Optimizing Mobility: A Study of Traffic Congestion and Route Planning in Cosmopolitan City

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Abstract: The demand for transport has been steadily increasing because of urbanization, which has resulted in a number of significant problems, including the overloading of infrastructure, disruptions to traffic flow, and vehicular emissions. As a direct consequence of this, finding solutions to these issues has emerged as one of the top priorities for governments all over the world. In cosmopolitan areas, the priority to target has been determined to be over-saturated intersections. These are intersections where the traffic density is high and the levels of vehicle exhaust pollution are large.

Chandigarh is one of the most rapidly developing cities in India. However, with the increasing population and number of vehicles, traffic congestion has become a serious problem, making it difficult for citizens to commute efficiently. Providing commuters with alternate routes that they would be willing to take is a crucial step in addressing traffic congestion. This idea has been described as a strategic routing dilemma, in which additional routes have to be recommended in addition to the already existing ones. The various routes issue, which involves finding various routes from a given starting point to a destination expands on this idea. Improving traffic control optimization to minimize overall travel time is a big problem because existing systems generally focus on adaptive techniques for typical traffic situations. This makes effective driver allocation across numerous routes critical. Optimizing control plans during serious accidents, especially when many lanes or entire intersections are affected, is still a problem. In order to tackle this issue, it is required to provide a novel optimization framework that combines the dependability of genetic algorithms (GA) with the speed and efficiency of fast machine learning (ML) techniques. A genetic algorithm was utilized to efficiently choose advantageous courses using a traffic congestion index. The effectiveness of the suggested genetic algorithm was then evaluated by comparing it to other optimization approaches. The results illustrated that the genetic algorithm found the ideal solution more quickly than the other optimization strategies. Furthermore, in order to predict vehicular traffic patterns using the number of registered vehicles within a city, a variety of modeling techniques are employed out of which the autoregressive integrated moving average (ARIMA) model turns out to be an effective method for predicting short-term traffic.

Keywords: Traffic Congestion, Travel Time, Traffic Management, Machine Learning, Genetic Algorithm, Autoregressive integrated moving average, Traffic pattern, Congestion Index.

1. Introduction:

Chandigarh, known for its meticulous planning, has undergone significant transformations over time, deviating from its original vision. The city has experienced drastic changes, with notable increases in population, businesses, markets, educational institutions, and the number of vehicles traversing its roads. A random survey reveals that nearly every household in the city owns a vehicle, resulting in heightened traffic congestion on the roadways. The current situation reflects an imbalance between the volume of traffic and the capacity originally planned for roads and parking facilities.

The rapid population growth has been observed in the city. Chandigarh's population has expanded rapidly from 1.05 million in 2011 to 1.46 million in 2021 and is expected to be 2.09 million in 2031. Also, the city has the highest vehicular density **878 registered motor vehicles per thousand persons** which can be considered as one of the main root causes of congestion in the city.

In Chandigarh, rise in the ownership of private vehicles is caused by changes in the socio-economic makeup of the population over time. The comfort and convenience it provides are the main reasons people choose private transportation over public transportation. However, there are few options to improve the road network due to the constrained amount of road space that is available in metropolitan areas. As a result of the intense pressure coming from both inside and outside, the effectiveness of the current infrastructure is currently weakened. Due to the city's continuous urbanization, floating traffic has expanded significantly, which has caused a wide range of problems, including congestion and increased vehicle emissions.

1.1 Review of Literature:

Mao, T. et al. (2022) address the issue of non-recurring event traffic control optimization. They propose a novel methodology that combines GA and quick ML methods to optimize traffic control strategies for serious occurrences. By using a GA algorithm with the network's trip time as the objective function, they fine-tune the algorithm to acquire the best parameters. Regression models are trained to forecast the overall journey time, and the extreme-gradient decision-tree (XGBT) regression model is chosen and hyper-tuned for improved accuracy. **Mehdi, H. et al. (2022)** focus on accurate traffic forecasting for efficient resource management in cloud computing. They introduce a combination model called fuzzy autoregressive integrated moving average (FARIMA) for cloud-based traffic forecasting. This model integrates the benefits of ARIMA and fuzzy regression models, providing accurate predictions with fewer historical data points. They also utilize the sliding window method to enhance prediction accuracy. **Abidin, N. Z. et al. (2022)** tackle urban traffic congestion in Kuala Lumpur by introducing the SD-GA model. This model combines SD and GA techniques to optimize travel demand variables and predict congestion levels. The study identifies bus fare subsidies and bus route expansion rate as significant variables impacting the mode share and congestion index. The findings offer valuable insights for transportation professionals to mitigate traffic problems and maximize mode share.

Hai, D. T. et al. (2022) emphasize the importance of improving traffic signal timing in oversaturated crossroads. They develop a performance index model using a GA and evaluate the interplay between crucial components, including vehicle exhaust emissions. The model provides an optimization framework for traffic signal timing, considering various parameters and emphasizing emissions reduction. The study validates the model's effectiveness through a Taiwanese case study. **Ma, F. (2022)** proposes a dynamic path optimization strategy based on a genetic algorithm to address traffic congestion. This strategy optimizes multimedia urban road paths by considering stringent time constraints and classifying customers into categories. The genetic algorithm and decomposition coordination algorithm are combined to generate efficient scheduling systems for distribution organizations.

