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Theory and Methodology

An application of neurofuzzy modeling: The vehicle assignment problem

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Abstract

When assigning vehicles to transportation requests, dispatchers usually have built-in fuzzy rules which they use to assign a given amount of freight to be sent to a given distance a given vehicle. Fuzzy systems equipped with learning capabilities can be trained to control complex processes like the dispatcher. They usually begin with a few very crude rules obtained from the dispatcher. Or they may work out the rules from the observed dispatcher's behavior. In this paper, a neural network is used to refine and adapt the fuzzy system to achieve better performance. As a result of the study, on a real set of numerical data, it was shown that the proposed feedforward adaptive neural networks with supervised learning capabilities can be used to tune the initial fuzzy systems.

Keywords: Vehicle assignments; Neurofuzzy modeling; Simulated annealing

1. Introduction

Management personnel in all transportation industries face a complex decision making environment where a large number of planning and operational tasks have to be solved. For example, transportation companies receive a large number of requests every day from clients wanting to send goods to different destinations. Their fleets of vehicles most often consist of several different types of vehicles. Each transportation request is characterized by a large number of parameters, including the most important: type of freight, amount of freight (weight and volume), loading and unloading sites, preferred time of loading and/or unloading and the distance the freight is to be transported. The common practice is that dispatchers assign vehicles to transportation requests. The dispatcher's knowledge can be considered as experience based – heuristic knowledge. That knowledge is implicit, and dispatchers that apply it neither think about it nor are aware of having it. Experienced dispatchers most often properly solve problems but they have difficulties when describing their motives. Besides, "Personality and cognitive

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style can influence individual decision styles" (Er, 1988).

The simplest form of knowledge representation is in the form of rules. Rules consist of two parts: the first part starts with IF and the second part continues from THEN. The first part represents the condition preceding the second part (If premise Then consequence). Experienced dispatchers usually have built-in criteria ("rules") which they use to assign a given amount of freight to be sent to a given distance a given vehicle with given structural and technical-operational characteristics (capacity, ability to carry freight to certain distances,...). Since fuzzy sets can describe qualitative and imprecise information, fuzzy logic is used as a tool to transform the dispatcher's heuristic rules into an automatic strategy. A fuzzy system (fuzzy logic controller) provides an algorithm that converts the linguistic control strategy based on the observed dispatcher's behavior and knowledge into an automatic control strategy.

The major problems in the construction of fuzzy systems are the extraction of explicit dispatcher's heuristic control rules and the determination of the appropriate membership functions of the input/output variables. In some applications, the final set of fuzzy rules and the choice of membership functions are defined by trial and error. Mendel (1995) claims: "Prior to 1992, all fuzzy logic systems reported in the open literature fixed the parameters of the membership functions somewhat arbitrarily, e.g., the locations and spreads of the membership functions were chosen by the designer independent of the numerical training data. Then, at the first IEEE Conference on Fuzzy Systems, held in San Diego, three different groups of researchers presented the same idea: *tune the parameters of a fuzzy logic system using the numerical training data*".

The main objective of this paper is to research the possibility of improving the performance of the fuzzy system in order to improve the quality of decisions. The method used for tuning the initial fuzzy system is mapping of a fuzzy system into a feedforward neural network trainable with supervised learning. As a result of the study, it was shown that the proposed fuzzy system equipped with learning capability can be used to imitate the actual dispatcher's assignment policy.

Putz and Weber (1996) presented a systematic overview of approaches for automatic generation of fuzzy systems (neural networks, genetic algorithms, rule based approaches and other). The basic principles of neurofuzzy modeling are given in the works of Jang and Sun (1995), Jang (1997), Lin and Lee (1996), Kasabov (1996) and Brown and Harris (1994).

This paper is organized as follows. The problem is described in Section 2. The proposed solution of the problem and a numerical example are given in Sections 3 and 4, respectively.

2. Statement of problem

The problem considered in this paper is the daily assignment of a fleet of available vehicles to a certain number of transportation requests. It is stated explicitly in the work of Milosavljević et al. (1996). A transportation company receives a large number of requests every day from clients wanting to send goods to different destinations. It has several different types of vehicle at its disposal. Individual types of vehicle differ from each other in terms of structural and technical-operational characteristics. The transportation company has a depot from which the vehicles depart and to which they return after completing their trips. Since the vehicle returns to the depot after serving a node, the routes the vehicle is to take are known. Each transportation request is characterized by four parameters: (1) the node where freight is to be delivered; (2) the amount of freight to be transported; (3) the distance to which freight is to be transported (the distance between depot and a certain node); (4) the number of trips along route that can be made by one vehicle during the time period under consideration (one day). It is assumed that the vehicle can serve any node within the geographical region under consideration at least once a day and return to the depot. One type or a variety of vehicle types can take part in the delivery to each node. In this research the case when only one type of vehicle takes part in serving a node is considered.

Depending on the characteristics of the transportation requests and how the transportation company operates, vehicle assignments to transportation requests can be made several times a day, once a day, once a week, etc. Without loss of generality, the case when dispatching is carried out every day based on the principle "today for tomorrow" is considered. In other words, dispatchers have a set amount of time (one day) to match available vehicles to transportation tasks which are to begin the following day.

