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VEHICLE ROUTING IN THE CASE OF UNCERTAIN CUSTOMER DEMANDS AND SOFT TIME WINDOWS: A NEURO-FUZZY LOGIC APPROACH

Dragan Radovanović

Primary school principal, "Vuk Karadžić", Sočanica, Serbia

* draganr29@gmail.com

Vehicle routing, with its many variants, is one of the most important and frequently solved problems in transportation engineering. The aim of this paper is to develop a decision-making support tool for addressing the issue of dispatching vehicles in scenarios characterized by uncertain demands within soft time windows. In real-world scenarios, it is not uncommon for customer demands to exhibit flexibility, where certain early arrivals or delays may be deemed acceptable. Therefore, this paper introduces vehicle routing in more realistic contexts, offering potential practical implementations. The methodology for solving the problem is based on a fuzzy logic system whose membership functions are additionally adjusted using a neural network. Such a tool, neuro-fuzzy logic, is suitable for solving a defined routing problem since it can consider all the mentioned uncertainties in the distribution systems. Each user is assigned a performance index that considers travel time, demand, and delivery time windows. Then, the performance index is used as input data in the proposed vehicle routing tool based on the Clarke-Wright algorithm. The described approach has been tested on a concrete example, mimicking a distribution network resembling real-world conditions, incorporating estimated travel times between customers. The results demonstrate that the proposed approach can effectively handle customer demands, with an average delay of 5.05 minutes during the 80-minute distribution. In future research, some environmental factors could be included in the proposed model. In addition, one of the directions of future research could be vehicle re-routing using the ideas from this paper.

Keywords: vehicle routing, uncertain demands, soft time windows, fuzzy logic, neural networks

1 INTRODUCTION

The transportation of people and goods is one of the most important undertakings of today's society. Every day, a significant number of resources are spent on fuel, transportation, and equipment to get people or goods to the right place at the right time. In such a complex and vast system, even small improvements can result in significant savings. For this reason, a growing number of engineers and researchers are striving to find ways to improve today's transportation system from the standpoint of efficiency, safety, and environmental compatibility.

Furthermore, transportation is one of the largest polluters in the world [1]. In addition to various technological advances in this area, optimizing the operation of the vehicle fleet can also help reduce CO_2 emissions [2]. The principle is clear: fewer vehicles spending less time on the network means less pollution. It has been shown that solving route choice and vehicle routing problems can significantly reduce hazardous gas emissions [3].

The vehicle routing problem generally consists of the following: At a given location (garage, depot...), there are m vehicles, and n customers need to be supplied with certain goods. It is necessary to determine the best routes for the delivery vehicles while serving the customers in a transportation network. The goal is to determine the routes with a minimum value of a predefined objective function, usually the total transportation cost.

In real-world goods distribution systems, customers often allow flexibility regarding the timing of goods delivery. It is common for delivery requests to be expressed with vague statements such as "around 3 o'clock" or even within a broader timeframe like "between 2 and 3 o'clock." This time flexibility can arise from stochastic subjective factors related to customers, such as management organization within the customer company, the personality characteristics of the individuals in charge, the state of supplies, etc. Furthermore, while traffic congestion contributes to variations in travel time, weather conditions and seasonal variations are the next factors that affect delivery schedules.

For certain vehicle routing problems, customer demands can also be uncertain. Typical examples include garbage collections and postal deliveries, where the quantity of garbage and the number of postal units can vary with each distribution. Additionally, customer demand may fluctuate due to a variety of factors, such as changing trends, promotional campaigns, and economic crises, as customers endeavor to align their supply with end-user spending patterns.

The motivation for this study stems from the recognition of the complexities and uncertainties inherent in real-world distribution systems. Traditional vehicle routing approaches often struggle to effectively handle uncertain demands and soft time windows, which are common in practical scenarios. Therefore, there is a need for a decision-making support tool that can address these challenges and provide more efficient and reliable routing strategies.

Since its inception by Zadeh in 1965 [4], fuzzy theory has established itself as a valuable tool for managing ambiguous information. In the pursuit of devising an efficient routing strategy for real-world applications, a fuzzy logic system has been developed to account for available delivery time and uncertain customer demands. The capabilities of the initial fuzzy logic system are essentially improved to better understand and adapt to patterns in customer demands and delivery time windows within the same delivery network through the upgrade to an Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS, initially proposed by Jang 1993 [5], combines the strengths of neural networks and fuzzy logic to learn from historical data and, in this paper, provide more accurate predictions about routing strategies.

This study aims to address vehicle routing with uncertain demands and soft time windows by developing and testing a novel decision-making tool based on neuro-fuzzy logic. The contributions of this paper can be summarized as follows:

1. Development and introduction of a decision-making support tool tailored for vehicle routing in scenarios characterized by uncertain demands and soft time windows.
2. Introduction of a neuro-fuzzy logic methodology to effectively handle uncertainties inherent in distribution systems, improving the adaptability and robustness of routing strategies.
3. Implementation of a performance index for users, considering various factors such as travel time, demand, and delivery windows, to support routing decisions and improve overall efficiency.

The paper is organized as follows: After a brief introduction and a review of relevant studies from the literature, the second section is dedicated to methodology. This is followed by a practical example, which is followed by the results and discussion. The last section is devoted to conclusions and future research.

2 LITERATURE REVIEW

There are numerous mathematical formulations of the vehicle routing problem. One of the first and most widely accepted was proposed by Balinski and Quandt in [6]. The vehicle routing problem is reduced to a combinatorial optimization problem and can be solved by algorithms for finding the route of a travelling salesman. Further development of the mathematical formulation and application of dynamic programming in solving the classical vehicle routing problem can be found in the paper of Laporte and Nobert [7]. The application of genetic algorithms to solve the vehicle routing problem can be found in the paper of Prins [8]. Using a real network, the author proved the efficiency of the proposed algorithm. A more comprehensive presentation of the classical vehicle routing problem and algorithms for its solution can be found in the paper by Toth and Vigo [9]. An up-to-date literature review of the state of the art can be found in the paper by authors Konstantakopoulos, Gayialis, and Kechagias [10].

In the field system of goods distribution, delivery vehicles have a limited capacity. Customers have a certain demand for goods, and it is necessary to determine the number of vehicles for distribution and, more importantly, their routes, unlike the classical routing problem, where it is assumed that the vehicle has an unlimited capacity. The problem of routing vehicles with limited capacity was posed in the work of Dantzig and Ramser [11] and has since attracted the attention of many researchers. Routing problems of this type are generally reduced to combinatorial optimization problems. Heuristic approaches have been proposed by the following papers [12-14]. Metaheuristic approaches can be found in papers [15-16].

In the routing problem with time windows, each of the customers has made a demand regarding the arrival time of the delivery vehicle. If the distributor does not comply, it must pay additional penalties for non-compliance. Metaheuristic approaches have achieved the most significant results in solving vehicle routing problems with time windows. Tabu search has been applied by the following authors: Potvin et al. [17]. An example of problem-solving with simulated annealing can be found in the paper of Chiang and Russell [18]. Genetic algorithms have been used by the following authors to solve the subject problem [19-20]. Bee colony optimization based on group intelligence of these insects was applied in the paper of Nikolić and Teodorović [21].

