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Optimized Solution For Commuting Indian Customized Bus Service

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The research investigates customized bus services, a novel approach to public transportation. This system allows passengers to request a pickup and drop-off at their desired locations, offering increased convenience, flexibility, and punctuality compared to traditional bus routes. The current bus system poses significant challenges for city residents and the economy. Long travel times, delays, and inconvenience plague frequent riders. Additionally, existing state bus networks often lack comprehensive coverage, leaving gaps in service for certain areas. The computational complexity of managing traditional routes further hinders efficiency. As urban populations surge and congestion worsens in cities like Mumbai, the need for adaptable and convenient transportation options becomes ever more critical. This research delves into the concept and operational principles of customized bus services. Following a comprehensive literature review and analysis, an optimization model is proposed to address route design, timetable creation, and stop deployment. This model aims to maximize passenger satisfaction while minimizing travel costs. A swarm-based meta heuristic approach is then employed to generate optimal solutions for the proposed model.

Keywords: Customized bus service, Optimization, Route design, Stop deployment, Evolutionary algorithm.

1. INTRODUCTION

As in the rapid growth in technology and high population growth for convenient and effective travel the new transportation service has been developed which is known as Customized Transportation Service. In today's world at primary level the private sector uses customization in the travel system. To travel inter or intra cities, people also used the Customized Bus Service (CBS). The customized bus service (CBs) or it can also be referred as "on-demand-transit" is an innovative and diversified transportation service for passengers to travel from source to destination [4]. This service uses an algorithm to match passenger requirements with vehicle facilities and generate a route that minimizes the total travel time and distance. Customized bus service is typically implemented using a mobile app or website. Passengers can use the app or website to request a ride, specify them stop points locations, and track the arrival of their vehicle. Once a ride is requested, the app or website will match the passenger with a vehicle and generate a route. The passenger will then receive an estimated arrival time and can track the vehicle's location on a map.Customized bus service offers a number of advantages over traditional bus service. Customized buses are more fuel-efficient than traditional buses, and they can help to reduce traffic congestion. This is because the buses are only on the road when there is a demand for them. Customized bus service is often more affordable than traditional taxi or ride-hailing services. Customized bus service can be more accessible to people with disabilities or other special needs than traditional public transportation options. Customized bus service can help tobuild community by connecting people with different backgrounds and destinations. Customized bus service is still a relatively new concept, but it is rapidly gaining popularity in cities around the world. It is particularly well-suited for urban areas with high population density and complex transportation networks. CBS uses real-time data and various algorithms to optimize it according to passenger's demand, thus this means buses can bedynamically routed to various parts of cities considering fringe parts of cities where bus frequencies are less and areas with high demands. CBS's major goals is to transport the majority of passengers to its destination and reduce the empty and unutilized buses on the road. Traditional bus system networks lack to cover entire cities, CBS overcomes this issue and tries to fulfill all passenger demands. CBs choose more efficient routes andavoid congested areas which leads to faster travel time and reliable services. This helps in cities, especially densely populated cities where traffic is a major challenge. CBs also provides convenient connections to major transit hubs, making it easier for passengers to access trains and subways or other modes of transportations. The areas can also reach neighborhoods and areas which are underserved by traditional fixed routes, providing better access to public transportation for a broader range of residents. Based on public demand or special events or emergencies the schedule of CBs can also be rescheduled in real time. Passengers can request rides on online platforms via smartphones or other devices tailoring the services to their specific needs such as specific pickup and drop off points. CBs eliminate fixed routes and reduce the number of empty buses on the road thus the operational cost reduces. Some customized bus systems leverage private sector participation, leading to cost-sharing arrangements that can benefit both the public and private entities. With the use of an advanced algorithm system can predict peak hour demand patterns based on historical data and events and adjust service accordingly. In some cases, cities may allocate dedicated bus lanes or priority signal timings to ensure that CBS can navigate through traffic more quickly during peak hours. Modern technology can be used to provide real-time updates of CBs which help passengers to effectively plan their routes. Few examples are In London, the company operates a customized bus service called "ViaVan"[12]. The service is available in all 33 boroughs of the city, and passengers can request a ride using the ViaVan app. The general processes for CB service include request collection, stop deployment, optimal route designing and timetable development. First step of the CB service is to collect passenger requests. This can be done through travel demand dataset, mobile application, surveys, etc.

The passenger travel request comprises their pickup point, pickup time, destination point and reaching time. Next step is to check if any existing CB line fulfills the passenger demand. If any CB line meets the passenger demand, the passenger can book a seat for that line. If no CB line satisfies the passenger request, the request is added to the request pool. Next the requests from the request pool are used to either change existing CB lines ordesign new CB lines for unsatisfied requests. Then the passengers can reserve the newly published CB lines.

All the unsatisfied requests from the request pool are used to design CB service. The Customized Bus Service Design Problem (CBSDP) includes the following procedures. First step is to divide the passengers into different clusters with similar pickup areas and destination areas. Then stops are deployed in the pickup area and destination area for each cluster, with certain constraints. These constraints include, minimum number of stops and minimum walking distance for passengers. The timetable development and routing are the next step. Mathematical models are used for timetable development and routing problems. The proposed mathematical models' function is to optimize the CB service cost. This optimization includes minimizing the system operation cost and maximizing the efficiency. The CB timetable formulation and route designing problem is a variant of pickup and delivery problem with time windows.

Currently, existing works on CBSDP completes the process of stop deployment, timetable formulation and route designing with some feasible CB service framework [4]. But the frameworks are implemented using some computationally expensive methods. Author study makes significant contributions to the field of customized bus (CB) system planning and operation. First, it establishes a comprehensive model for deploying CB stops, formulating timetables, and planning routes. The model takes into account the needs of both bus companies and passengers, and it can be adapted to different real-world scenarios. Second, the study proposes a clustering method to group passengers together based on their pickup and destination points. This clustering method allows the model to efficiently identify groups of passengers with similar travel needs, which can lead to more efficient and cost-effective route planning. Third, the study uses an Artificial-Bee-Colony algo. (ABC algorithm) with Differential-Evolution (DE) to solve the proposed model. ABC-DE is a meta-heuristic algorithm, which means that it is able to find good solutions to complex optimization problems without the need for exhaustive search. This makes ABC-DE a computationally efficient algorithm for solving the CB system planning problem. Finally, the study evaluates the proposed model using real road networks and real travel demand for crowded Indian cities like Mumbai. The results of the evaluation show that the proposed model is effective in improving passenger travel comfort and efficiency.

