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# IMPLEMENTATION OF COMPUTATIONALLY EFFICIENT TAGUCHI ROBUST DESIGN PROCEDURE FOR DEVELOPMENT OF ANN FUEL CONSUMPTION PREDICTION MODELS

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**Abstract.** Reduction of passenger cars fuel consumption and associated emissions are two major goals of sustainable transport over the last years. Passenger car fuel consumption is directly related to a number of technological aspects of a given car, driver behaviour, road and weather conditions and, especially at urban level, road structure and traffic flow and conditions. In this paper, passenger car fuel consumption was assumed to be a function of three input variables, i.e. day of week, hour of day and city zone. Over the period of 6 months (during 2015) a car was driven in the randomly chosen routes in the city of Niš (Serbia) in the period from 8 to 23 h. The fuel consumption data recorded through on-board diagnostics equipment were used for the development of Artificial Neural Network (ANN) models. In order to efficiently deal with a number of ANN design issues, to avoid usual trial and error procedure and develop robust, high performance ANN models, the Taguchi method was applied. For experimentation with ANN design parameters (transfer function, the number of neurons in the first hidden layer, the number of neurons in the second hidden layer, training algorithm), the standard $L_{18}$ orthogonal array with two replications was selected. Statistical results indicate the dominant influence of the training algorithm, followed by the ANN topology, i.e. interaction of the number of neurons in hidden layers, on the ANN models performance. It has been observed that 3-8-8-1 ANN model represents an optimal model for prediction of passenger car fuel consumption. This model has logistic sigmoid transfer functions in hidden layers trained with scaled conjugate gradient algorithm. By using the Taguchi optimized ANN models, analysis of passenger car fuel consumption has been discussed based on traffic conditions, i.e. different days of the week and hours of the day, for each city zone and separately for summer and winter periods.

**Keywords:** fuel consumption, traffic conditions, artificial neural network, Taguchi method, on-board measurements, city traffic modelling, prediction model.

## Introduction

Ever increasing population, transportation growth and the number of passenger cars in cities create concerns about the road transportation sustainability. It is estimated that passenger cars represent the single largest energy consumer and $CO_2$ emitter among all energy-demand technologies labelled in the EU (Haq, Weiss 2016). In order to ensure a regular traffic there is a need to identify the randomly occurring disturbances that affect the transportation system and to eliminate or reduce their impacts on the traffic (Bouamrane *et al.* 2005). Transportation sector depends exclusively on fossil fuels, non-renewable energy sources, which have harmful impacts on both the environment and human health. The increasing amount of road users has led to the situation that road network capacities seem to be exceeded in many areas due to high traffic load creating personal inconveniences of road users being stuck in traffic (Dallmeyer *et al.* 2012). Because of unpredictable fuel prices (Moret *et al.* 2016), fuel consumption is one of

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the major concerns for consumers which use passenger cars in everyday urban and highway transport. As fuel consumption is in direct relationship with car emissions, prediction and estimation of passenger cars fuel consumption represents a basis for any attempt to ensure energy savings and costs as well as to minimize harmful effects of fuel burning on environment such as air pollution, acid rains, smog, built up of carbon dioxide, changes in the heat balance of the Earth, etc. (Çay *et al.* 2013).

It has been revealed that vehicle fuel consumption functions are too complex to be approximated in practice due to numerous variables affecting their outcome (Ahn *et al.* 2002). In particular, most of the proposed mathematical models consider a set of parameters from different categories such as vehicle engine, traffic, road, vehicle, weather and driver related categories (Van den Brink, Van Wee 2001; Ahn *et al.* 2002). Thus, for example, for a given vehicle and engine type fuel consumption in a random trip depends to varying degrees on a number of parameters such as speed and acceleration patterns, gear changing management, road grade and surface, traffic density and velocity, number of vehicle stops, weather conditions such as temperature, wind speed, etc.

Weather conditions such as rain, snow, fog and ambient temperature which are not stable and may vary depending on geographical location, weather pattern and season may influence to a great extent fuel consumption by affecting the way the car is driven and by influencing aerodynamic and rolling resistances, the operation of car auxiliary units and engine (Fontaras *et al.* 2017). As noted by Cartenì *et al.* (2010), traffic flow, geometric infrastructure and environmental specifications have strong influence on fuel consumption, making the need for development of geographically specific fuel consumption prediction models more obvious. One should also note that significant differences between the New European Driving Cycle (NEDC) with real-world driving cycles that are representative for a given city and country may exist (Duarte *et al.* 2016; Tietge *et al.* 2017).

Importance of fuel consumption estimation and prediction has attracted a number of researchers which have perceived this important topic from various aspects and in different context. Since prediction of vehicle fuel consumption in given conditions may be quite complex and uncertain, involving a number of influencing and interrelated variables, a number of researchers focused on the application of Artificial Neural Networks (ANNs) for modelling these interdependencies. In addition to few applications of Radial Basis Function (RBF) ANNs (Wu, Liu 2012; Huang *et al.* 2016; Kumar *et al.* 2016), ANNs of MultiLayer Perceptron (MLP) type have been predominantly applied. A review of related work with the focus of MLP ANNs application is summarized in Table 1.

ANNs, inspired by human brain functionalities, are computational models which consists of a number of simple processing elements operating in parallel, able to acquire, store and utilize experiential knowledge (Zurada 1992; Haykin 1998), exceeding the possibilities of many other conventional modelling methods (Oğuz *et al.* 2010; Rahimi-Ajdadi, Abbaspour-Gilandeh 2011; Huang *et al.* 2016). In situations where the process/system variables to be studied have complex or nonlinear relationships, that cannot be described analytically because there is no sufficient knowledge level of underlying governing mechanisms and laws, ANN's universal function approximation capability may provide effective means for predictive modelling.

Table 1. Review of MLP ANNs application for fuel consumption prediction

| Reference | Application | Number of inputs / ANN topology | Transfer functions in hidden layer | Training algorithms applied | ANN design |
|---|---|---|---|---|---|
| Arcaklioğlu, Çelıkten (2005) | Prediction of torque, power, brake mean effective pressure, BSFC, fuel flow, and exhaust emissions | 3 / **1-5**, 1-6, 1-7, 1-8, 1-9, 1-10, 1-11, 1-12, 1-13, 1-14, 1-15, 2-9-7, 2-10-7, 2-9-5, 2-8-7 | LS | **SCGA**, PRCGA, LMA | TEM |
| Parlak *et al.* (2006) | BSFC and exhaust temperature of a diesel engine | 3 / 1-7 | LS | LMA | not stated |
| Sayin *et al.* (2007) | Prediction of BSFC, brake thermal efficiency, exhaust gas temperature and exhaust emissions | 4 / Different architectures, **1-15** chosen | LS | LMA | TEM |
| Kara Togun, Baysec (2010) | Torque and BSFC of a gasoline engine | 3 / Different architectures, **1-13, 1-15** chosen | **LS** | **LMA** | TEM |
| Oğuz *et al.* (2010) | Prediction of power, moment, hourly fuel consumption and BSFC of diesel engine using bio fuels | 2 / From 1-1 to 1-50, **1-28** | TS | GDMA | TEM |