In practice, customers are often not so decisive when it comes to the arrival time of goods. Therefore, the authors, who wanted to approximate the real system, developed a routing problem with soft time windows. This problem can be reduced to a combinatorial optimization problem, which was shown in the paper of Taillard et al. [22]. A specific interactive algorithm for vehicle route construction was developed by Figliozzi [23]. Using examples from the literature, the author has shown that this algorithm is competitive with others. The introduction of the concept of Customer Service Index and the application of fuzzy logic to solve the problem in question can be found in the paper of Tang et al. [24]. The algorithm developed in this material is based on a similar idea, i.e., the definition of the customer's priority index.

A realistic distribution system often assumes that customer demands are not exactly defined. The application of fuzzy logic in solving this type of vehicle routing problem can be found in the paper Teodorović and Pavković [25]. The hybrid approach of applying metaheuristics based on the artificial intelligence of bees and phase logic is the work of Lučić and Teodorović [26]. The application of data clustering for routing vehicles with uncertain customer demands can be found in the paper of Sungur, Ordonez, and Dessouky [27]. The authors generated routes based on the principle of least cost per network link and demonstrated the justification of their approach with a practical example.

In this paper, the problem of vehicle routing for the case where customer demand is uncertain and the time windows for delivering goods to the customer are of the "soft" type is considered. The problem that the author addresses in this paper can be formulated as follows: For the given distribution network consisting of customers and links between these customers, find the routes for the delivery. The constraints are such that the customers` demands are uncertain, delivery is with soft time windows, and vehicles have limited capacity.

The authors Tas et al. [28] attempted to solve a similar problem by reducing it to combinatorial optimization and applying tabu search. In their case, travel times to customers were assumed to be uncertain, which is common in this field, but they did not consider customer demand to be uncertain values, but rather distribution costs. Xu, Yan, and Li [29] addressed the same problem defined in this paper using particle swarm optimization, while Yang, Wang, and Wu [30] used genetic algorithms. Khodashenas et al. [31] addressed an integrated multi-depot vehicle routing problem (MDVRP) with simultaneous pickup and delivery (SPD) and package layout, considering unpredictable pickup, delivery, and transfer costs. They employed the NSGA II and MOALO algorithms to solve this problem. Yadegari et al. [32] introduce a novel fuzzy mixed-integer nonlinear mathematical model to address the two-echelon allocation-routing problem under uncertainty.

As shown in the literature review, many authors have reduced the vehicle routing problem to combinatorial optimization problems. Then, they found solutions using operational research methods (mostly metaheuristics). Considering the nature of the problem and the given constraint of goods demand and delivery times, it is not always possible to accurately predict the transportation time of the vehicles in the network and the vehicle routes according to their capacity. The reason for this is the frequent congestion of the network, especially in the morning hours, the presence of traffic signals at intersections, the possible closure of some streets due to work or traffic accidents, and various other limitations of the network.

After all that has been discussed, reducing the given problem to combinatorial optimization problems carries the risk of yielding results that are "precisely incorrect." In other words, the models may fail to accurately address the practical demands of field distribution.

The idea of combining two problems into one, i.e., solving the vehicle routing problem when there are soft time windows and uncertain customer demands, as far as the author is aware, has not been considered with a neuro-fuzzy approach. Due to the nature of the problem, a combination of fuzzy logic and neural networks has proven to be a reliable method for dealing with uncertainties and is well-suited for the problem stated in this paper.

3 METHODOLOGY

This section consists of two parts. The details about the neuro-fuzzy algorithm for the vehicle routing problem are explained in the first part. A model for vehicle routing is presented where the demand of the transportation network nodes (customers) is uncertain. Moreover, the exact time when the goods are to be delivered is not fixed, but it is also not entirely clear when this will happen. In the field, this case is most common, especially when it comes to the distribution of perishable food products, etc. In other words, customers have not precisely formulated the demands regarding the arrival time of the vehicle but have allowed certain deviations (for example, 7 h and 20 min or between 7 h and 7 h and 15 min). Time windows defined in this way are called "soft" time windows, in contrast to classical time window routing problems where the distributor must pay a penalty for each deviation. In the second subsection, it is shown how outputs from the neuro-fuzzy system are used to come up with routes for delivery vehicles.

3.1 Neuro-fuzzy algorithm for vehicle routing

Since customer demands are stated to be uncertain (fuzzy) and it is not always possible to accurately determine the travel time of vehicles in the network, a fuzzy logic system for vehicle routing was developed. It is assumed that fuzzy logic is suitable for solving the vehicle routing problem posed in this way due to its ability to approximate highly nonlinear and complex quantities.

3.1.1 Mathematical formulation of the input variables

The demands expressed by customers are defined as fuzzy variables. For example, a customer may demand 14 to 16 units of goods or about 22 units of goods. The delivery time is also not precisely defined. For example, the goods must arrive by about 8 a.m. In addition to these quantities, the travel time from the base (depot) to each customer is also defined for this model. As explained earlier, this time cannot be taken as an exact quantity. The available delivery time is the difference between the travel time from the depot to the customer and their desired delivery time.

Within this model, it is understood that goods are distributed from one base. The base can be a distribution center, a depot, or a warehouse. The problem of vehicle routing with more than one base will not be considered.

The estimated travel time from the depot to the customer can be obtained using the "Google" application "Google Maps-Live traffic". This application approximates the travel time from an origin to a destination based on historical data on traffic volumes and vehicle speeds retrieved from users' cell phones. In real-time, the "Google" application is also used to navigate vehicles through the network and offer them the route with the shortest travel time.

For cities not covered by this application (or for which not all options of this application are available), it is also possible to obtain the approximate travel time on the street network links. The transportation network G consists of n links, and each link is denoted by (i,j), where i is the index of the upstream intersection and j is the index of the downstream intersection. Let t_{ij} denote the travel time of a vehicle along the link (i,j). The travel time t_{ij} is calculated using a well-known formula [33] (Equation 1):

$$t_{ij} = t_{ij}^0 \cdot \left[1 + \alpha \cdot \left(\frac{q_{ij}}{c_{ij}} \right)^{\beta} \right] \quad (1)$$

where (Equation 2):

$$t_{ij}^0 = \frac{l_{ij}}{v_{ij}} \quad (2)$$

where:

t_{ij}^0 - transport time on the link (i,j) as a function of free flow speed [s],

l_{ij} - link length (i,j) (m),

v_{ij} - free flow speed (m/s),

q_{ij} - the flow of vehicles on the link (i,j) (veh/h),

c_{ij} - link capacity (i,j) (veh/h).

The values for the parameters were obtained empirically: α = 0.15 and β = 4. The link capacity and the vehicle demands on the link are known in advance. Vehicle demands are estimated based on historical data.

Let us denote by g_j the average delay at the j-th intersection. The delay can be calculated using a well-known formula [34]. To calculate the delay, it is necessary to have the signal plans of all intersections in the network. The calculation of delay is not described in detail here, as this would be a significant digression from the main problem. The structure and method of calculating delay are well-known in the literature and can be found in the HCM [34].

Denote by N_{ij}^k the set of links and by N_j^k the set of intersections that must be traversed to get from the base to the k-th customer. Finally, the total estimated travel time from the base to the k-th customer (t_k) is calculated as (Equation 3):

$$t_k = \sum_{ij=1}^{\left|N_{ij}^k\right|} t_{ij} + \sum_{ij=1}^{\left|N_j^k\right|} t_{ij} \ \text{(s)} \quad (3)$$

The problem of determining the set N_{ij}^k (and therefore set N_j^k) reduces the problem of determining the shortest distance from one to all other nodes. The only difference is that the network links are weighted by travel time instead of Euclidean link length. The most used algorithm for solving the shortest path through the transportation network problem is the well-known Dijkstra's algorithm [35].

