Green logistic vehicle routing problem: Routing light delivery vehicles in urban areas using a neuro-fuzzy model

Goran Ćirović, Dragan Pamučar, Darko Božanić

The Belgrade University College of Civil Engineering and Geodesy, Serbia
University of Defence in Belgrade, Department of Logistic, Serbia
University of Defence in Belgrade, Military Academy, Serbia

Keywords:
Environmentally friendly vehicles
Vehicle routing
Green logistics
Neuro-fuzzy
Simulated annealing

Abstract

Today's growth in the level of traffic in cities is leading to both congestion and environmental pollution (exhaust emissions and noise), as well as increased costs. Traffic congestion makes cities less pleasant places to live in, a particular problem being the negative impact on health as a result of increased exhaust emissions. In addition to these emissions, another major effect of transport which can lead to serious health problems is noise (EEA, 2013a, 2013b). There is a strong tendency in the world towards the development of "clean" motor vehicles that do not pollute the environment, that is, that do not emit harmful substances in their exhaust fumes and which create less noise without causing other types of pollution. The growth in the influence of transport on the environment has resulted in planners formulating procedures which take into account the effect of traffic on the quality of life in urban areas. This paper presents a model for the routing of light delivery vehicles by logistics operators. The model presented takes into account the fact that logistics operators have a limited number of environmentally friendly vehicles (EFV) available to them. When defining a route, EFV vehicles and environmentally unfriendly vehicles (EUV) are considered separately. For solving the problem of routing in the model, an adaptive neural network was used which was trained by a simulated annealing algorithm. The adaptive neural network was used for assessing the performance of the network branches. The input parameters of the neural network were the logistics operating costs and environmental parameters (exhaust emissions and noise) for the given vehicle route. Each of the input parameters of the neural network was thoroughly examined. The input parameters were broken down into elements which further describe the state of the environment, noise and logistics operating costs. After obtaining the performance of the network links for calculating the route for EFV and EUV vehicles a modified Clark–Wright algorithm was used. The proposed model was tested on a network which simulates the conditions in the very centre of Belgrade. All of the input parameters of the model were obtained on the basis of 40 automatic measuring stations for monitoring the air quality (SEA, 2012).

1. Introduction

In its simplest possible form, logistics can be described as the process of delivering a product (service) in the required quantities, in good condition, to the appointed place at the appointed time, to a specific customer at an agreed price. The expansion of logistics came along with the growing trend of globalization and decentralization of production, the functioning of which depends significantly on the quality of logistics activities. The area of logistics has constantly expanded and developed, adapting to the demands of technology and the environment. Today, logistics is present in all areas of society. At the same time as its development, there has been a growth in environmental awareness, and it is indeed noticeable that in the 21st century environmental problems occupy an important place in the priority list of the world's problems.

Today it is difficult to imagine any system without logistics support. However, the realization of key logistics processes (transport, handling, storage) conflicts with the requirements for environmental protection, with transport being characterized as one of the major environmental pollutants. For precisely this reason, this paper focuses on the organization of the transport process, more specifically on green transport within the framework of...
green logistics, which during the implementation of the logistics process, uses an approach involving environmental preservation. According to research carried out in Japan and Great Britain (Murphy & Poist, 2003), heavy goods vehicles generate noise between 88 and 92 dB, and light goods vehicles between 79 and 81 dB. If we bear in mind that noise which exceeds 60 dB is harmful to human health, then it is not difficult to conclude that on this basis road transport is the greatest cause of adverse effects on the environment. Traffic noise, as the main source of noise in urban areas, is a very significant ecological problem in terms of its serious damage to the health of the population, also causing a reduction in labor productivity. Recent data on the threat of environmental noise to the population was obtained after the first round in the production of strategic noise maps for agglomerations in European Union countries. Data from the European Environment Agency (2013a, 2013b) indicate that in urban areas 54% of the population (56,001,200 people) are exposed to full-day noise levels exceeding 55 dB(A) and 15% of the population (15,754,500 individuals) full-day noise levels greater than 65 dB(A). In addition, away from the agglomeration another 33,437,244 residents live in areas where the full-day noise level is greater than 55 dB(A), of whom 7,657,083 residents are in areas where the full-day noise level is greater than 65 dB(A). From a total of 89,438,444 residents who are subject to full-day levels of noise greater than 55 dB(A) almost 89 million are exposed to noise generated by traffic (road, rail and air). The number of people exposed to full-day levels of noise greater than 55 dB(A) arising from road traffic is almost 68 million, indicating road traffic to be the dominant source of noise. A report by the European Environment Agency (2013a, 2013b) showed that in most European cities, three out of five people are exposed to harmful levels of traffic noise. Research carried out by Schreyer et al. (2004) has shown that in the European Union the external costs of traffic accidents occurring as a result of the deterioration of air quality and an increase in noise level amounts to between 0.5% and 3.7% of the gross domestic product of EU countries.

Many industrialized countries and developing countries have adopted different regulations to define the maximum permissible level of noise emissions of motor vehicles, the noise inside the vehicle as well as noise emissions in urban areas. However, even with very “quiet” motor vehicles and laws favoring their use, it will be many years before existing outdated fleets are completely replaced. Bearing this in mind, the model presented in this paper recognises the fact that logistics operators in urban zones use not only EFV but also EUV vehicles.

Besides noise, another significant consequence of transport that can lead to serious health problems is harmful exhaust emissions (EEA, 2013a; EEA, 2013b). Transport is responsible for about 14% of the total carbon dioxide emissions (CO$_2$) (Yazan, Petruzelli, & Albino, 2011). Of the total amount of harmful substances emitted 50% is caused by traffic, while in urban areas its share can be as high as 90%. Road traffic, as a specific branch of traffic, significantly contributes to air pollution. This type of transport causes 86% of the carbon monoxide (CO), 33% of the hydrocarbon (CH) and 42% of the nitrogen oxide (NO$_x$) pollution. In addition, petrol engines are the main sources of lead pollution, and diesel engines emit large amounts of soot and smoke. Moreover, different types of transport have different rates of energy consumption (and thus different fuel emissions) for carrying out the same transport task. The largest consumer is road transport, which accounts for 82% of the total energy consumption in transport, followed by air with 13%, rail with 3% and river with 2% (Bapna, Thakur, & Nair, 2002).

