The potential of regression factor analysis to predict highway traffic in conditions of high tourism seasonality

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ABSTRACT The impact of traffic flows on the economy, society, and the environment is obvious and complex. This paper presents a linear regression model created using the factors influencing traffic from a case study of a regional highway in the turbulent period from 2019 to 2024. The model was tested on a highway that is subject to distinct seasonal fluctuations on an important transport connection between Central Europe and tourist destinations in the northern Mediterranean. The model was tested to predict traffic intensity and flows and to give reliable inputs for the management of the highway's economic, technical, safety, and ecological aspects for future development. The result of the model was checked and found to be reliable, which opens up the possibility of creating similar models for other strategic traffic routes in Central Europe, in order to manage traffic flows in a measurable, responsible, and sustainable way.

KEY WORDS highway – tourism traffic flow – tourism seasonality – traffic forecasting – regression traffic model – highway management

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1. Introduction

The road connectivity of the world at all levels is increasing from year to year regardless of all contemporary challenges, above all those concerning environmental and economic sustainability. Globalization is progressively decreasing the effect of geographical distance on worldwide connections which is evident also in the regional tourism and transport gravity models (Rosselló-Nadal, Santana-Gallego 2024). One of the most important segments in road connectivity are highways, which enable the physical transport of people and goods over longer distances. In this paper, on the example of the regional level of highway connectivity, the strength of the isolated factors influencing the volume of traffic are tested. Also, the research is focused on the possibility of predicting the future volume of traffic to determine more efficiently and reliably the economic, environmental, and safety challenges posed by the trend of increasing traffic intensity.

The growing volume of road traffic creates an increasing need for the management of traffic systems, for which it is necessary to develop robust methods of analysis and forecasting (Avila, Mezić 2020). One of the major factors in increasing the intensity of regional and international road traffic is tourism and therefore forecasting of traffic plays a major role in tourism planning (Cho 2003; Liu, Wang, Shen 2015; Wang, Ye 2016; Wang et al. 2019; Feng 2023). The commitment to develop tourism would be much easier if it were possible to analyse current and past traffic flows with the scope to predict the nature of changes (Cho 2003).

2. Theoretical framework

By reviewing the literature that argues the problem of traffic flows and intensity on highways and expressway there is a significant number of works on traffic dynamics and traffic problems especially in everyday daily mobility in public transport of urban areas, but also it is visible a lack of work on the regional level (Gartner, Messer, Rathi 2001; Lee, Tseng, Tsai 2009; Bernard 2022; Chawla et al. 2022; Kraft, Blažek, Marada 2022; Mahapatra et al. 2024). This paper is not the first that tries to predict traffic intensity using regression analysis, such as Clark (2003); Sun et al. (2003); Vlahogianni, Karlaftis, Golias (2014), and Zhu et al. (2016), which argue short-term traffic prediction problems and possibilities of traffic forecasting. Analysing the field of research that connects tourism and highway flows there are some specific works on traffic volume forecasts and characteristics of so-called tourism highways which underline the seasonal variation of intermittent traffic volume, regional development aspects, impacts on the economic, social, environmental dimension and discontinuity of the traffic flows (Šolman 2010; Crnjak, Kristek 2012; Ivanova, Masarova 2013; Liu, Wang, Shen 2015; Tsou, Cheng, Tseng 2015; Rolfe, Flint 2018; Zhang, Hu, Lin 2020; Filčák, Rochovská, Horňák 2021; Boto-García, Pérez 2023). In recent years there are also published papers like Wang, Zhang, Wolshon (2023) that are offering methods to analyse the short and long-term impacts of traffic restriction policies under COVID-19, which has become an important aspect of growing resilience in the transport sector. It is also visible there is a growing number of newer research which are arguing challenges of state-of-the-art new technology and its consequences on traffic flows. Papers like Han, Wang, Leclercq (2023) argues contemporary dynamic traffic control, addressing the challenges associated with implementing reinforcement learning traffic control strategies in practice, and identifying promising directions for future research. Also, Mohammadian et al. (2023) research argue interesting aspects of potentials, limitations, and critical issues of various modelling frameworks of connected and automated vehicles which are expected to reshape traffic flow dynamics. Research which should not be neglected either are which are focused on so-called tourist roads and their specifics which are often connected to factors affecting traffic flows for example local climatic comfort conditions or specific events and their influence on tourism seasonality (Akin, Sisiopiku, Skabardonis 2011; Schiefelbusch et al. 2007; Datla, Sharma 2008; Koetse, Rietveld 2009; Kardani-Yazd et al. 2019; Bergantino et al. 2023). To conclude, analysing of the existing papers, a research gap is visible in the field of research on the intensity of traffic flows over regional highway distances and seasonal periods, especially the flows under the influence of tourism with its seasonality oscillations.

Considering the observed gaps in the researched field, this work is focused on the research of the factors affecting the traffic on the regional Croatian A1 highway (Fig. 1) over six years (2019–2024) aiming to shape the regression model capable of predicting future traffic highway flows. It is important to underline the role of the picked case study of Highway A1 which connects the two most populated areas in Croatia, the inland region of the capital of Zagreb and the second-populated town of Split on the coast. Highway A1 with its 484,1 km (HAC 2024) is also important because it is the shortest high-speed road connection between the central European inland tourist markets (Slovenia, Hungary, Austria, Czechia, Slovakia, Germany, Poland...) and Mediterranean Adriatic tourist region of Dalmatia which offers not only attractive coastal areas but also its significant number of islands which are connected with the coast by ferry boats.

Highway A1 has an important role in the tourism sector as a crucial sector of the Croatian economy (Baričević, Marušić, Malovrh 2017). Regardless of the mayor role of the A1 Highway, and especially its influence on tourist seasonal flows, for the development of the local and national economy, there is no large number of works that research highway traffic, its seasonality, factors, or other specificities of the A1 and connections with tourism. Among the works that research the A1 Highway, and are related to the seasonality of traffic flows, regional development

Fig. 1 – Map of A1 Highway

and tourism, only a few works stand out: Sić (2009); Baričević, Marušić, Malovrh (2017); Naletina, Zelenika, Petljak (2018); Rupčić, Gašparović (2019).