3.1.2 Formation of a fuzzy logic system

Input variables in the fuzzy logic system are customers' demands (X_{1k}) and available time for delivery to the customers (X_{2k}). The output variable is the customer priority index (Y_k). In other words, the fuzzy logic system evaluates the priority index for each customer based on their product demands and available delivery time.

Gaussian curves were used as membership functions for input variables in the fuzzy logic system (FLS) (Figure 1). Gaussian curves were chosen because they are suitable for manipulation when tuning the FLS, as well as because they describe the input variables well and provide satisfactory system sensitivity.

A Sugeno-type FLS is formed based on the input and output variables. The intervals in which the input and output variables can be found are given in Table 1.

Table 1. Domain of functions X_1, X_2 and Y

Function	Domain [min, max]
X_1 (the units of goods)	[2, 17]
X_2 (minutes)	[4, 16]
Y	[1, 10]

The function domains given in Table 1 may be determined in other ways, depending on the specific conditions and network on which the distribution is performed. The membership functions of the input variables are shown in Figure 1.

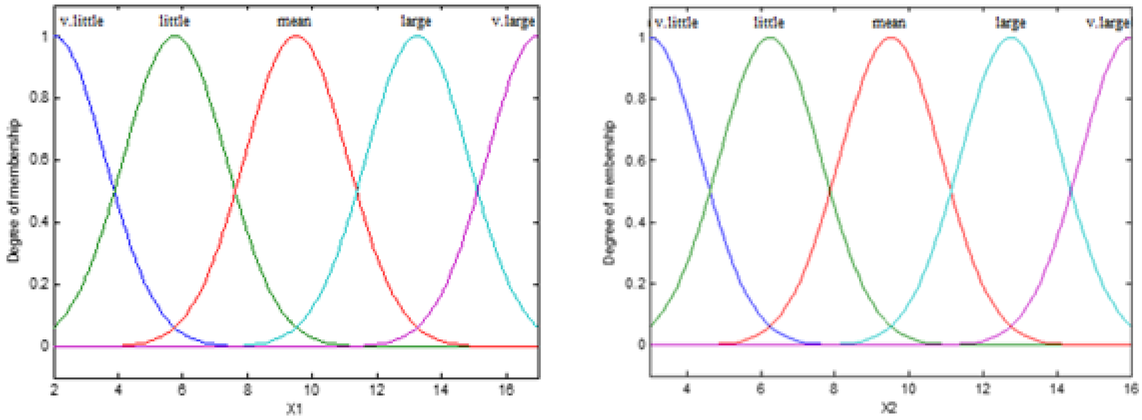


Fig. 1. Input variables of FLS with membership functions

The parameters of the input variable X_1 are very little gmf (1.593, 2); little gmf (1.593, 5.75); mean gmf (1.593, 9.5); large gmf (1.593, 13.5); very large gmf (1.593, 17). The parameters of the input variable X_2 are very little gmf (1.381, 3); little gmf (1.381, 6.25); mean gmf (1.381, 9.5); large gmf (1.381, 12.75); very large gmf (1.381, 16). Where gmf is the abbreviation for the Gaussian membership function.

The output variable Y expresses the degree of priority of the customer served in the distribution. In other words, this variable expresses how much one of the customers has an advantage over another customer in the distribution.

The Sugeno-type fuzzy logic system differs from the basic Mamdani type in that the output variables are specified as constant values. In the Mamdani type, the output variables are given in the same way as the input variables: by a fuzzy set. The reason for choosing the Sugeno type is that the neural network can change the membership functions of the fuzzy logic system, thus providing the basis for the application of a hybrid algorithm of neural networks and fuzzy logic. The number of output membership functions must precisely match the number of rules, which, in this case, is 25. The corresponding values of output membership functions are shown in Table 2.

After determining the input variables of the FLS, it is necessary to create a rule base, which is given in Table 2. Depending on the values of the input variables, a fuzzy rules base was formed, so that greater importance is given to the customers who need more goods and for whom the availability of delivery time is lower compared to other customers. The approach of giving greater importance to the customers who demand more goods has an indirect effect on the profit of the distributor.

Table 2. The fuzzy rules base

Rule #	IF (X_1 and X_2)		THEN	Rule #	IF (X_1 and X_2)		THEN	Rule #	IF (X_1 and X_2)		THEN
	X_1	X_2	Y		X_1	X_2	Y		X_1	X_2	Y
1.	V. little	V. little	5.5	10.	Little	V. large	9	19.	Large	Large	5.5
2.	V. little	Little	7	11.	Mean	V. little	3	20.	Large	V. large	6
3.	V. little	Mean	8	12.	Mean	Little	5	21.	V. large	V. little	1
4.	V. little	Large	9	13.	Mean	Mean	6	22.	V. large	Little	2.5
5.	V. little	V. large	10	14.	Mean	Large	7	23.	V. large	Mean	3.5
6.	Little	V. little	5	15.	Mean	V. large	8	24.	V. large	Large	4.5
7.	Little	Little	6	16.	Large	V. little	2	25.	V. large	V. large	5.5
8.	Little	Mean	8	17.	Large	Little	3	The membership functions of output variables present the Y values in this table			
9.	Little	Large	8.5	18.	Large	Mean	5				

Due to the extreme sensitivity and unpredictability of the system and the nature of the input variables, a neuro-fuzzy logic system was formed. Using 500 input-output data pairs, a neural network was trained to "fine-tune" the parameters of the membership functions of the input variables. The dataset utilized for training the ANFIS model is hypothetical.

3.1.3 Architecture of neuro-fuzzy logic system

Due to all the above, FLS was upgraded to ANFIS (Figure 2). ANFIS (Adaptive neuro-fuzzy inference system) was used to further tune the FLS membership functions. This was achieved by training a neural network. In this work, the "backpropagation" algorithm was used for the training of ANFIS. This hybrid algorithm was proposed by [32].

Neuro-fuzzy logic attempts to take advantage of both systems of approximate reasoning and combine them into a powerful hybrid model. Fuzzy logic is a flexible and powerful tool for finding solutions to problems that involve vaguely defined variables, or those that are not exactly defined. This possibility of fuzzy logic is applicable in solving traffic problems, which includes the problem of vehicle routing. The role of the neural network is to "train" the fuzzy logic system with field data, contributing to its response to changes in input variables in the realistic system. Together, these two tools constitute a powerful hybrid algorithm for approximating various parameters and quantities characterized by pronounced nonlinearity and unpredictability, as shown by numerous examples in literature and engineering practice.