The increased demand placed on logistics distribution systems has led to the construction of distribution centers and terminals near or within urban areas. By developing the “just in time” concept, many production systems have almost lost their storage function which not only required investment, but also generated significant running costs. This has resulted in the transfer of certain stock to the transport system. Part of the stock is actually in transit, which causes greater congestion and pollution in cities, with the environment and society bearing the cost. This has been confirmed by empirical research in the UK, where out of a sample of 87 companies a 39% reduction in the number and capacity of storage facilities was recorded, while 1/3 of the companies recorded an increased volume of delivery transport (McKinnon, 2008).

A large concentration of logistics activities in populated areas causes a great deal of air pollution as well as noise. One of the solutions to this for logistics operators is the introduction of EFV. These vehicles have found their place in the prevention of global warming and reduction of pollution caused by CO, CO$_2$, CH, NO$_x$, SO$_2$ (sulfur dioxide) and particulate emissions (PM$_{10}$ and PM$_{2.5}$). In addition, EFV are especially important in terms of reducing the emission of vibrations and noise as specific forms of environmental pollution which are especially prevalent in urban areas. EFV vehicles are characterized by reduced emissions of harmful substances and are fuelled by gas, liquefied petroleum gas, ethanol, methanol, biodiesel, hydrogen and electrical energy.

Based on the environmental directives promoted by the European Union, logistics operators in cities have begun to renew their fleets by introducing EFV. As the number of these vehicles is currently limited, implementation needs to be carried out together with the existing vehicles in such a way to maximize the impact on reducing pollution. The dramatic increase in the impact of traffic on air quality in cities has influenced the emergence of new procedures that will take into account the impact of transport on the quality of the environment in urban areas. There is no single solution for all urban problems, but city authorities insist that logistics operators focus on an integrated approach in order to respond in the best possible way to the problems that arise. This is achieved by combining knowledge from various areas of technology such as the development of new vehicles, economic incentives and new procedures for the creation of green EFV routes. In this paper, the term EFV of logistics operators is understood as light delivery vehicles with reduced emission levels.

Several ecologically oriented extensions of the VRP have been introduced which aim at minimizing fuel consumption or the amount of CO$_2$ emissions. For any of these problems, the evaluation of transportation plans relies on an estimation of the quantity of fuel consumed while completing the required task. There are a variety of methods for estimating the fuel consumption and emissions of road transportation which depend on a wide range of parameters. For an overview on methods see for example Frey, Zhang, and Rouphail (2010). Most of the estimation methods are based on analytical emission models, and they differ in terms of the principles on which they are based and the parameters they take into account for estimation. A comparison of several vehicle emission models for road freight transportation can be found in Demir, Bektas, and Laporte (2011). In addition to comparing different methods for estimating fuel consumption and pollution, Demir et al. (2011) analyze the discrepancies between the results yielded by the models on the one hand and the results recorded for the on-road consumption of real vehicles on the other hand.

Kara, Kara, and Yetis (2007) present a model for the problem that minimizes the load weight carried by the vehicles. They claim that their model aims at minimizing the energy required for the routed vehicles. More recent models are based on methods for estimating fuel and pollution which depend on specific parameters.
and actually consider the total weight including the dead weight of the carrying vehicles, e.g. Peng and Wang (2009). These recent models take several factors into account, e.g. the average speed (Figliozzi, 2010), congestion influencing the average speed combined with acceleration rates (Figliozzi, 2010), topology (Scott, Urquhart, & Hart, 2010; Ubeda, Arcelus, & Faulin, 2010) and the payload (Jaramillo, 2010; Peng & Wang, 2009; Scott et al., 2010).

An overview on issues linking Green Logistics with vehicle routing and scheduling can be found in Sbihi and Eglese (2007) and in Sbihi and Eglese (2010). In these papers the authors focus on aspects of time-dependent problems, the transportation of hazardous material and the dynamic optimization of real-time models. Related to these aspects, they discuss environmental objectives, as well as the characteristics of vehicle routing problems that involve the consideration of additional constraints. Jabali, Van Woensel, and de Kok (2012) study the trade-off between minimizing CO₂ emissions and minimizing total travel times. As CO₂ emissions are directly related to vehicle speed, time dependent travel times are included in their optimization models. Three different models are presented and compared: a model for the minimization of the total travel time, a model for minimizing the total CO₂ emission depending on travel times and speed, and a cost-based model that optimizes a weighted average of travel time, emission and fuel costs.

The so-called Green Single Vehicle Routing Problem introduced in the articles by Jaramillo (2010) as well as Peng and Wang (2009) aims to minimize the the number of vehicles required for a round trip measured in the total ton miles related to the trip. Kuo (2010) also proposes a model for minimizing the total fuel consumption for the time-dependent vehicle routing problem where fuel consumption depends on speed, time of travel, and loading weight. The author presents a simulated annealing algorithm for solving this problem. In Kuo and Wang (2011) the problem which was previously presented in Kuo (2010) is considered once more and this time it is solved with a Tabu Search Algorithm instead of using a simulated annealing approach. Bektaş and Laporte (2011) present and compare several ecologically oriented extensions of the classical VRP. These extensions are based on objective functions that account not just for travel distance, but also for the amount of greenhouse emissions, fuel, travel times and costs. In their paper, mathematical models are described for these extended problems with different orientations, such as distance-minimizing, weighted load-minimizing, energy-minimizing, and cost-minimizing.

Ubeda et al. (2010) analyze the effects of various degrees of vehicle utilization on carbon dioxide emission. The authors analyze the differences in CO₂ emissions between a distance and an emission minimization approach. Scott et al. (2010) investigate the influence of gradient and payload correction factors used within CO₂ emission models. The authors test the degree of influence on the solutions of shortest path problems and traveling salesman problems when applied to freight delivery. For the estimation of the fuel consumption, their study employs the COPERT model presented in Ntzachristos and Samaras (2000).

In addition to the research mentioned there have been a number of studies published that discuss the organization of green transportation and identify the problem of pollution. Bektaş and Laporte (2011) developed a model for green vehicle routing which is an extension of the classical VRP. In the developed model the objective function is obtained by observing not only the Euclidean distance between nodes on the network and the travel time, but also on the basis of the concentration of exhaust gases on the link and fuel consumption. Xiao, Zhao, Kaku, and Xu (2011) pay special attention to the rate of fuel consumption in relation to the vehicle load. Xiao et al. (2011) carried out optimization of the classic VRP problem using a simulated annealing algorithm. The results show that the model can reduce fuel consumption by an average of 5% compared to the standard VRP models. Erdogan & Miller-Hooks (2012) introduce the Green Vehicle Routing Problem (G-VRP). In their paper they present the problem of routing a fleet of vehicles which uses biofuels and their modification of the Clark Wright algorithm using heuristic procedures. The use of vehicles which run on biofuels is considered when attempting to overcome the difficulties which exist when using vehicles running on fossil fuels. The basic problems of using vehicles which run on fossil fuels are identified as increased exhaust emissions (NOx, SO₂, and CO) and a limited range of vehicles in combination with a limited infrastructure for filling the vehicle with the required fuel.