*End of Table 1*

| Reference | Application | Number of inputs / ANN topology | Transfer functions in hidden layer | Training algorithms applied | ANN design |
|---|---|---|---|---|---|
| Yusaf *et al.* (2010) | Torque and BSFC of a diesel engine | 2 / 1-19, 1-20, 1-21, **1-22**, 1-23, 1-24, 1-25, 2-13-13, 2-22-22 | **TS**, LS, L | **LMA**, GDMA | TEM |
| Rahimi-Ajdadi, Abbaspour-Gilandeh (2011) | Tractor fuel consumption | 6 / **2-24-26***, 2-12-14, 2-10-10, 2-18-16 | **TS**, LS, L | GDMA, SCGA, **LMA**, QNA, GDALRA | TEM |
| Wu, Liu (2011) | Car fuel consumption | 5 / 1-250 | TS | GDMA | not stated |
| Uzun (2012) | Prediction of BSFC | 3 / different architectures, **1-5** chosen | LS | SCGA | TEM |
| Çay *et al.* (2013) | Prediction of BSFC and exhaust emissions | 4 / 1-5, 1-6, **1-7**, 1-8, 1-9, 1-10, 1-11, 1-12, 1-13, 1-14, 1-15, | LS | QNA, RBA, LMA, **SCGA** | OFAT |
| Kannan *et al.* (2013) | Prediction of performance, emission and combustion characteristics of diesel engine fuelled with biodiesel | 2 / **2-11-11**, 2-14-14, 3-14-14, 4-13-13, 4-15-15 | LS | **SCGA**, LMA, GDMA | TEM |
| Özener *et al.* (2013) | Prediction of torque, power, BSFC and pollutant emissions of a turbo charged diesel engine | 10 / 1-1, 1-2, 1-3, 1-4, 1-5, 1-6, 1-7, 1-8, 1-9, 1-10, **1-11**, 1-12, 1-13, 1-14, 1-15, 1-16, 1-17, 1-18, 1-19, 1-20 | TS | LMA | OFAT |
| Masikos *et al.* (2014) | Energy consumption of fully electrical vehicle | 12 / 1-x-x | TS | SCGA | not stated |
| Siami-Irdemoosa, Dindarloo (2015) | Mining dump trucks fuel consumption | 6 / 2-2-2, 2-3-3, 2-6-6, 2-3-9, 2-9-3, **2-9-9**, 2-6-9, 2-9-6, 2-15-15, 2-30-15, 2-30-30, 1-3,1-4, 1-5, 1-6, 1-8, 1-9, 1-15, 1-30 | not stated | GDMA | TEM |
| Kumar *et al.* (2016) | Prediction of brake thermal efficiency, BSFC, exhaust gas temperature and emissions | 5 / 1-10, 1-15, 1-20, 1-25, **1-30**, 1-35, 1-40, | TS | RBA, GDMA, GDALRA, SCGA, **LMA** | TEM |
| Present study | Prediction of passenger car fuel consumption in urban area during summer and winter periods | 3 / 1-4, 2-4-4, 2-4-8, 1-8, 2-8-4, 2-8-8, 1-12, 2-12-4, 2-12-8 | LS, TS | GDMA, **LMA**, SCGA | Taguchi's robust design method |

*Notes:*
- *2-24-26 means two hidden layers with 24 neurons in the first and 26 neurons in the second hidden layer;
- BSFC – break specific fuel consumption;
- L – linear, LS – log-sigmoid, TS – tan-sigmoid;
- QNA – Quasi-Newton algorithm, RBA – resilient backpropagation algorithm, LMA – Levenberg–Marquardt algorithm, SCGA – scaled conjugate gradient algorithm, GDMA – Gradient descent with momentum algorithm, GDALRA – Gradient descent with adaptive learning rate algorithm, PRCGA – Polak–Ribière conjugate gradient algorithm;
- OFAT – one-factor-at-a- time method, TEM – trial and error method.

Based on the researcher's remarks, some important abilities and features of ANN applied to fuel consumption prediction include the following: (1) ANNs are able to learn, associate, and be error tolerant providing better prediction results in comparison to regression models (Rahimi-Ajdadi, Abbaspour-Gilandeh 2011); (2) can handle large and complex systems with many interrelated parameters (Arcaklioğlu, Çelıkten 2005; Kara Togun, Baysec 2010); (3) possess powerful modelling capability to identify complex relationships from input–output data and generalize a wide range of experimental conditions (Parlak *et al.* 2006); (4) the use of ANN models is quicker, more convenient and cost-effective than fully experimental studies (Uzun 2012); (5) can contain multiple input variables to predict multiple output variables (Kannan *et al.* 2013); (6) the ANN approach represents fast calculation methodology that does not require complex mathematical equations to explain a non-linear and multi-dimensional system (Özener *et al.* 2013); (7) the massive volume and complexity of field dataset make this data-driven approach is more suitable in comparison to other modelling methods, particularly regression-based models which's development may be a vary laborious, if not unfeasible, task (Huang *et al.* 2016). Also, as noted by Oğuz *et al.* (2010), the prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods but the selection of an appropriate ANN topology is important in terms of model accuracy and model simplicity. However, related literature review shows that trial and error still remained the most frequently applied method for ANN design.

While searching for most acceptable ANN (based chosen criteria and suitable for the problem being solved), seven training algorithms, up to two hidden layers, three transfer functions in hidden layer and different number of hidden neurons, up to 250 in a layer, were tested. Moreover, on the basis of results, obtained in computational and time expansive experimentations, different conclusions were drawn, without any particular and practical guidelines for ANN design.

Literature review reveals that use of MLP ANNs for modelling fuel consumption is common. However, the overall aim of this study was to illustrate implementation of computationally efficient Taguchi's robust design procedure for development of ANN mathematical models for predicting passenger car fuel consumption at urban scale under various traffic conditions in summer and winter periods. More specifically, ANN mathematical models were developed considering three input variables, i.e. day of week, hour of day and city zone and by using the experimentally measured data for fuel consumption recorded through on-board equipment for the period of six months. In order to develop high performance model with improved robustness and reliability, and at the same time reduce time and computational recourses, the Taguchi's robust design method was used to assist in optimal selection of the ANN design parameters. To the authors' best knowledge, although the ANN have been previously applied to fuel consumption prediction in different contexts, the application of the computationally efficient Taguchi's robust design procedure for ANN design has not been studied previously and is one of the main subjects of this study. Investigation of the interaction effects of the considered input parameters on the fuel consumption was conducted by means of four 3D surface plots. Comparison of the fuel consumption of passenger cars at urban scale in summer and winter periods is also discussed.

## 1. ANN modelling issues and Taguchi's robust design method

ANNs are adaptive systems consisting of a number of simple processing elements (neurons), grouped into one or more layers, that are interconnected with adjustable parameters (synaptic weights). Modification of these adjustable parameters allows the ANN to learn an arbitrary vector mapping input space $X$ to the output space $y = f(X)$ (Duch, Jankowski 1997).

For a given set of data, development of a high precision, robust ANN model is affected by a number of factors, particularly related to model topology and training algorithm settings (Figure 1). Among them, however, the specification of an appropriate topology is a key issue because it governs the model's capacity to provide adequate function approximation. As noted by Çay *et al.* (2013) the most important factor which determines its success in practice, after the selection of ANN architecture, is the training algorithm.

