TRAVEL TIME REDUCTION DURING CONGESTION UNDER HETEROGENEOUS TRAFFIC CONDITIONS

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Abstract: Traffic congestion is a serious problem which traffic engineers all over the world are trying to solve. Congestion increases the uncertainty in travel times leading to human stress and unsafe traffic situations. Better management of traffic through intelligent transportation systems (ITS) applications, especially by predicting the congestion on various roads and informing the travelers regarding the same is one possible solution. Accurate and quick prediction is one of the important factors on which the reliability of such a system depends. If one is able to predict congestion on a roadway, then the travelers can be warned of the same either pre-trip or enroute so that they can take well informed travel decisions. The number of vehicles in a given stretch of a roadway is one of the most commonly used congestion indicator. Also, the travelers in general will be more interested to know what they can expect when they make the trip in future rather than the present scenario. This makes the short term prediction to future time intervals important. In this study, some of the reported techniques for density prediction under homogeneous traffic conditions are attempted under heterogeneous traffic conditions in order to determine their feasibility under the Indian traffic scenario.

***Index Terms* – traffic, optimization, congestion**

I. INTRODUCTION

Traffic on the Indian city roads has increased tremendously due to the increasing rate of urbanization. Globalization of the Indian economy and the improvement in economic status of the people has also induced greater impact on the transportation system. Increasing inadequacy of public transport, rising rate of vehicle ownership and migration of people to urban fringes have led to extensive use of private modes, clogging the road network. The traffic movements in city roads have been compounded by frequent interruptions, resulting in drastic reduction in speed, leading to congestion. Traffic congestion in urban areas has long been a problem noticed by inhabitants of Central Business District (CBD), but it has now spread and intensified in the urban fringes and nearby suburban areas too. People use variety of modes of transport to meet their travel demand. The advancement in automobile technology has brought in a variety of two wheelers and cars in the market matching to one's budget and purpose, thereby adding more congestion. The planning of suburban areas is not sustainable and is not successful in containing the travel demand of the people within the locality. The people from the newly developed areas travel towards the city for their needs adding further congestion. The congested traffic flow has led to increase in vehicular emissions which have degraded the urban air quality. Traffic congestion has far reaching multiplying effects on the economy, environment and general quality of life. None of the towns in India has a logical balance of the modal share of different transport modes. Restricting the growth of the usage of motor vehicle do not seem to be possible in the near future, given the economic and other benefits of increased mobility. Development of road infrastructure cannot be matched with the transport demand due to financial and spatial restrictions. The available option is to mitigate congestion by use of the available resources optimally. Continuous efforts have been taken by the transportation professional and authorities in developed countries to measure and devise means of reducing congestion. The causal factors of congestion in Indian context need to be understood to arrive at policies for mitigation. A clear understanding of the heterogeneous traffic operations on urban artenals and quantitative measure of congestion is required to devise policies to manage the usage of motor vehicles causing minimum damage to the environment.

Comparison of Homogeneous and Heterogeneous Motorized Traffic

Homogeneous traffic flow has attracted much attention, not only for exclusively single lane roads but also for more complex configurations [1]. We focus here however on factor that contributes to heterogeneous traffic flow inability for a single lane. A major issue is clearly that of bottlenecks. Bottleneck conditions are crucial for single lane flow when right turning (RT) and long vehicle (LV) proportions increase. The focus of the research community on homogeneous, ignores many important features of real heterogeneous traffic and it is clear that more experimental work on heterogeneity is needed. Heterogeneous motorised traffic flow characteristics for single lane roads are essential to understanding urban traffic problems. Such models would be of significant help to traffic planners, in making key decisions. Simulation modelling is an increasingly popular and effective tool for analysing a wide variety of dynamic problems, which are not amenable to study by other means

Effects of congestion

Congestion has a large number of ill effects on drivers, environment, health and the economy in the following ways.

- Drivers who encounter unexpected traffic may be late for work and other appointments causing a loss in productivity and their valuable time.
- Since congestion leads to increase in travel time i,e., vehicles are made to travel for more time than required which consumes large amount of fuel there by causing fuel loss and economic loss to the drivers.
- One of the most harmful effects of traffic congestion is its impact on the environment. Despite the growing number of vehicles, cars stopped in traffic still produce a large volume of harmful carbon emissions. Increase in pollutants (because of both the additional fuel burned and more toxic gases produced while internal combustion engines are in idle or in stop-and-go traffic)
- Drivers who become impatient may be more likely to drive aggressively and dangerously and leads to high potential for traffic accidents
- Negative impact on people's psychological state, which may affect productivity at work and personal relationships
- Slow and inefficient emergency response and delivery services
- Decrease in road surface lifetime: When a vehicle moves over the surface, the areas of contact (where the vehicles' tyres touch the road) are deflected downwards under the weight of the vehicle and as the vehicle moves forward, the deflection corrects itself to its original position.
- Vehicle maintenance costs; 'Wear and tear' on mechanical components of vehicles such as the clutch and brakes is also considerably increased under stop-start driving conditions and hence increasing the vehicle maintenance costs.
- One beneficial effect of traffic congestion is its ability to encourage drivers to consider other transportation options like a subway, light rail or bus service. These options reduce traffic on the roads, thereby reducing congestion and environmental pollution.