The objective of the research was to examine the relationships between traffic flow intensity on regional Highway A1 and economic factors tied to tourism seasonality (Fig. 2). The initial phase of the study involved testing relationships using a regression model to identify key predictors, which enabled the development of a short-term traffic intensity forecasting model for Highway A1. In the next step, the forecasting results served as a foundation for the proposed highway management framework, aimed at improving the efficient and sustainable management of the highway.

Figure 2 underlines the importance of seasonality as the crucial characteristic of the Highway A1. The graph is showing a visible connection between tourism flows and the intensity of traffic with its summer maximums on Highway A1.

The basic research question of this research is "Is it possible to make a reliable regression model that predicts highway traffic flows?", and the derived more concrete research question is "Which are variables that can be used to predict traffic flows on Highway A1?". To answer the research questions the variables influencing the traffic on the highway were selected and tested. Selected variables for the regression model are observed with their changes on a monthly basis and oscillations over the turbulent multi-year period from 2019 to 2024. The research is based on regression analysis to obtain a statistically reliable model for predicting future changes in the intensity of traffic on the Highway A1. Because this paper analyses the period from 2019 to 2024 there were many challenges that were shaping the

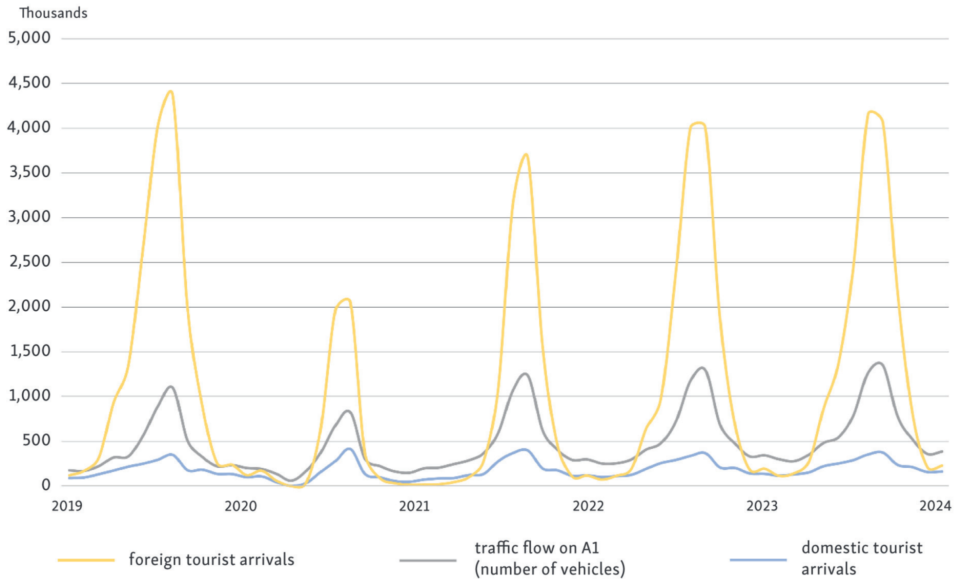


Fig. 2 – Tourism arrivals and traffic flow values. Source: CBS (2024b) and CH (2024).

traffic flows, like the ordinary economic mainly touristic factors but also some extraordinary like COVID-19 pandemics, consequences of the war in Ukraine and inflation on domestic and connected European markets.

The paper also addressed several general issues related to traffic sustainability, including highway congestion management, regional planning aspects of highway management, and certain environmental impacts of highway traffic intensity (Forman, Alexander 1988; Afrin, Yodo 2020; Lin et al. 2023.).

The research is based on the primary hypothesis (H-1) and further elaborated with a secondary hypothesis for picked predictors (H-2 to H8). The H-1 states that the intensity of traffic on Highway A1 is connected to the seasonality of tourism in Croatia.

To investigate the H-1 hypothesis more closely, further are analysed individual economic variables (predictors of traffic intensity):
- H-2: The growth of unemployment at the national level has a negative impact on the intensity of traffic on the A1 highway.
- H-3: The increase in the value of the CEIZ index has a positive impact on the intensity of traffic on the A1 highway.
- H-4: The increase in the number of domestic tourists has a positive impact on the intensity of traffic on the A1 highway.
- H-5: The increase of the inflation (price index) has a negative impact on the intensity of traffic on the A1 highway.

- H-6: The increase in the number of COVID-19 cases has a negative impact on the intensity of traffic on the A1 highway.
- H-7: The increase in the number of foreign tourists has a positive impact on the intensity of traffic on the A1 highway.
- H-8: The growth of employment at the national level has a positive impact on the intensity of traffic on the A1 highway.

The connection between the national unemployment rate and tourism is visible in the influence of unemployment trends, which have similar monthly values with the intensity of tourism and circulations of tourists. This is reflected in the seasonal offer of jobs in tourism, which is reflected not only at the local level on the coast but also by the seasonal employment of labour from the interior of the country.

The Croatian economy is largely influenced by tourism, and this study uses the Coincident Economic Index of the Zagreb Institute of Economics (CEIZ) to connect tourism with current national business cycle conditions (Bakarić et al. 2016). The current state of the national economy generates investment potential in tourism, which increases the intensity of logistical activities that use the highway as a supply route to the coast, where tourism is dominant.

The number of domestic tourists was also taken as a predictor in this study because the total domestic national tourism market is the second most important for tourism movements in Croatia (the first foreign tourist market is German, CBS 2024b). Also, the specifics of the pandemic period have underlined the importance of the domestic tourist market as the closest and most reliable for tourism. The importance of domestic tourists as a predictor in this study is valuable because of the influence of this variable in regression analysis for the intensity of traffic in pre and post-seasonal tourist circulation (spring and autumn periods).

The increase in the inflation (price index) caused by pandemics and war in Ukraine has reduced the economic standard of the average person and it is to assume it will cause a negative impact on tourism and the intensity of traffic on the A1 highway.

The number of COVID-19 cases was taken as an independent variable in the regression analysis because of its crucial role as a game changer in the tourism market in a part of the researched period.

