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PREDICTION OF THE FREIGHT TRAIN ENERGY CONSUMPTION WITH THE TIME SERIES MODELS

Predrag Grozdanović

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

✉ *p.grozdanovic@sf.bg.ac.rs*

Miloš Nikolić

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

✉ *m.nikolic@sf.bg.ac.rs*

Milica Šelmić

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

✉ *m.selmic@sf.bg.ac.rs*

Dragana Macura

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

✉ *d.macura@sf.bg.ac.rs*

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Abstract: As the backbone of environmentally sustainable transport, rail transport is one of the most preferred modes since it emits three times less CO2 and particulates per ton-mile than road transport. Besides these ecological benefits, rail transport is the most cost-effective. The global energy crisis creates significant problems and challenges for rail companies when planning transportation activity costs. Companies must carefully consider energy spending and ways to decrease it. In this paper, the authors considered the problem of predicting freight train energy consumption to help companies plan their budgets. For that purpose, the authors applied three time series methods: the moving average, the weighted moving average, and the exponential smoothing method. These methods were applied to actual data collected in the Republic of Serbia. The results showed that the exponential smoothing method performs better than the other two approaches. Nevertheless, there is still room for improvement in the presented approaches, such as fine-tuning the parameters used and comparing them to other relevant techniques used for the forecast.

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Introduction

Railway transport is one of the ecologically preferable modes of transport. It generates significantly less (about 75%) greenhouse gas emissions than road transport. Following the European Union (EU) standards, it is reasonable to expect rail transport to be used even more.

The European Green Deal (2020) aims to reduce transport-related greenhouse gas emissions by 55% by 2030 and 90% by 2050, compared to 1990. A consequence of these objectives is the increasing energy consumption. Train energy consumption is a basic and the most significant issue related to rail traction costs (Ćalić et al., 2019).

Railway companies consume large amounts of electric energy and fossil fuels for transport activities. During the last couple of decades, companies have tried to switch from diesel fuels to electric power. Because of that, electric power is now the most significant energy source used for rail transport.

Optimization of energy consumption leads to better transport organization, lower transport costs and pricing, and, more precisely, revenue settlement. Also, energy consumption prediction is significant for optimal energy planning, management and conservation.

The surge in energy costs induced by the war in Ukraine causes some difficulties for transport companies. Higher energy prices lead to an increase in transport costs, so companies have to be very careful in planning their transport activities.

Until now, few papers from relevant literature have dealt with models of train energy consumption forecast.

Ćalić et al. (2019) provided a model for train energy consumption prediction. To forecast freight train energy consumption per year, they applied the Wang-Mendel method to combine numerical and linguistic information into a common framework – a fuzzy rule base. In their following paper (Nikolić et al. (2020)), the same authors presented and discussed a strategy for the adjustment of fuzzy logic membership functions using the variant of the Bee Colony Optimization algorithm based on the improvement of complete solutions and showed its real-life application to the problem of the estimation of freight train energy consumption. Wang Mendel method was used for energy consumption forecasting by Jozi et al. (2017). Results showed that the proposed method using the combination of energy consumption data and environmental temperature could provide more reliable forecasts for energy consumption than other methods experimented with, namely based on artificial neural networks and support vector machines. Authors Yang et al. (2010) presented an improved Wang Mendel method for electric load forecasting. They combined this approach with particle swarm optimization.