Thus, the problem analyzed and solved by Milosavljević et al. (1996) is to determine the vehicle type to meet each transportation request. The problem belongs to a class of assignment problems. The classical approach to solving this type of problems is through mathematical programming. The objective is to design a set of vehicle assignments to transportation requests that incurs minimum costs, while assuring that constraints describing proper utilization of vehicles and "coverage" of the planned transportation tasks (satisfaction of transportation requests) are not violated. However, there are certain disadvantages incorporated in the mathematical programming approach. The main one is the fact that it is hard to quantify the goals that motivate dispatchers, that is, to formulate a reasonable objective function and hard constraints. Besides, the information at the dispatcher's disposal is most often imprecise or/and given in qualitative form. It is often impossible to precisely determine assignment costs. Some transportation requests are "more important" than others. In other words, some clients have signed long-term transportation contracts, and others randomly request transport that will engage transportation capacities for longer or shorter periods of time. Some vehicle types are more "suitable" for certain types of transportation tasks than other. Naturally, vehicles with a 4.4 ton capacity are more suitable to deliver goods within a city area than those with a 14 ton capacity. On the other hand, 14 ton vehicles are considerably more suitable than 4.4 ton or 7 ton vehicles for long-distance transport. Therefore, the conventional approach can hardly reflect the knowledge and the intelligence of a dispatcher, i.e., the ability to deal with uncertainty and imprecision.

In addition to the characteristics of the transportation request, when assigning a specific type of vehicle to a specific transportation request, the dispatcher must also bear in mind the total number of available vehicles, the available number of vehicles by vehicle type, the number of vehicles temporarily out of working order, and vehicles undergoing technical examinations or preventive maintenance work. In the research done by Milosavljević et al. (1996) these constraints are taken care of by the developed heuristic algorithm. The assumption in this paper is that the number of available vehicles by vehicle type is unlimited; i.e., the model imitates the dispatcher's decision regarding choice of a vehicle type under no constraints.

2.1. Initial fuzzy systems for assignment of vehicles to transportation requests

Milosavljević et al. (1996) observed and analyzed dispatchers' behavior and concluded that every dispatcher has a pronounced subjective feeling about which type of vehicle corresponds to which transportation request. This subjective feeling concerns both the suitability of the vehicle in terms of the distance to be traveled and the vehicle capacity in terms of the amount of freight to be transported. Milosavljević et al. (1996) noted that the dispatchers have certain preferences: (1) "very strong" preference is given to a decision that will meet the request with a vehicle type having "high" suitability in terms of distance and "high" capacity utilization, or (2) "very weak" preference is given to a decision that will meet the request with a vehicle that has "low" suitability regarding distance and "low" capacity utilization.

The heuristic algorithm used to assign vehicles to planned transportation requests developed by Milosavljević et al. (1996) is tested on a fleet of vehicles containing three different types of vehicle with capacities 4.4, 7 and 14 tons. For every type of vehicle, they developed a corresponding fuzzy system (Mamdani's model) to determine the dispatcher's preference strength ("very weak" (VWP), "weak" (WP), "medium" (MP), "strong" (SP), "very strong" (VSP)) in terms of meeting a specific transportation request with the type of vehicle in question. They noticed that the dispatchers consider the suitability of different types of vehicles as being "low" (LS), "medium" (MS) and "high" (HS) depending on the given distance the freight is to be transported. Also, the capacity utilization (the relationship between the amount of freight and the vehicle's declared capacity, expressed as a percentage) is estimated by the dispatcher as "low" (LCU), "medium" (MCU) or "high" (HCU). The developed fuzzy systems for each type of vehicle are shown in Fig. 1. They differ from each other in terms of the number of rules they contain, and the shapes of the membership functions of individual fuzzy sets. The membership functions of the input/output variables are considered as the initial membership functions. They will be shown in Section 4.

The major problems in the construction of fuzzy systems are the extraction of explicit dispatcher's heuristic control rules and the determination of the appropriate membership functions of the input/output variables. It implies a long and elaborate communication with a number of experienced dispatchers, which could be very difficult. For example, the specification of the membership functions is quite subjective, which means that the membership functions specified for the same concept (for example, low vehicle capacity utilization) by different dispatchers may vary considerably. Thus, the performance of the developed fuzzy system depends on the number of available dispatchers and our ability to extract their assignment policy.

The problem considered in this paper is tuning the membership functions of the input/output variables. Based on real numerical training data (input/output pairs), the neural network is used to tune and adapt the initial fuzzy system to achieve better performance.

3. Tuning the fuzzy systems for assignment of vehicles to transportation requests: Neurofuzzy modeling

The term neurofuzzy modeling refers to the way of applying various learning rules developed in the neural network literature to fuzzy systems. Compared to black-box modeling techniques like neural networks, fuzzy systems are to a certain degree transparent to interpretation and analysis. Fuzzy systems require that we work out the fuzzy rules operating to different degrees and estimate the parameters of the membership functions (as well as functional forms for membership functions).

(a)

		Capacity utilization		
		LCU	MCU	HCU
Suitability	LS	MP	SP	SP
	MS	WP	WP	MP
	HS	VWP	VWP	WP

(b)

		Capacity utilization		
		LCU	MCU	HCU
Suitability	LS	VWP	VWP	WP
	MS	MP	SP	SP
	HS	WP	WP	MP

(c)

		Capacity utilization		
		LCU	MCU	HCU
Suitability	LS	VWP	WP	MP
	MS	MP	SP	SP
	HS	SP	VSP	VSP

Fig. 1. The initial fuzzy systems that determine the dispatcher's preference in meeting a transportation request with a vehicle of 4.4 (a), 7 (b) and 14 (c) tons capacities.

We can use neural networks to estimate the parameters of fuzzy systems. But neural networks require an accurate (statistically representative) set of numerical training data (Kosko, 1992).

The basic goal of neurofuzzy modeling in this application is to decrease the dispatcher's role in the construction of fuzzy systems relying primarily on past numerical examples of the dispatcher's decisions. In this paper, the aim of learning is to set the appropriate membership functions of the input/output variables (they are different for each type of vehicle). It is assumed that the fuzzy rules are properly extracted from the dispatcher. The basic assumption is that one type of vehicle is used to meet every transportation request. Considering the developed fuzzy systems by Milosavljević et al. (1996), a neural network is configured individually for every type of vehicle. However, the basic structure of a five layered adaptive neural network that has exactly the same function as the fuzzy system (Mamdani and Assilian, 1975) is the same.