The number of foreign tourists was taken as a predictor in this study because in the majority of coastal destinations in Croatia, most of the tourists are not domestic (CBS 2024b). Foreign tourists travel dominantly by car to the Croatian coast and they largely use A1 Highway. So, there must be a strong connection between foreign tourists‘ arrival and the intensity of traffic on the A1 Highway.

The connection between the national employment rate and tourism is visible in the seasonal employment trends, which have similar monthly values (CES 2024).

The intensity of tourism and circulation of tourists is reflected in the seasonal offer of jobs in tourism, which is reflected not only at the local level on the coast but also by the seasonal employment of labour from the interior of the country and also in the number of works permits for foreign working force.

3. Methodology and data

The input data in this research was collected for the period from 2019 to 2024 on a monthly basis at the national level and was used as a basis for calculating the variables for the linear regression model run in SPSS. The data used for the model was obtained from state agencies, institutes, or ministries that offer reliable statistical information (Croatian Bureau of Statistics, Croatian Employment Service, Croatian Institute of Public Health, Croatian Highways, Institute of Economics – Zagreb).

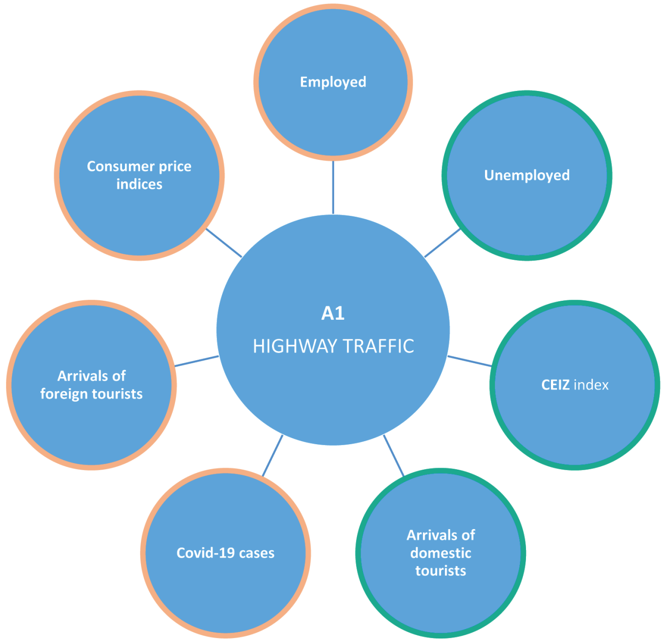
The analysis of input data was performed at the level of monthly indicators and characteristic seasonal periods characteristic for tourism pendulum flows (Fig. 2 and Fig. 4). The results of the research were interpreted based on input factors and a regression model was made to single out the variables that shape traffic intensity on the A1 highway.

3.1. Description of statistically reliable (absolute numerical and ln) dependent and independent variables of multiple regression model

Dependent variable: A1 – monthly traffic on the A1 highway was taken from the state company that manages highways (Croatian Highways) and the data on the monthly traffic of vehicles on the highway was taken from the official website: (HAC 2024). Traffic intensity on a Highway A1 is measured by the number of vehicles entering and exiting the Highway.

Independent variables: The independent variables used in the regression model provide a comprehensive framework for analysing factors influencing traffic on the A1 highway. The variables β_1 unemp and β_7 emp, representing the number of unemployed and employed persons (per 1,000), are sourced from the Croatian Employment Service (CES), which monitors national labour market in Croatia. Monthly data, reflecting the number of unemployed and employed individuals as of the last day of each month, are retrieved from the CES (CES 2024). The β_2 ceiz_index, based on the Coincident Economic Index (CEIZ) developed by the Institute of Economics, Zagreb, is a monthly composite indicator of the current business cycle, with its methodology detailed in Rašić Bakarić, Tkalec, Vizek (2016). Index values are obtained from the Institute (IEZ 2024). The variables β_3

Fig. 3 – Full list of initial multiple regression independent (absolute numeric and ln) variables. The three variables that remained in the final model at the end of the selection process (out of the original seven variables) and which satisfy the autocorrelation, multicollinearity and heteroskedasticity conditions are shown in green.



dom_tour and β_6 for_tour, representing the number of domestic and foreign tourists (per 1,000), are derived from monthly data provided by the Croatian Bureau of Statistics (CBS), specifically from their First Releases on Tourism Arrivals and Nights (CBS 2024b). The β_4 price_indices variable, capturing monthly movements of domestic price indices in Croatia, is sourced from the CBS Statistics in Line on Consumer Price Indices (CBS 2024a). The β_5 ln_covid variable, representing the natural logarithm of COVID-19 cases in Croatia, is based on data reported by the Croatian Institute of Public Health (CIPH 2024). But it should be taken into account that The World Health Organization (WHO) declared the start of the global pandemic on March 11, 2020, and its end on May 5, 2023, while the Croatian Institute of Public Health (CIPH) announced the end of the pandemic state in Croatia on May 11, 2023 (CIPH 2024).

3.2. Initial selection of variables

Initial multiple ln linear regression model: ln A1 = $\beta_0 + \beta_1$ unemp + β_2 ceiz_index + β_3 dom_tour + β_4 price_indices + β_5 ln_covid + β_6 for_tour + β_7 emp

At the beginning of the analytic process, the full list (Fig. 3) of the input modelling, independent variables related to the dependent variable was: (1) general economic variables (number of unemployed persons, the number of employed persons, the CEIZ index, consumer prices indices); (2) tourism indicators (the number of domestic and foreign tourist arrivals); (3) one specific indicator related to the particularity of the observed pandemic period (the number of recorded COVID-19 cases).

In creating models with different combinations of variables, the best combination was selected to develop a statistically robust model that simultaneously respects the prerequisites and limitations required by regression analysis. When including all seven variables simultaneously in the model, the model showed that it does not meet the basic conditions for reliable results according to the conditions of autocorrelation (Durbin-Watson test) and multicollinearity (variance inflation factor).