Jia et al. (2009) summarize the domestic and international research achievements on transportation energy consumption. This paper also analyses the characteristics and shortcomings of the existing research. Taylan & Demirbas (2016) studied the key factors driving fuel and energy demand. Neural networks that calculate the energy consumption of electric trains are used in the paper by Fernández et al. (2016). These networks have been trained based on an extensive consumption data set measured in line 1 of the Valencia Metro Network. Wang & Rakha (2017) show the framework of electric train energy consumption modelling considering instantaneous regenerative braking efficiency in support of a rail simulation system. The presented model is calibrated with data from Portland, Oregon, using an unconstrained nonlinear optimization procedure and validated using data from Chicago, Illinois, by comparing model predictions against the National Transit Database estimates. Author Liu (2018) used regression analysis to examine the causes of changes in energy consumption of Chinese national rail transport. Pineda-Jaramillo et al. (2020) used four basic features (train speed, acceleration, track slope and radius of curvature) from Metro Valencia (Spain). They predicted the traction power using different machine learning models, obtaining that a random forest model outperforms other approaches in such tasks. The results showed the possibility of using basic features to predict the traction power in a metropolitan railway line and the chance of using these models to assess different strategies to increase the energy efficiency in these lines. The development of railway vehicles powered by fuel cell and battery systems was the focus of the paper by Deng et al. (2021). They proposed a new casual energy management strategy based on Pontryagin's Minimum Principle within the framework of Model Predictive Control. The authors of the paper Tang et al. (2021) develop binary nonlinear fitting regression and support vector regression models to predict total electricity, traction electricity, and electricity consumption of heating ventilation air conditioning systems in subway lines and the electricity consumption of chillers in a subway station. The main motivation for this paper is to provide roughly estimated amount of rail companies' future costs on energy and other resources. In this paper, we analyse the precision of the three-time series models in the prediction of electric energy consumption for rail freight transport.

The rest of the paper is organized as follows: the t**ime series models are explained** in the next section. The results of the applied models obtained are given in the third section. Finally, the conclusion remarks and future research directions are presented in the fourth section.

1. Time Series Models

Time series models belong to the group of quantitative forecasting techniques. These methods for predicting future events are based on information from the past. Therefore, the forecast is similar to the information in the past data. In addition to the information in the data, the analyst has an essential influence on the quality of the forecast. The analyst influences the forecast through the correct definition of method parameters based on his experience. The primary hypothesis in time series forecasting is that the main factors of the past will continue their trend in the future. It is important to note that when applying some of the time series methods, it is necessary to ensure that the data collected are in the same time series (days, months, years). The most important question with any forecast is how significant the error in the forecast is. Based on this, it can be said that the best method is the one that gives the smallest error. In Teodorović & Nikolić (2020), the following three-time series methods are explained in detail:

- The moving average method,
- The weighted moving average method,
- The exponential smoothing method.

1.1 Moving Average Method

The moving average model uses t time periods to forecast demand in the (t+1) time period. With this method, the analyst has the task of defining the value of the parameter n, which represents the number of time periods that will be used to forecast demand in the (t+1) time period. The analyst chooses the value for the parameter *n* for which the most minor forecast error is realized. The predicted value with the moving average method is calculated using the following formula:

$$F_{t+1} = \frac{A_t + A_{t-1} + \cdots + A_{t-n}}{n} \tag{1}$$

where:

t – current time period,

F_{t+1} – forecast for t+1 period,

n – the number of past time periods used for the forecast,

A_i – actual demand in the i-th time period.

1.2 Weighted Moving Average Method

The weighted moving average method uses the logic of the moving average method with the possibility of a more significant influence on the analyst's experience. Greater participation of the analyst in forecasting is realized through his ability to give higher importance to specific data, which he considers to be more authoritative than others participating in the forecast. The analyst assigns different significance to the data using weighting coefficients or weights. In this way, the analyst, with his experience and good knowledge of the area in which he makes the forecast, can influence the forecast error reduction. With this method, it is essential to note that the weighting coefficient *wi* must be a number between 0 and 1, whereby the sum of the weighting coefficients must equal 1 (equation 3). The predicted value with the weighted moving average method is calculated using the following formula:

$$F_{t+1} = w_t A_t + w_{t-1} A_{t-1} + \cdots + w_{t-n} A_{t-n} \tag{2}$$

$$w_t + w_{t-1} + \cdots + w_{t-n} = 1 \tag{3}$$

where:

t – current time period,

F_{t+1} – forecast for t+1 period

n – the number of past time periods used for the forecast

A_i – actual demand in the i-th time period

w_i – the importance the analyst gives to the i-th time period

1.3 Exponential Smoothing

The exponential smoothing method differs from the previous two methods, and its idea is to give the most importance to the most recent observation. In this method, the future forecast for period t+1 depends on the last forecasted value for period t and the forecast error. The forecast error is the difference between the actual value of demand in period t and the forecasted value for that period. It can be seen from equation (4) that the new forecast is equal to the old forecast increased by the error's size multiplied by the α coefficient. α coefficient is also called the smoothing constant, representing the analyst's reaction to the forecast error. The constant α can take a value from the interval [0,1], where the higher the value for α, the greater the analyst's reaction to the difference between the actual and predicted values. The expected value with the exponential smoothing method is calculated using the following formula (5):

