OKU Fen Bilimleri Enstitüsü Dergisi
6(2): 1137-1158, 2023

OKU Journal of The Institute of Science and Technology, 6(2): 1137-1158, 2023

Osmaniye Korkut Ata Üniversitesi
Fen Bilimleri Enstitüsü
Dergisi

Osmaniye Korkut Ata University
Journal of The Institute of Science and Technology

Implementing of Time Series Analysis Based Decision Support System for Traffic Density Monitoring

Ahmet YÜCEL[1*]

[1]Ankara Yıldırım Beyazıt University, Faculty of Applied Sciences, Department of Finance and Banking, 06650, Şereflikoçhisar/Ankara

[1]https://orcid.org/0000-0002-2364-9449
[*]Corresponding author: ayucel@ybu.edu.tr

Research Article

Article History:
Received: 24.05.2022
Accepted: 10.10.2022
Published online 05.07.2023

Keywords:
LSTM
GRU
Time series analysis
Decision support systems
Artificial neural network

ABSTRACT

In direct proportion to developments in bandwidth technologies for Internet data transmission networks, the use of the internet in daily life is becoming more common. The concept of the Internet of Things (IoT) refers to the new technological ecosystem consisting of numerous objects that can be added to these technologies. One of the most important visions of the IoT is the concept of a smart city. This concept, which means that every component in cities, from communications to transportation, is connected to the internet and controlled and monitored by artificial intelligence-based computer algorithms, promises to ensure that increasingly crowded cities function in an orderly manner without descending into chaos. This study proposes a decision support system based on time series analysis that monitors traffic density in cities and makes future predictions. The proposed procedure is an Artificial Neural Network (ANN) based Time Series (TS) decision support technique. The study used the number of vehicles passing by three randomly selected junctions every hour as data. The relative effects of vehicle density at the junctions were calculated and traffic flow models were designed. The most appropriate traffic flow model is determined based on the accuracy of the forecast data provided by the models created. When the data are considered stable, predictions can be made with 93% accuracy for the ANN-based TS models J1 and J2 and 66% for J3. For the dynamic model, according to the design of the traffic flow, it was found that the model of serially connected traffic between the junctions has the highest accuracy with a joint mean value of 0.86.

Trafik Yoğunluğunun Takibi için Zaman Serileri Analizi Tabanlı Karar Destek Sisteminin Uygulanması

Araştırma Makalesi

Makale Tarihçesi:
Geliş tarihi: 24.05.2022
Kabul tarihi:10.10.2022
Online Yayınlanma: 05.07.2023

Anahtar Kelimeler:
LSTM
GRU
Zaman serileri analizi
Karar destek sistemleri
Yapay sinir ağları

ÖZ

İnternet veri aktarım ağ bant genişliği teknolojilerindeki gelişmelerle doğru orantılı olarak, internetin günlük hayatta kullanımı daha yaygın hale gelmektedir. Nesnelerin interneti (IoT) kavramı, bu teknolojilere eklemlenebilecek sayısız nesnenin oluşturduğu yeni teknolojik ekosistemi ifade etmektedir. IoT kavramının en önemli vizyonlarının başında akıllı şehir konsepti gelmektedir. Şehirlerde, iletişimden ulaşıma kadar her bir bileşenin internete bağlı şekilde, yapay zekaya dayalı bilgisayar algoritmalarıyla kontrol ve takip edilmesi anlamına gelen bu konsept, gittikçe daha kalabalık hale gelen şehirlerin, bir kaosa girmeden düzen içinde işlemesini sağlamayı vaat etmektedir. Bu çalışmada, şehir trafik akış yoğunluğunu takip eden ve geleceğe yönelik öngörüler sağlayan, zaman serisi analizine dayalı bir karar destek yöntemi önerilmektedir. Önerilen yaklaşım, yapay sinir ağı tabanlı bir zaman serisi karar destek yöntemidir. Çalışmada şehir trafiğinde belirlenen rastgele kavşaklardan, saatlik geçen araç sayıları veri olarak kullanılmıştır. Kavşakların sahip olduğu araç yoğunluğunun bağıl etkileri hesaplanmış ve trafik akışıyla ilgili modeller tasarlanmıştır. Oluşturulan modellerin sağladığı tahminsel verilerin doğruluk oranına göre en uygun trafik akış modeli belirlenmektedir. Veriler sabit kabul edildiğinde, yapay sinir ağı tabanlı zaman serisi modelleri J1 ve J2 için %93 ve J3 için %66 doğrulukla tahminler yapılabilmektedir. Dinamik veri modeli için, bağıl etkileşime sahip trafik akışı tasarımına göre, kavşaklar arasında seri bağlı trafik modelinin 0.86 ile en yüksek doğruluğa sahip olduğu bulunmuştur.

To Cite: Yücel A. Implementing of Time Series Analysis Based Decision Support System for Traffic Density Monitoring. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2023; 6(2): 1137-1158.

Introduction

Urban problems resulting from inadequate infrastructure increase as the population living in cities increases (Kuddus et al., 2020). One of the biggest problems, especially in big cities, is traffic. Collecting and analyzing data is becoming more and more important to solve traffic problems in major cities. Control centers immediately analyze traffic data from thousands of camera systems distributed throughout the city in an attempt to manage urban traffic (Xing et al., 2022). In addition to information obtained from major junctions, data can also be obtained from vehicles' navigation devices and GPS (Espinosa et al., 2019). This type of continuously generated data needs to be collected and analyzed simultaneously. After the data are evaluated using various analysis tools, some solutions are developed and measures are taken to ensure that the traffic flows smoothly and that the passengers travel safely (Chen et al., 2021).

The traffic problem is not a new phenomenon. Local governments have been trying to develop different solutions in this regard for a long time. One of the most popular solutions was to build more roads, to reduce congestion and make it easier for people to move around the city (Karimi et al., 2022). However, these solutions have proven insufficient and ineffective (Nugmanova et al., 2019) as we have seen that the more roads are built, the more cars are on them.

The city is like a living organism that evolves and changes with the people living in it. Cities are becoming smarter and more connected with the development of technology. The idea of a smart city is so that it can use data to make decisions on how best to manage its resources and infrastructure, which in turn will reduce environmental impacts and energy usage.

Traffic monitoring is the process of collecting data on traffic flows and analyzing it with the help of artificial intelligence. In order to make the traffic of the city more efficient, smart cities are implementing technology that can be used to monitor traffic flow. One of these implementations is the use of traffic flow junctions. Junctions are a critical part of any city's traffic infrastructure. Traffic flow junctions are the intersections of two or more roads. These junctions are usually controlled by traffic lights, roundabouts, or stop signs, but they can also be controlled by other devices like an automated system (Masuduzzaman et al., 2022). They help to regulate the flow of traffic and in turn keep the city running smoothly (Ahmed et al., 2020). They also report how many vehicles have passed through that point of the city in a given period and predict when it will be busy or not (Ahmed et al., 2020).

The Internet of Things (IoT) is a new hub of integrated electronic devices and software that allows objects to collect and exchange data between the components of the hub. (Ponnusamy et al., 2021). The use of IoT devices has been on the rise in recent years. This is because more and more people are getting connected to the internet and they want to be able to control their appliances from a distance. IoT devices are also used in smart cities (Ponnusamy et al., 2021). They can be used for traffic data, numbers of vehicles per hour, parking spaces, water levels etc (Ponnusamy et al., 2021). This type of technology is important because it helps make sure that traffic flows smoothly, which makes the city more efficient and less stressful for drivers (Bearn et al., 2018). IoT devices also help monitor pollution levels by predicting when they will increase or decrease based on the number of cars going through a junction at any given time (Shahid et al., 2021). The process starts with collecting data on when and where the cars are traveling. Data collection is done using sensors or cameras installed in vehicles. The data collected by the tracking devices can then be stored and analyzed by artificial intelligence algorithms so that the city administration can take necessary actions to improve the quality of life in that area. Also the tracking data is used to optimize traffic flow, reduce emissions, and make the city greener (Shahid et al., 2021).

Data analysis is a very broad term that covers many different fields, from statistics to machine learning, from business intelligence to predictive analytics. Data analysts can work in any industry or company that relies on large amounts of data. TS analysis a very common type of data analysis which involves looking at trends over a period of time. Traffic flow data analysis is a complex task, which requires a lot of time and technical support. An artificial neural network (ANN) is one of the most widely used machine learning algorithms inspired by the structure and function of the biological neural network (Dey, 2016). The first neural network was developed in 1943 by Warren McCulloch and Walter Pitts (McCulloch et al., 1943). It was an abstract mathematical model that could be used to solve logical problems. In the late 1940s, Donald Hebb came up with a learning rule for neural networks called Hebbian learning (Lim, 2021), which is still widely used today.

ANN are used to analyze traffic flow data in order to forecast future traffic flow. Neural networks are made up of nodes, which are like neurons in the human brain (He et al., 2021). The connections between nodes resemble synapses in our brains (Grosan et al., 2011). The connections can be either weighted or unweighted, depending on how the ANN was trained to work. The ANN use the past and present traffic flow data to predict future traffic patterns. Neural networks can be used for data analysis and time series forecasting which is one of the most popular techniques for prediction in artificial intelligence.

