International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7219
***Article Received**: 27 April 2023 **Revised:** 12 June 2023 **Accepted:** 28 June 2023*

PAARGAMAN: Passenger Demand Provoked (On-The-Fly) Routing Of Intelligent Public Transport Vehicle with Dynamic Route Updation, Generation, and Suggestion

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Abstract: Demand-based public bus service meets the need of passengers with less money, time, and resources by reducing the number of private vehicles on the road. In contrast, dynamic real-time demand-based routing faces challenges like elevated travel time due to the requested assignment based on the paths and vehicle availability. Hence, this research introduces a novel framework named Passenger Influence Bus Service-Intelligent Public Transport System (PIBS-IPTS) for efficient routing of available vehicles based on the demand of passengers. For this, optimal paths are elected from the known routes of the general vehicle through the Cuckoo Search (CS) optimization algorithm. Then efficient route prediction is employed by the Artificial Neural Network (ANN) for passenger flow. Here, the unavailability of the passenger request, such as source location or Destination locations, or the unavailability of both locations is updated while employing the path generation process. The path generation process ensures the reduction of request drops generated by the passenger, which elevates the usage of the general bus service. Here, for the optimal selection of routes from the identified routing paths, a multi-objective function based on traffic density, route condition, and route mobility is employed for the selection of a near-optimal global solution. The method's performance is analyzed using MAE, RMSE, and MAPE and obtained the best values of 0.69, 0.72, and 0.74, respectively.

Keywords: Intelligent public transport system, passenger demand, routing, neural networks, Internet of things, optimization.

I. INTRODUCTION

The enormous population growth leads to the elevation of vehicles, which creates multidimensional challenges and issues for transportation management. The problems concerning current transport management need a shift with out-of-the-box and innovative solutions for efficient transport management shortly, which is possible through the Internet of things (IoT). The IoT is the network comprised of actuators, sensors, software and electronic devices to share, process, and collect data for real-world applications integrated with software-based systems, which minimizes the human burden in daily lives. Thus, considering the benefits of the IoT for smart transportation leads to the development of Intelligent Transport Systems (ITS). Using the cutting-edge technology and innovative methods, the issues concerning multivariate problems are solved through ITS [1, 2]. The services based on different transportation modes and the innovative models with user-friendly criteria make the ITS a holistic transport management system. Here, the innovative solutions for better transportation management utilize the IoT sensors in the network. The role of the sensors is to gather information on a real-time basis, and gathered information is used for feeding the subsystems of the network, like data processors and communication channels [3-5]. Thus, the operation of the ITS requires enormous data for modelling the data-driven techniques for enhancing the efficiency of the process. Ships, aeroplanes, track trucks, or public transportation services are improved through better traffic management plans using the gathered information from real-time data. The goal of the services is to reach the destination with the shortest and best routes with minimal traffic, which makes the ITS revolution for enhanced performance [6, 7]. The comfort perception (CP) of the user using the ITS service is required for the improved performance of the model, which is obtained by considering the user's demands [8].

The public bus system demand-based modern transportation does not adhere to static timetables and routes. Variable types like hybrid, flex-route, flexible, demand-

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responsive, demand-adaptive, dial-a-ride, and on-demand are the various terms utilized for the usage of modern general transportation [9, 10]. In demand-based transportation, the individual's need is considered while planning the general bus routing through flexible criteria [11, 12]. For processing the Demand-Responsive Public Bus Systems (DR-PBS), the user's details, like departure time, and the source and destination places, need to be gathered. The user's information is acquired through smart stops, roadside units (RSUs), mobile devices, or real-time data. Modern demand-based responsive transportation needs to serve the user when traditional bus service has a large variance between the normal and peak times or lower transportation facilities in rural areas [13]. Traditional public transportation travels on a static path with fixed timing and routes that fill the buses almost empty to the brim [14]. Here, the overfilled public vehicle frustrates the user or the open general vehicle wastes resources that cause economic loss; thus, both situations are undesirable. Hence, modern demand-based available transportation considers the best paths based on the user's needs with a shorter time frame than the traditional mechanism [9].

A massive amount of research has been introduced by researchers for smart transportation based on ITS. The ITS based on the fixed path routing criteria requires an enormous amount of time; hence, dynamic routing is considered an essential criterion for smart public vehicle transportation. The dynamic routing of the vehicle is utilized by auto-rickshaws or Demand Responsive Transit (DRT), or hired taxis [15]. The cost concerning dynamic routing increases based on the fleet size. Public vehicle routing based on dynamic routing has network and fleet size limitations. Also, the demand of the passenger needs to be known by the route generator before the starting of the vehicle [17, 18]. Dynamic vehicle routing by considering the larger fleet size with the route updates is employed in this research based on the passenger request.

Smart transportation using intelligent transportation is essential for resource management and reducing traffic congestion, in which the efficient routing of the vehicles based on user demand plays a crucial role. Several methods were designed for the optimal routing of vehicles based on user demand. Still, the inefficient routing, higher travel cost, and higher travel time limit the model's performance, which motivates the development of a novel technique to fulfil the challenges. Thus, PIBS-IPTS is introduced to overcome the limitations faced by conventional methods. The significant contributions of the research are:

- ***Proposed Route Generation Technique***: The new paths requested by the passenger are updated using the Routing update process in the route generation algorithm, in which three various cases, like unavailability of source location, destination location or unavailability of both, are updated in the route generation criteria for the minimization of requested drop probability to enhance the usage of general bus service.
- ***Proposed Multi-objective function for optimal route selection***: The optimal path selection is employed using the CS algorithm. The fitness of the CS algorithm is generated based on traffic density, route condition and routes mobility for the acquisition of the near global optimal solution.
- ***Performance Analysis***: The proposed PIBS-IPTS is analyzed using assessment measures like MAE, RMSE and MAPE to show the robustness of the developed technique.

The proposed PIBS-IPTS is organized as follows: The related works were reviewed to identify the problem statement and are detailed in Section 2. The methodology of PIBS-IPTS is described in Section 3, and its analysis based on the outcome is illustrated in Section 4. Finally, Section 5 concludes the research.

II. RELATED WORKS

The traditional methods concerning the intelligent transportation system with dynamic routing based on user demand are elucidated here. A machine learning-based vehicle scheduling based on user demand was introduced by Rajkumar, S.C. and Deborah, L.J [19] for vehicle traffic optimization. In this, the instant reservation of seats in the vehicles was accomplished by real-time sensors through efficient communication. Then, based on the demand of the passenger, the seats were reserved by considering the convenient travel time. The devised method established more accurate scheduling and obtained minimal usage of my vehicle in the city by enhancing general vehicle usage.

Zhou, Z. and Roncoli, C. [20] introduced a ridesharing approach based on user requests in a congested network with optimal vehicle assignment to reduce costs. Here, consider factors like time constraints, waiting time, and the vehicle's capacity was considered for the user request processing. The available vehicles on the particular route were identified, and the path with the shortest distance was utilized for vehicle routes. This helps to avoid the overutilization of resources, which in turn minimizes the cost required for travel. In addition, the prediction module was included for predicting the travel time by considering the departure time and the present traffic conditions. Here, using traffic and dynamic paths while

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assigning the issue optimally ensures a reasonable computation time.