2. CASE STUDY

The Customized Bus System (CBS) represents a significant advancement in urban transportation, offering flexible and efficient travel solutions tailored to passenger needs. Unlike traditional fixed-route buses, CBS operates on demand, using real-time data and sophisticated algorithms to optimize routes and schedules. Despite its potential, the current state of CBS is marred by several challenges. One major issue is the computational complexity involved in real-time route optimization, which can be resource-intensive and slow, leading to delays and inefficiencies. Furthermore, many existing systems struggle with accurately predicting demand patterns, resulting in either oversupply or undersupply of services. Accessibility remains a problem as well; while CBS aims to cover underserved areas, it often fails to do so consistently, leaving gaps in service. Additionally, integrating CBS with other forms of public transport and ensuring seamless connectivity is an ongoing challenge. The financial sustainability of CBS is also a concern, as the costs associated with advanced technology and dynamic routing can be high. Operational costs can escalate due to the need for constant data processing and algorithmic adjustments. Another critical issue is passenger satisfaction, which can be impacted by unreliable service times and a lack of real-time updates. Despite these challenges, the use of hybrid optimization algorithms, such as the Artificial Bee Colony combined with Differential Evolution, shows promise in addressing many of these issues. These algorithms can improve the efficiency and reliability of CBS by better handling the computational demands and optimizing route planning in real-time. Implementing such advanced solutions could lead to more resilient and user-friendly CBS, enhancing urban mobility and reducing congestion. However, ongoing research and development, along with supportive policies and infrastructure investment, are crucial for overcoming the current limitations and realizing the full potential of CBS.

3. LITERATURE REVIEW

Customized Bus (CB) is a new type of public transportation system that is still under development. In order to learn more about CB and how to design effective CB services, A Review of CB Service Design.

This paper examines current research in CB service design. The review identified various theories, concepts, function descriptions, technical details, data collection and preprocessing methods, advantages, limitations, and findings associated with multiple existing CB systems. The key takeaways from this review are summarized in Tables 3.1 and 3.2.

Table 3.1: Literature Review Analysis

Sr. No.	**Research Paper Details**	**Functional Description**	**Technical Description**	**Data Collection and Preprocessing**
1	Using Pessimistic Values and Optimistic value to obtain optimize route for CB , 2023 [3]	1) The paper proposes a two-level model for the route optimization of customized buses and a PSO algorithm to give a solution to the proposed model. 2) The proposed model takes into account the degree of optimism of passengers and the capacity constraints of the buses.	1) The algorithm takes into account the passenger’s level of optimism and their tolerance of bus delays 2) Results showed that the algorithm was able to find effective solutions to the problem, even with a large number of variables and uncertainty in passenger demand.	1) A real-world dataset of bus routes and passenger demand in the city of Nanchang, China. 2) A synthetic dataset that was generated using a simulation model.
2	E-Vehicle Scheduling for CB Services	1) The paper proposes a biphase optimization flow for scheduling a fleet of MAEV to	1) A ride-sharing company can use Lagrangian relaxation to	1) Studies on the use of on-demand bus services.

	which is Modular Autonom ous , 2023 [14]	serve a set of customized on-demand bus requests. 2) During the initial planning phase, a Mixed-Integer Programming (MIP) model is created to simultaneously optimize the routing and charging of Modular Autonomous Electric Vehicles (MAEVs), along with passenger assignment and vehicle capacity management for pre-booked seats. 3) During the second phase, researchers employed a Decentralized Deep Learning (DDP) approach to design and optimize three dispatching models. This optimization ensures that the operations of Multi-Agent Electric Vehicles (MAEVs) effectively cater to travel demands.	optimize the pricing of its rides. 2) Dynamic dispatching can ensure that passengers are transported efficiently.	2) Technical papers on the optimization of transportation systems. 3) Historical travel demand data from the Beijing public transportation system. 4) Information on the capabilities of modular autonomous electric vehicles (MAEVs), such as their range and charging time
3	Many space time combinati on s problem for optimal route,202 2 [1]	1) The paper came up with a new MIP model for the PMDPTW. The model is able to capture the key features of the problem, such as the multiple delivery nodes, the time windows, and the vehicle capacity	1) Cloud computing is used by businesses/Governm ent to plan and optimize their delivery routes, or by individuals to track and manage their deliveries. 2) Developing a cloud-based	1)Dataset was generated using a simulation model.

		constraints. 2) The paper develops a new tabu search algorithm for solving the model. 3) The results show that the proposed approach is able to find good solutions to the PMDPTW, even for large problem instances.	software solution for optimizing delivery routes. This software solution could use a variety of data inputs, such as customer locations, delivery time windows, and traffic conditions, to generate optimal delivery routes for drivers.	
4	Customized Bus Routing and Scheduling focused on booked Trip Requests, 2022 [5]	1) The paper proposes a two-step approach for routing and dispatching customized buses. 2) In the first step, a routing algorithm is used. The routing algorithm takes into account the travel time between stops, the capacity of the buses, and the preferences of the passengers. 3) In the second step, a departure time determination algorithm is used. The departure time determination algorithm takes into account the travel duration to the 1st stop, the waiting time of the passengers, and the traffic conditions	1) The application of genetic algorithms resulted in improvement in the efficiency of the bus scheduling, it has led to a reduction in passenger wait times and an increase in passenger satisfaction. 2) Discrete event simulation was used to determine the optimal number of buses required to meet the demand of reserved trip requests,evaluate the impact of different traffic conditions on the on-time performance of buses,and evaluate the satisfaction of passengers.	1)The data collection process was conducted by doing surveys.
5	Complete Optimizatio n of CB Lines using	1) The paper proposes a multi-objective robust optimization model for the problem of customized bus	1)Results show that the proposed method outperforms a hybrid algorithm dependent on K-means and	1)Monte Carlo simulation approach was used to generate a set of realistic

