OPEN ACCESS
Indo-JC
Indonesia Journal of Computing
ISSN 2460-9056
socj.telkomuniversity.ac.id/indojc

Ind. Journal on Computing
Vol. 7, Issue. 2, August 2022. pp. 93-102
doi:10.34818/indojc.2022.7.2.659

Forecasting Fuel Consumption Based-On OBD II Data

Satrio Nurcahya #1, Bayu Erfianto #2, Setyorini #3

 # School of Computing, Telkom University
Bandung, Indonesia

[1] satrionurcahya@students.telkomuniversity.ac.id
[2] erfianto@telkomuniversity.ac.id
[3] 3setyorini@telkomuniversity.ac.id

Abstract

A Cyber-Physical System consists of computing devices that communicate with each other by interacting with the physical world, assisted by sensors and actuators with an iterative response. The Intelligent Transportation System aims to apply information and communication technology to every transportation area. When implementing the intelligent transportation system in vehicles, especially in terms of fuel consumption, vehicles must begin to analyze the use of fuel used to provide users so that users can be more effective. Regarding the analysis of fuel consumption, several researchers have done this with several existing methods such as ANN, SVM, and the like. The Multivariate time series method is used to solve the forecast analysis of vehicle fuel consumption. In this study, data from vehicles obtained from OBD-II will be processed using the multivariate time series method with output in the form of analysis and visual data from the forecast with parameters related to RPM, TPS, and fuel consumption. So the expected result is the relationship between RPM, TPS, and fuel consumption, as well as the creation of a system model to get sample data about RPM, TPS, and fuel consumption.

Keywords: RPM, TPS, fuel consumption, OBD-II, forecast

Abstrak

Cyber-Physical System terdiri atas perangkat komputasi yang berkomunikasi satu sama lain dengan interaksi terhadap dunia fisik dibantu oleh sensor dan aktuator dengan suatu perulangan respon. *Intelligent Transportation System* yang bertujuan untuk menerapkan teknologi informasi dan komunikasi pada setiap wilayah transportasi. Menerapkan ITS pada kendaraan terutama pada aspek konsumsi bahan bakar maka kendaraan harus mulai dapat menganalisa penggunaan bahan bakar yang sedang digunakan tersebut untuk memberikan pada pengguna supaya pengguna dapat lebih efektif. Terkait analisa konsumsi bahan bakar ini sudah banyak dilakukan oleh beberapa peneliti dengan beberapa metode yang ada seperti ANN, SVM dan sejenisnya. Penggunaan metode *Multivariate time series* digunakan sebagai solusi terhadap analisa forecast konsumsi bahan bakar kendaraan. Pada penelitian ini data dari kendaraan yang didapatkan dari OBD-II akan diproses dengan metode *Multivariate time series* dengan keluaran berupa analisa dan visual data dari forecast tersebut dengan parameter terkait RPM, TPS dan konsumsi bahan bakar. Sehingga hasil yang diharapkan berupa didapatkannya hubungan antar RPM, TPS dan konsumsi bahan bakar serta terbentuknya model sistem untuk mendapatkan sampel data terkait RPM, TPS dan konsumsi bahan bakar.

Kata Kunci: RPM, TPS, konsumsi bahan bakar, OBD-II, ramalan

Received on April, 2022. Accepted on July, 2022

I. Introduction

The development of information technology at this time is comprehensive, as almost all fields today are related to information technology. One is in health, agriculture, education, transportation, and other social fields. The application of computers, sensors, signals, and related electronics has played an essential role in today's transportation system in the form of instruments used to meet specific goals under different conditions [1]. This form of application is in the form of an Intelligent Transportation System (ITS), which aims to apply information and communication technology (ICT) in every transportation area, such as land transportation, sea transportation, and air transportation, accompanied by providing a good service for users and transportation providers [1]. ITS consists of a system responsible for using information such as conditions or scenarios of an event that will be processed by the system so that it can process and integrate that information to provide results to users and transportation providers [2]. In the development of ITS, there will always be challenges or related issues such as the increasing number of trips made by individuals, which causes severe congestion, especially for densely populated areas, which will result in lost time used by users, as well as increased noise, fuel consumption, and emissions of harmful substances into the environment [3]. Implementing this ITS will help ease traffic flow in large or densely populated cities by reducing time spent in traffic jams. At the same time, it will reduce fuel consumption, chemical emissions, and monetary losses [3].