In recent years, both the evolution of operational research and increase in computing strength have prompted great interest in this problem. Cipriani, Fusco, and Petrelli (2006) formulated the green vehicle routing problem as a problem of non-linear optimization taking into account both discrete and constant variables. A group of Italian authors (Beltran, Carrese, Cipriani, & Petrelli, 2009) investigated the implementation of green fleets of buses in an urban network, where they took into account all of the traffic in the network. Assuming user equilibrium in the network, they developed a model for the allocation of the green fleets using genetic algorithms. They took sensitive areas into account (residential zones, parks, etc.) and made a green route beside them, which had a great impact on the reduction of pollution. Some of the most significant works in the area of EVF routing are those by Baaj and Mahmassani (1995), Ceder and Israeli (1993) and Carrese and Gori (2002). They developed a new approach based on metaheuristic techniques: genetic algorithms, simulated annealing and tabu search. In addition to the mentioned works, Ngamchhai and Lovell (2003) proposed the use of genetic algorithms for solving the problem of EVF routing, while Fan and Macemehl (2006) considered the transport requirements in terms of EVF distribution according to different types of transport. In addition to these studies, the problem of green vehicle routing has been dealt with by other authors (Faulin, Juan, Lera, & Grasman, 2011; Suzuki, 2011). A detailed presentation and description of studies which consider the problem of vehicle routing, as well as the problem of routing “green” vehicles can be found in Lin, Choy, Ho, Chung, and Lam (2014). Examples of the application of a neuro-fuzzy approach, and the theoretical basis for this approach can be found in works by Shing and Jang (1993), Shing and Jang (1995) and Shi and Mizumoto (2000).

By analyzing the available literature, the conclusion can be reached that so far there has been no consideration of the problem of EVF routing using a neuro-fuzzy approach which takes into account the parameters of the environment and logistics operating costs and their impact on EVF routing. The problem lies in designing green EVF routes which minimize the harmful effects of transportation using light delivery vehicles in urban areas. This approach becomes more important if we take into account the fact that in the future it can be expected that transport companies, particularly in countries with developed industries, have an increasing number of EFVs in their fleets.

Local authorities are putting much effort into including as many vehicles as possible with reduced emissions in their urban transport. However, there has been a noticeable lack of reliable methodology to support such implementation. In order to optimize the “green” capacity, a system has been developed to support decision-making when routing light delivery vehicles with reduced emission levels in urban areas. The aim of this paper is to propose a model for the allocation of EFV in urban areas, taking into account the environmental parameters on the given route. The problem is presented as one of nonlinear optimization with fuzzy values of the input parameters, and is solved using neuro-fuzzy logic. The advantage of this model lies in the fact that it considers a number of factors that affect the input variables. However, management of urban systems is a challenge because of the complexity.
of those systems in circumstances which cannot always be exactly forseen.

This paper presents a model for the routing of light delivery vehicles by logistics operators. The model takes into account the fact that logistics operators have a limited number of EFV vehicles. When defining the routes, EFV and EUV are considered separately. An adaptive neural network is used for solving the problem of routing in the model. The adaptive neural network was trained with a simulated annealing algorithm and was used to determine the performance of the branches of the network. The input parameters of the neural network were logistics operating costs and and the state of the environmental parameters (exhaust emissions and noise) for the given vehicle route. Each of the input parameters of the neural network was thoroughly examined. The input parameters were broken down into elements that further describe the state of the environment and the logistics operating costs. The advantage of this model is reflected in the fact that it takes into account a greater number of factors which affect the input variables. For example, when considering the input variable Exhaust emissions, the parameters taken into account are those which describe oxides of sulfur emissions, nitrogen oxide emissions, carbon monoxide emissions and particulate emissions. By means of mathematical transformation the given parameters are brought together and they describe the input variable Exhaust emissions. In exactly the same way the remaining input variables of the neuro-fuzzy model (noise and logistics operating costs) are broken down. After running the input parameters through the neural network, the Performance link (PL) is obtained at the output for every link in the network. After obtaining the PL values of the network the defined routes for light delivery vehicles are reached using a modified Clark–Wright algorithm. A detailed description of the individual phases of the model is given in the following section of the paper. After describing the phases of the model the architecture of the developed adaptive neural network is presented, the input parameters are defined and the process of training the network is shown. The final section of the paper shows how the model was tested on the routing of light delivery vehicles in the old centre of Belgrade.

2. Neuro-fuzzy model for the routing of delivery vehicles by logistics operators in urban areas

The problem presented in this paper is the problem of determining a set of routes by means of which light delivery vehicles in urban areas can provide their service in such a way that the logistics operating costs and the state of the environmental parameters are minimal (Fig. 1b). Let there be n nodes within the observed urban zone in which the delivery is made which are available to work. We mark demand with $q_i (i = 1, 2, \ldots, n)$ in the $i$th node (Fig. 1a). The means of transport are stationed at point B which is most commonly referred to as the base or depot. All means of transport used for a particular task must begin and end their journey at point B. Let the capacity of the means of transportation be greater than the demand at any node.

This problem is known as the standard vehicle routing problem. In order to make a more detailed mathematical formulation of the routing problem the following binary variables are introduced:

$$y_{ik} = \begin{cases} 1 & \text{if the } k \text{th means of transport services the } i \text{th node} \\ 0 & \text{the opposite.} \end{cases}$$

$$x_{ij} = \begin{cases} 1 & \text{if the } k \text{th means of transport travels from node } i \text{ to node } j \\ 0 & \text{the opposite.} \end{cases}$$

We denote the performance link (PL) with $c_{ij}$ in the network from node $i$ to node $j$. Also, we use $m$ to denote the number of vehicles providing the service, and $Q_k$ for the capacity of the $k$th means of transport. The mathematical formulation of the problem of routing vehicles can be presented in the way it is described in the following section. It is necessary to minimize the criterion function

$$\sum_{i,j,k} c_{ij} x_{ijk}$$

in accordance with the following constraints:

$$\sum_i y_{ik} = \begin{cases} 1 & i = 2, 3, \ldots, n \\ m & i = 1 \end{cases}$$

$$\sum_i q_i y_{ik} \leq Q_k, \quad i = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, m$$

$$\sum_i x_{ijk} = y_{ik}, \quad i = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, m$$

$$\sum_{i,j,k} x_{ijk} \leq |S| - 1 \quad \forall S \subseteq \{2, \ldots, n\}, \quad k = 1, 2, \ldots, m$$

$$y_{ik} = \{0, 1\} \quad i = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, m$$

$$x_{ijk} = \{0, 1\} \quad i, j = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, m$$

The criterion function we want to minimize in this case is the sum of the total performance of the links in the network.

