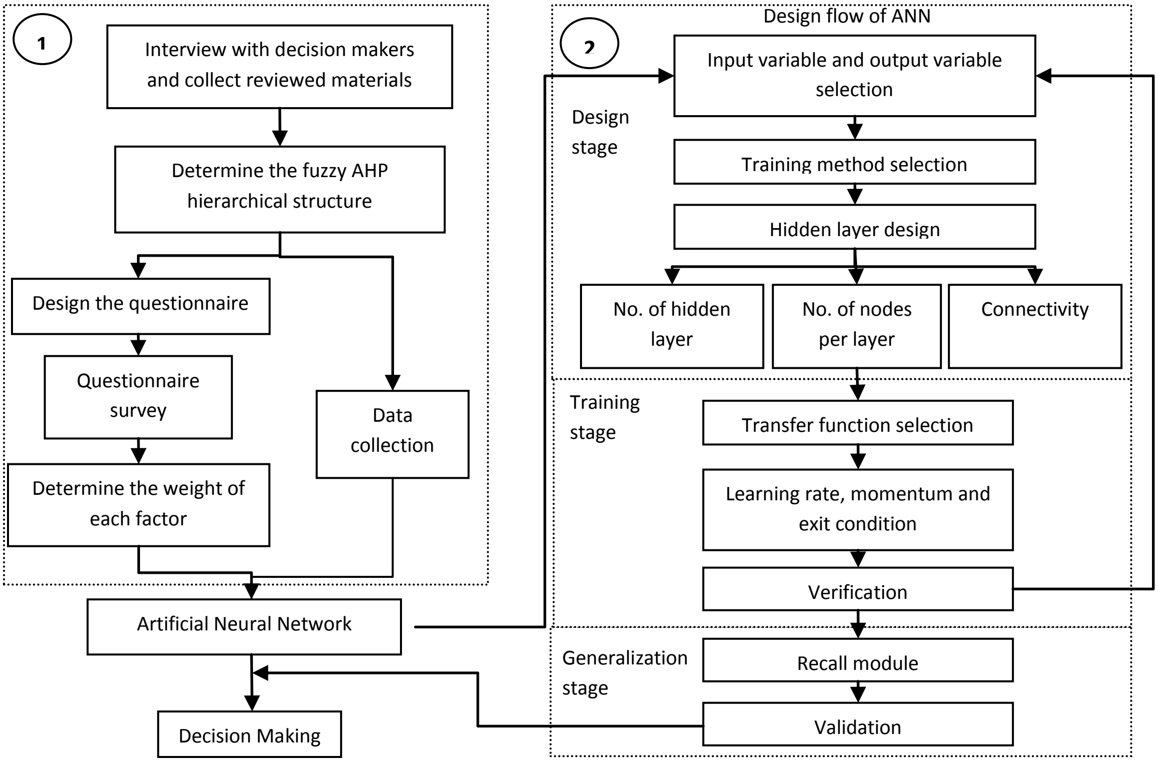

Figure 1 The structural design of the proposed model of intermodal freight logistics centre selection

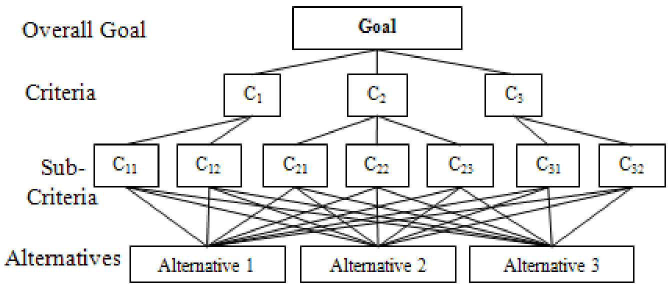

Figure 2 The AHP hierarchy structure

The AHP approach requires the translation of perceptions into numerical scales, frequently through mechanisms such as a Likert scale (1-3-5, 1-3-9 or 1-5-9) to quantify the “decision makers” strength of feeling between any two attributes” with respect to any given criterion. Subsequently, AHP makes use of a suitable process to estimate relative weights of the decision elements and culminates into their aggregation in order to arrive at the outcome.

However, people's assessments of the qualitative attributes are always subjective and thus imprecise, and the linguistic terms that people use to express their feelings or judgments are vague in nature (Kuo et al., 2009). Even though the scale has the advantages of simplicity and ease of use, it does not take into account the uncertainty associated with the mapping of one's perception (or judgement) to a number and hence provides a constrained choice of limited numerical ratings to various verbal attitudes of the decision makers. Therefore, fuzzy set theory can be applied to AHP in determining the relationships in order to obtain a more robust and more quantitatively oriented AHP process.