One example of the application of ITS is the development of cars. At this time, cars are like "computers on wheels." This is because vehicles have an on-board unit (OBU) that has applications for ITS, which helps consider information about vehicles and their environment [1][3]. One that does develop is fuel consumption efficiency, accompanied by a reduction in substance emissions in vehicles. Even though there are alternative uses such as vehicles with electric or diesel fuel, it will still not be too good if there is waste in the use of this type of fuel. This is even more transparent based on data from the International Energy Agency (IEA), stating that from 2017 to 2019, global average fuel consumption increased by only 0.9%, compared to an average annual decline of 2.6% between 2010 and 2015. The IEA also said that fuel consumption also depends on how efficiently the vehicle's ability to convert fuel into energy [4]. Based on this, to use ITS in vehicles, especially when it comes to fuel consumption, vehicles must start to be able to analyze how fuel is used by users so that users can drive more efficiently, which will also help them save money.

There have been many studies conducted to analyze the efficiency of fuel consumption. The researchers used the conceptual approaches of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in the data analysis process; the data was obtained directly with the help of a tool called Onboard Diagnostics-II (OBD-II), which functions as a recording device while the vehicle is running. One of the studies related to this is in the form of predicting fuel consumption using an in-vehicle information system assisted by OBD-II to see a comparison of three vehicles on the same path with the data processed using the Support Vector Machine (SVM) method combined with Lagrange Interpolation where the parameters used in addition to fuel consumption are the two components that exist in the vehicle [5]. In addition to these studies, some studies develop a model of fuel consumption in a vehicle equipped with a fuel engine component; this model is developed using the Artificial Neural Network (ANN) method, which is simulated with the Stuttgart Neural Network Simulator (SNNS) package [6].

For the modeling process and the data analysis process, in addition to the two methods mentioned, there is also a time-based method, namely time series analyst, which uses several parameters and aims to predict data that will appear in the future so that it will be used in the form of Multivariate time series Forecasting. Multivariate time series can contain more and more complete information systems so that as much as possible can be performed for a more accurate reconstruction of the vector data space [7]. So research on multivariate time series forecasting has a more practical understanding because it has different characteristics from univariate time series [7].

This research uses the Cyber-Physical System (CPS) approach to the Intelligence Transportation System (ITS) because CPS is made up of computers that talk to each other by interacting with the real world with the help of sensors, actuators, and a response loop [8]. The method used is Multivariate Time Series Forecasting to predict data related to fuel consumption, Revolutions Per Minute (RPM), and throttle position sensor (TPS). The OBD-II tool helps with the process of getting data, and the Python programming language is used to process the Multivariate Forecasting process and get visuals and data analysis.

Therefore, from this research, the results obtained can be used as a reference for further fuel consumption and intelligent transportation systems research. Because in implementing an Intelligent Transportation System, one of the crucial elements is how a vehicle can be more effective in consuming its fuel [1][2]. The philosophical context here makes this research an early stage before the vehicle can form its recommendation system to manage its fuel consumption better because intelligent vehicles are also a form of implementing cyber-physical systems in intelligent transportation systems where vehicles can provide information to users regarding the conditions of the vehicle and its surroundings [2][3].

II. LITERATURE REVIEW

he related research carried out in this research was carried out using several previous studies as a guide or example for the research carried out. The applications taken are journals on Onboard Diagnostics-II (OBD-II), Fuel Consumption, and Multivariate Time Series Forecasting, which are used for research, as well as several books on the Intelligence Transportation System (ITS) and Cyber Physical System (CPS) as the basis or background for this research.