To test the predictive potential of the model ln_A1, four initial variables were excluded from the prediction model. The reasons for omitting these variables are as follows: (1) the price indices exhibited lower statistical reliability, with a p-value greater than 0.05; (2) the COVID-19 pandemic was declared over as a public health emergency by both the World Health Organization (WHO) and the National Health Agency. Additionally, statistical data for COVID-19 cases were affected by administrative changes in government policy during the pandemic, which compromised the homogeneity of the dataset. Furthermore, variables derived from: (3) employment and (4) foreign tourist arrivals showed that they did not meet the conditions for regression due to autocorrelation. Therefore, of the initial seven variables at the end of the selection, three variables remained in the final model, which meets the conditions of autocorrelation, multicollinearity as well as conditions of heteroskedasticity (marked green in Fig. 3).

3.3. Final multiple ln linear regression model (ln_A1)

Final model: $ln\_A1 = \beta_0 + \beta_1\ unemp + \beta_2\ ceiz\_index + \beta_3\ dom\_tour$. Before interpretation of the model results, the condition of regression heteroskedasticity was checked by conducting the Breusch-Pagan and Abried-Whites tests. To

Table 1 – Descriptive statistics of variables

Variables	Mean	Std. Deviation	N
ln_A1	12.92	0.65	72
β_1 unemp	122,772.71	21,944.04	72
β_2 ceiz_index	0.11	2.56	72
β_3 dom_tour	191,121.71	101,089.88	72

Source: Author analysis (SPSS)

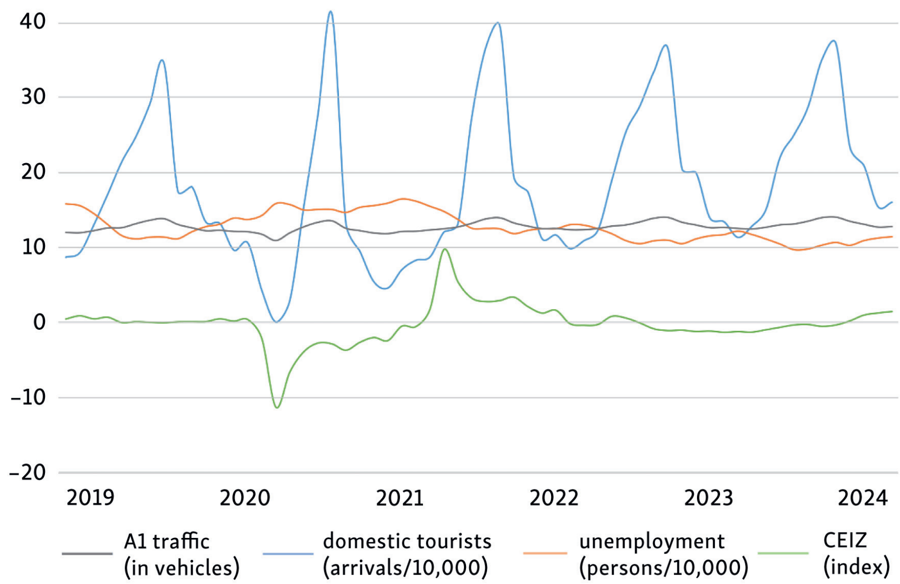


Fig. 4 – Values of ln_A1 model variables. Source: CES (2024), CIPH (2024) and IEZ (2024).

check whether the residuals from the regression analysis are independent, the Durbin-Watson (DW) test is used. The DW value for the Model is 1.462 indicating no limiting autocorrelation. Pearson's correlation coefficient and Variance Inflation Factors (VIF) were used to detect multicollinearity conditions. The values of the Pearson correlation coefficients for the relations between all variables are below 0.3, which means that the correlation between the variables is very weak, while the Pearson correlation coefficients between the variables of the unemployed and the number of domestic tourists is −0.598, which indicates a moderate negative correlation. VIF values are between 1.098 and 1.620, which also indicates a low mutual correlation of the variables used. Overall, it was concluded that with the selected variables within the narrowed selection, the regression model provides valid support for further analysis and interpretation (Fig. 4, Table 1).

4. Results and discussion

The final best selection of three independent variables that gave statistically reliable indicators is shown in Table 2 and highlighted in Figure 3 with a green colour. The best model variable selection has three independent variables: unemployment (β_1 unemp), number of domestic tourists (β_3 dom_tour), and variable ceiz index (β_2 ceiz_index).

4.1. Interpretation of ln_A1 coefficient model results at annual scale

The regression model results (Table 2) provide insights into the variables influencing traffic on the A1 highway. Specifically, the coefficient β_1 unemp indicates that a decrease of 1,000 unemployed persons is associated with a 0.05% increase in the annual number of vehicles. The β_2 ceiz_index shows that a 1% rise in the CEIZ index corresponds to a 2.2% increase in annual highway traffic. Additionally, the β_3 dom_tour coefficient reveals that an increase of 1,000 domestic tourists leads to a 0.05% rise in the annual number of vehicles on the A1 highway.

4.2. Testing the traffic prediction model on the A1 highway

Table 3 shows the predicted change compared to the real measured traffic on the A1 Highway in the period from 2021 to 2024. The full-year values from 2021 to 2023 are used to predict traffic for 2024. In the first step, the average annual change from 2021 to 2023 is calculated, and in the second step, the coefficients of three

Table 2 – Regression analysis of highway traffic on A1 (ln_A1), period 2021–2024

Variable	Regression model ln_A1 Coefficient
Intercept	12.476
β_1 unemp	−0.0005
β_2 ceiz_index	0.022
β_3 dom_tour	0.0005
n	72
R^2	0.925
adj R^2	0.921
F	278.418
p	< 0.001

Source: Author analysis

Table 3 – The predicted change from the ln_A1 regression model variables, period 2021–2024

	Average difference 2023/2021	Predicted annual change of variables for 2024 (Based on model ln A1 for period 2023/2021)	Real measured change of traffic on A1 Highway in 2024
Average Unemployment (persons)	−13,948	+0.70 %	
Average CEIZ (index)	−1.46	−3.21 %	
Total Domestic tourists (persons)	+251,539	+12.58 %	
Overall change for period (%)		*+10.07 %*	*8.82 %*

Source: CES (2024), IEZ (2024), CBS (2024b), CBS (2024a), CIPH (2024)

Table 4 –The predicted change from the ln_A1 regression model variables, period 2022–2025