The issue concern the scheduling and vehicle routing for the dynamic environment with the flexible routing strategy designed by Zheng, Y *et al.* [21]. Here, the dynamic requests of the user, cancellations, and variations in travel time were considered for the dynamic event scheduling. In this, the detection of the optimal path was employed for the vehicle routing while considering the offline scenario, in which the costs like vehicle cost and passenger cost were considered the objective function for solving the optimization issue in routing. However, in online scheduling, the queuing of the user request is employed for processing the dynamic user request. It employed flexibility in reserving the tickets for the enhancement of real-time processing.

The travel demand-based vehicle routing for the real-time application with the optimal schedule was devised by Han, S *et al.* [22]. In this, the user's demand is utilized for scheduling the vehicle, in which several scheduling strategies were developed based on the vehicle routing. Finally, the optimal route is acquired using the genetic Algorithm using the heuristic insertion criteria. The interference between the vehicles while routing is achieved through the holistic planning of the hierarchical model. The stable service level increases the number of users compared to the dynamic criteria.

The user requested based vehicle routing by considering the trip choice was designed by Wang, L *et al.* [6] using the discrete choice model. In this, the users' choices were combined based on demand, and then the deliveries and pickups were devised through the efficient routing technique. The vehicle's route is employed optimally by considering the capacity of constraints and the time. The dynamic scheduling of the vehicle is employed through the batch processing criteria, in which batches of user trips are considered for scheduling. It enhanced the efficiency of the method through the minimization of vehicle detours. The challenges and benefits of the prior methods are depicted in Table 1.

Table 1: Literature Review

Reference	Technique Used	Benefits	Challenges
Rajkumar, S.C. and Deborah, L.J [19]	Dynamic Scheduling Algorithm for vehicle scheduling based on user demand	The traffic in the city was optimized through promising solutions for user demand.	The optimal Prediction using machine learning can enhance the accuracy of the method.
Zhou, Z. and Roncoli, C. [20]	Dynamic assignment of vehicles based on user request	The traffic avoidance approach minimized the waiting time and average travel time.	The traffic of the network gets affected due to the failure while considering the other private vehicles in the analysis.
Zheng, Y *et al.*[21]	Flexible vehicle routing and scheduling for the dynamic environment through optimal routing	The user's idle time and waiting time were minimized through optimal routing.	Consider significant attributes like travel time for optimal routing to maintain the method's performance.
Han, S *et al.*[22]	Optimal hierarchical scheduling for real-time responsive, customized buses	The latency of the method was minimal while using the tight time window-based scheduling of vehicles.	The challenge of the technique was that multiple vehicles were considered for scheduling the user demands.
Wang, L *et al.* [6]	Demand-based optimal routing for customized bus	The trip request-based routing with minimized detours elevates the efficiency of the method.	The computational complexity was higher.

A. Problem Statement

Public transportation is widely utilized by the population of the cities, in which the automation of transportation is essential for smart cities, which is possible through intelligent transportation systems. Efficient smart transportation requires minimal traffic congestion with the consideration of user demand, which is possible through a better routing strategy. The user request-based vehicle routing assures the usage of public transportation, which helps to minimize the usage of private vehicles, which reduces traffic congestion and hazardous gas emissions. Several methods were developed for the user demand based on routing techniques, but several issues still need to be solved. Some of the issues are:

- The failure to include the optimization technique for reduction of the cost required for travelling and the complexity in solving the non-linear optimization raises the computation overhead and hence limits the performance of the method [20].
- The non-optimal routing makes a trade-off between the user demand and the transporter, limiting the passenger's real-time travel demands [22].

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- Selecting the right vehicle for travelling from one location to the other is a challenging task for users with minimal time and cost [19].
- The delays concerning user request queuing, overutilization of the available resources, and traffic congestion affect the public transportation system due to the inefficient dynamic user request handling criteria [21].
- The failure to consider the significant attributes and particular variables made the model more complex and not applicable to real-world processing issues [6].

III. PROPOSED METHODOLOGY

The IoT network with passengers, sensors, software, and electronic devices is utilized for demand-based vehicle routing obtained through an Intelligent Transport System (ITS). Using cutting-edge technology and innovative methods, the issues concerning multivariate problems are solved using ITS. Hence, Passenger Influence Bus Service-Intelligent Public Transport System (PIBS-IPTS) is proposed for demand-based public bus service. The proposed PIBS-IPTS follows three modules, the IoT Bus module, the computation module, and the prediction module. In the IoT module, the passenger request is utilized to assign the Public Transit Vehicle (PTV) and issue the ticket through the Ticket Issuing Counter (TIC). Then, the possible routes are identified through the existing routes of the general bus service. Suppose the requested route needs to be specified in the existing routes. In that case, route updation is employed by considering three different criteria: unavailability of a source location, unavailability of a destination location, and unavailability of both the source and destination locations. Route updation assures the reduction of request drops and further elevates the usage of public bus service. The optimal paths are chosen from the generated routes using the CS algorithm, in which fitness is evaluated based on multi-objective factors like traffic density, route condition, and route mobility for efficient optimal routes. The chosen optimal routes are fed into the ANN to predict the best route for passenger flow. The block diagram of the PIBS-IPTS is depicted in Figure 1.

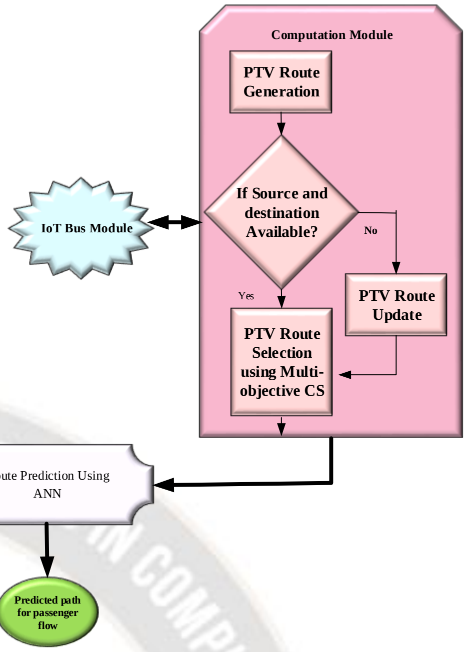

Figure 1: Block diagram of proposed PIBS-IPTS

A. IoT Bus Module

Modern transportation, along with the citizen-friendly infrastructure, availability and safety factors to be utilized in the Public Transport System (PTS), motivated the research. The country's economic growth depends on transportation growth, in which demand-based routing helps enhance public vehicle usage. Hence, a novel framework is proposed in this research for the demand-based efficient routing of the passenger based on the IoT scenario. Let the destination and source location of the passenger is indicated as L_i^D and L_i^S and $(PTV_1, PTV_2, PTV_3, \ldots\ldots PTV_n)$ refers to the Public Transit Vehicles (PTV), which n indicates the total number of vehicles. The Ticket Issuing Counters (TIC) is represented as $(TIC_1^k, TIC_2^k, \ldots\ldots TIC_p^k)$ in which its total count is notated as p for the k^{th} PTVS notated as $PTVS_k$. Here, the TIC is located in the Public Transit Vehicle Stations (PTVS), denoted as $(PTVS_1, PTVS_2, \ldots\ldots PTVS_m)$. The server receives all requests T_i from the passenger for establishing efficient routes through route updation to fulfilling the demand. The system model is depicted in Figure 2.