One of the articles used as a reference in this research is entitled "Fuel Consumption Using OBD-II and Support Vector Machine Model," conducted by Tamer Abukhalil, Harbi Almahafzah, Malek Alksasbeh, and Bassam A. Y. Alqaralleh from Al-Hussein Bin Talal University, 2020. This article describes a method for estimating gasoline fuel consumption using the OBD-II vehicle information system. In this research, the method approach used is an experimental method using the Support Vector Machine (SVM) classifier combined with Lagrange Interpolation, which aims to determine the relationship between two vehicle parameters and fuel consumption [5]. Although both use RPM, TPS, and fuel consumption parameters and use OBD-II tools, the difference is that this study uses three types of vehicles in one lane without using certain conditions during the trip and emphasizes predictions using the SVM. At the same time, this research focuses on using one vehicle with certain conditions to test how well the multivariate time series algorithm with the VAR model does forecast.

A. Onboard Diagnoses-II (OBD-II)

The OBD scanner is used to communicate with the vehicle's ECU. The OBD scanner is a tool to diagnose problems with the vehicle's electrical and exhaust systems [9]. When a failure is detected, the ECU stores the failed code in memory so the scanner can read it. The OBD-II standard also lists the parameters that can be watched and gives each one a code called a parameter identification ID (PID) [7, 8].

The OBD-II standard inherits the standard diagnostic code and communication interface (ISO J1979) and communication between OBD and Can Bus (ISO 15765). With a Bluetooth wireless connection to the OBD port, the low-cost ELM 327 connector can collect all externally available control unit data and send it to a dedicated application. This lets users track vehicle information with a mobile unit that meets ISO J1979 [7, 11, 12].

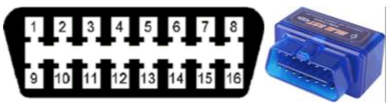

Figure 1 Pinout OBD-II ELM 327

Using the ELM 327 is not as difficult as it seems with many pins available. All that is needed is a PC or smart device with a program that supports reading or capturing the Wi-Fi signal provided by the ELM 327 [13]. It states that the ELM 327 is designed to act as a bridge between the standard serial OBD port and automatically detect and interpret nine OBD protocols [13].

TABLE I
Pin description on OBD-II ELM 327

Pin	Description	Pin	Description	Pin	Description	Pin	Description
1	Vendor Option	5	Signal Ground	9	Vendor Option	13	Vendor Option
2	J1850 Bus +	6	CAN (J-2234) High	10	J1850 Bus	14	CAN (J-2234) Low
3	Vendor Option	7	ISO 9141-2 K-Line	11	Vendor Option	15	ISO 9141-2 Low
4	Chassis Ground	8	Vendor Option	12	Vendor Option	16	Battery Power

B. Multivariate time series Forecast

The process of observing sequentially in a specific time using existing datasets as a guide is known as time series analysis form of a time series [15]. The analysis process with this time series can be used for dependency analysis, so we need a model that can be dynamic and can be used according to application needs [15]. Multivariable time series is a prediction technique using correlations between time series to improve overall prediction accuracy. Predicting complex time series patterns and how variables depend on each other [10] is the key to predicting multivariable time series.

Time-series estimation and prediction methods Using classical and sophisticated forecasting tools, forecasting techniques can be broadly categorized into qualitative and quantitative methods [10], [14]. Qualitative forecasts are often used to provide insight into the problem. However, while some data analysis can be performed, expectations are based on studying mathematics in areas such as mathematical biology, physics, and chemistry [10]. Quantitative forecasts do help to measure problems by generating data that can be converted into numerical data or practical statistics. Quantitative methods produce much more structured and reliable results than qualitative methods [10].