The summation of all these effects yields a considerable loss for the society and the economy of an urban area

Traffic congestion

A system is said to be congested when the demand exceeds the capacity of the section. Traffic congestion can be defined in the following two ways:

1. Congestion is the travel time or delay in excess of that normally incurred under light or free flow traffic condition.
2. Unacceptable congestion is travel time or delay in excess of agreed norm which may vary by type of transport facility, travel mode, geographical location, and time of the day.

RELATED WORK

Lanhang Ye et.al (2017) the objective of this study was to develop a heterogeneous traffic-flow model to study the possible impact of connected and autonomous vehicles (CAVs) on the traffic flow. Based on a recently proposed two-state safe-speed model (TSM), a two-lane cellular automaton (CA) model was developed, wherein both the CAVs and conventional vehicles were incorporated in the heterogeneous traffic flow. In particular, operation rules for CAVs are established considering the new characteristics of this emerging technology, including autonomous driving through the adaptive cruise control and inter-vehicle connection via short-range communication. Simulations were conducted under various CAV-penetration rates in the heterogeneous flow. The impact of CAVs on the road capacity was numerically investigated. The simulation results indicate that the road capacity increases with an increase in the CAV-penetration rate within the heterogeneous flow. Up to a CAV-penetration rate of 30%, the road capacity increases gradually; the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rate exceeds 30%, the growth rate is largely decided by the capability of the CAV. The greater the capability, the higher the road-capacity growth rate. The relationship between the CAV-penetration rate and the road capacity is numerically analyzed, providing some insights into the possible impact of the CAVs on traffic systems.

D. Higgins et.al (2017) proposed that despite decades of research, it is unclear under which circumstances travel is most onerous. While studies have found that some individuals derive positive utility from aspects of commuting, others have shown that traffic congestion can entail important time, monetary, and mental stress costs. Moreover, responses to traffic congestion-related stressors differs by individual characteristics. In response, this research captures how exposure to traffic congestion events, the duration of this exposure, and individual trait susceptibility to congestion affect the utility of commuting. Working through the lens of individual satisfaction with the duration of their commute, we show that not every minute of travel is valued the same by car commuters in Canadian cities. Results suggest a complex relationship between travel time, congestion, and individual predisposition to congestion-related stress. While improvements in travel time matter for increasing commute satisfaction, it is reductions in travel in congested conditions that matter most, particularly among those susceptible to congestion-related stressors.

L. Hamilton et.al (2016) this study explored the impact of bicycle-sharing infrastructure on urban transportation. We estimate a causal effect of the Capital Bike share on traffic congestion
in the metropolitan Washington, D.C., area. We exploit a unique traffic dataset that is finely defined on a spatial and temporal scale. Our approach examines within-city commuting decisions as opposed to traffic patterns on major thruways. Empirical results suggest that the availability of a bike share reduces traffic congestion upwards of 4% within a neighborhood. In addition, we estimate heterogeneous treatment effects using panel quantile regression. Results indicate that the congestion-reducing impact of bike shares is concentrated in highly congested areas.

Amit Agarwal et.al (2017) proposed that the growing pace of urbanization increases the need of simulation models to handle large scale scenarios in reasonable time. The present study proposes a fast spatial queue model, which is anchored to an agent-based travel demand simulation framework. The existing queue model is extended to produce more realistic ow dynamics by introducing backward traveling holes to mixed traffic conditions. In this approach, the space freed by a leading vehicle is not immediately available to the following vehicle. The resulting dynamics resembles the Newell's simplified kinematic wave model. The space freed corresponding to each leaving vehicle is named as `hole' and, as following vehicles occupy the space freed by leading vehicles, the hole travels backward. This results in triangular fundamental diagrams for traffic ow. The robustness of the model is tested with ow density and average bike passing rate contours. Spatio-temporal trajectories are presented to differentiate the queuing patterns. Finally, a comparison of the computational performance of the different link and traffic dynamics of the queue model is made.

J. Fagnant et.al (2016) proposed that shared autonomous (fully-automated) vehicles (SAVs) represent an emerging transportation mode for driverless and on-demand transport. Early actors include Google and Europe's CityMobil2, who are seeking early pilot deployments in low-speed settings. This work seeks to understand SAVs' potential for U.S. urban areas via multiple applications across the Austin, Texas, network. This work describes advances to existing agent- and network-based SAV simulations by enabling dynamic ride-sharing (DRS, to pool multiple travelers with similar origins, destinations and departure times in the same vehicle), optimizing fleet sizing, and anticipating profitability for operators in settings with no speed limitations on the vehicles and at adoption levels below 10 percent of all personal trip-making in the region. Results suggest that DRS reduces total service times (wait times plus in-vehicle travel times) and travel costs for SAV users, even after accounting for extra passenger pick-ups, drop-offs and non-direct routings.