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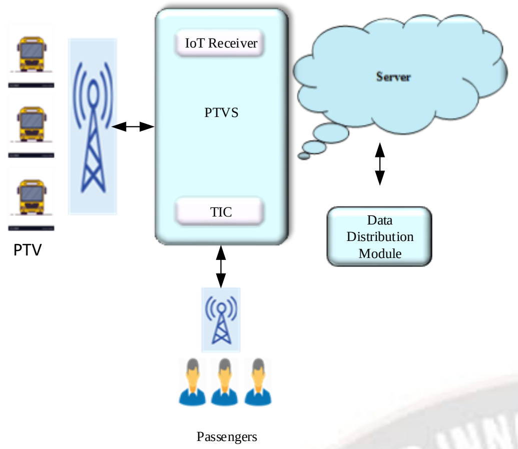

Figure 2: System Model of IoT Bus Module

The major components of the IoT Bus Module are:

- ***User Demands/Requests***: The passenger $U = \{u_1, u_2, u_3, \ldots u_n\}$, request the ITS to generate the ticket for the travel demands $T = \{T_1, T_2, \ldots T_n\}$ from the PTS. The demand of the passenger comprises four components like $\{T_i, L_i^S, L_i^D, PTS_{id}\}$, in which the destination and the source location are indicated as L_i^D and L_i^S. The registered public vehicle is notated as PTS_{id}, and the time stamp is indicated as T_i. The DUAROUTER Algorithm is utilized for demand generation using the SUMO tool.

- ***Public Transit Vehicle (PTV)***: The demand or request of the passenger is processed by PTV_{id}, Public transit vehicle. Here, the route selection based on the Multi-objective CS is utilized for selecting the optimal route, and the request is entered as u_i. The request drop happened due to the failure in assigning routes and is indicated as P_b.

- ***Ticket Issuing Counter (TIC)***: TIC generates the ticket for the passenger based on the demand and forwards it to the server, where the route selection and allocation are employed and returned to the TIC. Then, the TIC generates the ticket and issues it to the passenger. The generated TIC contains the information provided in equation (1).

$$TKT_{u_i}^{PTSV_{id}} = \sigma\left(L_i^S, L_i^D, PTSV_{id}, T_i, B_T, A_T\right) \qquad (1)$$

Where, the Public Transit Stoppage Vehicle (PTSV) identity is notated as $PTSV_{id}$ the time when the request is made is denoted as T_i. The Estimated Travel Time and Estimated Waiting Time are computed based on T_i and referred B_T *and* A_T.

B. Computation Module

The Computational module received the messages generated PTS_j by the IoT modules, working in coherence with each other as described above. The server module consists of majorly three algorithms: Route generation, Route selection, and Prediction.

1) Detection of all Possible Paths: The detection of all possible paths based on the source and the destination locations is gathered on the routing history. For the general bus service, some static paths are followed by the bus initially. Then, all the possible routes are updated based on the user's request. If there is no possible route for the passenger request, then route updation is employed.

a) Route Updation: The route updation is employed when the requested route is unavailable in the routing table. Here, for the route updation three various strategies are utilized. The three strategies are the non-availability of the source location, the destination location, or both the source and the destination location.

Case 1: The destination is unavailable, and the source is available in at least one route of the PTV_Route_Table: In this criteria, based on Figure 3, the route updation is employed for fulfilling the demand of the passenger. Thus, a destination is added to the routing table by updating the route. Here, the threshold (MAXτ) is utilized by the route update algorithm while updating the route by considering the total travel time and the route length. The route that exceeds the threshold will be dropped due to the infinite journey and divergence of the route.

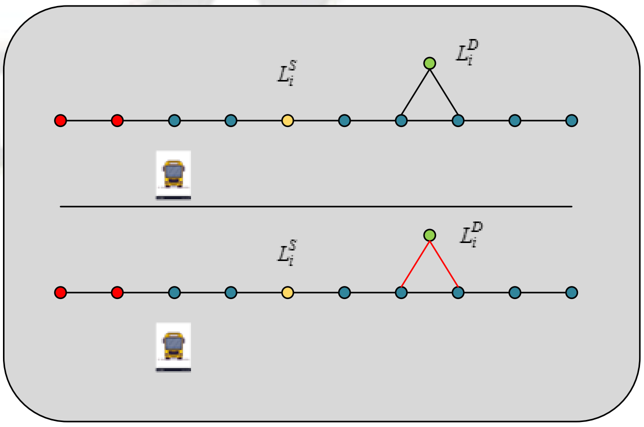

Figure 3: Route updation for unavailable destination

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Case 2: The source is unavailable, and the destination is available in at least one route of the PTV_Route_Table: In this criterion, based on Figure 4, the route updation is employed for fulfilling the demand of the passenger. Again, a threshold is used to update the unavailable source location that takes into account the vehicle time of all commuters to minimize unwanted travel time.

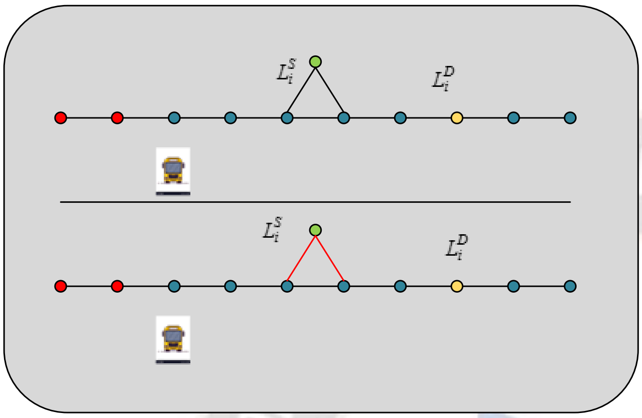

Figure 4: Route updation for unavailable source

Case 3: If neither Source L_i^S nor Destination L_i^D is unavailable, then Re_Update_Route is employed. Here, all the possible ways are analyzed and updated, as shown in figure 5, to fulfil the demand of the passenger. Figure 5 demonstrates a situation where neither Source nor the Destination exists in any route. This is the most critical case to handle. The Algorithm first tries to add a source into all possible PTV routes assuming that a destination exists in them. After adding the source, it calls the method of adding the destination for that request. After updating the route, optimal routes are detected through the CS.

