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**Lane-Based Short-Term Urban Traffic Parameters Forecasting Using Multivariate
Artificial Neural Network and Locally Weighted Regression Models: A Genetic Approach**

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Abstract

Short-term prediction of traffic conditions on urban arterials has recently become increasingly important because of its vital role in the basic traffic management functions and trip decision-making processes. Such information is useful for optimal infrastructure operation, routing and trip scheduling. However, forecasting models offering a high accuracy at a fine temporal resolution (e.g., 1 or 5 min) and, especially, lane-based are still rare and need special attention. Given the dynamic and stochastic nature of traffic, this study proposes a genetically optimized artificial neural network (GA-ANN) and locally weighted regression (GA-LWR) multivariate models, for short-term traffic prediction using a combination of multiple traffic variables such as volume, occupancy and speed, during peak and off-peak periods. The proposed 5-min GA-ANN and GA-LWR disaggregate multivariate models show lower average and the 95th percentile (P95) errors, when compared to those reported in the literature. In particular, for peak and off-peak time prediction, the GA-ANN disaggregate multivariate models result in most of average errors of 2-5% and the 95th percentile errors of 9-10%. On the other hand, for peak and off-peak time traffic prediction, the GA-LWR disaggregate multivariate models show most of the average errors lower than 5% and of 95th percentile errors are lower than 10%. Meanwhile, for peak and off-peak time prediction, both GA-ANN and GA-LWR disaggregates models show lower MSE of 0.11-1.84. Hence, such techniques are believed useful for developing a robust urban traffic forecasting system.

Keywords: Short-term forecasting, Genetic algorithms, Artificial neural network, Locally weighted regression, Aggregate model, Disaggregate model.

1. Introduction

Intelligent transportation systems (ITS), in recent years, have achieved enormous developments. ITS applications improve the overall efficiency of transportation systems and mitigate transportation related issues using information and communication technologies. Increasing traffic demand requires an efficient and proper operation of transportation infrastructure. Literature on short-term traffic flow forecasting has undergone a significant development. It has been noticed from the literature that traffic forecasting is a crucial task in the area of ITS. During the peak hours, when the amount of traffic demand exceeds the available capacity of the road network, congestion occurs and it creates bottlenecks in urban areas. Traffic forecasting, especially short-term traffic flow forecasting is momentous to modern ITS. It is the process of estimating anticipated traffic conditions using historical traffic information and intelligent controls. The history of short-term traffic forecasting is long and many researchers (Vlahogianni et al. 2014; Smith & Demetsky 1994) have made numerous contributions in many ways given its diversity in nature.

The lane-based analysis explores traffic characteristics of each lane separately to analyse different traffic patterns during peak and off-peak time of the day. Lane-based routing is a valuable strategy for reducing serious traffic delays during the peak traffic period. The available infrastructure is limited in terms of the capacity, so it is important to utilize the available capacity in an optimal way, hence lane-based routing system will not only enhance the available network capacity but also help mitigate traffic jams. It contributes to enhancing traffic operation and implementing better traffic control and signal system.

Literature shows that most of the previous studies have focused on rural and highway

66 traffic predictions and most of them are direction-based. Although various methodologies have
67 been proposed and applied for, forecasting short-term traffic, and the ultimate goal remains the
68 same: to obtain the forecasting results as precisely and quickly as possible. Researchers are
69 improving and optimizing the existing methodologies to develop new models in this area.

70 It has been noticed from previous studies that genetic algorithms are one of the best
71 optimization techniques available to optimize complex and non-linear dynamic behavior of traffic.
72 In this study, two types of models are proposed and developed. 1) the aggregate multivariate
73 model: this model forecasts traffic data of six-intervals of 5-min window each weekday. 2) the
74 disaggregate multivariate model: this model only forecasts one-interval of 5-min window each
75 weekday. Both models are used to predict short-term traffic pattern using multiple traffic variables
76 during peak and off-peak period.

77 Given the heterogeneous nature of urban traffic, inputs consisting of a combination of
78 multiple traffic variables will play a vital role in developing a robust model, which will help predict
79 current traffic conditions using rich historical data. Hence, short-term lane-based forecasting using
80 multivariate models could offer a higher accuracy at a fine temporal resolution (e.g., 1 or 5 min).