$$F_{t+1} = F_t + \alpha(A_t - F_t) \quad (4)$$

$$F_{t+1} = F_t + \alpha \cdot e_t \quad (5)$$

where:

t – current time period,

F_{t+1} – forecast for (t+1) period,

F_t – forecast for period t,

A_i – actual demand in the i-th time period,

e_i – forecast error for the i-th time period,

α – smoothing constant.

2. Forecasting Average Energy Consumption Using Time Series Models

1) This section presents three time series methods to predict the Average Energy Consumption (AEC) [kWh] per year for rail freight transport. The developed models of train energy consumption forecasting aimed to help railway management improve their decision-making abilities, create good input for developing business and financial plans, improve the cost-effectiveness assessment of a specific traction system, and better assess profitability and return on investment. The consumption of electricity for hauling freight trains depends on various parameters, such as the power of the locomotive, corrected virtual coefficient, train speed and section length and other factors. In the paper

of Ćalić et al. (2019) it was defined that three variables influence energy consumption when hauling freight trains:

2) Train kilometre (TK) [km] - the number of kilometres that all electric locomotives have travelled by hauling freight trains during one year. The greater the number of kilometres travelled, the greater the electricity consumption. Data are provided annually.
3) Average weight of trains (AVT) [ton] – provides information on how much a freight train is loaded on average. An electric locomotive hauling heavy freight trains consumes more electrical energy. Data are provided annually.
4) Non-productive kilometres (NPC) [km] – shows the number of kilometres travelled by electric locomotives when they are out of traction or not at the forefront of railway traction. Data are provided annually.

Based on the presented three input values in the paper by Ćalić et al. (2019), the average electricity consumption [kWh] was estimated annually for rail freight transport based on a defined fuzzy logic system. AEC represents the amount of electrical energy all locomotives consume while hauling freight trains. In the paper of Ćalić et al. (2019), data on electricity consumption were available from 2007 to 2014. In the paper of Nikolić et al. (2020), the model presented by Ćalić et al. (2019) was improved, and the set of available consumption data was increased from 2002 to 2019. Available data on electricity consumption when hauling freight trains are shown in Table 1.

Table 1: Data on electricity consumption on railways (Nikolić et al., 2020)

	Input 1	**Input 2**	**Input 3**	**Output**
Year	**TK (10^6)**	**AWT**	**NPK (10^3)**	**AEC (10^6)**
2002	3.84	948.00	659.54	95.86
2003	4.18	970.03	692.98	109.21
2005	5.36	996.58	894.61	132.07
2006	6.16	1038.51	939.53	146.15
2007	4.91	943.00	957.82	132.72
2008	6.89	1018.00	973.95	172.12
2009	6.55	1150.00	1044.12	153.10
2010	5.09	998.00	841.23	114.57
2011	5.15	1100.00	690.25	118.59
2012	4.06	971.00	761.42	92.50
2013	4.63	912.00	693.91	110.20
2014	5.85	840.00	995.36	112.09
2017	5.09	1062.00	1020.73	130.31
2018	4.53	1212.00	656.11	119.32
2019	4.36	1108.00	623.45	103.74

On the available electricity consumption data, three-time series methods described in this paper were applied: the moving average, the weighted moving average and the exponential smoothing. It should be noted that the prediction with these methods is entirely based on past data. The basic hypothesis of each of these three methods is that the main factors of the past will continue their trend in the future.

1.4 Forecasting of Average Energy Consumption by the Moving Average Method

At the beginning of the use of this method, the analyst is obliged to define *n*, that is, the number of previous years that will participate in forecasting electricity consumption for the following year. A good practice is that when applying the moving average method, it is tested for several values of *n*, and thus, the value of *n* is chosen to give the best forecast based on the observed data. For the data shown in Table 1, the method was applied for the following values *n* = 2, *n* = 3 and *n* = 4.