There are different *fuzzy* AHP models in the literature which are constructed for different problems in the areas of location selection problem. In the proposed model, namely *fuzzy* AHP methodology to determine the weight factors was applied by using Chang (1996)'s model. The steps of Chang's extent analysis model can be given as follows:

Step 1: A fuzzy number is a special fuzzy set $F = \{x, \mu\, \mathrm{F}(x), x \in R\}$, where x takes values on the real line, R: $(-\infty \leq x \leq \infty)$ and $\mu\, \mathrm{F}(x)$ is a continuous mapping from R to the close interval [0, 1]. A triangular fuzzy number can be denoted as $M = (l, m, u)$. Its membership function $\mu\, \mathrm{F}(x)$: $R \rightarrow [0, 1]$ is equal to:

$$\mu \mathrm{M(x)} = \begin{cases} (x-l)/(m-l) & l \leq x \leq m, \\ (x-u)/(m-u) & m \leq x \leq u, \\ 0, & otherwise, \end{cases} \tag{1}$$

where $l \leq m \leq u$. l and u are the lower and upper value of the support of M, respectively, and m is the mid-value of M. When $i = m = u$, it is a non-fuzzy number by convention.

$$\begin{aligned} & M_1 + M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2); \quad M_1 \otimes M_2 \approx (l_1 l_2, m_1 m_2, u_1 u_2), \\ & \lambda \otimes M1 = (\lambda l_1, \lambda m_1, \lambda u_1) \qquad \lambda > 0, \lambda \in R, \\ & M_1^{-1} \approx \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right) \end{aligned} \tag{2}$$

A linguistic variable is a variable whose values are expressed in linguistic terms. The concept of a linguistic variable is very useful in dealing with situations, which are too complex or not well defined to be reasonably described in conventional quantitative expressions (Zimmermann, 1991).

The linguistic variables that are utilized in the model can be expressed in positive triangular fuzzy numbers for each criterion as in Figure 3. The linguistic variables matching and the corresponding membership functions are provided in Table 1. The proposed methodology employs a Likert scale of fuzzy numbers starting from $\tilde{1}$ to $\tilde{9}$ symbolize with tilde (~) for the fuzzy AHP approach. Table 1 depicts the AHP and fuzzy AHP comparison scale considering the linguistic variables that describes the importance of attributes and alternatives to improve the scaling scheme for the judgment matrices.

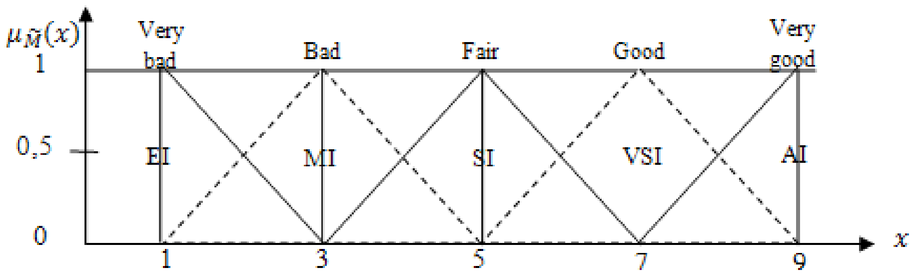

Figure 3 Linguistic variables for the importance weight of each criterion

Step 2: By using triangularly, fuzzy numbers via pair wise comparison, the fuzzy judgment matrix $\tilde{A}(a_{ij})$ can be expressed mathematically as in equitation (3):

$$\tilde{A} = \begin{cases} 1 & \tilde{a}_{12} & \tilde{a}_{13} & \ldots & \tilde{a}_{1(n-1)} & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \tilde{a}_{23} & \ldots & \tilde{a}_{2(n-1)} & \tilde{a}_{2n} \\ . & . & . & \ldots & . & . \\ \tilde{a}_{(n-1)1} & \tilde{a}_{(n-1)2} & \tilde{a}_{(n-1)3} & \ldots & 1 & \tilde{a}_{(n-1)n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \tilde{a}_{n3} & \ldots & \tilde{a}_{n(n-1)} & 1 \end{cases} \tag{3}$$

The judgment matrix $\tilde{A}$ is an n x n fuzzy matrix containing fuzzy numbers $\tilde{a}_{ij}$.

$$\tilde{a}_{ij} = \begin{cases} 1 & i = j \\ \tilde{1},\tilde{3},\tilde{5},\tilde{7},\tilde{9}\, or \ldots \;\; \tilde{1}^{-1},\tilde{3}^{-1},\tilde{5}^{-1},\tilde{7}^{-1},\tilde{9}^{-1} & i \neq j \end{cases} \tag{4}$$

Let $X = \{x_1, x_2, x_3, \ldots, x_n\}$ be an objective set, whereas $U = \{u_1, u_2, u_3, \ldots, u_n\}$ be a goal set. According to the fuzzy extent analysis model, each object is taken and extent analysis for each goal, g_i, is performed respectively. Resulting in m extent analysis values for each objective can be obtained with the following signs:

$$M_{gi}^1, M_{gi}^2, \ldots.., M_{gi}^m, \qquad i = 1,2, \ldots..,n. \tag{5}$$

Where all the $M_{gi}^1 (j = 1,2, \ldots..,m)$ are triangular fuzzy number can be denoted as $M= (l, m, u)$ where $l \leq m \leq u$, l and u stand for the lower and upper value of the support of M, respectively, and m is the mid-value of M.