Younas, I. & Aramco, S. (2021) focus on addressing traffic congestion in large cities, specifically the London route issue. They propose a genetic algorithm-based solution to optimize routing and reduce road congestion. The method involves optimizing routes using a lookup table that mimics real-time traffic conditions, aiming to provide near-optimal routing solutions for commuters.

Gore, N. et al. (2021) investigate the relationship between traffic congestion and travel time reliability (TTR). Theyintroduce a probabilistic technique based on hazard function and journey time data to measure congestion and create reliability-based level-of-service (LOS) criteria for motorways. The study emphasizes the importance of considering variouselements when defining congestion and presents a methodology to evaluate motorway performance based on CI and TTR. **Liu, S.Y. et al. (2021)** focus on accurate train passenger flow forecasting for efficient rail transit systems. They demonstratethat the ARIMA model performs better in forecasting rail transit flow, considering the time-series structure of underground passenger flow data. **Bother, M. (2021)** addresses traffic congestion by recommending alternate routes to drivers. They propose the Multiple- Routes problem and develop the Multiple-Routes evolutionary algorithm (MREA) as a heuristic solver. The MREA finds multiple routes for drivers to disperse over, reducing the overall trip time. The study shows promising results using real-world data from Berlin, Germany. **Oinam, Y. et al. (2020)** emphasize the importance of creating a congestion index to identify and mitigate traffic congestion. They study the congestion index for the Navalur-Kelambakkam stretch in India, considering various factors and conducting a thorough analysis. The findings highlight vulnerable areas and suggest strategies to alleviate congestion, such as widening highways and implementing efficient parking systems.

Liu, B. et al. (2020) introduce the SDLSTM-ARIMA model for accurate traffic flow prediction. This model combines long short-term memory neural networks with the ARIMA model to address issues of instability and limited adaptability. The model considers traffic data temporal singularity to improve prediction accuracy and exhibits superior performance comparedto traditional methods. **Ma, T. et al. (2020)** propose the NN-ARIMA model for traffic condition forecasting across an entire network. This model integrates the statistical ARIMA model with the ML algorithm MLP to capture location-specific traffic features and overall movement patterns. The study demonstrates that post-processing MLP residuals using the ARIMA model significantly enhance prediction accuracy. **Alghamdi, T. et al. (2019)** utilize ARIMA-based modeling to investigate critical variables affecting traffic congestion rates. They develop a short-term time series model that can handle non-Gaussian traffic data, enabling effective congestion management and precise forecasting of atypical traffic conditions. **Sofronova, E.A. et al. (2019)** focus on regulating traffic flows in metropolitan road networks. They formulate an ideal control problem using finite-difference equations and implement a variation genetic algorithm to optimize traffic control parameters. **Wang, W.X. et al. (2018)** examine various traffic congestion evaluation indices. They propose traffic congestion index calculation methods using fuzzy mathematics theory, comparing different approaches based on trip speed and extensive parameters. Their findings indicate the limitations of using saturation alone and emphasize the need to consider multiple factors when calculating congestion indices.

Jha K. et al. (2013) compare time series analysis (TS) with other forecasting techniques for estimating vehicle populations. The study demonstrates the higher accuracy of TS analysis in estimating future vehicle populations using data from PeMS in California. **Horvat, A. & Tošic, A. (2012)** focus on using evolutionary algorithms to optimize traffic flows. They develop a traffic simulator and utilize genetic algorithms to evaluate various optimization strategies, emphasizing the efficiency of their method.

2. Background:

Researchers and practitioners in the fields of data science and time series analysis have demonstrated a growing interest in building predictive models that can precisely forecast future trends using previous data. A large number of fields, including finance, economics, weather forecasting, and sales forecasting, among others, benefit from the capacity to predict future patterns. Numerous strategies have been developed to solve this issue, with the aim of creating algorithms that can efficiently capture the built-in patterns and structures contained in the data. These algorithms are made to examine past data and find trends, seasonality, cyclic patterns, and other important characteristics that might help produce precise forecasts. Predictive model development requires a number of processes.

The historical data is first gathered and preprocessed to make sure it is of good quality and suitable for analysis. Taking care of missing numbers, handling outliers, and, if necessary, transforming the data are all included in this. The next step is to identify the data patterns using a variety of modeling methodologies. Both more advanced machine-learning algorithms and more traditional statistical techniques are among these methods. The modeling approach to adopt is determined by the characteristics of the data and the specific requirements of the forecasting task. One method that is widely used in time series forecasting is the autoregressive integrated moving average (ARIMA) model. Due to the fact that ARIMA models take into account the autoregressive (AR) component, which captures the relationship between an observation and its past values, the moving average (MA) component, which accounts for the impact of previous errors on the current observation, and the integrated (I) component, which deals with non-stationarity in the data, they have been found to be effective for analyzing and forecasting time series data. Other popular techniques include exponential smoothing methods like the Holt-Winters model, which mixes smoothing factors to capture patterns and seasonal oscillations, as well as more complex machine learning algorithms like neural networks and support vector machines. The effectiveness of these predictive models is frequently evaluated using a range of metrics, including mean absolute error (MAE), root mean square error (RMSE), or mean absolute percentage error (MAPE), in order to examine the accuracy and dependability of the forecasts. The improvement of forecasting algorithms' accuracy and robustness is a continual research endeavor in the field of developing efficient prediction models. Researchers hope to give decision-makers useful information and trustworthy projections to aid in informed decision-making and planning processes by utilizing historical data and utilizing sophisticated modeling approaches.