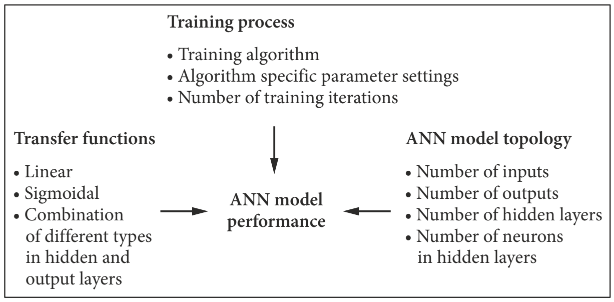


Figure 1. Three main factor groups affecting the ANN model performance

The detailed analysis and discussion of all related factors is beyond the scope of this paper. However, the ANN design parameters, identified from the literature review, are briefly discussed since they represent influential factors for the development of ANN models for fuel consumption prediction.

### 1.1. Transfer functions

The transfer function is a mathematical function which forms the neuron's output from the input signals. The choice of transfer functions in ANNs is of crucial importance for their performance (Duch, Jankowski 1997). The most common form of transfer functions used in ANNs is sigmoid (log-sigmoid and tan-sigmoid) as these transfer functions introduce a certain level of non-linearity into the model, thus providing powerful modelling capabilities. In order for ANN to perform non-linear approximation, a sigmoid transfer function must be used in at least one layer, preferably hidden layer, whereas the use of linear transfer functions in output layer is sufficient in most cases. Above all, the use of linear transfer functions in output layers of ANNs is adequate, considering that, when they are used in output layers, they avoid large weights, which may decrease the performance of ANN by affecting its generalization capability and causing paralysis during training process (Ghosh *et al.* 2005). Tan-sigmoid, log-sigmoid and linear transfer functions are given by the following equations, respectively (Zurada 1992; Patterson 1996):

$$y_j = \frac{2}{1+\exp\left(-2\cdot\left(b_j+\sum_{i=1}^{q} w_{ij}\cdot x_i\right)\right)}-1; \quad (1)$$

$$y_j = \frac{1}{1+\exp\left(-\left(b_j+\sum_{i=1}^{q} w_{ij}\cdot x_i\right)\right)}; \quad (2)$$

$$y_j = b_j + \sum_{i=1}^{q} w_{ij}\cdot x_i, \quad (3)$$

where: $x_i$ is the input from $i$-th neuron from the previous layer; $y_j$ is the output of $j$-th neuron; $w_{ij}$ is weight coefficient between $i$-th and $j$-th neuron in the adjacent layer; $b_j$ is the bias of the $j$-th neuron; $q$ is the number of neurons in previous layer.

### 1.2. ANN topology

Neurons in ANNs are interconnected information-processing units that are grouped into input, output and one or more hidden layers. Each interconnection between neurons from adjacent layers is characterized by certain synaptic weight and each neuron in hidden and output layer posse's bias value. These values represent free parameters that are adjusted during ANN training process and are used together with transfer functions for function approximation. The number of neurons in input and output layer is equal to the number of independent and dependent variables, thus it is automatically specified by the given modelling problem. With the use of nonlinear transfer functions, neurons in hidden layers enable ANN to approximate the underlying complex, nonlinear functions. By increasing the number of hidden layers and neurons, computational power of the ANN is also increased (Aliev, R. A., Aliev, R. R. 2001). However, the complexity of the ANN model in terms of free parameters to be determined during the training process also increases and eventually, if too many hidden neurons are used, a well-known over-fitting problem may occur which is reflected by the fact that ANN loses generalization capability. Actually, it has been mathematically proven that the ANN with one or two hidden layers can approximate any arbitrary functional dependence with a given accuracy, thus the problem of ANN topology definition can be reduced to determining the optimal number of hidden neurons (Cybenko 1989). To this aim a number of researchers proposed various methodologies to estimate the number of hidden neurons. However, as noted by Sha and Edwards (2007), in order for an ANN to be mathematically defined it is necessary that the number of free parameters i.e. synaptic weights and biases be less than or equal to the number of available data for ANN training $N_{tr}$. Following this logic, the number of hidden neurons in the case of ANNs with two hidden neurons can be determined as follows. For the double hidden layer ANN architecture with single output, with n input neurons, m neurons in the first hidden layer and p neurons in the second hidden layer, the total number of synaptic weights and biases can be expressed as:

$$T = m\cdot(n+1)+p\cdot(m+2)+1. \quad (4)$$

Thus for the double hidden layer ANNs with single output, the upper limit of the $m$ neurons in the first hidden layer can be determined by using the following equation:

$$m_{upper} \le \frac{N_{tr}-2p-1}{n+p+1}. \quad (5)$$

The proposed equation can be used to determine the appropriate number of neurons in ANNs with two hidden layers so as to take the full modelling potential of the ANNs. Considering different number of training data and input variables (from the literature review), with respect to proposed equation, the largest possible ANN topologies, in the case when there is more than one neuron in at least one hidden layer, are summarized in Table 2.

Table 2. Possible topologies of MLP ANNs with two hidden layers

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $N_{tr}$ = 50 | $n$ = 3 | $m$ | 7 | 6 | 5 | 4 | 3 | | | | | | |
| | | $p$ | 2 | 3 | 4 | 5 | 7 | | | | | | |
| | $n$ = 4 | $m$ | 6 | 5 | 4 | 3 | | | | | | | |
| | | $p$ | 2 | 3 | 4 | 6 | | | | | | | |
| $N_{tr}$ = 100 | $n$ = 3 | $m$ | 15 | 13 | 11 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 |
| | | $p$ | 2 | 3 | 4 | 5 | 6 | 7 | 9 | 11 | 13 | 17 | 22 |
| | $n$ = 4 | $m$ | 13 | 11 | 10 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | |
| | | $p$ | 2 | 3 | 4 | 5 | 7 | 8 | 10 | 13 | 17 | 22 | |

### 1.3. Training algorithms

In order to establish the precise relationship between the input and output variables, it is necessary to determine the values for synaptic weights and biases, which initially, before the ANN training process, take small random values. ANN training is essentially an optimization problem, in which the goal is to determine values of synaptic weights and biases so as to minimize the error between ANN prediction and desired output. A number of ANN training algorithms were proposed in literature. However, discussion in this study is limited only to those which have been previously successfully used for training ANNs for fuel consumption prediction: gradient descent algorithm, scaled conjugate gradient algorithm and Levenberg–Marquardt algorithm.

*Gradient Descent Algorithm (GDA).* GDA is one of the most popular ANN training algorithms. The GDA starts at some random point in the synaptic weights hyperspace and moves "downhill" in the steepest descent direction in each iteration, i.e. where performance function is decreasing most rapidly (Wilson, Martinez 2003). This first order optimization algorithm has problems of local minima and slow convergence.

*Scaled Conjugate Gradient Algorithm (SCGA).* In contrast to the basic GDA, conjugate gradient algorithms adjust synaptic weights and biases along conjugate directions. In the first iteration, these algorithms start out by searching in the steepest descent direction (negative of the gradient), followed by the line search to determine the optimal distance to move along the current search direction and eventually next search direction is determined so that it is conjugate to previous search directions (Demuth *et al.* 2008). The SCGA, proposed by Møller (1993), is a variation of a standard conjugate gradient algorithm and was designed to avoid the time-consuming line search along conjugate directions, but it requires greater number of iterations to converge.

*Levenberg–Marquardt Algorithm (LMA).* The LMA modifies synaptic weights in a group way, after the application of all ANN training vectors (Slowik, Bialko 2008). This algorithm combines advantages of the steepest descent method, i.e. minimization along the gradient direction, and the Gauss–Newton algorithm, i.e. using a quadratic approximation to speed up the convergence (Yu, Wilamowski 2011). Although LMA is local and there is no guarantee to find a global solution. This algorithm stands for one of the most effective training algorithms for the feed-forward neural networks (Slowik, Bialko 2008).