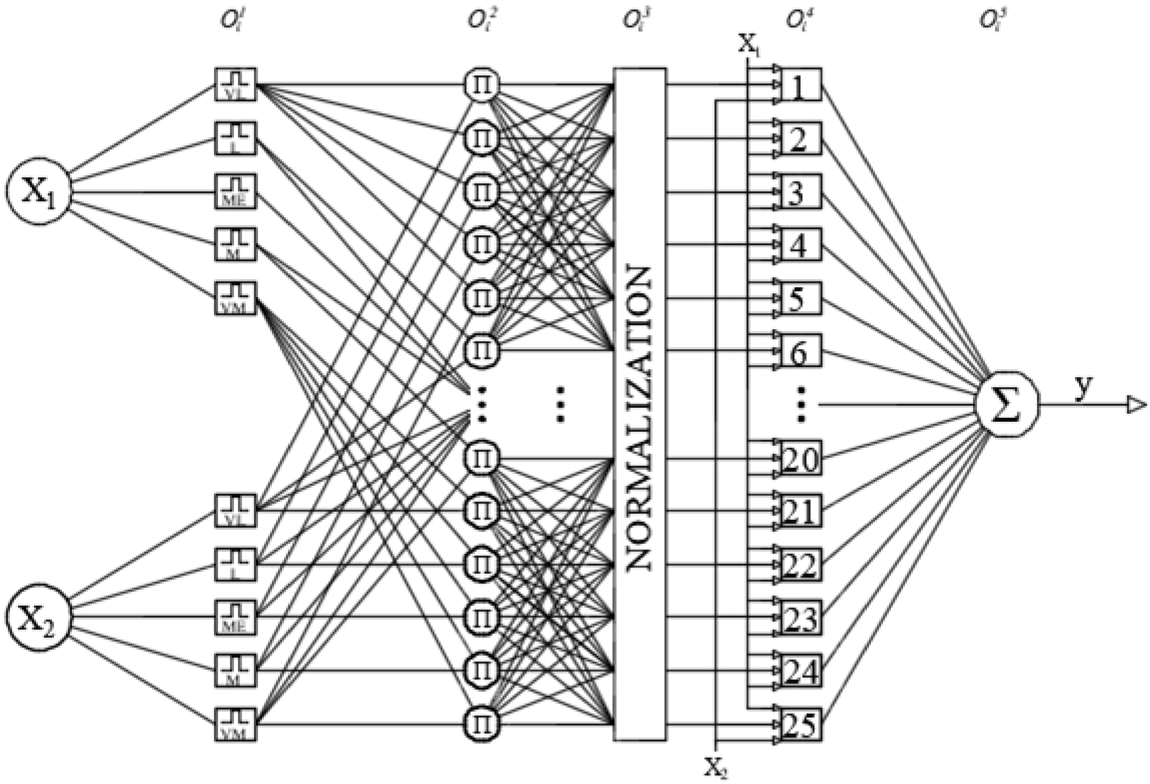


Fig. 2. Neuro-fuzzy network architecture and output generation

Figure 2 graphically shows the fuzzy inference mechanism for obtaining the output function *f* based on the input values [X_1, X_2]. The weighting coefficients ω_1 and ω_2 are obtained from the degree of membership in the premise, while the output function f_{yi} is the weighted average of each of the THEN parts of the rule. Each network node in the same layer performs the same type of function. The outputs of the *i*-th node in the *j*-th layer are marked with O_i^j.

Layer 1. The nodes of the first layer represent verbal categories of input variables that are quantified by fuzzy sets. Each node of the first layer is an adaptive node and is described by a membership function $\mu_{xi}(x_i), i = 1,...5$.

Membership functions are described in the form of Gaussian curves characterized by two parameters: function centre (*c*) and function width (*σ*), (Equation 4):

$$Gaussian(x,c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (4)$$

Since fuzzy rules are expressed in the form: "If - condition, Then - consequence", categories of input variables quantified by fuzzy sets are displayed by adaptive nodes of the first layer.

Layer 2. Each node of this layer calculates the minimum value of the two input values of the adaptive neural network. The output values of the nodes of the second layer represent the significance of the rules (Equation 5):

$$O_i^2 = \omega_i = \mu_{Ai}(x_1) \cdot \mu_{Bi}(x_2) \quad (5)$$

Layer 3. Each *i*-th node (out of a total of *n*) in this layer calculates the total weight of the *i*-th rule from the rule base according to the expression (Equation 6):

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i}, \qquad i = 1,2, \ldots, n \tag{6}$$

Layer 4. The fourth layer has 25 adaptive nodes representing the output size Y (priority index for each customer). Each node of this layer is connected to a normalized neuron from the previous layer. Defuzzification of neurons is done as follows (Equation 7):

$$O_i^4 = \overline{\omega_i} \cdot f_i = \overline{\omega_i} \cdot \left(p_i x_1 + q_i x_2 + r_i\right), \qquad i = 1,2, \ldots, n \tag{7}$$

where n is the total number of rules in the fuzzy rule base, while p_i, q_i and r_i are the parameters of the i-th rule's consequence.

Layer 5. The only node of the fifth layer is a fixed node in which the output result of ANFIS is calculated. It is a fuzzy set with certain degrees of membership of the possible values of Y for a particular customer during the distribution. The final defuzzification is performed in the node of the fifth layer. The output value is a crisp number located in the interval [1, 10], (Equation 8):

$$O_i^5 = \sum_i \overline{\omega_i} \cdot f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{8}$$

3.1.4 Training of ANFIS

The output function of ANFIS, shown by Equation 9, is linearly dependent on the parameters from the consequences of the fuzzy rule.

$$f = \overline{\omega_1} \cdot f_1 + \overline{\omega_2} \cdot f_2 = \left(\overline{\omega_1} \cdot x_1\right) \cdot p_1 + \left(\overline{\omega_1} \cdot x_2\right) \cdot q_1 + \left(\overline{\omega_2} \cdot x_1\right) \cdot p_2 + \left(\overline{\omega_2} \cdot x_2\right) \cdot q_2 \tag{9}$$

Then, for the k-th pair of input-output data pairs, the output from the ANFIS network (E_k) can be calculated as (Equation 10):

$$E_k = \left(T_k - O_k\right)^2 \tag{10}$$

where T_k and O_k are the desired output and obtained output from ANFISA, respectively. Then, for the entire set of 500 input-output training pairs, it is possible to calculate the average error E as (Equation 11):

$$E = \sqrt{\frac{\sum_{k=1}^{500} E_k}{500}} \tag{11}$$

During the backward pass, the error signal is propagated, and the previous parameters are "updated" according to the corresponding rule from the database [5].

The activation functions of neurons are required for the network to learn non-linear functions. Without nonlinearity, neurons would have no more capabilities than an ordinary perceptron network (consisting only of inputs and outputs). As an activation function in ANFIS models, the so-called "bell" function is most often used in the following form (Equation 12):

$$y = \left(1 + \left(x - \frac{s}{r}\right)^t\right)^{-1} \tag{12}$$

where: r, s, and t are control parameters that adjust the slope, center, and width of the “bell” function, respectively.

The most commonly used Neural Network (NN) training algorithm is backpropagation [36]. Backpropagation learns schemes by comparing the output of the neural network to the desired output and calculating errors for each node in the network. The neural network adjusts the connection weights according to the error values assigned to each node. The calculation starts with the output layer, goes through the hidden layers and ends at the input layer. After modifying the parameters, new inputs are fed to the network. Training will not end until the network can produce outputs with satisfactory accuracy. During the training process, the fuzzy set membership functions are "fine-tuned" by numerical input-output data pairs. The resulting membership functions are shown in Figure 3.

The parameters of the input variables X_1 after training are very little gmf (0.46, 2.91); little gmf (1.32, 5.55); mean gmf (2.04, 8.85); large gmf (2.46, 12.84); v. large gmf (0.85, 17.16). The parameters of the input size X_2 after training are very little gmf (1.68, 2.51); little gmf (1.98, 6.43); mean gmf (1.5, 9.49); large gmf (1.02, 12.76); very large gmf (1.1, 16.16).

