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VEHICLE ROUTE SELECTION WITH AN ADAPTIVE NEURO FUZZY INFERENCE SYSTEM IN UNCERTAINTY CONDITIONS

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Abstract: *A useful routing system should have the capability of supporting the driver effectively in deciding on an optimum route to his preference. This paper describes the problem of choice of road route under conditions of uncertainty which drivers are faced with as they carry out their task of transportation. The choice of road route depends on the needs stated in the transport requirements, the location of the users and the conditions under which the transport task is performed. The route guidance system developed in this paper is an Adaptive Neuro Fuzzy Inference Guidance System (ANFIGS) that provides instructions to drivers based upon "optimum" route solutions. A dynamic route guidance (DRG) system routes drivers using the current traffic conditions. ANFIGS can provide actual routing advice to the driver in light of the real-time traffic conditions. In the DRG system for the choice of road route, the experiential knowledge of drivers and dispatchers is accumulated in a neuro-fuzzy network which has the capability of generalizing a solution. The adaptive neuro-fuzzy network is trained to select an optimal road route on the basis of standard and additional criteria. As a result of the research, it is shown that the suggested adaptable fuzzy system, which has the ability to learn, has the capability of imitating the decision making process of the drivers and dispatchers and of showing a level of competence which is comparable with the level of their competence.*

Key words: *Neuro-Fuzzy Model, Vehicle Assignment Problem, Route Selection.*

1. Introduction

The vehicle routing problem (VRP) has played a very important role in the distribution and supply chain management, in addition to many other areas. During

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the past five decades, many have engaged in research on various types of vehicle routing problems and have had a lot of success. Most of them have aimed at static VRPs, and all their information is assumed to be known and not to be changed during the whole process. However, most vehicle routing problems are dynamic in the real world. Dispatchers often need to readjust the vehicles routes to improve vehicle efficiency and enhance service quality when accidents or unexpected incidents occur. With advances in modern communication technology to enable people to quickly access and process real-time data, the dynamic vehicle routing problem (DVRP) is being given more and more attention. In dynamic vehicle routing problems, the situation is essentially different. Transport requests arrive in time according to a stochastic pattern, and the task is to route the vehicles in an orderly fashion to satisfy the demand.

Relative to the static problem, the dynamic problem has many notable features (Bertsimas & Simchi-Levi, 1996). They include that the time dimension is essential, future information is imprecise or unknown, rerouting and reassignment decisions may be warranted, faster solution speed is necessary and so on. In particular, it must be dynamic, given that the decision-making is based on incomplete, uncertain and changing information. Thus, it is not possible for the decision maker to solve the entire problem at once (Gendreau et al., 2006). Reviews on the problem can be found in Bertsimas and Simchi-Levi (1996) and Ghiani et al. (2003).

In the last decades, there have been many attempts to solve the problem of assigning vehicles to transportation routes. In its simplest form, the vehicle assignment problem (VAP) can be formulated as a linear programming problem (Yongheng & Grossmann, 2015) and solved with an application of the simplex method (Pilla et al., 2012), the assignment algorithm often called the Hungarian method (Rais et al., 2014), network algorithms (Salari & Naji-Azimi, 2012) or the transportation method (Veluscek et al., 2015), as well as its extensions (Masson et al., 2015). In real life situations, however, VAP is more complicated and requires more advanced methods to be solved. Some authors (Pilla et al., 2012; Lobel, 1997; Rouillon et al., 2006), formulate VAP in terms of the linear, integer or mixed integer programming problem. Some others (Milenković et al., 2015) transform the linear, discrete model into a non-linear, continuous form. In both cases, the problems are formulated either in a deterministic or non-deterministic form. Many models are based on the queuing theory, too (Werth et al., 2014) and they consider either a homogeneous (Masson et al., 2015) or a non-homogeneous fleet (Milenković et al., 2015). Some of the models combine VAP with other fleet management problems, such as fleet sizing and vehicle routing (Maalouf et al., 2014) or vehicle scheduling (Lobel, 1997; Pillac et al., 2011) within time and capacity constraints. The models usually refer to specific transportation environments, such as urban transportation (Pamučar & Ćirović, 2015; Pamučar et al., 2016) rail transportation (Shi et al., 2015) or air transportation (Teodorović & Pavković, 1996; Yuzhen et al., 2015). In the majority of cases, the proposed vehicle assignment models have a single objective character, however, different objective functions are considered. The most popular are: total transportation costs (Rouillon et al., 2006), profit (Rouillon et al., 2006; Maalouf et al., 2014) or empty rides (flows) (Lobel, 1997). Depending on the specific characteristics of VAP and the complexity of the decision models, various solution procedures and algorithms are applied to solve specific instances of VAP.

Yuzhen et al. (2015) present interesting considerations on the assignment of airplanes to particular transportation routes. They formulated VAP in terms of mixed integer mathematical programming with price-wise linear constraints. The decision problem is solved by a Cplex solver for the GAMS system and a heuristic procedure for the rounding of non integer solutions.

The most up to date approaches to modeling and solving VAP involve: stakeholders' analysis leading to multiple objective formulations of the problem (Ćirović et al., 2014), analysis of uncertainty and imprecision of data (Pamučar et al., 2016a; Shi et al., 2015) and the application of artificial intelligence methods in the problem solving procedures (Maalouf et al., 2014; Pamučar & Ćirović, 2015; Ćirović et al., 2014).

Ćirović and Pamučar (2013) claim that multiple criteria formulations of different categories of transportation decision problems are more realistic than their single criterion equivalents. Preetvanti & Saxena (2003) investigate another variant of a transportation problem focused on optimization of the total transportation time between certain origins and destinations. The authors consider three non-linear, time oriented criteria, such as: riding time, loading time and unloading time, and a set of numerous constraints. The problem is solved by a heuristic procedure that utilizes a specific and original structure of the problem. The optimal solution defines the minimum flow of materials in the transportation network and the minimum time required to distribute this flow in a network. The computational efficiency of the proposed algorithm is analyzed on a real life case study focused on the transportation of iron ore in the steel industry.

Teodorović and Pavković (1996) formulate a VAP for a road transportation company. The authors consider a heterogeneous fleet operating from a central depot and define types of vehicles allocated to specific transportation jobs. The decision problem is formulated in terms of fuzzy mathematical programming and solved by an original heuristic procedure. Fuzzy numbers are applied to model the dispatcher's preferences and different categories of constraints associated with fleet assignment. Further extension of this research is presented in the articles of Vukadinovic et al. (1999) in which neural networks are applied to generate a set of fuzzy decision rules allocating vehicles to transportation routes. Due to the fact that in many real life situations VAP is characterized by high computational complexity, especially when it is combined with other fleet management problems, several authors apply heuristic procedures to solve the analyzed problems. In some cases heuristics are combined with other well-known techniques, such as branch-and-bound algorithms (Piu et al., 2015). In the last several years metaheuristic algorithms have earned great popularity as solution procedures for an assignment problem (Sicilia et al., 2015; Ying et al., 2015).

However, as can be seen from the presented literature, there is no available literature dealing with the selection of a road route under the conditions of uncertainty. This paper describes the problems of choice of road route under the conditions of uncertainty which are faced by transport units as they carry out their transportation task. The choice of road route depends on the needs expressed in the transport requirements of transport units in the Petroleum Industry of Serbia (PIS) and the location the users themselves. Transport units receive a high number of transport requests from other users. One of the characteristics of a transport request is the choice of route by which the vehicle is required to carry out the request which is given to the transport unit.

The route guidance system developed in this paper is an Adaptive Neuro Fuzzy Inference Guidance System (ANFIGS) that provides instructions to drivers based upon "optimum" route solutions. A driver can make the destination known to the system. A dynamic route guidance (DRG) system can route drivers using the current traffic conditions. The system can provide actual routing advice to the driver in light of the real-time traffic conditions. It is based on real-time information regarding conditions and incidents in the traffic network, and it is conceived so as to integrate the routing and the traffic control functions.