	random demand, 2021 [21]	lines optimization. 2) The model focuses on reducing the total travel time of passengers as well as the carbon emission of customized bus lines, while taking into account the uncertainty of traffic conditions. 3) The model is built as a mixed-integer nonlinear programming problem. 4) To solve the problem, a 3rd stage hybrid method based on the NSGA-II algorithm.	multi-order genetic algorithm in terms of solution quality and computing time.	scenarios for the customized bus requests.
6	Shifting from conventional to customized bus services: Study of Beijing ,2021 [2]	1) Real-time data is used to identify areas with high demand for bus service. 2) This data can come from a variety of sources, such as GPS data from buses, passenger counts at bus stops, and social media data. 3) Once areas with high demand have been identified, buses can be routed to those areas. This can be done by adjusting the bus schedules or by creating new bus routes. 4) Results tells that Customized bus	1)The algorithm will consider the passenger demand and diversion behavior to determine the optimal route for the customized bus. The customized bus can be scheduled to operate during the same time as the conventional bus, or it can be scheduled to operate at a different time to avoid the overcrowding.	1) The Beijing Bus Passenger Survey Dataset was collected by the Beijing Municipal Commission of Transport. 2) It contains information including their origin, destination, travel time, and mode of transportation.

		service can highly reduce the travel time of passengers.		
7	Interactiv e Auxiliary System-Base d Customiz ed Bus Route Planning Method, 2021 [23]	1) In the first phase, the necessary data is collected and preprocessed. This includes data on the road network, the locations of bus stops, and the demand for bus service. 2) In the second phase, the customized bus routes are planned using a combination of particle swarm optimization, ant colony optimization,genetic algorithm, simulated annealing and tabu search. 3) Interactive auxiliary system analysis. In this phase, the planned bus routes are evaluated using an interactive auxiliary system. This system allows users to interact with the planned routes and to provide feedback.	1) PSO is able to find better solutions in a relatively short amount of time. 2) The SA algorithm was compared to a number of other optimization algorithms, and it was found to outperform all of them regarding quality of the solutions produced.	1) Shenzhen Municipal Public Transport Bureau database contains information on the location, capacity, and accessibility of all bus stops in Shenzhen. 2) GPS trajectory data of buses in Shenzhen data was collected from the bus companies in Shenzhen and contains information on the location, speed, and direction of buses at each time step.
8	Designin g Passenger Incentive Schemes for request driven CB	1) The paper argues that by offering incentives to passengers, it is possible to attract them to aggregated all locations and reduce the vehicle detour duration. It's a 2 step process.	1) Reduce costs:- The proposed approach can help to reduce the costs of operating a DRCBS by optimizing the routes and schedules of the buses. 2) Improve	1) Passenger surveys were used to collect information about passenger demographics, travel behavior, and preferences for incentives. 2) Traffic data

	Service, 2021 [20]	2) In the 1st step,a discrete choice model is employed for the estimation of passenger trip choice probabilities, considering the impact of factors such as monetary incentives, walking duration, and travel duration. 3) In the 2nd step,a vehicle routing model that relies on addressing the stop points problem is employed to create vehicle routes and schedules for the purpose of accommodating the impacted passengers	efficiency: Improve the efficiency of DRCBSs by reducing the amount of time that buses are spent driving empty. This can lead to reduced emissions.	was used to estimate the travel time between stops in the absence of buses
9	Improving the Efficiency of driven CB Service using ACO , 2021 [26]	1) It's a state DRCB system that uses an improved ACO algorithm and clustering algorithms to plan the bus lines and stations. 2) The ACO algorithm is used to find the optimized bus routes, while the clustering algorithms are used to group the passenger requests into clusters. 3) The proposed DRCB system is designed to improve the effectivity and flexibility of bus transporatationservices in low-traffic areas	1) Designing new CCB networks: The ACO algorithm can be used to design new CCB networks that are adapted to the specific requirements of a community or region. This could help to improve public transportation access and ridership in underserved areas. 2) Customer churn prediction: Clustering algorithms can be used to identify customers who are at risk of canceling their	1) Beijing Taxi Open Data Platform dataset contains information on the stop points locations, the start and end times, and the number of passengers for each taxi trip. 2) The synthetic dataset was generated using a simulation model.

			subscription or service.	
10	Optimized Intra-cities Bus line scheduling for Staggered Commuting in Post-pandemic condition Era, 2021 [27]	1) The paper proposes a method for planning multi regional CB routes during the coronavirus pandemic. 2) The proposed method takes into account the staggered commuting patterns of passengers, which are the different times at which people start and end their workdays. This is done by first dividing the route into subregions and then planning the route for each sub-region separately. 3) The route for each sub-region is planned using an improved Q-learning algorithm, which takes into account the travel time cost of all passengers, as well as the staggered commuting patterns.	1) Optimal CB route is found that minimizes the social total travel cost, which can help to reduce traffic congestion and travel time for commuters. 2) The application can be used to design CB routes that take into account the staggered commuting needs of commuters, which can help to reduce the risk of virus transmission.	1) The actual operating route and time of arrival of the bus. 2) The GPS data included the location , speed, and the number of travelers on the bus. 3) The data from the field surveys and the GPS data was then used to develop a model for planning. The model took into account the following factors: travel demand of passengers,capacity of the buses,distance between stops,traffic conditions,staggered commuting schedule during the COVID-19 pandemic
11	Joint Optimizatio n of Stop Planning, Routing, and Timetabling for	1) The paper quotes an integrated optimal method for the planning, routing, and scheduling of customized buses (CBs). 2) They are typically used in metropolitan	1) On-demand transportation companies: The model can be used to optimize the dispatching of vehicles to meet passenger demand in real time.	1) This data was collected from a survey of passengers in the city of Hangzhou. 2) The survey asked passengers