This paper will discuss the use of ANN to predict traffic patterns in a city. The use of ANN based TS will help in understanding the traffic patterns and finding out the intersections that have high traffic volume. This is done by collecting data from junctions and intersections, then creating a model based on that data and predicting future results based on it.

Related work

Time series (TS) analysis is a statistical procedure that is used to analyze data that has been collected over time. TS can be used to detect the trends existing in data and forcast future data. The data collected in TS analysis can be anything from stock prices (Liang et al., 2013; Wu et al., 2022), to website services (Singh et al., 2020), or even patients who are diagnosed with a disease (Li et al., 2022). A TS is a sequence of data points in chronological order. ANN are a type of machine learning algorithm that can be used to analyze time series data. Withington et al. analyzed a TS of data on the dog's searching behavior when it pressed its nose against the sample cup to smell the contents, which were generated by pressure sensors to detect the dog's response to various diseases for which the dog was trained. The goal of this study was to determine whether ANN could be used to classify sensor generated data when sniffing samples. ANN MLP-based TS model performed best among the four different neural network architectures (Withington et al., 2021).

Decision support systems (DSS) are computerized tools that are designed to provide information and advice to help people make better decisions. They are used in a wide range of industries, including healthcare (Govindan et al., 2020), finance (Soni et al., 2022), and manufacturing (Mumali, 2022). DSS can be classified into two types; expert and interactive systems. ANN-based TS models are expert decision support systems.

Pattern recognition can be used to identify patterns in time series data (Jastrzebska, 2022), such as stock prices or weather data. This can be done by looking for repeating patterns in the data, such as peaks or troughs. Chhajer et al. proposes an outline of AI and ML as predictive instruments in the stock market. Also, they give some application of ANN, in the stock market prediction (Chhajer et al., 2022).

Time series can be used to predict future events, such as the next stock market crash (Wu et al., 2022) or the next flu epidemic, to analyze past events, such as how long it takes for a new product to reach its peak sales, to find patterns in data, such as when people are most likely to buy a certain product, to find trends in data, such as whether people are buying more or less of a certain product over time. Wu et al. analyzes the consequences of business digital transformation on stock price crash risk. They detected that the transformation can remarkably reduce market crash risk (Wu et al., 2022). Wang et al. developed a TS prediction model of Covid-19 pandemic. This study highlights the significance of preventative steps to control and reduce the spread of the disease (Wang et al., 2020).

Huang et al. presents a new concept for traffic flow modeling anointed Time Series Decomposition (TSD). TSD functions as pattern recognition tool such that it extracts the systematic pattern of traffic flow and introduces a illustrated motivations for each pattern (Huang et al., 2022). Bijl et al. examine the significant consequences of the COVID-19 on the traffic flow rate and introduces a comparison of methods for the TS prediction of Traffic Flow Rate at hourly and daily intensity levels. In addition, Bijl et al. propose some models to eliminate the future consequences of the pandemic (Bijl et al., 2022). Lim et al. propose a TS model that forecasts future values for different types of shipment traffic based on a deep learning method (Lim et al., 2021).

The rest of the article is organized as follows. Chapter 3 provides details on the data and analysis methodology. In Chapter 4, the results of the proposed machine learning models are shared. Chapter 5 provides an overview of the results obtained and some suggestions for future work.

Material and Methods

The structured data used in this study were obtained from Kaggle.com, a subsidiary of Google LLC, a major statistical analysis platform that makes data available online worldwide, and where data scientists share machine learning ideas. The data contains the total number of vehicles passing 3 different junctions per hour (00:00 - 23:00) in an anonymous city between January 2015 and June 2017. It contains a total of 43,776 cases.

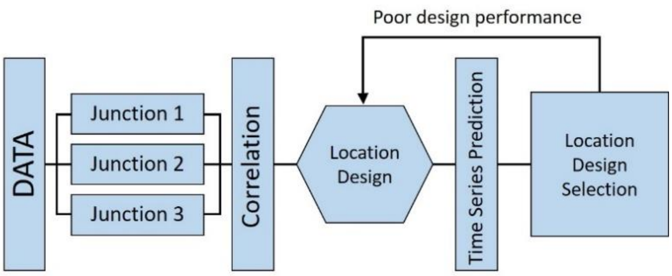

Figure 1. Methodology

Decision making is the process of selecting a course of path from among multiple alternatives. The best path is the one that minimizes the total cost of process. The decision making process can be broken down into three steps: problem identification, goal setting, and solution evaluation. The first step in the decision making process is to identify the problem or issue at hand. The second step is to set goals for what you want to achieve by solving this problem or issue. The third step in the decision making process is to evaluate possible solutions and choose one that best meets your goals. In this study, a novel decision-making methodology (as depicted in Figure 1) based on time series analysis is proposed. This approach consists of three sequential steps. In the first step, data are collected and classified by junctions. In the second step, the correlation values between junctions are calculated. The correlation information was used to determine the extent to which vehicle traffic of one junction affects the vehicle traffic of other junctions. This can be expressed as the relative effect of the locations of the junctions. In the third stage, the first 27-month portion of the data covering a 30-month period was set as the training set and the last 3-month portion was set as the testing set. TS Models trained on the training set were applied to the testing set. The similarity ratio between the predicted and actual (observational) values indicates the performance of the models. Models with acceptable performance are used in location design selection. In cases where the performance of the models is not sufficient, the location designing step is repeated and new designs are created and the TS step is restarted.

Machine learning methods. Machine learning models (ML) are built through experimental iterations. Each iteration can be expressed as a trial-and-error experimental step. Therefore, the performance of the model largely depends on the quality of the data set. In this study, the TS algorithm was used as the ML method. TS is a probability distribution model of observations that has some characteristic features that repeat at fixed intervals. These intervals are generally expressed as trends or seasonality. The main goal of a TS model is to reveal these two time-based components. Trend refers to the periodic increase or decrease in observed values. Seasonality, daily, monthly, yearly, etc., can be expressed as a distinct distribution pattern that repeats at fixed time intervals.

The seasonality variables are Daily_D and Monthly_D. Daily_D shows the change in the number of vehicles passing through the junctions on consecutive days and at the same time of day. Monthly_D shows the change in the number of vehicles passing through the junctions in the same month of the year.

Results and Discussion

The dataset consists of a total of 43,776 cases evenly distributed among 3 junctions. There are 14,592 cases per junction, recorded every hour on a daily basis. The number of vehicles passing through the junctions is recorded under the variables V_J1, V_J2, and V_J3 for junction 1 (J1), junction 2 (J2), and junction 3 (J3), respectively. The average daily number of vehicles passing the junctions was 45.05, 14.25, and 13.69, respectively, for a total of 608 cases for each hour.