2.1 Autoregressive Integrated Moving Average (ARIMA):

The method most frequently used to study traffic congestion is ARIMA. This method operates by predicting the variation of traffic data throughout the course of the time domain. The ARIMA is just one method for evaluating the state of road traffic at the moment. Numerous studies have employed the ARIMA methodology to conduct time series analysis since traffic data is typically scattered. The ARIMA model's parameters must then be estimated in order to produce a forecast.

By using data collected from the variable itself to estimate its trend, ARIMA models are used to predict variables. This model focuses on analyzing a single variable at a time and regressing the variables on their own historical values. Understanding the variable's stochastic and probabilistic properties is a prerequisite for applying this strategy. The main application of ARIMA models is predicting future trends and movements of variables. Prediction intervals are generated based on sound mathematics and statistical theory. Using a traditional ARIMA model, one can directly capture the autocorrelation in the time series. There are three statistically significant parameters (AR, I, and MA) in the ARIMA model:

Autoregressive window size (p), difference order (d), as well as moving average window size (q). First, use the lag -1 difference for a moving trend or seasonal difference to specify these three parameters, and then fit an ARIMA model to the data. The following formula may be used to determine ARMA (p, q):

AR (p) Model

$$\boldsymbol{Y_t} = \emptyset\mathbf{1} * \boldsymbol{Y_{t-1}} + \emptyset\mathbf{2} * \boldsymbol{Y_{t-2}} + \emptyset\mathbf{3} * \boldsymbol{Y_{t-3}} + \text{---------------} + \emptyset\boldsymbol{p} * \boldsymbol{Y_{t-p}} + \boldsymbol{\mu t} \quad \text{--} (1)$$

MA (q) Model

$$\boldsymbol{Y_t} = \boldsymbol{\mu t} + \boldsymbol{\theta 1} * \boldsymbol{\mu t{-}1} + \boldsymbol{\theta 2} * \boldsymbol{\mu t{-}2} + \boldsymbol{\theta 3} * \boldsymbol{\mu t{-}3} + \text{-------------} \boldsymbol{\theta q} * \boldsymbol{\mu t{-}q} \quad \text{-------------------------------} (2)$$

ARMA (p,q) Models in general can be written as shown in the equation given below:

$$\boldsymbol{Yt} = \emptyset\mathbf{1} * \boldsymbol{Yt{-}1} + \boldsymbol{\mu t} + \boldsymbol{\theta 1} * \boldsymbol{\mu t{-}1} + \boldsymbol{\theta 2} * \boldsymbol{\mu t{-}2} + \text{-----------} + \boldsymbol{\theta q} * \boldsymbol{\mu t{-}q} \quad \text{--------------------------------} (3)$$

Methods often used to ascertain these characteristics include visual inspections of time series to discover patterns, partial correlation analyses, and other forms of correlation analysis. Because delays have an impact on the value of the dependent traffic flow variable, measured in time T, ignoring delays might negatively affect the standard errors of predicted coefficients when using non-normal distribution data to apply the model.

2.2 Genetic Algorithm:

By allocating traffic flow optimally and determining more direct routes for vehicles, genetic algorithms (GAs) can be used to solve the issue of traffic congestion on highways. Here is a concrete illustration of how to apply a genetic algorithm to the problem of traffic congestion:

1. Formulation of the Problem: The problem and its goals must be defined as a first step. In order to do this, the traffic network must be specified, including all of the roads, intersections, and traffic flow information. Usually, the goal is to avoid overall traffic congestion, shorten travel times, or increase traffic throughput.
2. Chromosome Representation: Every possible outcome in genetic algorithms is represented by a chromosome. The mix of routes or the timing of traffic signals in instances with congested traffic. For instance, it might contain the road segments or crossroads that a vehicle must pass through in a specific order.
3. Initialization: To represent various combinations of routes or traffic signal timing, an initial population of chromosomes is generated at random.
4. Evaluation of Fitness: Each chromosome is assessed according to its fitness, which is a measure of how well it performs in terms of easing congestion or enhancing traffic flow. Considerations like trip time, wait lengths, or average vehicle speed can be used to gauge fitness.
5. Selection: People who are more likely to be chosen as parents for reproduction are those with higher fitness values. The parents are chosen from the current population using selection techniques like tournament selection or roulette wheel selection.
6. Crossover: Selected parents are subjected to crossover in order to produce new offspring. Crossover in the context of a congested road may

entail switching route segments between parents or combining various traffic signal timings to produce new signal designs.

7. Mutation: To find novel solutions, mutation introduces minute, random changes in the chromosomes. A portion of the routes or the timing of the traffic signals may need to be changed in the case of traffic congestion.
8. Evaluation and Replacement: The fitness of the new offspring is assessed, and depending on their fitness values, a portion of the population is replaced with the offspring. Over time, this process contributes to the population's general quality improvement.
9. Iteration: The algorithm explores and improves the solutions by repeatedly performing Steps 5-8 (selection, crossover, mutation, evaluation, and replacement).
10. Termination: The algorithm ends when a stopping condition is satisfied, such as when the number of generations reaches a certain threshold, the level of congestion reduction is adequate, or the computing time limit is reached.