Table 1 Linguistic expression for fuzzy scale of relative weights of criteria and performance values of alternatives (an example of one judge)

Intensity of fuzzy AHP scale (l, m, u)	Numeric ratings for AHP	Linguistic variables scale for importance weight of criteria	Linguistic variables scale for performance values of alternatives
$\tilde{1}$ (1,1,3)	1	Equally important (EI)	Very bad
$\tilde{3}$ (1,3,5)	3	Moderately important (MI)	Bad
$\tilde{5}$ (3,5,7)	5	Strongly important (SI)	Fair
$\tilde{7}$ (5,7,9)	7	Very strongly important (VSI)	Good
$\tilde{9}$ (7,9,9)	9	Absolutely important (AI)	Very Good

Intermediate values between two adjacent judgments are, $\tilde{2},\tilde{4},\tilde{6},\tilde{8}$ which are used to represent compromise between the priorities listed above.

Step 3: The value of fuzzy synthetic extent with respect to the i th object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} \tag{6}$$

Where the degree of possibility of $M_1 \geq M_2$ is defined as:

$$V(M_1 \geq M_2) = \sup_{y \geq x} [\min\ (\mu_{M1}(x) = \mu_{M2}(y)] \tag{7}$$

When a pair (x, y) exist such that $x \geq y$ and $\mu_{M1}(x) = \mu_{M2}(y)$, the equality equation $V(M_1 \geq M_2) = 1$. Since $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are convex fuzzy numbers and can be expressed like that:

$$V(M_1 \geq M_2) = 1 \quad if \quad m_1 \geq m_2 \tag{8}$$

$$V(M_1 \geq M_2) = \text{hgt}\ (M_1 \cap M_2)\ =\ \mu_{M1}(d) \tag{9}$$

Where, d is the ordinate of the highest intersection point D between μ_{M1} and μ_{M2} (Figure 4). When M_1 and M_2, the ordinate of D is given by the following equation:

$$V(M_2 \geq M_1) = \text{hgt}\ (M_1 \cap M_2)\ =\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \tag{10}$$

To compare M_1 and M_2 both values of $V\ (M_1 \geq M_2)$ and $V\ (M_2 \geq M_1)$ are required.

Step 4: The degree possibility of a convex fuzzy number to be greater than k convex fuzzy numbers M_i (i = 1, 2, ... k) can be defined by

$$\begin{aligned} &V(M \geq M_1, M_2, ..., M_k) = V[(M \geq M_1)\ and\ (M \geq M_2)\ and .... \\ &....and\ (M \geq M_k)] = \min V(M \geq M_i),\ \ i = 1,2,3,....k. \end{aligned} \tag{11}$$

Assuming that

$$d'(A_i) = \min V(S_i \geq S_k) \tag{12}$$

For k = 1, 2, ..., n; $k \neq i$. Then, the weight vector is obtained as follows:

$$W' = (d'(A_1), d'(A_2), ..., d'(A_n))^T \tag{13}$$

Where A_i (i = 1, 2, …., n) are n elements.

Step 5: After normalization, the normalized vectors are defined as:

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \tag{14}$$

Where W is a non-fuzzy number.