Table 1. Descriptive Statistics

*M: Multiple Mode

	Daily_D	N	Mean	Med.	Mode	Freq. of Mode	Min.	Max.	Var.	Std.Dev.	Skew.	Kurtosis
V_J1	00:00	608	45.74	44	35	20	13	92	331.28	18.20	0.26	-0.90
	01:00	608	39.16	37	28	19	12	81	242.07	15.56	0.30	-0.88
	02:00	608	33.91	32	18	22	5	69	187.44	13.69	0.25	-0.99
	03:00	608	29.43	27	22	26	6	57	146.12	12.09	0.29	-1.06
	04:00	608	25.65	23	18	40	8	48	108.36	10.41	0.31	-1.10
	05:00	608	24.07	23	17	36	6	47	95.54	9.77	0.25	-1.06
	06:00	608	26.08	25	17	29	7	53	123.18	11.10	0.33	-1.02
	07:00	608	29.53	27	27	24	7	59	157.77	12.56	0.36	-0.94
	08:00	608	32.74	31	31	25	8	67	192.44	13.87	0.33	-0.91
	09:00	608	39	37	36	18	8	78	240.76	15.52	0.37	-0.74
	10:00	608	49.53	47	50	18	11	107	402.79	20.07	0.51	-0.42
	11:00	608	56.19	53	M.	19	10	136	599.75	24.49	0.57	-0.28
	12:00	608	57.25	54.50	41	15	12	129	643.88	25.37	0.51	-0.49
	13:00	608	51.08	48	34	17	11	118	489	22.11	0.53	-0.48
	14:00	608	54.73	50	42	17	11	143	635.44	25.21	0.60	-0.30
	15:00	608	54.22	50	M.	15	11	134	621.12	24.92	0.56	-0.46
	16:00	608	51.91	49	50	15	10	134	552.14	23.50	0.60	-0.23
	17:00	608	51.85	49	M.	16	13	135	541.86	23.28	0.59	-0.12
	18:00	608	55.41	52	28	17	12	141	602.53	24.55	0.55	-0.22
	19:00	608	58.80	57	M.	17	13	156	623.63	24.97	0.53	-0.25
	20:00	608	57.40	55	39	16	15	126	577.22	24.03	0.38	-0.76
	21:00	608	54.54	52	34	18	15	114	511.92	22.63	0.33	-0.89
	22:00	608	52.96	51	37	20	14	104	458.64	21.42	0.29	-0.97
	23:00	608	50.09	49	M.	16	14	99	398.59	19.96	0.26	-0.92
	ALL	14592	45.05	40	35	294	5	156	529.38	23.01	0.80	0.19
V_J2	00:00	608	15.66	14	14	51	2	38	50.86	7.13	0.98	0.46
	01:00	608	14.12	13	12	52	1	35	43.48	6.59	0.83	0.03
	02:00	608	13	12	12	58	1	30	34.13	5.84	0.84	-0.05
	03:00	608	11.47	10	80	78	2	26	23.75	4.87	0.69	-0.24
	04:00	608	10	9	80	74	2	21	16.54	4.07	0.65	-0.33
	05:00	608	9.22	8	60	82	1	20	14.37	3.79	0.71	-0.03
	06:00	608	9.26	8	60	77	3	23	15.83	3.98	0.75	-0.04
	07:00	608	10.06	9	90	76	2	23	19.35	4.40	0.82	0.12
	08:00	608	10.75	10	M.	65	2	25	21.69	4.66	0.79	0.06
	09:00	608	11.61	11	90	65	2	26	25.09	5.01	0.80	0.10
	10:00	608	13.03	12	10	61	1	32	32.27	5.68	1	0.61
	11:00	608	14.62	14	14	53	1	36	46.58	6.82	1.06	0.84
	12:00	608	15.66	14.50	15	54	2	45	58.42	7.64	1.23	1.35
	13:00	608	14.66	13	11	48	2	39	51.97	7.21	1.17	1.06
	14:00	608	16.31	15	16	47	1	43	71.59	8.46	1.15	0.99
	15:00	608	16.80	15	14	40	1	47	74.05	8.61	1.09	0.83
	16:00	608	16.49	15	13	43	2	43	63.81	7.99	1.06	0.82
	17:00	608	16.43	15	14	50	3	47	61.09	7.82	1.05	0.92
	18:00	608	16.78	15	15	44	1	43	71.17	8.44	1.16	1.04
	19:00	608	17.88	16	17	48	2	48	77.33	8.79	1.23	1.29
	20:00	608	18.06	16	17	40	3	48	74.46	8.63	1.10	0.76
	21:00	608	17.24	16	10	43	3	41	64.58	8.04	0.97	0.28
	22:00	608	16.82	15	M.	53	1	40	56.52	7.52	0.93	0.21
	23:00	608	16.17	15	11	44	1	41	53.58	7.32	0.95	0.38
	ALL	14592	14.25	13	10	1032	1	48	54.78	7.40	1.29	1.78
V_J3	00:00	608	14.17	12	11	59	1	109	100.70	10.04	3.55	21.53
	01:00	608	9.86	9	10	61	1	51	25.48	5.05	1.84	8.60
	02:00	608	8.06	8	70	79	1	31	12.97	3.60	1.09	3.81
	03:00	608	6.78	7	70	88	1	19	8.77	2.96	0.64	0.78
	04:00	608	5.98	6	60	98	1	16	6.20	2.49	0.48	0.27
	05:00	608	5.69	6	60	118	1	15	5.39	2.32	0.55	0.69

06:00	608	6.24	6	50	110	1	19	7.63	2.76	0.88	1.74
07:00	608	7.55	7	70	84	1	26	12.52	3.54	1.21	3.12
08:00	608	9.06	9	90	66	1	36	19.95	4.47	1.30	4.04
09:00	608	11.43	10.50	90	57	1	53	38.10	6.17	1.89	7.21
10:00	608	15	14	12	47	1	61	65.25	8.08	1.49	4.29
11:00	608	17.19	16	17	46	1	57	76.75	8.76	1.10	2.26
12:00	608	17.71	17	13	37	2	54	76.50	8.75	0.85	1.20
13:00	608	16.05	15	13	46	2	57	61.71	7.86	0.82	1.32
14:00	608	17.57	16	15	38	1	162	108.92	10.44	4.82	60.18
15:00	608	17.37	16	15	38	1	83	79.15	8.90	1.26	5.53
16:00	608	16.88	16	15	44	2	71	76.42	8.74	1.59	6.63
17:00	608	16.90	16	20	37	1	62	74.87	8.65	1.10	2.37
18:00	608	17.93	16	13	41	1	132	156.09	12.49	3.76	23.99
19:00	608	19.13	16	14	32	2	180	218.53	14.78	3.80	27.99
20:00	608	20.20	15	14	40	1	173	360.14	18.98	3.35	15.29
21:00	608	18.72	15	10	35	2	125	246.13	15.69	2.91	11.59
22:00	608	17.39	15	12	38	2	111	135.44	11.64	2.57	12.96
23:00	608	15.80	14	12	46	1	77	87.38	9.35	1.66	5.08
ALL	14592	13.69	11	60	962	1	180	108.91	10.44	3.49	27.36

When the daily averages are examined, it is observed that the lowest daily density occurs at all junctions between 04:00 and 05:00. The average daily vehicle densities between these hours were 24.07, 9.22, and 5.69, respectively. Similarly, the highest daily vehicle density is observed between 19:00 and 20:00. The average number of vehicles between these hours were 58.80, 18.06, and 20.20. respectively. The aggregated results are presented in Table 1 and also summarized in Figure 2.

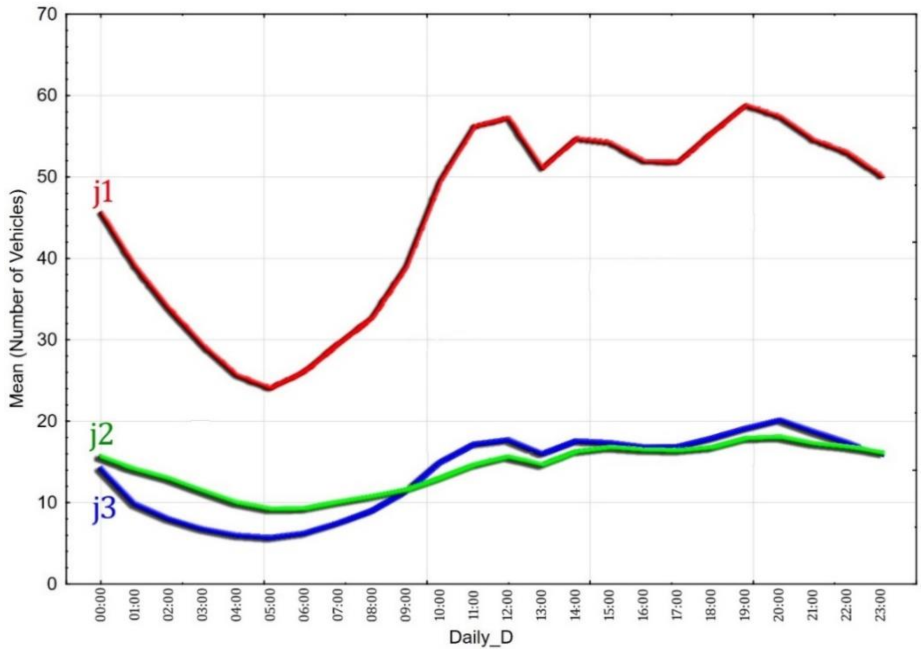

Figure 2. The average daily vehicle numbers per hour

A vehicle may pass through more than one junction during its journey. Some of them are successively located on the same route, while others are located on independent routes. By calculating the correlation values between the junctions, an attempt was made to understand the relative position of the junctions. A strong or high correlation means that there is a strong linear relationship between the two variables. Table 2 shows the correlation values between variables V_J1, V_J2, and V_J3. The correlation values highlighted in red (at a confidence level of $\alpha = 0.05$) are correlations that were found to be statistically significant according to the correlation analysis. The results show that there is a statistically significant but not very strong correlation of 0.53 and 0.43 between V_J3 and V_J1 and V_J2. respectively. On the other hand, there is a statistically significant and strong correlation of 0.87 between V_J1 and V_J2. These results imply that a linear or non-linear model based on these two variables has a high accuracy.

Table 2. Correlation scores (all day)

	V_J2	V_J3
V_J1	0.87	0.53
V_J2		0.43

When the correlation between the junctions was calculated separately by specific times of day, it was found that the correlation between V_J1 and V_J2 ranged from 0.79 to 0.89. The correlation weakened between 04:00 and 05:00 when the traffic density decreased and strengthened in the hours when the traffic density increased. Especially, between 15:00 and 17:00, the correlation value reached the highest level. It was found that the correlation of V_J3 with V_J1 and V_J2 ranged from0.25 –0.55 and 0.14 –0.51, respectively. It was observed that the correlation of V_J3 with V_J1 and V_J2 decreased to the lowest values between 19:00 and 21:00. when the daily traffic density was the highest. The aggregated results are presented in Table 3.