81 This paper is divided into separate sections as follows. The next section of this paper
82 gives a brief review of inclusive research in the area of short-term traffic forecasting. The third
83 section presents details about the optimization and modelling techniques used. The fourth section
84 presents the details about study data and initial processing. The fifth section provides relevant
85 details about the study models. The sixth section describes the implementation of GA designed
86 ANN and LWR aggregate and disaggregate multivariate models. The seventh section gives
87 detailed discussion about models and results. Last, the paper will present the principal findings,

88 relevant conclusions, and recommendations of this study.

89 **2. A Review of Short-Term Traffic Forecasting**

90 ITS, in recent years have showed great progress. The main aim of such systems is to
91 improve the current traffic conditions using advanced information and communication tools.
92 Traffic congestion is one of the major concern of developed and developing countries. To
93 overcome the rapidly increasing traffic problems, it is important to introduce such models, which
94 will enhance the traffic prediction accuracy (Khan & Maini 2000).

95 Short-term traffic forecasting is an important component of today's modern ITS.
96 Researchers have focused on developing short-term traffic forecasting methodologies that can be
97 used to estimate near-term traffic characteristics such as traffic flow, speed and occupancy
98 (Vlahogianni et al. 2014). Accuracy of short-term traffic forecasting algorithms extensively
99 depends on the system's availability and methods used. It is essential to understand the working
100 process behind all the methods to get an idea of the limitations associated with each of them.
101 Numerous methodologies have been applied to short-term traffic forecasting depending on data
102 types. The objectives are to develop such a system, which is used to increase the operational
103 efficiency and capacity of the transportation network. Many methods and procedures are adopted
104 to predict different traffic parameters, such as time series analysis, real-time methods, historical
105 methods, statistical methods and machine learning methods (Kumar et al. 2013).

106 The work of Box and Jenkins 1970 opened a gateway to time-series methods for short-term
107 traffic prediction. In the early 90's, autoregressive integrated moving average (ARIMA), family
108 of models were extensively used for traffic forecasting (Hamed et al. 1995; Kirby et al. 1997;

109 Levin & Tsao 1980).

110 The forecasts produced using seasonal ARIMA (SARIMA) model produced more accurate
111 results than non-seasonal ARIMA models as SARIMA models dealing better with the seasonality
112 of the traffic and showed average errors of 7.41% (Williams et al. 1998). The non-parametric
113 regression approaches show better accuracy than traditional ARIMA models and Kalman filtering
114 models (Smith & Demetsky 1997; Smith et al. 2002; Okutani & Stephanedes 1984). The ARIMA
115 models and other time-series methods are linear by nature. However, traffic patterns are nonlinear
116 and random by nature. Hence, these methods cannot fully address the traffic dynamics and
117 therefore the prediction errors are generally high.

118 Artificial neural networks (ANNs) are among the most widely used alternatives for
119 modelling heterogeneous traffic conditions, since they can approximate almost any function,
120 regardless of its degree of nonlinearity and without prior knowledge of its functional form
121 (Vlahogianni et al. 2005). As per extant literature, academicians have widely used ANN models
122 to predict short-term traffic conditions (Centiner et al. 2010; Hu et al. 2010; Pamula 2011;
123 Dougherty & Cobbett 1997). ANN urban traffic modelling and prediction results based on
124 simulation showed higher accuracy, especially for short-term traffic flow (Ledoux 1997). ANN
125 models were used to predict short-term traffic volume and results showed that such learning
126 produced better results (Yasdi 1999). ANN was used to predict traffic parameters using historical
127 traffic data to predict short-term traffic and results showed that artificial neural network performed
128 well for traffic flow prediction, even when the time window increased from 5-min to 30-min (4).