One objective of such a dynamic route guidance system is to balance the level of service on all major network links so as to increase the efficiency, speed, safety and quality of travel (e.g. to minimize travel time). This system could prove to be extremely useful when transportation needs to be carried out under conditions, when a traffic accident has taken place or when work is being carried out on damaged roads.

In the DRG system for selecting a road route, which is presented in this paper, the experiential knowledge of drivers who run transport vehicles in transport units is accumulated in a neuro-fuzzy network which has the capacity to generalize solutions. The driver's preference is modeled as a fuzzy expert system, and his reaction to the advice and information provided by the DRG system is stored. The previous choices of the driver, in particular deviations from the recommendation, are then used for training the system so that it is made adaptive to the driver. The adaptive neuro-fuzzy network is trained to select the optimal travel route on the basis of criteria (type of road surface, travel distance, travel time, route capacity, traffic capacity, road capacity, the existence of alternative roads along the length of the route).

The paper is organized as follows. At the end of Introduction, the problem of selecting a road route under conditions of uncertainty is described, and the available literature which considers the issues described above is presented. The second section shows the modeling of the ANFIS model, the training algorithm and the data set which is used for training the model. In the third section of the paper, the developed model is tested on the example of choice of transport route based on the stated transport requirements of a users.

2. Development of an ANFIS model for selecting a transport route under conditions of uncertainty

One of the most important functions of transport management in the PIS is transport and supply. Supply means the procurement, deployment, storage and care of material reserves, including determining the type and amount of reserves at each level. Each day, transport units receive a large number of transport requests from other users who want to carry different types of load (liquefied petroleum gas, oil, gasoline etc.) to various destinations. Each transportation request is characterized by a large number of attributes, among which the most significant are type of goods, quantity of goods (weight and volume), place of loading and unloading, the preferred time of loading and/or unloading, and the distance to which the goods are shipped.

Since the transport fleet has many different types of vehicles, dispatchers have to make decisions every day about which type of vehicle is most suitable to perform the task. One of the essential prerequisites for the choice of vehicle is the choice of route for carrying out the transport request. The criteria by which the transport manager selects and makes a decision regarding which route the vehicle should use for the task are: Type of road surface, Travel distance, Travel time, Route capacity, Traffic capacity, Road capacity and The existence of alternative roads along the length of the route.

Experienced dispatchers have constructed criteria which they use for selecting a route for carrying out a transport assignment. When selecting routes, vehicles are chosen with the structural and technical characteristics which satisfy the conditions for transporting particular types of load. Fuzzy sets can quantify linguistic i.e. qualitative and imprecise information that occurs when making decisions. Thus, fuzzy reasoning can be used as a technique by which descriptive heuristic rules are translated into automatic management strategy i.e. decision-making. By developing a fuzzy system it is possible to transform the deployment strategy for vehicles on specific routes into an automatic control strategy.

2.1. Description of the problem

The problem being considered is the daily assignment of available vehicles for a specified number of transportation requests and transport routes. The vehicle for carrying out a transportation task comes from a base to which it is returned when the task is completed. The reasons for this tactical method are that transporting different types of load in the same vehicle is not allowed and the fact that different types of loads belong to different users.

The problem under consideration belongs to the task of scheduling (assignment). The problem of scheduling belongs to the problem of linear programming, that is, the problem of transport. It consists of allocating *n* activities or resources to *m* the individual carrying out the action or the place, with the purpose of achieving maximum efficiency. In our case it means that it is necessary to define the goal function i.e. to allocate vehicles to transport routes with minimum transport costs within the limitations, and treating the problem as a mathematical programming problem. The main deficiency of an approach based on mathematical programming is that it is not easy to formulate the goal function and to determine the "hard" constraints. Besides this, the information available to the dispatcher and drivers is often imprecise and given in descriptive form.

As a result of the above, a conventional approach cannot take into account all of the relevant imprecise parameters. In the majority of cases, this phase in the decision-making process of traffic support organs is reduced to the experiential knowledge of the decision-maker. However, a problem arises when a decision regarding the selection of routes needs to be made by an individual without sufficient experiential knowledge. A solution to the given problem is presented in this paper using an ANFIS model.

2.2. Designing the ANFIS model

An integral part of an ANFIS model is a fuzzy reasoning system. The problems which an analyst encounters when developing a fuzzy system are determining the set of linguistic rules used by the dispatcher and the parameters of the membership functions of the input/output pairs. Generating the membership functions of fuzzy sets and the rules according to which dispatchers act involves much communication with a large number of experienced dispatchers. Membership functions of fuzzy sets, which describe the same concept, and which are proposed by different dispatchers can be very different. For this reason the characteristics of the developed fuzzy system depend on the number of available dispatchers and the ability to formulate their deployment strategy. It is intended for the fuzzy system to comprise of seven input variables, which are Type of road surface, Travel distance, Travel time, Route Capacity, Traffic capacity, Road capacity and The existence of alternative roads along the length of the route. In addition to the eight input variables, the fuzzy system has a single output variable, Preference of the dispatcher to select a particular route for carrying out a particular transport assignment.

ANFIS implements a Takagi Sugeno Kang (Pap et al., 2000; Pamučar et al, 2016b) fuzzy inference system in which the conclusion of a fuzzy rule is constituted by a weighted linear combination of the crisp inputs rather than by a fuzzy set. The relative importance of criteria and the degree of their influence on the dispatchers' preference of choice are gained by normalization of weights (w_{ki}) in the following way (Jovanović et al., 2014):

$$w_{ki} = \frac{\lambda_j w'_{ki}}{\sum_{j=1}^{K} \lambda_j w'_{ki}} = \frac{\sqrt[n]{\prod_{j=1}^{n} \lambda_j w_{ki}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} \lambda_j w_{ki}}} \tag{1}$$

where λ_j, $\lambda_j \in [0,1]$ is the preference of the j-th decision maker, i.e., the degree of confidence, w'_{ki} is the weight ratio of the i criteria to the k decision maker; w_{ki} normalization of weights; n is the total number of decision makers participating in the research. The degree of confidence is specified for each decision maker individually, based on their degree of confidence. In order to define the weight ratios, ten ($n=10$) decision makers were interviewed. The described criteria are listed in Table 1.

Table 1. Criteria for evaluating transport vehicle routes

Criterion		Num.	Ling.	K^-	K^+	Weights
K_1	Type of road surface (TRS)		•		•	0.18
K_2	Travel distance (TD)	•		•		0.15
K_3	Travel time (TT)	•		•		0.12
K_4	Route capacity (RCC)		•		•	0.10
K_5	Road capacity (RC)		•		•	0.14
K_6	Traffic capacity (TC)		•		•	0.15
K_7	The existence of alternative roads along the length of the route (EAR)		•		•	0.16

The composite of C_i $(i=1,2,...,7)$ is made of two subsets: C^+, subset of the criteria of beneficial type, higher values desirable and C^-, subset of the criteria of cost type, lower values desirable. The values of some input variables are described by means of linguistic descriptors.

Defuzzification of the linguistic variables (criteria) K_4, K_5, K_6 and K_7 is carried out using the scale shown in Table 2a, while defuzzification of the linguistic variable K_1 is carried out using the scale shown in Table 2b.