Felix Steck et.al (2016) this study addressed the impact of autonomous driving on value of travel time savings (VTTS) and mode choices for commuting trips using stated choice experiments. Two use cases were addressed a privately owned and a shared autonomous vehicle –compared to other modes of transportation. The collected data were analyzed by performing a mixed logit model. The results show that mode-related factors such as time elements, especially in-vehicle time and cost, play a crucial role for mode choices that include autonomous vehicles. The study provides empirical evidence that autonomous driving may lead to a reduction in the VTTS for commuting trips. We found that driving autonomously in a privately owned vehicle might reduce the VTTS by 31% compared to driving manually and is perceived similarly to in-vehicle time in public transportation. Also, riding in a shared autonomous vehicle is perceived 10% less negatively than driving manually. The study provides important insights on VTTS by autonomous driving for commuting trips and can be a base for future research to build upon.

Reddy Kancharla et.al (2018) proposed that traditionally, vehicle routing problems (VRP) were solved with the objective of minimizing total distance traveled. The rationale behind minimizing distance was perhaps that fuel consumption depends on distance traveled. Fuel consumption depends on several other factors besides distance. Recently, several authors have focused on directly minimizing total fuel consumed considering load carried and/or speed. However, it is surprising that none have considered the significant effect of acceleration on fuel consumption. Since fuel cost represents a significant fraction of operating cost, incorrect fuel consumption estimation may result in suboptimal routes and schedules. Here, we estimate fuel consumption while considering the effect of load, speed, and acceleration. We achieve this by using driving cycles (speed-time profile of a vehicle) that can be easily obtained from Global Positioning System (GPS) data. Modified versions of several standard VRP instances are used to test the effect of estimated fuel consumption using driving cycles. Test results show that using driving cycles results in an average fuel savings of 8-12% compared to using average speed.

Giuseppe Musolino et.al (2016) this paper presented a procedure for the solution of the Vehicle Routing Problem (VRP) based on reliable link travel times. They are obtained as a combination of spatially disaggregated and aggregated data about simulated traffic conditions on an urban road network. The disaggregated data concern the congested link travel times, which are traditionally used as variable to be minimized in VRP. The novelty of this research article consists in the introduction of spatially aggregated data, which are estimated by means of the Network Fundamental Diagram (NFD). In a within-day dynamic context, they are a measure of reliability of travel times because they could anticipate the latter ones' variation in the short term. The equation of reliable link travel times is composed of a congestion term, expressing the traditional congested link travel times (or generalized costs), and a reliability term, which depends on the fundamental diagram of the link and the NFD of the homogeneous cluster of adjacent links. The proposed procedure has been validated and applied for two real test cases. NFDs data are used in the proposed link travel time function to calculate reliable travel times. The reliable link travel times are used for the solution of VRP to obtain optimal routes of freight vehicles.

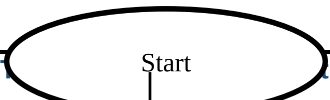
PROPOSED APPROACH

STEP1: Data Collection and Extraction The study stretch selected for the present study was two bus transit routes, namely 5C and 23C in India. These routes cover the wide range of geometric and traffic conditions on urban arterials. The selected stretches are a typical representation of urban routes in India comprising road links of different categories like major arterials, and collector streets with varying geometrics and volume levels. The traffic is highly heterogeneous in nature with mix of vehicles of different static and dynamic characteristics such as two-wheeler, three-wheeler, light motor vehicle and heavy motor vehicles. The lane discipline is also poor with no exclusive bus lanes and the buses have to share the road with other vehicles.

Step2: Congestion Analysis and Modelling The methodology proposed here aims to find the relationship between the personal vehicle(s) CI which is the variable of interest (dependent variable) and the public transit CI, which is taken as an independent variable. As road width and presence/absence of intersection influences traffic congestion, they have also been considered as additional independent variables to quantify congestion levels for vehicles in the stream, using only buses as probes. The methodology proposed here uses regression technique for determining the model parameters.