129 Hybrid methods have been presented in the literature. A combination of multiple regression
130 analysis and neural network approach was used to estimate average and peak hourly traffic

volumes (Lingras & Adamo 1996). A nonparametric dynamic time-delay recurrent wavelet neural network model was used to forecast traffic flow (Jiang & Adeli 2005) and the developed models produced satisfactory results when applied to long-term and short-term traffic flow forecasting. A combination of genetic algorithm and neural network was used for short-term traffic flow prediction and the developed MPL network performed well and produced satisfactory results on both univariate and multivariate traffic flow data types, acquired from an urban signalized arterial road (Vlahogianni et al. 2005). A fuzzy neural network known as the pseudo outer-product fuzzy neural network was used for short-term traffic flow prediction and the developed models produced higher accuracy as compared to traditional feed-forward neural networks (Quek et al. 2006). Two non-parametric models, non-parametric regression (NPR) and the Gaussian maximum likelihood (GML) was used for daily traffic flow forecasting based on historical data type collected for the annual traffic census (ATC) in Hong Kong and results showed that these models produced better results; especially the NPR model forecasts produced better results than the GML model (Lam et al. 2006). A nearest neighbour form of nonparametric regression, coupled with a monitoring system was used to monitor the current traffic conditions and verify the results, based on historical data to evaluate the traffic flow deviation from the past traffic flow (Turochy 2006). Two Wavelet networks were used to predict short-term traffic flow and the developed models showed better results compared with the well-known back-propagation neural network (BPNN) and radial basis function neural network (RBFNN) models. The results showed that the developed models produced lower errors than the BPNN and RBFNN models (Xie & Zhang 2006).

In recent, many researchers used Support Vector Machine and Lagrange support vector regression (LSVR) for short-term traffic flow forecasting (Theja & Vanajakskshi 2010; Liu et al. 2007). It has been noticed from literature that there are a handful studies related to genetically

designed hybrid models for traffic flow (hourly-based) forecasting. The genetically designed neural network and regression models, factor models, and ARIMA models were used to estimate missing traffic counts and the designed models produced lower average and the 95th percentile errors, especially for refine models with stable counts. Meanwhile, even unstable traffic patterns produced lower average and the 95th percentile errors (Zhong et al. 2004). A hybrid genetically optimized regression and time delay neural network models were used to predict hourly-based traffic volumes for different types of road and the developed the refined regression models showed lower average and 95th percentile errors as compared to time delay neural network models (Zhong et al. 2005). Hybrid models have received much attention because of their capability to model heterogeneous traffic flow conditions and results are more accurate and more promising, than standalone approaches (Zeng et al. 2008). A hybrid wavelet transform (WT) and support vector machine (SVM) model were used for short-term traffic flow prediction (Yonghui et al. 2011). Meanwhile, a hybrid Chaos–Wavelet Analysis-Support Vector Machine (C-WSVM) was used for short-term real traffic speed data forecasting and found that the developed model produced high satisfactory results (Wang & Shi 2013). A hybrid approach integrating the fuzzy C-means (FCM)-based imputation method with genetic algorithm was used to estimate missing traffic volume data and the developed model performed well compared to conventional Exponential Smoothing, and ARIMA methods and showed average RMSE error of 42.84% (Tang et al. 2015). An absorbing Markov chain (AMC) model was developed to predict short-term traffic volume using historical time series data, which significantly outperformed SARIMA and neural network models (Mei et al. 2015).

Locally weighted regression (LWR) is a memory-based nonparametric approach and it mapped the real-valued input vectors to the real-valued output vectors. Local modelling can learn

locally as opposed to global models like neural network and it is used to predict the future traffic patterns using the past available traffic data (Friedman 1995; Cleveland & Devlin 1988). The memory-based methods are often favoured over other global methods, when dealing with non-stationary input distribution. It uses spatially localized algorithms, such as nearest neighbor methods, kernel regression and lazy learning (Atkeson et al. 1997) and it has found that local linear methods are more accurate than other methods such as k-nearest and the kernel smoothing methods. Local modelling is preferred other than global modelling like neural network because such models not only offer a higher accuracy but also they can avoid negative interference generated by global models (Atkeson et al. 1997b). The LWR learning systems grow as it tries to compute the model and these models are comparatively inexpensive to compute and used to forecast short-term traffic flow (Sun et al. 2003).