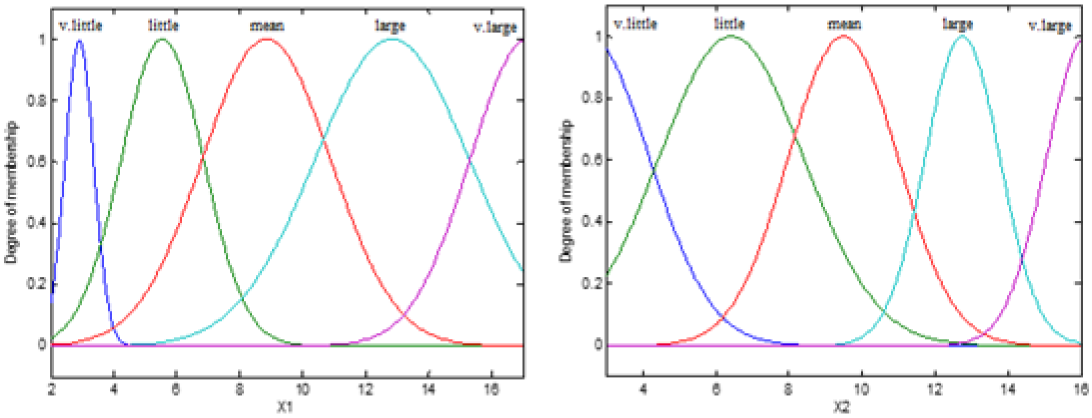
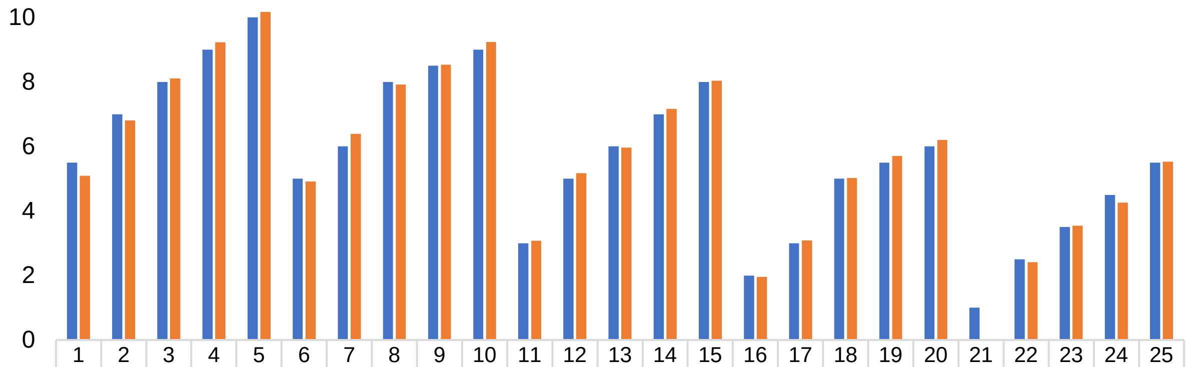


Fig. 3. Membership functions after NN training

After training, the corresponding values of output membership functions undergo "fine-tuning." Figure 4 illustrates the changes in Y values (output membership functions, i.e. the consequence part of the rule base) before and after the tuning process.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Before tuning	5,5	7	8	9	10	5	6	8	8,5	9	3	5	6	7	8	2	3	5	5,5	6	1	2,5	3,5	4,5	5,5
After tuning	5,09	6,81	8,11	9,23	10,2	4,91	6,39	7,92	8,54	9,23	3,08	5,17	5,96	7,16	8,04	1,95	3,09	5,03	5,7	6,21	0,01	2,41	3,55	4,26	5,52

Fig. 4. Y values before and after tuning

After 300 epochs (iterations), the error is reduced to an acceptable value. The process of error reduction through epochs (iterations) is given in Figure 5.

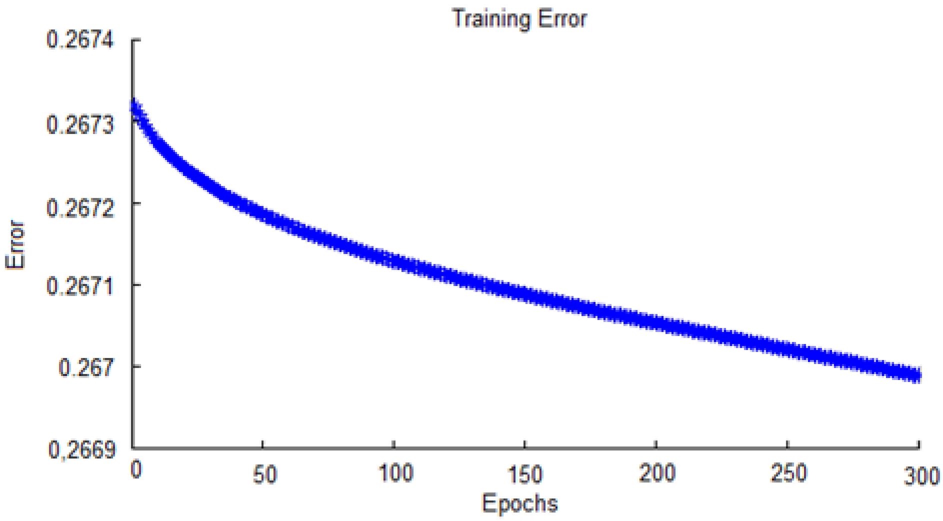


Fig. 5. Error reduction through epochs

Figure 6 shows the 3D dependence of input and output variables. In other words, the figure shows the sensitivity of the output variable (Y) concerning the input variables (X_1 and X_2) before and after the learning process.

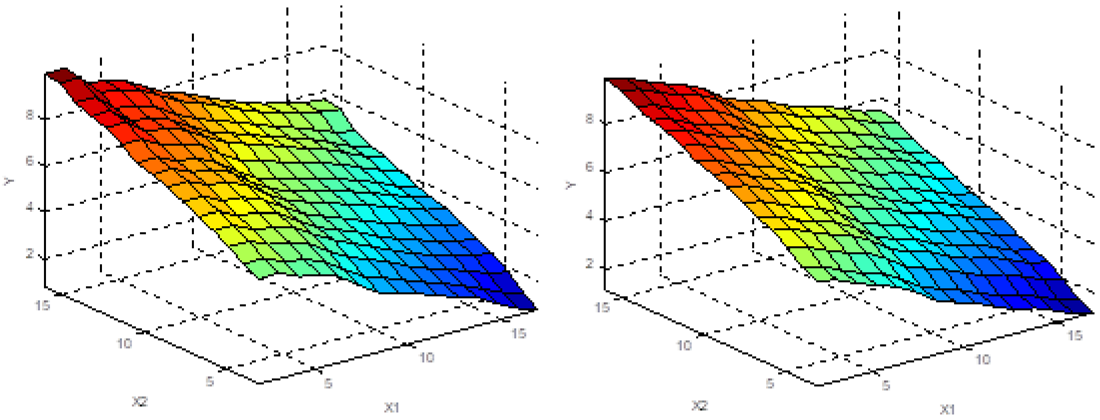


Fig. 6. 3D dependence of FLS (left) and ANFIS (right) models

Figure 6 shows the sensitivity of the output to the input values when evaluating customers` priorities during the distribution. This sensitivity is somewhat more pronounced for higher values of the input variables. After training the NN with real-like input-output data, a slightly more complex 3D structure of this dependency is seen compared to the FIS, which leads to a more accurate estimate of the output variable.