Step3: After fixing the latitude and longitude range of each bus stop, a program in MATLAB has been written which will check for the lowest speed value (denoted as Kt , where t is the GPS time) corresponding to the selected bus stop range. For finding the time of start of deceleration, each pair of speed values (Kt and Kt-1, Kt-1 and Kt-2, Kt-2 and Kt-3, etc.) will be checked, until the speed Kt-n >Kt-(n+1), where n=0, 1, 2, 3… The time corresponding to Kt-n is considered as the time of start of deceleration. In other words, for finding the time of start of deceleration, each pair of successive speed values (prior to the lowest speed) will be checked, until the prior speed (Kt-(n+1)) in the pair is lower. A similar procedure is adopted for finding the time of end of acceleration. For finding the time of end of acceleration, each pair of speed values (Kt and Kt+1, Kt+1 and Kt+2, Kt+2 and Kt+3, etc.) will be checked, After removing the bus stop dwell times, the bus travel time was correlated with the corresponding personal vehicle travel time in each section as explained in the following section to check whether buses could be considered as probes.

Flow Chart of Proposed Methodology



RESULT AND ANALYSIS

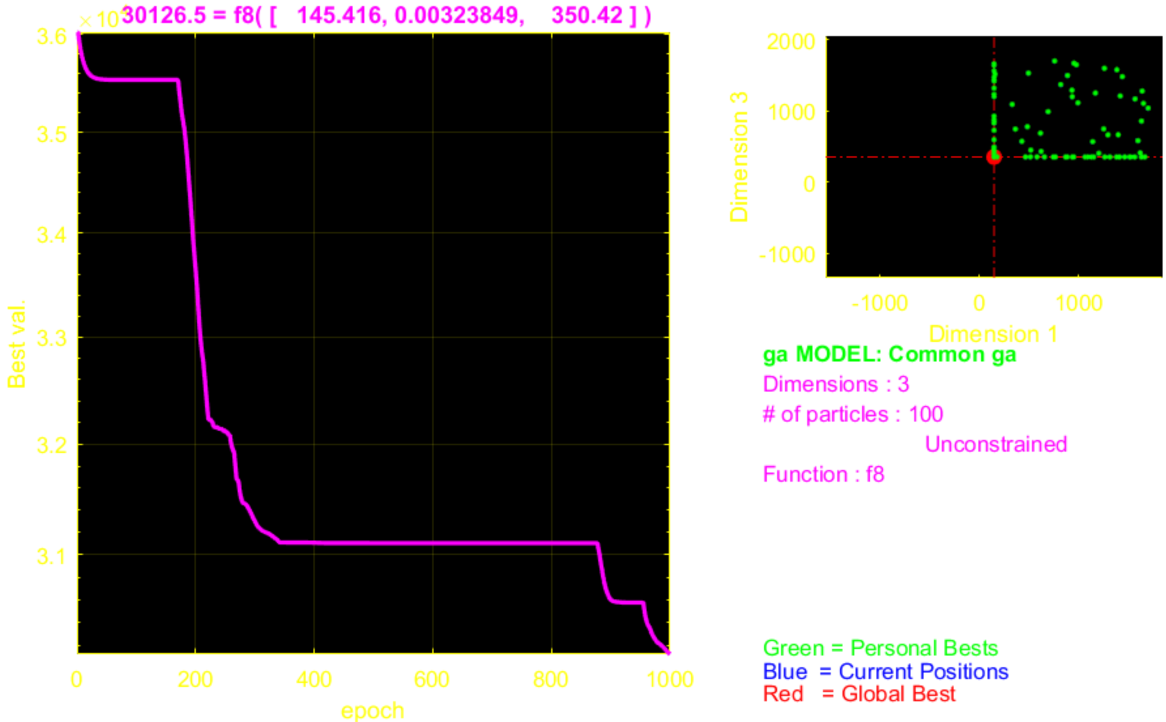


Fig5.1 Optimize values of strain by PSO

ITERATION	Pressure value(LBS)	Fitness value	Strain Pressure(LBS)
50	0.5	2000	2.34
100	0.25	12000	2.67
150	1.34	50000	4.34
200	0.345	53000	5.67
250	1.45	23000	6.45
300	0.3	20000	7.45
350	0.1	10000	8.9
400	-0.45	7000	9
450	-0.45	60000	9.45

Table 5.1 Comparison of PSO and GA Strain Pressures

Fig 5.1 and table 5.1 shows the strain pressure optimizes by particle swarm optimization and genetic algorithm. Table 5.1 shows that if the pressure will optimize and fitness value increases. In case of PSO it also converges when increasing the iterations. So its analysis shows that PSO optimization improves the strain pressure because of optimization of the fitness function.