III. Research Method

At this stage, it will explain how the process of obtaining data so that it becomes a dataset that is used for analysis and explains the stages shown in Figure 3. To obtain data, OBD-II ELM 327, which does connect to a four-wheeled vehicle as an object whose data will be taken, is tested with several travel conditions such as flat road conditions, traffic jams, severe road conditions, and slightly downhill road conditions, as shown in Figure 2.

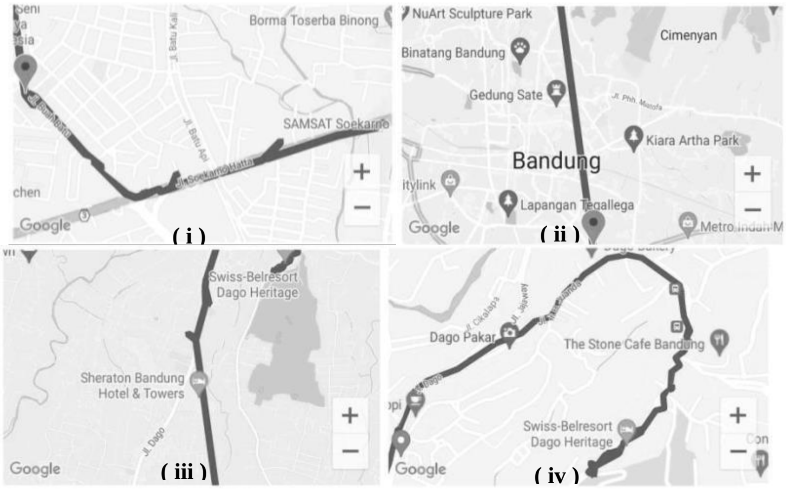

Figure 2 (i) Congested Road Conditions; (ii) Current Road Condition; (iii) Uphill Road Condition; (iv) Deteriorating Road Condition

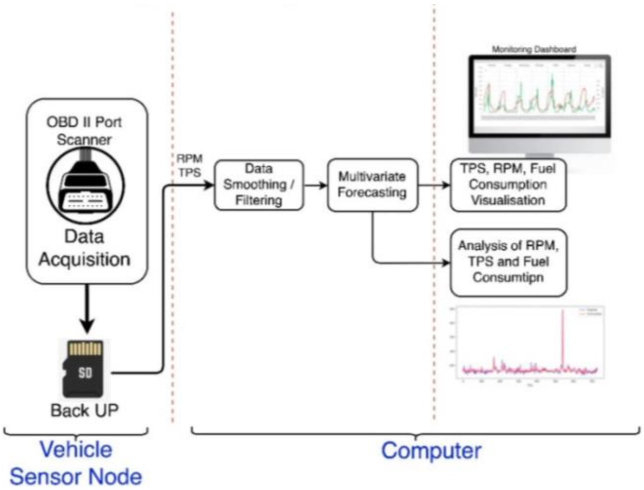

Figure 3 Research Activity Block Diagram

In the block diagram of Figure 3 for the vehicle sensor node, the activities in Figure 2 are the process of getting the data that has been described previously for a vehicle, and certain road conditions are used to see the effect of fuel consumption, RPM, and TPS. Because the OBD-II used comes from ELM 327, the data is stored in the application and exported into mobile data to be uploaded to Google Drive so that it can be accessed by a notebook. It can be processed. The dataset obtained has many variables or parameters, so it must be simplified so that only data that contains the required parameters is obtained, namely fuel consumption, RPM, and TPS. The simplification process also makes the dataset a time series, so that time series analysis can be carried out.