Table 3. Correlation scores (hourly)

Time (a.m)	V_J2	V_J3	Junction	V_J2	V_J3	Time (p.m)
00:00	0.87	0.32 0.25	V_J1 V_J2	0.86	0.53 0.48	**12:00**
01:00	0.87	0.45 0.39	V_J1 V_J2	0.86	0.52 0.45	**13:00**
02:00	0.84	0.47 0.39	V_J1 V_J2	0.88	0.51 0.48	**14:00**
03:00	0.82	0.51 0.41	V_J1 V_J2	0.89	0.55 0.51	**15:00**
04:00	0.79	0.49 0.39	V_J1 V_J2	0.89	0.48 0.43	**16:00**
05:00	0.79	0.48 0.36	V_J1 V_J2	0.89	0.52 0.49	**17:00**
06:00	0.81	0.47 0.41	V_J1 V_J2	0.88	0.41 0.36	**18:00**
07:00	0.84	0.46 0.40	V_J1 V_J2	0.86	0.32 0.24	**19:00**
08:00	0.84	0.47 0.40	V_J1 V_J2	0.88	0.25 0.14	**20:00**
09:00	0.83	0.40 0.34	V_J1 V_J2	0.87	0.27 0.17	**21:00**
10:00	0.84	0.43 0.41	V_J1 V_J2	0.86	0.34 0.27	**22:00**
11:00	0.85	0.48 0.43	V_J1 V_J2	0.88	0.39 0.33	**23:00**

It is a natural routine of city life that traffic density increases or decreases at certain times of the day for reasons such as work, education, health, etc. Also, traffic density increases or decreases at certain times of the year for reasons such as school, vacations, tourism, etc. The correlation between V_J1 and V_J2 ranged from 0.69 to 0.94 when calculated on a monthly basis. The correlations of V_J3 with V_J1 and V_J2 were found to vary between 0.30 – 0.78 and 0.20 – 0.74. respectively. It was found that the ranges calculated on a monthly basis are larger than the ranges of the correlation values obtained in the calculation on a daily basis. This indicates that the change in traffic density during certain periods of the year (consecutive months) is greater than the change at certain times of the day. While the correlation between V_J1 and V_J2 drops to its lowest value in August, it reaches its highest values in May - June. Similarly, the correlations of V_J3 with V_J1 and V_J2 decrease to their lowest value in July and reach their highest value in June. The aggregated results can be found in Table 4.

Table 4. Correlation scores (monthly)

Monthly_D	V_J2	V_J3	Junction	V_J2	V_J3	Monthly_D
January	0.88	0.55 0.50	V_J1 V_J2	0.82	0.30 0.20	**July**
February	0.87	0.47 0.41	V_J1 V_J2	0.69	0.50 0.40	**August**
March	0.92	0.54 0.44	V_J1 V_J2	0.81	0.53 0.40	**September**
April	0.92	0.55 0.44	V_J1 V_J2	0.81	0.44 0.30	**October**
May	0.93	0.50 0.43	V_J1 V_J2	0.87	0.54 0.44	**November**
June	0.94	0.78 0.74	V_J1 V_J2	0.80	0.68 0.49	**December**

The correlation analysis shows that there is a strong and linear relationship between V_J1 and V_J2. This indicates that J1 and J2 are affected by the same traffic flow. Furthermore, since it is known that J1 has more vehicles than J2, the following possible sequences for the locations of J1, J2, and J3 with respect to traffic flow are obtained (as shown in (a) and (b) of Figure 3 and (c), (d), (e), and (f) of Figure 4):

1. J1 and J2 are connected in series and J3, J1 and J2 are connected in parallel. The traffic flow is in the direction J1 → J2. There is an outflow to the 4th junction between J1 and J2.

2. J1 and J2 are connected in series and J3, J1 and J2 are connected in parallel. The traffic flow is in the direction of J2 → J1. There is an inflow from the 4th junction between J1 and J2.

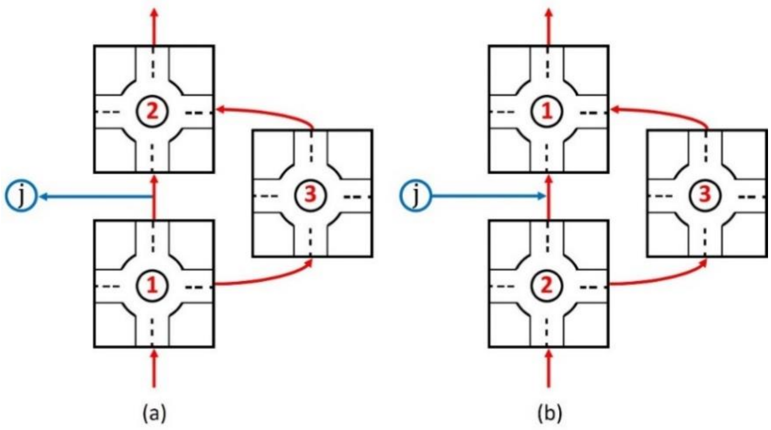

Figure 3. Parallel connected traffic flow models

3. J1, J2 and J3 are connected in series. The traffic flow is in the direction J1→J2→J3. There is an outflow to the 4th junction between J1 - J2 and J2 - J3.

4. J1, J2 and J3 are connected in series. The traffic flow is in the direction of J2→J1→J3. There is an inflow from the 4th junction between J2 and J1. There is an outflow toward the 4th junction between J1 and J3.

5. J1, J2 and J3 are connected in series. The traffic flow is in the direction of J3→J1→J2. There is an inflow from the 4th junction between J3 and J1. There is an outflow toward the 4th junction between J1 and J2.

6. J1, J2 and J3 are connected in series. The traffic flow is in the direction J3→J2→J1. There is an inflow from the 4th junction between J3 - J2 and J2 - J1.

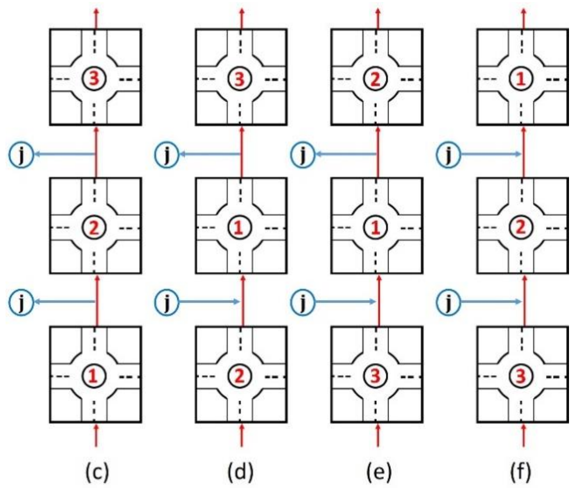

Figure 4. Serial connected traffic flow models

The artificial neural network (ANN) based TS algorithm used in this study predicts the number of vehicles for the three junctions. The ANN is trained on the input data and then it predicts the output values for new input data. The ANN learns from the training set and improves its prediction accuracy with each iteration. The performance of the models is measured using the correlation coefficient as a similarity measure. In addition to the above traffic flow models, decision making models based on TS were built for different variables and with different ANN network models. In the TS models, V_J1, V_J2, and V_J3 were assigned as dependent variables and other variables were assigned as independent variables. In all models, the first 27 months of data were used to train the models, and the trained models were applied to the last 3 months of data. The similarity between the observed data and the model-based predicted data shows the performance of the model. The most successful ANN-based TS network models for estimating V_J1, V_J2, and V_J3 are MLP 38-8-1, MLP 38-6-1, and MLP 38-7-1, respectively, and the performance of the models was calculated to be 0.93, 0.93, and 0.66, respectively. In the design of the models, V_J2, V_J3, Daily_D, Monthly_D; V_J1, V_J3, Daily_D, Monthly_D; and V_J1, V_J2, Daily_D, Monthly_D are used as independent variables. Aggregated results are presented in Table 5 and also summarized in Figure 6.

Table 5. ANN-based TS network models

Index	Net. name	Test perf.	Test error	Train. algor. BFGS	Err. funct.	Hidden activ.	Output activ.	Dep. Var.	Indep. Var.	MAE	MAPE
1	MLP 38-8-1	0.93	44.79	39	SOS	Tanh	Tanh	V_J1	V_J2, V_J3, Daily_D, Monthly_D	7.27	0.11
2	MLP 37-3-1	0.91	59.49	17	SOS	Logi.	Exp.	V_J1	V_J2, Daily_D, Monthly_D	7.61	0.11
3	MLP 37-4-1	0.79	437.17	26	SOS	Tanh	Iden.	V_J1	V_J3, Daily_D, Monthly_D	25.58	0.37
4	MLP 36-8-1	0.77	749.96	7	SOS	Logi.	Logi.	V_J1	Daily_D, Monthly_D	33.97	0.50
5	MLP 38-6-1	0.93	10.74	38	SOS	Logi.	Iden.	V_J2	V_J1, V_J3, Daily_D, Monthly_D	3.79	0.16
6	MLP 37-8-1	0.93	17.43	12	SOS	Exp.	Exp.	V_J2	V_J1, Daily_D, Monthly_D	3.90	0.16
7	MLP 37-7-1	0.72	85.46	37	SOS	Logi.	Tanh	V_J2	V_J3, Daily_D, Monthly_D	11.30	0.46
8	MLP 36-9-1	0.68	106	33	SOS	Exp.	Exp.	V_J2	Daily_D, Monthly_D	12.70	0.52
9	MLP 38-7-1	0.66	33.4	79	SOS	Tanh	Tanh	V_J3	V_J1, V_J2, Daily_D, Monthly_D	5.03	0.29
10	MLP 37-6-1	0.66	33.89	72	SOS	Logi.	Iden.	V_J3	V_J1, Daily_D, Monthly_D	4.98	0.28
11	MLP 37-4-1	0.64	36.31	21	SOS	Tanh	Logi.	V_J3	V_J2, Daily_D, Monthly_D	5.19	0.30
12	MLP 36-6-1	0.59	54.59	15	SOS	Exp.	Iden.	V_J3	Daily_D, Monthly_D	6.49	0.37
13	MLP 38-8-2	0.93	44.80	39	SOS	Tanh	Tanh	V_J1	V_J2, V_J3, Daily_D, Monthly_D	4.17	0.40

The observed values of variables V_J1, V_J2, and V_J3 for the last 3 months (test set) are presented in Figure 5. The recurrent seasonal effect for each variable is also shown in the graph. The success of a TS model is measured by its ability to produce predictions that correlate strongly with observed values and reveal the seasonality pattern in the distribution of the data. The correlation values (model performance) of the model predictions are given in Table 5. In addition, the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) values for each model are presented in Table 5. In order to observe the evolution of the accuracy rates produced by the hidden layers, different activation, and hidden layer functions are investigated. The convolutional neural network (CNN) based on several activation functions were applied for the same combination dependent/independent variables. The results are presented in Table 6.