Table 1 short Summary of previous studies

Year of the study	Authors	Data used/Data Type	Forecasting techniques used	Accuracy	Note
1998	Williams et al.	hourly traffic flows	Statistical models for forecasting on two urban freeways	Average seasonal ARIMA = 7.41%	ARIMA = autoregressive integrated moving average
				ESM 7.49%	ESM =Winters exponential smoothing
2005	Vlahogianni et al.	Traffic flow	Genetically designed optimized and meta-optimized neural network	UGDMAE=14%	UGDMAE = Univariate Gradient Descent Mean Absolute Error
				UGDMAPE =21.71%.	UGDMAPE =Multivariate Gradient Descent Mean Absolute Percentage Error
				MGDMAE =13%	MGDMAE= Multi Gradient Descent Mean Absolute Error
				MGDMAPE =20.39%	MGDMAPE = Multivariate Gradient Descent Mean Absolute Percentage Error
2013	Kumar et al	Traffic flow and speed(15-minute)	Artificial Neural Network (ANN)	MAE =37%	MAE = Mean Absolute Error
2014	Jian Wang, Deng, & Guo	Traffic flow (15-minute)	Advanced Bayesian combination method	MAPE=13.2%	Mean Absolute Percentage Error
2015	J. tang et al.	Traffic flow	Genetically designed hybrid model	MDAPE (%)= 14.19	Median Absolute Percentage Error
				Average RMSE = 42.84 %	RMSE = Root Mean square Error
2016	Cai et al.	Traffic flow and speed (Hourly)	Spatiotemporal correlative k-nearest neighbor model	MAPE (%) = 15.99	Mean Absolute Percentage Error(MAPE)

Table 1 shows the short summary of previous studies, data types and forecasting techniques used. The limitations of the existing research lie in that most of the models carry out short-term traffic forecasting at the link level, using univariate variable (historical traffic flow) and with an unsatisfactory accuracy.

2.1 Introduction to GA

Researchers have applied GAs to a wide range of difficult optimization problems that are quite challenging to solve using traditional mathematical models. Mathematical models use mathematical techniques to solve the problem. These models are used to solve a variety of optimization problems related to transportation planning, designing, and scheduling but it is quite challenging to solve using traditional mathematical models. The advantage of mathematical models is that mostly high-level management understands them easily as these models provide definite solution. On the other hand, they have a few drawbacks as well. In traditional mathematical models, it is quite hard to specify mathematical relationships analytically. Regarding these issues, the genetic algorithm can provide an alternative way when the mathematical model becomes inefficient due to high execution time in solving difficult problems (e.g., selecting a set of final input variables from a large number of candidate input variables). Genetic algorithm is a heuristic method, which is used to find the global minimum in the search domain, help to determine which individuals should survive, which should reproduce, which should no longer survive and should die. The mathematical form of GA was first developed by John Holland 1975. It is one of the most widely used stochastic search methods to solve various problems and its solutions are usually far better than other random search methods (Davis & Nihan 1991). The GAs usually breeds according to a predetermined, fixed number of generations and further these generations are populated with

predetermined fixed number of binary strings. The main advantages of GAs over other search methods are that GAs can solve problems using “the string” fitness to direct the search. GAs require no specific knowledge regarding the search space and it works on population rather than an individual point in the search space, which makes this algorithm more attractive than other gradient search methods. The GAs need only a single measure of flow just to compare an individual to the other individual. The performance of any genetic algorithm generally depends on the type of operators used. The main operators of the genetic algorithm are crossover, mutation, fitness and selection.

In the genetic algorithm, crossover is the procedure of picking out two members of the population for the reproduction process. The operation of mutation allows a new individual to be created. It begins by selecting an individual from the population based on its fitness. Fitness is probably the main concept in Darwinian evolutionary theory. Fitness is measured in terms of an individual’s ability to compete for the resources to survive. The selection process refers as choosing one or two parents from the population of individuals for the reproduction process. The selection process is based on an individual’s fitness value, higher the fitness value, more chances to be selected to continue the reproduction process and eventually it will increase the convergence of the genetic algorithm. The process of selecting an individual is one of the major aspects of tuning the GA algorithm.

3. Data Format and Initial Processing

In this study, data from four urban arterial lanes are used to scrutinize traffic flow, speed and occupancy patterns during peak and off-peak hours of each weekday. The data are collected from an urban arterial road in Beijing, China using loop detectors in intervals of 5-minute. The

input data set contains 3 months (July to September) traffic flow, speed and occupancy information. The data are further filtered by deleting the weekends. Normally, weekends are the least congested with smoother traffic during peak and off-peak hours. Data extraction tool was designed to extract data in 5-min intervals (288 observations each weekday) for both peak and off-peak periods.