	Average difference 2023/2021	Predicted annual change of variables for 2024 (Based on model ln A1 for period 2023/2021)	Real measured change of traffic on A1 Highway in 2024
Average Unemployment (persons)	−10,414	+0.52 %	
Average CEIZ (index)	+0.91	+2.00 %	
Total Domestic tourists (persons)	+208,396	+10.42 %	
Overall change for period (%)		*+12.94 %*	*to be determined in 2025*

Source: CES (2024), IEZ (2024), CBS (2024b), CBS (2024a), CIPH (2024)

variables from the ln_A1 regression model are used to calculate the predicted annual traffic for 2024. The predicted annual change for 2024, based on the ln_A1 model, shows an increase in traffic intensity on the A1 Highway of 10.07%. The measured change in traffic intensity on the A1 Highway for 2024 is 8.82%. The difference between the predicted and measured traffic intensity is 1.25%. The fit is not perfect, but the predicted result demonstrates the high reliability of the coefficients from the ln_A1 model for predicting traffic in the near future.

4.3. Forecasting the traffic intensity on A1 Highway for 2025

Table 4 provides a forecast of traffic intensity on the A1 Highway for 2025, based on the predictive capabilities of the ln_A1 model for period 2021–2024. The model has been used to estimate short-term traffic for 2025, based on average annual data from 2022 to 2024. To generate the forecast, a two-step methodology was employed (as described in Chapter 3.2). In the first step, the average annual change of the prediction variables is calculated. In the second step, the coefficients from the ln_A1 regression model were applied to project the anticipated annual change for 2025. The result indicates that traffic intensity on the A1 Highway is expected to rise by 12.94% in 2025.

This projected increase points to a significant uptick in Highway usage. Such a forecast suggests that the A1 Highway could experience notable pressure on its capacity, which may have implications for infrastructure planning and resources in the coming year. However, while the model provides a robust statistical foundation for this prediction, it is important to acknowledge the influence of external factors that could alter this scenario; specifically, the volatile geopolitical situation and potential repercussions on changes in economic conditions.

4.4. Management implementation framework for the results of the regression model ln_A1

The designed regression model enables the prediction of the intensity of traffic on the Highway A1, which further has valuable repercussions on the management in economic, technical, safety, and environmental aspects (Fig. 5).

The prediction of the highway traffic intensity increase or decrease is of great importance for the economic management of the highway (Ashuri et al. 2012). The economic sustainability of the highway can be managed from the projection of revenue from highway tolls which can be used for the management of expenses for financial costs such as liquidity maintenance, credit management, planning of permanent employment, employing seasonal labour force, investment in wages or raising the skills of the workforce. Technical aspects connected with the projection of the traffic intensity can be used for the projection of the necessary measures on highway general maintenance (Steele et al. 2003; Di Sivo, Ladiana 2011; Hinkka et al. 2016;), and management of the specific aspects of road seasonal needs for adaptation, or planning of interventions on the road for upgrading the highway infrastructure. Results from the regression model can be of valuable importance for upgrading the safety of the highway (De Luca, Dell'Acqua 2012; Horrey et al. 2012; Lang, Schreiner 2015) by projection of the traffic congestion shifts in the earlier periods of the tourist season and weekends. The model's result can be used for managing traffic flows, particularly by predicting congestion at crucial highway

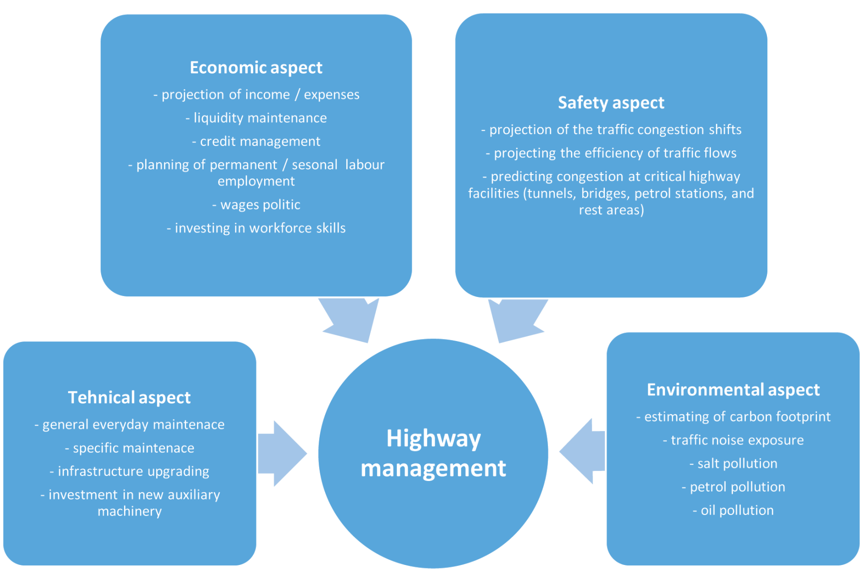


Fig. 5 – Highway management implementation framework for the results of the regression model ln_A1

facilities such as tunnels, bridges, petrol stations, and rest areas (Mcllroy, Banks, Parnell 2022). In addition to the above, an important aspect of contemporary road infrastructure management is environmental sustainability. From the intensity of the traffic on the highway, it is possible to estimate the impact on the environment from the aspect of carbon footprint (Louhghalam, Akbarian, Ulm 2017; Wu et al. 2017; Grofelnik, Kovačić 2023a; Grofelnik, Kovačić 2023b), traffic noise exposure from the highway (Amoatey et al. 2020; Mishra, Parida, Rangnekar 2010), and surface water pollution with petrol, oil, and salt (Baltrenas, Kazlauskiene 2009; Krykhtina et al. 2021).

5. Conclusion

The research has confirmed the initial hypothesis and demonstrated that seasonal fluctuations in traffic intensity on the A1 Highway are associated with specific highlighted national economic variables. The relationship between traffic intensity on the A1 Highway and highlighted variables, as described in the interpretation of the regression model (Chapter 3.1.–3.3.), can be used as a ponders in short-term traffic intensity forecasting.