Fig. 1. Nodes which require service and transport means and routes which complete the service task.
In this paper the given problem is presented using a neuro-fuzzy model and a modified Clarke–Wright (CW) algorithm. The scheduling of light delivery vehicles in urban areas on green routes is set out as a problem of optimization of logistics operating costs and air quality and noise level. The solution to the problem is proposed using an Adaptive Neuro Fuzzy Inference System (ANFIS) which takes into account three criteria in the allocation of vehicles: \( x_1 \) – logistics operating costs, \( x_2 \) – exhaust emissions and \( x_3 \) – noise level. PLs are obtained as output from the ANFIS. PLs are obtained through putting the input parameters (logistics operating costs, exhaust emissions and noise) through an adaptive neural network.

Elements of Fig. 2: Input variables, determining the performance of the network links using a neuro-fuzzy model, Performance of the links in the network, Modified Clarke–Wright algorithm, Routing EFV vehicles, Routing EUV vehicles, Routes for EFV and EUV vehicles.

The scheduling of vehicles is carried out in two phases (Fig. 2). The First phase is the calculation of the input parameters of the ANFIS and defining the PLs of the network.

In the second phase the PL values \( (c_{ij}) \) are assigned to the branches in the network and the green routes are defined for EFV and EUV light delivery vehicles using a modified CW algorithm. EFV vehicle routing using the CW algorithm consists of the following steps:

**Step 1.** For each pair of nodes required to serve, calculate the saving of the PL network \( (C_{ij}) \) according to the expression (8)

\[
C_{ij} = c_{Bi} + c_{Bj} - c_{ij}
\]

**Step 2.** Carry out ranking of the savings performance and put them in descending order (from the largest to the smallest). Make a list of savings which begin with the highest PL savings.

**Step 3.** When considering the savings \( C_{ij} \) include an appropriate branch \((i,j)\) in a partial route as long as it does not breach the existing operational restrictions:

(a) If none of the nodes \( i \) or \( j \) have been included in a partial route.

(b) If one of the nodes \( i \) or \( j \) has already been included in an existing partial route and if that node is not an internal node in the route.

(c) If both nodes \( i \) and \( j \) are included in two different partial routes and neither of those nodes is internal to the routes. Then join the partial routes to become one route.

**Step 4.** When all the savings have been considered the algorithm is completed.

EUV vehicle routing using the CW algorithm consists of the following steps:

**Step 1.** For every pair of nodes necessary for service calculate the savings for the network performance links \( (C_{0ij}) \) according to expression (8).

**Step 2.** Carry out ranking of the performance savings and put them in ascending order (from the smallest to the largest). Make a list of the savings which begins with the lowest PL savings.

After calculating the modified savings, steps 3 and 4 are repeated as described in EFV vehicle routing.

Fig. 2. Model for creating green routes for light delivery vehicles in urban areas.
The following section of the paper describes the process of defining the input parameters of the ANFIS and the architecture of the adaptive neuro-fuzzy network.

### 3. Configuration of the neuro-fuzzy network and defining the input parameters: neuro-fuzzy modeling

An integral part of the ANFIS is a fuzzy logic system (FLS) of reasoning. One of the basic problems facing the analyst when developing an FLS is determining the set of linguistic rules and determining the parameters of the membership functions of the input/output pairs. The initial fuzzy system is mapped into a five layered adaptive neural network with a restricted connectivity structure that is shown in Fig. 3.

The proposed neural network is referred to as a five layered network because five layers perform operations. The adaptive network shown in Fig. 3 is a feedforward layered network because the output of each unit propagates from the input side (left) to the output side (right).

Based on analysis of the given literature references, three criteria were identified which affect the routing of delivery vehicles in urban areas, that is, which influence the definition of the PLs in the network. The input variables of the ANFIS are: Logistics operating costs (LOC), Exhaust emissions (EE) and Noise (N). In addition to the three input variables, the ANFIS has one output variable \( y \), the link performance.

The intervals of the input and output variables of the ANFIS are shown in Table 1.

![Fig. 3. A five layered feedforward adaptive neural network.](image)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( x_2 )</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( x_3 )</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( y )</td>
<td>([0,10])</td>
</tr>
</tbody>
</table>

where \( C_{km} \) represents the vehicle operating costs per kilometer; \( l_i \) the Euclidean length of the link; \( C_h \) personnel costs of individual vehicles per hour of driving; \( t_{pb} \) time spent driving the vehicle in the link.

The criterion Exhaust emissions \( (x_2) \) is obtained using the expression (10)

\[
f_{x_2} = \omega_1 \cdot SO_2 + \omega_2 \cdot CO + \omega_3 \cdot NO_x + \omega_4 \cdot (PM_{10} + PM_{2.5}) \quad (10)
\]

where \( \omega_i \) represents the weighting factor of the components for assessing the air quality – \( SO_2, CO, NO_x, PM_{10} \) and \( PM_{2.5} \). When considering the parameters for assessing the air quality as representative chemical compounds describing the state of the air, the compounds \( SO_2, CO, NO_x, PM_{10} \) and \( PM_{2.5} \) were chosen because of their harmful effects on the environment. Namely, the quantity of sulfur oxides emitted directly depends on their content in the fuel and the combustion mode of the engine, and the harmful effects are reflected in the acidification of the existing ecosystem. Emission of nitrogen oxides was chosen because of their multiple harmful effects on the ecosystem (acidification of the environment, destruction of ozone in the upper layers of the atmosphere, etc.). Carbon monoxide was chosen because of its strong cytotoxicity to living beings and also because it is one of the greatest air polluters. The
exhaust emissions of internal combustion engines are one of the biggest polluters of the atmosphere of this gas. Particulate matter was chosen since it consists of a mixture of solid and liquid particles of both organic and non-organic substances which, as a complex mixture, have a very negative effect on the human organism (by inhalation they are introduced and deposited in the respiratory system). The main components of particulate matter are sulfates, nitrates, ammonia, sodium chloride, carbon, mineral dust and water (SEA, 2012; SEA, 2013). The concentration of particulate matter in the ambient air is generally quantified today by measuring the concentration of PM$_{10}$ (particles with a diameter of less than 10 μm) or PM$_{2.5}$ (diameter less than 2.5 μm).