Fig. 1 Average peak and off-peak traffic flow (5-min intervals)

Fig 1 shows average peak and off-peak traffic flow only in intervals of 5-min. Fig 1 shows that traffic flows differ significantly among lanes. For peak and off-peak period, the aggregate models are developed so that a single model is used to forecast traffic parameters (flow, density or speed) of six observations of 5-min each during weekdays (e.g., Peak time: ob1: 7:25 am to 7:30 am, ob2: 7:30 am to 7: 35 am, ob3: 7:35 am to 7:40 am, ob4: 7:40 am to 7:45 am, ob5: 7:45 am to 7:50 am, ob6: 7:50 am to 7 :55 am). Meanwhile, the peak and off-peak period, the disaggregate models are developed so that one model is developed for forecasting a particular traffic parameter

during a given 5-min interval over weekdays (peak: 7:25 am to 7:30 am; off-peak 11:25 am to 11:30 am).

Fig. 2 Data collection and extraction flowchart

Fig 2 shows data collection and extraction flowchart for the study models. Both peak and off-peak time traffic flow speed and occupancy data sets are used to train and test the proposed models.

3.1 Study models

Although various methodologies have been proposed and applied for, forecasting short-term urban traffic, and the ultimate goal remains the same: to obtain the forecasting results as precisely and quickly as possible. Researchers have been focusing on developing such methodologies, which are used to improve and optimize the existing methods to provide better short-term traffic forecasting tools.

Fig. 3 Study flow diagram

The data were extracted separately for traffic flow, speed and occupancy (Fig. 3). Later, genetic algorithm is designed to optimize the extracted data sets. Within each generation, the objective function of the genetic algorithm is to extract those independent variables from a set of candidate variables, which have the highest linear correlation with the dependent variable by assuming that this period contains all the necessary information needed to predict next 5-min traffic flow, speed and occupancy.

Then GA algorithm will evolve and produce the next generation, and the same objective function is applied to pick up the subset, which has the highest linear correlation with the

dependent variable. This process repeats until either the number of generations to be evolved is reached or GA is converged.

Finally, genetically designed artificial neural networks (ANN) and locally weighted regression (LWR) multivariate models are developed to forecast lane-based (5-min) traffic variables such as;

$$V_{t1} = K_{t-1}S_{t-1}, K_{t-2}S_{t-2}, k_{t-3}S_{t-3}.....K_{t-n}S_{t-n} \tag{1}$$

$$V_{t2} = V_{t-1}S_{t-1}, V_{t-2}S_{t-2}, V_{t-3}S_{t-3}.....V_{t-n}S_{t-n} \tag{2}$$

$$V_{t3} = V_{t-1}K_{t-1}, V_{t-2}K_{t-2}, V_{t-3}K_{t-3}..... V_{t-n}K_{t-n} \tag{3}$$

- V_t = Traffic flow at time t
- K_t = Traffic occupancy at time t
- S_t = Traffic speed at time t

The optimized sets are further combined to develop more robust forecasting models under the case there are missing values within one or more input variables (Equation 1, 2 and 3).

4. Traffic Prediction Using GA Designed ANN and LWR Multivariate Models

GA’s fitness function plays a vital role in data optimization (maximization/ minimization). The fitness function evaluates how good a solution is. The fitness function makes sure that the best individuals will continue to survive in the next generation and worst individuals will no longer take part in the selection process and die. This process continues until the genetic algorithm reaches the predefined termination criteria. The objective function of GA is designed to pick variables with higher linear correlation. In the objective function of the genetic algorithm, the input data sets are

converted into the regression matrix. The sum of square error (SSE) and R-squared are used to find the relation between the independent variables and dependent variables. The R-squared values are assigned to all input candidates. These objective scores are further converted into fitness scores by comparing every individual candidate against another individual candidate in the population. The mathematical formula for the objective function used to compute the linear correlation coefficient “r” is given as:

$$r = \frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}} \quad (4)$$

Where, “r” is called as linear correlation coefficient which is used to find the linear relationship between two sets of variables (independent and dependent variables), “n” represents the number of pairs of the data being used. Normally, the value of r resides between $-1 < r < +1$. The “+” sign represents the positive linear relationship while “-” represents the negative linear relationship among the variables. If “r” is greater than 0.8, it means both variables have strong linear relationship and if “r” is less than 0.5 it means both variables have weak linear relationship while 0 means there is no linear correlation among the variables or have a very weak relationship.