The regression model showed that not all initial variables are usable for predicting traffic intensity on the picked Highway A1 case study, but underlined the specific importance of three variables (unemployment, CEIZ index, and the number of domestic tourist arrivals). The regression model taking into account the variables in a monthly time series of a total of six years, predicts the growth of traffic intensity in 2025 at a level of 12.94%. Before projecting traffic prediction for 2025 the model was tested on previous period and results of prediction for 2024 showed growth of traffic by 10.07% which is close to measured growth of 8.82%. The results of testing variables from the regression model ln_A1 are showing that in short time series it is possible to predict traffic flows on major highway corridors.

The research demonstrated that the relationship between the selected specific variables enabled the prediction of future regional traffic intensity to support projections for improving the management of regional highways. The research results provide a framework for highway management (Fig. 5) and encourage the development of new regression models based on new case studies of regional highways. The implementation of findings from the research would enhance predictions and improvements in the efficient and sustainable management of highways across economic, technical, safety, and environmental aspects.

Although the research successfully tested the designed regression model of traffic prediction on the A1 regional highway, the main limiting factor for this and similar future research is the statistical availability of economic, social, and environmental variables on a monthly level over a longer period. By increasing the number and variety of variables in the regression model in future research, an even more reliable tool could be designed to predict the intensity of highway traffic flows. For the next step, the research should be internationalized to connect the influence of factors in a wider geographical area especially in Central Europe (Slovenia, Hungary, Austria, Czechia, Slovakia, Germany, Poland…). It will be challenging to modify the model on a more complex highway network to test the potential of the regression model to predict the traffic flows of a broader international character but it would result in a more robust and reliable model. Also, while the presented model showed reliable statistical foundation for prediction on A1 highway, it is important to keep in mind the influence of external factors that could change the bigger economic picture in contemporary volatile geopolitical climate with potential repercussions on changes in economic conditions.

References

AFRIN, T., YODO, N. (2020): A survey of road traffic congestion measures towards a sustainable and resilient transportation system. Sustainability, 12, 11, 4660. https://doi.org/10.3390/su12114660

AKIN, D., SISIOPIKU, V. P., SKABARDONIS, A. (2011): Impacts of weather on traffic flow characteristics of urban freeways in Istanbul. Procedia-Social and Behavioral Sciences, 16, 89–99. https://doi.org/10.1016/j.sbspro.2011.04.432

AMOATEY, P., OMIDVARBONA, H., BAAWAIN, M.S., AL-MAYAHI, A., AL-MAMUN, A., AL-HARTHY, I. (2020): Exposure assessment to road traffic noise levels and health effects in an arid urban area. Environmental Science and Pollution Research, 27, 35051–35064. https://doi.org/10.1007/s11356-020-09785-y

ASHURI, B., KASHANI, H., MOLENAAR, K.R., LEE, S., LU, J. (2012): Risk-neutral pricing approach for evaluating BOT highway projects with government minimum revenue guarantee options. Journal of construction engineering and management, 138, 4, 545–557. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000447

AVILA, A.M., MEZIĆ, I. (2020): Data-driven analysis and forecasting of highway traffic Dynamics. Nature Communications, 11, 2090. https://doi.org/10.1038/s41467-020-15582-5

BALTRENAS, P., KAZLAUSKIENE, A. (2009): Sustainable ecological development reducing negative effects of road maintenance salts. Technological and Economic development of Economy, 15, 1, 178–188. https://doi.org/10.3846/1392-8619.2009.15.178-188

BARIČEVIĆ, H., MARUŠIĆ, E., MALOVRH, A. (2017): Logistics determinants of the port of Gaženica in the context of tourism development. Pomorstvo, 31, 1, 18–26.

BERGANTINO, A.S., BUONAROTA, M., BUONGIORNO, A., INTINI, M. (2023): Regional multimodal accessibility: Policies and strategies for sustainable tourism destinations in coastal areas. Research in Transportation Business & Management, 48, 100872. https://doi.org/10.1016/j.rtbm.2022.100872

BERNARD, J. (2022): Public transport accessibility: Simulation of the usability of public transport in everyday situations. Geografie, 127, 2, 145–168. https://doi.org/10.37040/geografie.2022.002

BOTO-GARCÍA, D., PÉREZ, L. (2023): The effect of high-speed rail connectivity and accessibility on tourism seasonality. Journal of Transport Geography, 107, 103546. https://doi.org/10.1016/j.jtrangeo.2023.103546

CHAWLA, P., HASURKAR, R., BOGADI, C.R., KORLAPATI, N.S., RAJENDRAN, R., RAVICHANDRAN, S., TOLEM, S.C., GAO, J.Z. (2022): Real-time traffic congestion prediction using big data and machine learning techniques. World Journal of Engineering, 10.1108/WJE–07–2021–0428. https://doi.org/10.1108/WJE-07-2021-0428

CHO, V. (2003): A comparison of three different approaches to tourist arrival forecasting. Tourism management, 24, 3, 323–330. https://doi.org/10.1016/S0261-5177(02)00068-7

CLARK, S. (2003): Traffic prediction using multivariate nonparametric regression. Journal of transportation engineering, 129, 2, 161–168. https://doi.org/10.1061/(ASCE)0733-947X(2003)129:2(161)

CRNJAK, M., KRISTEK, P. (2012): Gospodarski aspekti prometnih koridora u Republici Hrvatskoj ili Hrvatska „nova vrata Europe". Ceste i mostovi, 58, 1–6, 11–23.

DATLA, S., SHARMA, S. (2008): Impact of cold and snow on temporal and spatial variations of highway traffic volumes. Journal of Transport Geography, 16, 5, 358–372. https://doi.org/10.1016/j.jtrangeo.2007.12.003

DE LUCA, M., DELL'ACQUA, G. (2012): Freeway safety management: case studies in Italy. Transport, 27, 3, 320–326. https://doi.org/10.3846/16484142.2012.724447

DI SIVO, M., LADIANA, D. (2011): Decision-support tools for municipal infrastructure maintenance management. Procedia Computer Science, 3, 36–41. https://doi.org/10.1016/j.procs.2010.12.007

FENG, X. B. (2023): Coupling and coordinated development of traffic accessibility and regional tourism economy. Research in Transportation Business & Management, 49, 101010. https://doi.org/10.1016/j.rtbm.2023.101010

FILČÁK, R., ROCHOVSKÁ, A., HORŇÁK, M. (2021): Evaluation of Slovakia's R1 expressway enhancement impacts on local socio-economic development: expert panel approach. Geografie, 126, 1, 29–53. https://doi.org/10.37040/geografie2021126010029

FORMAN, R.T., ALEXANDER, L.E. (1998): Roads and their major ecological effects. Annual review of ecology and systematics, 29, 1, 207–231. https://doi.org/10.1146/annurev.ecolsys.29.1.207

GARTNER, N.H., MESSER, C.J., RATHI, A.K. (2001): Traffic flow theory: a state- of-the art report. In Revised Monograph on Traffic Flow Theory, https://rosap.ntl.bts.gov/view/dot/35775 (21. 6. 2024).