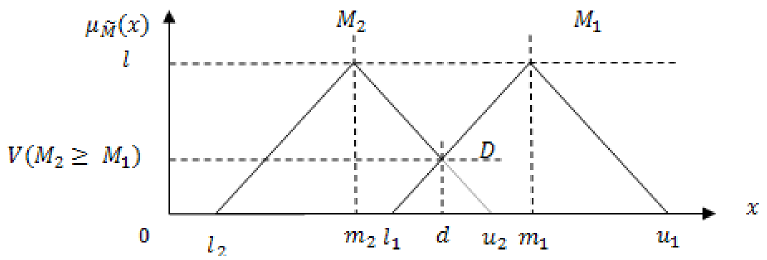

Figure 4 Intersection point d between two triangular fuzzy numbers M_1 and M_2

3.2. General structure of artificial neural networks

Neural networks; or artificial neural networks (ANN) were developed to simulate the human brain's cognitive learning process by trial and error (Marakas, 2003). Trafalis et al. (2002) refer to ANN models as algorithms for intellectual tasks such as learning, classification, recognition, estimation and optimization that are based on the concept of how the human brain works. However, in the past decade, they also attracted substantial attention in business industry. The ANNs are usually implemented by using electronic components or are simulated in software in a digital computer. ANNs have proved to be efficient in modelling complex and poorly understood problems for which sufficient data are collected. ANN is a technology that has been mainly used for prediction, clustering, classification and alerting to abnormal patterns (Haykin, 2008). The capability of learning examples is probably the most important property of neural networks in applications and can be used to train a neural network with the records of past response of a complex system (Wei et al., 1997).

An ANN model is composed of a large number of information-processing elements called *neurons*. Figure 5 shows the model of a neuron, which is connected by transfer functions in layers and a (artificial neural) network.
In mathematical terms, a neuron k can be described by (Haykin, 2008):

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{15}$$

$$y_k = \varphi (u_k + b_k) \tag{16}$$

where x_1, x_2, ..., x_m are the *inputs signals,* w_{k1}, w_{k2}, … …, w_{km} are the *synaptic weights* (*connecting strength*) of neuron k; u_k is the *linear combiner output* due to the input signals; the model of a neuron also includes and external *bias*, denoted by b_k, which has the effect of increasing or lowering the net input of the activation function and $\Phi(.)$ is the *nonlinear activation function*; and y_k is the *output signal* of the neuron. Such a neuron (with a threshold type activation function) is referred in the literature as the *McCulloch-Pitts model*, in recognition of the pioneering work done by McCulloch and Pitts (1943) (Haykin, 2008).

In a *layered* neural network the neurons are organized in the form of layers. They have at least two layers: an *input* and an *output* layer. The input layer consists of neurons that receive input from the external environment. The output layer consists of neurons that communicate the output of the system to the user or external to the environment. The layers between the input and the output layer (if any) are called hidden layers, whose computation nodes are correspondingly called *hidden neurons* or *hidden units*. Figure 6 shows the general structure of the one-hidden-layer ANN. Neural networks with this kind of architecture is also called as *multilayer perceptron*. The ANN's input layer with some neurons represents the previous sales data, say period $t - m$ to period $t - 1$, which are connected to the hidden layer. The hidden layer with some neurons is connected with the output layer with one single neuron which represents the sales for period t (Kuo and Xue, 1998), m indicates the sample number and T and O are the desired and actual outputs, respectively.

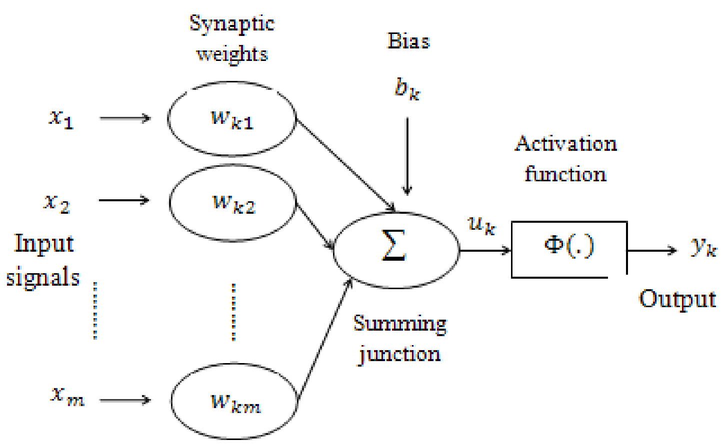

Figure 5 Schematic no-linear structure model of an artificial neuron

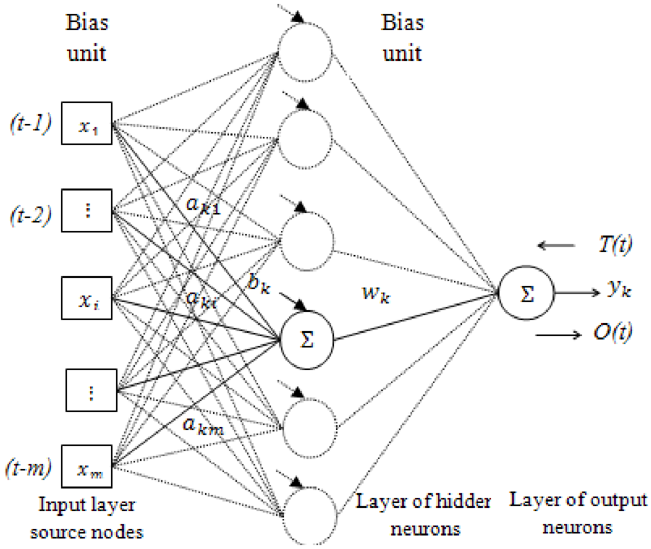

Figure 6 The ANN structure (A fully connected feed-forward NN with one hidden layer)

3.3. Integration of fuzzy AHP and ANN model

The hybrid model described in the paper (see Figure 1) focuses on a systematic location selection algorithm via two-dimensional analysis which consists of fuzzy set theory and artificial neural networks. The method is used for categorizing and selecting the evaluation main and sub-criteria with respect of decision makers (stakeholders) who can able to determine those criteria and determining the most appropriate freight logistics centre.