The main problem faced by the analyst when developing a fuzzy system is determining the base of fuzzy rules and the membership function parameters of the fuzzy sets which describe the input and output variables. For all the input variables of the fuzzy model, as well as the type of membership function, it is also necessary to determine the number of membership functions for each input. A larger number of membership functions requires an increase in the number of rules, which can make setting up the system more difficult. It is therefore recommended, in accordance with the nature of the variables, to begin with the lowest number of membership functions. However, reducing the number of membership functions must not result in an incomplete description of the input variables. Starting from the given postulates it is defined that input variables in the fuzzy model have at least three linguistic values. The membership function parameters and their nature are shown in Table 3. Gaussian curves are used in the fuzzy system since they describe the entry variables well and ensure that the sensitivity of the system is satisfactory. Adjusting the membership function to the form of a Gaussian curve ensures the smallest error at the output of the ANFIS model.

Table 2. Linguistic variables (criteria) K_1, K_4, K_5, K_6 and K_7

a) Linguistic variables (criteria) K_4, K_5, K_6 and K_7

Linguistic variables	Triangular fuzzy number
Very Low	(0;0;0,1)
Low	(0;0,1;0,3)
Medium Low	(0,1;0,3;0,5)
Medium	(0,3;0,5;0,7)
Medium High	(0,5;0,7;0,9)
High	(0,7;0,9;1)
Very High	(0,9;1;1)

b) Linguistic variables (criteria) K_1

Road surface	Triangular fuzzy number
Dirt	(0;0;0,25)
Natural	(0;0,25;0,55)
Gravel	(0,25;0,55;0,75)
Metalled	(0,55;0,75;0,1)
Contemporary	(0,75;1;1)

When a comparison between the output of the fuzzy system and the desired set of solutions was made, the designed fuzzy system did not give satisfactory results. The difference between the expected results and the value of the criteria functions obtained at the output of the system was not satisfactory i.e. it was not within the limits of tolerance. An attempt to gain satisfactory values by changing the type and parameters of the membership functions at the output did not give the expected results.

Table 3. Parameters of the membership functions before training the ANFIS model

MF/ Input	MF 1	MF 2	MF 3
K_1	gmf (0,10;-0,04;0,12;0,09)	gmf (0,1404;0,478)	gmf (0,16;0,88;0,10;1,08)
K_2	gmf (0,169;0,09178)	gmf (0,1924;0,492)	smf (0,3608;0,9748)
K_3	zmf (0,072;0,6053)	gmf (0,139;0,5092)	smf (0,3659;0,8917)
K_4	zmf (0,4249;2,34;-0,0821)	gmf (0,16;0,46;0,15;0,53)	smf (0,147;0,856)
K_5	gmf (0,17;0,1618)	gmf (0,21;1,462;0,534)	gmf (0,201;0,8424)
K_6	gmf (0,246;2,247;6,94)	gmf (0,214;0,50)	gmf (0,18;0,89;0,14;1,04)
K_7	zmf (0,518;3,825;-0,18)	gmf (0,21;1,402;0,50)	smf (0,5439;0,914)

*zmf (Z-shaped membership function), smf (S-shaped membership function), gmf (Gaussian membership function).

Table 4, shows the comparative values of the criteria functions at the output of the fuzzy system (f_{FIS}) and the required criteria functions ($f_{dispatcher}$). In addition to the criteria functions in Table 4, it also shows the values of the criteria on the basis of which the transport route is chosen, which are at the same time the input variables of the fuzzy system.

In the example given in Table 4 a total of 25 transport requests were processed, and a schedule was completed for 25 transportation routes.

Table 4. Characteristics of twenty five transportation routes

Route no.	K_1	K_2	K_3	K_4	K_5	K_6	K_7	*$f_{dispatcher}$	*f_{FIS}
1.	0.992	134.75	0.281	5	0.204	0.044	0.237	0.51	0.339
2.	0.795	119.07	0.147	8	0.787	0.437	0.329	0.56	0.487
3.	0.913	121.19	0.426	12	0.482	0.625	0.410	0.64	0.799
4.	0.071	91.66	0.076	12	0.058	0.583	0.283	0.22	0.197
5.	0.509	26.35	0.902	11	0.041	0.352	0.219	0.48	0.290
6.	0.638	114.95	0.374	9	0.844	0.568	0.119	0.60	0.418
7.	0.924	85.72	0.726	12	0.929	0.811	0.748	0.97	0.508
8.	0.087	119.79	0.308	7	0.954	0.761	0.817	0.94	0.758
9.	0.915	148.74	0.917	10	0.200	0.004	0.215	0.71	0.588
10.	0.270	139.12	0.44	5	0.133	0.999	0.788	0.72	0.658
11.	0.231	57.15	0.497	13	0.883	0.884	0.613	0.91	0.671
12.	0.066	147.34	0.888	10	0.537	0.529	0.712	0.96	0.462
13.	0.037	116.3	0.510	14	0.425	0.762	0.496	0.69	0.691
14.	0.905	134.38	0.128	7	0.471	0.678	0.712	0.67	0.731
15.	0.599	72.20	0.807	6	0.286	0.210	0.035	0.56	0.520
16.	0.567	126.18	0.576	11	0.285	0.757	0.588	0.76	0.812
17.	0.551	121.09	0.152	9	0.837	0.405	0.324	0.69	0.566
18.	0.954	28.01	0.143	14	0.555	0.446	0.947	0.82	0.631
19.	0.488	75.93	0.891	6	0.330	0.954	0.293	0.78	0.911
20.	0.636	113.79	0.587	12	0.464	0.250	0.116	0.61	0.496
21.	0.735	42.83	0.817	9	0.731	0.516	0.529	0.97	0.768
22.	0.666	96.42	0.971	8	0.223	0.052	0.800	0.95	0.650
23.	0.017	48.14	0.499	11	0.349	0.138	0.695	0.71	0.954
24.	0.950	62.12	0.666	11	0.929	0.029	0.367	0.98	0.611
25.	0.467	97.30	0.147	12	0.238	0.326	0.886	0.91	0.512

* f_{FIS} output of the fuzzy system and $f_{dispatcher}$ the required criteria functions

By analysing the data given, an average error of 0.481 was obtained. Since the desired values were not obtained by the fuzzy system, it was mapped into a five-layered adaptive neural network (ANFIS), Figure 1.

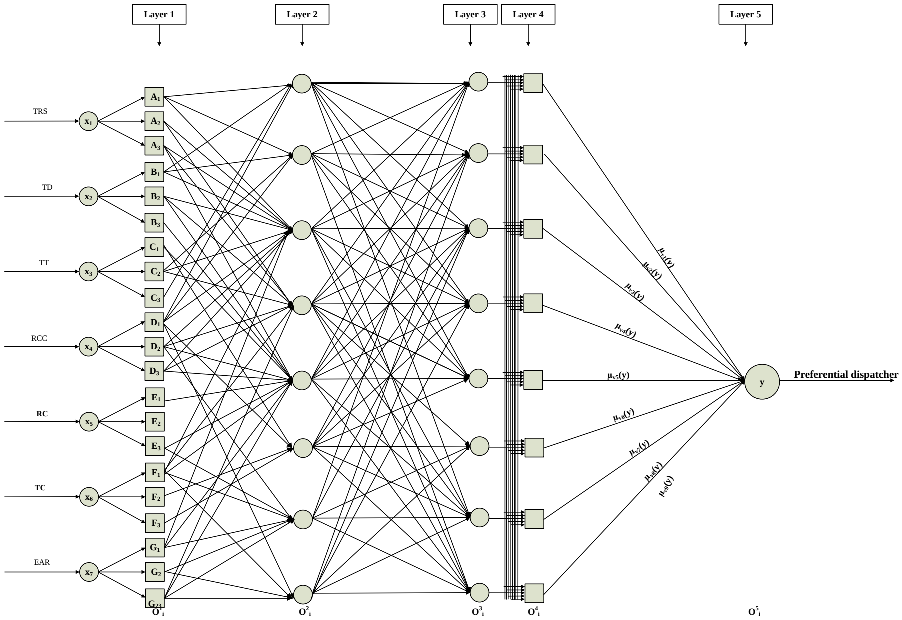

Figure 1. Structure of the ANFIS system

The fuzzy logic system was mapped into an adaptive neural network as the error which occurred at the output of the fuzzy system was unacceptable. In other words, the difference between the desired set of solutions and the set of solutions obtained by the fuzzy system was unacceptable. According to experts, acceptable error is less then or equal to 0.08.