Although the afore mentioned training algorithms can perform well over a wide variety of problems, it was reported that LMA and SCGA are especially suitable for training medium and larger sized ANNs, respectively (Demuth *et al.* 2008; Slowik, Bialko 2008; Yu, Wilamowski 2011). A detailed discussion of training algorithms is beyond the scope of this paper and reader should consider referential literature (Cybenko 1989; Zurada 1992; Patterson 1996; Haykin 1998; Aliev, R. A., Aliev, R. R. 2001).

### 1.4. ANN model performance

Once an ANN model is developed, it is necessary to perform its validation by using data that were never before presented so as to assess the generalization performance of the ANN model. The most important measure of performance is the accuracy of the prediction and to this aim various statistical methods can be used with Mean Absolute Percentage Error (MAPE) being one of the most stringent. If one insists on a small prediction error on the testing data and acceptable error on the training data, i.e. development of ANN models with good generalization, ANN performance can be accessed by the following equation:

$$ANN_{performance} = 0.75 \cdot MAPE_{test} + 0.25 \cdot MAPE_{trening}, \quad (6)$$

where: $MAPE_{test}$ and $MAPE_{trening}$ are MAPEs on testing and training data, respectively.

### 1.5. Taguchi's robust design method

Aimed to improve the quality of products and processes, Taguchi's robust design method is unique and powerful approach widely used in engineering domain. The ultimate goal is to identify optimal settings for control parameters making the products and processes robust, i.e. insensitive to the various causes of variation (noise) which cannot be controlled or are too expensive to control (Phadke 1989; Ross 1995; Taguchi *et al.* 2004). To this aim, Taguchi proposed the use of Orthogonal Arrays (OAs), Signal-to-Noise (*S*/*N*) ratio and ANalysis Of Means (ANOM). Related to ANN model development, initialization of ANN weights and biases using a given method can be considered as noise.

OAs are special, partial factor experimental plans that are used to cover the entire experimental hyperspace of interest and with a minimum number of trials compared to traditional design of experiment approach. Rows in OAs represent experimental trials with different combinations of parameter levels while columns represent single control parameter and its level settings. These are used to systematically study the main effects of control parameters and in some cases the effects of the interactions between two control parameters.

For each combination of control parameter level settings, the mean and variance of the considered response are combined into summary statistic known as *S*/*N* ratio. Taguchi empirically determined that *S*/*N* ratios give near optimal combination of parameter levels, where the variance is minimal and mean value is kept close to the target value. Depending on the quality characteristics, different *S*/*N* ratios may be applicable, including smaller-the-better, larger-the-better and nominal-the-best. For example, in any mathematical modelling it is desirable to develop accurate mathematical model having as small as possible prediction error, therefore smaller-the-better *S*/*N* ratio can be chosen and calculated as (Phadke 1989):

$$\eta \equiv S/N = -10 \cdot \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right), \quad (7)$$

where: $y_i$ is the $i$-th response value; $n$ is the number of observations in an experimental trial.

The optimum level of a parameter is the level that gives the highest *S*/*N* ratio. The predicted *S*/*N* ratio using the optimal levels of the parameters $\hat{\eta}_{opt}$ can be calculated as (Phadke 1989):

$$\hat{\eta}_{opt} = \overline{\eta} + \sum_{i=1}^{m}\left(\overline{\eta}_{i,opt} - \overline{\eta}\right), \quad (8)$$

where: $\overline{\eta}_{i,opt}$ is the mean *S*/*N* ratio for $i$-th parameter at the optimal level; $m$ is the number of parameters that significantly affect the quality characteristic; $\overline{\eta}$ is the total mean *S*/*N* ratio.

The process of estimating the mean *S*/*N* ratios for each parameter and each of its levels is called ANOM. The effect of parameter $Q$ at level $k$ can be calculated as (Marinković, Madić 2011):

$$\overline{\eta}_{Qk} = \frac{1}{n_{Qk}} \cdot \sum_{l=1}^{n_{Qk}} \left( (S/N)_{Qk} \right)_l, \tag{9}$$

where: $n_{Qk}$ is the number of appearances of parameter $Q$ at level $k$ in experimental plan; $(S/N)_{Qk}$ is the $S/N$ ratio related to parameter $Q$ at level $k$.

ANOM is usually performed using response graphs providing simple visual identification of the quantitative and qualitative effects of parameter changes. Although ANOM can be used as a statistical tool for determining optimal parameter settings, in some cases ANalysis Of VAriance (ANOVA) is preferred as it allows estimation of the relative significance of each process parameter in terms of percent contribution on the overall response.

## 2. Data collection and ANN model development

### 2.1. Data collection and pre-processing

In the first stage of this research, experimental data from passenger car On-Board Diagnostics (OBDII) interface were collected during normal daily commute operation in the city of Niš over a period of 6 months. OBDII is current (as of 1996) standard in the diagnostic connector, its pinout, signalling protocols and messaging format.

Widely available ELM327 based OBDII device was used for data collection. This device integrates OBDII interface, global positioning system receiver and cellular network general packet radio service modem for wireless communication with the backend data-collection server (Figure 2). During data collection phase, the device was collecting standard vehicle operating parameters including ignition status, engine RPM, current fuel consumption, vehicle battery voltage and standard fault codes. Timestamp and geographic coordinates are added to each collected data tuple by device software and one data packet is sent to backend data collection service in a JSON format using mobile telco operator network. The data collection service is a standard REST API Web service developed in-house specifically for this study. The back-end server uses geospatial database (PostGIS) which contains detailed road network data for the city experiment was conducted in. This road network data was used to map-match each received data tuple to specific road network segment. Further, this map-matched information allowed collected OBDII data classification and segmentation. Spatial database road network data includes road type (motorway, secondary, primary, footway, tertiary, etc.), number of lanes, direction (one-way/two-way), etc. In future research, this extended spatial info can allow a more detailed classification of collected OBDII data using various criteria.

For the experimentation purposes road network of the city was classified into two zones: Zone 1 – narrow city center; Zone 2 – wider city center area (Figure 3).

### 2.2. Implementation of Taguchi's robust design method for ANN model development

The purpose of ANN based mathematical modelling in this study is to model the underlying relationships between independent variables (day of week, hour of day and city zone) and fuel consumption of the passenger car in the city of Niš. On the other hand, the idea of the Taguchi method application was to develop high performance ANN model, which is robust and accurate by considering different influential factors related to ANN design and training such as transfer function $A$, number of neurons in the first hidden layer $B$, number of neurons in the second hidden layer $C$ and training algorithm $D$.