	Customized Bus Services, 2021 [4]	areas to alleviate traffic congestion and improve air quality. 3) The proposed optimization method takes into account the spatial and temporal accessibility of travelers, as well as the operating cost of the CB system. The objective of the optimal is to maximize travelers accessibility while minimizing operating cost.	2) Improving urban planning: By considering the spatial and temporal needs of public transportation users, theSTN model can help to create more livable and sustainable cities.	about their travel needs, including their origin and destination, their preferred departure and arrival times, and their willingness to walk to bus stops. 3) This data was obtained from the city of Hangzhou's Department of Transportation. 4) The data includes the road network, including the length and capacity of each road segment.
12	Flexible Time-Dependent Routing for Urban Customized Buses, 2021 [16]	1) The paper proposes a A methodology for urban customized bus routing that takes into account the flexibility of paths between nodes to be visited and how it varies with time. 2) The proposed method is based on a MILP model. 3) The model considers the decision-making conditions in bus route planning, path choice between nodes,	1) The algorithm can be used to find routes that minimize the total travel duration of the buses. This can lead to significant fuel savings for the company. 2) The algorithm can be used to find routes that reduce the total travel duration of the traveler which lead to improved passenger satisfaction. 3) The algorithm can be used to find routes	1) The passenger demand data was collected through a mobile app . 2) The geographic data was collected from a variety of sources, including OpenStreetMap and Google Maps. The traffic data was collected from a traffic information

		and passenger assignment.	that can serve more passengers which increase the revenue of the company.	service. 3) The geographic data was converted to a graph representation, and the travel times between different locations were calculated using a shortest path algorithm.
13	Multi-Sourc e Data Analysis to Explore the Factors Influenci ng Demand-Res ponsive Customiz ed Bus Ridership ,20 21 [18]	1) The paper uses a utilizing a negative binomial regression model for the examination of multi-source data, including DRCB trip data, weather data, and built environment data 2) The model identifies a number of factors that are significantly associated with DRCB ridership	1) Customer segmentation: Segment customers into different groups based on their demographics. 2) Quality control: SVMs can be used to identify defects in services. This information can then be used to improve quality control processes.	1) GPS data was collected from the DRT buses. This data was used to track the movement of the buses and to identify the factors that influenced the demand for the service. 2) Land use data was collected from the Beijing Municipal Bureau of Planning. This data was used to control for the impact of land use on DRT ridership.
14	An AI-Driven Approach to Optimizin g	1) Each route has a number of shuttles assigned to it that is not greater than the number of shuttles available. 2) The total no. of	1) The hybrid TS-VNS algorithm is used to reduce the complete system cost, 2) The model can also satisfy	1) The travel times between all pairs of metro stations and bus stops were estimated using a traffic

	Demand-Responsive Community Shuttles, 2020 [28]	passengers served by each shuttle is close to the capacity of the shuttle. 3) The travel time between stops is less than or equal to a maximum travel time. 4) The hold time of passengers is less than or equal to a maximum waiting time.	constraints such as route length, departure time, shortest path and vehicle capacity.	simulator. 2) The demand for the shuttle service was estimated using a survey of potential users.
15	A Model and Case Study of the CBR Problem with Time period Restrictions, 2019 [15]	1) The MILP model seeks to reduce the overall operational expenses of the CB system, while adhering to various constraints that includes the spatio-temporal needs of passengers, bus capacity, and time period limitations. 2) The paper proposes a heuristic algorithm for addressing the MILP model. 3) The heuristic algorithm depends on the genetic algorithm.	1) using standard optimization solvers becomes possible when employing a space-time network to depict the customized bus routing problem with time period constraints. 2) It allows the time period restrictions of the passengers be easily incorporated into the problem formulation. 3) It allows the problem to be scaled up to large instances.	1) The travel demand data which provides information on the origin, destination, and desired travel time of the traveler was collected from surveys of passengers who were using the customized bus service. 2) Road network data was collected from a digital map of Beijing city. The road network data provides information on the road network, including the road lengths, traffic speeds, and traffic signals.
16	Clustering	1) The suggested approach employs a	1) The DBSCAN algorithm tries the	1) The data for the dataset was

	Passenger Trip Data to Inform CCB Planning, 2019 [13]	pairwise density-based spatial clustering algorithm for grouping passenger trip data. 2) The algorithm takes into consideration the spatial distribution of the passenger trip data and the travel time between the origin and destination locations.	passenger trip data to cluster the data into groups of potential passengers. 2) It allows the potential passengers to be grouped together based on their travel characteristics, which can be used to design customized commuter bus routes and services.	collected from bus digital card data.It is a type of travel data that records the tap-on and tap-off times of passengers using a bus smart card. 2) This data can be used to track the origin and destination of passengers, as well as the time and date of their trips.
17	Represent ati ve SI Algorith ms for Optimizat io n: A Review of Applicati ons , 2019 [25]	1) The paper provides a comprehensive review of SIA for solving optimization problems. 2) SIAs are metaheuristic algorithms inspired by the collective behavior of natural systems . 3) SIAs have been successfully applied to a different variety of optimization.	1) Particle swarm algorithms such as the Artificial Bee Colony algorithm (ABC) can be used for route optimization for customized bus systems. 2) ABC can be used for real time optimization as it is less computationally expensive than some other particle swarm algorithms.	1) Google Scholar, a search engine for academic literature. 2) Other online databases and repositories.
18	Customiz ed Bus Model for Metro Congestio n Relief, 2019 [17]	1) The paper proposes a model for transferring overflowing passengers from metro stations to customized buses. 2) The model works by first identifying the	1) A ride-hailing company could use the algorithm to optimize the matching of riders and drivers 2) A public transportation agency could use the	1) Metro travelers data for the stop points of each metro traveler was collected for a period of one month.