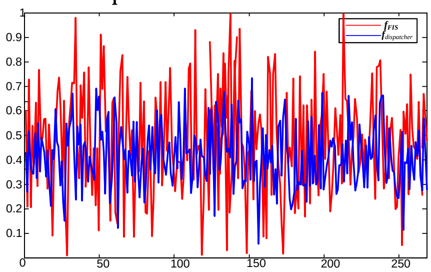

Figure 2. Comparison between the fuzzy system output and the desired data set

Figure 2 shows a graph of the values of the criteria functions at the output of the fuzzy system and the required values of the criteria functions.

As already mentioned, a neuro-fuzzy network consists of five layers.

Layer 1. The nodes of the first layer are verbal categories of the input variables quantified by fuzzy sets. Each node of the first layer is an adaptive node, described by a membership function, $\mu_{x_i}(x)$, $i=1,2,...,5$. The membership functions are described by the Gaussian distribution characterised by two parameters c (the centre of the function) and σ (the width of the function) (Pamučar et al, 2016c):

$$Gaussian(x,c,\sigma)=e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{2}$$

As the fuzzy rules are the if-then rules, „If - premise, Then - consequence“, the categories of input variables quantified by fuzzy sets are shown as adaptive nodes of the first layer.

Layer 2. Each node of this layer calculates the minimum value (ω_i) of three input values of the adaptive neural network. The output values of the Layer 2 nodes are the rule signification:

$$O_i^2 = \omega_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2) \times \ldots \times \mu_{C_i}(x_7) \tag{3}$$

Layer 3. Each *i*-node in this layer calculates the total weight ($\overline{\omega_i}$) of the *i*-rule from the rule base by the following equation

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i}, i = 1, 2, \ldots, n \tag{4}$$

Layer 4. This layer has 8 adaptive nodes representing the preference that a certain link (node) of the network is allocated the highest "Preferential dispatcher" value. Each neuron in this layer is connected to the respective normalization neuron in the third layer, and also receives initial input signals $x_1, x_2, \ldots, x_7$. A defuzzification neuron computed the "weighted consequent value" of a given rule as:

$$O_i^4 = \overline{\omega_i} f_i = \overline{\omega_i}(p_1 x_1 + q_1 x_2 + r_1 x_3 + s_1), \; i = 1, 2, \ldots, n \tag{5}$$

Where *n* is the total number of rules in the rule base, and p_i, q_i, r_i and s_i are consequent parameters of the rule *i*.

Layer 5. The only node of Layer 5 is the fixed node where the ANFIS output result is calculated. This is a fuzzy set with defined degrees of membership of possible "Preferential dispatcher" values of the given link (node) of the network. Defuzzification is carried out in the fifth-layer node. The output result is a real number in the interval [0,1]:

$$O_1^5 = Overalloutput = \sum_{i=1}^{8} \overline{\omega_i} f_i = \frac{\sum_{i=1}^{8} \overline{\omega_i}(p_1 x_1 + q_1 x_2 + r_1 x_3 + s_1)}{\sum_{i=1}^{8} \overline{\omega_i}} \tag{6}$$

Where:

$$\omega_1 = \mu_{A_1}(x_1) \times \mu_{B_2}(x_2) \times \ldots \times \mu_{G_3}(x_7) \tag{7}$$

$$\omega_2 = \mu_{A_1}(x_1) \times \mu_{B_1}(x_2) \times \ldots \times \mu_{G_2}(x_7) \tag{8}$$

...

$$\omega_8 = \mu_{A_3}(x_1) \times \mu_{A_2}(x_2) \times \ldots \times \mu_{A_1}(x_7) \tag{9}$$

($\times$ is the T-norm).

2.3. Forming a data set for training the ANFIS model

If with $x = \left(x^l(r), x^u(r)\right)$ and $y = \left(y^l(r), y^u(r)\right)$, $0 \le r \le 1$, $x, y \in X$, we define the fuzzy numbers which are used to evaluate the observed alternatives in relation to the defined optimization criteria, then for the fuzzy numbers *x* and *y* the following relationships are valid (Pamučar et al, 2013):

$$x = y \to x^l(r) = y^l(r) \wedge x^u(r) = y^u(r), \; (0 \le r \le 1) \tag{10}$$

$$x + y = \left(x^l(r) + y^l(r), x^u(r) + y^u(r)\right) \tag{11}$$

$$Kx = \begin{cases} \left(kx^{l}(r), x^{u}(r)\right), k \geq 0 \\ \left(kx^{u}(r), x^{l}(r)\right), k \leq 0 \end{cases} \tag{12}$$

Let $\{A_1, A_2, ..., A_n\}$ denote the set of routes evaluated by experts $E_g\ (g = 1, 2, ..., k)$ in relation to the observed set of criteria $C_j\ (j = 1, 2, ..., n)$. Then the problem of fuzzy multi-criteria decision making can be represented in the matrix form as:

$$D = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & x_{m3} & \dots & x_{mn} \end{bmatrix} \tag{13}$$

Where x_{ij} is the value of the criteria function of the given route A_i in relation to a criterion C_j. Summarizing the values in the rows of the matrix *D* is carried out using the following transformation:

$$RS_k = \sum_{k=1}^{m} x_{kj} = \left(\sum_{k=1}^{m} x^{l}{}_{kj}(r), \sum_{k=1}^{m} x^{u}{}_{kj}(r) \right) \tag{14}$$

Normalization of the summarized values in rows is carried out using the following transformation

$$S_k = \frac{RS_i}{\sum_{k=1}^{m} RS_k} = \left(\frac{\sum_{j=1}^{n} x^{l}{}_{kj}(r)}{\sum_{k=1}^{m}\sum_{j=1}^{n} x^{l}{}_{kj}(r)}, \frac{\sum_{j=1}^{n} x^{u}{}_{kj}(r)}{\sum_{k=1}^{m}\sum_{j=1}^{n} x^{u}{}_{kj}(r)} \right) \tag{15}$$

The weight coefficient of each criteria is obtained by forming a matrix *W* in which comparison is made in pairs of criteria based on of decisions made by experts who participated in the study.

$$W = \begin{array}{c} \\ E_1 \\ E_2 \\ \vdots \\ E_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \dots & \vdots \\ w_{k1} & w_{k2} & \dots & w_{kn} \end{pmatrix} \end{array} = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_k \end{bmatrix} \tag{16}$$

By multiplying the entries of matrices *D* and *W* and by using the previously mentioned arithmetical operations, we obtain the final values of the criteria functions which describe the significance of each of the observed routes

$$F = D\times W = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & x_{m3} & \dots & x_{mn} \end{bmatrix} \times \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ \vdots \\ W_n \end{bmatrix}$$
$$= \begin{bmatrix} x_{11}\times W_1 & x_{12}\times W_2 & x_{13}\times W_3 & \dots & x_{1n}\times W_n \\ x_{21}\times W_1 & x_{22}\times W_2 & x_{23}\times W_3 & \dots & x_{2n}\times W_n \\ x_{31}\times W_1 & x_{32}\times W_2 & x_{33}\times W_3 & \dots & x_{3n}\times W_n \\ \dots & \dots & \dots & \dots & \dots \\ x_{m1}\times W_1 & x_{m2}\times W_2 & x_{m3}\times W_3 & \dots & x_{mn}\times W_n \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \vdots \\ f_n \end{bmatrix} \tag{17}$$

The next step is to determine the ideal solution from the given set of values of criteria functions. The ideal solution A^{+} and the negative ideal solution A^{-} are obtained using the relation (Pamučar et al, 2017)

$$A^{+} = \left\{ f_1^{+}, f_2^{+}, \dots, f_n^{+} \right\} \tag{18}$$

$$A^{-} = \left\{ f_1^{-}, f_2^{-}, \dots, f_n^{-} \right\} \tag{19}$$

where

$J = \left\{ j = 1, 2, \dots, m \middle| j \text{ belongs to criteria which are maximized} \right\}$,

$J' = \left\{ j = 1, 2, \dots, m \middle| j \text{ belongs to criteria which are minimized} \right\}$

As the best alternatives, those which have the highest value f_{ij} in relation to the criteria which are maximized and the lowest f_{ij} in relation to the criteria which are minimized are chosen.