3.1. Network configuration

Specifying the set of processing units connected through directed links and what they represent is typically the first stage of specifying a neural network. The initial fuzzy system (for a vehicle with a capacity of 14 tons) is mapped into a five layered adaptive neural network with a restricted connectivity structure that is shown in Fig. 2. The proposed neural network is referred to as a five layered network because five layers perform operations. The adaptive network shown in Fig. 2 is a feedforward layered network because the output of each unit propagates from the input side (left) to the output side (right). The number of configured neural networks corresponds to the number of vehicle types.

3.2. Pattern of connectivity

Neural networks are designed to establish and compute a function from input space to output space. The examples of the dispatcher's assignment policy are expressed as input–output vectors and training and testing pairs are formed.

In this paper, the network that has a fixed structure is configured based on the operation of the fuzzy system (Mamdani's model). The input layer consists of 2 units representing: distance to which the freight is to be transported, x_1 (needed to determine vehicle suitability in terms of distance), and amount of freight, x_2 (needed to determine vehicle capacity utilization). It simply transfers inputs further via the interconnections to the hidden or first layer. The first unit in the input layer is connected with the first 3 units in the first layer. The second unit in the input layer is connected with the second 3 units in the first layer. The strengths of connections between the units in the input layer and the units in the first layer are crisp numbers equal to 1.

The first layer consists of 3 + 3 units representing the number of verbal descriptions quantified by fuzzy sets ("low", "medium", "high") for each input variable. The input variables are vehicle suitability in terms of distance and vehicle capacity utilization. The vehicle capacity utilization is the relationship between the amount of freight transported by a vehicle and the vehicle's capacity. Every unit in the first layer is an adaptive unit with an output being the membership value of the premise part. (A fuzzy If–Then rule assumes the form: If premise Then consequence.) For example, the output from the first unit (representing the membership function – "low vehicle suitability", LS) is the grade of membership of a distance x_1 to a fuzzy set "low suitability", $\mu_{LS}(x_1)$.

The number of units in the second layer equals the number of fuzzy rules. The number of fuzzy rules is equal to the number of cells in the rectangle shown in Fig. 1(c). Rule 1 corresponds to the first cell (NW corner), etc. Every unit in this layer is a fixed unit that calculates the minimum value of incoming two inputs. The outputs from this layer are firing strengths of rules. For example, the output from the first unit in the second layer is $w_1 = \min\{\mu_{LS}(x_1), \mu_{LCU}(x_2)\}$.

The third layer has five adaptive units representing strength of the dispatcher's preference ("very weak", "weak", "medium", "strong", "very strong") in meeting a specific transportation

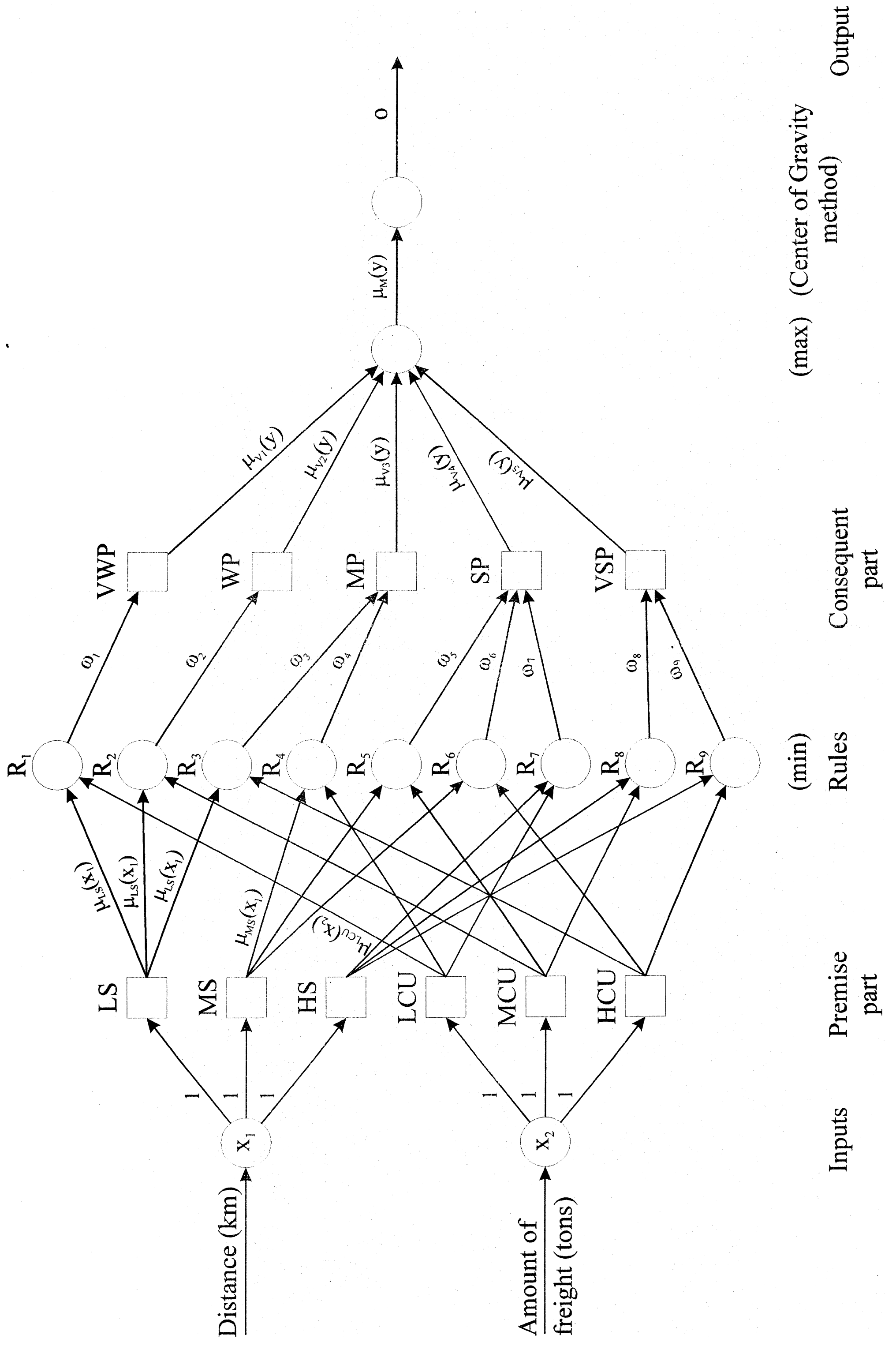

Fig. 2. A five layered feedforward adaptive neural network configured for a vehicle with a capacity of 14 tons.