GROFELNIK, H., KOVAČIĆ, N. (2023a): Factors Influencing the Carbon Footprint of Major Road Infrastructure – A Case Study of the Učka Tunnel. Sustainability, 15, 5, 4461. https://doi.org/10.3390/su15054461

GROFELNIK, H., KOVAČIĆ, N. (2023b): Determining the impact of tourism on the environment by extracting the carbon footprint of road infrastructure in natural protected areas-case study of the Učka nature park, Proceedings of 7th International Conference Tourism in Southern and Eastern Europe – ToSEE 2023, 143–153. https://doi.org/10.20867/tosee.07.10

HAN, Y., WANG, M., LECLERCQ, L. (2023): Leveraging reinforcement learning for dynamic traffic control: A survey and challenges for field implementation. Communications in Transportation Research, 3, 100104. https://doi.org/10.1016/j.commtr.2023.100104

HINKKA, V., PILLI-SIHVOLA, E., MANTSINEN, H., LEVIÄKANGAS, P., AAPAOJA, A., HAUTALA, R. (2016): Integrated winter road maintenance management – New directions for cold regions research. Cold Regions Science and Technology, 121, 108–117. https://doi.org/10.1016/j.coldregions.2015.10.014

HORREY, W.J., LESCH, M.F., DAINOFF, M.J., ROBERTSON, M.M., NOY, Y.I. (2012): On-board safety monitoring systems for driving: Review, knowledge gaps, and framework. Journal of safety research, 43, 1, 49–58. https://doi.org/10.1016/j.jsr.2011.11.004

IVANOVA, E., MASAROVA, J. (2013): Importance of road infrastructure in the economic development and competitiveness. Economics and management, 18, 2, 263–274. https://doi.org/10.5755/j01.em.18. 2. 4253

KARDANI-YAZD, N., KARDANI-YAZD, N., MANSOURI DANESHVAR, M.R. (2019): A rapid method for evaluating the variables affecting traffic flow in a touristic road, Iran. Environmental Systems Research, 8, 1–11. https://doi.org/10.1186/s40068-019-0162-0

KOETSE, M.J., RIETVELD, P. (2009): The impact of climate change and weather on transport: an overview of empirical findings. Transp Res Part D Transp Environ, 14, 3, 205–221. https://doi.org/10.1016/j.trd.2008.12.004

KRAFT, S., BLAŽEK, V., MARADA, M. (2022): Exploring the daily mobility rhythms in an urban environment: Using the data from intelligent transport systems. Geografie, 127, 2, 127–144. https://doi.org/10.37040/geografie.2022.004

KRYKHTINA, Y.O., DOMBROVSKA, S.M., MAISTRO, S.V., STANKEVYCH, S.V. (2021): Review of public policy for reducing the transport environmental impact. Ukrainian Journal of Ecology, 11, 2, 12–15. https://doi.org/10.15421/2021_63

LANG, U., SCHREINER, R. (2015): Managing security in intelligent transport systems. In 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 48–53. https://doi.org/10.1109/ITSC.2015.16

LEE, W.H., TSENG, S.S., TSAI, S.H. (2009): A knowledge based real-time travel time prediction system for urban network. Expert systems with Applications, 36, 3, 4239–4247. https://doi.org/10.1016/j.eswa.2008.03.018

LIN, S., MARSDEN, G., PANGBOURNE, K., LIU, Q. (2023): Lessons from highway management reforms in a less developed province in China. Research in Transportation Business & Management, 49, 100989. https://doi.org/10.1016/j.rtbm.2023.100989

LIU, Z., WANG, X., SHEN, S. (2015): Methods of Traffic Demand Forecast on Tourism Highway. In: 2015 International conference on Engineering Management, Engineering Education and Information Technology, 162–166. https://doi.org/10.2991/emeeit-15.2015.33

LOUHGHALAM, A., AKBARIAN, M., ULM, F.J. (2017): Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions. Journal of Cleaner Production, 142, 956–964. https://doi.org/10.1016/j.jclepro.2016.06.198

MAHAPATRA, S., PATNAIK, S., RATH, K.C., SETHY, K.M., DAS, S.R. (2024): Regression-Based Model for Prediction of Road Traffic Congestion: A Case Study of Janpath Segment in Bhubaneswar City. In: Nakamatsu, K., Patnaik, S., Kountchev, R. (eds) AI Technologies and Virtual Reality. AIVR 2023. Smart Innovation, Systems and Technologies, 382. Springer, Singapore. https://doi.org/10.1007/978-981-99-9018-4_4

MCLLROY, R.C., BANKS, V.A., PARNELL, K.J. (2022): 25 Years of road safety: The journey from thinking humans to systems-thinking. Applied ergonomics, 98, 103592. https://doi.org/10.1016/j.apergo.2021.103592

MISHRA, R.K., PARIDA, M., RANGNEKAR, S. (2010): Evaluation and analysis of traffic noise along bus rapid transit system corridor. International Journal of Environmental Science & Technology, 7, 737–750. https://doi.org/10.1007/BF03326183