The first phase involves a fuzzy AHP structure developed to determine the ratings of logistics location selection criteria in accordance with a survey which was executed by stake holders. The questionnaire was constructed using the fuzzy AHP concept. This questionnaire targets the following business role players; operators, organizers, infrastructure operators, customers, community and government which are seen in depth in Figure 7.

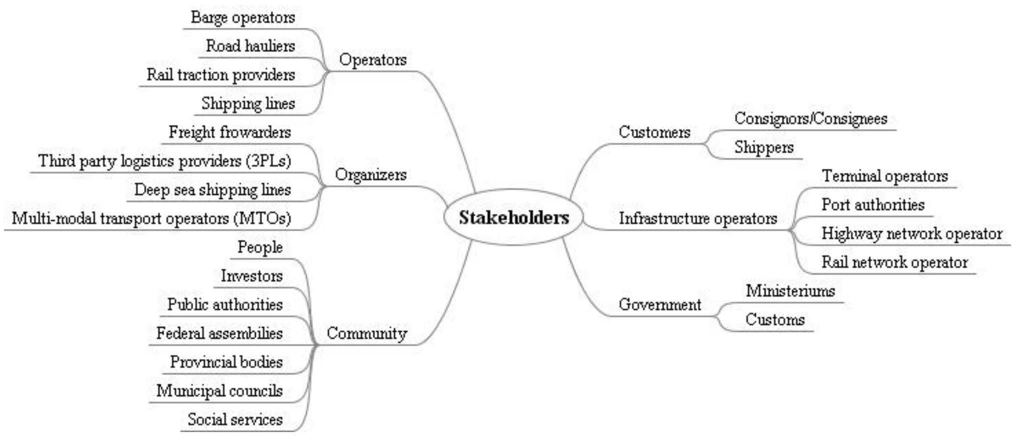

Figure 7 Stakeholders for location selection

The main criteria and sub-criteria were determined in Figure 8 with a hierarchical structure. After interviews with decision makers and the intensive literature review we determined five main evaluation criteria: Environmental effect, international market location, intermodal operation and management, national stability and economical scale and also sub-criteria for every main criterion for location selection problem. In this study, stakeholders' opinions are expressed in linguistic terms for degree of evaluation as detailed in Table 1 previously, namely: (1) equally important (EI), (2) moderately important (MI), (3) strongly important (SI), (4) very strongly important (VSI), (5) absolutely important (AI). To avoid getting subjective results in each questionnaire, interviewers were asked to select standard ranges of each scale which ranges from 1 to 9 (1 means equally important and 9 means absolutely important). Table 2 shows the relative importance of the weights factors as to linguistic terms where each stakeholder expressed own decision for each main criterion, then the fuzzy evaluation matrix according to the each stakeholder were calculated. Table 3 shows the evaluation matrix according to government where first of all vector was calculated W'=(0,920;0,065;0,670;0,546;1,000) afterwards the normalized weight vectors of the evaluation factors was calculated via normalization as: W= $(0,287;0,020;0,209;0,170;0,312)^T$. This process was executed for each stakeholder. Table 4 shows a brief outlook of importance degrees of weighted factors for every stakeholder that expressed their own opinion to determine the weight of evaluation criteria.

Table 2 The relative importance of the weights factors

Resource rating by the		ES	IO&M	NS	IML	EE
Government (GV)	Economical scale (ES)		SI		SI	
	Intermodal operation and management (IO&M)					
	National stability (NS)	EI	EI			MI
	International market location (IML)		EI	MI		
	Environmental effect (EE)	MI	SI		SI	
Community (CO)	Economical scale (ES)		AI		SI	SI
	Intermodal operation and management (IO&M)			EI		SI
	National stability (NS)	SI				SI
	International market location (IML)		EI	EI		
	Environmental effect (EE)				SI	
Operators (OP)	Economical scale (ES)		SI		EI	
	Intermodal operation and management (IO&M)			EI		SI
	National stability (NS)	SI			MI	
	International market location (IML)		EI			
	Environmental effect (EE)	MI		EI	EI	
Organizers (OG)	Economical scale (ES)		SI			SI
	Intermodal operation and management (IO&M)			MI		EI
	National stability (NS)	EI			SI	
	International market location (IML)	EI	EI			
	Environmental effect (EE)			EI	EI	
Customers (CU)	Economical scale (ES)		EI	EI		MI
	Intermodal operation and management (IO&M)			MI		EI
	National stability (NS)				MI	
	International market location (IML)	MI	EI			VSI
	Environmental effect (EE)			MI		
Infrastructure Operators (IO)	Economical scale (ES)		MI		EI	
	Intermodal operation and management (IO&M)			MI	EI	VSI
	National stability (NS)	SI				
	International market location (IML)			VSI		EI
	Environmental effect (EE)	EI		SI		