The noise ($x_2$) criterion. A theoretical solution for the problem of modeling the level of traffic noise is very complicated due to the large number of different variables that affect the noise, and because of the lack of analytical equations that describe the correlation relationships between the levels of noise and individual factors which affect it. The developed theoretical models include the characteristics of the noise source for calculating the emission of the noise source and modeling the propagation from the place where they are emitted to the place of noise immersion, that is, the calculation point. Theoretical models are more precise, but their calculation is time-consuming and they are only used for the formation of engineering models. For this reason, mathematical models are developed which are based on experimental results of measuring the noise level and establishing correlations with the traffic parameters.

Many authors have offered a large number of mathematical models (linear and nonlinear, statistical, based on fuzzy logic and neural networks) to describe traffic noise, with different levels of accuracy and which differ in terms of the factors they take into account. All available models are based on establishing a functional relationship between the parameter of noise emissions and the parameters of traffic and roads. Some of the most widely used have been defined by Burgess (1977), (Eq. (11)), Josse (1972), (Eq. (12)) and Fagotti & Poggi (1995), (Eq. (13)):

\[
L_{eq} = 55.5 + 10.2 \log Q - 0.3p - 19.3 \log (L/2)
\]  
\[
L_{eq} = 38.8 + 15 \log Q - 10 \log L
\]  
\[
L_{eq} = 10 \log (N_c + N_{nb} + 8N_{hp} + 88N_b) + 33.5
\]  

where: $p$ – is the percentage of heavy vehicles, $L$ – is the road width (in meters), $Q$ – is the total number of vehicles per hour, $N_c$ – is the number of light (passenger) vehicles per hour, $N_{nb}$ – is the number of motorcycles per hour, $N_{hp}$ – is the number of heavy (goods) vehicles per hour, $N_b$ – is the number of buses per hour. The total number of vehicles in an hour ($Q$) in the above equations is expressed as an equivalent number of vehicles and is obtained under the assumption that one heavy vehicle is equivalent to 6 light vehicles, and one motorcycle to 3 light vehicles.

The majority of the mathematical models are obtained on the basis of experimental data. This has the consequence that each model in itself includes certain features of the place where the data was collected and characteristics specific to that particular traffic flow. This does not ensure an accurate approximation of the trend of change for the equivalent noise level depending on a set number of physical parameters which define traffic and roads. Therefore each model should be very cautiously applied to the conditions that apply in other urban areas. For this reason, there is a need for the development of a mathematical model which calculates traffic noise whilst taking into account the structure of the vehicles and the characteristics of the roads in specific urban areas.

Serbia does not have a developed model for calculating road traffic noise emissions, but instead uses software packages for noise calculation or other available models. Using an already existing model for modeling the level of traffic noise in the territory of Belgrade does not have characteristic universality since each model contains certain characteristics of the place where the measurements were taken and specific features of the traffic flow of the urban area studied. For the purpose of this research, the model for determining equivalent noise levels of road transport was used, developed by Prascevic and Cveticovic (2013). This model was developed within the framework of their research methodology for determining equivalent noise levels for road traffic in the city of Niš.

\[
f_x = 10 \log (N_c + 3.7N_{nb} + 1.9N_b) + 38.2, \quad 55 \text{ dB(A)} < f_x < 65 \text{ dB(A)}
\]  
\[
f_x = 10 \log (N_c + 11.7N_{nb} + 3.1N_b) + 44.3, \quad 65 \text{ dB(A)} < Leq < 120 \text{ dB(A)}
\]

where the number of passenger vehicles is $(N_p)$, the number of heavy vehicles is $(N_h)$ and the number of buses is $(N_b)$. The equivalent noise level of road traffic at a distance of 7.5 m from the road was determined on the basis of the number of passenger vehicles, the number of heavy vehicles and the number of buses in an hour. Based on the structure of traffic flow, the equivalent level of road traffic was calculated using Eq. (14). If the noise level obtained was less than or equal to 65 dB(A) then the noise level was recalculated using Eq. (15).

The limit values of the input parameter variables $f_{x1}$, $f_{x2}$, and $f_{x3}$ which are characterized as the greatest and highest allowed values of the given parameters were defined on the basis of recommendations by the Serbian Environmental protection agency, following the recommendations by Tao and Xinniao (1998). Table 2 shows the parameter values proposed for Serbia. The parameter values shown depend on the economic situation and economic policies of each country where the proposed algorithm would be applied. On the basis of data from the Serbian Agency for environmental protection the defined limit values are SO$_2$ [0.125] μg/m$^3$, CO [0.1] μg/m$^3$ (maximum annual eight-hour value) and NO$_2$ [0.85] μg/m$^3$. The World Health Organization (WHO, 2012), in the Guidelines for the limit values of particulate matter, does not define the level of concentration (PM$_{10}$ and PM$_{2.5}$) as the lower threshold, but rather, it is the concentration below which there is no impact on human health. The defined values are only the recommended values which represent the concentrations that can be realistically achieved in order for the effects on human health to be kept to a minimum. Table 3 presents an overview of the limit values for the concentration of PM$_{2.5}$, PM$_{10}$, BS (soot) and TSP (total suspended particles) defined by the regulations of the Republic of Serbia (Law on Ambient Air protection., 2009; the Bylaw on monitoring conditions and air quality requirements, 2010), by EU Directive (Directive on Ambient Air Quality, 2008) and the recommendations of the WHO (2012).

In order for the criteria functions ($f_{x1}$, $f_{x2}$, $f_{x3}$) to go through the ANFIS it is necessary to carry out their normalization. Since $f_{x1}$ belongs to the group of cost criteria (lower values desirable) the normalization process is carried out according to the formula (16)

\[
f_{x1} = 1 - \frac{f_{x1} - f_{x1}^{\text{min}}}{f_{x1}^{\text{max}} - f_{x1}^{\text{min}}}
\]  

The process of normalization for benefit criteria (higher values desirable) $f_{x2}$ and $f_{x3}$ is carried out according to the formula (17).

\[
f_{x2} = \frac{f_{x2}}{f_{x2}^{\text{max}}}
\]  

\[
f_{x3} = \frac{f_{x3}}{f_{x3}^{\text{max}}}
\]
3.1. Pattern of connectivity

The neural network is designed to establish and compute a function from input space to output space. In this paper, the network that has a fixed structure is configured based on the operation of the fuzzy system (the Takagi–Sugeno model). The input layer consists of 3 units representing: Logistics operating costs \((x_1)\), Exhaust emissions \((x_2)\) and noise \((x_3)\). It simply transfers inputs further via the interconnections to the hidden or first layer. All units in the input layer \((x_1, x_2 \text{ and } x_3)\) are connected with the 5 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 \(3 + 5\) units representing the number of verbal descriptions quantified by fuzzy sets ("very low", "low", "medium", "high", "very high") for each input variable (Fig. 4).