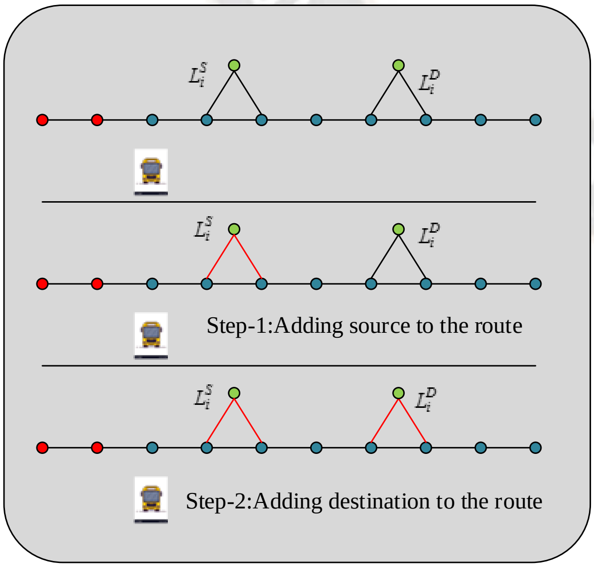

Figure 5: Route updation for unavailable Source and Destination

2) Optimal Routes selection using CS: The optimal routes from all identified paths are selected using the CS, in which the multi-objective fitness function is utilized.

Proposed Multi-objective Fitness Function: The fitness of the CS for identifying the optimal routes is employed based on the multi-objective factor like traffic density, condition of the route and mobility of the route.

(i) Traffic Density: The total number of vehicles in the IoT network at a particular time is measured for the detection of traffic density and is denoted as TD. The normalized traffic density is represented as TD_{norm}.

(ii) Condition of the route: The condition of the route[23] is estimated based on the present, and past information concerning the dynamic factors like routes, vehicles, staff, and formulation for the evaluation of route condition is expressed as,

$$P\left(M \middle| I_{context}^{c}, I_{context}^{h}\right) = \bigcup_{v=1}^{3} P\left(M \middle| I_{context}^{cv}, I_{context}^{hv}\right) \tag{2}$$

Where, the Context information corresponding to the current information is notated as $I_{context}^{c}$, and the Context information corresponding to the past information is notated as $I_{context}^{h}$. Here, the foggy condition is referred to as $v=1$, the sunny condition is referred $v=2$ to, and the rainy condition is notated as $v=3$. The normalized condition of the route is defined as RC_{norm}.

(iii) Mobility of the route: The dynamic state of the route, like traffic jams, accidents, density and movements, is utilized for the detection of route mobility [23] and is formulated as,

$$P\left(K_T^i \middle| \bigcup_w \left\{K_{T-1}^w, I_{context(T-1)}^{w,h}\right\}, I_{context(T)}^{w,c}\right) \tag{3}$$

Where the set of routes is notated as K^w, the contextual information set is notated as w, which refers to the traffic jam, accidents, density and movements; and the routes dynamic state is referred K_T^i to as. Here, the normalized mobility of the route is defined as RM_{norm}.

Then, the proposed multi-objective fitness function is expressed as,

$$PTS_{fitness} = \frac{(1 - TD_{norm}) + RC_{norm} + RM_{norm}}{3} \tag{4}$$

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Where, the fitness of the CS algorithm for identifying the optimal routes is notated as $PTS_{fitness}$.

a) Motivation behind the selection of CS: The Cuckoo Search (CS) is widely utilized for solving optimization issues concerning multimodal optimization issues in vehicle routing. The method's rate of convergence, accuracy, and efficiency is higher due to the minimizing and maximizing capability of the desired parameter. The acquisition of the global best optimal solution for identifying the optimal routes is obtained effectively by the CS [24] [25]. The CS was designed based on the brood parasitism behaviour of the bird cuckoo, along with the levy fight mechanism. The Cuckoo lays the egg in the stranger's nest to enhance the survival rate. When the stranger identifies the egg as a cuckoo's egg, it destroys the egg or flies away to the other nest by abandoning the nest. Then, the Cuckoo searches for another best nest for laying the egg using the levy flight mechanism. In the proposed optimal route identification strategy, the egg laid by the Cuckoo in the most appropriate nest is the solution for identifying the optimal routes. The total number of nests in the sight area is the population size, which depicts all the identified paths in the previous stage detailed in section 3.2.1. The abandoning of the nest is nothing but the discarding of the worst routes identified. The search mechanism utilized by the Cuckoo for laying the egg is diversification criteria, and detecting the best nest for laying the egg is the optimal solution obtained in the intensification phase. The balanced intensification and diversification provide the world's optimal routing solution.

b) Mathematical Modeling: The CS for the optimal route selection from the identified all possible paths is detailed in this section.

Initialization: Let $Q^{\tau} = \{Q_1^{\tau}, Q_2^{\tau}, ...Q_H^{\tau}\}$ be the population of the Algorithm, in which the number of eggs is notated as H. Then, the total number of iterations is indicated as $\tau_{\max}$ and initialized with the value 0. The eggs in the sight area have the dimensional vector of size s, which is represented as $Q_{m,1}^{\tau}, Q_{m,2}^{\tau}, ...Q_{m,s}^{\tau}$. Here, the proposed multi-objective fitness function is utilized to detect the best optimal route.

Estimation of Fitness: The near-optimal solution estimation compared to the target solution based on the multi-objective fitness function is employed using the equation (4), which helps to detect the optimal best solution.

Levy Flight: The new solutions for identifying the optimal routes are obtained through the levy flight criteria of the Cuckoo in laying eggs. The change in position p_m is included with the past iteration Q_m^{τ} for acquiring the current best solution $Q_m^{\tau+1}(m \in [1,2,....H])$. Here H refers to the number of eggs and m the Cuckoo in the sight area. Here, the change in position p_m is estimated using Mantegna's Algorithm and is formulated as,

$$p_m = \frac{x}{|y|^{1/\alpha}} \tag{5}$$

Where the dimension of factors $x\, and\, y$ are expressed as $x(\{x_1, x_2, ...x_s\})$ and $y(\{y_1, y_2, ...y_s\})$ respectively, and the constant α is assigned with the value of $\alpha = 3/2$. The values for the factors $x\, and\, y$ are obtained through the expression,

$$x \sim H\left(0, \delta_x^2\right), \quad y \sim H\left(0, \delta_y^2\right),$$

$$\delta_x = \left(\frac{\Gamma(1+\alpha).\sin(\pi.\alpha/2)}{\Gamma((1+\alpha)/2).\alpha.2^{(\alpha-1)/2}}\right), \quad \delta_y = 1 \tag{6}$$

Where, the gamma distribution is notated as $\Gamma(.)$. Then, the change in position is expressed as,

$$q_m = 0.01 \cdot p_m \oplus \left(Q_m^{\tau} - Q^{good}\right) \tag{7}$$

Where, the better position is notated as Q^{good} and the location during the past iteration is notated as Q_m^{τ}. The multiplication performed based on the entry is notated as $\oplus$. Then, the position updation of the solution by the search agent is expressed as,

$$Q_m^{\tau+1} = Q_m^{\tau} + q_m \tag{8}$$

Solution Updation: The new value is assigned for a solution based on the probability by generating a random number l within the interval of $[0,1]$ and is represented as $R_k \in [0,1]$. Here, the new solution updation is employed when the value of the probability factor R_k is higher than the generated random number; else, the position remains unchanged and exists in the old position for all the individuals $Q_m^{\tau}(m \in [1,2,....H])$. The solution updation for detecting the optimal routes is expressed as,

$$Q_m^{\tau+1} = \begin{cases} Q_m^{\tau} + e \cdot \left(Q_{r1}^{\tau} - Q_{r2}^{\tau}\right), & for\, R_k \\ Q_m^{\tau}, & for\,(1 - R_k) \end{cases} \tag{9}$$

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Estimating the Feasibility: The feasibility of the updated solution is employed through the re-estimation of the fitness function presented in equation (4). Then the solution updation is employed as,

$$Q_m^{\tau+1} = \begin{cases} Q_m^{\tau+1}, & if \ f\left(Q_m^{\tau+1}\right) < f\left(Q_m^{\tau}\right) \\ Q_m^{\tau} & Otherwise \end{cases} \quad (10)$$

Where the $f(\cdot)$ refers to the fitness of the routing solutions generated in the present and the past iterations by the CS criteria.