3.2 Vehicle routing algorithm

Once the priority indices for each customer are known, the formation of vehicle routes for distribution can begin. As a result, the algorithm provides the required number of vehicles for the distribution of goods and their routes. It is only necessary to know in advance the capacity of the vehicle, i.e., the number of units of goods it can transport. The flowchart of the vehicle routing algorithm is shown in Figure 7.

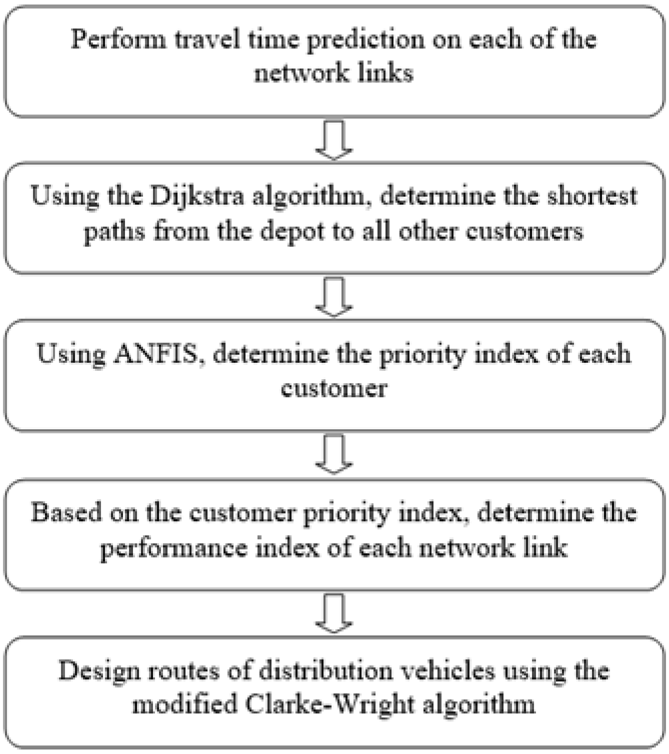


Fig. 7. Flowchart of the vehicle routing algorithm

The first three steps of the above algorithm have already been explained in detail in earlier sections. Let us denote by IP_k the priority index of each of the k customers, and by IP_{ij} the performance index of each of the (i,j) links of the network. Let us assume that k-th customer is in the i-th node of the network and the k+1 customer is in the neighbouring j-th node of the network. The performance index of the (i,j)-th link of the network is determined as the sum of the priority indices of the k-th and k+1 customer. In other words, the performance index of a network link is equal to the sum of the priority indices of the customers connected by that link.

A modified Clarke-Wright algorithm [37] for planning vehicle routes consists of the following steps:

Step 1: Instead of calculating the savings, as in the classical version of the algorithm, sort the links of the network by their performance index, from the highest to the lowest value.

Step 2: Consider the sorted links one by one and include them in partial routes in such a way that the following constraints are not violated:

a) None of the nodes of the link was included in any partial route,
b) One of the nodes of the link is already included in the partial route, but only if it is an external node of the partial route,
c) Both nodes of the link are already involved in two different partial routes, neither of them being external. In this case, the two partial routes are merged into a new partial route.

Step 3. When all customers are included in the partial routes, finish with the algorithm.

The number of partial routes will be equal to the number of vehicles required for the distribution of goods through the given transport network.

When adopting a new partial route, it is mandatory to consider whether the capacity of the vehicle is affected. If the capacity of the *v*-th vehicle is denoted by N_v, the total demand of the *k*-th customer by d_k, and the number of customers included in the *r*-th route by K_r, the following condition should be satisfied (Equation 13):

$$\sum_{k=1}^{|K_r|} d_k \le N_v \tag{13}$$

If there are still unserved customers left after passing all the links from the list, one must merge them on one of the routes, not to exceed the capacity limit of the vehicle. If there are still unserved customers, create a new route that connects the unserved customers using the Clarke Wright algorithm described above. Weight links between customers with a performance index. Additionally, if there is no link between some pairs of customers, find the shortest route between these customers based on the travel time criterion and calculate the average value of the performance index of the links that make up this route. If there is no direct link between the base and the first customer on the route, reach it via the shortest route according to the criterion of travel time. The same applies to the route from the last served customer to the base.

The algorithm does not allow sharing of shipments, which is one of the limitations of this approach. In other words, a customer cannot be served by two vehicles. Although this can lead to some savings, it is not a practical solution because it complicates the distribution process. The algorithm assumes that the number of vehicles per link and their capacity are known in advance. Based on these data, the travel time on a link is estimated as a significant input variable of the model. It is also assumed that the variations in vehicle volume and link capacity were recorded, which will be later used to generate data for training the neural network.

4 NUMERICAL EXAMPLE

In the distribution network, shown in Figure 8, the proposed algorithm for vehicle routing was tested. Figure 8 shows the travel times by links expressed in minutes. Let it be adopted that the distribution of goods begins at 7 a.m.

The network in Figure 8 does not represent a street network but a network of calculated shortest paths among customers according to the criterion of travel time. In other words, the given distribution network is a sub-network of the street network. The shortest distances between customers on the street network can be found using the already mentioned Dijkstra algorithm.

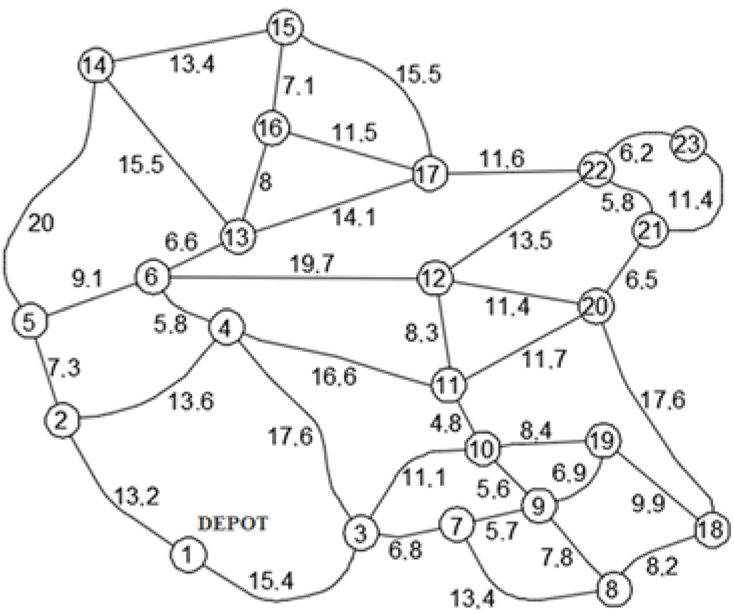


Fig. 8. The distribution network for testing

The base (depot) is located in node 1, and distribution is performed by vehicles with a capacity of N_v = 50 loading units. The unloading time per unit is constant and is t_{unl} = 10 s. By applying Dijkstra's algorithm, travel times from the base to each *k*-th customer were obtained and presented in Table 3. Table 3 also contains data on the available time for each customer and their demands, expressed in units of goods. The available time for delivery indicates the number of minutes within which the operator must complete the delivery after the pre-defined earliest delivery time. All time-dependent data are in minutes. The last column of Table 3 shows the priority indices determined for each *k*-th customer using the ANFIS algorithm.