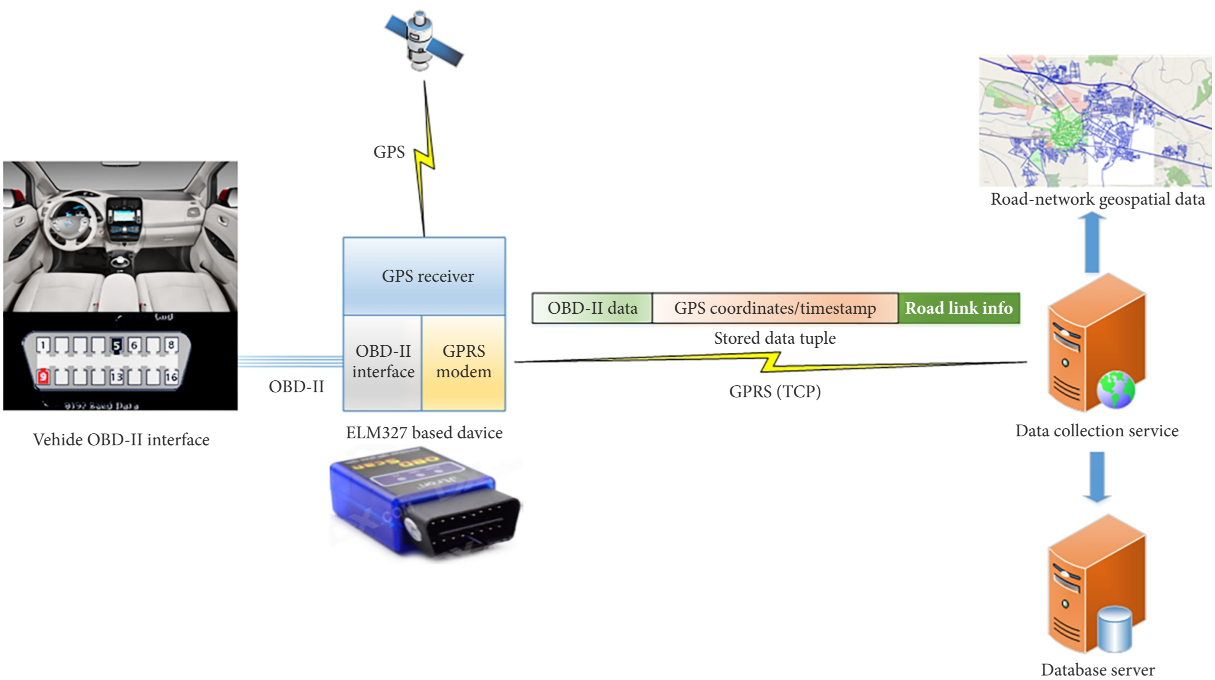


Figure 2. Experimental data collection setup

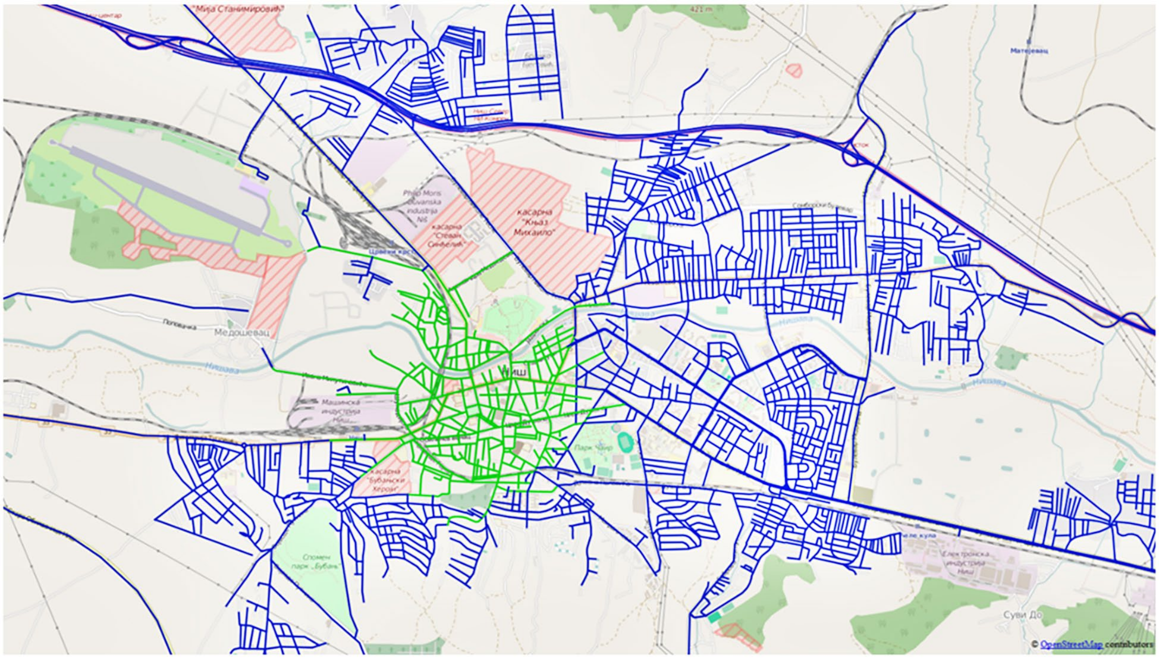

Figure 3. City streets divided into 2 zones overlayed over Open Street Maps (Zone 1 – green, Zone 2 – blue)

Considering the literature review, discussion and proposed guidelines for ANN model development, four ANN parameters *A*–*D* were varied at two and three levels (Table 3). That is, in sum, 9 different ANN topologies (3 single hidden and 6 double hidden layers) with different transfer functions, trained with different algorithms were developed and tested.

Since this case study considers three ANN parameter factors at three levels and one at two levels, there are $3 \times (3 - 1) + 1 \times (2 - 1) + 1 = 8$ degrees of freedom, thus the standard $L_{18}(2^1 \times 3^7)$ OA was selected (Taguchi *et al.* 2004) (Table 4). This mixed design is highly recommended, because interactions are distributed uniformly to all columns (Phadke 1989). Note that *A* and *D* are discrete, while *B* and *C* are continuous. As control factor *A* has only two levels it was assigned to column 1, while the others were assigned to column 2, 3 and 4, respectively.

For each experiment trial, i.e. combination of ANN design parameters, two replications were used, that is in sum 18 × 2 = 36 ANN models were developed. For each developed ANN model, performance, in accordance with equation 6, was estimated, upon which *S*/*N* ratios for each experimental trial were calculated (Table 4). It has to be noted that for all ANN models linear transfer function was used in the output layer whereas Nguyen–Widrow method was used for weights and biases initialization. Also, in order to deal with bias–variance trade-off and convergence to local minima, the training process of 1000 iterations was repeated in some cases several times using different initial weights and biases.

By analysing ANNs training process, it was observed that LMA has the fastest convergence followed by SCGA and GDA. However, SCGA proved to be very robust, i.e. different weights initialization patterns had minimal effect on global convergence.

On the basis of the calculated *S*/*N* values given in Table 4 and by using the ANOM, i.e. Equation (9), the mean effects of each design parameter on mean *S*/*N* ratio are presented in a graphical form, whereas the optimal levels are marked by circles.

Note that the overall mean value of *S*/*N* ratios for the experimental region defined by the design parameters levels in Figure 4 was calculated as:

$$m = \frac{1}{18} \cdot \sum_{i=1}^{18} \eta_i, \quad (10)$$

where: the subscript *i* represents the *i*-th experiment in the OA.