Table 3 The fuzzy evaluation matrix according to the government

	ES	IO&M	NS	IML	EE	W
ES	(1,1,1)	(3,5,7)	(1/3,1,1)	(3,5,7)	(1/5,1/3,1)	0,29
IO&M	(1/7,1/5,1/3)	(1,1,1)	(1/3,1,1)	(1/3,1,1)	(1/7,1/5,1/3)	0,02
NS	(1,1,3)	(1,1,3)	(1,1,1)	(1/5,1/3,1)	(1,3,5)	0,21
IML	(1/7,1/5,1/3)	(1,1,3)	(1,3,5)	(1,1,1)	(1/7,1/5,1/3)	0,17
EE	(1,3,5)	(3,5,7)	(1/5,1/3,1)	(3,5,7)	(1,1,1)	0,31

W =Alternative priority weight

$V(S_{ES} \geq S_{IO\&M}, S_{NS}, S_{IML}, S_{EE}) = 0{,}92$ $V(S_{EE} \geq S_{ES}, S_{IO\&M}, S_{NS}, S_{IML}) = 1{,}00$ $V(S_{IML} \geq S_{ES}, S_{IO\&M}, S_{NS}, S_{EE}) = 0{,}55$

$V(S_{IO\&M} \geq S_{ES}, S_{NS}, S_{IML}, S_{EE}) = 0{,}07$ $V(S_{NS} \geq S_{ES}, S_{IO\&M}, S_{IML}, S_{EE}) = 0{,}67$