Table 2: AEC forecast results using the moving medium method

Year	AEC (10^6)	AEC* (10^6)					
		***n* = 2**	**Error**	***n* = 3**	**Error**	***n* = 4**	**Error**
2002	95.86						
2003	109.21						
2005	132.07	102.54	29.53				
2006	146.15	120.64	25.51	112.38	33.77		
2007	132.72	139.11	-6.39	129.14	3.58	120.82	11.90
2008	172.12	139.44	32.68	136.98	35.14	130.04	42.08
2009	153.10	152.42	**0.68**	150.33	2.77	145.77	7.34
2010	114.57	162.61	**-48.04**	152.65	**-38.08**	151.02	-36.46
2011	118.59	133.84	-15.25	146.60	-28.01	143.13	-24.54
2012	92.50	116.58	-24.08	128.75	-36.25	139.59	-47.09
2013	110.20	105.54	4.66	108.55	**1.65**	119.69	-9.49
2014	112.09	101.35	10.74	107.10	5.00	108.96	**3.13**
2017	130.31	111.15	19.16	104.93	25.38	108.35	21.96
2018	119.32	121.20	-1.88	117.53	1.79	111.28	8.04
2019	103.74	124.82	-21.07	120.57	-16.83	117.98	-14.24
Err.	**MAX**	**-48.04**		**-38.08**		**-47.08**	
	MIN	**0.68**		**1.65**		**3.13**	
	AVG	**18.44**		**19.02**		**20.57**	
	<= 15 %	**7 of 13**		**5 of 12**		**6 of 11**	

In the case when $n = 2$, data for two previous years is needed to make a forecast. For this reason, Table 2 shows no forecasted value for the first two years, but the forecast starts from the third year. Analogously, for $n = 3$, the first three years will not be forecasted, the first four in the case when $n = 4$. From the results obtained by the moving average method for $n = 2$, it can be seen that the best forecast was made for 2009, in which the error is only 0.68, while the biggest error in the forecast was obtained for 2010. For 2010, it was forecasted that 48.04 million kWh more electricity would be consumed than was consumed that year. The forecast error was when $n = 2$ was less or equal to 15% for 7 out of 13 predicted values. Also, from the table, it can be seen that the average forecast error increases with increasing the value of n. Based on the results shown in the table, i.e. large deviations between the actual consumption of AEC and the forecasted AEC*, it can be concluded that the moving average method is not the best for the data shown, which does not have a constant trend. Still, there are variations from year to year.

1.5 Prediction of Average Energy Consumption by Weighted Moving Average Method

In addition to the importance of the value of parameter n, with the weighted moving average method, the analyst is obliged to assign an appropriate significance to each historical data based on his experience. An analyst can assign more importance to newer or older data and more importance only to specific years. As already explained, significance is assigned using weighting coefficients, the sum of which must equal 1. This method was tested for the same n values as the moving average method to compare them.

Regarding the parameter n, the same values are defined for it as in the previous method. In the case of $n = 2$, the analyst assigned to older data the importance of $w1 = 0.3$, while assigned to the more recent data from the nearer year the importance of $w2 = 0.7$. From the results obtained by the weighted moving average for $n = 2$, it can be seen that the best forecast was made for 2018, in which the error is only -5.52, while the biggest error in the forecast was obtained for 2010. For 2010, it was forecasted to consume 44.04 million kWh more electricity than it was really consumed. The forecast error in the case when $n = 2$ was less or equal to 15% for 8 out of 13 predicted values. Unlike the moving average method, with this method, the average forecast error decreases with increasing value of n. The average error during the forecast for $n = 2$ was 18.19, and in the case of $n = 3$, it was reduced to 17.59, i.e., n = 4 to 17. The obtained average error can be reduced even more by better defining the weighting coefficients, i.e. by assigning the importance of data differently. Based on the results shown in Table 3, it can be concluded that the weighted moving average method proved to be better than the moving average method for forecasting electricity consumption over the available data.