request with a type of vehicle in question. Each unit in this layer calculates intersection of a fuzzy set (consequent) with the maximum of incoming rules' firing strengths. For example, the fourth unit calculates intersection of a fuzzy set "strong preference" with the maximum of rules' R_5, R_6, R_7 firing strengths: $\mu_{V4}(y) = \min\{w_i,\ \mu_{SP}(y)\}$, where $w_i = \max\{w_5,\ w_6,\ w_7\}$.

The single unit in the fourth layer is a fixed unit that computes the overall output of the fuzzy system: $\mu_M(y) = \max\ \{\mu_{V1}(y),\ \mu_{V2}(y),\ \mu_{V3}(y),\ \mu_{V4}(y),\ \mu_{V5}(y)\}$. The obtained output is then defuzzified in the single unit in the fifth layer. The selection of final crisp value can be made in various ways. In this paper the action which is closest to the center of gravity has been computed (Center-of-Gravity method). The network's output, o, is a real value among 0 and 1. The dispatcher's or targeted output equals either 0 or 1, meaning that the vehicle is either assigned to meet a specific transportation request or not.

3.3. Supervised learning (a simulated annealing algorithm)

In order to recover and emulate the dispatcher's assignment policy by fuzzy system, the aim of learning is to set the membership functions of the input/output variables to some adequate functions. When a known input, describing a transportation request, is applied to all trained networks, a maximum of networks outputs (the model output) is chosen. Since the trained neural network corresponds to the vehicle type, the maximum value of output determines the vehicle type to be assigned to meet a transportation request. The resulting choice of a vehicle type is then compared with the targeted or dispatcher's choice. The neural networks performances are measured as the deviation between the targeted output and the model output across all numerical examples of the dispatcher's decisions. This discrepancy or the error measure is considered as the objective function and the heuristic simulated annealing is used to minimize it. Since the application of a simulated annealing requires a large number of experiments, the training process was very long. However, the tuned fuzzy systems yield results superior to those obtained by the initial fuzzy controllers and can be used in real time.

In this paper, the objective function that has to be minimized is calculated as a sum of differences between the model output (maximum of the networks outputs) and the targeted output over all training pairs. The heuristic simulated annealing is used to minimize the objective function. The statistical training method such as the simulated annealing requires the definition of an energy function (objective function) depending upon the parameters of the neural network. Whenever a new set of membership functions is generated randomly, the resulting energy is determined. If the obtained energy is improved, then a new set of membership functions is memorized, otherwise the acceptance or the rejection of the change is decided according to a given probability distribution. The possibility that the change that worsens (increases) the energy is retained implies that the algorithm would hardly be trapped in local energy minima. In this research, the fact that the algorithm would hardly be trapped in local minima, i.e., it will converge to a global minimum, was the main reason to chose this method as a learning rule. The disadvantage of using the simulated annealing algorithm as a learning rule of the neural network is a very long training period.

Many authors claim simulated annealing to be a generally applicable optimization technique, and a rich variety of applications supports this claim. Golden and Skicsim (1985) use simulated annealing to solve routing and location problems. Teodorović and Pavković (1992) use simulated annealing to solve the vehicle routing problem in the case of a stochastic demand. Vukadinović et al. (1996, 1997) train neural networks by a simulated annealing algorithm in order to learn from the examples of dispatcher's decisions and simulate the dispatcher's decision making process.

The simulated annealing algorithm based on the approaches of Kirkpatrick et al. (1983), Golden and Skicsim (1985), consists of the following steps:

Step 1: Develop a proper annealing schedule $\{t_1, t_2, \ldots, t_K\}$ consisting of a sequence of temperatures (control parameters), $t_1 > t_2 > \cdots > t_K$, and the amount of time required to reach the equilibrium at each temperature. Set $i = 1$.

Step 2: Generate a set of initial membership functions. For all the input vectors in a training set obtain the model output (maximum of the networks outputs) and calculate the objective function value (OF_{old}). The objective function minimizes the sum of errors between the targeted outputs and the model outputs.

Step 3: Generate a new set of membership functions by a small perturbation. The middle values (one in a case of a triangle or two in a case of a trapezoid) that are changed are uniformly distributed on arbitrarily defined intervals. Obtain the model output (maximum of the networks outputs) with the same input vectors (for the complete training set) and calculate the new objective function value (OF_{new}). Evaluate the change in the objective function

$$(\delta = OF_{new} - OF_{old}).$$

If $\delta < 0$, go to Step 5. Else go to Step 4.

Step 4: ($\delta \geqslant 0$) Compare a random variable, r, drawn from a uniform distribution on the [0, 1] interval, with the probability of accepting the new set of membership functions $P(\delta) = \exp(-\delta/t_i)$.

If $r < P(\delta)$, go to Step 5, else keep the old set of membership functions, and go to Step 3.

Step 5: ($\delta < 0$ or $r < P(\delta)$) Memorize the new set of membership functions and the new objective function value.