Genetic algorithms have been used in various traffic management applications, including traffic signal optimization, route planning, and traffic flow control. They offer a flexible and effective approach to addressing traffic congestion by considering multiple factors and finding solutions that balance the overall traffic conditions.

3. Methodology:

The planning and optimization of the routes for the given set of nodes are achieved by using both quantitative and qualitative methods; qualitative methods are utilized to collect data on the number of registrations over the decade in Chandigarh. At the same time, quantitative methods are used to obtain data regarding current traffic and citizen choices towards transportation facilities. The traffic congestion among several city nodes is estimated by analyzing the collected quantitative data. The traffic congestion between nodes i and j is estimated as the ratio of the average time to travel during peak hours to the average time to travel during off-peak hours.

$$\boldsymbol{T_c^{ij}} = \boldsymbol{T_{avg}^{Peak}} \Big/ \boldsymbol{T_{avg}^{off\ peak}} \quad \text{---------------------- (4)}$$

This further utilized is to formulate the objective function (f) as follows,

$$\text{Min} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}((T_{ij} + d_{ij})X_{ij}) \quad \text{-- (5)}$$

$$0 \le X_{ij} \le 1 \qquad \text{i, j = 1 ..… n; -- (6)}$$

$$u_i \in Z \qquad i = 1, \ldots., n; \quad \text{-- (7)}$$

$$\sum_{i=0, i \neq j}^{n} X_{ij} = 1 \quad i = 1, \ldots.., n; \quad \text{-- (8)}$$

$$\sum_{j=0,\, j \neq i}^{n} X_{ij} = 1 \quad i = 1, \ldots.., n; \text{-- (9)}$$

$$u_i - u_j + nX_{ij} \le n - 1 \quad 1 \le i \neq j \le n. \quad \text{-- (10)}$$

where, 'n' represents the total number of links that connect S and O.

$\boldsymbol{T_{ij}}$ → Congestion between node i as well as node j.

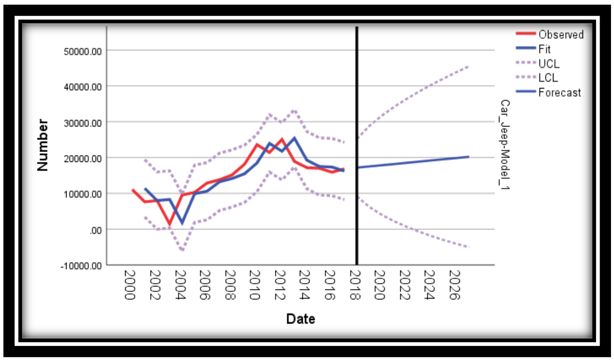
d_{ij} → Distance between node i as well as node j.

The above objective function is minimized using a Genetic algorithm to ensure a root between the nodes S and O, which is the least congested and shortest distance. Along with the proposed route planning algorithm, a brief forecasting analysis (ARIMA) is performed to predict vehicle density in the near future.

4. Results and Discussion:

The data for the past ten years' vehicle registration is obtained from CEIC's data website and utilized in the Fit ARIMA model.

4.1 ARIMA-Sequence Plot:



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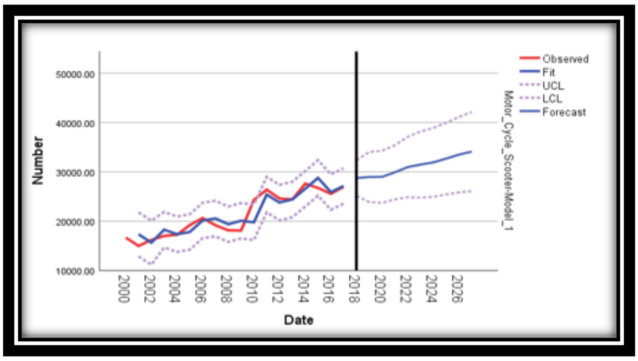

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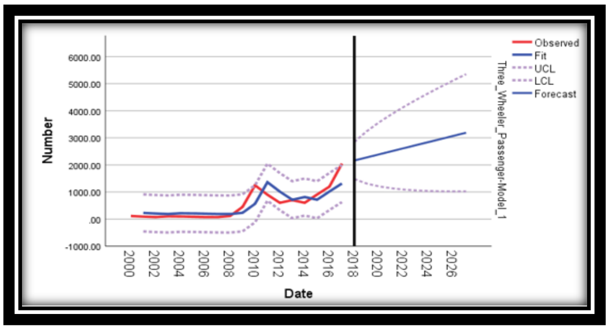

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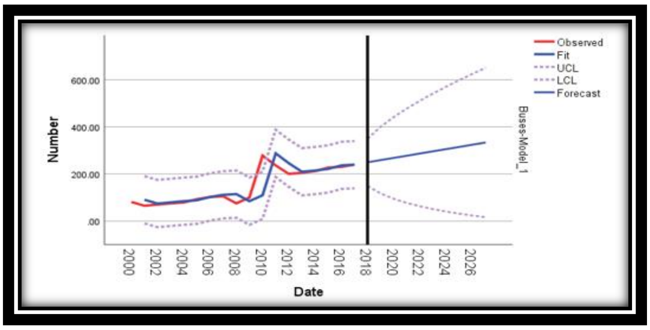