After the dataset is in the form of a time series, a multivariate time series forecasting process will be carried out using the VAR model. The choice of this model is because the model is the most widely used by researchers, has similarities with ordinary regression models, and is relatively easy to adapt to models in the form of actual time series [15]. By using the observed time series vectors up to length N from a multivariate process, the process of developing models that exist in the appropriate VAR for the series is carried out iteratively using a three-step specification procedure such as models, parameter estimation, and inspection [16] [17] [18]. So the mathematical approach can be used using the following equation:

$$Y_{1,t} = \alpha_1 + \beta_{11,1}Y_{1,t-1} + \beta_{12,1}Y_{2,t-1} + \epsilon_{1,t}$$

$$Y_{2,t} = \alpha_2 + \beta_{21,1}Y_{1,t-1} + \beta_{22,1}Y_{2,t-1} + \epsilon_{2,t}$$

From there, the mathematical equation will be implemented as a VAR model to carry out the forecast process. After the multivariate forecasting process is carried out, a visual of the forecast results will be made, which displays a comparison between the primary data and the data tested for the forecast [15]. Furthermore, an analysis of the visual will provide an analysis related to the process used, assisted by performance evaluation for each parameter by testing using the Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R-Square) so that it can provide better validation. To get a program related to the evaluation using a mathematical equation approach as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \qquad MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \qquad R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

IV. RESULTS AND DISCUSSION

The last stage is a form of research results that have been used based on an explanation of the research method. After the process of getting the data is completed, the initial data will be like Figure 4 in the form of a simple sample. The process for tidying the data so it can be a time series is shown in Figure 5. The data set is ready for the VAR model to be used to make predictions for a number of different time series.

SECONDS	PID	VALUE	UNITS	LATITUDE	LONGTITUDE
46695.725017	Altitude (GPS)	699.100037	m	-6.945726	107.64134
46695.725017	Speed (GPS)	0.000000	km/h	-6.945726	107.64134
46695.738017	Average speed (GPS)	0.000000	km/h	-6.945726	107.64134
46695.738017	Speed (GPS)	0.000000	km/h	-6.945726	107.64134
46695.739017	Altitude (GPS)	699.100037	m	-6.945726	107.64134

Figure 4 The Results of The Raw Data That has Been Obtained From The OBD-II ELM 327

	RPM	TPS	Fuel Consumption
date			
2022-05-22 13:05:30	1465.0	24.313725	0.000751
2022-05-22 13:05:31	1500.0	25.882353	0.001568
2022-05-22 13:05:32	1583.0	26.666667	0.002646
2022-05-22 13:05:34	1688.0	26.666667	0.003507
2022-05-22 13:05:35	1824.0	23.137255	0.003974

Figure 5 The form of data that has become a time series dataset

By looking at the data results based on Figure 6, Then can see the pattern of data owned by each parameter, such as fuel consumption, RPM, and TPS. Another purpose that can see is also to observe the parameters to see their respective relationships.

Figure 6 Visual Based on Data That has Been in The Form of a Time Series

From this data, using a multivariate time series forecast, prediction results will be obtained by taking several samples of existing data and generating output from existing data to see how accurate the VAR model is. After analyzing the multivariate time series forecast with the VAR model from the simplified data and according to the parameters In addition to looking at the relationship between parameters by observing Figure 6, another method uses Grangercausalitytests. From looking at the relationship, it can be seen by testing each parameter with other parameters. It turns out that there is a link between the parameters, so when the model is run, it gives the following results:

TABLE II
SAMPLE DATA AND FORECAST RESULTS FROM THE SAMPLE

date	fuel consump	RPM	TPS	fuel_predict	rpm_predict	tps_predict
2022-05-22 13:45:31	1.125467	1950.0	18.823529	1.109120	1923.773648	19.553482
2022-05-22 13:45:32	1.125764	2121.0	19.607843	1.119856	2057.406269	22.579292
2022-05-22 13:45:33	1.125993	2346.0	20.392157	1.113489	1996.072682	23.170359
2022-05-22 13:45:34	1.125993	2479.0	21.568627	1.108956	1996.589992	23.782850
2022-05-22 13:45:36	1.125993	2473.0	25.490196	1.108271	1931.749554	23.650774
2022-05-22 13:45:37	1.125993	2475.0	25.490196	1.109333	1890.807730	22.683555
2022-05-22 13:45:38	1.128172	2442.0	25.490196	1.100465	1860.007405	21.044429
2022-05-22 13:45:39	1.129029	2175.0	25.490196	1.101104	1903.242064	20.437629
2022-05-22 13:45:40	1.129860	1814.0	20.784314	1.098918	1950.556672	20.369020
2022-05-22 13:45:41	1.130904	1529.0	23.921569	1.094501	2004.210544	20.737099
2022-05-22 13:45:42	1.131236	1371.0	23.137255	1.092086	2049.208459	21.704908
2022-05-22 13:45:32	1.125764	2121.0	19.607843	1.119856	2057.406269	22.579292