Step 6: If the thermal equilibrium has been reached at the temperature t_i, set $i = i + 1$. Steady state or equilibrium is reached when we observe that an improvement of the objective function is highly unlikely. An epoch is an interval between checking if the equilibrium is reached. The epoch implies λ exchanges of all membership functions, where λ is a pre-defined number. The best solution, i.e., the least sum of errors between the model outputs and targeted outputs, obtained through λ exchanges of the membership functions, represents the epoch. Consider the case where k epochs have already been generated. After the next epoch, the equilibrium is reached if:

$$\frac{|OFV_{k+1} - OFV_p|}{OFV_{k+1}} < \varepsilon, \quad k = 1, \ldots, MEP - 1,$$

where OFV_{k+1} is the objective function value that represents the k + 1st epoch, OFV_p the least objective function value of all previous epochs' solutions and ε, a pre-defined constant.

The maximum number of generated epochs at one temperature if the thermal equilibrium is not reached in the meantime, MEP, is set in advance.

If $i > K$, the algorithm is completed.

The solutions obtained by a simulated annealing algorithm do not depend on the initial solution and usually approximate the optimal solution. However, the annealing schedule, i.e., the way the temperature gradually decreases, and the initial temperature influences the performance of the algorithm. Initially, a temperature is given a high value; then, it is slowly reduced until some small value, for which no deteriorations are accepted any more, is reached. Thus, the convergence of the obtained values for the membership functions is inherited from the convergence of the simulated annealing algorithm.

4. Numerical example

In this paper, the method used for tuning the fuzzy systems is mapping of a fuzzy system into a feedforward neural network trainable with supervised learning. The initial fuzzy systems developed by Milosavljević et al. (1996) correspond to three different types of vehicle with capacities 4.4, 7 and 14 tons. Their fuzzy rule bases are shown in Fig. 1. The initial and the tuned membership functions for the input/output variables are shown in Figs. 3–5.

The application of simulated annealing requires a large number of experiments. The initial temperature and the number of temperatures are varied during numerous experiments. The best result is obtained when an array of 40 temperatures ($t_{i+1} = 0.9t_i$) and an initial temperature $t_1 = 40$ are used (Fig. 6).

The maximum number of generated epochs at one temperature MEP = 30. In other words, 30 epochs are generated if the thermal equilibrium is not reached in the meantime. The epoch implied 20 exchanges of all middle values of the membership functions. The value of ε used to check if the equilibrium is reached was 0.05.

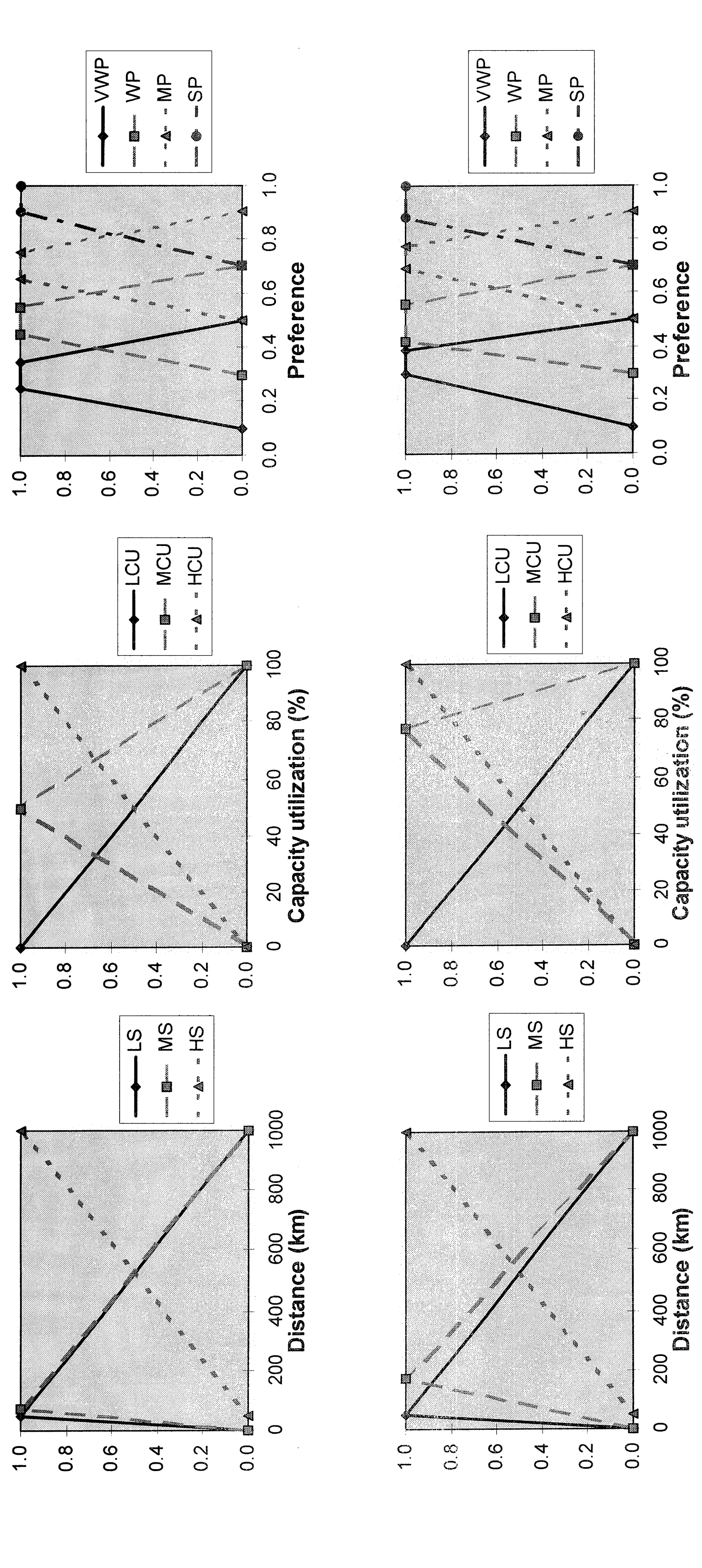

Fig. 3. The initial (first row) and the final (second row) membership functions for the input/output variables that correspond to a vehicle with a capacity of 4.4 tons.