The positive ideal and negative ideal solutions are represented by fuzzy numbers. The following relations describe the ideal positive solution (A^{+})

$$A^{+} = \left(A^{+^{l}}(r), A^{+^{u}}(r) \right),\ \ 0 \le r \le 1 \tag{20}$$

where

$$\begin{aligned} A^{+^{l}}(r) &= \left(f_1^{+^{l}}(r), f^{+^{l}}(r), \dots, f^{+^{l}}(r) \right), \\ A^{+^{u}}(r) &= \left(f_1^{+^{u}}(r), f_1^{+^{u}}(r), \dots, f_1^{+^{u}}(r) \right),\ \ 0 \le r \le 1 \end{aligned} \tag{21}$$

The ideal negative solution A^{-} is calculated in exactly the same way. The distance between the fuzzy numbers *x* and *y* is calculated as

$$D(x,y) = \left(\int_0^1 \left(\left| x^{l}(r) - y^{l}(r) \right|^2 + \left| x^{u}(r) - y^{u}(r) \right|^2 \right) dr \right)^{1/2} \tag{22}$$

The next step is to calculate *n* dimensional Euclidean distances of all observed alternatives for the ideal and the negative ideal solution

$$d_i^{+} = \left(\int_0^1 \left(\sum\nolimits_{j\in J'} \left[f_{ij}^{l}(r) - f_j^{+^{l}}(r) \right]^2 + \sum\nolimits_{j\in J} \left[f_{ij}^{u}(r) - f_j^{+^{u}}(r) \right]^2 \right) + dr \right)^{1/2} \tag{23}$$

$$d_i^- = \left(\int_0^1 \left(\sum_{j\in J'} \left[f_{ij}^u(r) - f_j^{-u}(r) \right]^2 + \sum_{j\in J} \left[f_{ij}^l(r) - f_j^{-l}(r) \right]^2 \right) + dr \right)^{1/2} \tag{24}$$

where $i = 1, 2, \ldots, m$.

For each alternative the relative distance of the coefficients d_i^+ and d_i^- is calculated according to the relation

$$Q_i^+ = \frac{d_i^-}{d_i^+ + d_i^-},\ i = 1, 2, \ldots, m \tag{25}$$

where is the alternative A_i closer to an ideal solution if Q_i^+ ($0 \le Q_i^+ \le 1$) is closer to a value of 1.

3. Training the ANFIS model: Supervised Learning Problem

Parameter learning for many control problems, system identification, adaptive control and classification problems can be reduced to a function approximation problem where, given a function, we want to adjust the FLS parameters as to best approximate it. FLS could be regarded as a nonlinear parametric mapping between the input and output. We can express it as $y = f(x, w)$ where y is the scalar FLS output, x is the *n*-dimensional input vector and w is the p-dimensional vector containing all the FLS's adjustable parameters.

If there is a difference between the obtained and expected data, modifications are made to the connections between the neurons in order to reduce error i.e., membership functions are tuned into adaptive nodes.

By training the neural net with numerical examples of made decisions, the initial forms of input/output functions of adherence to the phase of composites are readjusted. The values of the membership functions after training the ANFIS system are shown in Table 5.

After obtaining the values of the criteria functions, the processed experimental data are accessed using the clustering technique. By cluster we mean a finite number of similar points which can be classified into the same group, by one or more distinctive features. The center of the cluster can be considered as the representative of a group of data. In this way, a large amount of experimental data is reduced to a smaller number of representative cluster centers and the study continues with a smaller number of data. This processing of data is essential in order to remove unnecessary similar data, as well as contradictory data.

Table 5. Values of function parameters after training the ANFIS system

MF/Input	MF 1	MF 2	MF 3
K_1	gmf(0,005;-0,04;0,4;0,18)	gmf (0,4588;0,478)	gmf (0,39;0,86;0,1;1,07)
K_2	gmf (0,298;0,274)	gmf (0,2853;0,555)	smf (0,2896;1,27)
K_3	zmf (-0,0232;0,8503)	gmf (0,3851;0,376)	smf (0,1705;1,01)
K_4	zmf (0,4464;1,13;-0,0239)	gmf (0,28;0,49;0,24;0,51)	smf (0,0187;1,06)

MF/Input	MF 1	MF 2	MF 3
K_5	gmf (0,313;0,1793)	gmf (0,367;2,022;0,66)	gmf (0,2911;1,03)
K_6	gmf (0,598;2,07;-0,1341)	gmf (0,3305;0,607)	gmf (0,346;0,0704;0,996)
K_7	zmf (0,634;1,99;-0,183)	gmf (0,346;1,11;0,535)	smf (0,1682;1,01)
*zmf (Z-shaped membership function), smf (S-shaped membership function), gmf (Gaussian membership function)			

The fuzzy clustering technique is used in this research [35]. Nasibov and Ulutagay developed an iteration procedure which is based on the minimization of the function representing the geometric distance from any given point to the cluster center, but with an additional weighting factor based on the membership function (μ) of the analyzed point (k). The distance between two points tested from the data set for variable v is calculated as the minimum negative value of similarity

$$d_k = \min_v \{\mu_v\} \tag{26}$$

The degree of membership in a cluster (m_{ik}) for each point is defined as

$$m_{ik} = \frac{1}{\sum \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{q-1}}} \tag{27}$$

where $d_{ik} = \|u_k - c_i\|$ is the distance of point k from the cluster centre c_i and q weighting exponent. The two points which have the lowest value d_k are considered to be the nearest points. Since neuro-fuzzy networks have the ability to generalize the obtained data, for the study the set (F') of $F' = 3550$ of the criteria functions was identified. By using the clustering techniques described and a toolbox developed in the Matlab software package to implement the clustering techniques, the set F' was reduced to a total of $F''=248$ values of the criteria functions. A comparison of the set of criteria functions F' and F'' can be seen in Figure 3.

