EVALUATION OF THE INFLUENCE OF TERRAIN AND TRAFFIC ROAD CONDITIONS ON THE DRIVER'S DRIVING PERFORMANCES BY APPLYING MACHINE LEARNING

Davor B. VUJANOVIĆ* *, Slađana R. JANKOVIĆ, Marko A. STOKIĆ, Stefan S. ZDRAVKOVIĆ

University of Belgrade, Faculty of Transport and Traffic Engineering, Belgrade, Serbia

* Corresponding author; e-mail: d.vujanovic@sf.bg.ac.rs

In this paper, research is done in the influence of different terrain and traffic conditions on road sections on the driver's driving performances, i.e. on the car energy efficiency and CO_2 emission. A methodology aimed at determining to which extent unfavorable traffic and/or terrain conditions on a road section contribute to the driver's worse driving performances, and also to determine when the driver's aggressive driving style is responsible for greater fuel consumption and greater CO_2 emission is proposed. In order to apply the proposed methodology, a research study was carried out in a cargo transportation company and 12 drives who drove the same vehicle on five different road sections were selected. As many as 284 014 of the instances of the data about the defined parameters of the road section and the driver's driving style were collected, based on which and with the help of machine learning a prediction of the scores for the road section and the scores for the driver's driving style was performed. The obtained results have shown that the proposed methodology is a useful tool for managers enabling them to simply and quickly determine potential room for increasing the energy efficiency of the vehicle fleet and decreasing CO_2 emission.

Key words: *driving style, traffic condition, terrain condition, machine learning, energy efficiency, CO_2 emission, fuel consumption, vehicle fleet*

1. Introduction

Transportation and logistics companies with a vehicle fleet in goods road transportation have the aim to realize all planned transportation tasks in the observed time, simultaneously generating as low costs as possible so as to make a bigger profit. As fuel consumption for the realization of transportation tasks has a significant share in costs [1–3], an increase in the energy efficiency of a vehicle fleet is one of the significant measures for achieving the goal of the considered companies [4–6] and is yet increasingly gaining in importance when the environment is observed since road transportation has a dominant share in final energy consumption in the transportation sector [7–9].

Exerting an influence on the driver's style represents one of the measures that may contribute to an increase in energy efficiency. The considered companies frequently send their drivers to an "eco-driving" training course which may result in instantaneous savings in fuel consumption even up to 15% [10]. No more significant savings of "eco-driving" training courses, however, are achieved in the long-term observation period since drivers tend to return to their old vehicle driving habits after a certain time has passed [11]. The reasons for said are, first of all, drivers' insufficient awareness of the influence a driving style has on fuel consumption [12], as well as a frequent nonexistence of a system for rewarding energy efficient drivers in the considered companies [13]. In order to achieve the long-term effects of "eco-driving" training courses, too, there is a need to supervise the driver's driving style through the constant supervision of the values of the vehicle parameters that influence fuel consumption [14]. In the paper [15], the authors scored the driver's driving style in passenger cars by using the following vehicle parameters: the engine speed, the vehicle acceleration/deceleration and the accelerator pedal position. They determined that the higher the score for the driver (a passive driving style), the smaller specific fuel consumption (in *l/100 km*), and *vice versa*. In the research study conducted in [16], a fuzzy logic system type-2 (FLS2) model was developed by using the following vehicle parameters: the engine speed (*ES*), vehicle acceleration/deceleration (*ACC*) and the accelerator pedal position (*APP*). The same authors established a fact that, apart from the performed "eco-driving" training course, there were yet significant differences in the achieved driving scores that had caused an increase in specific fuel consumption by as much as 52.64%, the other fuel consumption influential factors (such as traffic conditions, terrain conditions and so on) simultaneously being brought to an equal footing with each other.

In the paper [17], a set of multivariate regression models were developed and a fact was established that the route characteristics such as average commercial speed on the route, the frequency of a longitudinal road ascent/descent exceeding 5% exert a significant influence on the energy efficiency of a bus vehicle fleet, among other things. In the conducted research study [18], it was considered that fuel consumption could double if the road slope were greater than 4%. Beside the influence of the road slope on fuel consumption, traffic conditions such as driving in dense urban areas with traffic congestion have a major influence on fuel consumption and therefore on fuel savings as well [19,20]. Since road sections differ from one another as per terrain and traffic conditions, drivers often justify such excessive fuel consumption by stating unfavorable terrain or traffic conditions along the section, not questioning their driving performances. To determine the driver's driving performances on a particular section, contemporary information technologies can be utilized on a vehicle [21]. Using telematics systems on a vehicle, however, provides us with large amounts of diverse parameters that require a longer time for their professional analysis, thus making it more difficult for managers to make timely decisions [22]. For the reason of all that, managers are deprived of a possibility to quickly and without major cost investments determine when it is unfavorable terrain or traffic conditions on a section that have contributed to the driver's worse driving performances and when it is exclusively bad driving performances (i.e. the driver's aggressive style) that were the reason for greater fuel consumption.

In this paper, research was done in the extent to which different terrain and traffic conditions on a section influence the achieved driving performances, i.e. the driver's driving style, and how all that together influences the vehicle energy efficiency and the environment (through CO_2 emission) at the same time. Based on the literature review and the authors' own experience, the following parameters describing terrain and traffic conditions on a section: the longitudinal ascent/descent on a road section, i.e. the slope of a road section (*SRS*) (in *%*) and average vehicle speed in a timeframe (*ASTF*) (in *km/h*) were determined. According to the paper [16], the parameters that trustworthily describe the driver's driving style are as follows: the engine speed – *ES* (rpm), the accelerator pedal position – *APP* (%) and the vehicle acceleration/deceleration – *ACC* (m/s^2). A methodology for the evaluation of a road section and the driver's driving style from the aspect of energy efficiency was developed using machine learning. The methodology aims to determine the extent to which unfavorable traffic and/or terrain conditions have an influence on the driver's driving style and thus simultaneously on the energy efficiency of the vehicle fleet and CO_2 emission by comparing the score for the road section and the score for the driver's driving style.