Finally, the designed genetic algorithm is used to optimize the given input data sets (flow, speed and occupancy). The GA selects a set of final variables from 288 candidate variables (independent variables) of higher linear correlation.

Fig. 4 The relationship between the fitness value of GA objective function and number of final input variables for traffic parameters.

It is evident from the fitness values that set of 24 final variables show higher r-squared value (Fig. 4) for all four lanes. Hence, the set of 24 candidates from 288 candidates are selected as input to GA-ANN and GA-LWR models.

4.1 Traffic prediction using GA designed multivariate ANN model

Multilayer perceptron (MLP) network has been used for prediction of multivariate models. The final input variables from GA are divide into two samples. The training sample is use to train the Artificial Neural Network, while the testing sample is use to track training errors, which will help to prevent overtraining problems. For GA-ANN aggregate multivariate model, 70% (20 days: 20×6 = 120 observations) is used for training purpose while 30% (9 days: 9×6 = 54 observations) is used for testing purpose. Meanwhile, for GA-ANN disaggregate multivariate model; 70% (20 days: 20× 1 = 20 observations) is used for training purpose while remaining 30% (9 days: 9×1 = 9 observations) is used for testing purpose.

Total number of input neurons is 24 and total number of units in the hidden layer is set at 12. Empirical rule states that the number of hidden neurons in ANN should be equal to half or less than the total inputs (Panchal et al. 2011). Trial and error approach has been used to build best performance network. The final GA-ANN structure in the study contains 24 inputs, 12 neurons in hidden layer and single output.

4.2 The prototype of ANN and LWR aggregate and disaggregate multivariate models

For peak and off-peak time traffic parameters prediction, the GA designed ANN (GA-ANN) and LWR (GA-LWR) aggregate multivariate models contain six observations of 5-min (Flow, speed and occupancy) each weekday. The GA-ANN and GA-LWR aggregate multivariate models are used to predict peak and off-peak traffic parameters for 30-min window. However, the GA designed ANN and LWR disaggregate multivariate models contain one observation of 5-min window for both peak and off-peak.

Fig. 5 The prototype of ANN and LWR aggregate and disaggregate multivariate model (V_{t1})

The variables for developing multilayer ANN and LWR aggregate multivariate model are:

- Total days = n
- Days = $X1, X2, \dots, Xn$
- First observation = I
- Last observation ($OB6$) = $I+5$

The variables for developing ANN and LWR disaggregate multivariate model are:

- Total number of days = n (29)

– $X_1(K_{t-1}S_{t-1}) = \text{first day (day)}$

– $X_n(K_{t-1}S_{t-1}) = n \text{ days}$

To evaluate the prediction performance of GA-ANN and GA-LWR aggregate and disaggregate multivariate models, Absolute Percent Error (APE), Mean Absolute Deviation (MAD), Mean Square Error (MSE) Mean Absolute Percentage Error (MAPE) and Root-Mean-Square Error (RMSE) is used.

5. Study Results and Discussions

The designed GA-ANN and GA-LWR aggregate and disaggregate multivariate models are used to predict 5-min and 30-min traffic variables into future for each weekday. The prototype of ANN and LWR aggregate and disaggregate multivariate models (for both peak and off-peak period) are presented above in Fig.5. The aggregate and disaggregate multivariate models are designed and tested for combination of multi traffic variables such as; V_{t1} (occupancy and speed), V_{t2} (volume and speed) and V_{t3} (volume and occupancy), during peak and off-peak periods.