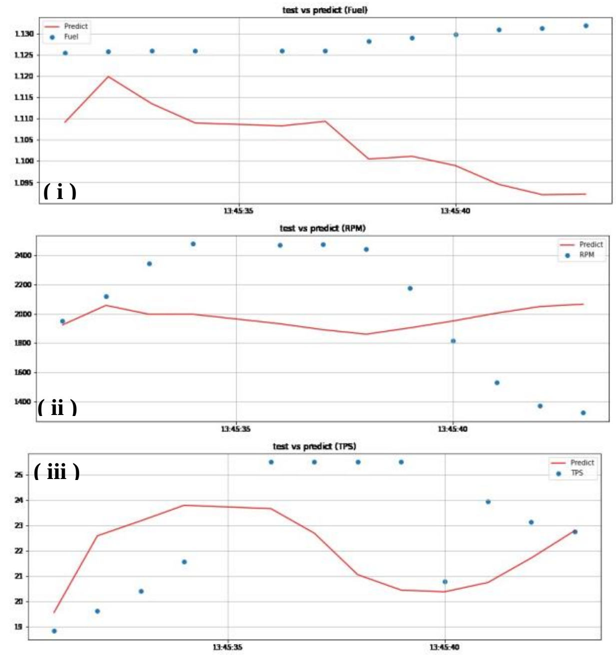

Figure 7 Visual Data between Sample Data (points) and Forecast Results (lines). (i) fuel consumption, (ii) RPM, (iii) TPS

The data shown in table 2 and the visuals shown in Figure 7 show that the forecast results generated with the original sample data are not accurate; the data displayed is exactly the same but still conforms to the data given. To see more clearly how the accuracy can see in Figure 8, the result of the correlation check.

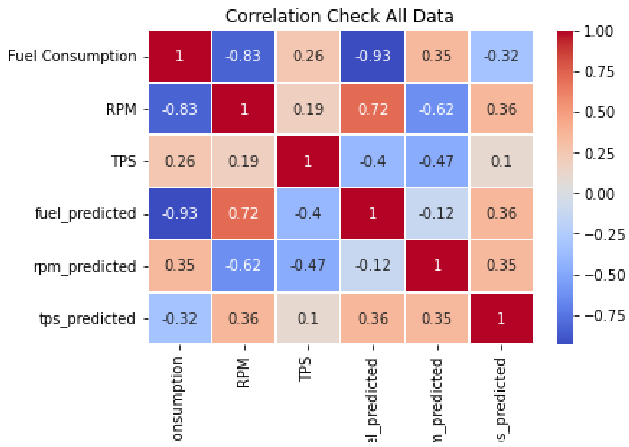

Figure 8 Correlation Check Data Sample and Forecast Result

From the results of this correlation, it can see how the relationship between each initial parameter used and the forecast results that have been carried out is unique. In this case, the correlation between fuel consumption and fuel consumption is predicted to have a value of -0.93 even though it can be seen from the visual shown in Figure 7 that there is a difference which gets more significant in the end. In addition, the correlation between RPM and predicted RPM also has a value of -0.63; only TPS with TPS predicted has a value of 0.1. Even so, based on the results of the model evaluation conducted by looking for the MSE, MAE, RMSE, and R-Squared values, as shown in table 3, the fuel consumption has a small value, even close to 0 (zero). The TPS is also tiny but in the range of 2, which is different from the RPM of significant value.