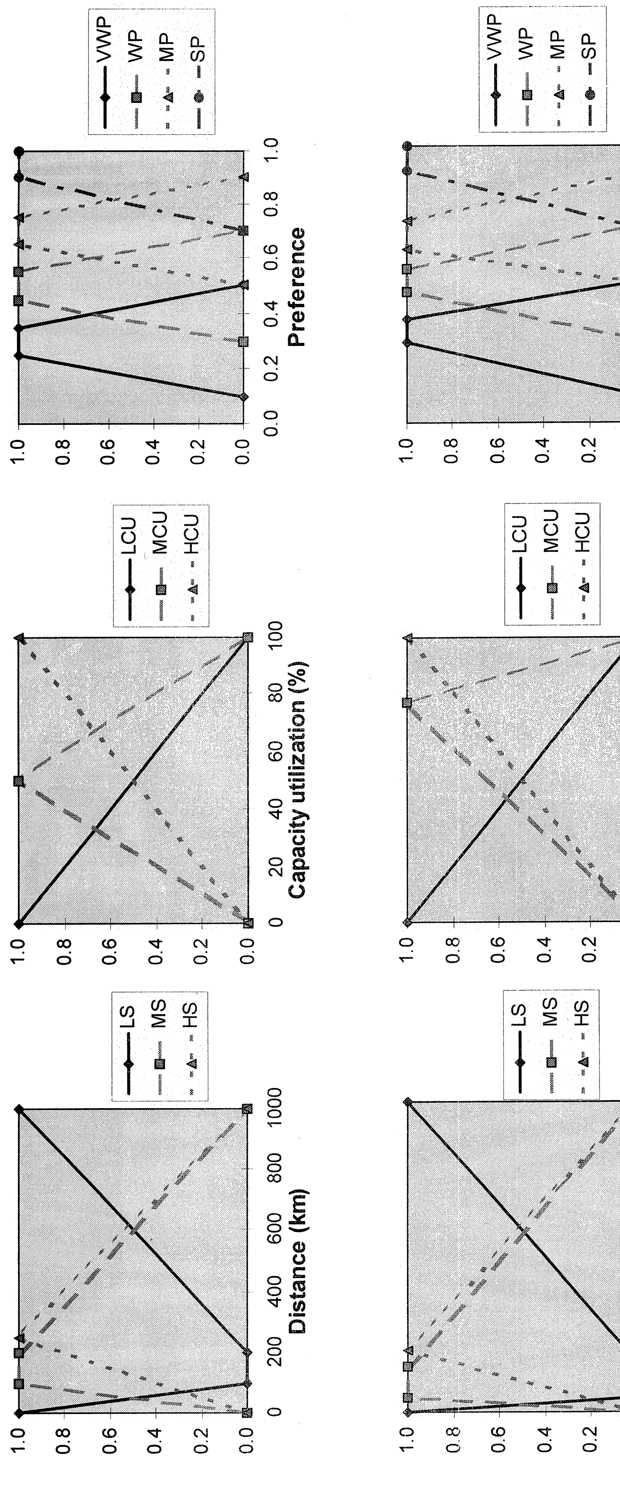

Fig. 4. The initial (first row) and the final (second row) membership functions for the input/output variables that correspond to a vehicle with a capacity of 7 tons.