Table 6. Convolutional neural network (CNN) based on several activation functions.

CNN MLP Net. name	Train. perf.	Test perf.	Valid. perf.	Train. err.	Test err.	Valid. err.	Train. Algor. BFGS	Err. Funct.	Hidden activ.	Output activ.	MAE	MAPE
62-13-1	0.88	0.88	0.87	59.13	63.14	64.36	50	SOS	Iden.	Exp.	8.81	0.19
62-14-1	0.95	0.95	0.95	24.34	26.66	26.85	254	SOS	Logi.	Logi.	5.48	0.12
62-17-1	0.93	0.94	0.93	35.47	34.04	36.55	59	SOS	Exp.	Iden.	6.34	0.14
62-11-1	0.88	0.88	0.87	60.74	63.61	65.89	34	SOS	Iden.	Exp.	9.06	0.20
62-19-1	0.93	0.94	0.93	35.44	34.20	36.35	56	SOS	Exp.	Iden.	6.33	0.14
62-18-1	0.88	0.88	0.87	60.00	62.89	64.66	36	SOS	Iden.	Exp.	8.97	0.19
62-8-1	0.93	0.94	0.93	35.14	33.93	35.82	57	SOS	Exp.	Tanh	6.28	0.14
62-8-1	0.88	0.88	0.87	59.20	63.00	64.34	51	SOS	Iden.	Exp.	8.84	0.19
62-10-1	0.91	0.92	0.91	45.33	45.62	46.42	32	SOS	Iden.	Logi.	7.53	0.16
62-17-1	0.93	0.94	0.93	36.16	34.27	37.09	51	SOS	Exp.	Iden.	6.31	0.14
62-11-1	0.93	0.94	0.93	33.18	33.81	34.72	76	SOS	Exp.	Tanh	6.23	0.13
62-12-1	0.93	0.94	0.93	35.62	34.42	36.61	59	SOS	Exp.	Iden.	6.35	0.14
62-18-1	0.95	0.95	0.94	26.32	29.68	29.22	269	SOS	Exp.	Logi.	5.82	0.13
62-10-1	0.95	0.95	0.95	24.83	27.33	26.78	341	SOS	Logi.	Logi.	5.49	0.12
62-20-1	0.95	0.95	0.95	24.28	27.59	27.05	194	SOS	Tanh	Logi.	5.53	0.12
62-18-1	0.95	0.95	0.95	24.62	27.32	27.64	275	SOS	Tanh	Iden.	5.56	0.12
62-14-1	0.94	0.95	0.95	27.88	30.01	28.40	141	SOS	Exp.	Exp.	5.85	0.13
62-16-1	0.95	0.95	0.95	24.33	27.40	27.25	361	SOS	Logi.	Tanh	5.53	0.12
62-13-1	0.91	0.92	0.91	45.33	45.62	46.45	52	SOS	Iden.	Logi.	7.53	0.16
62-15-1	0.93	0.94	0.93	35.42	34.23	36.86	63	SOS	Exp.	Iden.	6.34	0.14

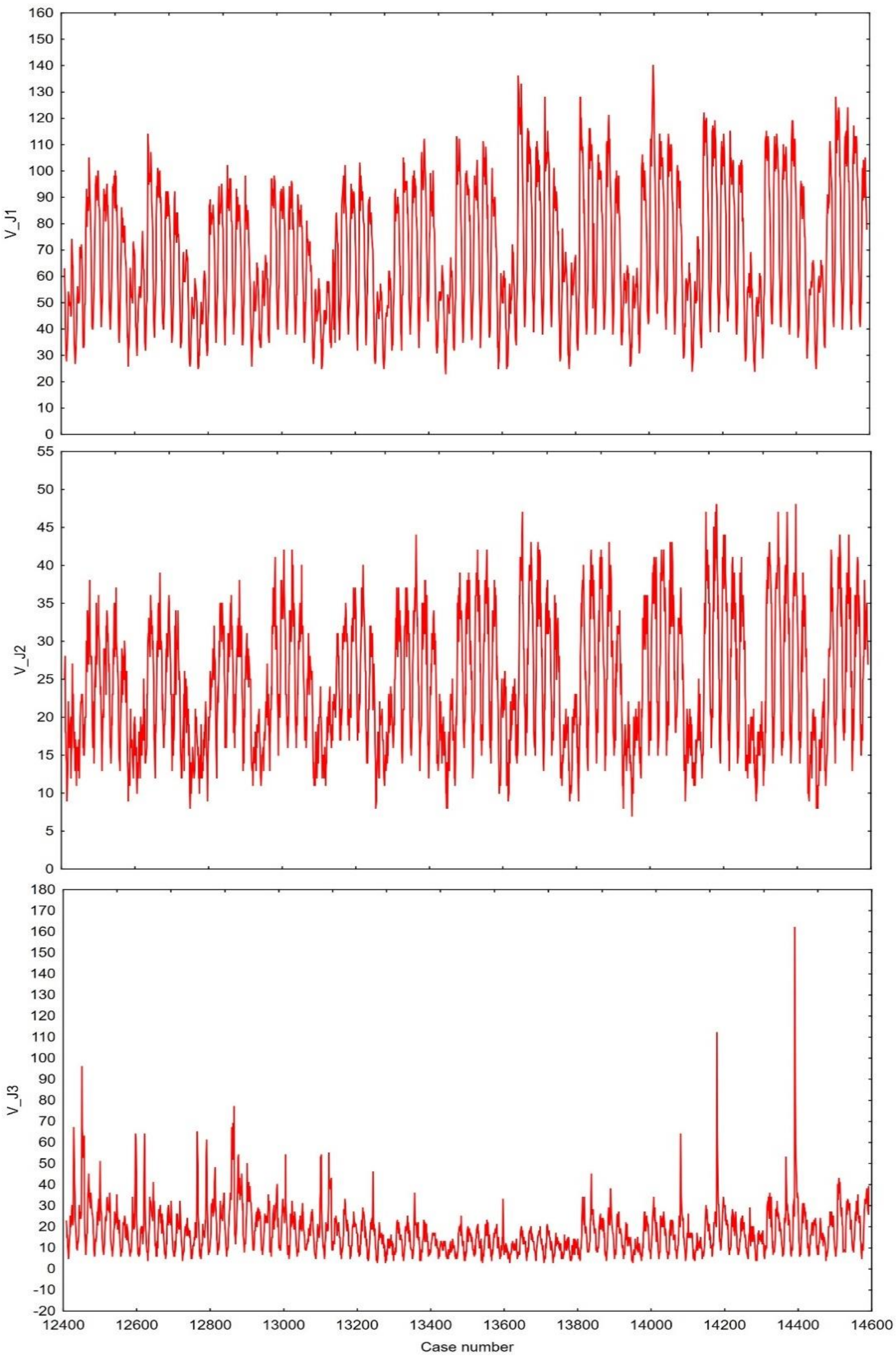

Figure 5. The observational values of V_J1. V_J2. and V_J3 in testing set

The visual results are also very useful to observe the seasonal effect. Figure 6 shows the plots generated based on the predicted data for each TS model. To observe the contributions of the continuous and categorical variables to the model, 4 different models were created with 4 different combinations of independent variables. These combinations are listed in the ' *Indep. Var.*' column in Table 5. The TS models that provide the best predictions for V_J1, V_J2, and V_J3 are MLP 38-8-1, MLP 38-6-1, and MLP 38-7-1, respectively. It can be seen that the models largely provide the distributions and seasonal patterns shown in Figure 5. For the later models, it is observed that although the model outputs are acceptable, they fail to detect the seasonal pattern.