Every unit in the first layer is an adaptive unit with its output being the membership value of the premise part.

The number of units in the second layer equals the number of fuzzy rules. Every unit in this layer is a fixed unit that calculates the intersection of a fuzzy set (consequent) with the maximum firing strength of incoming rules. Each unit in this layer calculates the intersection of a fuzzy set "strong preference" with the maximum firing strength of rules \(R_5, R_6, R_7\): \(\mu_{y_5}(y) = \min\{w_i\mu_{y_5}(y)\}\), 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 ANFIS:

\[
\mu_{y_5}(y) = \max\{\mu_{y_1}(y), \mu_{y_2}(y), \mu_{y_3}(y), \mu_{y_4}(y), \mu_{y_5}(y)\} \tag{18}
\]

The obtained output is then defuzzified in the single unit in the fifth layer. Selection of the 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 output value is a real number that lies in the interval \([0, 1]\):

\[
O = \text{Overall output} = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \tag{19}
\]

3.2. Supervised learning (a simulated annealing algorithm)

The aim of learning is to set the membership functions of the input/output variables to some adequate functions. The neural
network performances are measured as the deviation between the targeted output and the model output across all numerical examples. This discrepancy or the error measure is considered as the objective function, and heuristic simulated annealing is used to minimize it. Since the application of simulated annealing requires a large number of experiments, the training process is very long. However, the tuned FIS yields 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 the sum of differences between the model output (maximum of the networks outputs) and the targeted output over all training pairs. Heuristic simulated annealing is used to minimize the objective function. A statistical training method such as 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 a 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 choose this method as a learning rule. The disadvantage of using the simulated annealing algorithm as a learning rule for the neural network is its very long training period.

The simulated annealing algorithm based on the approaches of Kirkpatrick, Gellat, and Vecchi (1983) and 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). The epoch implied is retained implies that the algorithm would hardly be trapped in local energy minima.

**Step 2.** Generate a set of initial membership functions. Obtain the model output for all the input vectors in a training set (maximum of the network outputs) and calculate the objective function value \( F_{0, \text{old}} \). 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. Obtain the model output (maximum of the network outputs) with the same input vectors (for the complete training set) and calculate the new objective function value \( F_{0, \text{new}} \). Evaluate the change in the objective function \( \delta = F_{0, \text{new}} - F_{0, \text{old}} \). If \( \delta < 0 \), go to Step 5, otherwise go to Step 4.

**Step 4.** (\( \delta \geq 0 \)) 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 \( P(\delta) = \exp(-\delta/t) \). If \( r < P(\delta) \), go to Step 5, otherwise keep the old set of membership functions, and go to Step 3.

**Step 5.** (\( \delta < 0 \) or \( r \geq P(\delta) \)) 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 \( t_k \), 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 \( \lambda \) exchanges of all membership functions, where \( \lambda \) is a predefined number. The best solution, i.e., the lowest sum of errors between the model outputs and targeted outputs, obtained through \( \lambda \) exchanges of the membership functions, represents the epoch. Consider the case where \( k \) epochs have already been generated. After the next epoch, equilibrium is reached if:

\[
|F_{0, \text{old}} - F_{0, \text{new}}| < \varepsilon, \quad k = 1, \ldots, M_{ep} - 1
\]

where \( F_{0, \text{old}} \) is the objective function value that represents the \( k \) + 1st epoch, \( F_{0, \text{new}} \) is the lowest objective function value of all previous epochs’ solutions and \( \varepsilon \), a pre-defined constant.

The maximum number of generated epochs at one temperature if the thermal equilibrium is not reached in the meantime, \( M_{ep} \), 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 both influence the performance of the algorithm. Initially, a temperature is given a high value; then, it is slowly reduced until a 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.

While training the ANFIS there was a change in the parameters of the membership function of the input variables (Fig. 3b). After completing the final phase of training the ANFIS, the final parameters of the membership function were obtained (Table 4).

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 55 temperatures \( \{t_1 = 0.85t_k\} \) and an initial temperature \( t_1 = 55 \) are used.

The maximum number of generated epochs at one temperature \( M_{ep} = 40 \). In other words, 40 epochs are generated if the thermal equilibrium is not reached in the meantime. The epoch implied 25 exchanges of all middle values of the membership functions. The value of \( \varepsilon \) is used to check if the equilibrium reached is 0.07.

Training the ANFIS was carried out through five phases, each of which had a total of 11 temperatures (total 55). The first training phase was completed after the first 11 temperatures, \([0, t_{11}]\). After completing the first phase, the error obtained at the output had a mean value of 1.371 (Fig. 5a).

In the following phase, after the next 11 temperatures ([12–22]), the error obtained at the output had a mean value of 0.984 (Fig. 5b), which is a reduction of 28.22% in relation to the previous value. The third and fourth phases lasted for a total of 22 temperatures ([23–44]). After the fourth phase of training, error at the