Table 3. ANN design parameters and their levels

| Design parameter | Symbol | Parameter levels | | |
|---|---|---|---|---|
| | | Level 1 (low) | Level 2 (middle) | Level 3 (high) |
| Transfer function | *A* | tan-sigmoid | log-sigmoid | – |
| Number of neurons in the first hidden layer | *B* | 4 | 8 | 12 |
| Number of neurons in the second hidden layer | *C* | 0 | 4 | 8 |
| Training algorithm | *D* | LMA | SCGA | GDA |

Table 4. The experiment settings $L_{18}$ ($2^1 \times 3^7$)

| Trial | Design parameters | | | | ANN performance [%] | | $S/N$ ratio [dB] |
|---|---|---|---|---|---|---|---|
| | *A* | *B* | *C* | *D* | | | |
| 1 | tan-sigmoid | 4 | 0 | LMA | 12.65 | 13.21 | –23.23 |
| 2 | tan-sigmoid | 4 | 4 | SCGA | 13.91 | 13.57 | –22.76 |
| 3 | tan-sigmoid | 4 | 8 | GDA | 12.75 | 13.70 | –22.43 |
| 4 | tan-sigmoid | 8 | 0 | LMA | 13.41 | 12.71 | –22.32 |
| 5 | tan-sigmoid | 8 | 4 | SCGA | 12.55 | 12.68 | –22.02 |
| 6 | tan-sigmoid | 8 | 8 | GDA | 13.13 | 14.22 | –22.73 |
| 7 | tan-sigmoid | 12 | 0 | SCGA | 11.46 | 12.36 | –21.52 |
| 8 | tan-sigmoid | 12 | 4 | GDA | 12.88 | 14.47 | –22.73 |
| 9 | tan-sigmoid | 12 | 8 | LMA | 13.35 | 13.42 | –22.53 |
| 10 | log-sigmoid | 4 | 0 | GDA | 15.14 | 12.14 | –22.75 |
| 11 | log-sigmoid | 4 | 4 | LMA | 12.80 | 12.63 | –22.08 |
| 12 | log-sigmoid | 4 | 8 | SCGA | 11.62 | 12.42 | –21.60 |
| 13 | log-sigmoid | 8 | 0 | SCGA | 11.78 | 13.29 | –21.98 |
| 14 | log-sigmoid | 8 | 4 | GDA | 12.80 | 12.62 | –22.08 |
| 15 | log-sigmoid | 8 | 8 | LMA | 12.25 | 11.49 | –21.49 |
| 16 | log-sigmoid | 12 | 0 | GDA | 12.63 | 13.73 | –22.41 |
| 17 | log-sigmoid | 12 | 4 | LMA | 12.40 | 12.79 | –22.01 |
| 18 | log-sigmoid | 12 | 8 | SCGA | 12.67 | 13.14 | –22.22 |

Figure 4 makes evident that the optimal combination of the design parameter levels is $A_2B_2C_3D_2$. In other words, double hidden layer ANN model having 8 hidden neurons in each hidden layer, using log-sigmoid transfer function in hidden layers, trained with SCGA represents the optimal ANN model (Figure 5).

Note that the slope of lines in Figure 4 determines the power of the design parameters effects on the $S/N$ ratios. Graphs from Figure 4 clearly suggest a dominant influence, in a quantitative sense, of training algorithm on the change in the $S/N$ ratios. However, in order to determine relative importance of design parameters ρ, contribution of each ANN design parameter to the change in the $S/N$ ratios and finally, estimate the error variance, the ANOVA analysis was performed using the $S/N$ ratios (Table 5). Due to the possibility of interaction between design parameters, additional analysis based on interaction plots has been carried out. It results in the fact that interaction $B \times C$ was also included in the ANOVA analysis, because of its significance.

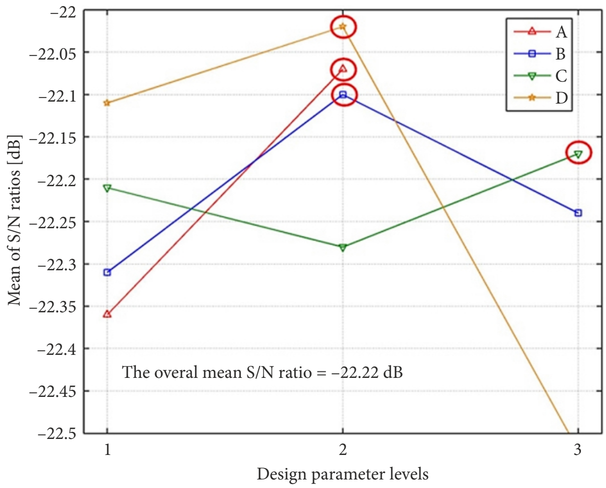


Figure 4. Mean $S/N$ ratios for main effects

The percentage contribution of source to the total variation defines parameter sensitivity. It can be seen from Table 5 that changing the design parameters levels contributes approximately 86% of the total variation in the ANN performance. The ANOVA results indicate that the training algorithm is the most significant parameter contributing 43% to the changes in ANN performance.

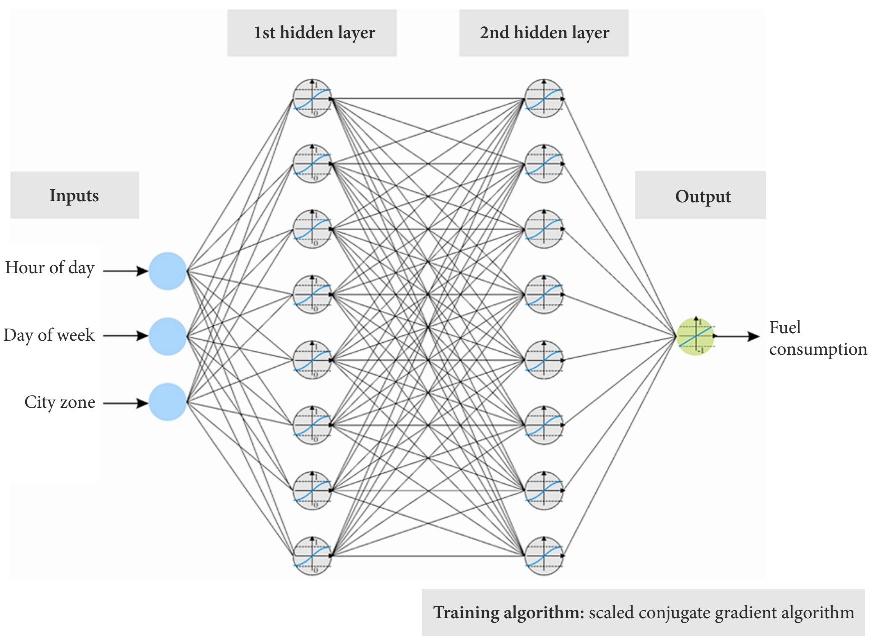


Figure 5. Optimal MLP ANN model for prediction of passenger fuel consumption

Table 5. ANOVA results for $S/N$ ratios

| Source of variation | Degrees of Freedom (DOF) | Sum of Squares (SS) | Mean Square (MS) | $F$ | ρ [%] |
|---|---|---|---|---|---|
| $A$ | 1 | 0.393 | 0.393 | 7.44 | 11.15 |
| $B$ | 2 | 0.132 | 0.066 | 1.25 | 3.75 |
| $C$ | 2 | 0.04 | 0.02 | 0.38 | 1.13 |
| $D$ | 2 | 1.528 | 0.764 | 14.46 | 43.35 |
| $B \times C$ | 4 | 1.115 | 0.279 | 5.28 | 31.63 |
| Error | 6 | 0.317 | 0.053 | – | 8.99 |
| Total | 17 | 3.525 | – | – | 100 |

The interaction between the number of hidden neurons in the first and the second hidden layer contributes approximately 32%. Finally, the transfer function contributes approximately 11%.