The paper has the following structure: in Chapter Two, the developed methodology is explained, within the framework of which the machine learning method is presented; Chapter Three is dedicated to the description of the conducted research study, in which the proposed methodology was applied; the obtained results and the discussion are presented in Chapter Four, whereas Chapter Five provides the conclusions and directions of future research efforts.

2. Methodology for the Evaluation of a Road Section and the Driver's Driving Style by Applying Machine Learning

In this study, the machine learning method uses the data pertaining to the driver's driving ratings for the recorded values of the driving parameters (*ES*, *ACC*, *APP*) and the data of the road section ratings for the recorded values of the section parameters (*SRS*, *ASTF*). When appropriate datasets for training and testing are available, the application of the machine learning technique is simple, fast and efficient, and as for the rating, it does not require complicated expert rules or expert questionnaires.

2.1 Machine learning method

Machine learning was applied so as to simply and quickly calculate the scores for the road section and the scores for the driver's driving style, which would enable efficient support in real time. The term 'machine learning' was first used by the author of the paper [23]. Many authors have modified the driver's behavior by using machine learning. The authors of the paper [24] used the clustering technique, machine learning algorithms and deep learning algorithms to classify drivers' behaviors into those eco-friendly and those which are not. In the paper [25], deep learning was used as one of the subfields of machine learning for modelling drivers' behavior. The most frequently used types of machine learning algorithms in the papers are SVM (Support Vector Machines), NN (Neural Networks), BL (Bayesian Learners) and EL (Ensemble Learners), whereas the algorithms of the Decision Trees (DT) types and Instance Based (IB) algorithms are present to a much lesser extent [26]. In this research study, several different machine learning algorithms were used for the prediction of the scores for the sections and the scores for the drivers, while a comparative analysis of their performances is simultaneously shown in the obtained results.

The machine learning process consists of the following phases: the data preparation, the model training, the model validation, the model testing and the model application, i.e. the target variable prediction [27]. The approach known as cross-validation was used in this research study to validate the model. Several different performance measures were used to score the successfulness of numerical prediction; they are calculated according to the expressions (1-5) in the following manner [27]:

$$\text{Mean-absolute error} = \frac{|p_1 - a_1| + \ldots + |p_n - a_n|}{n} \tag{1}$$

$$\text{Root mean-squared error} = \sqrt{\frac{(p_1-a_1)^2+\ldots+(p_n-a_n)^2}{n}} \tag{2}$$

$$\text{Root relative-squared error} = \sqrt{\frac{(p_1-a_1)^2+\ldots+(p_n-a_n)^2}{(a_1-\bar{a})^2+\ldots+(a_n-\bar{a})^2}} \tag{3}$$

$$\text{Relative-absolute error} = \frac{|p_1-a_1|+\ldots+|p_n-a_n|}{|a_1-\bar{a}|+\ldots+|a_n-\bar{a}|} \tag{4}$$

$$\text{Correlation coefficient} = \frac{\dfrac{\sum_{i=1}^{n}(p_i-\bar{p})(a_i-\bar{a})}{n-1}}{\sqrt{\dfrac{\sum_{i=1}^{n}(p_i-\bar{p})^2}{n-1} \cdot \dfrac{\sum_{i=1}^{n}(a_i-\bar{a})^2}{n-1}}} \tag{5}$$

where p_1, p_2,…,p_n are the predicted values of the target variable, and the value $\bar{p}$ is the average of the predicted values of the target variable, whereas the values a_1, a_2,…,a_n are the real values of the target variable, and the value $\bar{a}$ is the average of the real values of the target variable, n simultaneously being the number of the model validation instances.

In order to estimate how successful the selected models will be when applied to some new data, their performance measures are calculated on the test dataset. After that, the model performances obtained on the test dataset are subjected to a comparison with the performances obtained on the training dataset. The model with the best performances on the training dataset and on the test dataset is selected. The machine learning model that was selected as the best after the testing phase is applied to the prediction dataset.

2.2 Methodology structure

The methodology (Figure 1) has the aim to determine the score for the road section and the score for the driver's driving style based on machine learning from the aspect of the vehicle energy efficiency. By comparing the final score for the section with the final score for the driver's driving style on the section, it is possible to determine the extent to which fuel consumption is a result of the influence of traffic and/or terrain conditions, and to which extent the same is a result of an (in) adequate driving style.

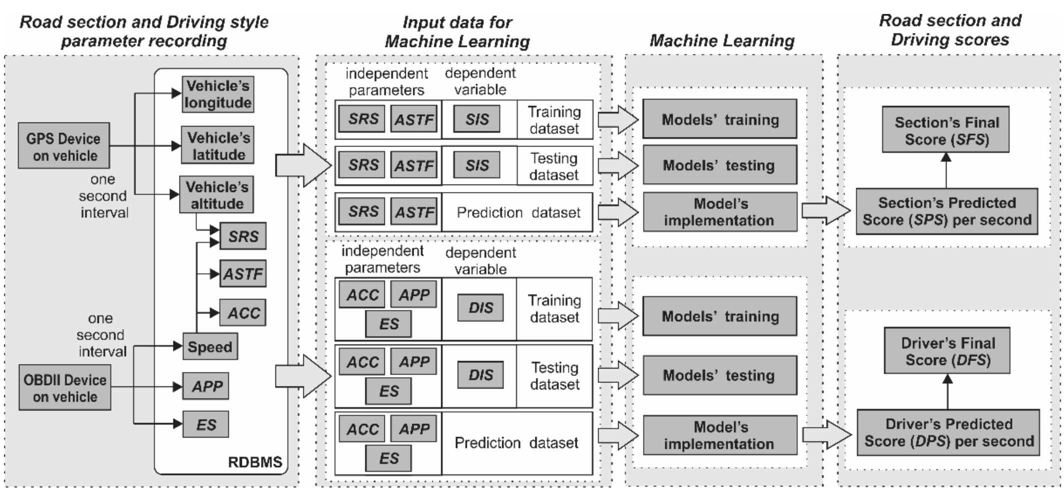

Figure 1: The schematic presentation of the road section rating and the driver's driving style rating methodology