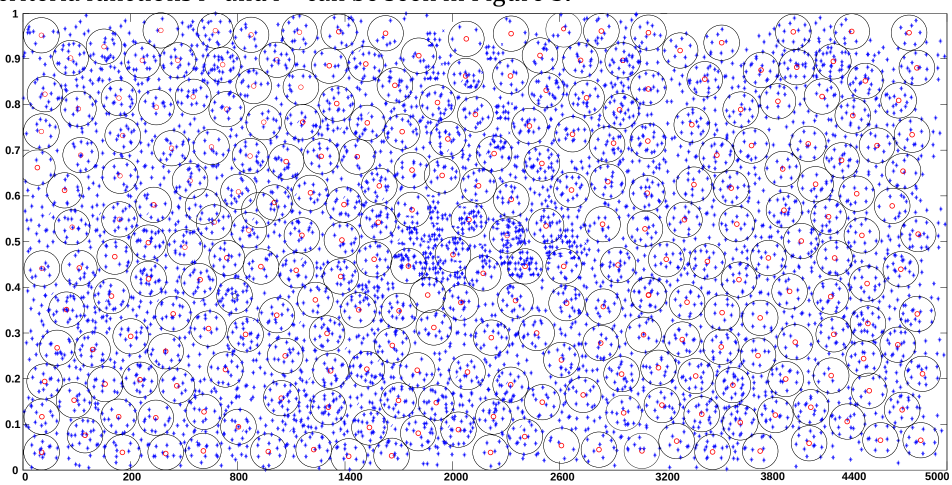

Figure 3. The set of criteria functions (points) before and after the application of clustering techniques

Training of the adaptive neuro-fuzzy network is carried out with the set F'' and a base of fuzzy rules is formed. If the initial set of criteria functions (F or F') had been used for forming the base of rules and training the neuro-fuzzy system, all data would be treated with the same significance and it would be impossible to create a base of rules which, as output from the neuro-fuzzy system, give a result with the minimum deviation from the required values. With a type of system such as the one studied, it is possible to generate a neuro-fuzzy system with a minimum number of fuzzy rules. In addition, the time required for training the neuro-fuzzy system is significantly reduced. The proposed neural net is trained on 248 dispatcher decisions. When planning a trip or during a trip, the driver (dispatcher) can modify the relative importance of the various route attributes using some settings on a panel. This is a convenient way for specifying the driver's preference, which could be useful for planning a special purpose trip. The driver (dispatcher) inputs his origin and destination to the system, and a set of route candidates is obtained.

For each route candidate, the attribute scores are inputs into the fuzzy-neural network, and the output is the overall score of that route candidate. With the computation of this overall score, a ranking of the set of route candidates is performed. The driver (dispatcher) can accept the recommendation from the system. Alternatively, he can choose an alternate route. Any derivation from the recommendation will be stored, and this information is used for forming the training pairs of the fuzzy-neural network. Hence, the system can be made adaptive to the decision-making of the driver or dispatcher. The composite of data for training that neural net is gained by surveying the heads that have a minimum of 15 years' working experience in the jobs of organizing transport support.

The back propagation algorithm is used for training. The data form a training composite x_k, $k=1,2,\ldots n$, where n is the overall number of input values of the ANFIS model, which are periodically transmitted through the net. Figure 4 shows a graph of the training process of the ANFIS model and the reduction in error at the output of the system.

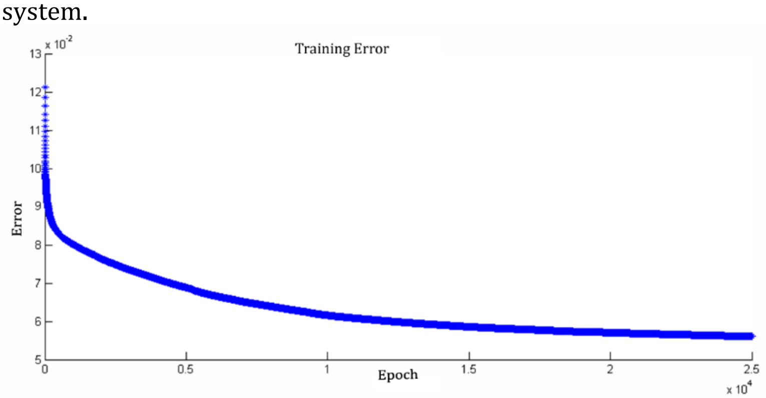

Figure 4. Error variation process during training of ANFIS

While training the ANFIS model, the data from the training set are periodically passed through the network. Training the ANFIS model was carried out in four phases, which lasted a total of 250 epochs. The first training phase of the ANFIS model was completed after 70 epochs. After completion of the first phase, an error of 0.250 was obtained at the output (Figure 5a). In the following phase, after 120 epochs, an error of 0.1547 was obtained at the output (Figure 5b), which compared to the previous phase is a 38.12 % reduction in error. The third phase of training the ANFIS model was completed after 200 epochs and an error of 0.089 was obtained (Figure 5c), which in relation to the second phase is a reduction in error of 42.46 %. In the fourth and final phase, which was completed after 250 epochs, at the output from the model the error was 0.0353 (Figure 5d), which compared to the third phase is a reduction in error of 60.33 %. Upon completion of the fourth phase, it was concluded that the error obtained at the output of the ANFIS model was negligible (acceptable error ≤ 0.08). In addition, the conclusion is that the neuro-fuzzy network is trained and capable of generalizing to new entry data.

The five-layered adaptive net is tested on twenty five dispatcher decisions. For each route, the data from the transport requirement are transmitted through the ANFIS system, hence gaining certain values of input functions. The transport route is chosen as:

$$F_r = \max(f_r) \tag{28}$$

Where r represents number of routes.

After training, a sensitivity analysis of the ANFIS model was performed. The sensitivity analysis was conducted in seven phases. In each phase, the sensitivity of the system was analyzed on one input criterion. At the same time, in each phase of the sensitivity analysis each of the observed criteria were given values in the interval $[K_{i\min}, K_{i\max}]$, where $K_{i\min}$ is the minimum value, and $K_{i\max}$ is the maximum value of the input criterion. When changing the input parameters of the observed criterion the parameters of the remaining input criteria did not change.

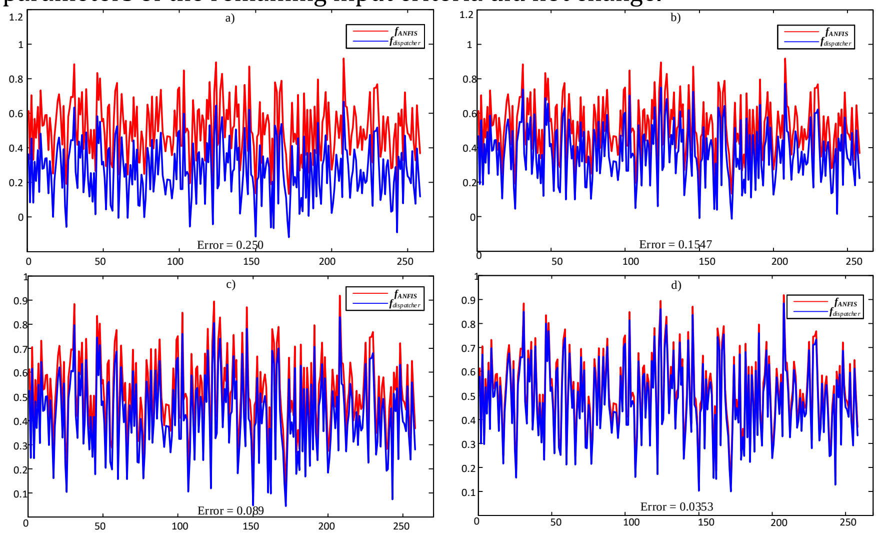

Figure 5. Training data - ANFIS output

Thus, different values of the output criteria functions of the ANFIS model were obtained. In each phase, a set of 40 input values of the criteria K_i were passed through the ANFIS model as shown in Table 6 (20 input values) and in Table A.1 (20 input values).

In this way, criteria function values were obtained which show response and sensitivity of the system to changing only one of the observed criteria. Figure 6 shows the sensitivity of the ANFIS model and the values of the criteria functions obtained in phases I, II, V and VII.