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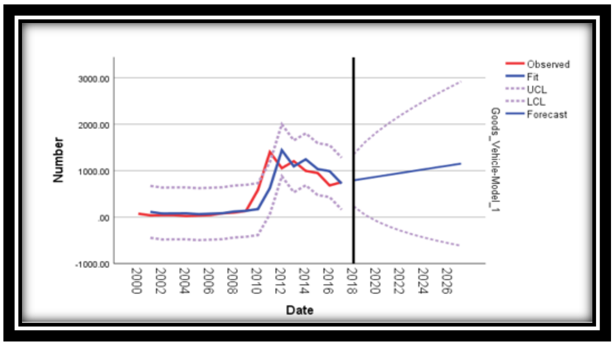

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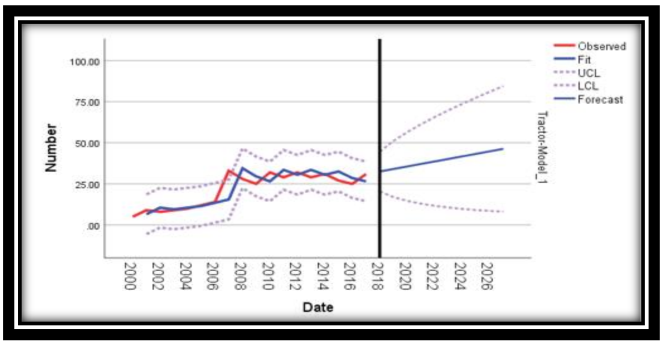


(f)

Fig.1: Observed & Forecasted Registrations of (a) Car/Jeep, (b) Motor Cycle/Scooter, (c) Three-Wheeler Passenger,
(d) Buses, (e) Goods Vehicle, (f) Tractor
(*LCL-Lower Control Limit, * UCL- Upper Control Limit)

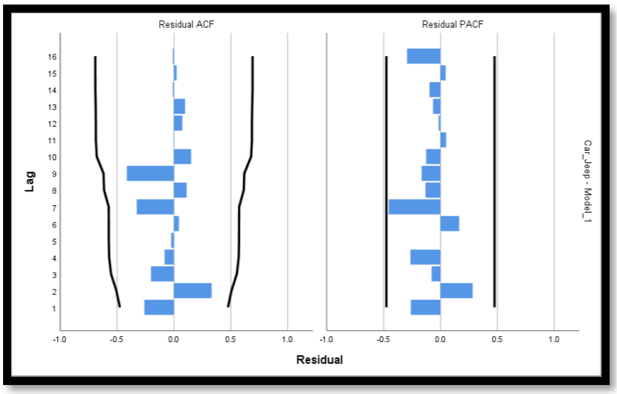
The above figures show the observed and forecasted values of Cars/Jeeps, Buses, Motor Cycle/Scooters, Goods Vehicle, Three-Wheeler passengers and Tractors registrations with the Registration & Licensing Authority, Chandigarh. The fitted model, trained on historical data, is then used to make predictions. The forecasted outcomes show a rising trend with minor seasonal and interval variations. There has been a significant rise in the registration of vehicles, which indicates that there will be an increase in traffic in the upcoming years.

Several statistical measures are computed, including the Bayesian information criterion (BIC) normalization factor, the maximum absolute error, the mean absolute error, the maximum absolute error, the R-squared value, and the highest absolute percentage error.

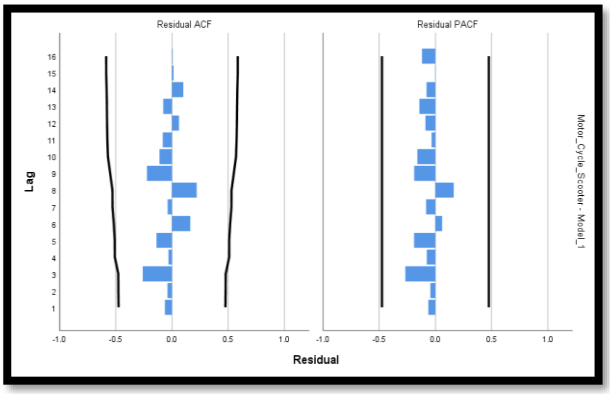
Because of this, the ARIMA model could be the most appropriate for making predictions. The ARMA/ARIMA forecasting model is the most effective tool for analyzing and projecting linear time series. The forecasting model predicts future traffic based on historical time series data on vehicle registrations from 2000–2017, including Cars/Jeeps, Motor-Cycles/Scooters, Three-wheeler passenger, Buses, Goods Vehicles, and Tractors.