In order to determine the observed scores, it is necessary that the defined parameters should first be recorded in real exploitation conditions. With the help of GPS device, GPS coordinates are obtained together with the current altitude of a vehicle, whereas the current vehicle speed is obtained by means of OBDII. Both devices operate on a 1Hz frequency, i.e. they measure data in a 1 second interval. Based on these data, it is possible to calculate the value of the *SRS* at the i^{th} moment (in the i^{th} second) based on the following expression:

$$\mathrm{SRS_i} = \frac{\Delta\mathrm{Altitude}}{\sqrt{\left(\frac{\mathrm{V_c}}{3.6}\cdot\Delta\mathrm{t}\right)^2 - (\Delta\mathrm{Altitude})^2}}\cdot 100 \tag{6}$$

where $\Delta Altitude$ [m] is the altitude difference in the two observed adjacent recorded intervals, Δt [s] is the time difference in the two observed adjacent recorded intervals and $\mathrm{V_c}$ [km/h] is the current speed at the i^{th} moment. Depending on the achieved value, the *SRS* parameter is given one of the scores (from the worst 1 to the best score 5) in the following manner: the score 1 for *SRS*>4%, the score 2 for 2<*SRS*≤4%, the score 3 for 0<*SRS*≤2%, the score 4 for -2<*SRS*≤0%, and the score 5 for *SRS*≤-2%.

Based on the knowledge of the values of the vehicle speed, the *ASTF* parameter value at the i^{th} moment (in the i^{th} second) is calculated in a 45-second interval prior to and after the i^{th} moment based on the following expression:

$$ASTF_i = \frac{1}{91}\sum_{j=i-45}^{i+45} V_j \qquad i \in \{46,\dots,n-45\} \tag{7}$$

where V_j is the speed achieved in the j^{th} interval for the i^{th} moment of observation, and *n* is the total number of the records. Depending on the achieved value, the *ASTF* parameter is given one of the scores (from the worst 1 to the best score 5) in the following manner: the score 1 for *ASTF*<30km/h, the score 2 for 30≤*ASTF*<50km/h, the score 3 for 50≤*ASTF*<70km/h, the score 4 for 70≤*ASTF*<80km/h, and the score 5 for *ASTF*≥80km/h. The machine learning section input score (*SIS*) is calculated in every second by means of the addition of the obtained scores for the *ASTF* and *SRS* parameters based on the following expression:

$$SIS = SRS\ score + ASTF\ score \tag{8}$$

Simultaneously, *SIS* values ranging from 2 to 10 are possible (the score 2 being the worst, and the score 10 being the best). With the help of OBDII device, the *ES* and *APP* parameters are obtained apart from the vehicle speed. Based on the current vehicle speeds, the vehicle acceleration, i.e. the *ACC* parameter, is also calculated. The input score of the driver's driving style (the driver's input score – *DIS*) for machine learning is obtained in every second based on the *ES*, *APP* and *ACC* parameters and using the FLS2 model, according to the paper [16]. Simultaneously, *DIS* values ranging from 1 to 10 are possible (the score 1 being the worst, and the score 10 being the best). All the recorded and obtained parameter values, as well as the calculated *DIS* and *SIS* input values, are entered into the relational database management system (RDBMS) and datasets for the machine learning phases (training, testing and prediction) are formed from them. The values of the *SRS* and *ASTF* parameters and the input value of *SIS* calculated based on the expression (8) are used to evaluate the road section. The *SRS* and *ASTF* parameters are independent attributes, whereas *SIS* is the dependent variable. The *ES*, *APP* and *ACC* parameters are the independent attributes, whereas *DIS* is the dependent variable. As the final result, the section predicted scores (*SPS*) are obtained together with the driver's driving style predicted scores (*DPS*) in every second. The section final score (*SFS*) is calculated as the arithmetic mean of the *SPS* values, whereas the driver's driving style final score (*DFS*) is calculated as the arithmetic mean of the *DPS* values on the considered road section (Fig. 1).

In order for the proposed methodology not to be too complicated, it does not include the other, less significant factors relevant for fuel consumption, such as the vehicle load mass or the weather conditions. The inclusion of the influences of the vehicle load mass and the weather conditions on fuel consumption within the framework of the proposed methodology would require a significantly longer period of time to have the data recorded and analyzed.

3. Conducted Research

The proposed methodology was applied in the Delmax Ltd. Company. The company has its own vehicle fleet for cargo transportation. The research study was carried out in the period from April to June 2021. One van that was performing the planned transportation tasks within the framework of real exploitation conditions was used. The used van was manufactured in 2017, had a 96-kW power engine, whereas the maximum allowed vehicle mass was 3500 kg. During the research study, the van was transporting very similar cargo amounts so as to prevent the influence of a different cargo mass on fuel consumption. The van tire pressure was as prescribed and equal, whereas the weather conditions were without precipitations and without the wind so as to avoid the influence of the mentioned factors on fuel consumption.

Based on the conversation made with the company managers, a total of 12 male drivers of 35 to 60 years of age and with over 5 years of professional driving experience and who had but recently gone through an "eco-driving" training course were selected. Each driver drove the selected vehicle on the same intercity route of the total length 330 km during one single day. During the period of research on the considered route, there were no road maintenance works or more serious traffic accidents. To determine the influence of different terrain and traffic conditions on the driver's driving performances (the driving style) and fuel consumption, as well as CO_2 emission, a total of the five route road sections (Table 1) different from each other were selected and analyzed. The considered road sections are of the same road category and do not have any sharp curves.