370 **Table 2** The GA-ANN and GA-LWR disaggregate multivariate models for V_{t1} , V_{t2} and V_{t3} prediction (Lane 1)

	GA-ANN						GA-LWR					
	Lane 1						Lane 1					
	Peak			Off-peak			Peak			Off-peak		
	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}
Average	11.6%	12.1%	7.5%	4.0%	3.9%	4.3%	10.9%	7.0%	7.1%	6.1%	5.1%	5.6%
95 th Percentile	29.6%	21.1%	22.3%	12.0%	11.2%	12.5%	26.2%	12.5%	15.5%	10.1%	10.2%	11.9%
MAD	0.26	0.59	0.10	0.05	1.44	1.52	0.27	1.58	1.86	0.22	0.72	0.92
MSE	0.48	1.13	1.84	0.02	2.78	3.21	0.11	1.63	1.02	0.08	1.24	1.48
RMSE	0.69	1.06	3.98	0.14	1.66	1.79	0.34	1.25	1.00	0.28	1.11	1.21
MAPE	5.60	1.89	6.00	2.17	1.30	6.72	10.34	0.90	4.14	10.02	0.59	4.12

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372 **Table 3** The GA-ANN and GA-LWR disaggregate multivariate models for V_{t1} , V_{t2} and V_{t3} prediction (Lane 4)

	GA-ANN						GA-LWR					
	Lane 4						Lane 4					
	Peak			Off-peak			Peak			Off-peak		
	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}	V_{t1}	V_{t2}	V_{t3}
Average	21.4%	9.5%	16.6%	5.6%	4.6%	5.5%	15.6%	7.6%	22.3%	7.5%	3.3%	7.8%
95 th	42.7%	28.9%	36.8%	11.7%	9.2%	12.9%	37.9%	17.6%	46.3%	12.9%	9.7%	14.7%
MAD	0.09	1.84	0.74	0.25	1.53	1.05	0.07	3.18	1.38	0.16	1.20	0.79
MSE	0.03	1.73	0.86	0.13	1.98	1.54	0.01	1.02	1.17	0.04	3.98	1.47
RMSE	0.17	1.31	0.93	0.36	1.40	1.24	0.09	1.00	1.08	0.21	2.00	1.21
MAPE	7.26	1.46	8.32	6.53	1.05	3.42	12.61	2.53	14.56	7.20	0.79	2.38

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Table 2 shows peak and Table 3 shows off-peak time traffic prediction errors for GA-ANN and GA-LWR disaggregate multivariate models, which are found to provide most accurate results. Please note that, due to the limited space, the results for all other models are not presented here. For peak time traffic prediction, the GA-ANN aggregate multivariate models result in most of average errors of 16-119% and most of the 95th percentile errors of 45-348%. Meanwhile, for off-peak time traffic prediction, the GA-ANN aggregate multivariate models result in most of average errors of 11-54% and most of the 95th percentile errors of 28-285%.

On the contrary, for peak time traffic prediction, the GA-LWR aggregate multivariate models result in most of average errors of 17-113% and most of the 95th percentile errors of 55-503%. Meanwhile, for off-peak time traffic prediction, the GA-LWR aggregate multivariate models result in most of average errors of 10-61% and most of the 95th percentile errors of 26-312%.

However, for off-peak traffic prediction, the GA-ANN disaggregate V_{t1} multivariate model results in most of average errors of 4-5% and most of the 95th percentile errors of 11-14% for each of the four lanes. Meanwhile, for off-peak traffic prediction, the GA-ANN disaggregate V_{t2} multivariate model results in most of average errors of 2-5% and most of the 95th percentile errors of 9-11% for each of the four lanes. However, for off-peak traffic prediction, the GA-ANN disaggregate V_{t3} multivariate model results in most of average errors of 3-5% and most of the 95th percentile errors of 11-12% for each of the four lanes.

Furthermore, for off-peak traffic prediction, the GA-LWR disaggregate V_{t2} multivariate model results in most of average errors lower than 2% and most of the 95th percentile errors are

lower than 10% for each of the four lanes. Meanwhile, for off-peak time prediction, the GA-LWR disaggregate V_{t1} and V_{t3} multivariate models show most of average of 5-7% and the 95th percentile errors of 10-15%, as shown in Table 2 and Table 3.

For lane-based short-term traffic prediction, the GA-ANN and GA-LWR disaggregate multivariate models show lower average and the 95th percentile errors. The developed GA-ANN and GA-LWR V_{t2} multivariate model performs better, when compared to V_{t1} and V_{t3} multivariate models. In complex designed models with multi variables (GA, ANN, and LWR) often need to find best optimal designed configured to obtain best results. However, the developed models are complicated due to its hybrid nature but the accuracy of the models compared to previous studies showed promising results and they can be a powerful tool especially in traffic management and control.