Table-1 (Model Summary for various classes of vehicle using SPSS)

Model ID	**Model Fit**										
	Fit Statistic	Mean	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Car_Jeep	Stationary R-squared	0	0	0	0	0	0	0	0	0	0
	R-squared	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Motor_cycle_scooter	Stationary R-squared	0.349	0.349	0.349	0.349	0.349	0.349	0.349	0.349	0.349	0.349
	R-squared	0.853	0.853	0.853	0.853	0.853	0.853	0.853	0.853	0.853	0.853
Three_Wheeler_Passenger	Stationary R-squared	0	0	0	0	0	0	0	0	0	0
	R-squared	0.676	0.676	0.676	0.676	0.676	0.676	0.676	0.676	0.676	0.676
Buses	Stationary R-squared	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16	-2.22E-16
	R-squared	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617
Goods_Vehicle	Stationary R-squared	0	0	0	0	0	0	0	0	0	0
	R-squared	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716
Tractor	Stationary R-squared	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16	2.22E-16
	R-squared	0.654	0.654	0.654	0.654	0.654	0.654	0.654	0.654	0.654	0.654



(a)



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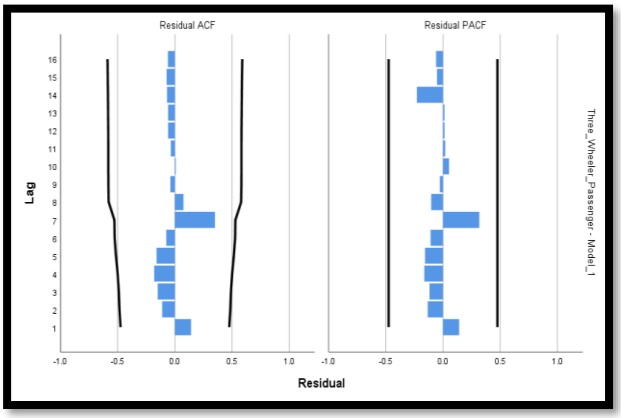

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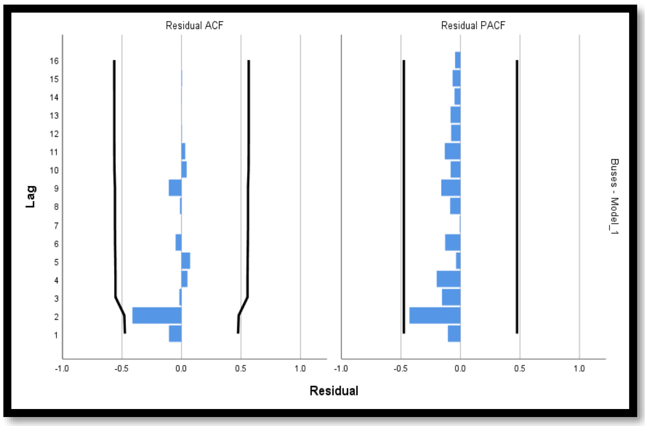

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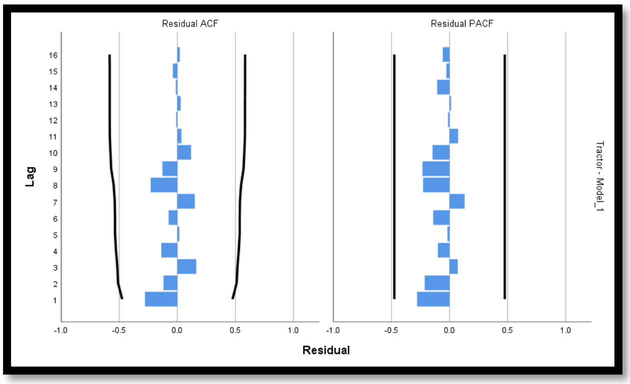

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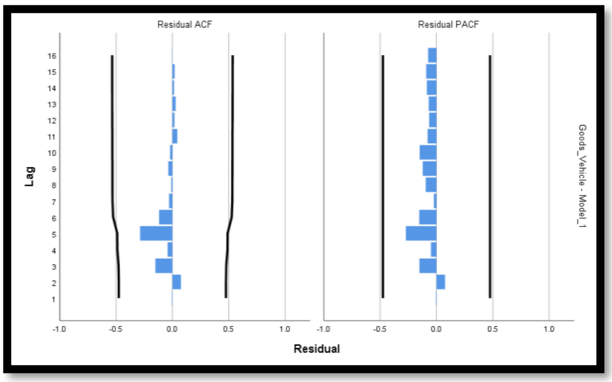

(f)

Fig.2: Residuals ACF & PACF of (a) Car/Jeep, (b) Motor Cycle/Scooter, (c) Three-Wheeler Passenger, (d) Buses, (e) Goods Vehicle, (f) Tractors (*ACF- Autocorrelation Function, * PACF- Partial Autocorrelation Function)

It shows anticipated case autocorrelation and partial autocorrelation at different lag lengths. Both the residual ACF and the residual PACF did not pass the 95% confidence level at any time during the lag period. It was revealed that neither the ACF nor the PACF between residuals at varied lag durations was statistically different. It was shown that the residuals did not exhibit any unusual pattern and were discrete, independent, and identically distributed; in other words, they displayed white noise. The table above provides 10-year predictions. The table shows that the registration of Cars/Jeeps, Motor Cycles/ Scooters, Three-Wheeler passengers, Buses, Goods Vehicle, and Tractors will increase in the coming ten years.