Table 1. The presentation of the data about the analyzed road sections

Section-related data	S1	S2	S3	S4	S5
Length (km)	14.8	14.0	6.0	6.0	28.8
Average longitudinal road ascent/descent (slope) (%)	0.24	0.90	-2.72	3.42	-0.55
Share of the length of the section in the settlement (%)	71	0	30	30	37

The recording and calculation of the defined parameters was so performed as described in Chapter 2.2. The collected data were automatedly stored in the RDBMS on a daily basis. The data set in order were exported from the database in the format necessary to build and apply the machine learning model. All the available records consisting of the *SRS*, *ASTF* and *SIS* data were divided into a set of the model training data (the two-thirds of the total number of the records) and a set of the model testing data (the one-third of the total number of the records). The machine learning models based on the following algorithms: LinearRegression, MultilayerPerceptron, M5P, Random Forest, Random Tree and REPTree were trained on the training dataset in the Weka software tool. Then, according to the expressions (1 to 5), the test dataset was used to calculate those models' performance measures on that dataset. The model that showed the best performances on both datasets was applied to a new prediction dataset consisting of the *SRS* and *ASTF* data. As the final result of the application of the machine model, the section predicted scores (*SPS*) in every driving second were obtained. Based on the obtained *SPS*, the section final scores (*SFS*) were calculated. In the identical manner, the models of machine learning on records were built and applied for the *ACC*, *APP*, *ES* and *DIS* data in order to calculate the driver's final score (*DFS*).

While performing transportation work, the data about the average specific fuel consumption – q (in l./100 km) on the considered sections were retrieved from the "on-board" computer on the vehicle. The amount of CO_2 emission (in kg/km) was calculated based on the linear dependence with the values q [28,29].

4. Obtained Results with Discussion

Based on the conducted research study, the values of the defined parameters for the section (*SRS*, *ASTF*) and the driver's driving style parameters (*ES*, *APP*, *ACC*) in every second were obtained, based on which the input *SIS* and *DIS* values were calculated. A total of 284014 records were made, on which the machine learning method was applied within the framework of the proposed methodology. In order to ensure the representativeness of the datasets on which the training and testing of the machine learning models was performed, the data describing the driving of 12 different drivers on the five different road sections were used. Recording the driving parameters of the different drivers allowed the predictive models to encompass the different driving styles. Recording the road section parameters on the different road sections enabled the machine learning models to include the different terrain and traffic conditions.

When the obtained values of the *SRS* and *ASTF* parameters as per considered sections are analyzed (Fig. 2), it is possible to perceive that the *SRS* value exceeding 4% is most frequently present on the section S4, which means that this section has the most unfavorable terrain conditions from the point of view of energy efficiency. On the other hand, the section S3 has the most frequent values *SRS* ≤ -2, which makes this section the most favorable as per terrain conditions. The sections S1, S2, and S5 are similar to one another as per terrain conditions and their *SRS* values are prevailingly from -2 to 2%. It is also noticed that the drivers most frequently achieved the *ASTF* value greater than 80 km/h and the rarest ASTF value below 30 km/h on the section S2. According to said, there are rare traffic bottlenecks on the section S2 and the vehicle may move at a greater vehicle speed. On the section S1, the drivers most frequently achieved the *ASTF* value in the interval from 30 to 50 km/h, but they also frequently achieved the *ASTF* value below 30 km/h. The section S1 is characterized by frequent higher traffic volume that influence reduction in the vehicle speed (Fig. 2).

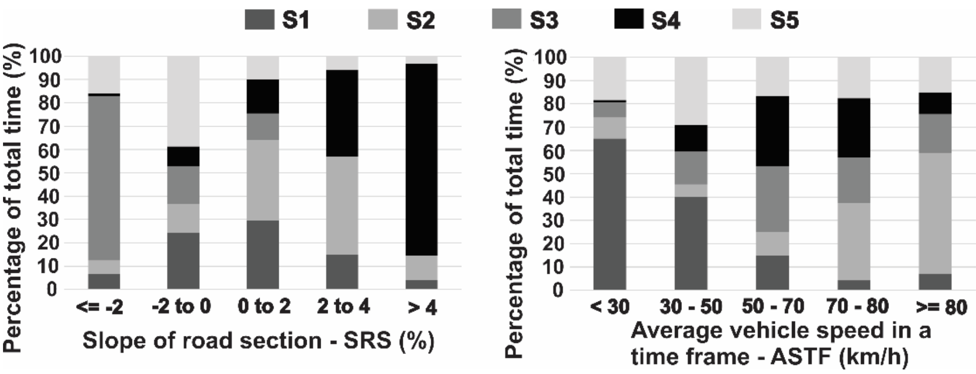

Figure 2: The time distribution of *SRS* and *ASTF* per road sections

Based on the analysis of the obtained data about the *ES*, *APP* and *ACC* parameters (Tab. 2), a fact was established that the highest average *ES* value achieved on the section S2 was 1842rpm, whereas the lowest average *ES* value achieved on the section S1 was 1509rpm. On the section S3, the lowest achieved average *APP* value was 10%, whereas the highest *APP* average value was that achieved on the sections S2 and S4 and was 33%. The mentioned differences appeared as a consequence of the different traffic and terrain conditions on the considered sections. Apart from that, it was determined that the driver D5 had achieved the lowest average *ES* value of 1421rpm, whereas the driver D11 had achieved the highest average *ES* value of 1839rpm. The driver D10 achieved the lowest average *APP* value of 19%, whereas the drivers D3 and D8 achieved the highest average *APP* value of 26% (Tab. 2). Those differences appeared as a consequence of the drivers' different driving styles.