		metro stations that are most congested. This is done by analyzing the no. of travelers entering and exiting each station. 3) After calculating the number of passengers exceeding capacity at each station, the model proceeds to allocate tailored buses to individual stations. 4) The overflowing passengers are then transported to their desired destinations by the customized buses.	algorithm to optimize the routes and schedules of customized buses to relieve congestion on its metro system. 3) A logistics firm has the potential to employ the algorithm for enhancing the efficiency of its vehicle routes and schedules.	2) Data for the road network and land use in the study area was gathered through GIS methods, sourced from the local government.
19	Adaptive Bus Dispatching Strategies for Personalized Public Transportati on, 2017 [6]	1) The system collects real-time information about the passengers' requests and the status of the buses. 2) The system uses the VRPTW solver to find the optimal flow for the buses to serve the passengers' requests and sends route information to the buses. 3) The buses follow the routes to serve the passengers' requests.	1) The MIP model is used to minimize the total cost of operation 2) GAs can be used to optimize the routing of vehicles, taking into account factors such as distance, traffic conditions, and delivery deadlines	1) Real-time traffic data was collected from traffic sensors installed on the road network. 2) Passenger demand data was collected from a survey of passengers. The survey asked passengers about their travel needs and preferences.
20	Stop Planning and Timetabling model for Customized Buses,	1) A model for the bus scheduling of CBs is proposed 2) The model is designed as an optimization challenge to maximize the number of passengers	1) IIGA has the potential to discover the optimal solution for reducing passengers' total travel time, the number of buses needed, and the	1) These surveys were conducted to collect information about where people lived, worked, and

	2017 [19]	served by CBs, minimize passenger travel time, reduce the total operating cost of CBs, and maximize the overall social benefit of CBs.	operating expenses of the bus company 2) IIGA, GA, SA could help bus companies to attract more passengers by reducing travel duration and improving the reliability of the transport service	went to school, as well as how they traveled on the travel patterns of residents. 2) GPS data was collected from buses in the study area to track their movements and traffic sensors data.

Table 3.2 : Research Review :- Advantages and Limitations

Sr. No.	**Research Paper Name**	**Advantages**	**Limitations**
1	Using Pessimistic Values and Optimisticvalue to obtain optimize route for CB , 2023 [3]	1)The suggested bilevel programming model adeptly encompasses the balance between the operating expenses of buses and the passenger travel demand. 2)The best value of the optimism coefficient is 0.4, which means that passengers are willing to tolerate a certain amount of delay in order to save money on transportation costs.	1) Consider only two types of passengers: optimistic and pessimistic. In reality, there is a spectrum of passenger behavior. 2)The paper uses a simple PSO algorithm to solve the optimization problem. More sophisticated algorithms may be able to find better solutions.

2	E-Vehicle Scheduling for CB Services whichis Modular Autonomous, 2023 [14]	1)MAEVs can help to reduce operating costs, as they areless expensive to maintain and operate than traditional buses. 2) MAEVs can help to improve passenger satisfaction,as they offer a more convenient and reliable service than traditional buses. 3)MAEVs can help to increase ridership, as they can provide a more attractive and accessible public transportation option.	1) The proposed optimization procedure is computationally expensive. 2) Paper also needs to evaluate how MAEVs will be deployed and managed in a way that is fair and equitable for all users.
3	Many space time combinations problemfor optimal route,2022 [1]	1)It can be used to model more complex delivery scenarios, such as those where multiple deliveries are made to the same customer or where deliveries must be made in a specific order.	1) The problem can be very large, with hundreds or thousands of customers and vehicles making it difficult to find a feasiblesolution, even using a heuristic or metaheuristic algorithm. 2) The time windows can be tight, making it difficult to find a solution.
4	Customized Bus Routing a ndScheduling Based on Reserved Trip Requests [5]	1)The genetic algorithm is a potent method capable of uncovering effective solutions for a diverse range of optimization challenges. 2)The suggested method also relies on a mixed-integer programming model, which proves to be a potent technique for addressing problems involving integer constraints	1) The paper only considers a single city. 2) The paper should consider the different preferences of the passengers.

5	Complete Optimization of CB Lines using random demand, 2021 [21]	1)It offers a new multipurpose robust optimizationmodel for customized bus line optimization. 3)It evaluates the offered model and algorithm using areal-world dataset.	1) The model was only evaluated on a single city (Beijing) dataset. 3) NSGA-II is computationally more expensive.
6	Shifting Public BusService from Standardto Tailored: An Empirical Investigation inBeijing [2]	1)Customized bus service can help to increase ridership on public transportation by providing a more convenient and comfortable option for passengers. 2)Customized bus service can help to reduce emissions and improve air quality by using smaller, more fuel-efficient buses.	1) The impact of the environment on the routingand departure hours of the buses can beconsidered. 2) CB routes may not serve all areas of the city, which can reduce accessibility for some passengers.
7	Interactive Auxiliary System-Based Customized Bus RoutePlanning Method [23]	1)The proposed method is a hybrid approach that combines several different metaheuristic algorithms. This makes the method more robust and efficient than traditional methods. 2)The proposed method uses an interactive auxiliary system to evaluate the planned bus routes. This allows users to interact with the planned routes and to provide feedback. 3)The effectiveness of the proposed method in generating high-quality bus routes that cater to user needs was demonstrated through its evaluation with a real-world dataset, yielding positive results..	1) The method is computationally expensive. 2) The method is less suitable for large-scale problems.
8	Designing Passenger Incentive	1)It proposes a novel method for integrating passenger incentives into the routing of demand-responsive customized bus (CB) systems.	1)It is based on a simulation model and the results may not be

	Schemes for request driven CB Service, 2021 [20]	2)The findings indicate that the suggested method can decrease the overall distance traveled, reduce time spent onboard, and enhance profitability.	generalizable to real-world applications. 2) Only a single incentive scheme is considered.
9	Improving the Efficiency of drivenCB Service using ABC , 2021 [26]	1)The paper proposes a novel ACO algorithm that isspecifically designed for the DRCB problem. 2)This makes the algorithm more efficient and effectivein finding the optimal bus routes.	1) The ACO algorithm is computationally expensive. 2) It is less suitable for real-time applications.
10	Optimized Intra-citiesBus line scheduling for Staggered Commuti ng in Post-pandemic condition Era, 2021 [27]	1) The paper proposes a novel method for planning CB routes during the COVID-19 pandemic that takes into account staggered commuting patterns. 2) The paper improves the traditional Q-learning algorithm to make it more suitable for planning CB routes. 3) The paper evaluates the proposed method using real-world data and shows that it can significantly optimize the travel period cost of travelers.	1) The method needs to be tested on passenger demand patterns. 2) The method could be modified to allow for flexible passenger time windows.
11	Joint Optimization of Stop Planning,Routing, and Timetabling for Customized BusServices [4]	1)Methods can be used to plan, route, and schedule CBs in a way that minimizes the inconvenience to passengers,and minimizes the cost to the operator. 2)The method is computationally efficient.	1) The paper is based on a mathematical model that may be less accurate in some cases. 2) The paper also does not consider multi mode customized buses.