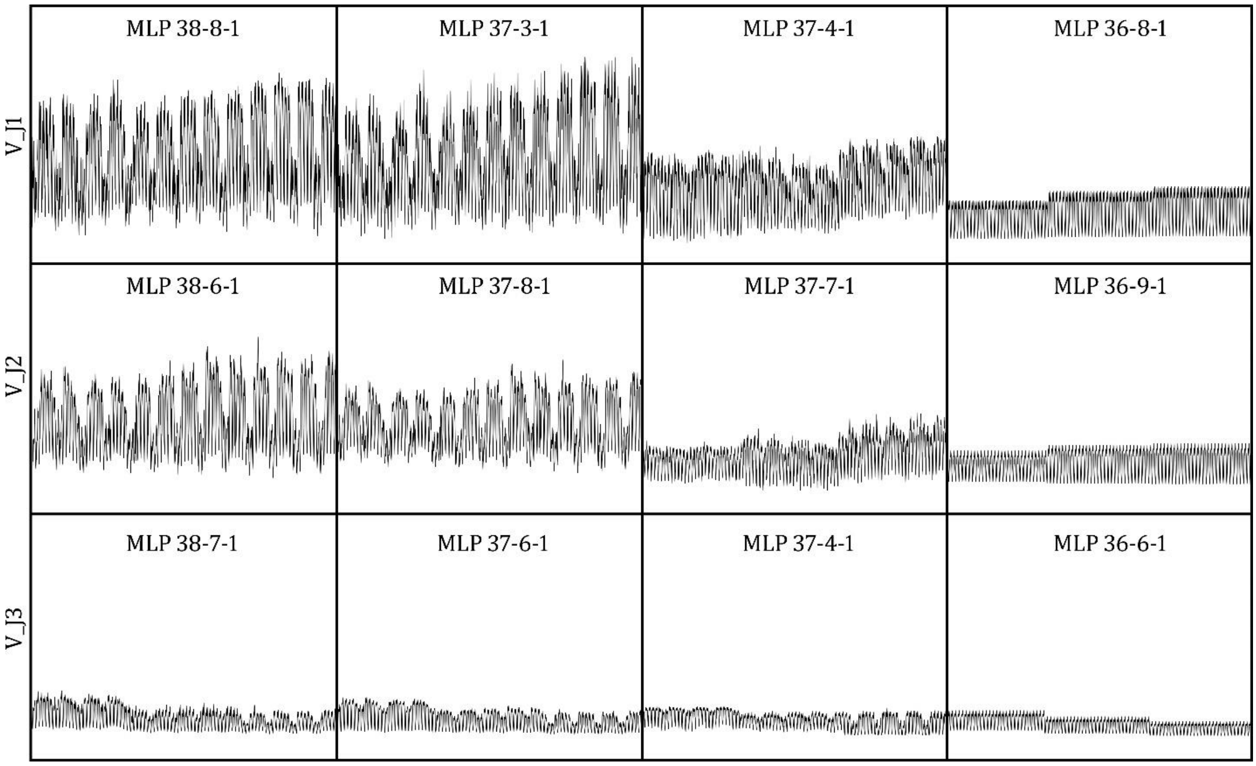

Figure 6. Line diagrams for the predictions of ANN-based TS network models

Assuming that the data are constant, predictions can be made with 93% accuracy for J1 and J2. and 66% for J3. However, if we consider that the data are accumulated in real time according to the traffic flow models shown in Figure 3 and Figure 4, we conclude that the models should be evaluated as connected nodes. In this case, the serially connected traffic model shown in Figure 4 (e) was found to have the highest accuracy with a joint mean of 0.86.

Also, in addition to CNN, other Recurrent-Neural-Networks (RNN) models; Gated Recurrent Unit (GRU), Long-Short-Term-Memory (LSTM), and bidirectional LSTM (bi-LSTM) are applied to predict the junction flow rates. In the proposed models, only the time variable was used as the independent variable, and the first 10,000 days of data were used as training and the remaining data as testing. For this purpose, models were created using Python codes written on Anaconda Jupyter Notebook. Results are presented in Tables 7, 8, and 9 for GRU, LSTM, and bi-LSTM, respectively.

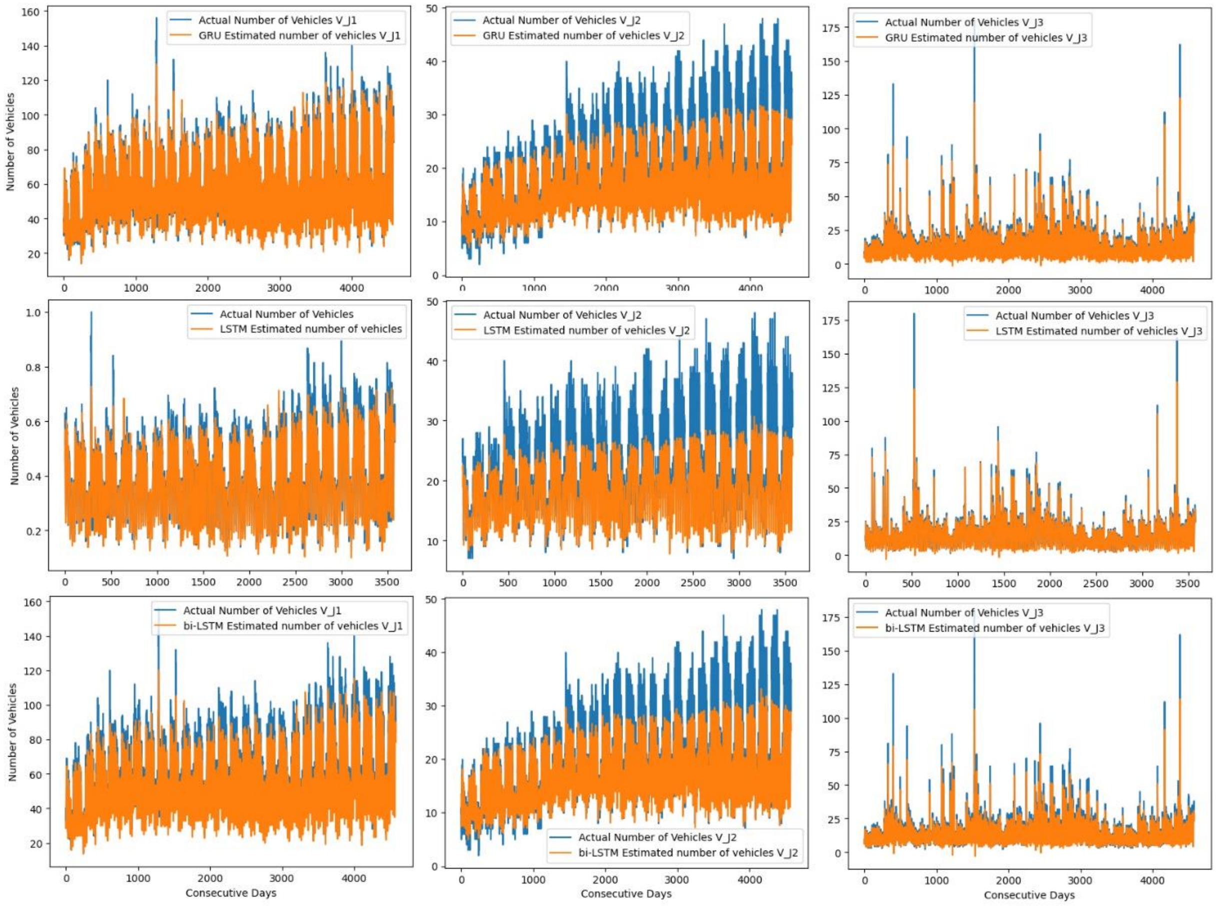

Figure 7. Plots of the TS based neural networks

In addition, the visuals showing the original and prediction data together are displayed in Figure 7 for all models. TS predictions based on the gated recurrent unit (GRU) models are presented in Table 7.

Table 7. TS predictions based on the gated recurrent unit models

	GRU - V_J1		**GRU - V_J2**		**GRU - V_J3**	
Epoch	**Step Length**	**Loss**	**Step Length**	**Loss**	**Step Length**	**Loss**
Epoch 1/23	39s 4ms/step	0.0016	43s 4ms/step	0.0033	4ms/step	0.0012
Epoch 2/23	36s 4ms/step	0.0013	36s 4ms/step	0.0028	4ms/step	9.62E+00
Epoch 3/23	36s 4ms/step	0.0011	36s 4ms/step	0.0028	4ms/step	9.31E+00
Epoch 4/23	38s 4ms/step	0.0011	36s 4ms/step	0.0028	4ms/step	9.27E+00
Epoch 5/23	41s 4ms/step	0.0010	35s 4ms/step	0.0028	4ms/step	8.96E+00
Epoch 6/23	35s 4ms/step	0.0010	35s 4ms/step	0.0028	4ms/step	8.81E+00
Epoch 7/23	37s 4ms/step	0.0010	35s 3ms/step	0.0028	5ms/step	8.79E+00
Epoch 8/23	42s 4ms/step	9.99E+00	35s 4ms/step	0.0028	5ms/step	8.65E+00
Epoch 9/23	37s 4ms/step	9.77E+00	35s 3ms/step	0.0027	5ms/step	8.66E+00
Epoch 10/23	42s 4ms/step	9.76E+00	35s 3ms/step	0.0027	5ms/step	8.64E+00
Epoch 11/23	42s 4ms/step	9.69E+00	36s 4ms/step	0.0027	5ms/step	8.56E+00
Epoch 12/23	47s 5ms/step	9.60E+00	35s 3ms/step	0.0027	5ms/step	8.63E+00
Epoch 13/23	44s 4ms/step	9.56E+00	35s 3ms/step	0.0027	6ms/step	8.62E+00
Epoch 14/23	43s 4ms/step	9.56E+00	35s 4ms/step	0.0027	5ms/step	8.64E+00
Epoch 15/23	43s 4ms/step	9.47E+00	35s 3ms/step	0.0027	5ms/step	8.55E+00
Epoch 16/23	38s 4ms/step	9.43E+00	35s 3ms/step	0.0027	5ms/step	8.56E+00
Epoch 17/23	42s 4ms/step	9.29E+00	35s 4ms/step	0.0027	5ms/step	8.52E+00
Epoch 18/23	43s 4ms/step	9.32E+00	35s 4ms/step	0.0027	5ms/step	8.41E+00
Epoch 19/23	44s 4ms/step	9.24E+00	35s 3ms/step	0.0027	5ms/step	8.38E+00