The training dataset for the prediction of the scores for the driver's driving style consisted of 122559 instances, the test dataset consisted of 61279 instances and the prediction dataset consisted of 48588 instances, which in total was 232426 instances. Based on the machine learning model performances calculated according to the expressions (1 to 5) on the training dataset (Tab. 3) and the test dataset, the model based on the Random Forest algorithm proved to be the best. The *DPS* values were obtained using this model. The coefficient of correlation between *DIS* and *DPS* in this model has a value 0.9998, whereas the mean absolute error has a value 0.0262. It can be seen that this model has the best performances according to the remaining error measures as well (Tab. 3).

Table 2. The achieved average *ES*, *APP* and *ACC* values as per drivers on the road sections

Section	Parameter	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
S1	*ES*(rpm)	1558	1567	1593	1343	1292	1223	1628	1666	1511	1548	1551	1626
	APP(%)	21	20	23	22	22	22	19	24	21	16	18	19
	ACC(m/s^2)	0.02	-0.01	0.01	0.02	0.01	0.00	0.02	0.01	0.00	0.00	0.01	0.01
S2	*ES*(rpm)	1779	1895	1924	1600	1523	1549	2001	2045	2255	1963	1868	1707
	APP(%)	31	33	37	34	31	34	34	35	43	29	29	28
	ACC(m/s^2)	0.01	0.00	0.01	0.01	0.01	0.00	0.00	-0.01	0.00	0.01	0.00	0.01
S3	*ES*(rpm)	1862	1931	1769	1630	1505	1598	1603	1693	1339	1658	1769	1878
	APP(%)	8	12	13	9	11	8	9	16	7	8	8	6
	ACC(m/s^2)	-0.04	-0.05	-0.04	-0.02	-0.01	-0.04	-0.04	0.00	-0.04	-0.04	-0.03	-0.04
S4	*ES*(rpm)	1666	1573	1812	1389	1443	1437	2062	1986	1731	1645	2236	1751
	APP(%)	33	32	38	31	35	35	35	36	35	26	29	29
	ACC(m/s^2)	0.04	0.04	0.05	0.02	0.02	0.04	0.02	0.02	0.05	0.01	0.05	0.05
S5	*ES*(rpm)	1488	1603	1626	1353	1344	1393	1657	1712	1601	1493	1771	1544
	APP(%)	16	19	21	20	18	21	21	21	18	15	19	18
	ACC(m/s^2)	-0.01	0.00	-0.02	-0.01	-0.01	0.00	0.00	0.00	-0.01	-0.01	0.00	-0.01

Table 3. The driver's scores prediction model performances – the training dataset

Algorithm	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
LinearRegression	0.8629	0.8682	1.1354	47.9015	50.5418
MultilayerPerceptron	0.967	0.4297	0.576	23.7063	25.6384
M5P	0.9992	0.0505	0.0877	2.7858	3.9019
Random Forest	0.9998	0.0262	0.0495	1.4482	2.2054
Random Tree	0.9993	0.0514	0.085	2.8367	3.7825
REPTree	0.9992	0.0583	0.0926	3.2174	4.1207

The training dataset for the section scores prediction consisted of 29635 instances, the test dataset consisted of 14817 instances and the prediction dataset consisted of 4136 instances, which in total was 48588 instances. In this model group, too, the best performances were those demonstrated by the Random-Forest-algorithm-based model. Applying this model to the prediction dataset, the *SPS* values were obtained. The coefficient of correlation between *SIS* and *SPS* in this model has a value of 0.9999, whereas the mean absolute error has a value of 0.001. Table 4 accounts for the *SIS* and *SPS* values, as well as those for *DIS* and *DPS*, on the selected subset of the test dataset.

Table 4. The presentation of a few consequent real and predicted scores for the sections and scores for the drivers inclusive of the values of the appropriate independent parameters

inst#	*ASTF*	*SRS*	*SIS*	*SPS*	ES	APP	ACC	*DIS*	DPS
1	80.15	0.73	8	8	1753	0.47	-0.28	8.66	8.64
2	79.91	1.06	7	7	1704	30.98	-0.27	6.60	6.58
3	79.68	1.75	7	7	1774	38.50	0	4.57	4.57
4	79.44	2.87	6	6	1888	33.33	0.83	3.50	3.46
5	79.19	3.24	6	6	1969	27.70	0.55	4.84	4.85

The achieved *SFS* and *DFS* values substantially differ from one another as per analyzed sections due to the different terrain and traffic conditions, but they also differ even between the drivers on the same sections because of their different driving styles (Tab. 5). By analyzing the obtained data about *SFS* and *DFS*, as well as q and CO_2 (Tab. 5), it was determined that the section S3 was the most favorable from the aspect of energy efficiency, on which the highest average *SFS* value was 7.7, only to be followed by the section S2 with 7.31, then S5 with 6.82 and S1 with 5.76, whereas the most unfavorable section was the section S4, on which the lowest average *SFS* value was 5.39. The mentioned differences in the *SFS* values were a consequence of the different terrain and traffic conditions on the analyzed sections. It was determined, however, that the drivers achieved the lowest average *DFS* value of only 5.49 on the section S2, which is one of the most favorable sections from the aspect of energy efficiency. As the section S2 enables a greater vehicle speed due to rare traffic bottlenecks, the drivers characterized by an aggressive driving style abused that convenience and frequently drove the vehicles at a very high speed. The same drivers were forced to drive their vehicles in an energy efficient manner on the sections S1 and S5, on which no greater vehicle speed is allowed, so they achieved the average value of *DFS* 7.24 on S1 and *DPS* 7.51 on S5.