### Table 4

| Parameters of the membership functions before and after training the ANFIS model. |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|                            | МF 1 (trimf)               | МF 2 (trimf)               | МF 3 (trimf)               | МF 4 (trimf)               | МF 5 (trimf)               |
| **Before training**         |                            |                            |                            |                            |                            |
| LOC                        | \([-0.026, 0.102, 0.239]\)  | \([0.126, 0.296, 0.465]\)  | \([0.525, 0.487, 0.637]\)  | \([0.529, 0.687, 0.847]\)  | \([0.706, 0.846, 1.025]\)  |
| EE                         | \([-0.018, 0.123, 0.284]\)  | \([0.131, 0.278, 0.426]\)  | \([0.286, 0.459, 0.632]\)  | \([0.481, 0.653, 0.840]\)  | \([0.70, 0.846, 1.011]\)   |
| N                          | \([-0.047, 0.100, 0.254]\)  | \([0.123, 0.292, 0.460]\)  | \([0.304, 0.502, 0.701]\)  | \([0.599, 0.722, 0.909]\)  | \([0.709, 0.935, 1.06]\)   |
| **After training**          |                            |                            |                            |                            |                            |
| LOC                        | \([-0.418, -0.018, 0.382]\) | \([-0.124, 0.252, 0.628]\) | \([0.121, 0.484, 0.846]\)  | \([0.304, 0.671, 1.299]\)  | \([0.585, 1.033, 1.481]\)  |
| EE                         | \([-0.394, -1.388e-017, 0.394]\) | \([-0.131, 0.238, 0.607]\) | \([0.084, 0.487, 0.889]\)  | \([0.343, 0.75, 1.157]\)   | \([0.567, 1.433]\)        |
| N                          | \([-0.244, 0.019, 0.283]\)  | \([-0.127, 0.195, 0.518]\)  | \([0.054, 0.433, 0.812]\)  | \([0.318, 0.742, 1.166]\)  | \([0.501, 1.034, 1.566]\)  |
output amounted to 0.319 (Fig. 5d), which compared to the previous phase is a reduction of 55%. After the fifth and final phase, completed after the last 11 temperatures ($t_{45-55}$), the error value at the output of the model was 0.146 (Fig. 6). Upon completion of the fifth phase it was concluded that the error obtained at the output was acceptable. It can also be concluded that the network is trained and able to generalize new input data.

After training it can be observed that the system is sensitive and that the output is gradual. The inert and over-sensitive parts of the system are removed, which would be the case with a fuzzy model (Fig. 7a). Presented in Fig. 7b is a set of output values of the ANFIS after training, that is, the scenario which describes the reaction of the system for individual input values.

The five-layered adaptive network was tested on 36 parameters which describe the network nodes, constructed to simulate the prevailing conditions in the centre of Belgrade. The criteria values which describe the given node were periodically put through the ANFIS, in this way obtaining the PLs of the network nodes.

4. Testing the model

The consequences of intensive climate change in recent decades are reflected in almost all parts of the world. The growing number of catastrophes as a result of weather conditions is a cause for concern, but there is a willingness to try and reduce or prevent further climate change. For this purpose it is necessary to reduce the emission of gases which cause the greenhouse effect, and whose concentration in the atmosphere has sharply increased, above all as a consequence of using fossil fuels in traffic and in industry. In the case of the transport sector, one of the main measures for achieving this goal is a redirection in the flow of goods towards more ecologically acceptable branches of transport and the use of EFV vehicles.

Traffic congestion, which is very pronounced in the so-called peak traffic periods, is extremely harmful to the environment and causes many negative consequences, such as: additional fuel consumption, extra pollution, arriving late to work or school, supply problems, a reduction in the productivity and effect of transport vehicles and others. In addition, the majority of harmful gases (around 1/3) are a result of traffic, namely 65% of carbon monoxide, 45% of hydrocarbons and 49% of nitrogen oxides (EEA, 2013a, 2013b).

In order to inform the public about air quality, in Serbia the Environmental Protection Agency was established, which provides the results of automatic air quality monitoring in real time. For managing the air quality it is important to have the data on current levels of air pollutants obtained by these measurements, as well as
data on the emission of harmful substances in the air which cause the pollution. For this purpose, 40 automatic measuring stations were placed in Belgrade in order to monitor the quality of the air. Verified values and assessment of air quality according to zones in Serbia are presented in annual SEA reports on the state of the air quality in the Republic of Serbia. The SEA report (2012) states that the greatest emissions of greenhouse gases are in Belgrade, Novi Sad, Pančevo and Smederevo. The report also states that in Belgrade, over 50% of the greenhouse gases are a result of exhaust emissions. Table 5 shows the emission of pollutants by motor vehicles in Belgrade during city driving (SEA, 2012). The data is based on an individual motor vehicle after 1000 km of city driving.

Given the data presented in Table 5 and the SEA (2012) report, the local authorities in Belgrade have begun to subsidize the purchase of EFV in order to reduce the environmental pollution in the city. The plan for the next four years is for logistics operators to have around 50% EFV in their fleets. However, in addition to purchasing EFV, logistics operators will face the problem of how to allocate EFV vehicles. For solving the problem of routing green vehicles in Belgrade, the model developed in this paper can be successfully used.

The next section presents a neuro-fuzzy model implemented on a test network which simulates conditions in the centre of Belgrade. Fig. 8 shows the test network, which consists of 9 nodes. The capacity of the vehicles which carry out the service is \( V = 130 \). The requirements of the nodes are shown beside the nodes as indicated in Fig. 8.

Input parameters of the adaptive neural network (Table 6) were obtained from the limit values for the period 2010–2013 (SEA, 2013).

After defining the initial parameters of the network and calculating the PLs using the ANFIS model, the algorithm for routing EFV is implemented.

The first phase is calculating the input parameters of the ANFIS and defining the PLs for the network.

In the second phase PL values \( (C_t) \) are assigned to the branches of the network and green routes for EFV and EUV light delivery vehicles are defined using a modified CW algorithm. Defining a route for EFV and EUV using the CW algorithm consists of the following steps:

Step 1. Calculation of the input parameters for the ANFIS and definition of the network PLs using the neuro-fuzzy model (Table 6). When defining EFV and EUV routes for each pair of nodes calculate the PL network savings \( (C_t - C_i) \) according to expression (8).

Step 2. Carry out ranking of the PL savings and and put them in descending order (from the highest to the lowest) for the EFV.
vehicles. Carry out ranking of the PL savings for EUV vehicles and arrange them in ascending order (from the lowest to the highest). Make a list of savings that begins with the lowest savings performance (for EUV vehicles) and the highest savings performance (for EFV vehicles), Table 7.

Step 3. Determine the route between all pairs of nodes. Carry out a review of savings \( (C_{ij}^{EFV}) \) and construct routes for EFV and EUV vehicles whilst respecting the limitations defined earlier in this paper. After analyzing the savings from Table 7, routes are constructed for EFV vehicles (Fig. 9a) and for EUV vehicles (Fig. 9b).

When defining routes it was assumed that the number of EFV is limited and that a maximum of one can be assigned to one of the routes. Under these assumptions step 3 of the recommended algorithm was used and vehicles were assigned to the given routes.

5. Discussion and conclusions

In line with world trends, this paper contains a model developed to optimize the implementation of EFV vehicles on the existing road network taking into account air pollution, noise level and operating and user costs. The criteria for modeling the user and operator costs are in accordance with the literature mentioned here and logical indicators of the given quantities, such as unit labor costs. For the criterion of environmental quality, substances are taken into account which are byproducts of vehicle usage, and which are detrimental to the health of humans and animals, such as noise level, which affects the general state of people and their quality of life.