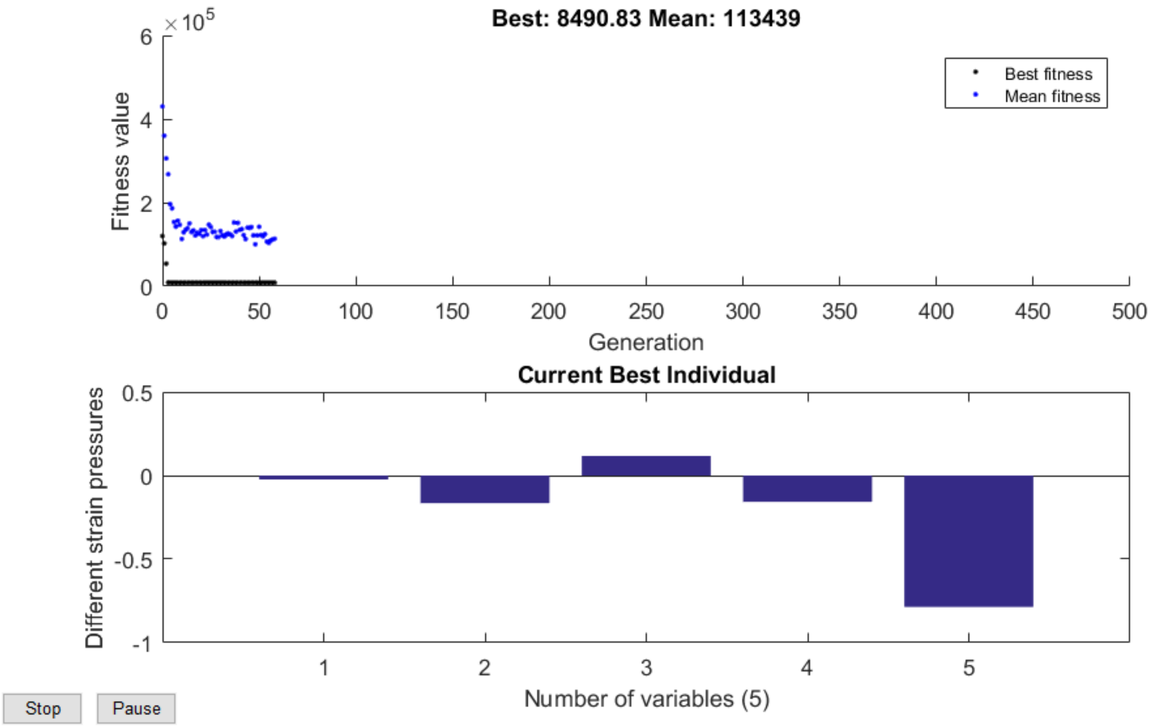


Fig5.2 Optimize values of strain by GA

Fig 5.2 and table 5.1 shows the strain pressure optimizes by genetic algorithm. Table 5.1 shows the pressure will optimize and fitness value will increase. In case of GA it also converges when increasing the iterations. So its analysis shows that PSO optimization improves the strain pressure because of optimizing the fitness function. On comparing with GA, PSO is more effective in optimization because of global and local strain pressure on Pavement.