MOHAMMADIAN, S., ZHENG, Z., HAQUE, M.M., BHASKAR, A. (2023): Continuum modeling of freeway traffic flows: State-of-the-art, challenges and future directions in the era of

connected and automated vehicles. Communications in Transportation Research, 3, 100107. https://doi.org/10.1016/j.commtr.2023.100107
NALETINA, D., ZELENIKA, G., PETLJAK, K. (2018): Empirijsko istraživanje zadovoljstva korisnika hrvatskim autocestama. Business Excellence, 12, 2, 81–101. https://doi.org/10.22598/pi-be/2018.12.2.81
RAŠIĆ BAKARIĆ, I., TKALEC, M., VIZEK, M. (2016): Constructing a composite coincident indicator for a post-transition country. Economic research-Ekonomska istraživanja, 29, 1, 434–446. https://doi.org/10.1080/1331677X.2016.1174388
ROLFE, J., FLINT, N. (2018): Assessing the economic benefits of a tourist access road: A case study in regional coastal Australia. Economic Analysis and Policy, 58, 167–178. https://doi.org/10.1016/j.eap.2017.09.003
ROSSELLÓ-NADAL, J., SANTANA-GALLEGO, M. (2024): Toward a smaller world. The distance puzzle and international border for tourism. Journal of Transport Geography, 115, 103809. https://doi.org/10.1016/j.jtrangeo.2024.103809
RUPČIĆ, N., GAŠPAROVIĆ, T. (2019): Analiza troškova i koristi izgradnje autoceste A1. Oeconomica Jadertina, 9, 1, 58–77. https://doi.org/10.15291/oec.2838
SCHIEFELBUSCH, M., JAIN, A., SCHÄFER, T., MÜLLER, D. (2007): Transport and tourism: roadmap to integrated planning developing and assessing integrated travel chains. Journal of Transport Geography, 15, 2, 94–103. https://doi.org/10.1016/j.jtrangeo.2006.12.009
SIĆ, M. (2009): Utjecaj autoceste Zagreb–Split na regionalni razvoj Like. Hrvatski geografski glasnik, 71, 1, 87–100. https://doi.org/10.21861/HGG.2009.71.01.05
STEELE, K., COLE, G., PARKE, G., CLARKE, B., HARDING, J. (2003): Highway bridges and environment – Sustainable perspectives. In: Proceedings of the Institution of Civil Engineers-Civil Engineering, 156, 4, 176–182. https://doi.org/10.1680/cien.2003.156.4.176
SUN, H., LIU, H. X., XIAO, H., HE, R.R., RAN, B. (2003): Use of local linear regression model for short-term traffic forecasting. Transportation Research Record, 1836, 1, 143–150. https://doi.org/10.3141/1836-18
ŠOLMAN, S. (2010): Uloga cestovnog prometa u turizmu Hrvatske. Acta turistica nova, 4, 2, 231–246.
TSOU, K.W., CHENG, H.T., TSENG, F.Y. (2015): Exploring the relationship between multilevel highway networks and local development patterns – A case study of Taiwan. Journal of Transport Geography, 43, 160–170. https://doi.org/10.1016/j.jtrangeo.2015.01.015
VLAHOGIANNI, E.I., KARLAFTIS, M.G., GOLIAS, J.C. (2014): Short-term traffic forecasting: Where we are and where we're going. Transportation Research Part C: Emerging Technologies, 43, 3–19. https://doi.org/10.1016/j.trc.2014.01.005
WANG, C., YE, Z. (2016): Traffic flow forecasting based on a hybrid model. Journal of Intelligent Transportation Systems, 20, 5, 428–437. https://doi.org/10.1080/15472450.2015.1091735
WANG, R., ZHANG, Z., WOLSHON, B. (2023): Estimating long-term and short-term impact of COVID-19 activity restriction on regional highway traffic demand: A case study in Zhejiang Province, China. International journal of disaster risk reduction, 85, 103517. https://doi.org/10.1016/j.ijdrr.2022.103517
WANG, Z., CHEN, Y., SU, J., GUO, Y., ZHAO, Y., TANG, W., ZENG, C., CHEN, J. (2019): Measurement and prediction of regional traffic volume in holidays. In: 2019 IEEE Intelligent Transportation Systems Conference (ITSC). 486–491. https://doi.org/10.1109/ITSC.2019.8917230
WU, Y., ZHANG, S., HAO, J., LIU, H., WU, X., HU, J., WALSH, M.P., WALLINGTON, T.J., ZHANG, K.M., STEVANOVIC, S. (2017): On-road vehicle emissions and their control in China: A review and outlook. Science of the Total Environment, 574, 332–349. https://doi.org/10.1016/j.scitotenv.2016.09.040

ZHANG, X., HU, Y., LIN, Y. (2020): The influence of highway on local economy: Evidence from China's Yangtze River Delta region. Journal of Transport Geography, 82, 102600. https://doi.org/10.1016/j.jtrangeo.2019.102600

ZHU, Z., PENG, B., XIONG, C., ZHANG, L. (2016): Short-term traffic flow prediction with linear conditional Gaussian Bayesian network. Journal of advanced transportation, 50, 6, 1111–1123. https://doi.org/10.1002/atr.1392

Data sources

CBS (2024a): Croatian Bureau of Statistics, Consumer Price Indices, https://podaci.dzs.hr/en/statistics/prices/ (21. 6. 2024).

CBS (2024b): Croatian Bureau of Statistics, Tourism Arrivals and Nights, https://podaci.dzs.hr/en/statistics/tourism/tourist-arrivals-and-nights/ (21. 6. 2024).

CES (2024): Croatian Employment Service, Employment – Unemployment, https://statistika.hzz.hr/Statistika.aspx?tipIzvjestaja=1 (21. 6. 2024).

CH (2024): Croatian Highways, Traffic Data, A1 Highway, https://www.hac.hr/hr/promet-i-sigurnost/promet/prosjecni-mjesecni-dnevni-promet (21. 6. 2024).

CIPH (2024): Croatian Institute of Public Health – COVID-19, https://www.hzjz.hr/en/?s=covid (21. 6. 2024).

HAC (2024): Hrvatske autoceste d.o.o., Limited Liability Company for Operation, Construction and Maintenance of Motorways, Report on Motorways, https://www.hac.hr/hr/promet-i-sigurnost/promet/prosjecni-mjesecni-dnevni-promet (21. 6. 2024).

IEZ (2024): Institute of Economics, Zagreb – CEIZ index, https://www.eizg.hr/indices-351/ceiz-index/352 (21. 6. 2024).

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