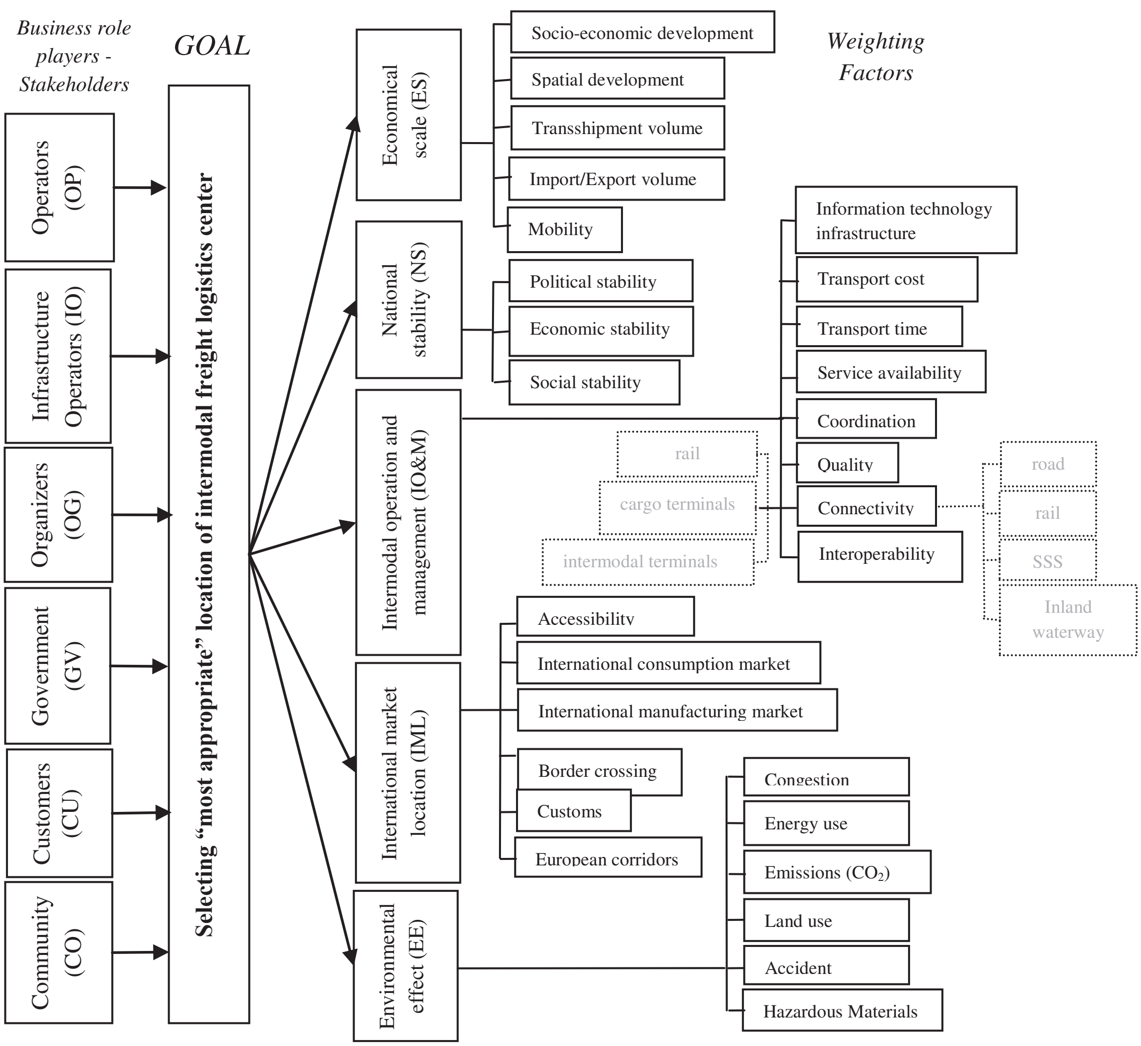

Figure 8 The hierarchical structure of the framework

Table 4 Importance degrees of weighted factors according to stakeholders

Evaluation Criteria	GV	CO	OP	OG	CU	IO
Economical scale	0,29	**0,44**	0,21	**0,30**	0,23	0,16
Intermodal operation and management	0,02	0,17	0,21	0,19	0,19	**0,26**
National stability	0,21	0,29	**0,25**	0,23	0,16	0,16
International market location	0,17	0,02	0,13	0,14	**0,26**	0,24
Environmental effect	**0,31**	0,08	0,19	0,14	0,15	0,19

All these process were executed for every stakeholder and for each evaluation criteria with Chang's extent analysis (1996). Table 5 shows all importance degrees of weighted factors according to first level evaluation criteria and stakeholders.

Table 5 Importance degrees of weighted factors

		GV	CO	OP	OG	CU	IO
Crt	Sub-Criteria	Alternative priority weight (*W*)					
Economical scale	Socio-economic development C_{11}	**0,32**	**0,31**	0,21	0,30	0,23	0,21
	Spatial development C_{12}	0,31	0,28	0,20	**0,33**	0,16	0,18
	Transhipment volume C_{13}	0,21	0,19	**0,27**	0,22	**0,30**	0,20
	Import/Export volume C_{14}	0,11	0,15	0,23	0,15	0,22	**0,26**
	Mobility C_{15}	0,05	0,08	0,09	0,00	0,10	0,15
Nat. Stabil.	Political stability C_{21}	**0,41**	0,30	**0,38**	0,30	0,29	**0,37**
	Economic stability C_{22}	0,32	**0,38**	0,30	0,33	**0,38**	0,30
	Social stability C_{23}	0,27	0,32	0,32	**0,37**	0,33	0,33
Intermodal operation and management	Information technology infrastructure C_{31}	0,12	0,13	0,17	0,14	0,16	**0,18**
	Transport cost C_{32}	**0,18**	0,15	0,16	**0,16**	**0,19**	0,16
	Transport time C_{33}	0,16	0,13	**0,20**	0,13	0,14	0,06
	Service availability C_{34}	0,06	0,09	0,07	0,13	0,09	0,12
	Coordination C_{35}	0,09	0,11	0,05	0,15	0,00	0,06
	Quality C_{36}	0,12	**0,16**	0,11	0,13	0,15	0,14
	Connectivity C_{37}	0,13	0,10	0,10	0,09	0,14	0,16
	Interoperability C_{38}	0,14	0,13	0,14	0,07	0,14	**0,18**
International market location	Accessibility C_{41}	0,25	0,20	**0,39**	0,31	0,33	**0,44**
	International consumption market C_{42}	0,30	0,33	0,30	0,27	**0,40**	0,24
	International manufacturing market C_{43}	**0,45**	**0,47**	0,31	**0,42**	0,27	0,32
	Border crossing C_{44}	0,19	0,15	0,24	0,17	0,11	0,31
	Customs C_{45}	0,26	0,25	0,24	0,20	0,34	0,19
	European corridors C_{46}	0,21	0,15	0,29	0,37	0,26	0,24
Environmental effect	Congestion C_{51}	**0,34**	**0,44**	0,22	0,27	**0,29**	0,26
	Energy use C_{52}	0,19	0,22	0,19	**0,28**	0,26	0,27
	Emissions C_{53}	0,26	0,24	0,22	0,23	0,22	0,23
	Land use C_{54}	0,23	0,14	0,08	0,21	0,27	0,17
	Accident C_{55}	0,15	0,21	**0,29**	0,18	0,18	**0,32**
	Hazardous Materials C_{56}	0,16	0,19	0,22	0,10	0,07	0,00