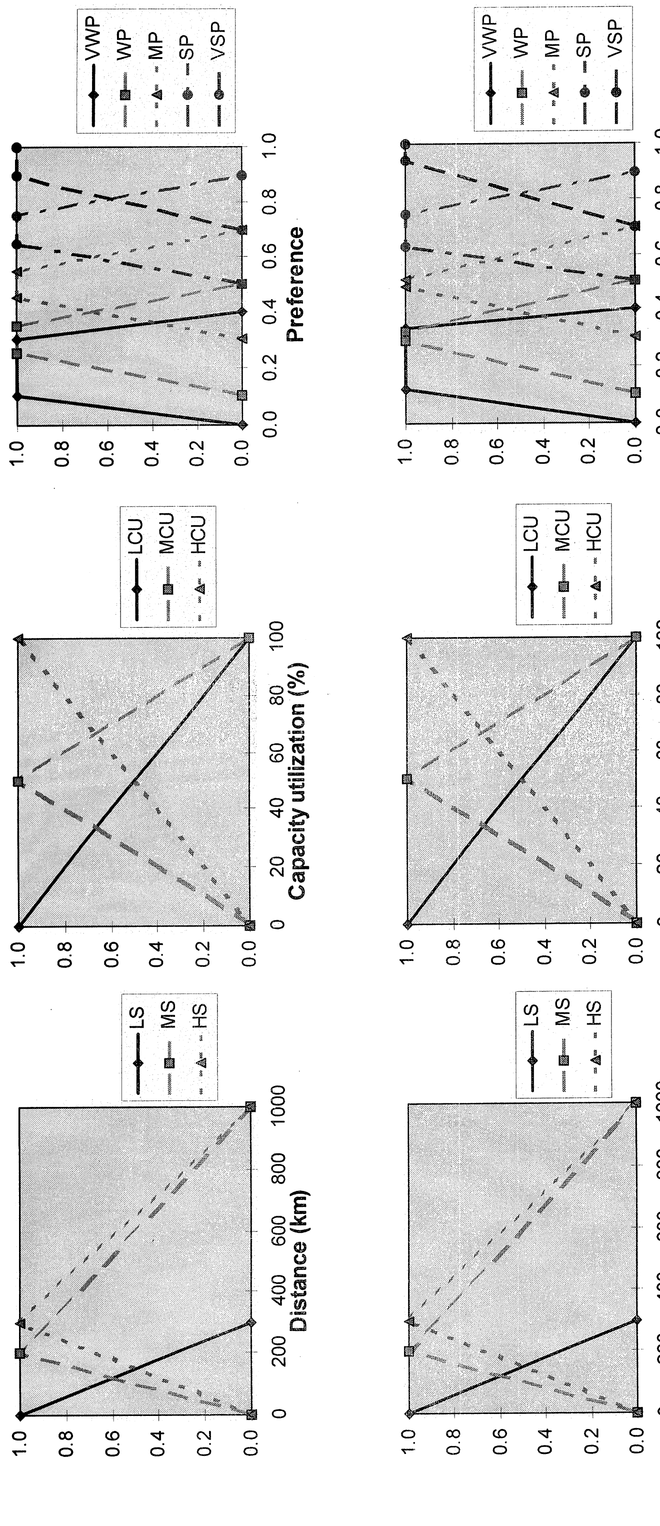

Fig. 5. The initial (first row) and the final (second row) membership functions for the input/output variables that correspond to a vehicle with a capacity of 14 tons.

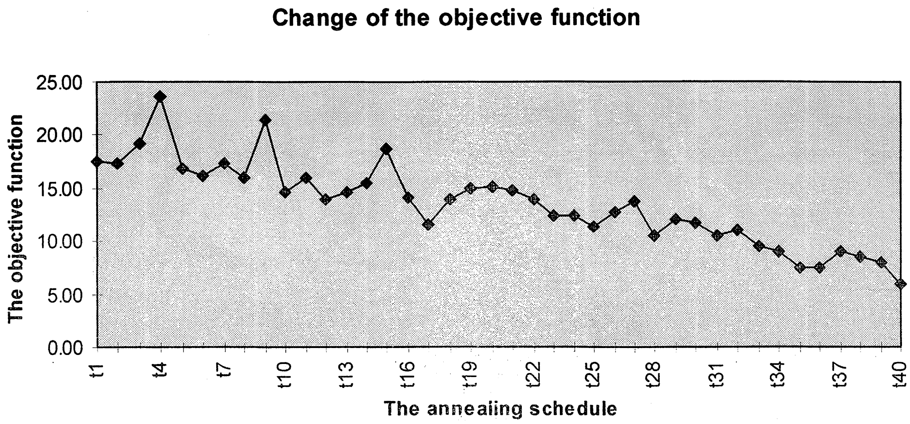

Fig. 6. Change of the objective function.

The main difficulty in using a neurofuzzy modeling is in obtaining good training data. The reliance on the obtained result will be enhanced if sufficient and representative training data are available. Some authors suggest that as many as 100 data points is needed for each unit in a hidden layer (Hall and Smith, 1992). However, many researchers report quite acceptable results from relatively small training data set. In general, the more data the better the solution. The purpose of testing a neural network behavior on real (unseen) data is to provide an evidence about the adequacy of the network. As Dougherty (1995) claims: "It is important to remember that much more data are often required for training then testing; therefore where data are limited it may be better to reserve what real data are available for the testing phase, as this allows more credible results to be produced".

The three developed neural networks (corresponding to three vehicle types) are trained on 100 different examples of the dispatcher's decisions, and tested on 60 examples. The Tables 1 and 2 show the characteristics of the transportation requests to be met as well as the decisions made by the dispatcher and the model. Incompatibility of the decisions is denoted by "***".

Regarding the training pairs, the tuned fuzzy systems predict the dispatcher's decision in 97% of the cases. The networks are tested on 60 examples and the following result is obtained: in 95% of the cases the tuned fuzzy systems predict the dispatcher's decision.

Based on the obtained results it may be concluded that the proposed neurofuzzy models can assist and guide the dispatcher to assign vehicle types to meet transportation requests.

5. Conclusion

When assigning vehicles to transportation requests, dispatchers usually have built-in vague rules which they use to assign a given amount of freight to be sent to a given distance a given vehicle. Although fuzzy systems are numerical systems, they convert the linguistic control strategy based on the observed dispatcher's behavior and knowledge into an automatic control strategy. But the fuzzy framework does not eliminate the burden of knowledge acquisition. The major problems in the construction of a fuzzy system are the extraction of explicit dispatcher's heuristic control rules and the determination of the parameters of membership functions of the input/output variables. Thus, the performance of the developed fuzzy system depends on the number of available dispatchers and our ability to extract their assignment policy during structured, time-consuming interviews.

The main objective of this paper, that can be considered as a potential application to vehicle

Table 1
Characteristics of 100 transportation requests to be met (training pairs)

A	B	C	D	A	B	C	D
1.8	101	1	2***	18	80	2	2
2.5	60	1	1	18.3	48	2	2
3	19	1	1	18.8	111	2	2
3.5	56	1	1	19	52	2	2
3.5	75	1	1	19.2	80	2	2
3.8	60	1	1	19.5	89	2	2
4	43	1	1	19.8	130	2	2
4.2	72	1	1	20	45	2	1***
4.4	75	1	1	20.3	130	2	2
4.9	84	2	2	21	101	2	2
5	74	2	2	21	104	2	2
5	125	2	2	21.4	36	1	1
5.7	106	2	2	22	52	1	1
6	41	2	1***	22	66	1	1
6	98	2	2	22.7	57	2	2
6.3	92	2	2	23	311	3	3
6.7	138	2	2	23	371	3	3
7	130	2	2	24	281	3	3
7	190	2	2	24	305	3	3
7.6	48	1	1	24.5	330	3	3
7.8	29	1	1	24.7	262	3	3
8	28	1	1	25	12	1	1
8	29	1	1	25	370	3	3
8	41	1	1	26	45	1	1
8.3	42	1	1	27	114	2	2
8.4	67	1	1	27	115	2	2
9.8	341	3	3	27	291	3	3
9.8	440	3	3	27	420	3	3
10	498	3	3	27.2	115	2	2
10.8	362	3	3	28	650	3	3
11	264	3	3	29	35	1	1
12	26	1	1	29.2	36	1	1
12	297	3	3	30	14	1	1
12	420	3	3	30	25	1	1
12.5	400	3	3	30.3	60	1	1
12.9	25	1	1	31	100	2	2
13	27	1	1	31.8	68	2	2
13.5	321	3	3	32.6	130	2	2
14	260	3	3	33	115	2	2
15	23	1	1	33.1	100	2	2
15.6	40	1	1	35	105	2	2
15.7	17	1	1	38	20	1	1
16	28	1	1	38	360	3	3
16.2	17	1	1	39	11	1	1
16.5	28	1	1	40	280	3	3
16.8	52	1	1	41	371	3	3
16.9	26	1	1	44	12	1	1
17	31	1	1	51	355	3	3
17.2	62	1	1	54	257	3	3
18	62	2	2	56	125	2	2