Table 6. Set of data used for analyzing the sensitivity of the ANFIS model

No.	TRS		TD		...	TC		EAR	
	Input K_1	Output F_1	Input K_2	Output F_2	...	Input K_6	Output F_6	Input K_7	Output F_7
1.	0.788	0.871	8623.95	0.843		0.343	0.605	0.502	0.933
2.	0.795	0.863	29478.21	0.289		0.606	0.790	0.889	0.489
3.	0.428	0.459	30419.01	0.286		0.783	0.871	0.910	0.382
4.	0.428	0.459	25087.84	0.422		0.511	0.709	0.838	0.705
5.	0.228	0.232	30889.4	0.272		0.796	0.888	0.917	0.355
6.	0.795	0.863	29635.01	0.301		0.588	0.777	0.881	0.534
7.	0.249	0.443	12857.52	0.767		0.356	0.617	0.595	0.916
8.	0.615	0.665	7055.96	0.887		0.335	0.598	0.463	0.942
9.	0.822	0.878	20383.87	0.518		0.404	0.668	0.741	0.811
10.	0.819	0.873	13171.12	0.422		0.503	0.703	0.821	0.724
11.	0.422	0.451	26342.23	0.355	...	0.538	0.723	0.866	0.641
12.	0.430	0.461	10819.13	0.671		0.379	0.636	0.685	0.859
13.	0.611	0.661	26655.83	0.347		0.549	0.738	0.866	0.605
14.	0.831	0.915	8153.55	0.887		0.341	0.601	0.481	0.938
15.	0.781	0.877	31359.8	0.712		0.362	0.620	0.619	0.902
16.	0.43	0.461	30262.21	0.689		0.375	0.635	0.677	0.866
17.	0.842	0.924	21167.87	0.546		0.402	0.665	0.733	0.822
18.	0.260	0.253	13798.31	0.789		0.351	0.613	0.569	0.926
19.	0.586	0.623	21167.87	0.258		0.83	0.897	0.923	0.297
20.	0.835	0.918	6271.96	0.887		0.321	0.585	0.401	0.945

The sensitivity of the model and the values of the criteria functions obtained in phases III, IV and VI are shown graphically in Appendix B (Figure B.1.) By looking at the graph of the sensitivity analysis (Figure 6 and Figure B.1.) we can conclude that the output values of the criteria functions of the ANFIS model depend on the weight values of the criteria K_i (Table 1) and on the nature of the criteria themselves (benefit or cost criteria). Figure 6 shows the four criteria which have the greatest weight as defined in the database of rules. Sensitivity analysis showed that benefit-type criteria with higher input values correspond with higher values of the output functions. In addition, it was found that small changes in the values of input criteria with greater weight lead to proportional increase in the value of output functions. However, with cost-type criteria the value of the output functions is inversely proportional to the values of the input criteria. Figure B.1. shows the four criteria with the lowest weight. By analyzing the graph in Figure B.1. we can conclude that in the case of criteria with low weight, the conditions defined in Table 1 are met.

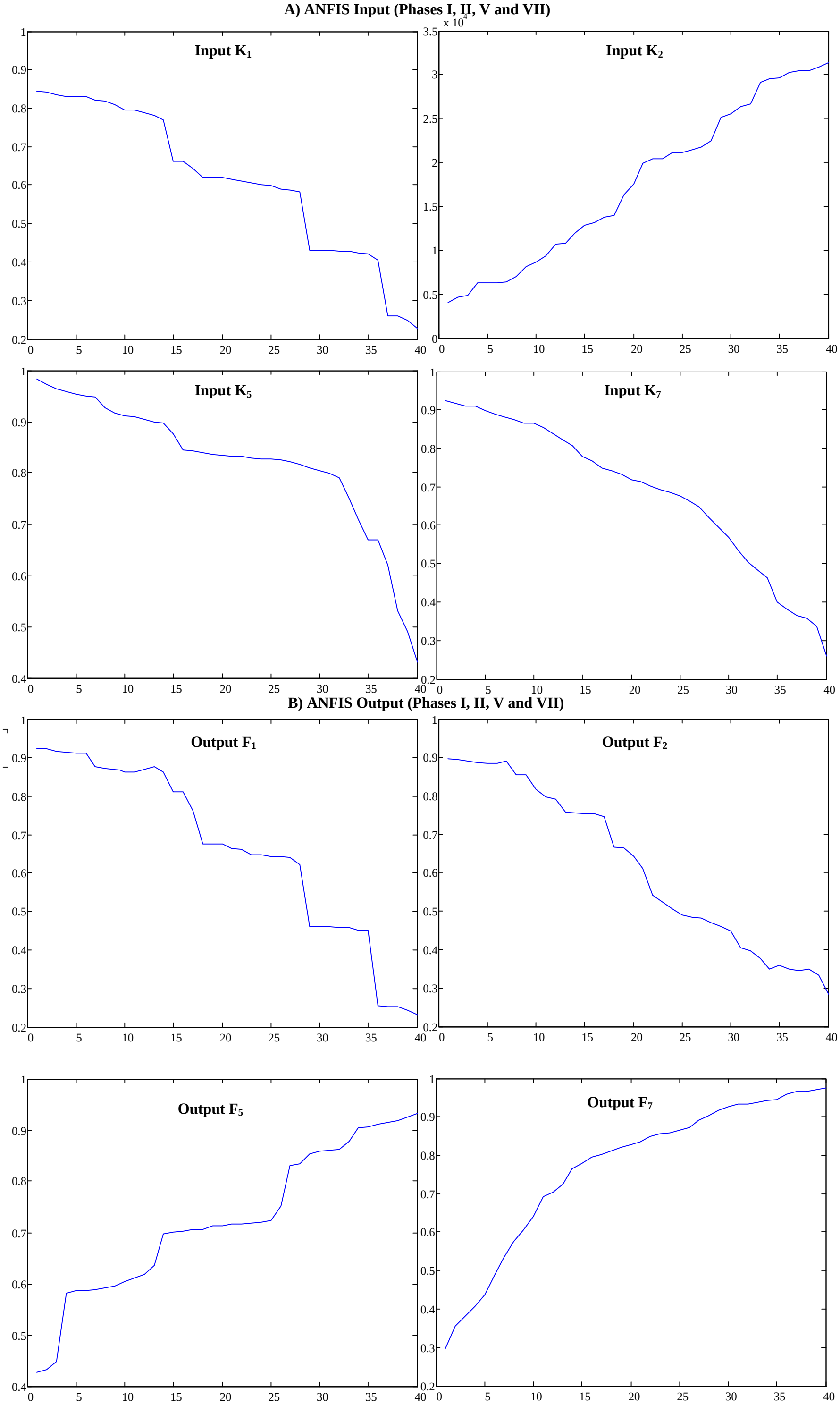

Figure 6. Sensitivity analysis of the ANFIS model (Phases I, II, V and VII)

4. Results

Twenty five transport requirements are considered. The transport task is described in terms of the time of loading and unloading, location where the user is set, as well as the possibility of using alternative directions. Table 7 shows a comparison between the results obtained using the developed ANFIS model and the preferences of the dispatcher when choosing a route for the transport requests. When selecting a route for each individual transportation request, four alternative routes were considered. Based on the characteristics of the routes considered, the dispatchers and the ANFIS model identified the most suitable route for carrying out the given transport request.

Table 7. Comparative review of decisions and ANFIS model

Number of transport requests	Selection of routes for the transport request	
	Dispatcher	ANFIS
1.	R_3	R_2, R_3
2.	R_3	R_3
3.	R_4	R_4
4.	R_3	R_3
5.	R_2	R_2
6.	R_1	R_1
7.	R_3	R_3
8.	R_3	R_3, R_4
9.	R_3	R_3
10.	R_3	R_3, R_4
11.	R_1	R_1
12.	R_3	R_3
13.	R_3	R_3, R_4
14.	R_3	R_3, R_4
15.	R_1	R_1, R_2
16.	R_3	R_3
17.	R_3	R_3, R_4
18.	R_4	R_4
19.	R_3	R_3, R_4
20.	R_1	R_1, R_2
21.	R_4	R_4
22.	R_4	R_4
23.	R_1	R_1, R_2
24.	R_1	R_1
25.	R_4	R_4

The numerical results of Table 7 imply the applicability of the proposed model used as a decision-making tool for vehicle route assignment. As seen in Table 7 the decisions regarding the selection of routes for transportation vehicles obtained at the output of the ANFIS model are identical to the decisions made by the dispatchers. For transport requests numbered 1, 8, 10, 13, 14, 15, 17, 19, 20 and 23, the ANFIS model offered other routes as an alternative, which is acceptable, and in some situations even desirable, since the PIS has a hetergenous structure of its fleet.