TABLE III
PREDICTIVE EVALUATION VALUE ON EACH PARAMETER

	Mean	RMSE	MSE	MAE	R-Squared
Fuel Consumption	1.1280199358416767	0.026254517648860064	0.0006892996969743046	0.023992426863688205	-8.659616184430186
RPM	2041.3333333333333	471.33152298411716	222153.40455852737	411.3423716015747	-49.835730071992145
TPS	22.7450980392157	2.7523288677292728	7.5753141961359	2.325563784482736	-3.098483694216288

From the research results obtained by all, then from this study stated some accuracy with initial expectations. The first relates to the relationship between RPM, TPS, and fuel consumption; if look at the correlation checks in Figure 8, where if look at fuel consumption, it only has a better relationship with TPS, it also applies to RPM, which has a better relationship with TPS. Quite different from the Granger causality test, which does also carry out where the time of the Granger test does carry out between fuel consumption and rpm and vice versa rpm and fuel consumption showed that the p-value of each parameter relationship was low so that between fuel consumption and rpm and vice versa rpm and fuel consumption have a granger or relationship or affect. For the parameters of fuel consumption and TPS and vice versa, TPS and fuel consumption are the same as checking for correlations that do influence each other or are related. Finally, RPM and TPS have a low p-value, but TPS and RPM have a high enough p-value, so it can say that RPM and TPS have a granger or an effect, but for TPS and RPM, they do not have a granger or can affect.

In addition, the results of the use of multivariate time series forecasting where this case uses the VAR model, which gives positive results with satisfactory evaluation results for each parameter. So that the prediction or forecast results have a good enough value to be used as further data if this research is to develop. In addition, it also states that using data originating from OBD-II, which converts into an influential time series for making predictions in order to make the vehicle know how much fuel consumption has been carried out and provide some information or warnings so that vehicle users can be more effective in driving the vehicle. However, this research has not yet reached that stage because the aim is to find out how practical the application of multivariate time series forecasts is for processing data from OBD-II tools.

V. CONCLUSION

The results conclude that the parameters between RPM, TPS, and fuel consumption have a relationship or are related to each other, as shown in the Grangercausalitytests process for each parameter and shown in Figure 8 for each correlation check performed. Using the VAR Model for multivariate time series forecasts can say that the model can be used for data taken from OBD-II; the low evaluation value indicates this. Finally, the forecast results obtained can be stated to be quite good because the comparisons made in table 2 and the visuals in Figure 7 show that the difference is not too bad and is clarified by table 3, which shows the results of the evaluation carried out with values for several low parameters. So it can be concluded that, based on the research and literature review conducted, OBD-II ELM 327 has unique data, where, depending on the settings given, the captured PID will be adjusted as long as it connects to the vehicle. The data must be cleaned up again to make it easier to process, whereas this study only focused on RPM, TPS, and fuel consumption and also made a table containing date data so that the data formed was in the form of a time series. After the time series data, the multivariate time series forecast method is chosen to test whether the prediction or forecast formed can be used as the formation of new information or not. This study shows that multivariate time series forecasts can be used to process data from OBD-II tools but must first be converted into time series with good evaluation results and correlations between parameters. However, the model used is only VAR in this study because the VAR model is the most common model to be used, so there is still a chance for several other models to be tested.

ACKNOWLEDGMENT

The author would like to thank the author's friends who have helped in the work of this research, both moral and material support author and the lecturers who supported and provided input so that this research was complete.