Hence, it is crucial to plan a strategy to suggest an optimal route to save citizens time and energy. However, the collected quantitative data is utilized to identify traffic congestion on each link and is further used in the optimization process to select the optimal path between the nodes of interest.

Optimal Paths obtained are listed as follows:

Case1: Optimal path between Sector 1 and Sector 30

Table-2 (Optimal path)

Shortest distance between S1 and S30	Distance	Congestion Index
S1→S8→S7→S30	6.1 km	10.888
S1→S8→S7→S27→S30	6.8 km	13.998
S1→S7→S20→S30	6.0 km	11.332
S1→S8→S20→S30	7.7 km	12.443
S1→S8→S27→S30	6.0 km	12.887

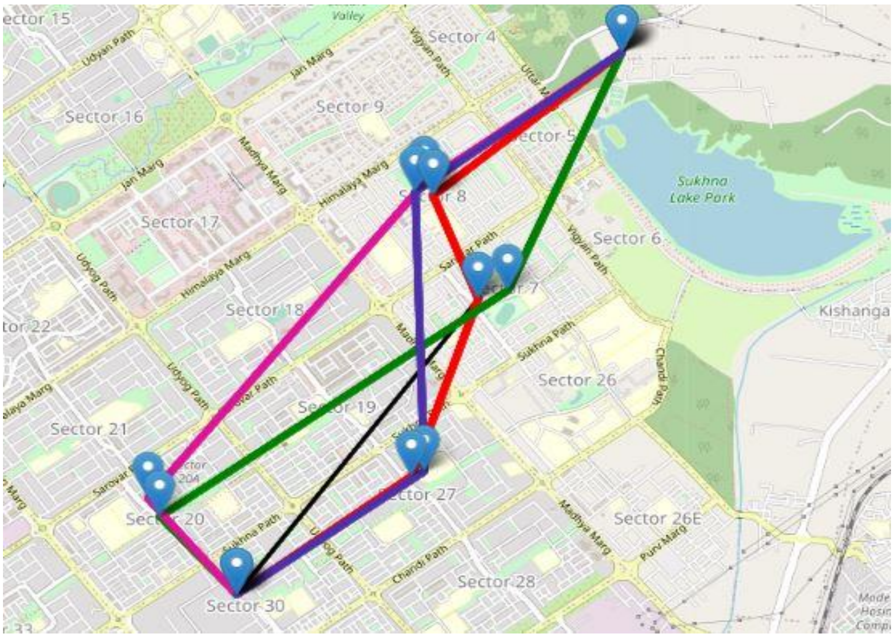

Fig.3: Alternate Routes from Sector 1 to Sector 30

Case2: Optimal path between Sector 5 and Sector 15

Table-3 (Optimal path)

Shortest distance between S5 and S15	Distance	Congestion Index
S5→S9→S15	5.7 km	3.332
S5→S7→S8→S15	7.2 km	5.332
S5→S10→S15	4.6 km	3.998
S5→S11→S15	5.4 km	3.554
S5→S3→S15	6.0 km	2.665

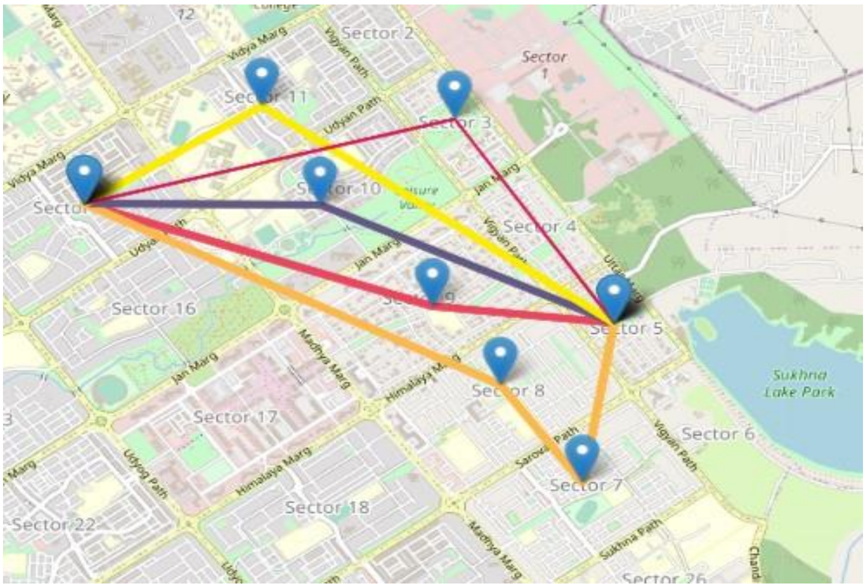

Fig.4: Alternate Routes from Sector 5 to Sector 15

Case3: Optimal path between sector 15 and sector 30

Table-4 (Optimal path)

Shortest distance between S15 and S30	Distance	Congestion Index
S15→S18→S30	6.6 km	4.221
S15→S16→S30	5.4 km	8.888
S15→S22→S30	5.5 km	6.221
S15→S27→S30	7.2 km	6.665
S15→S24→S30	7.3 km	6.221