Epoch 20/23	43s 4ms/step	9.23E+00	35s 4ms/step	0.0027	5ms/step	8.42E+00
Epoch 21/23	42s 4ms/step	9.18E+00	35s 3ms/step	0.0027	5ms/step	8.43E+00
Epoch 22/23	38s 4ms/step	9.12E+00	35s 3ms/step	0.0027	5ms/step	8.47E+00
Epoch 23/23	39s 4ms/step	9.01E+00	35s 3ms/step	0.0027	5ms/step	8.39E+00

The results show that bi-LSTM models reduce the amount of loss in each iteration to lower levels than other models, with 8.83E+00, 0.0027, and 8.38E+00 for V_J1, V_J2, and V_J3, respectively. It shows that it has reached low loss values and is the most successful model. In Figure 7, the models' prediction values (Orange) and observational values (blue) are given together. The blue areas are reduced in Bi-LSTM. TS predictions based on the long-short-term-memory models are presented in Table 8.

Table 8. TS predictions based on the long-short-term-memory models

	LSTM - V_J1		**LSTM - V_J2**		**LSTM - V_J3**	
Epoch	**Step Length**	**Loss**	**Step Length**	**Loss**	**Step Length**	**Loss**
Epoch 1/23	65s 6ms/step	0.0017	58s 5ms/step	0.0033	55s 5ms/step	0.0011
Epoch 2/23	56s 5ms/step	0.0013	57s 5ms/step	0.0030	56s 5ms/step	9.69E+00
Epoch 3/23	62s 6ms/step	0.0012	57s 5ms/step	0.0029	57s 5ms/step	9.34E+00
Epoch 4/23	54s 5ms/step	0.0011	58s 5ms/step	0.0029	57s 5ms/step	9.03E+00
Epoch 5/23	52s 5ms/step	0.0011	58s 5ms/step	0.0029	56s 5ms/step	9.07E+00
Epoch 6/23	46s 4ms/step	0.0011	56s 5ms/step	0.0028	56s 5ms/step	8.82E+00
Epoch 7/23	59s 5ms/step	0.0011	59s 5ms/step	0.0028	55s 5ms/step	8.94E+00
Epoch 8/23	49s 4ms/step	0.0011	59s 5ms/step	0.0028	58s 5ms/step	8.92E+00
Epoch 9/23	48s 4ms/step	0.0010	56s 5ms/step	0.0028	56s 5ms/step	8.84E+00
Epoch 10/23	49s 4ms/step	0.0010	57s 5ms/step	0.0028	85s 8ms/step	8.84E+00
Epoch 11/23	42s 4ms/step	0.0010	57s 5ms/step	0.0028	67s 6ms/step	8.80E+00
Epoch 12/23	49s 4ms/step	0.0010	58s 5ms/step	0.0028	44s 4ms/step	8.79E+00
Epoch 13/23	44s 4ms/step	0.0010	56s 5ms/step	0.0028	41s 4ms/step	8.69E+00
Epoch 14/23	53s 5ms/step	9.84E+00	56s 5ms/step	0.0027	41s 4ms/step	8.62E+00
Epoch 15/23	57s 5ms/step	9.82E+00	56s 5ms/step	0.0027	41s 4ms/step	8.67E+00
Epoch 16/23	44s 4ms/step	9.83E+00	55s 5ms/step	0.0027	41s 4ms/step	8.63E+00
Epoch 17/23	46s 4ms/step	9.77E+00	66s 6ms/step	0.0027	41s 4ms/step	8.56E+00
Epoch 18/23	52s 5ms/step	9.69E+00	61s 6ms/step	0.0027	41s 4ms/step	8.57E+00
Epoch 19/23	46s 4ms/step	9.52E+00	58s 5ms/step	0.0027	41s 4ms/step	8.45E+00
Epoch 20/23	46s 4ms/step	9.56E+00	57s 5ms/step	0.0027	41s 4ms/step	8.58E+00
Epoch 21/23	49s 4ms/step	9.50E+00	57s 5ms/step	0.0027	41s 4ms/step	8.51E+00
Epoch 22/23	52s 5ms/step	9.46E+00	57s 5ms/step	0.0027	42s 4ms/step	8.51E+00
Epoch 23/23	63s 6ms/step	9.52E+00	61s 6ms/step	0.0027	41s 4ms/step	8.45E+00

Bi-LSTM provides less loss rates than LSTM. Also, bi-LSTM running time takes shorter than LSTM. TS predictions based on the bi-directional long-short-term-memory models are presented in Table 9.

Table 9. TS predictions based on the bi-directional long-short-term-memory models

	bi-LSTM - V_J1		**bi-LSTM - V_J2**		**bi-LSTM - V_J3**	
Epoch	**Step Length**	**Loss**	**Step Length**	**Loss**	**Step Length**	**Loss**
Epoch 1/23	56s 5ms/step	0.0016	57s 5ms/step	0.0032	54s 5ms/step	0.0011
Epoch 2/23	54s 5ms/step	0.0012	47s 5ms/step	0.0029	47s 5ms/step	9.54E+00
Epoch 3/23	53s 5ms/step	0.0011	48s 5ms/step	0.0029	48s 5ms/step	9.14E+00
Epoch 4/23	48s 5ms/step	0.0011	49s 5ms/step	0.0028	47s 5ms/step	8.80E+00
Epoch 5/23	54s 5ms/step	0.0010	49s 5ms/step	0.0028	48s 5ms/step	8.96E+00
Epoch 6/23	47s 5ms/step	0.0010	48s 5ms/step	0.0028	48s 5ms/step	8.71E+00
Epoch 7/23	49s 5ms/step	0.0010	48s 5ms/step	0.0028	48s 5ms/step	8.84E+00
Epoch 8/23	53s 5ms/step	9.88E+00	48s 5ms/step	0.0028	48s 5ms/step	8.62E+00
Epoch 9/23	50s 5ms/step	9.89E+00	48s 5ms/step	0.0027	48s 5ms/step	8.67E+00

Epoch 10/23	53s 5ms/step	9.61E+00	48s 5ms/step	0.0027	48s 5ms/step	8.63E+00
Epoch 11/23	50s 5ms/step	9.51E+00	48s 5ms/step	0.0027	48s 5ms/step	8.55E+00
Epoch 12/23	49s 5ms/step	9.44E+00	48s 5ms/step	0.0027	48s 5ms/step	8.57E+00
Epoch 13/23	47s 5ms/step	9.41E+00	49s 5ms/step	0.0027	49s 5ms/step	8.61E+00
Epoch 14/23	54s 5ms/step	9.29E+00	48s 5ms/step	0.0027	48s 5ms/step	8.52E+00
Epoch 15/23	47s 5ms/step	9.22E+00	48s 5ms/step	0.0027	50s 5ms/step	8.47E+00
Epoch 16/23	51s 5ms/step	9.21E+00	48s 5ms/step	0.0027	48s 5ms/step	8.56E+00
Epoch 17/23	53s 5ms/step	9.12E+00	49s 5ms/step	0.0027	48s 5ms/step	8.42E+00
Epoch 18/23	51s 5ms/step	9.02E+00	48s 5ms/step	0.0027	49s 5ms/step	8.43E+00
Epoch 19/23	49s 5ms/step	8.97E+00	48s 5ms/step	0.0027	48s 5ms/step	8.49E+00
Epoch 20/23	43s 4ms/step	8.96E+00	48s 5ms/step	0.0027	49s 5ms/step	8.44E+00
Epoch 21/23	44s 4ms/step	8.94E+00	48s 5ms/step	0.0027	49s 5ms/step	8.42E+00
Epoch 22/23	46s 5ms/step	8.85E+00	48s 5ms/step	0.0027	49s 5ms/step	8.44E+00
Epoch 23/23	46s 5ms/step	8.83E+00	49s 5ms/step	0.0027	49s 5ms/step	8.38E+00

Conclusion and future research recommendation

In this study, a novel estimation approach based on time series analysis is presented. In the study, the relationship between the number of vehicles passing through 3 random junctions in urban traffic every hour throughout the day was modeled. Accordingly, the relative effects of the traffic flow formed at the junctions were calculated and the corresponding models were designed. The proposed methodology is an ANN-based TS decision support approach. There are two seasonal variables in the data. One is Daily_D, which represents certain hours of the day, and the other is Monthly_D, which represents certain months (or periods) of the year. Using these variables, the correlation values between the traffic flows of Junctions were calculated. After the correlation analysis, it was found that there was a high correlation between J1 and J2 at any time of the day, with the correlation relationship being highest level, especially between 15:00 and 17:00. In addition, it was found that the correlation of traffic flows between the two junctions increased between March and June, reaching the value of 0.94, while the correlation decreased during the summer months, falling to the value of 0.69 in August. It was concluded that the urban locations of J1 and J2 are connected in series with each other. In addition, J3 was found to have relatively low correlation with other junctions and may be connected in parallel or in series.