6. Conclusions and Recommendations

In this study, genetically designed ANN (GA-ANN) and LWR (GA-LWR) multivariate models for forecasting short-term urban traffic are proposed and tested. Genetic algorithms are used to optimize the input datasets. The input datasets are in intervals of 5-min window each weekday. GA is used to optimally select 24 final input variables from the given candidate input dataset of 288 initial input variables. The 24 final GA optimized datasets are input to ANN and LWR multivariate models for prediction of traffic parameters.

In this study, two types of models are developed and tested. 1) Aggregate multivariate model and 2) disaggregate multivariate model. Both models and their prototypes are already discussed in earlier sections. The aggregate multivariate model is developed using traffic

parameters data of every 5-min window with a 30-min window (e.g., 7:25 – 7:55 am peak and 11:25-11:55 am off-peak period from Monday to Friday). Meanwhile, disaggregate multivariate model is developed based on data of a particular 5-min window of each weekday (7:25 – 7:30 am for peak period and 11:25-11:30 am for off-peak period from Monday to Friday). The GA-ANN and GA-LWR aggregate and disaggregate multivariate models are used to predict short-term traffic parameters for 5-min and 30-min window respectively. It is found that, during the peak and off-peak window, all four lanes show distinctive traffic patterns.

The proposed GA-ANN and GA-LWR disaggregate multivariate models show lower forecasting errors and such robust models will predict traffic parameters in a highly accurate manner. Short-term prediction of traffic parameters (e.g., such as flow, speed and density) is a crucial element of current ITS, yet complex to accomplish mathematically because of their dynamic nature. To accommodate the increasing traffic demand, better forecasting techniques should be taken into account. In general, lane-based traffic forecasting with a temporal resolution of 5-min window has rarely been studied before, especially with a combined input consisting of multiple traffic parameters. The present study eliminates this existing research gap with the proposed hybrid multivariate models coupling GA, ANN and LWR. The present study proposed an optimized framework for modelling the dynamic of traffic through the forms of hybrid multivariate neural network and locally weighted regression methods.

The GA designed ANN (GA-ANN) and LWR (GA-LWR) aggregate and disaggregate multivariate models are used to predict lane-based short-term traffic parameters. To predict peak and off-peak time 5-min traffic condition into future, the GA-ANN and GA-LWR models are developed and tested. For peak and off-peak time traffic prediction, the GA-ANN and GA-LWR

aggregate multivariate models show higher average errors and the 95th percentile errors. On the other hand, for the peak and off-peak time traffic prediction, the GA-ANN and GA-LWR disaggregate multivariate models show satisfactory results with lower average and 95th percentile errors. Hence, for short-term traffic parameters prediction, the GA-ANN and GA-LWR disaggregate multivariate models show lower average and 95th errors, when compared to GA-ANN and GA-LWR aggregate multivariate models.

When compared to the previous studies, where most of the average errors are higher than 10% (Table 1), the genetically designed GA-ANN and GA-LWR disaggregate multivariate models show lower average errors. Moreover, the GA-ANN and GA-LWR disaggregate multivariate model V_{t2} shows promising results where most of the average errors are lower than 5% for each of four lanes. Nevertheless, for peak and off-peak time prediction, both GA-ANN and GA-LWR models showed lower MSE of 0.11-1.84 when compared to previous studies (Table 1). Results imply that genetically designed models have a much better ability to capture high traffic variation, which is of primary importance to traffic prediction and major shortcoming of other approaches such as ARIMA models. The contributions of this paper is to develop lane-based short-term forecasting models using advanced techniques (such as GA, ANN, and LWR), which also have a higher accuracy than the existing models reported in the literature.

A great care was taken to present plausible models for short-term traffic forecast. Despite of this all, the present study has few limitations. Data were from a specific city and specific road type; thus, models are only tested on data sets collected from that particular type of urban road. Various factors such as road conditions, accidents, weather conditions, etc. are excluded during the model design and development. A few related research topics can be explored in the future

including that, the model should be tested on other facility types, such as freeways and rural road types. Other parameters like weather condition and other information (e.g., accidents) should be included to make models more robust.

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