The $S/N$ ratio using the optimal levels of the parameters $A_2B_2C_3D_2$, determined with the use of Equation (8), was calculated as $\hat{\eta}_{opt} = -21.67$ dB. The final step in the application of the Taguchi method is the verification of quality improvement, i.e. in this case the improvement of ANN model performance. Since ANN model with the optimal combination of the main parameters levels does not exist in the experimental matrix (Table 4), new ANN models were trained with the above-mentioned optimal level settings. The observed $S/N$ ratio values from the confirmation experiment were obtained as $\hat{\eta}_{exp} = -21.21$ dB.

In order to statistically judge the closeness of the predicted and observed value of $S/N$ ratio, the Confidence Interval (CI) was determined using the following relation (Ross 1995):

$$CI = \sqrt{F_{\alpha(1,f_e)} \cdot V_e \cdot \left( \frac{1}{n} + \frac{1}{n_{ver}} \right)}, \tag{11}$$

where: $F_{\alpha(1,f_e)} = 5.99$ is the $F$ value from statistic table at a 95% confidence level; $f_e$ is degrees of freedom for the error; $V_e$ is the mean square of error; $n_{ver}$ is the confirmation test trial number; $n$ is defined as:

$$n = \frac{N}{1+\nu}, \tag{12}$$

where: $N$ is the total number of trials in experimental matrix; ν is the total degrees of freedom of all design parameters.

In this study, the CI value of 0.61 was obtained. Since the difference between $\hat{\eta}_{opt}$ and $\hat{\varsigma}_{exp}$ is within the CI value, it can be concluded that the chosen experimental design is functionally adequate and that the applied procedure to determine optimal ANN design parameters is statistically confirmed and valid. Therefore, the developed ANN model is used thereafter for further investigation regarding fuel consumption prediction in the city of Niš.

## 3. Results and discussion

Analysis and discussion of passenger car fuel consumption in the city of Niš during summer and winter periods was performed by means of four 3D surface plots showing the interactions effects of hour of day and days of week for two considered city zones (Figures 6 and 7).

Overall, the average fuel consumption decreases from 8.88 l/100 km for city Zone 1 to 8.36 l/100 km for city Zone 2. More specifically, during working days, average fuel consumption for Zone 1 is 9.03 l/100 km and is decreased to about 8.25 l/100 km for Zone 2. This decrease of about 9% is a consequence of less intense traffic flow and crowd, i.e. less traffic intensity in wider city zones. However, this difference during the weekend days, possibly due to ease of traffic congestion in the city center throughout the day, is almost negligible with average fuel consumptions of 8.48 and 8.38 l/100 km in city Zones 1 and 2, respectively. As could be clearly observed, the fuel consumption is particularly increased in the afternoon

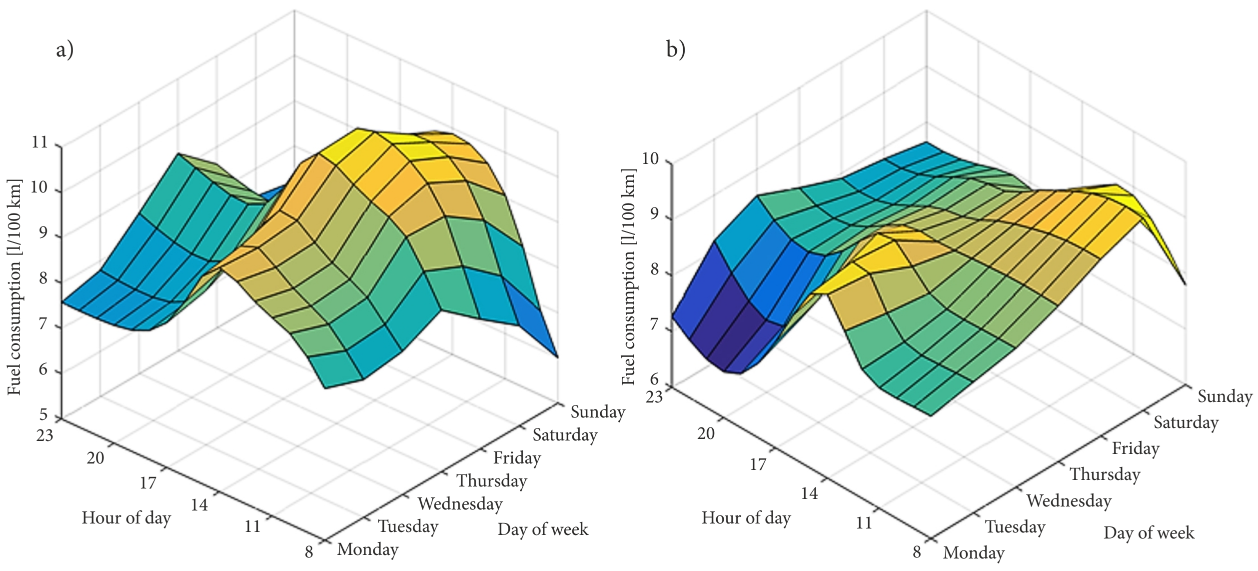


Figure 6. Passenger car fuel consumption in the city of Niš during summer: a – Zone 1; b – Zone 2

hours when people return from work and high traffic intensity occurs with large lines of vehicles in central city streets. As a consequence, each single route in the city center inevitably involves a number of vehicle stops on traffic lights as well as a number of speed changes with different acceleration/deceleration patterns which results in higher fuel consumption. In these afternoon rush hours between 14 h and 16 h, the average fuel consumption rises up to 11 l/100 km in the city Zone 1. A research from the city of Poznan (Poland) reports that average fuel consumption for a test vehicle (petrol engine, 1.6 $cm^3$ capacity, 83 kW max output power) in normal city conditions is about 9 l/100 km and rise to as much as 12…14 l/100 km in a very high level of traffic congestion (Igliński 2009).

From Figure 6b, one can notice another interesting observation which is reflected in the fact that the deviations from average fuel consumption are much less pronounced in city Zone 2. Ability to maintain constant speed with accompanying smaller fluctuations at certain road sections in city Zone 2 may be logical explanation for this observation.

By using the experimental data for winter period and ANN design parameters, as obtained by the Taguchi method, second ANN mathematical model for the prediction of fuel consumption was developed. This model, having excellent performances with average MAPE values on training and testing of 4.15 and 3.84% respectively, was used to analyse fuel consumption during winter period (Figure 7).

As observed from Figure 7 there is a small difference between fuel consumption in city zones when considering working days and weekend days separately. On average, the fuel consumption decreases from 9.21 l/100 km for city Zone 1 to 9.13 l/100 km for city Zone 2. Figure 7 indicates that there is fuel consumption increase in the morning hours and this may be attributed to slower engine heating due to lower ambient temperatures, especially over relatively short distances. As noted by Murrell (1980), fuel consumption rates increase at low temperatures and with high winds, which result in aerodynamic losses. In general, from Figures 6 and 7 one can also observe that fuel consumption in the morning hours is higher than in evening hours because of substantially different traffic conditions which characterize these two periods. However, comparison of Figures 6a and 7a shows that there is no evident increase in fuel consumption during afternoon hours. In other words, less traffic flow with crowds is noticeable. It seems that in the case of the city of Niš, one can conclude that people, due to weather and road conditions, prefer to use public transport or taxis over their own cars, thus avoiding possible risky driving situations that may occur during adverse weather conditions.