REFERENCES

[1] A. Perallos, U. Hernandez-Jayo, E. Onieva, and I. Garcia-Zuazola, *Intelligent Transport Systems Technologies and Applications*. WILEY, 2016.
[2] R. I. Meneguette, R. E. De Grande, and A. A. F. Loureiro, *Intelligent Transport System in Smart Cities*. 2018.
[3] A. Sobota, M. J. Klos, and G. Karo, *Intelligent Transport Systems and Travel Behaviour*, vol. 505. 2017.
[4] L. Paoli, “Fuel Consumption of Cars and Vans – Analysis,” *Iea*, 2020. https://www.iea.org/reports/fuel-consumption-of-cars-and-vans (accessed Nov. 25, 2021).
[5] T. Abukhalil, H. Almahafzah, M. Alksasbeh, and B. A. Y. Alqaralleh, “Fuel Consumption Using OBD-II and Support Vector Machine Model,” *J. Robot.*, vol. 2020, 2020, doi: 10.1155/2020/9450178.
[6] K. WITASZEK, “Modeling of fuel consumption using artificial neural networks,” *Diagnostyka*, vol. 21, no. 4, pp. 103–113, 2020, doi: 10.29354/diag/130610.
[7] X. Ji, H. Zhang, J. Li, X. Zhao, S. Li, and R. Chen, “Multivariate time series prediction of high dimensional data based on deep reinforcement learning,” *E3S Web Conf.*, vol. 256, pp. 0–3, 2021, doi: 10.1051/e3sconf/202125602038.
[8] R. Alur, *Principles of Cyber-Physical Systems*. 2015.
[9] S. A. Nugroho, E. Ariyanto, and A. Rakhmatsyah, “Utilization of Onboard Diagnostic II (OBD-II) on four wheel vehicles for car data recorder prototype,” *2018 6th Int. Conf. Inf. Commun. Technol. ICoICT 2018*, vol. 0, no. c, pp. 7–11, 2018, doi: 10.1109/ICoICT.2018.8528741.
[10] E. Spiliotis, V. Assimakopoulos, and K. Nikolopoulos, “Forecasting with a hybrid method utilizing data smoothing, a variation of the Theta method and shrinkage of seasonal factors,” *Int. J. Prod. Econ.*, vol. 209, pp. 92–102, 2019, doi: 10.1016/j.ijpe.2018.01.020.
[11] H. Guimarães, V. Silva, L. C. Sales, A. Maia, and B. Murta, “An OBD-II based vehicular data tracking system for fuel consumption and emissions improvement,” no. June 2021, 2018, doi: 10.26678/abcm.cobem2017.cob17-1451.
[12] Y. J. Pan, T. C. Yu, and R. S. Cheng, “Using OBD-II data to explore driving behavior model,” *Proc. 2017 IEEE Int. Conf. Appl. Syst. Innov. Appl. Syst. Innov. Mod. Technol. ICASI 2017*, pp. 1816–1818, 2017, doi: 10.1109/ICASI.2017.7988297.
[13] Elm Electronics Inc., “ELM327 OBD to RS232 Interpreter,” pp. 1–5, 2014, [Online]. Available: https://www.elmelectronics.com/wp-content/uploads/2016/07/ELM327DS.pdf.
[14] K. Meißner and J. Rieck, “Multivariate Forecasting of Road Accidents Based on Geographically Separated Data,” *Vietnam J. Comput. Sci.*, vol. 8, no. 3, pp. 433–454, 2021, doi: 10.1142/S2196888821500196.
[15] G. E. P. BOX, G. M. JENKINS, G. C. REINSEL, and G. M. LJUNG, *TIME SERIES ANALYSIS Forecasting and Control Fifth Edition*. 2016.
[16] C. Huang, "Research on the linkage relationship between different levels of money supply and economic growth based on VAR model," in *2020 2nd International Conference on Economic Management and Model Engineering (ICEMME)*, Chongqing, 2020.
[17] R. Wang, "Research on the Relationship between China’s Import and Export Trade and Confidence Index–Dynamic Analysis based on VAR Model," in *2020 2nd International Conference on Economic Management and Model Engineering (ICEMME)*, Chongqing, 2020.
[18] G. Qingying, Z. Yanjie and C. Zheang, "Application of VAR Model based on Distributed Least Squares Estimation Algorithm," in *2020 International Conference on Information Science, Parallel and Distributed Systems (ISPDS)*, Xi'an, 2020.