Stopping Criteria: The accomplishment of the global best optimal solution for detecting the optimal route or the accomplishment of $\tau_{\max}$ stops the iteration. The pseudo-code is presented in Algorithm 1.

Algorithm 1: Pseudo-code for the CS algorithm

Pseudo-code for the CS algorithm
Input: Initialize the population, iteration and the probability factor
Initialize the population as: $Q^{\tau} = \left\{Q_1^0, Q_2^0, \ldots\ldots Q_H^0\right\}$
Repeat until $\tau_{\max}$
Estimate the fitness for all the population in the sight area using equation (4)
Update the solution based on the levy flight using equation (8)
Evaluate the feasibility using equation (10)
Update the solution obtained based on the probability factor using equation (9)
Evaluate the feasibility using equation (10)
Update the global best solution
End

3) Prediction of the best route using ANN: The optimal routes selected from the CS are fed into the ANN to predict the best route for passenger flow. The ANN can change the network structure per the requirement and provide better results based on the information learning. Besides, the ANN learns the complex features from the data and makes the generalization more appropriate for the unknown data [26]. Thus, the Prediction of the best route from the identified optimal routes is devised using the ANN in the proposed demand-based routing technique. Here, the factors like traffic density, routing time, and vehicle load are considered for predicting the best route.

Vehicle load: The total number of passengers in the vehicle is extracted for all the optimal routes and is denoted as VL.

Routing Time: The time required for the passenger to travel from the source and the destination place, which is indicated as RT.

Traffic density: The traffic density of all the optimal routes is measured by counting the vehicles in the particular route and is notated as TD.

The minimum of these factors $VL, RT \, and TD$ is utilized to predict the best path from all identified optimal routes. The architecture of the ANN utilized for the Prediction of the best route is presented in Figure 6 [27].

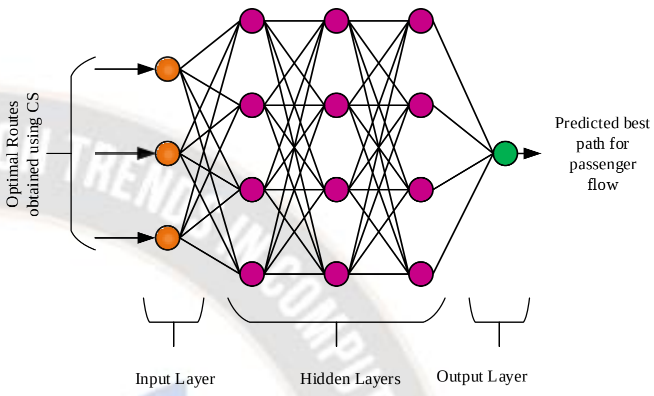

Figure 6: Architecture of ANN-based route prediction

The layers utilized in the ANN, along with the functioning, are:

Input Layer: The optimal routes detected using the CS algorithm are fed as input to the input layer of the ANN for the Prediction of the best route.

Hidden Layer: The transformation of input into the non-linear function is employed in the hidden layer. Here, the weights are assigned to the input and fed into the activation function for making the non-linearity.

Output Layer: The Prediction of the best route for the passenger flow is obtained in the output layer. It is estimated based on the input along with the weight and bias of the neuron and is formulated as,

$$PO = \sum (wei * input) + bias \quad (11)$$

Where, the weight is notated as wei, the bias is indicated as $bias$ and the input is defined as $input$ and the predicted route is notated as PO, respectively. Thus, considering all the available routes, the best route is predicted for the passenger flow.

IV. RESULTS AND DISCUSSION

The introduced PIBS-IPTS is implemented using MATLAB tool and discussed based on the assessment measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), respectively.

International Journal on Recent and Innovation Trends in Computing and Communication
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DOI: https://doi.org/10.17762/ijritcc.v11i8s.7219
***Article Received**: 27 April 2023 **Revised:** 12 June 2023 **Accepted:** 28 June 2023*

A. Assessment Measures

Assessment measures like MAPE, RMSE and MAE are utilized to interpret the introduced PIBA-IPTS technique by varying the number of vehicles in the network. The description of the assessment measures are:

- ***MAPE***: The normalized MAE based on the predicted outcome of the introduced PIBA-IPTS is measured through MAPE and is formulated as,

$$P_{MAPE} = \frac{100}{W}\sum_{i=1}^{W}\left[\frac{PO-\hat{PO}}{PO}\right] \quad (12)$$

Where, the MAPE is notated as P_{MAPE}, and the total number of data samples is represented as W. The output acquired by the introduced PIBS-IPTS is defined as $\hat{PO}$, and the expected result is notated as PO.

- ***RMSE***: The squared variation between the expected outcome of the PIBS-IPTS and the predicted outcome is measured through the MSE that indicates the standard deviation of residuals. It is formulated as,

$$P_{RMSE} = \sqrt{\frac{1}{W}\sum_{i=1}^{W}\left(PO-\hat{PO}\right)^2} \quad (13)$$

Where, the RMSE is notated as P_{RMSE}.

- ***MAE***: The absolute variation between the expected outcome of the PIBS-IPTS and the predicted outcome is measured through the MAE. It is formulated as,

$$P_{MAE} = \frac{1}{W}\sum_{i=1}^{W}\left|PO-\hat{PO}\right| \quad (14)$$

Where, the MAE is notated as P_{MAE}.

- ***Request Drop***: The request drop is defined as the number of demands raised by the passenger not processed by the proposed PIBS-IPTS method.
- ***Average Response Time***: The time taken by the proposed PIBS-IPTS to return the response to the requested passenger is measured through the response time evaluation. The average response time is measured within a particular time limit.
- ***Average Waiting Time***: The time gap between the ticket issuing and the vehicle's arrival at the source location is the waiting time taken by the proposed PIBS-IPTS. The average waiting time is measured within a particular time limit.
- ***Average Travel Time***: The time taken by the passenger from the source location to the destination location is the travel time evaluated by the proposed PIBS-IPTS. The average travel time is measured within a particular time limit.

B. Experimental Results

Figure 7 illustrates the routing of the proposed PIBS-IPTS method. The initial routes present in the bus routing based on the history are depicted in Table 2, and the bus routing after updating the routes based on the PTV updation is depicted in Table 3.