The achieved *DFS* values are inversely proportional to the values q and CO_2 (Tab. 5). The lowest average value of q 6.7 l/100km was achieved on the energy most favorable section S3, on which the highest average *DFS* value of 7.76 was also achieved. The highest average value of q 9.21 l/100km, however, was not achieved on the energy most unfavorable section S4, but on the section S2, on which an aggressive driving style is enabled to the greatest extent, where the average *DFS* value is only 5.49. Based on the average *SFS* value, a fact was established that the terrain and traffic conditions on the analyzed sections differ from each other by 46.22%, which influenced the difference in specific fuel consumption–*q* and CO_2 emission by 48.98%. To a certain extent, that was also contributed to by the different driving styles practiced by the tested drivers. If the driver met the condition that DFS>SFS, it can be accepted that the unfavorable terrain and traffic conditions on the section were the only one reason for the obtained potentially higher value of *q* and CO_2. When the driver did not meet the condition that *DFS>SFS*, then it is absolutely certain that the driver's aggressive style had also contributed to a higher value of *q* and CO_2 apart from the unfavorable terrain and traffic conditions on the road section. The analysis of the data given in Tab. 5 shows that the condition that *DFS>SFS* on the section S1 was met by all the 12 drivers, whereas that condition was only met by the driver D5 on the section S2.

Table 5. The achieved SFS and DFS values, fuel consumption and CO_2 emission as per drivers and road sections

Section	Drivers	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
S1	*SFS*	5.99	5.95	5.95	5.61	5.82	5.61	5.62	6.10	5.84	5.33	5.61	5.68
	DFS	7.23	7.40	6.92	7.91	7.77	7.98	6.61	6.29	7.01	7.15	7.53	7.14
	q (*l/100km*)	7.1	6.9	7.4	6.5	6.6	6.5	7.7	8.0	7.3	7.1	6.8	7.1
	CO_2 (kg/km)	0.18	0.18	0.19	0.17	0.17	0.17	0.20	0.21	0.19	0.19	0.18	0.19
S2	*SFS*	7.82	7.62	7.23	7.04	6.45	6.94	7.74	7.42	7.89	7.17	7.36	6.98
	DFS	6.10	5.45	5.08	6.13	6.62	6.20	4.89	4.53	3.57	5.24	5.63	6.45
	q (*l/100km*)	8.3	9.2	9.8	8.2	7.7	8.1	10.1	10.8	12.5	9.5	8.9	7.8
	CO_2 (kg/km)	0.22	0.24	0.26	0.21	0.20	0.21	0.26	0.28	0.33	0.25	0.23	0.20
S3	*SFS*	8.25	8.53	7.40	7.75	7.86	8.10	7.52	8.19	6.81	7.52	7.21	7.28
	DFS	7.27	6.82	7.37	8.12	8.42	8.31	7.77	7.25	8.64	8.11	7.65	7.36
	q (*l/100km*)	7.0	7.5	6.9	6.4	6.2	6.2	6.6	7.1	6.0	6.4	6.7	7.0
	CO_2 (kg/km)	0.18	0.19	0.18	0.17	0.16	0.16	0.17	0.18	0.16	0.17	0.18	0.18
S4	*SFS*	5.21	5.34	5.93	5.05	5.59	5.74	5.11	6.07	5.20	4.49	5.48	5.45
	DFS	6.37	7.04	5.51	7.08	6.49	6.60	4.49	4.43	5.74	6.52	3.41	5.98
	q (*l/100km*)	7.9	7.2	9.1	7.2	7.8	7.7	10.9	11.0	8.7	7.8	12.9	8.4
	CO_2 (kg/km)	0.21	0.19	0.24	0.19	0.20	0.20	0.28	0.29	0.23	0.20	0.34	0.22
S5	*SFS*	6.53	6.99	7.17	6.67	6.73	6.85	6.96	7.01	6.70	6.64	6.86	6.76
	DFS	8.17	7.48	7.02	8.10	8.18	8.05	6.82	6.51	7.54	7.96	6.55	7.78
	q (*l/100km*)	6.3	6.9	7.3	6.4	6.3	6.4	7.5	7.8	6.8	6.5	7.7	6.6
	CO_2 (kg/km)	0.17	0.18	0.19	0.17	0.17	0.17	0.19	0.20	0.18	0.17	0.20	0.17

The driver D5 met the condition that *DFS>SFS* on all the considered road sections, which makes him a driver characterized by a moderate (passive) driving style, thus contributing to a lower value of q and CO_2. The drivers D3, D7, D8 and D11 did not meet the condition that *DFS>SFS* on the largest number of the considered road sections, which classifies them into the drives characterized by an aggressive driving style, because of which they achieved the unnecessarily greater values *q* and CO_2.

5. Conclusion

In this paper, research was done in the influence of the terrain and traffic characteristics of a road section on the driver's driving performances and how, taken together, the same influences fuel consumption and CO_2 emission. A methodology for the evaluation of a road section and the driver's driving style by applying machine learning was proposed. The application of machine learning enables a simple and quick calculation of the section score and the driver's driving style score. It was determined on a sample of 281 014 data in total that there was a very high agreement between the predicted *SPS* and *DPS* values and the input *SIS* and *DIS* values. The correlation coefficient between *SIS* and *SPS* has the value 0.9999, with the mean absolute error 0.001, and the correlation coefficient between *DIS* and *DPS* has the value 0.9998, with the mean absolute error 0.0262. Comparing the section score (*SFS*) with the driver's driving style score (*DFS*), it can be determined whether it is exclusively the unfavorable terrain and/or traffic conditions on the section that have influenced the driver's worse driving performances, or it is also the driver's aggressive driving style that has contributed to a greater fuel consumption and higher CO_2 emission. The proposed methodology was applied to the 12 drivers who drove the same vehicle on the five road sections with different terrain and traffic conditions during one day within the framework of the transportation tasks assigned to them in the company, and the following conclusion were made:

- the drivers with a higher *DFS* value had a lower specific fuel consumption-q and CO_2 emission. On the road section S3, driver D5 achieved the *DFS* value 8.42 and the q value 6.2 l/100 km, whereas on the road section S4, driver D11 achieved a lower *DFS* value of only 3.41, thus having a much greater q value of 12.9 l/100 km (Table 5);
- the less favorable terrain and/or traffic conditions on the section, the greater the value of q and CO_2. The considered drivers achieved an average q value of only 6.7 l/100km on the most favorable road section S3 (*SFS*=7.70), whereas on the unfavorable road section S4 (*SFS*=5.39), they achieved an average q value of as much as 8.9 l/100km (Tab. 5);
- favorable terrain and traffic conditions on the section do not always have an influence on a lower value of q and CO_2 because of the demonstration of some drivers' aggressive driving style in those conditions. Because of the drivers with an aggressive driving style, the average q value achieved on the favorable road section S2 (*SFS*=7.31) was as much as 9.2 l/100 km, whereas on the less favorable road section S1 (*SFS*=5.76), the average q value was 7.1 l/100 km (Table 5);
- when the driver has met the condition that *DFS*>*SFS* on some road section, a potentially greater fuel consumption and CO_2 emission are considered to have exclusively occurred because of unfavorable terrain and/or traffic conditions on the road section, not because of the driver's driving style. On the road section S4, Drivers D3, D7, D8 and D11 did not meet the condition that *DFS*>*SFS*, so they achieved a much greater value of q and CO_2 compared to all the other drivers, and the reason for that being their aggressive driving style (Table 5);
- the drivers who met the condition that *DFS*>*SFS* on the majority of the observed road sections are energy efficient drivers with characterized by a moderate (passive) driving style, whereas the drivers who did not meet the condition that *DFS*>*SFS* on the majority of the road sections are energy inefficient drivers characterized by an aggressive driving style. Driver D5 with a moderate driving style was the only one to meet the condition that *DFS*>*SFS* on all the five road sections, thus achieving the average q value of only 6.92 l/100 km, whereas drivers D3, D7, D8 and D11 with an aggressive driving style did not meet the condition that *DFS*>*SFS* on the largest number of the road sections, thus achieving greater average q values of 8.10 l/100 km, 8.54 l/100 km, 8.93 l/100 km, and 8.61 l/100 km, respectively. The driving style of the other drivers classified them in-between driver D5 and drivers D3, D7, D8 and D11 (Table 5).

It can be concluded that being knowledgeable of the *SFS* and *DFS* values is significantly helpful for the managers of the considered companies when they have to determine the influence of the terrain and traffic conditions of a road section on the achieved driver's driving performances. The proposed methodology represents a tool useful for managers with the aim of increasing the energy efficiency of the vehicle fleet and protecting the environment. The proposed methodology was applied to vans, but it can also be applied to other commercial vehicles, such as trucks or articulated vehicles with semi-trailer and passenger vehicles as well. Future directions for research will be directed towards the determination of the influence of the cargo mass in the vehicle on the driver's driving performances.

Acknowledgements

Support for this research was provided by the Ministry of Education, Science and Technological Development of the Republic of Serbia (Grant No. TR36010). The authors are grateful to the company Delmax Ltd. for providing necessary drivers and vehicle for this research and to company Inova Tech Ltd. for providing necessary devices and technical support.

Nomenclature

ACC	–	Acceleration/deceleration [m/s^2]
a_i	–	the ith actual value of the target variable [–]
APP	–	Accelerator pedal position [%]
ASTF	–	Average vehicle speed in a time frame [km/h]
CO_2	–	Specific CO_2 emissions [kg/km]
DFS	–	Driver's Final Score [–]
DIS	–	Driver's Input Score [–]
DPS	–	Driver's Predicted Score [–]
ES	–	Engine speed [rpm]
pi	–	the ith predicted value of the target variable [–]
q	–	Specific fuel consumption [l/100km]
SFS	–	Section's Final Score [–]
SIS	–	Section's Input Score [–]
SPS	–	Section's Predicted Score [–]
SRS	–	Slope of road section [%]

Acronyms

FLS2	–	Fuzzy Logic System type-2;	GPS	–	Global Positioning System;
OBDII	–	On-board diagnostics;	RDBMS	–	Relational Database Management System;
D1-D12	–	Tested drivers;	S1-S5	–	Analyzed road sections.

References

[1] Poliak, M., et. al., Identification of costs structure change in road transport companies, *Communications - Scientific Letters of the University of Zilina*, *21* (2019), 3, pp. 8–12.

[2] Ivković, I.S., et. al., Influence of road and traffic conditions on fuel consumption and fuel cost for different bus technologies, *Thermal Science*, *21* (2017), 1, pp. 693–706. doi: https://doi.org/10.2298/TSCI160301135I

[3] Kovács, G., Optimization method and software for fuel cost reduction in case of road transport activity, *Acta Polytechnica*, *57* (2017), 3, pp. 201–8. doi: https://doi.org/10.14311/AP.2017.57.0201

[4] Palander, T., et. al., Comparison of energy efficiency indicators of road transportation for modeling environmental sustainability in "green" circular industry, *Sustainability*, *12* (2020), 7, pp. 2740. doi: https://doi.org/10.3390/su12072740

[5] Stokic, M., et. al., A New Comprehensive Approach for Efficient Road Vehicle Procurement Using Hybrid DANP-TOPSIS Method, *Sustainability*, *12* (2020), 10, pp. 4044. doi: https://doi.org/10.3390/su12104044