Table 3. Input data and customers priority index

Customer (k)	Travel time from the base (min)	The earliest time of delivery	Availability time (min)	Demand for goods (per unit of goods ± 3)	IP
BASE	0	7:00	0	0	0
2	13.2	7:20	7	8	6.2
3	15.4	7:40	5	13	8.3
4	26.8	7:55	3	8	7.3
5	20.5	8:20	4	15	9
6	29.6	8:35	5	12	8
7	22.2	7:25	2	7	7
8	35.6	7:45	9	5	4.1
9	27.9	7:30	2	4	5.7
10	26.5	8:30	3	4	5.6
11	31.3	8:30	3	10	7.6
12	39.6	8:40	5	7	6.4
13	36.2	7:40	3	7	6.6
14	40.5	7:50	10	13	6.7
15	51.3	8:05	14	5	2.7
16	44.2	7:55	11	4	3.1
17	50.3	7:55	5	12	8.1
18	43.8	8:00	16	10	3.8
19	34.8	8:10	15	8	3.5
20	43	8:10	7	10	6.6
21	49.5	8:15	11	16	7.2
22	53.1	8:15	7	5	5.1
23	59.3	8:20	11	9	5.1

Due to the relatively (fuzzy) expressed demands, a tolerance of ± 3 units of goods per route is allowed for the delivered goods.

Based on the customer priority indexes, performance indices are determined for each network link. The values of links performance indices are sorted from the highest to the lowest value and listed in Table 4.

The links leading from the base to the neighboring nodes have a lower IP value per link, but this does not affect the distribution because these are the links that vehicles must pass through to reach other customers. This is because node 1 (the base) has no demand for goods.

Table 4. Sorted performance indexes by network links

Link	IP	Link	IP	Link	IP
5-6	17	20-21	13.8	15-17	10.8
5-14	15.6	2-4	13.5	18-20	10.4
3-4	15.6	13-14	13.3	22-23	10.2
4-6	15.3	17-22	13.2	8-9	9.8
3-7	15.3	10-11	13.2	13-16	9.8
2-5	15.2	12-20	12.9	14-15	9.4
4-11	14.9	7-9	12.7	9-19	9.2
13-17	14.8	21-22	12.3	10-19	9.1
6-13	14.7	21-23	12.2	1-3	8.3
6-12	14.4	12-22	11.5	8-18	7.9
11-20	14.2	9-10	11.3	18-19	7.3
11-12	14	16-17	11.3	1-2	6.2
3-10	13.9	7-8	11	15-16	5.8

Finally, by applying the modified Clarke-Wright algorithm, the final vehicle routes are as follows:

Route of the 1st (first) vehicle: **B-9-7-3-4-11-20-B**

Route of the 2nd (second) vehicle: **B-16-13-17-22-21-23-B**

Route of the 3rd (third) vehicle: **B-15-14-5-6-12-B**

Route of the 4th (fourth) vehicle: **B-2-8-18-19-10-B**

Some customers served by vehicles on routes 1, 2, and 3 receive one unit of the goods less than the average value they ordered. Example: Customer 9 has ordered about 4 units of goods, and 3 units of goods are delivered to him, the same is true for customer 15. To which customer less or more goods are delivered, the deliverer decides, and the algorithm offers it how many units of goods he can take away or add to the customers on the route.

If the delay (or earlier arrival) of the vehicle at the *k*-th customer is marked with t_{del}, the values of this demand per customer are shown in Table 5.

Negative values in Table 5 indicate that a vehicle arrives before the scheduled time, while positive numbers indicate that vehicles are late for customer delivery. Zeros indicate that a vehicle arrived within the defined time window for delivery.

Table 5. Delays and early arrivals by customers (in minutes)

k	2	3	4	5	6	7	8	9	10	11	12
t_{del}	-7	0	4	4	0	5	9	2	2	-10	0
k	13	14	15	16	17	18	19	20	21	22	23
t_{del}	10	6	-12	-11	8	0	0	15	2	0	4

Based on Table 5, it can be concluded that the average deviation from the delivery time interval is 5.05 minutes. Again, it is at the discretion of the distributor how early (or later) to start distributing the goods. This depends on a case-by-case basis (customer habits and demand, available workforce, etc.).

Figure 9. shows the actual arrival time of the delivery vehicle for each customer that creates the distribution network. Additionally, it illustrates the earliest and latest arrival times per customer, facilitating the identification of deviations in vehicle arrival from the pre-defined "soft" time window.

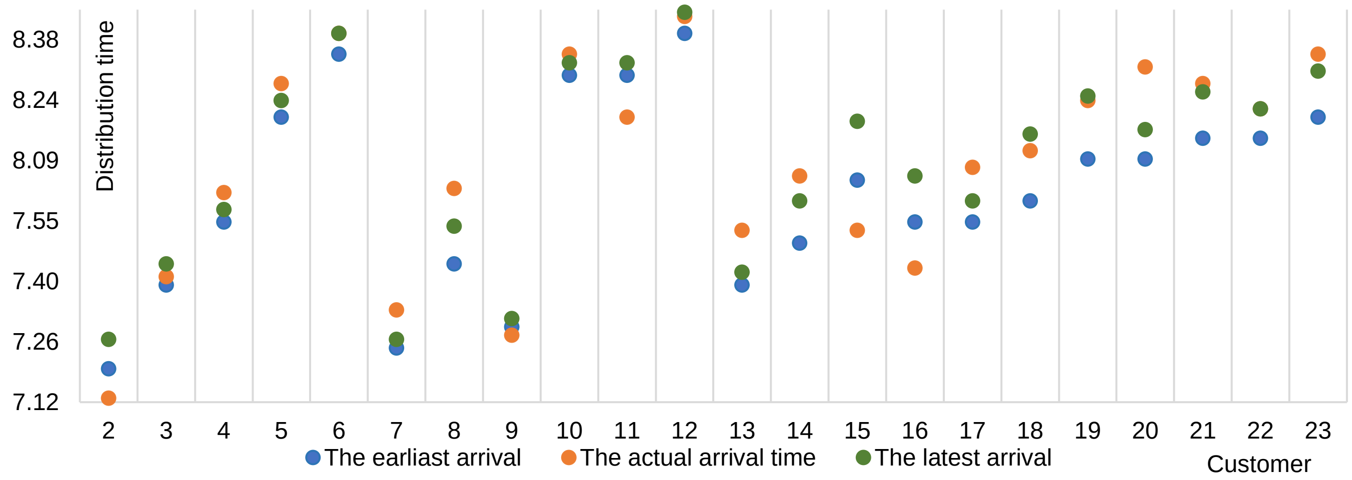


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Fig. 9. The deviation of arrival time from customers' time windows

From Figure 9, it is evident that 3 customers are served within the time window, while the remaining customers arrive either earlier or later. The average early arrival time is 8.4 minutes, while the average late arrival time is 4.06 minutes. Those times can be considered acceptable within the distribution network in this example.

The considered example represents a complex network with complex requirements when distributing goods. The proposed algorithm has shown that it can propose solutions in such an environment and what are the consequences of the given solutions. Moreover, it is left to the distributor to make decisions about some details (when to start distribution and to which customer to deliver a little less or a little more goods) that depend on the specific conditions associated with the knowledge of the behavior and demands of the customers to whom to deliver. The algorithm proposed in this paper serves as a decision support tool for dispatchers.