Assuming that the data are stable, predictions can be made with 93% accuracy for the ANN-based TS models J1 and J2 and 66% for J3. According to the composition of traffic flow, it was found that the model of serially connected traffic between the junctions presented in Figure 4 (e) has the highest accuracy with a joint mean of 0.86 (Table 10).

Table 10. Joint mean performances

Model	Index	Perf.	Joint Mean Perf.
Figure 3 (a)	6	0.93	0.77
	10	0.66	
	7	0.72	
Figure 3 (b)	2	0.91	0.78
	11	0.64	
	3	0.79	
Figure 4 (c)	6	0.93	0.79
	11	0.64	

Figure 4 (d)	2	0.91	0.79
	10	0.66	
Figure 4 (e)	3	0.79	0.86
	6	0.93	
Figure 4 (f)	7	0.72	0.82
	2	0.91	

In this study, only the number of vehicles originating from only 3 junctions was investigated. However, this study can be considered as a pioneering work for a more comprehensive study considering pedestrian movements, transportation infrastructure capacity information, and environmental factors (workplace, school, hospital, etc.) in a larger urban traffic area. In addition, with the instantaneous flow of data made possible by Internet, camera, sensor, etc. technologies, dynamic use of the created models will be possible. This study, which shows that the algorithms of ML can be effectively used in decision support systems, will be an important basis for the development of the smart city concept, as it will provide highly accurate predictive data to governments and other policy makers.

Statement of Conflict of Interest

Author has declared no conflict of interest.

Author’s Contributions

The contribution of the authors is 100%.

Appendix 1. Python Coding

Coding of the statistical procedures used in this article can be found online at

Python Codings - Implementing of Time Series Analysis Based Decision Support System for Traffic Density Monitoring

References

Ahmed G., Hilmani A., Maizate A., Hassouni L. Automated real-time intelligent traffic control system for smart cities using wireless sensor networks. Wireless Communications And Mobile Computing 2020; DOI: 10.1155/2020/8841893

Bearn C., Mingus C., Watkins K. An adaption of the level of traffic stress based on evidence from the literature and widely available data. Research in Transportation Business Management 2018; 29: 50-62. DOI: 10.1016/j.rtbm.2018.12.002

Bijl BV., Gijsbertsen B., Loon SV., Reurich Y., Valk TD., Koch T., Dugundji E. A comparison of approaches for the time series forecasting of motorway traffic flow rate at hourly and daily aggregation levels. Procedia Computer Science 2022; 201: 213-222. DOI: 10.1016/j.procs.2022.03.030

Chen YT., Sun EW., Chang MF., Lin YB. Pragmatic real-time logistics management with traffic IoT infrastructure: Big data predictive analytics of freight travel time for Logistics 4.0. International Journal of Production Economics 2021; 238. DOI: 10.1016/j.ijpe.2021.108157

Chhajer P., Shah M., Kshirsagar A. The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction. Decision Analytics Journal 2022; 2. DOI: 10.1016/j.dajour.2021.100015

Dey A. Machine learning algorithms: a review. International Journal of Computer Science and Information Technologies 2016; 7(3): 1174-1179. http://www.ijcsit.com/

Espinosa SI., Ynoue R., Giannotti M., Ropkins K., De Freitas ED. Generating traffic flow and speed regional model data using internet GPS vehicle records. MethodsX 2019; 6: 2065-2075. DOI: 10.1016/j.mex.2019.08.018

Govindan K., Mina H., Alavi B. A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). Transportation Research Part E: Logistics and Transportation Review 2020; 138. DOI: 10.1016/j.tre.2020.101967

Grosan C., Abraham A. Artificial neural networks. Intelligent systems. Intelligent Systems Reference Library. Berlin, Heidelberg: Springer; 2011; 7. DOI: 10.1007/978-3-642-21004-4_12

He J., Yang H., He L., Zhao L. Neural networks based on vectorized neurons. Neurocomputing 2021; 465: 63-70. DOI: 10.1016/j.neucom.2021.09.006

Huang H., Chen J., Sun R., Wang S. Short-term traffic prediction based on time series decomposition. Physica A: Statistical Mechanics and its Applications 2022; 585. DOI: 10.1016/j.physa.2021.126441

Jastrzebska A. Time series classification through visual pattern recognition. Journal of King Saud University - Computer and Information Sciences 2022; 34(2): 134-142. DOI: 10.1016/j.jksuci.2019.12.012

Karimi H., Ghadirifaraz B., Boushehri S., Hosseininasab SM., Rafiei N. Reducing traffic congestion and increasing sustainability in special urban areas through one-way traffic reconfiguration. Transportation 2022; 49. DOI: 10.1007/s11116-020-10162-4

Kuddus MA., Tynan E., McBryde E. Urbanization: a problem for the rich and the poor? Public Health Reviews 2020; 41(1). DOI: 10.1186/s40985-019-0116-0

Li W., Zuo M., Zhao H., Xu Q., Chen D. Prediction of coronary heart disease based on combined reinforcement multitask progressive time-series networks,. Methods 2022; 198: 96-106. DOI: 10.1016/j.ymeth.2021.12.009

Liang X., Chen RC., He Y., Chen Y. Associating stock prices with web financial information time series based on support vector regression. Neurocomputing 2013; 115: 142-149. DOI: 10.1016/j.neucom.2013.01.011.

Lim S. Hebbian learning revisited and its inference underlying cognitive function. Current Opinion in Behavioral Sciences 2021; 38: 96-102. DOI: 10.1016/j.cobeha.2021.02.006

Lim S., Kim SJ., Park Y., Kwon N. A deep learning-based time series model with missing value handling techniques to predict various types of liquid cargo traffic. Expert Systems with Applications 2021; 184. DOI: 10.1016/j.eswa.2021.115532

Masuduzzaman M., Islam A., Sadia K., Shin SY. UAV-based MEC-assisted automated traffic management scheme using blockchain. Future Generation Computer Systems 2022. DOI: 10.1016/j.future.2022.04.018

McCulloch WS., Pitts W. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics 1943; 5(4), 115-133. DOI: 10.1007/BF02478259

Mumali F. Artificial neural network-based decision support systems in manufacturing processes: A systematic literature review. Computers Industrial Engineering 2022; 165. DOI: 10.1016/j.cie.2022.107964

Nugmanova A., Arndt WH., Hossain M., Kim JR. Effectiveness of ring roads in reducing traffic congestion in cities for long run: big almaty ring road case study. Sustainability 2019; 11(18). DOI: 10.3390/su11184973

Ponnusamy M., Alagarsamy A. Traffic monitoring in smart cities using internet of things assisted robotics. Materials Today: Proceedings 2021. DOI: 10.1016/j.matpr.2021.03.192

Shahid N., Shah MA., Khan A., Maple C., Jeon G. Towards greener smart cities and road traffic forecasting using air pollution data. Sustainable Cities and Society 2021; 72. DOI: 10.1016/j.scs.2021.103062

Singh VP., Pandey MK., Singh PS., Karthikeyan S. Neural net time series forecasting framework for time-aware web services recommendation. Procedia Computer Science 2020; 171: 1313-1322. DOI: 10.1016/j.procs.2020.04.140

Soni G., Kumar S., Mahto RV., Mangla SK., Mittal ML., Lim WM. A decision-making framework for Industry 4.0 technology implementation: The case of FinTech and sustainable supply chain finance for SMEs,. Technological Forecasting and Social Change 2022; 180. DOI: 10.1016/j.techfore.2022.121686

Wang P., Zheng X., Ai G., Liu D., Zhu B. Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: Case studies in Russia, Peru and Iran. Chaos, Solitons Fractals 2020; 140. DOI: 10.1016/j.chaos.2020.110214

Withington L., De Vera DD., Guest C., Mancini C., Piwek P. Artificial neural networks for classifying the time series sensor data generated by medical detection dogs. Expert Systems with Applications 2021; 184. DOI: 10.1016/j.eswa.2021.115564

Wu J., Xu K., Chen X., Li S., Zhao J. Utilizing the structural information of financial time series for stock prediction. Information Sciences 2022; 588. 405-424. DOI: 10.1016/j.ins.2021.12.089

Wu K., Fu Y., Kong D. Does the digital transformation of enterprises affect stock price crash risk? Finance Research Letters 2022; 48. DOI: 10.1016/j.frl.2022.102888

Xing J., Wu W., Cheng Q., Liu R. Traffic state estimation of urban road networks by multi-source data fusion: Review and new insights. Physica A: Statistical Mechanics and its Applications 2022; 595. DOI: 10.1016/j.physa.2022.127079