[6] Vujanović, D.B., et. al., A hybrid multi-criteria decision making model for the vehicle service center selection with the aim to increase the vehicle fleet energy efficiency, *Thermal Science*, *22* (2018), 3, pp. 1549–61. doi: https://doi.org/10.2298/TSCI170530208V
[7] Bakibillah, A.S.M., et. al., Fuzzy-tuned model predictive control for dynamic eco-driving on hilly roads, *Applied Soft Computing*, *99* (2021), pp. 106875. doi: https://doi.org/10.1016/j.asoc.2020.106875
[8] Krause, J., et. al., EU road vehicle energy consumption and CO2 emissions by 2050 – Expert-based scenarios, *Energy Policy*, *138* (2020), pp. 111224. doi: https://doi.org/10.1016/j.enpol.2019.111224
[9] Oka, S.N., Energy efficiency in Serbia: Research and development activities, in: *Sustainable Energy Technologies* (Ed. Hanjalić, K. et. al.), Springer, Dordrecht, The Netherlands, 2008, pp. 281–301. doi: https://doi.org/10.1007/978-1-4020-6724-2_16
[10] Huang, Y., et. al., Eco-driving technology for sustainable road transport: A review, *Renewable and Sustainable Energy Reviews*, *93* (2018), pp. 596–609. doi: https://doi.org/10.1016/j.rser.2018.05.030
[11] Brand, C., et. al., Lifestyle, efficiency and limits: modelling transport energy and emissions using a socio-technical approach, *Energy Efficiency*, *12* (2019), 1, pp. 187–207. doi: https://doi.org/10.1007/s12053-018-9678-9
[12] Yao, Y., et. al., Driving Simulator Study: Eco-Driving Training System Based on Individual Characteristics, *Transportation Research Record*, *2673* (2019), 8, pp. 463–76. doi: https://doi.org/10.1177/0361198119843260
[13] Schall, D.L., Mohnen, A., Incentivizing energy-efficient behavior at work: An empirical investigation using a natural field experiment on eco-driving, *Applied Energy*, *185* (2017), pp. 1757–68. doi: https://doi.org/10.1016/j.apenergy.2015.10.163
[14] Silva Cruz, I., Katz-Gerro, T., Urban public transport companies and strategies to promote sustainable consumption practices, *Journal of Cleaner Production*, *123* (2016), pp. 28–33. doi: https://doi.org/10.1016/j.jclepro.2015.12.007
[15] Stokic, M., et. al., Evaluation of driver's eco-driving skills based on fuzzy logic model – A realistic example of vehicle operation in real-world conditions, *Journal of Applied Engineering Science*, *17* (2019), 2, pp. 217–23. doi: https://doi.org/10.5937/jaes17-22106
[16] Zdravković, S., et. al., Evaluation of professional driver's eco-driving skills based on type-2 fuzzy logic model, *Neural Computing and Applications*, *33* (2021), 18, pp. 11541–54. doi: https://doi.org/10.1007/s00521-021-05823-z
[17] de Abreu e Silva, J., et. al., Influential vectors in fuel consumption by an urban bus operator: Bus route, driver behavior or vehicle type?, *Transportation Research Part D: Transport and Environment*, *38* (2015), pp. 94–104. doi: https://doi.org/10.1016/j.trd.2015.04.003
[18] Boriboonsomsin, K., Barth, M., Impacts of road grade on fuel consumption and carbon dioxide emissions evidenced by use of advanced navigation systems, *Transportation Research Record*, *2139* (2009), 1, pp. 21–30. doi: https://doi.org/10.3141/2139-03
[19] Saboohi, Y., Farzaneh, H., Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption, *Applied Energy*, *86* (2009), 10, pp. 1925–32. doi: https://doi.org/10.1016/j.apenergy.2008.12.017
[20] Smit, R., et. al., Assessing the impacts of ecodriving on fuel consumption and emissions for the Australian situation, *Proceedings*, ATRF 2010: 33rd Australasian Transport Research Forum, Canberra, Australia, 2010, Vol. 33, pp. 1–15.
[21] Eftekhari, H.R., Ghatee, M., Hybrid of discrete wavelet transform and adaptive neuro fuzzy inference system for overall driving behavior recognition, *Transportation Research Part F: Traffic Psychology and Behaviour*, *58* (2018), pp. 782–96. doi: https://doi.org/10.1016/j.trf.2018.06.044
[22] Said, H., et. al., Utilizing Telematics Data to Support Effective Equipment Fleet-Management Decisions: Utilization Rate and Hazard Functions, *Journal of Computing in Civil Engineering*, *30* (2016), 1, pp. 04014122. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000444
[23] Samuel, A.L., Some Studies in Machine Learning Using the Game of Checkers, *IBM Journal*, (1959), pp. 210–29.
[24] Peppes, N., et. al., Driving behaviour analysis using machine and deep learning methods for continuous streams of vehicular data, *Sensors*, *21* (2021), 14, pp. 4704. doi: https://doi.org/10.3390/s21144704
[25] Liu, J., et. al., Development of Driver-Behavior Model Based on WOA-RBM Deep Learning

Network, *Journal of Advanced Transportation*, *2020* (2020), pp. 1-11. doi: https://doi.org/10.1155/2020/8859891
[26] Elamrani Abou Elassad, Z., et. al., The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review, *Engineering Applications of Artificial Intelligence*, *87* (2020), pp. 103312. doi: https://doi.org/10.1016/j.engappai.2019.103312
[27] Witten, I.H., et. al., *Data mining: practical machine learning tools and techniques Fourth Edition*, Elsevier, Cambridge, United States, 2017
[28] ***, ACEA - European Automobile Manufacturers Association, WLTP FACTS, “https://www.wltpfacts.eu/link-between-co2-emissions-fuel-consumption/”
[29] ***, Carbon Dioxide Emissions Intensity for New Australian Light Vehicles, National Transport Commission - NTC, Melbourne, Australia, 2019.

Submitted: 19.10.2021.
Revised: 20.11.2021.
Accepted: 26.11.2021.