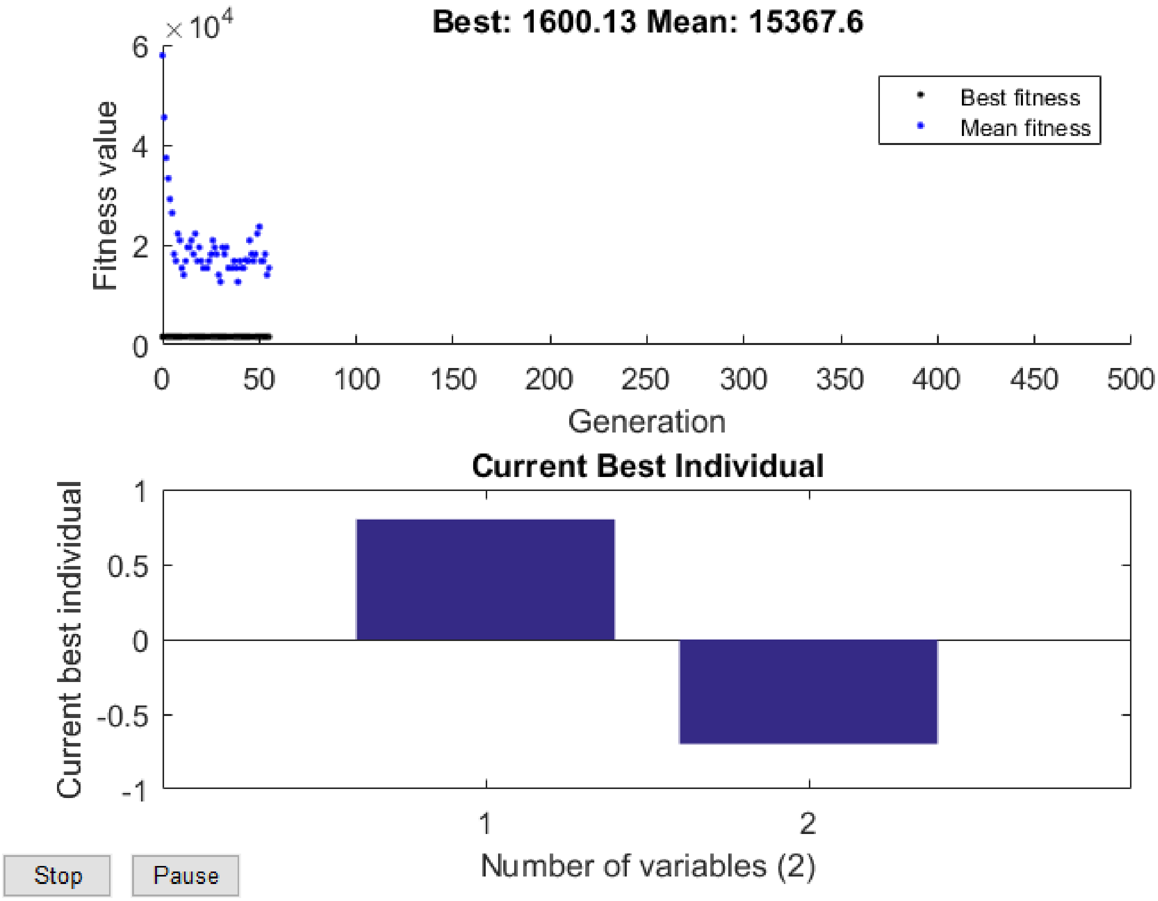


Fig5.3 Optimize values of fitness value of GA

Fig 5.3 shows the strain pressure optimization by particle swarm optimization and genetic algorithm. Table 5.1 shows the pressure will optimize and fitness value will increase. In case of GA fitness improves the strain pressure when fitness value increases.

PREDICTION IMPLEMENTATION

(a) GWO Initialize Condition: Initialize GWO parameters such as (G_P), variable size (G_A) vector a are linearly decreased 1to 0 and maximum number of iteration $iter_{max}$.

$\vec{A} = 2a.rand - a$ .... (1)

$\vec{c} = 2.rand$ .... (2)

Here, we generate the values of vector $\vec{A}$ and $\vec{C}$ by using random function.

(b) Random number of wolves: Random number of wolves expressed by 2-D array of features selection possibilities

$$W=\begin{bmatrix} G_1^i\ G_2^i\ G_3^i \ldots\ldots\ldots\ldots G_{A-1}^i\ G_A^i \\ G_1^{i+1}\ G_2^{i+2}\ G_3^{i+3} \ldots\ldots\ldots\ldots G_{A-1}^{i+1}\ G_A^i \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ G_P\ G_P G_P \ldots\ldots\ldots\ldots G_P G_P \\ G_1\ G_2 G_3 \ldots\ldots\ldots\ldots G_{A-1} G_P \end{bmatrix}$$

$G_J^i = initial\ value\ of\ ith\ pack\ of\ Jth\ volves.$

The given matrix presented above shows the pack of wolves on the basis of levels α, β, δ.

(c) Fitness Function

$\vec{F} = |C.G_P(t) - G(t)|$.................................... (4)

$\vec{G}(t+1) = G_1(t) - \vec{A}.\vec{D}$ .... (5)

Here, the behavior of prey is encircled during hunting process. Here, ‘t’ represents the current iterations A and C, which acts as coefficient vectors of the prey. $\vec{G}$ is the position vector of the grey wolf.

Identify the best Hunt

$\overrightarrow{D_\alpha} = |\vec{C}.\overrightarrow{G_\alpha} - \vec{G}|$.. (6)

$\overrightarrow{D_\beta} = |\vec{C}.\overrightarrow{G_\beta} - \vec{G}|$.. (7)

$\overrightarrow{D_\delta} = |\vec{C}.\overrightarrow{G_\delta} - \vec{G}|$.. (8)

$\overrightarrow{G_1} = G_\alpha - \vec{A}.(\overrightarrow{D_\alpha})$... (9)

$\overrightarrow{G_2} = G_\beta - \vec{A}.(\overrightarrow{D_\beta})$.. (10)

$\overrightarrow{G_3} = G_\delta - \vec{A}.(\overrightarrow{D_\delta})$....................................... (11)

In this process, identify the best hunt among all hunts that are guided by alpha, beta and delta participating occasionally.

(d) Updated Value: Here is the updated value of alpha.

$G\ (t+1) = \frac{\overrightarrow{G_1} + \overrightarrow{G_2} + \overrightarrow{G_3}}{3}$ .... (12)

(e) Stopping Condition: Checks the stopping condition by $iter_{max}$ if yes then stop.