12	Flexible Time-Dependent Routing for Urban Customized Buses [16]	1)Passengers can specify their desired stop pointslocations, within a certain time period. 2) By allowing buses to take more direct routes, thesystem can reduce fuel consumption and emissions. This has the potential to enhance air quality and mitigate the effects of climate change.	1) Face difficulty in picking up and droppingpassengers on time. 2) Paper also needs to consider coordination in routing of buses in the same area.
13	Multi-Source Data Analysis to Explore the Factors Influencing Demand-Responsive Customized BusRidership [18]	1)DRCB ridership is higher during morning and eveningpeak periods. This is likely because people are more likely to use DRCB to commute to and from work during these times. 2)DRCB ridership is lower on rainy days.	1) The study was conducted in a single city.
14	An AI-Driven Approach to Optimizing Demand-Responsive Community Shuttles [28]	1) This improves the efficiency and convenience ofcommunity shuttle services. 2)Reduces the number of empty seats and the amount oftime passengers spend waiting for shuttles.	1) System is expensive due to the large requirement of vehicles and drivers. 2) Systems get affected by change in passenger demands or traffic conditions.
15	A Model and Case Study of the CBR Problem with Timeperiod Restrictions, [15]	1)It tells a comprehensive mathematical model for the CBRP with time window restrictions. The model captures the key features of the problem, such as the spatial and temporal constraints, the traveler demand,and the operating value of the CB system.	1) MILP model is used in paper which does not guarantee optimal solution 2) Complex problems can affect system accuracy.

		2) The paper presents a heuristic algorithm designed toaddress the MILP mode..	
16	Clustering PassengerTrip Data to Inform Customized Commuter BusPlanning [13]	1) This approach introduces the use of a pairwise density-based spatial clustering algorithm for clustering passenger trip data, marking the 1st step towardsleveraging this technique for potential passenger analysisand CB line design. 2) The offered method is developed using real-world personal trip data, and the results show that it can effectively identify the potential passengers and line design of CB.	1) The System may not be able to identify clusters of passengers with small sizes. 2) System faces some difficulty in handling thenoisy data.
17	Representati ve SI Algorithms for Optimizati on: A Review of Applications [25]	1) SIAs are a powerful tool for solving optimizationproblems. 3) There are many different SIAs, each with its ownadvantages and disadvantages..	1) Paper does not consider newer and less well-known swarm intelligence algorithms 2) Paper does not delve into the theoretical aspects of swarm intelligence algorithms in great detail. 3) The limitations of swarm intelligence algorithms are not disclosed.
18	Customized BusModel for Metro Congestion Relief [17]	1) The simulation results showed that the modelsignificantly reduced metro congestion and improved theoverall transportation efficiency. 2) The findings demonstrated that the suggested model successfully diminished the average waiting time for passengers by 20%. 3) The model was also able to reduce the average travel time for passengers	1) The model completely stands on a simulation. 2) It hasn't yet seen implemented in a real-worldmetro system.

		by 15%. Additionally, the model was able to increase the capacity of the metro system by 10%.	
19	Adaptive Bus Dispatching Strategies for Personalized Public Transportation [6]	1) The strategy can significantly improve the operational efficiency of customized buses by matching the bus routes and schedules to the real-time passenger demand. 2) The strategy can also reduce the travel period and waiting period of passengers by routing buses along the most efficient paths	1) Algorithms work on assumptions that may not always be met in practice. 2) Paper needs to consider all scenarios.
20	Stop Planning and Timetabling model for Customized Buses [19]	1)Reduce the traveling time of traveler 2)Reduce the number of stops	1)Model works on the assumption that all passengers have known the same origin and destinations. 2)Designed model is computationally expensive and not feasible for large scale problems.

After conducting an exhaustive literature review and analysis, it has become evident that several critical limitations persist within the existing body of research. These limitations underscore the necessity for further investigation and innovation within the field of Customized Bus (CB) systems. The identified issues include:

1. A predominant focus of existing literature on CB systems emanates from similar cities in China [2], thereby limiting the diversity and applicability of insights across varied urban contexts.
2. The bus network in densely populated Indian cities such as Mumbai and suburban districts exhibits significant gaps, failing to adequately cover crucial areas. Moreover, service deficiencies persist, exacerbating the accessibility challenges faced by residents.
3. The current CB systems suffer from computational inefficiencies, rendering them impractical for addressing large-scale challenges associated with route design, timetable formulation, and other essential processes within CB system management.

This computational burden impedes the scalability and effectiveness of CB services, hindering their potential to meet the evolving needs of urban transportation networks.

By acknowledging and addressing these identified limitations, future research endeavours can strive towards developing more comprehensive and adaptable solutions that address the complex dynamics of urban mobility and enhance the efficacy of CB systems on a broader scale. A proposed solution involves the utilization of the Artificial Bee Colony algorithm (ABC), a meta-heuristic algorithm along with Differential Evolution (DE) for the CB system procedure. This approach mitigates computational expenses while addressing other critical challenges within CB system management.

4. SYSTEM DESIGN

The core processes of the Customized Bus service include collecting requests, halting operations, planning the best route, and creating a timetable [5]. The first step is requesting collection from the passengers. After the request collection, the next step is to determine if any already existing CB lines meet the passenger's needs. If so, then the passenger can reserve a seat on that line. If no CB line satisfies the passenger's request, the request is added to a request pool. The requests from the request pool are then utilized to modify existing CB lines or construct new CB lines for unsatisfied requests. The passengers can then make reservations for the new CB lines that have been released. The functional design of the CB system is shown in Fig 4.1. In the next section author have elaborated upon the functional design of the system shown in Fig 4.1.

Step 1: The process is initiated by collecting requests from the users. Before the user can submit the request, the user needs to be authenticated. For authentication, the app first collects the user’s request to log in. The app prompts the user to enter required data like username and password for authentication. The data entered by the user is then validated and then the user is verified to make a request for the CB. In author’s implementation this request are generated from raw data collected from BEST (The Brihanmumbai Electric Supply & Transport Undertaking).