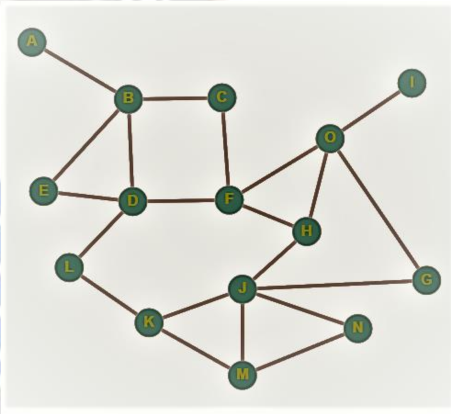

Figure 7: Proposed PIBS-IPTS bus routing

Table 2: Bus routing before Route Updation

No	Route
1	12to9 9to6 6to14 14to5 5to2 2to1 1to0 0to0 0to1 1to2 2to5 5to14 14to6 6to9 9to12
2	2to5 5to7 7to14 14to8 8to8 8to14 14to7 7to5 5to2 2to1 1to4 4to3
3	12to10 10to11 11to3 3to3 3to11 11to10 10to12 12to13 13to9 9to6 6to14
4	1to3 3to5 5to7 7to14 14to6 6to9 9to9 9to6 6to14 14to7 7to5 5to3 3to1 1to0
5	9to7 7to5 5to2 2to1 1to0 0to0 0to1 1to2 2to5 5to7 7to9 9to10 10to12
6	1to4 4to3 3to11 11to10 10to12 12to13 13to13 13to12 12to10 10to11 11to3 3to4 4to1
7	13to12 12to10 10to10 10to12 12to13 13to9 9to7 7to5 5to3 3to4
8	14to6 6to9 9to10 10to11 11to3 3to4 4to4 4to3 3to11 11to10 10to9 9to6 6to14 14to8

Table 3: Bus routing after PTV Route Updation

No	Route
1	12to2 2to6 6to10 10to11 11to11 11to10 10to6 6to2 2to12
2	4to5 5to2 2to6 6to8 8to8 8to6 6to2 2to5 5to4

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3	6to2 2to10 10to7 7to2 2to3 3to3 3to2 2to7 7to10 10to2 2to6
4	8to2 2to3 3to6 6to10 10to10 10to6 6to3 3to2 2to8
5	6to3 3to2 2to6 6to10 10to11 11to11 11to10 10to6 6to2 2to3 3to6
6	5to2 2to6 6to10 10to11 11to11 11to10 10to6 6to2 2to5
7	1to2 2to6 6to10 10to14 14to14 14to10 10to6 6to2 2to1
8	9to2 2to6 6to10 10to11 11to11 11to10 10to6 6to2 2to9

C. Analysis of PIBS-IPTS based on Route Generation

The analysis based on the route generation with and without the PTV route updation based on the request drop, average response time, average waiting time and travel time is detailed in this sub-section. Here, the proposed PIBS-IPTS performance is measured based on the request raised by the passenger concerning the routes Route-4, Route-6, Route-7 and Route-8. The number of requests considered for evaluating the proposed PIBS-IPTS is 1000, 2000, 3000, 5000 and 10,000.

1) Analysis based on Request Drop: The analysis based on the request dropped by the proposed PIBS-IPTS is depicted in Table 4, in which the maximal request dropped without generating the route is 1620 for Route-8. The same request drop with the route generation is 1542, which is a 4.81% minimal request drop compared to the request drop without route generation for Route-8. Hence, incorporating the route generation in the proposed PIBS-IPTS reduces the number of request drops.

Table 4: Analysis of PIBS-IPTS based on Request Drop

Request Drop				
Without route generation				
Number of requests/ Route	Route-4	Route-6	Route-7	Route-8
1000	314	125	88	182
2000	546	288	166	324
3000	818	418	236	495
5000	1299	711	398	812
10000	2620	1347	827	1620
With route generation				
1000	312	118	79	193
2000	576	305	163	322
3000	887	409	224	451
5000	1338	739	380	746
10000	2573	1380	834	1542

2) Analysis based on Average Response Time: Table 5 depicts the average response time evaluated by the introduced PIBS-IPTS. The average response time measured by PIBS-IPTS is 371.36 for 5000 passenger requests, which is 3.20% higher compared to the average response time with route generation for Route-8. In addition, as the number of demands raised by the passenger increases, the average response time also elevates. Route-4; estimates an average response time of 17.75 for 1000 requests, which is a 90.50% minimal average response time compared to the 10,000 requests without the route generation criteria.

Table 5: Analysis of PIBS-IPTS based on Average Response Time

Average Response Time				
Without route generation				
Number of requests/ Route	Route-4	Route-6	Route-7	Route-8
1000	17.75	17.07	19.16	48.83
2000	34.42	40.31	47.41	98.31
3000	50.64	72.95	84.03	168.49
5000	84.4	145.4	169.9	371.36
10000	186.84	463.41	530.45	1097.59
With route generation				
1000	17.35	16.32	18.47	46.99
2000	33.62	43.17	43.95	95.45
3000	52.19	68.69	84.62	168.82
5000	90.51	157.22	167.52	359.47
10000	186.21	462.59	520.24	1207.11

3) Analysis based on Average Waiting Time: The average waiting time assessed by the PIBS-IPTS is presented in Table 6. For route 7, the average waiting time evaluated for 3000 passenger requests is 4.22, which is 4.15% higher than the average waiting time with route generation. Hence, incorporating the route generation technique reduces the average waiting time of passengers for the vehicle, which elevates public transportation usage. Besides, the analysis depicts that the number of passenger requests doesn't impact the average waiting time because the analysis doesn't show any increase or decrease in the value based on the number of passenger requests.

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Table 6: Analysis of PIBS-IPTS based on Average Waiting Time

Average Waiting Time				
Without route generation				
Number of requests/ Route	Route-4	Route-6	Route-7	Route-8
1000	4.85	4.85	4.74	5.28
2000	4.96	4.09	4.56	4.96
3000	4.95	4.23	4.22	4.51
5000	4.98	3.56	3.62	4.6
10000	4.82	3.49	3.61	4.17
With route generation				
	Route-4	Route-6	Route-7	Route-8
1000	4.40	4.39	4.53	4.92
2000	4.57	3.69	4.26	4.94
3000	4.75	4.38	4.04	4.41
5000	4.56	3.50	3.53	4.21
10000	4.54	3.27	3.31	3.88

4) Analysis based on Average Travel Time: Table 7 depicts the average travel time estimated by the introduced PIBS-IPTS technique. The average travel time estimated by Route-6 is 5.01, which is 8.61% minimum compared to the average travel time estimated with route generation.