The parameters for calculating the input variables of the neuro-fuzzy system came from real data obtained from automatic measuring stations situated in Belgrade, and the model was tested on a network which simulates conditions in the centre of Belgrade. This testing could have been carried out using data from any city, which indicates it to be a widely applicable model. The model remains open for modification, as well as for further improvement and adaption to the requirements of the user, since it is possible, instead of the suggested method of obtaining input data, to use

![Fig. 8. Network architecture for routing green vehicles.](image-url)
other more advanced methods, which is particularly important when considering the input criterion of Noise. Thus, instead of the suggested model of Prascevic and Cvetkovic (2013) used in this study, it is possible to use any other which the user considers to be of good quality, that is, which better reflects the situation in question. Also, the structure of this model allows for the possibility of there being incomplete data. In other words, if there are no specific data on the input parameters, the model still functions on the same principle and gives valid results. This is very important when considering the input parameters for the criterion of Emissions, where users will often be in a situation where they have incomplete data due to a greater number of parameters, which cannot be easily measured. The application of the adaptive neural network makes it possible to continuously incorporate new theoretical and empirical knowledge that can be reached by using this and similar models in practice.

In addition it should be noted that this is a general model for the routing of light commercial vehicles by logistics operators, which is suitable for use in cities which face the problem of allocating their “green capacity” in the town network. One of the advantages of this model is that it takes into account the uncertainties which arise when predicting the operating costs, user costs and the environmental parameters in the city’s road network. In addition, the proposed model enables the planning of vehicle routes to maximize the positive impact on the environment, which is reflected in the reduction of harmful gas emissions and an increase in the air quality in areas with the highest concentration of population. The model for routing light commercial vehicles also takes into account the fact that logistics distributors have a limited number of EFV vehicles. Therefore, the model has specially constructed routes for EFV and EUV. Likewise, the algorithm supports any number of available EFV and EUV, which is consistent with the size of the network and the transport requirements.

As far as the author is aware, there has been no research so far as to whether the position of fuel filling stations for vehicles using “green” fuels would result in any changes in the proposed routes. It is becoming more common to hear the idea of electric vehicles becoming part of the fleets of logistics operators. Future research and improvement of the model should therefore take into account the problem of location for filling batteries on light delivery vehicles, and their optimal location in relation to the vehicle route. As a suitable technique for solving such a problem, in addition to neuro-fuzzy modeling, a mass serving system can also be used.

This model extends the theoretical framework of knowledge in the field of green vehicles. The existing problem is considered using new methodology, which creates a basis for further theoretical, and also practical advancement. The presented model also highlights new criteria (exhaust emissions, noise and operating costs) which have not been considered in models up to this point, and which are relevant to this issue. By introducing and describing new criteria in the model, the need for their consideration in further analysis of this and similar problems is pointed out.

This model has been developed to minimize air pollution, noise level and logistics operating costs. Precisely this makes it compliant with world trends, since traffic in general, but particularly goods transport, has a very complex effect on the environment, resulting in a range of negative consequences, which can be seen in air pollution, water pollution, noise, energy consumption, reduced safety, vibration and others. On the other hand, biofuels such as biogas, biomethane and natural gas are increasingly being used and are replacing traditional fossil fuels. Although the benefits of using EFV are well-known, their introduction is gradual, and their optimal allocation on routes is very important, which gives the model presented here great practical significance. The practical value of this algorithm lies in the fact that the collected experience of a number of experts is incorporated into the model, thus avoiding a situation in which the routing of EFV is limited to the knowledge of individuals who find themselves in a position where they have to solve these problems alone.

Table 7  Sorting the savings of the branches for EFV and EUV vehicles.

<table>
<thead>
<tr>
<th>EFV vehicles</th>
<th>EUV vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No.</strong></td>
<td><strong>Link</strong></td>
</tr>
<tr>
<td>1.</td>
<td>R$_{2-9}$</td>
</tr>
<tr>
<td>2.</td>
<td>R$_{3-7}$</td>
</tr>
<tr>
<td>3.</td>
<td>R$_{6-9}$</td>
</tr>
<tr>
<td>4.</td>
<td>R$_{2-9}$</td>
</tr>
<tr>
<td>5.</td>
<td>R$_{5-4}$</td>
</tr>
<tr>
<td>6.</td>
<td>R$_{8-6}$</td>
</tr>
<tr>
<td>7.</td>
<td>R$_{3-7}$</td>
</tr>
<tr>
<td>8.</td>
<td>R$_{4-9}$</td>
</tr>
<tr>
<td>9.</td>
<td>R$_{4-8}$</td>
</tr>
<tr>
<td>10.</td>
<td>R$_{2-6}$</td>
</tr>
<tr>
<td>11.</td>
<td>R$_{6-6}$</td>
</tr>
<tr>
<td>12.</td>
<td>R$_{4-7}$</td>
</tr>
<tr>
<td>13.</td>
<td>R$_{3-9}$</td>
</tr>
<tr>
<td>14.</td>
<td>R$_{2-3}$</td>
</tr>
<tr>
<td>15.</td>
<td>R$_{3-4}$</td>
</tr>
<tr>
<td>16.</td>
<td>R$_{5-5}$</td>
</tr>
<tr>
<td>17.</td>
<td>R$_{4-9}$</td>
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<tr>
<td>18.</td>
<td>R$_{6-6}$</td>
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<tr>
<td>19.</td>
<td>R$_{7-8}$</td>
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<tr>
<td>20.</td>
<td>R$_{5-5}$</td>
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<tr>
<td>21.</td>
<td>R$_{5-5}$</td>
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<td>22.</td>
<td>R$_{3-8}$</td>
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<tr>
<td>23.</td>
<td>R$_{8-8}$</td>
</tr>
<tr>
<td>24.</td>
<td>R$_{7-8}$</td>
</tr>
<tr>
<td>25.</td>
<td>R$_{6-7}$</td>
</tr>
<tr>
<td>26.</td>
<td>R$_{6-7}$</td>
</tr>
<tr>
<td>27.</td>
<td>R$_{7-9}$</td>
</tr>
<tr>
<td>28.</td>
<td>R$_{8-8}$</td>
</tr>
</tbody>
</table>

Fig. 9. Routes for EFV and EUV vehicles.
Acknowledgements

The work reported in this paper is a part of the investigation within the research project TR 36017 supported by the Ministry for Science and Technology, Republic of Serbia. This support is gratefully acknowledged.

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