Step 2: After the user has made a request for CB, the next process is to check if any existing CB lines fulfill that request. If an already existing CB line fulfills the user request, the user is notified about that line. The seat booking option is available for the user to book the seat on that line.

Step 3: Next process is the order generation. In the above process, if no existing CB line fulfills the user request the request will be transferred to the request pool, which is the collection of unfulfilled requests collected from the users across the platform. The next step in this process is to use the model to generate orders i.e. CB lines.

Step 4: After the order generation process, the users whose requests were not fulfilled are notified about the newly added CB lines. Now the users can book seats in the new CB lines if they want.

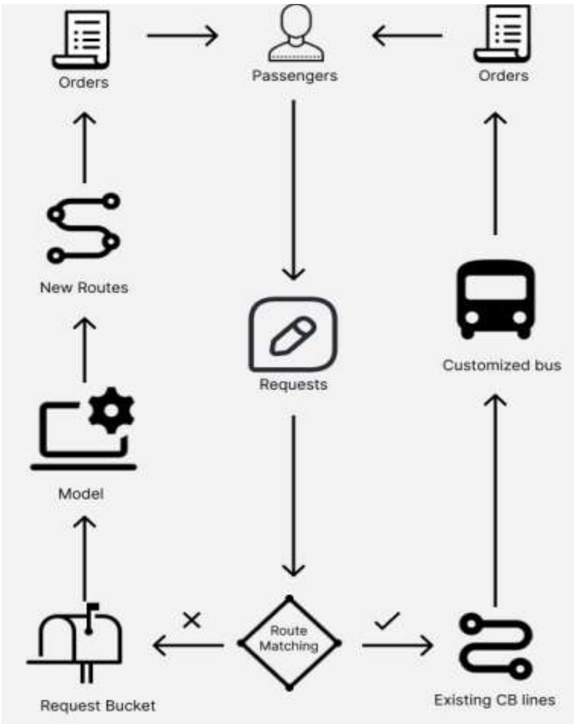

Fig. 4.1: System Design

5. PROBLEM DESCRIPTION

Traditional bus systems often face challenges like inflexible routes and long wait times for passengers. Customized bus systems aim to address these issues by offering on-demand services that dynamically adjust routes based on passenger requests. However, this introduces new complexities. Optimizing routes to efficiently serve multiple passengers with varying origin and destination points while minimizing travel time and operating costs is a significant challenge. Building upon the initial challenges, customized bus systems face several additional hurdles.

Introducing a customized bus system is a complex undertaking. A lack of sufficient funding and supporting infrastructure can hinder the development and study of customized bus systems in India. It requires careful planning, significant investment, and likely a phased approach to address the specific challenges faced by a city like Mumbai**.** Delays and unpredictable travel times would make an existing system unreliable. Demand for bus services can vary significantly throughout the day and across different locations. All this problem can be solved to certain extends by customized bus system. A customized system would need to be extremely flexible to accommodate these changes, which is logistically challenging. Many roads in Mumbai are narrow and lack the space needed for dedicated bus lanes or frequent bus stops. This further complicates route planning and efficiency.

The Passenger Demands and Travel Options problem is a core challenge in designing and operating a successful customized bus system. Also assigning passengers to the most efficient route that meets their needs while considering vehicle capacity and finding a solution that satisfies as many passengers demands as possible while keeping the system operational and cost-effective. Designing efficient routes, timetables, and scheduling for CB systems requires solving complex optimization problems. These problems involve numerous factors like minimizing travel time, maximizing passenger demand, and adhering to operational constraints. As the size and complexity of the CB system increase (more routes, stops, and passengers), the computational demands for optimization also grow exponentially. This can make existing algorithms slow and impractical for large-scale implementations. It's important to remember that research in this area is ongoing, and new advancements are constantly being made. As technology evolves and computational power increases, the feasibility of implementing large-scale CB systems is likely to improve.

6. SYSTEM IMPLEMENTATION

To validate the solution and to assess, the practical effectiveness of author proposed customized bus system implemented using the Artificial-Bee-Colony (ABC) and Differential-Evolution (DE) algorithms. This implementation translates the optimization algorithms and system design into a functional prototype, allowing us to evaluate its performance under realistic scenarios.

A. Algorithm

The proposed optimization algorithm is integration of Differential Evolution with algorithm Artificial-Bee-Colony as ABC-DE. ABC (Artificial Bee colony) is improved by combining with DE (Differential Evolution) in author implemented system. Artificial bee colony consist of 3 phases a) Employee bee phase b) Onlooker Bee Phase c) Scout Bee Phase [22]. DE algorithm uses concepts of Mutation and Crossover.

Initially Employee Bee phase is executed. The employed bee phase in the Artificial Bee Colony (ABC) algorithm mimics the foraging behaviour of honeybees seeking nectar. Employed bees are assigned one "food source" each, representing a proposed bus route and schedule solution. This initial assignment can be random or based on some prior knowledge. Each employed bee modifies its assigned solution by generating neighbour of solution using generate neighbour function. This change could involve adjustments to specific aspects of the solution by swapping or inserting new stops. The employed bee compares the fitness of the modified solution to the original solution. If the modified solution has a lower fitness value (meaning it's a more efficient or cost-effective route/schedule), the employed bee replaces the original solution with the modified one. This mimics how bees abandon less fruitful areas and focus on those with higher nectar quantities.

Next phase is Onlooker Bee Phase. The onlooker bee phase in the ABC algorithm is driven by a probabilistic selection mechanism that leverages fitness-proportionate selection. After employed bees return from their exploration, they communicate the fitness of their discovered solutions (potential bus routes and schedules). Onlooker bees observe this information sharing and probabilistically select employed bees to follow. The probability of an employed bee being chosen is directly proportional to the fitness of its associated solution. This means that solutions demonstrating higher efficiency, cost-effectiveness, or passenger satisfaction have a greater chance of being selected by the onlooker bees for further investigation. Onlooker Bee phase is improved by applying Mutation and crossover function on solution.