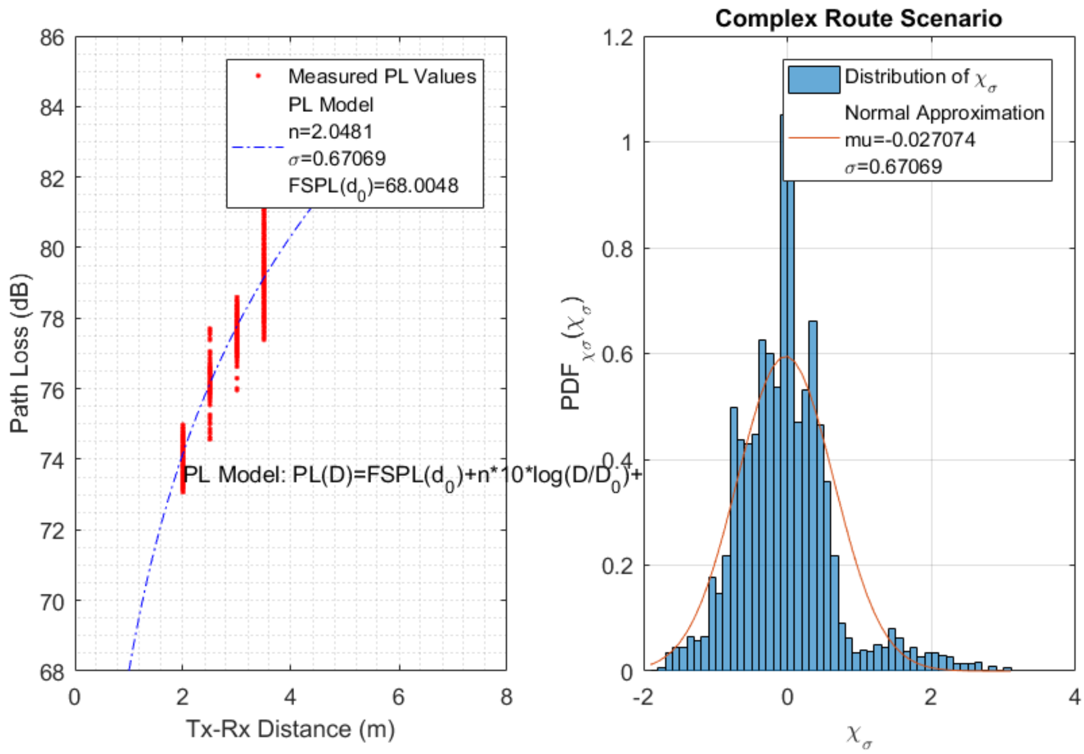


Fig 5.1 Model Performance by cost factor and path density factor without optimization or prediction

Fig 5.1 and table 5.1 shows the route choosing model performance on the basis of cost. On analyzing table 5.1 the comparison of cost and probability density function should be effective for reducing the cost of route. The cost of route selection reduces using optimization instead of prediction because optimization use learning approach and prediction use only dependency. So optimization improves accuracy of selecting effective route which also improves probability density function and reduces cost as well.

Distance (KM)	Path cost(prediction)	Path density Factor(prediction)	Path cost(Optimization)	Path density Factor(Optimization)
50	23.45	0.02	22.12	0.03
100	45.34	0.04	44	0.05
150	52.34	0.045	49.34	0.064
200	56.34	0.023	54.34	0.034
250	70.56	0.034	67.45	0.045
300	80.34	0.0222	78.45	0.0332
350	85.45	0.034	80.23	0.0343
400	90.34	0.045	88.34	0.056

Table5.1 Model Performance by cost factor and path density factor with and without optimization or prediction

Fig 5.2 and table 5.1 shows the route choosing model performance on the basis of cost. On analyzing table 5.1 the comparison of cost and probability density function should be effective for reducing the cost of route. The cost of route selection reduces using optimization instead of prediction because optimization use learning approach and prediction use only dependency. So optimization improves accuracy of selecting effective route which also improves probability density function and reduces cost as well.