Table 3: Forecast results using the AEC weighted moving average method

Year	AEC (10^6)	AEC* (10^6)					
		$n = 2$ $w_1 = 0.3$ $w_2 = 0.7$	Err.	$n = 3$ $w_1 = 0.2$ $w_2 = 0.3$ $w_3 = 0.5$	Err.	$n = 4$ $w_1 = 0.1$ $w_2 = 0.2$ $w_3 = 0.3$ $w_4 = 0.4$	Err.
2002	95.86						
2003	109.21						
2005	132.07	105.21	26.86				
2006	146.15	125.21	20.94	117.97	28.18		
2007	132.72	141.93	-9.20	134.54	-1.82	129.51	3.21
2008	172.12	136.75	35.37	136.62	35.50	134.27	37.85
2009	153.10	160.30	-7.20	155.11	-2.00	151.10	2.00
2010	114.57	158.81	**-44.24**	154.73	-40.16	154.04	**-39.47**
2011	118.59	126.13	-7.54	137.64	-19.05	139.45	-20.87
2012	92.50	117.38	-24.88	124.28	-31.78	129.64	-37.14
2013	110.20	100.33	9.87	104.74	5.46	110.80	**-0.60**
2014	112.09	104.89	7.20	106.57	5.53	107.00	5.09
2017	130.31	111.53	18.78	107.61	22.70	108.26	22.05
2018	119.32	124.84	**-5.52**	120.82	**-1.50**	117.04	2.28
2019	103.74	122.62	-18.88	121.17	-17.43	120.26	-16.52
Err.	**MAX**	**-44.23**		**-40.16**		**-39.46**	
	MIN	**-5.52**		**-1.50**		**-0.59**	
	AVG	**18.19**		**17.59**		**17.01**	
	<= 15 %	**8 of 13**		**5 of 12**		**5 of 11**	

The weighted moving average method can further improve the accuracy of the electricity consumption forecast by tuning the weighting coefficients. Given that the model performed best for the value of the parameter $n = 4$, the weighting coefficients were adjusted just for that case. The method was tested for three scenarios, as shown in Table 4. Based on the results, it can be seen that the forecasting error is the smallest when the data on electricity consumption from the last two years is the most important. Forecast accuracy increases in the first scenario when the most importance is given to the previous year. In contrast, the forecast error increases significantly in the third scenario when the analyst assigns the most importance to the oldest data. In this way, it was shown how the accuracy of the forecast can be increased by tuning the weighting coefficients. After adjusting the parameters, the forecasting error has been reduced from 17 to 16.24. The accuracy can be improved even more by testing the model for many scenarios, which is done in practice.

Table 4: Results of AEC forecast using the weighted moving average method with adjustment of coefficients

Year	AEC (10^6)	AEC* (10^6)					
		$w_1 = 0.05$ $w_2 = 0.1$ $w_3 = 0.25$ $w_4 = 0.6$	Err.	$w_1 = 0.05$ $w_2 = 0.05$ $w_3 = 0.4$ $w_4 = 0.5$	Err.	$w_1 = 0.4$ $w_2 = 0.3$ $w_3 = 0.2$ $w_4 = 0.1$	Err.
2002	95.86						
2003	109.21						
2005	132.07						
2006	146.15						
2007	132.72	136.42	-3.70	136.16	-3.43	112.14	20.59
2008	172.12	134.84	37.28	136.89	35.23	125.81	46.31
2009	153.10	157.67	-4.57	153.06	**0.04**	140.43	12.67
2010	114.57	155.47	**-40.90**	159.34	**-44.77**	148.01	-33.44
2011	118.59	130.87	-12.28	133.77	-15.18	146.80	-28.22
2012	92.50	123.71	-31.21	121.38	-28.88	149.55	**-57.05**
2013	110.20	104.26	5.94	107.07	3.13	128.58	-18.38
2014	112.09	106.83	5.26	103.76	8.33	110.92	**1.17**
2017	130.31	109.99	20.32	110.68	19.63	108.43	21.87
2018	119.32	121.85	**-2.53**	120.13	-0.81	105.51	13.81
2019	103.74	120.89	-17.15	122.90	-19.16	115.70	-11.96
Err.	**MAX**	**-40.90**		**-44.77**		**-57.04**	
	MIN	**-2.53**		**0.04**		**1.16**	
	AVG	**16.47**		**16.24**		**24.13**	
	<= 15 %	**5 of 11**		**5 of 11**		**2 of 11**	