Comparison of average fuel consumptions in city zones during summer and winter periods is summarized in Table 6.

Irrespective of considered city zones and days in the week, using the provided data one can calculate that average fuel consumption during summer is 8.5 l/100 km whereas in winter is 9.3 l/100 km. It has been previously reported that fuel consumption in winter is about 15…20% higher than in summer (Baker 1994). Smaller deviations in fuel consumption during winter and summer periods reported in this study (about 9%) may be due to today's even more advanced and efficient engines delivering the same power output with less fuel consumption and associated emissions at the same time.

Table 6. Comparison of average fuel consumption by city zones during summer and winter periods in the city of Niš

| Period | Days in the week | City Zone 1 | City Zone 2 |
|---|---|---|---|
| Summer | working days | 9.03 | 8.25 |
| | weekend days | 8.48 | 8.38 |
| Winter | working days | 9.21 | 9.13 |
| | weekend days | 9.29 | 9.41 |

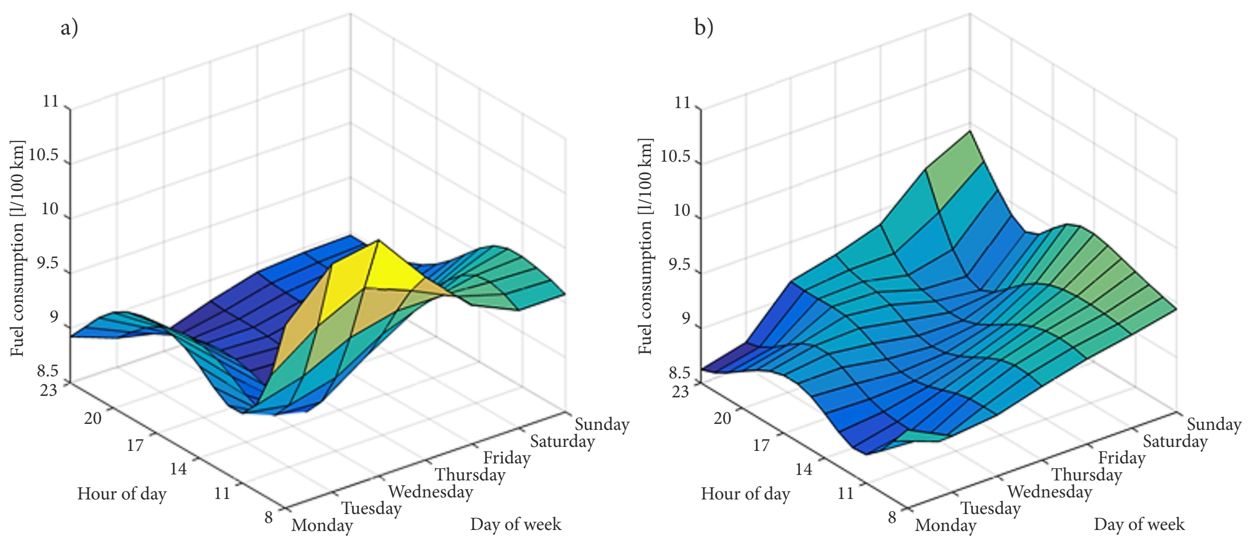


Figure 7. Passenger car fuel consumption in the city of Niš during winter: a – Zone 1; b – Zone 2

## Conclusions

The reduction of fuel consumption, emissions and traffic jams and congestions and increase in traffic safety are major tasks of any city's sustainable transportation system. As fuel consumption makes considerable share in transportation and emission costs, its estimation is of prime importance in city logistics. In this study, with the implementation of computationally efficient Taguchi's robust design procedure, two ANN models for the prediction of passenger car fuel consumption under various traffic conditions in summer and winter periods in the city of Niš (Serbia) were developed. Based on conducted analysis and obtained results, the following conclusions can be made:

- It has been observed that SCGA was able to provide fast ANN training and achieve better performance in comparison to conventional GDA as well as LMA. The algorithm proved to be stable and robust while being able to escape from local minimums irrespective of the different weights initialization schemes;
- It has been revealed statistically that the number of neurons in hidden layers may not be of much importance. However, the interaction between the number of neurons in the first and the second layer, which define the ANN topology, significantly determined ANN performance and is nearly equally important as the training algorithm;
- It has been observed that the same number of hidden neurons distributed in two layers represents appropriate ANN topology for fuel consumption prediction and in this sense confirms observations that have been reached by trial and error method (Siami-Irdemoosa, Dindarloo 2015; Kannan *et al.* 2013);
- The implementation of computationally efficient Taguchi's robust design procedure significantly decreased the number of experimentation trials with different combinations of ANN design parameters and ensured development of reliable model which can be used for passenger car fuel consumption prediction;
- It has been revealed that the passenger car fuel consumption in the city of Niš is predominantly affected by the time of day. In summer periods fuel consumption is increased in the afternoon rush hours due to increased traffic jams and congestions while in the winter period fuel consumption is increased in the morning hours due to prolonged engine pre-heating time due to lower ambient temperatures. Also, an increase of about 10% of fuel consumption was recorded during winter period and this can be directly mapped to increase in transportation costs;
- Specific traffic conditions that occur in the city of Niš and as modelled by the ANNs are reflected in the fact that due to lesser traffic intensity and ability to maintain constant speed over longer distances, there is a decrease in fuel consumption in wider city zones (Zone 2) in comparison to downtown areas (Zone 1).

Although the problem of fuel consumption prediction is very complex, involving a number of input variables having different influences and interdependencies, the use of ANNs in this study ensured quite accurate passenger car fuel consumption predictions. As a result of higher intensity traffic with occurrence of traffic jams and congestions during the summer period which was reflected through more intensive gear changes as well as speed and acceleration patterns, somewhat higher prediction errors of ANN model were obtained. On the other hand, lower traffic intensity and less frequent car speed changes with much lower acceleration/deceleration rates, which are pronounced during winter period due to weather and traffic conditions, resulted in much smaller ANN prediction errors. Finally, one needs to note one important characteristic of ANNs which is particularly beneficial for vehicle fuel consumption predictions. Namely, as traffic conditions in urban areas may be highly uncertain and unpredictable, the ability of ANNs to be retrained, i.e. to broaden or modify its knowledge if new training patterns are available, is very beneficial so as to predict fuel consumption in different traffic conditions for the same road segments.

Practical implications of this study pertain to the possible usage of the developed mathematical models for the estimation of travel costs and route optimization in the city of Niš for different city zones, days of the week and hours of the day. Also, predictions of fuel consumption can be used for estimation of $CO_2$ emissions. The future work will be focused on implementation of eco-driving programs and preparing an experimental database for development of new ANN models for fuel consumption prediction so as to compare possible fuel savings.

## Author contributions

Miloš Madic concieved the study and experiment design.

Bratislav Predić implemented data collection software and hardware, designed and implemented spatio-temporal database and performed geospatial analysis and preprocessing of the collected data. He also summarized collected ANN data.

Miloš Roganović interpreted collected vehicle telemetry data from the engine performance and consumption standpoint.

Darjan Karabašević created review of MLP ANN application for fuel consumption found in recent literature.

Dragiša Stanujkić performed results interpretation and visualization and proof read draft version of the paper.

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## Disclosure statement

The authors declare that there are no competing financial, professional or personal interest from other parties regarding publication of this paper.

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