A: Request amount of freight to be transported (in tons). B: Distance freight is to be transported (in kilometers). C: Dispatcher's decision. D: Model (maximum of the neural networks outputs) output.

Table 2
Characteristics of 60 transportation requests to be met (testing pairs)

A	B	C	D	A	B	C	D
3.6	66	1	1	20	255	2	2
4	36	1	1	20.3	220	2	2
4	76	1	1	21	165	2	2
4.2	80	1	1***	21	245	2	2
4.2	105	2	1	21.5	23	1	1
4.3	90	1	1	22	50	1	1
7	230	2	2	22.5	380	3	3
8.5	36	1	1	23	410	3	3
9.3	341	3	3	24	260	3	3
11	284	3	3	24	295	3	3
11	300	3	3	24	405	3	3
11.4	257	3	3	24.5	430	3	3
12	297	3	3	25	17	1	1
12.2	17	1	1	25	390	3	3
12.7	320	3	3	25.5	20	1	1
13	17	1	1	25.5	400	3	3
16	33	1	1	26	39	1	1
16.5	28	1	1	26	50	1	1
17	52	1	1	27	17	2	1***
17.3	63	1	1	27	160	2	2
17.8	60	2	2	27	180	2	2
17.8	164	2	2	27	415	3	3
18	40	2	1***	28	125	2	2
18	73	2	2	28	360	3	3
18	186	2	2	28	400	3	3
18.2	48	2	2	29	17	1	1
18.5	160	2	2	30	17	1	1
19	85	2	2	31.5	230	2	2
19	145	2	2	33	135	2	2
20	100	2	2	35	145	2	2

A: Request amount of freight to be transported (in tons). B: Distance freight is to be transported (in kilometers). C: Dispatcher's decision. D: Model (maximum of the neural networks outputs) output.

assignments, is to research the possibility of improving the performance of the developed fuzzy system. The method used for tuning the initial fuzzy system (developed by Milosavljević et al., 1996) is mapping of a fuzzy system into a feedforward neural network trainable with supervised learning. The aim of learning is to set the parameters of membership functions of the input/output variables (they are different for each type of vehicle).

Once the network has been trained on a large set of representative data, there is a justified belief that it (in the form of the fuzzy system) will perform reliably without frequent retraining when installed in the field. As a result of the study, it was shown that the proposed fuzzy system equipped with learning capability can be used to imitate the actual dispatcher's assignment policy.

References

Brown, M., Harris, C., 1994. Neurofuzzy Adaptive Modelling and Control, In: Grimble, M.J. (Ed.), Prentice Hall International Series in Systems and Control Engineering, UK.

Dougherty, M., 1995. A review of neural networks applied to transport. Transportation Research C 3/4, 247–260.

Er, M.C., 1988. Decision support systems: A summary, problems, and future trends. Decision Support Systems 4, 355–363.

Golden, B., Skicsim, C., 1985. Using simulated annealing to solve routing and location problems. Working paper MS/S 85-010, University of Maryland at College Park.

Hall, C., Smith, R., 1992. Pitfalls in the application of neural networks for process control. In: Warwick, K., Irwin, G.W.,

Hunt, K.J. (Eds.), Neural Networks for Control and Systems. IEE Control Engineering Series 46, pp. 243–256.
Jang, J.R.S., Sun, C.T., 1995. Neuro-fuzzy modeling and control. Proceedings of the IEEE 83 (3), 378–406.
Jang, J.R.S., 1997. Neuro-fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, Englewood Cliffs, NJ.
Kasabov, N.K., 1996. Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, Cambridge, MA.
Kirkpatrick, S., Gellat, L., Vecchi, M., 1983. Optimization by simulated annealing. Science 220, 671–680.
Kosko, B., 1992. Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence. Prentice-Hall, Englewood Cliffs, NJ.
Lin, C.T., Lee, C.S.G., 1996. Neural Fuzzy System: A Neuro-fuzzy Synergism to Intelligent Systems. Prentice-Hall, Englewood Cliffs, NJ.
Mamdani, E.H., Assilian, S., 1975. Experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man–Machine Studies 7, 1–13.
Mendel, J.M., 1995. Fuzzy logic systems for engineering: A tutorial. Proceedings of the IEEE 83 (3), 345–377.
Milosavljević, N., Teodorović, D., Papić, V., Pavković, G., 1996. A fuzzy approach to the vehicle assignment problem. Transportation Planning and Technology 20, 33–47.
Putz, A., Weber, R., 1996. Automatic adjustment of weights in fuzzy rule bases. EUFIT'96, September 2–5, pp. 933–938.
Teodorović, D., Pavković, G., 1992. A simulated annealing technique approach to the vehicle routing problem in the case of stochastic demand. Transportation Planning and Technology 16, 261–273.
Vukadinović, K., Teodorović, D., Pavković, G., Rosić, S., 1996. A neural network approach to mitigation of vehicle schedule disturbances. Transportation Planning and Technology 20, 93–102.
Vukadinović, K., Teodorović, D., Pavković, G., 1997. A neural network approach to the vessel dispatching problem. European Journal of Operational Research 102, 473–487.