1.6 Prediction of Average Energy Consumption by the Exponential Smoothing Method

In order to make a forecast of electricity consumption using the exponential smoothing method, only two data are needed: data on the forecasted value for the previous year and the value of the error during that forecast. As with the weighted moving average method, the analyst plays a vital role in this method. The analyst's task is to define the value of α coefficient, which can range between 0 and 1, and indicates the participation of the previous error in the future forecast. As with the earlier methods, this method was tested for different scenarios, that is, for different values of the smoothing coefficient, α ($\alpha = 0.4$, $\alpha = 0.5$, $\alpha = 0.6$ and $\alpha = 0.7$).

The forecast results obtained using the exponential smoothing method is shown in Table 5. For α = 0.4, it can be seen that the best forecast was made for 2018, with only -0.23, while the highest error in the forecast was obtained for 2008. For 2008 it was forecasted that 43.08% less electricity would be consumed than was consumed. The forecast error in the case when α = 0.4 was less or equal to 15% for 9 out of 14 predicted values. With this method, the average forecast error first decreases with an increase in the value of α, that is, with an increase in reaction to the error, and then increases from α = 0.5. The highest average forecast error was obtained for α = 0.4, and it was 17.22, and the lowest average error was obtained for α = 0.5, and it was 16.06.

Table 5: AEC forecast results using the exponential smoothing method

Year	**AEC (10^6)**	**AEC* (10^6)**							
		***α* =0.4**	**Err.**	***α* =0.5**	**Err.**	***α* =0.6**	**Err.**	***α* =0.7**	**Err.**
2002	95.86	95.86	0.00	95.86	0.00	95.86	0.00	95.86	0.00
2003	109.21	95.86	13.36	95.86	13.36	95.86	13.36	95.86	13.36
2005	132.07	101.20	30.87	103.20	28.87	103.87	28.20	105.21	26.86
2006	146.15	113.55	32.61	119.08	27.07	120.79	25.36	124.01	22.14
2007	132.72	126.59	6.13	133.97	**-1.25**	136.01	-3.28	139.51	-6.79
2008	172.12	129.04	**43.08**	133.28	38.83	134.04	38.08	134.76	37.36
2009	153.10	146.27	6.83	154.64	-1.54	156.89	-3.78	160.91	-7.81
2010	114.57	149.00	-34.44	153.80	**-39.23**	154.62	**-40.05**	155.45	**-40.88**
2011	118.59	135.23	-16.64	132.22	-13.64	130.59	-12.00	126.83	-8.25
2012	92.50	128.57	-36.07	124.72	-32.22	123.39	-30.89	121.06	-28.56
2013	110.20	114.14	-3.94	107.00	3.20	104.86	5.35	101.07	9.13
2014	112.09	112.57	-0.47	108.76	3.33	108.06	4.03	107.46	**4.63**
2017	130.31	112.38	17.93	110.59	19.72	110.48	19.83	110.70	19.61
2018	119.32	119.55	**-0.23**	121.44	-2.12	122.38	**-3.06**	124.43	-5.11
2019	103.74	119.46	-15.72	120.27	-16.53	120.54	-16.80	120.85	-17.11
Err.	**MAX**	**43.07**		**39.22**		**-40.04**		**-40.87**	
	MIN	**-0.22**		**-1.24**		**-3.05**		**4.63**	
	AVG	**17.22**		**16.06**		**16.27**		**16.51**	
	<= 15 %	**9 of 14**		**8 of 14**		**8 of 14**		**8 of 14**	

The obtained average error can be reduced even more by better defining α coefficient, that is, by choosing the α value from the interval from 0.5 to 0.6, because the smallest error was obtained for those two limit values. The method was tested for α coefficient values from the interval 0.5-0.6 with a step of 0.01. Due to the volume of data, Table 6 does not show the results of the method for each value of α, but only for the value of α = 0.52, for which the method gives the best results. Adjusting the α coefficient reduced the forecasting error from 16.06 to 15.91.