The problem of vehicle routing is a complex task with various nuances and challenges. It is difficult to account for all the factors that a distribution system might encounter. From this perspective, the proposed approach in this paper has the following limitations:

1. The algorithm assumes that goods are distributed from a single base, such as a distribution center, depot, or warehouse. This limitation may not be applicable in scenarios where there are multiple bases involved in the distribution network, such as in large-scale logistics operations covering multiple regions or cities;
2. Handling dynamic changes in demands and time windows poses a significant challenge. While your algorithm integrates fuzzy logic and ANFIS to manage uncertain demands and soft time windows, there may still be limitations in accurately modelling and predicting customer demands and delivery time variability. Factors such as sudden changes in demand patterns or unforeseen delivery delays may not be fully addressed by the current methodology;
3. The effectiveness of the neuro-fuzzy logic approach relies heavily on the availability and quality of historical data for learning and prediction. In scenarios where historical data is limited or unreliable, the performance of the algorithm may be compromised, leading to suboptimal routing strategies;
4. The performance of the ANFIS model may be sensitive to the selection of parameters and tuning of the fuzzy inference system. In practice, finding optimal parameter settings may require extensive experimentation and fine-tuning, which can be time-consuming and resource-intensive.

Addressing these limitations and providing insights into potential areas for improvement could strengthen the robustness and practical applicability of your proposed algorithm for solving the vehicle routing problem with uncertain demands and soft time windows.

5 CONCLUSIONS

This paper addresses the problem of vehicle routing in scenarios involving uncertain demands and soft time windows. The problem is tackled using a neuro-fuzzy logic approach, demonstrating its effectiveness in approximating customer performance indices. The model, based on the Clarke-Wright algorithm, used customer performance indices as inputs to generate delivery routes.

The proposed algorithm, serving as a decision-support tool, offers actionable insights into routing strategies. This allows operators to adapt to variable demand patterns and real delivery conditions. By streamlining delivery operations and improving service quality, organizations can gain a competitive edge in the marketplace, attracting and retaining customers while maximizing profitability. Furthermore, this research offers valuable insights that can benefit diverse stakeholders, from small-scale enterprises to multinational corporations.

The results of the numerical example suggest practical possibilities of neuro-fuzzy logic for the problem of vehicle routing when demand and travel time to customers are uncertain. The average deviation from the delivery time interval is 5.05 minutes over the 80-minute delivery service period. The approach to this problem shows the flexibility in this type of routing problem and fits the nature of the problem where there is no strict time constraint for the delivery of goods (as some of the most commonly used products in grocery stores). Further experiments are needed to prove all the advantages of the practical application of the approach proposed in this paper.

These findings may open new avenues of inquiry, such as the possibility of using the ideas in this paper to reroute delivery vehicles when some customers cancel orders, or some vehicles fail. Furthermore, the ecological factor could take its place as an input in the customer performance index. Because of the growing interest in ecological problems, this approach could be important in the future. Other lines of research may provide solutions to address the limitations of this paper, such as managing larger distribution networks with multiple depots. Additionally, considering the application of fuzzy linear programming for an optimization approach to the problem at hand could be beneficial. Finally, metaheuristic algorithms can be employed to fine-tune the membership function of the fuzzy logic system, potentially improving its performance.

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7 APPENDIX

The dataset for training ANFIS (200 out of 500 data)

#	X1	X2	IP	#	X1	X2	IP	#	X1	X2	IP	#	X1	X2	IP
1	11.4	5	3	51	10.3	3	3	101	14.6	8	4	151	9	7	5
2	16.5	8	3	52	12.7	14	6	102	13.2	5	3	152	15.7	13	5
3	7.1	13	8	53	16.9	12	4	103	16.3	12	4	153	15.5	9	4
4	10.1	3	3	54	3.2	4	6	104	3.8	3	5	154	9.8	9	5
5	11.2	16	7	55	14.2	12	5	105	13.4	13	6	155	10	6	4
6	12.2	11	5	56	8.7	11	6	106	8.3	6	5	156	14.9	8	4
7	2.6	12	9	57	10.3	15	7	107	6.5	15	9	157	3.2	8	7
8	2.5	12	9	58	4.1	5	6	108	10.8	11	6	158	5.6	3	5
9	16.5	3	1	59	5.9	9	7	109	4.8	14	9	159	12.9	13	6
10	9.4	5	4	60	11	11	6	110	15.8	7	3	160	4.7	14	9
11	11.5	11	5	61	7.7	9	6	111	10.5	9	5	161	3.9	12	8
12	2.6	11	8	62	8.8	9	6	112	12.8	12	5	162	2.5	11	8
13	8.6	11	6	63	3.3	10	8	113	9.8	16	7	163	16.6	16	6
14	16.2	14	5	64	9.6	8	5	114	8.2	13	7	164	11.5	7	4
15	14.2	7	3	65	12.6	8	4	115	5.5	3	5	165	10	6	4
16	3.3	3	5	66	3.2	16	10	116	10.4	5	4	166	12	9	5

#	X1	X2	IP	#	X1	X2	IP	#	X1	X2	IP	#	X1	X2	IP
17	16.9	9	3	67	15.6	7	3	117	4.7	8	7	167	7.2	9	6
18	8.6	16	8	68	4.5	7	6	118	5.5	15	9	168	13.8	16	6
19	3.9	7	7	69	17	11	4	119	15.8	3	1	169	5.4	6	6
20	13.5	3	2	70	7.1	15	8	120	4.4	8	7	170	7.2	13	8
21	13.6	4	2	71	6.2	13	8	121	5.1	11	8	171	10.3	6	4
22	5.4	11	7	72	3.7	15	9	122	7.6	16	8	172	14.9	11	5
23	14.2	13	5	73	2	4	6	123	8.6	4	4	173	11	13	6
24	8	7	5	74	10.7	13	6	124	5.6	13	8	174	15.1	16	6
25	12.9	5	3	75	13.2	10	5	125	6.9	6	6	175	16.8	5	2
26	8.6	12	7	76	3.1	12	9	126	12.8	10	5	176	10.8	5	4
27	2	7	7	77	9.8	13	7	127	10	8	5	177	8.6	12	7
28	2.4	11	8	78	6.7	5	5	128	10.6	9	5	178	13	16	6
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37	13.6	14	6	87	2	11	8	137	8.8	8	5	187	2.8	10	8
38	15.5	7	3	88	7.9	15	8	138	16.6	9	3	188	12.3	13	6
39	6.6	9	7	89	4.4	15	9	139	7.3	16	8	189	13.4	6	3
40	7.3	11	7	90	15.2	8	4	140	9	16	8	190	4.6	13	8
41	10.9	16	7	91	3.2	12	9	141	6.6	11	7	191	8.9	14	7
42	9.1	16	8	92	11.2	10	5	142	10	13	6	192	3.9	16	9
43	16.1	15	5	93	12.8	6	3	143	3.9	13	9	193	11.5	13	6
44	16.9	8	3	94	9.4	13	7	144	16.8	8	3	194	16.1	8	3
45	10.8	4	3	95	8	14	7	145	6.6	12	8	195	3.7	7	7
46	9.2	13	7	96	16.8	3	1	146	13.3	6	3	196	4.4	13	8
47	2.4	16	10	97	8.4	12	7	147	10.4	16	7	197	5.2	8	7
48	15.4	8	3	98	14.7	9	4	148	3.7	11	8	198	10.1	12	6
49	17	10	4	99	16.2	13	5	149	15.1	15	6	199	14.6	13	5
50	10.3	8	5	100	10	5	4	150	9.2	13	7	200	5.4	6	6

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