5. Conclusion

The hybrid neuro-fuzzy system briefly presented in this paper was successfully applied in designing an intelligent decision support system for route selection in uncertainty conditions. The research conducted proves that fuzzy neural networks are a very effective and useful instrument for the implementation of intelligent decision support systems for route selection. Developing the ANFIS model enabled the deployment strategy for vehicles on transport routes to be transformed into an automatic control strategy. The performance of the developed system depends on the number of experienced transport support managers, and the ability of analysts, after long communication with them, to formulate a decision-making strategy.

As a result of the research, it has been shown that the proposed adaptive fuzzy system, which has the ability to learn, can imitate the decision-making of transport support managers and demonstrate a level of expertise that is comparable to the level of their expertise.

By reviewing the performance of the trained neural network i.e. the adjusted fuzzy system and the results obtained, we can conclude that the ANFIS model can reproduce the decisions of dispatchers with great accuracy, and thus allocate vehicles to meet transport requirements. This is particularly important in situations when a decision needs to be made by a transport support organ which has a lack of sufficient experiential knowledge and in conditions when making a quality decision is influenced by a large number of uncertainties. In addition, the results in Table 7 imply the potential applicability of the proposed model used as a decision-making tool for route selection.

The proposed methodology could be used to solve other complex traffic and transportation problems characterized by uncertainty and the need for on-line control. Extension and modification of the proposed model for other operational cases may warrant more research. Further effort in training the proposed neuro-fuzzy based model with more valid data is also needed for practical applications.

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Appendix A

Table A.1. Set of data used for analyzing the sensitivity of the ANFIS model

No.	TRS		TD		...	TC		EAR	
	Input K_1	Output F_1	Input K_2	Output F_2	...	Input K_6	Output F_6	Input K_7	Output F_7
1.	0.583	0.641	19913.47	0.598		0.396	0.647	0.719	0.829
2.	0.845	0.925	22422.26	0.433		0.441	0.699	0.808	0.764
3.	0.830	0.912	4076.77	0.936		0.267	0.521	0.260	0.975
4.	0.770	0.862	4703.97	0.933		0.272	0.526	0.338	0.971
5.	0.430	0.261	21795.06	0.456		0.431	0.691	0.767	0.795
6.	0.620	0.675	21481.46	0.449		0.438	0.695	0.779	0.778
7.	0.621	0.676	10662.33	0.711		0.366	0.624	0.648	0.891
8.	0.423	0.238	25558.24	0.406		0.519	0.711	0.853	0.692
9.	0.605	0.482	20383.87	0.497		0.421	0.688	0.748	0.802
10	0.601	0.637	13955.11	0.661		0.385	0.640	0.701	0.849
11	0.644	0.762	29164.61	0.323	...	0.562	0.769	0.875	0.576
12	0.810	0.842	17561.49	0.636		0.389	0.642	0.713	0.836
13	0.621	0.676	11916.72	0.699		0.372	0.633	0.662	0.873
14	0.600	0.643	30419.01	0.289		0.681	0.821	0.898	0.438
15	0.661	0.811	6428.76	0.928		0.292	0.547	0.366	0.966
16	0.661	0.811	6271.96	0.921		0.316	0.573	0.382	0.958
17	0.405	0.255	16307.1	0.664		0.383	0.638	0.692	0.855
18	0.260	0.253	9407.94	0.818		0.346	0.609	0.533	0.933
19	0.589	0.643	6271.96	0.288		0.716	0.848	0.910	0.406
20	0.830	0.912	4860.77	0.928		0.276	0.531	0.359	0.966

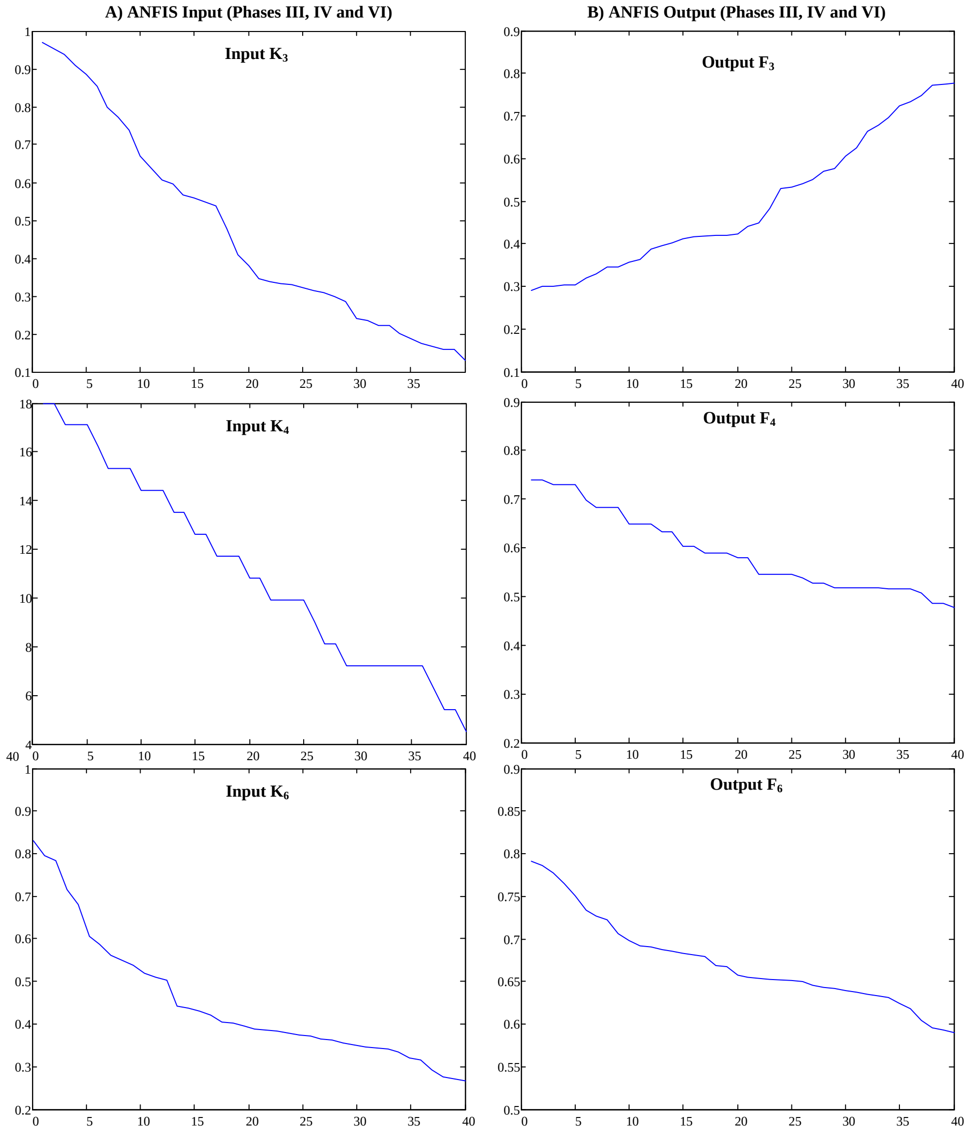

Figure B.1. Sensitivity analysis of the ANFIS model (Phases III, IV and VI)