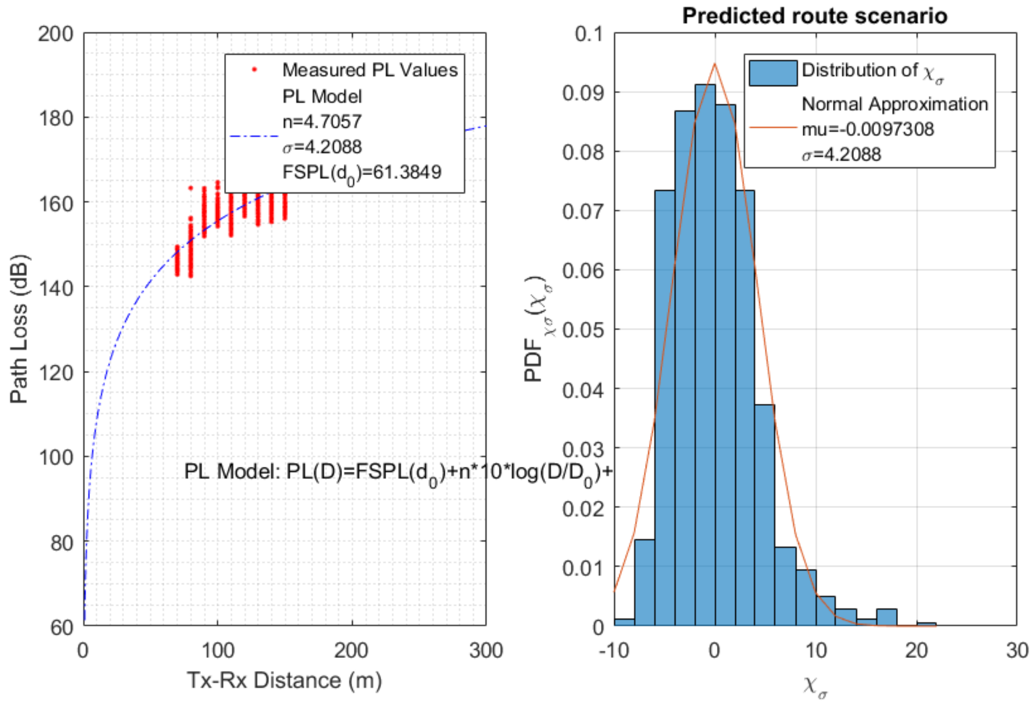


Fig 5.2 Model Performance by cost factor and path density factor with optimization

Fig 5.3 and table 5.3 show correlation between traffic and congestion which improves after reduction of cost by optimization which also improves the relation of correlation in fig 5.3

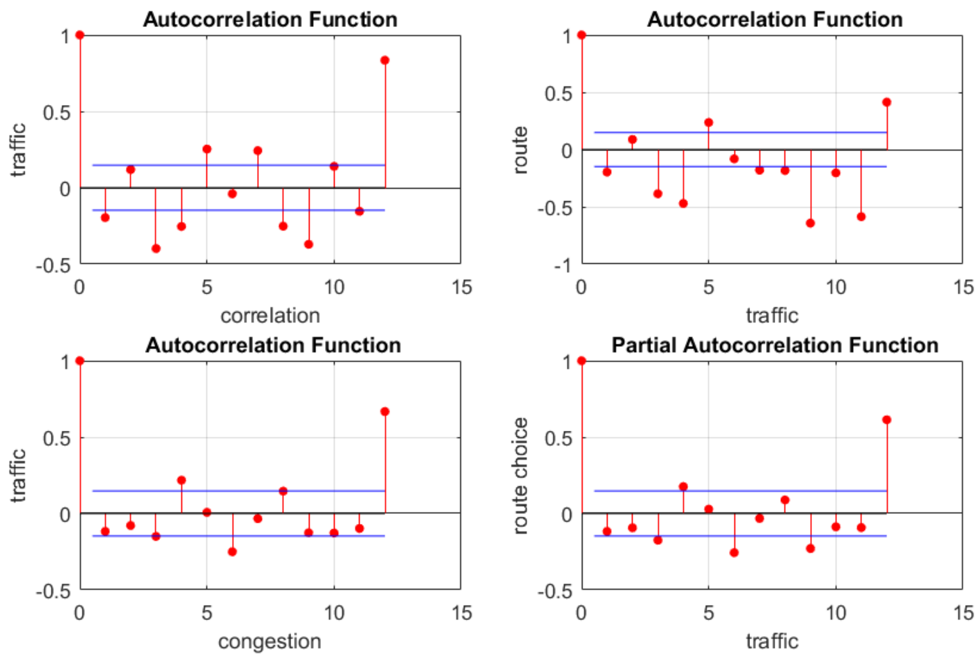


Fig 5.3 Model Performance by correlation on traffic and congestion

Traffic flow(NV/Sec)	correlation(traffic)	correlation(congestion)
20	0.345	0.234
40	-0.234	-0.344
60	-0.12	0.23
80	0.456	0.985
100	0.665	0.222
120	0.234	-0.456
140	-0.1233	0.3455

Table 5.3.Model Performance by correlation on traffic and congestion

CONCLUSION

Urbanization is increased in the last two decades which creates some issues in the urban areas. The demand for transportation facilities also increased due to urbanization. The urban population also increased due to peoples heading toward the employment in the cities to earn wages. The rapid growth of urban region also increased the industrialization which also enhances the demand of transportation to fulfill the requirements. As the urbanization increased per capita income of the peoples also increased and it leads the people to use personal vehicles. These vehicles enhance the congestion of traffic on roads and highways. The high rate of traffic on road leads to accidents and it is primary cause of accidental death in cities. The main reason of these problems is imbalanced and in sufficient transportation infrastructure. traffic congestion problem is a major issue for the peoples due to bas traffic management and road conditions. In traffic congestion vehicles on the roads occupy all the space at the same time and make the condition of jam on the road. Congestion on roads also enhances the total travel time of the vehicles and also enhances the capacity of fuel consumption. The travel time metric is an important metric in traffic congestion management. This study also determines the travel time and delay on the highways

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