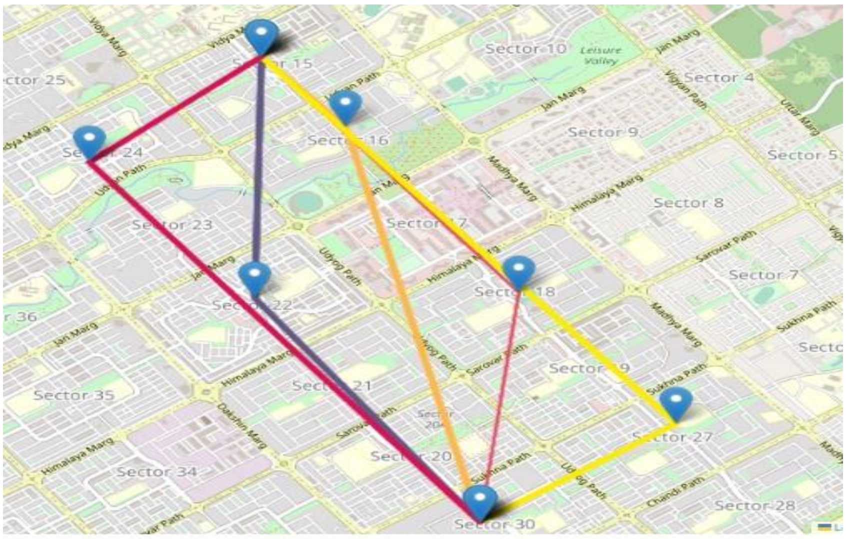

Fig.5: Alternate Routes from Sector 15 to Sector 30

The above tables (2, 3 & 4) show that the proposed route planning strategy can effectively find the shortest and least congested routes. However, the efficacy of the selected genetic algorithm is shown by a comparison with alternative optimization methods.

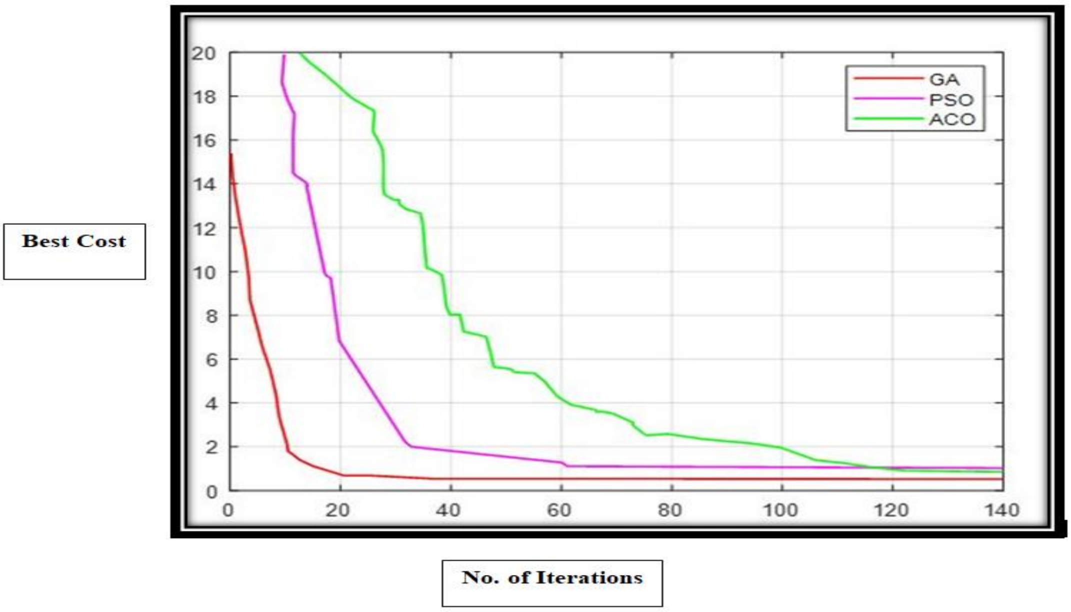

Fig.6: Genetic Algorithm Graph
(*PSO- Partial Swarm Optimization, *ACO- Ant Colony Optimization)

PSO and ACO are inferior to the genetic algorithm in terms of speed to the ideal solution. Another well-liked bio-inspired optimization technique that replicates natural selection and evolution is the genetic algorithm. It keeps a population of potential answers represented by chromosomes and generates new answers using genetic operators like crossover and mutation. The algorithm assesses each solution's fitness and chooses the top candidates to produce the next generation. The iterative procedure is continued until the optimal response becomes known.

5. Conclusion:

The study emphasizes the primary objective, which is to find the optimal route between two nodes while considering both the shortest distance and the level of congestion. The study uses a genetic algorithm and ARIMA forecasting, two different optimization methodologies, to accomplish this. By examining historical data on automotive registrations across the previous decade, the ARIMA technique is used to anticipate the degree of vehicle density in the near future. The genetic algorithm uses this information as input to find the best route by minimizing traffic and travel time for people. The effectiveness of the suggested genetic algorithm is also assessed by comparison with other optimization methods in the study. In a head-to-head comparison, the results show that the genetic algorithm performs better than other bio-inspired optimization algorithms in terms of convergence speed. Based on these results, it may be concluded that the proposed genetic algorithm provides an effective and efficient method for choosing the optimum path between two nodes, reducing traffic and trip time. It implies that this algorithm can be put into practice to improve the transport network and raise inhabitants' quality of life in general.

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