Table 6: AEC forecast results using the exponential smoothing method with coefficient adjustment

Year	**AEC (10^6)**	**AEC* (10^6)**							
		***α*=0.51**	**Err.**	***α* =0.52**	**Err.**	***α* =0.53**	**Err.**	***α* =0.54**	**Err.**
2002	95.86	95.86	0.00	95.86	0.00	95.86	0.00	95.86	0.00
2003	109.21	95.86	13.36	95.86	13.36	95.86	13.36	95.86	13.36
2005	132.07	102.67	29.40	102.80	29.27	102.94	29.13	103.07	29.00
2006	146.15	117.66	28.49	118.02	28.13	118.38	27.78	118.73	27.42
2007	132.72	132.19	0.53	132.65	**0.07**	133.10	**-0.37**	133.54	**-0.81**
2008	172.12	132.46	**39.66**	132.69	39.43	132.90	39.22	133.10	39.02
2009	153.10	152.69	**0.42**	153.19	-0.09	153.69	-0.58	154.17	-1.07
2010	114.57	152.90	-38.33	153.15	**-38.58**	153.38	**-38.81**	153.59	**-39.02**
2011	118.59	133.35	-14.76	133.09	-14.50	132.81	-14.22	132.52	-13.93
2012	92.50	125.82	-33.32	125.55	-33.04	125.27	-32.77	125.00	-32.49
2013	110.20	108.83	1.37	108.36	1.84	107.90	2.30	107.45	2.75
2014	112.09	109.53	2.56	109.32	2.77	109.12	2.97	108.93	3.16
2017	130.31	110.84	19.47	110.76	19.55	110.70	19.61	110.64	19.67
2018	119.32	120.77	-1.45	120.93	-1.61	121.09	-1.77	121.26	-1.94
2019	103.74	120.03	-16.29	120.09	-16.35	120.15	-16.41	120.21	-16.47
Err.	**MAX**	**39.66**		**-38.58**		**39.22**		**39.02**	
	MIN	**0.42**		**0.07**		**-0.37**		**-0.81**	
	AVG	**15.96**		**15.91**		**15.95**		**16.01**	
	<= 15 %	**9 of 14**		**8 of 14**		**8 of 14**		**8 of 14**	

4 Conclusion

This paper aimed to forecast future electricity consumption on the railways. For this purpose, the time series methods are applied and presented as a concrete example. The advantage of these methods is that they can be easily applied and do not require large amounts of data for prediction, as is the case with most commonly used techniques such as linear regression, logistic regression, random tree and others. With these methods, only data on electricity consumption for one year is sufficient to make a forecast for the following year. The exponential smoothing method is the best since it gives the smallest forecast error. Otherwise, methods in which the analyst can participate by defining various coefficients are very convenient because, in this way, he/she infiltrates his experience into future predictions. Of course, the analyst's subjectivity can be a disadvantage of such methods and a lack of knowledge if the analyst is not sufficiently knowledgeable in the field they are forecasting.

The forecast error with the methods used is even smaller when there is a distinct trend of growth, decline or constancy in the data. However, this paper has shown that these methods can provide satisfying accuracy even on data that varies, i.e., there is an increase or decrease from year to year, as was the case with the data on electricity consumption that was processed in this paper.

The accuracy of the proposed methods during forecasting can be further increased by tuning the parameters. Based on the data in this paper, the mentioned methods can be used to predict the input quantities that determine the electricity consumption and not only forecast the output quantity. Future time series methods can also be used to predict input quantities. Then, the electricity consumption represents the defuzzified value obtained by inserting input values into the fuzzy logic system created in the paper of Nikolić et al. (2020).

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PREDVIĐANJE POTROŠNJE ENERGIJE TERETNOG VOZA POMOĆU MODELA VREMENSKIH SERIJA