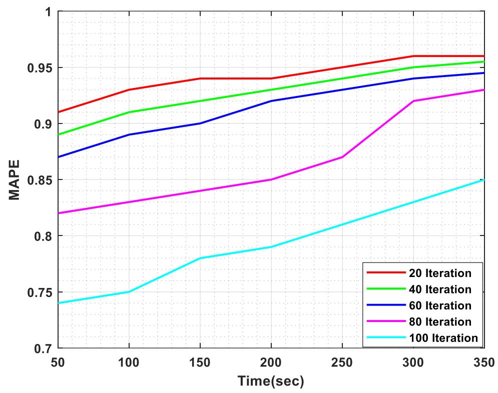
Table 7: Analysis of PIBS-IPTS based on Average Travel Time

Average Travel Time				
Without route generation				
Number of requests/ Route	Route-4	Route-6	Route-7	Route-8
1000	5	5.94	7.47	7.39
2000	4.83	5.01	5.17	7.01
3000	4.83	5.79	5.12	7.08
5000	4.65	5.1	5.63	7.18
10000	4.46	5.16	5.08	7.77
With route generation				
1000	4.50	5.63	7.38	7.27
2000	4.38	5.48	5.61	6.65
3000	5.23	5.70	4.87	6.42
5000	4.63	4.87	5.64	7.42
10000	4.19	4.86	5.28	7.15

D. Analysis of PIBS-IPTS

The performance of the introduced PIBS-IPTS is analyzed by varying the number of vehicles in the network to measure the robustness of various traffic densities. Here, the number of vehicles utilized for the analysis is 1000 and 5000.

1) Analysis with 1000 Vehicles: The Analysis of PIBS-IPTS using 1000 vehicles by varying the iteration of the optimal route selection criteria for the Prediction of the best route to process the passenger's request is portrayed in Figure 8. The analysis based on MAPE is presented in Figure 8(a), RMSE in Figure 8(b) and MAE in Figure 8(c). For example, the MAPE estimated by PIBS-IPTS at 300 sec with the 80^{th} iteration is 0.92, which is 4.17% enhanced performance compared to the value measured at the 20^{th} iteration, which indicates enhanced performance with the elevation in several iterations. The analysis based on RMSE and MAE provides improved performance with an increased number of iterations.



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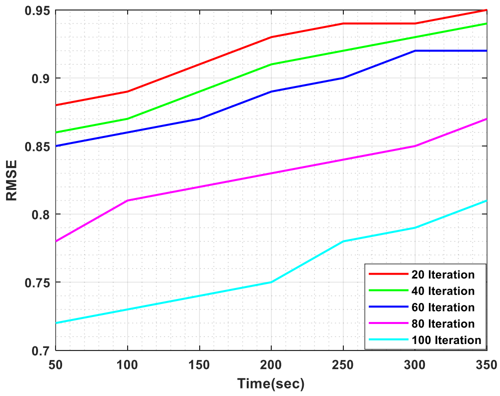

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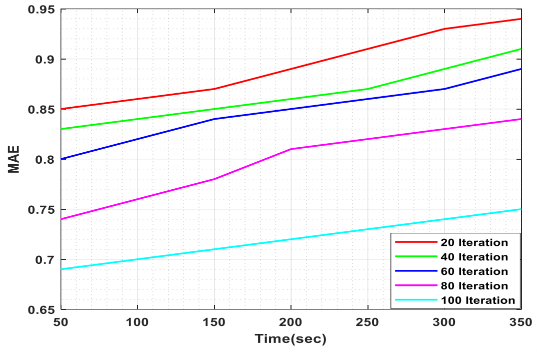
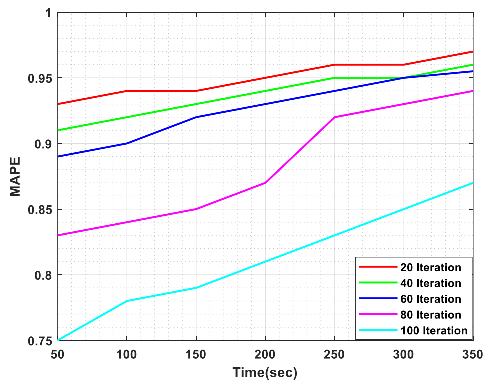


(c)

Figure 8: Analysis of PIBS-IPTS using 1000 vehicles in terms of (a) MAPE, (b) RMSE and (c) MAE

2) Analysis with 5000 Vehicles: The analysis of PIBS-IPTS using 5000 vehicles by varying the iteration of the optimal route selection criteria for the Prediction of the best route is portrayed in Figure 9. The analysis based on MAPE is presented in Figure 9(a), RMSE in Figure 9(b) and MAE in Figure 9(c). Here, the improved performance is also acquired with the increase in the number of iterations. The aim behind selecting optimal routes for the Prediction of passenger flow is to speed up the performance efficiently. In every iteration, the CS algorithm tries to find a solution closer to the issue: detecting the optimal routes based on the proposed multi-objective function. Hence, the number of iteration increases, and the CS algorithm progress towards acquiring a solution closer to the issue. Thus, the performance of PIBS-IPTS improved with the rise in iteration number.



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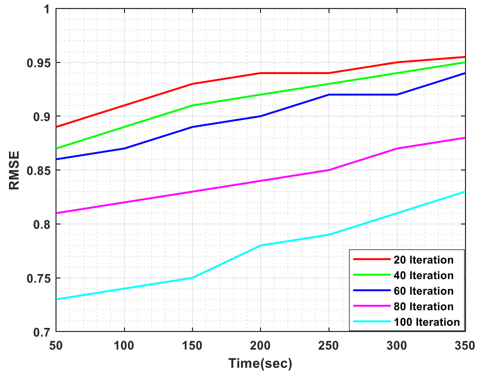

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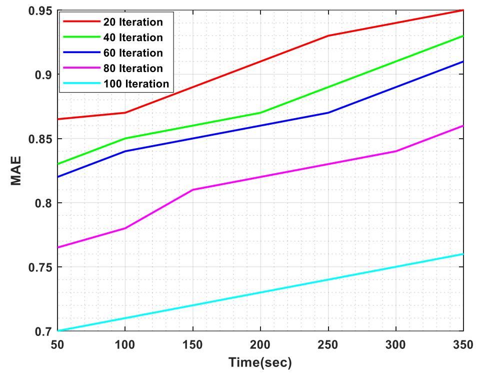

(c)

Figure 9: Analysis of PIBS-IPTS using 5000 vehicles in terms of (a) MAPE, (b) RMSE and (c) MAE

E. Comparative Analysis of PIBS-IPTS

The introduced PIBS-IPTS is compared with the prior methods like LSTM-MDN [1], RTRCB [4] and Customized DRT [7] to show performance improvement. The number of vehicles in the network is varied to show the scalability and robustness of the method.

1) Comparative Analysis with 1000 Vehicles: The comparative assessment of the introduced PIBS-IPTS is portrayed in Figure 10 based on the measures like MAPE, RMSE and MAE in Figure 10(a), Figure 10(b) and Figure 10(c), respectively. The MAE estimated by the introduced PIBS-IPTS at 350 sec is 0.75, which is 17.58%, 13.79%, and 11.76% elevated performance compared to the conventional LSTM-MDN, RTRCB and Customized DRT methods. Similarly, the introduced PIBS-IPTS acquired 0.81 RMSE and 0.85 MAPE at 350 sec using 1000 vehicles in the network. Here, the improved performance is acquired due to the inclusion of optimal routes selection criteria based on the multi-objective function and Prediction of the best route for the passenger flow based on the vehicle load, routing time and traffic density.