After determination of all weighted factors, we can eliminate unimportant sub-criteria from our framework. Here for the economical scale, mobility is not important factor, likewise for intermodal operation and management, connectivity, service availability and coordination can be eliminated to alleviate the complexity of the model. Afterwards we can go to *second phase* of the proposed model. In this phase the most appropriate location for intermodal freight logistic was determined with using an ANN structure.

The design flow of the ANN in the proposed model is divided into three categories (Figure 1), namely, (1) the design stage aims at selecting input and output variables, training method selection and hidden layer design, (2) the training stage is used to select a training method, adjust and verify the training parameters, (3) the generalization stage, is the stage in which the neural network classifies any unseen data pattern countered during the training stage to an acceptable pattern. (Choy et al., 2003). For the design stage, while remaining criteria from fuzzy AHP model were used as input node of ANN model, output node was represented by the selection weight of the most appropriate location. In our case *three places* were selected as a potential logistics centre. These centres have different kind of physical characteristics which weren't indicated in this study. For the training stage, we used multi-layer perceptron network model. For the evaluation of *three potential locations,* we used a standard ranges from 0 (bad) to 4 (excellent) according the perspective of decision-makers. Here, we had to define a new equation (17) to execute the performance criteria of each logistics centre location; M represents data matrix with decision-makers perspective and fuzzy weights; dm_{ij}, decision makers perspective for each logistics centre location places; W_j, non fuzzy weights.

$$M = dm_{ij} \otimes W_j \tag{17}$$

Computation was executed in three potential locations where location 1 had mean values for C_{11}, C_{22}, C_{32}, C_{43}, C_{51} and C_{55} whereas location 2; C_{13}, C_{33}, $C_{41}$and C_{52} and location 3; C_{38} and C_{42} respectively.

There are a number of optimization methods available: back-propagation, conjugate gradient, Newton and quasi-Newton methods, Levenberg-Marquardt algorithm (Chaudhuri and Bhattacharya, 2000; Haykin, 2008). In our case, Levenberg-Marquardt algorithm was selected.

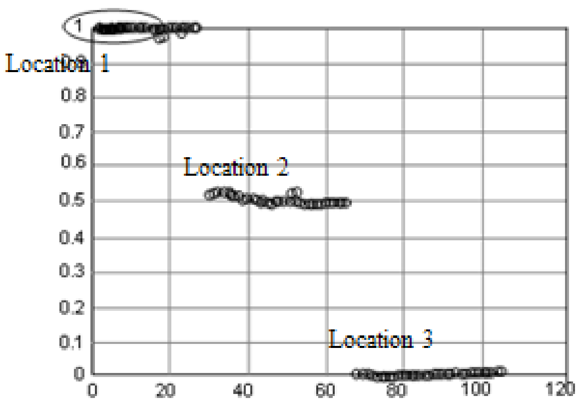

Figure 9 Result of the fuzzy AHP-ANN model as to Levenberg-Marquardt algorithm

The Neural network model was trained using the *Levenberg-Marquardt algorithm* using MATLAB v. 6.5. The *Levenberg-Marquardt algorithm* is a method of non-linear optimization and it obtained best results for the given test-sets and provided the lowest mean square error (MSE) value. The network was trained with 158 samples corresponding to 60% of the data set and tested with 30 samples which were selected in random form from the data set. The average error is found as MSE=3.44870e-005/0.0001 which shows that the result of the test is explicitly successful with 97% validation. Figure 9 shows the result of the fuzzy AHP-ANN model for the most appropriate location for intermodal freight logistics centre where location 1 serves as the best place.

4. Conclusion

The European common transport policy has a one of its main objectives the development of intermodal freight transportation, where there is an optimal integration of different transport modes enabling an efficient and cost-effective use of the transport system. Intermodal freight logistics centres can enable these aims to be sufficiently fulfilled. One of the most important strategic decisions in such logistics centres, concerns the location of facilities. This study attempted to present a scientific method with multi-criteria and multi-level decision making aspects to solve a location selection problem for intermodal freight logistics centres. A combination of fuzzy-AHP and ANN techniques was used to find a solution of these location decision problem within given alternatives of selection. This hybrid model can give better results for decision making problems while the fuzzy AHP was used to determine most important weight factors and ANN, to select the best location for an intermodal freight logistics centre.

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