Apstrakt: Kao okosnica ekološki održivog transporta, železnički transport je jedan od najpoželjnijih vidova transporta jer emituje tri puta manje CO2 i čestica po toni-milji od drumskog transporta. Pored ovih ekoloških prednosti, železnički transport je najisplativiji. Globalna energetska kriza stvara značajne probleme i izazove za železničke kompanije pri planiranju troškova transportnih aktivnosti. Kompanije moraju pažljivo da razmotre potrošnju energije i načine da je smanje. U ovom radu autori su razmatrali problem predviđanja potrošnje energije teretnih vozova kako bi pomogli kompanijama da planiraju svoje budžete. U tu svrhu autori su primenili tri metode vremenske serije: pokretni prosek, ponderisani pokretni prosek i metod eksponencijalnog glađenja. Ove metode su primenjene na stvarne podatke prikupljene u Republici Srbiji. Rezultati su pokazali da metoda eksponencijalnog izglađivanja radi bolje od druga dva pristupa. Ipak, još uvek ima prostora za poboljšanje predstavljenih pristupa, kao što je fino podešavanje korišćenih parametara i njihovo poređenje sa drugim relevantnim tehnikama koje se koriste za prognozu.

Ključne reči: teretni voz, potrošnja energije, modeli vremenskih serija, predviđanje.

Authors' biographies

Predrag Grozdanović was born in Lazarevac, on November 28, 1997, and lives in Lajkovac. He graduated at the University of Belgrade, Faculty of Transport and Traffic Engineering (FTTE) in 2020, on the Logistics module. In 2021 he defended his Master thesis on "Planning vehicle routes with the aim of optimize fuel consumption" on the module for Operational Research in Transport. In the same year, he started his PhD studies at the FTTE, where he is working as Teaching and Research Assistant. He was on a student exchange in the Czech Republic, at the University of Pardubice for a month as part of the CEPUS program. His research areas and goals are related to operations research applied to traffic and transport engineering, transport network designing, the development of vehicle routing algorithms with the goal of reduce environmental pollution, by solving location and routing problems in case of network disruptions, as well as working with a BIG data. In his career so far, he has published nine scientific papers, of which one at national, seven at international conferences and one in an international journal from the SCI list.

Miloš Nikolić was born in 1984 in Belgrade. He finished his doctoral studies at the University of Belgrade - Faculty of Transport and Traffic Engineering with the thesis "Disruption management in transportation by the Bee Colony Optimization metaheuristic." He has worked at the University of Belgrade since 2011. Currently, he is an Associate Professor at the Faculty of Transport and Traffic Engineering, University of Belgrade. Professor Nikolić was a Visiting Scholar at the University of California at Berkeley (2013, 2015/2016, and 2017). His research areas are applications of metaheuristic algorithms and operational research techniques for solving combinatorial optimization problems in transportation: transport network designing, disruption management in transportation, vehicle routing problems, etc. He is a co-author of the book "Quantitative Methods in Transportation", two book chapters, and many research papers published in scientific journals and conference proceedings.

Milica Šelmić was born in 1981 in Belgrade. She received the Ph.D. in Engineering, from the University of Belgrade - Faculty of Transport and Traffic Engineering, in 2011, with thesis entitled: "Locating facilities in the traffic networks using computational intelligence methods". She received the award from the Belgrade Chamber of Commerce for the best Ph.D. Thesis in 2011. She has been working at the University of Belgrade - Faculty of Transport and Traffic

Engineering since 2006, and from 2021 she was promoted as Full Professor. Her research areas are related to operations research applied to traffic and transport engineering, transport network designing, routing, location analysis, computational intelligence in traffic, applications of metaheuristic algorithms, multi-criteria decision making. She is a co-author of three chapters in international monographs, one textbook and over 100 papers research papers published in scientific journals and conference proceedings. During 2009 she attended summer school on collective intelligence in Leiden, Netherland. She is the head of Department of Operational Research in Transport.

Dragana Macura was born in1982 in Belgrade. She received the Ph.D. in Engineering, from the University of Belgrade - Faculty of Transport and Traffic Engineering, in 2012, with thesis entitled: “Multi-criteria model for selection and ranking the railway infrastructure projects”. She has been working at the University of Belgrade - Faculty of Transport and Traffic Engineering since 2007, and from 2022 she was promoted as Full Professor. Her research areas are related to railway transport, the transport market and marketing, multi-criteria decision making. She is a co-author of three national monographs, and over 90 papers research papers published in scientific journals and conference proceedings. During 2009 she attended summer school on collective intelligence in Leiden, Netherland. She is the head of the Department for Railway Management, Rollingstock and Traction.