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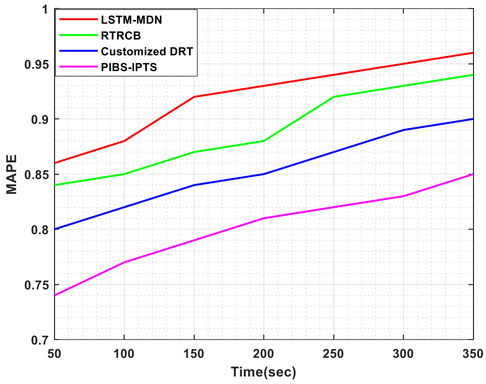

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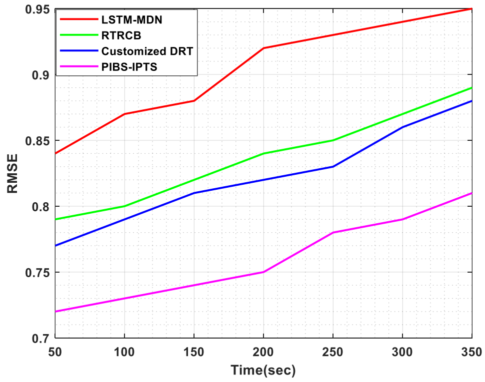

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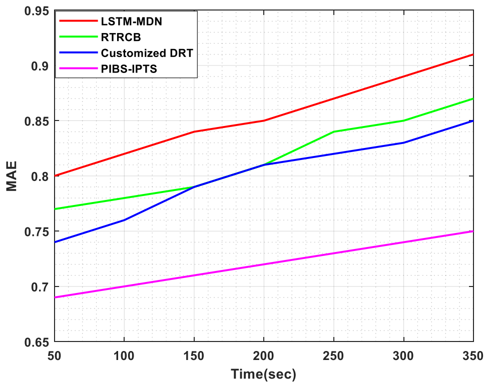
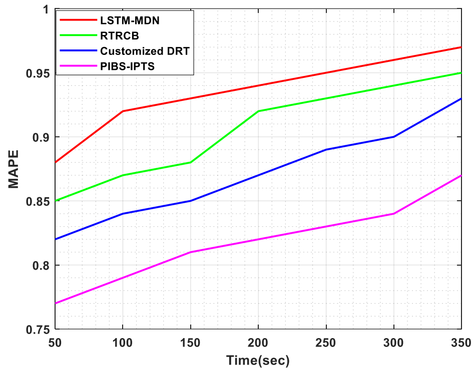


(c)

Figure 10: Comparison of PIBS-IPTS with 1000 vehicles in terms of (a) MAPE, (b) RMSE and (c) MAE

*2) Comparative Analysis with 5000 Vehicles:*The comparative assessment of the introduced PIBS-IPTS is portrayed in Figure 11 based on the measures like MAPE, RMSE and MAE in Figure 11(a), Figure 11(b), and Figure 11(c), respectively, by considering 5000 vehicles in the network. The MAPE acquired by the introduced PIBS-IPTS is 0.77 at 50sec, which is 12.50%, 9.41%, and 6.10% superior to the traditional LSTM-MDN, RTRCB and Customized DRT methods. Likewise, the MAE and the RMSE acquired by the introduced PIBS-IPTS for the same time are 0.7 and 0.73, respectively.



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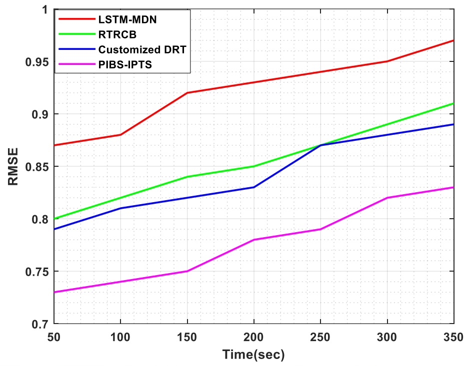

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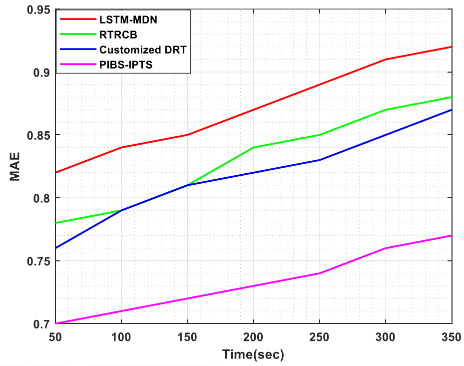

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Figure 11: Comparison of PIBS-IPTS with 5000 vehicles in terms of (a) MAPE, (b) RMSE and (c) MAE

F. Comparative Discussion

The best-case result accomplished by the PIBS-IPTS is presented in Table 8. The minimal MAE, RMSE, and MAPE accomplished by the introduced PIBS-IPTS are 0.69, 0.72, and 0.74, respectively. The minimal number of vehicles in the network of 1000 and with a time of 50 sec.

Table 8: Best case Comparative Discussion

Methods/ Metrics	LSTM-MDN	RTRCB	Customized DRT	PIBS-IPTS
Using 1000 Vehicles				
MAE	0.8	0.77	0.74	0.69
RMSE	0.84	0.79	0.77	0.72
MAPE	0.86	0.84	0.8	0.74
Using 5000 Vehicles				
MAE	0.82	0.78	0.76	0.7
RMSE	0.87	0.8	0.79	0.73
MAPE	0.88	0.85	0.82	0.77

From Table 2, the introduced PIBS- IPTS obtained a superior result compared to all the other state-of-art techniques. The LSTM-MDN utilizes the sequence learning-based Prediction and schedules the vehicle in a network. In the PIBS-IPTS technique, the optimal routes section and the Prediction and passenger scheduling capability enhance the method's performance. Likewise, the RTRCB utilizes the optimal routing of the vehicle using the Genetic Algorithm, but the Prediction was not incorporated like the proposed PIBS-IPTS method, which degrades the performance. The customized DRT utilizes dynamic vehicle routing through step-by-step optimization that elevates the computational complexity, affecting the method's performance.

V. CONCLUSION

The demand-based vehicle routing using the selection of the optimal route and the machine learning-based Prediction is employed by the proposed PIBS-IPTS method. Here, the demand-based vehicle routing identifies the entire possible path to make the passenger flow effectively from the vehicle routing paths. If the requested Source or Destination is unavailable in the existing routes, then the route updation is employed for demand-based vehicle routing. Besides, the optimal route selection using the CS algorithm based on the multi-objective functions assists in selecting the optimal best routes based on the traffic density, routes condition and route mobility. Finally, the Prediction using the ANN based on the minimal traffic path with minimal vehicle load and routing time helps to enhance the comfort perception of the passenger. The performance assessment of the PIBS-IPTS with the conventional methods acquired high performance based on the measures like MAPE, RMSE and MAE and accomplished the minimal values of 0.74, 0.72, and 0.69, respectively. Here, the error estimated by the introduced method needs to be reduced further, which will be fulfilled in the future by making the Prediction optimally using the hybrid optimization criteria.

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