Mutation plays the role of a change agent. Imagine mutation as a deliberate tweak in the genetic code of a solution. Within an algorithm, this means slightly altering the values that represent specific properties of a potential solution (like tweaking a bus route to include a different bus stop or changing the departure time). Mutation acts as a disruptor in optimization algorithms. It prevents stagnation by introducing small, random changes into existing solutions. This creates diversity within the solution population and allows the algorithm to explore areas of the solution space it might not have reached otherwise. Although mutation is often random, it has the potential to stumble upon unexpectedly favourable changes within a solution, leading to decreased fitness and better overall results. This process mirrors the way biological mutations sometimes result in advantageous new traits. The mutated solution along with original solution is pass to crossover. Crossover acts as a recombination mechanism, mimicking the way biological parents exchange genetic information to produce offspring. In an algorithm, two parent solutions (potential bus routes and schedules, for instance) are selected. A crossover point is determined, and segments of these parent solutions are exchanged. This means that portions of their "genetic code" (values representing route choices, scheduling decisions, etc.) are combined. The result is the creation of two new "offspring" solutions that inherit characteristics from both parents as depicted in Fig 6.2. The primary goal of crossover is to explore new combinations of promising traits found in existing solutions. Perhaps one parent solution excels in covering a specific area of the city, while the other has a very time-efficient route structure. Crossover allows the algorithm to create new solutions that potentially inherit the best of both worlds, leading to even better routes and schedules. Based on fitness value of solution, solution with minimum fitness value is choose and update to population. The addition of DE operations (Mutation and Crossover) improves ABC by expanding its searching capability in solution space. Last Phase is Scout Bee Phase. The scout bee phase in the Artificial Bee Colony (ABC) algorithm plays a vital role in maintaining diversity and preventing the search from getting trapped in local optima (suboptimal solutions). Each solution in the population has a counter that tracks how many times it has been modified without improvement. If this counter exceeds a predefined threshold (called the "abandonment limit"), the employed bee is responsible for that solution abandons it. This acts as a trigger – it signals that the solution area is likely depleted of significantly better options, akin to a food source running low on nectar. Once a solution is abandoned, a scout bee is activated. The scout bee generates a completely new and random solution throughout the search space. This is crucial for injecting fresh perspectives and preventing the algorithm from prematurely converging on a solution that might not be the overall best. The newly generated solution fitness is evaluated and if this less than original solution than original solution is replaced by newly generated solution. scout bees serve as the "explorers" of the ABC algorithm. They prevent stagnation and ensure continuous search for better solutions throughout the search space, increasing the likelihood of uncovering truly optimal bus routes and schedules.

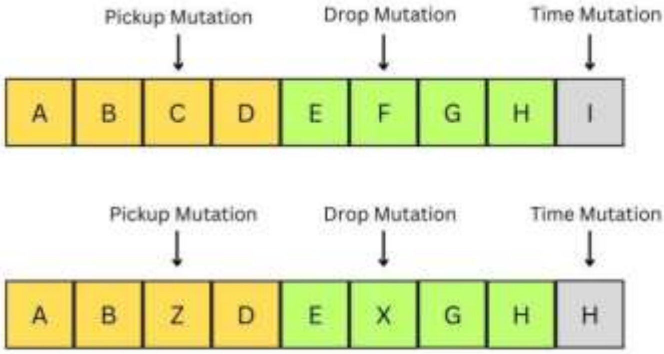

Fig. 6.1: Mutation in Solution

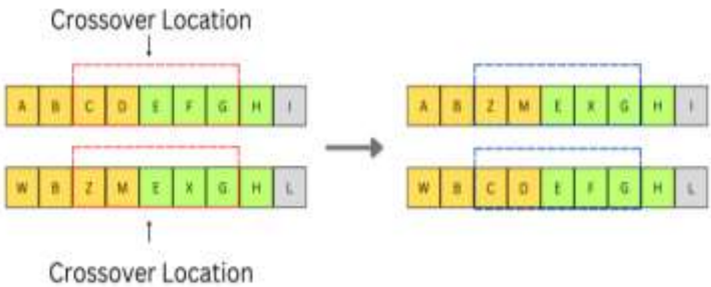

Fig. 6.2: Crossover in Solution

B. System Implementation

1. Data Collection and preprocessing:

Initial step involved collaborating with Mumbai BEST (The Brihanmumbai Electric Supply & Transport Undertaking) to acquire raw data on passenger movement [11]. They provided us with raw passenger flow information. This data required cleaning to ensure its accuracy.

Author addressed missing values and removed outliers during this process. Following the data cleaning stage, author transformed the raw data into a comprehensive new dataset that would be used for further analysis. From the passenger movement data, author generated passenger requests. From raw movement data author acquired total number of passengers travelling from certain existing bus stop to another bus stop per hour. For generating location of pickup address, all request were distributed evenly within residential zones over 500m radius of bus stop. Same step was repeated for generating destination address while considering commercial zones. All the request were probabilistically distributed according to passenger distribution for a day, which was acquired from raw passenger movement data.

2. Implementation of the Algorithm:

In this phase the data consist of passenger's request with starting, destination address and boarding time.

Step 1: - This data is divided into different cluster based on passenger's request. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm is used to cluster passenger based on their starting and destination location [13]. Three level clustering is done on data. First level clustering form clusters with similar starting address. Second level form clusters with similar destination and third level clustering form cluster with similar starting address and destination address. For each cluster distance matrix is generated where distances from each passenger to another passenger is store in matrix.

Step 2: - After dividing passenger based on their pickup and drop addresses, now stop is deployed. Mean shift clustering algorithm is used for identifying potential locations for new bus stops based on passenger density. The mean shift algorithm is applied to the passenger location data. This iteratively shifts each data point towards the densest region of points in its vicinity, defined by a chosen radius. The algorithm converges when data points no longer shift significantly, resulting in clusters of points representing areas with high passenger density. The centroids of these clusters represent potential locations for new bus stops. After stop deployment stop distance matrix is generated, where distances from each stop to another stop is store in matrix.

Step 3: - Since stops are deployed, bus routes i.e. solutions are developed using improved ABC algo. i.e. ABC with D.E. optimization algorithm (ABCDE). ABC-DE take population as input which is set of solution. This initial population is randomly generated.

Each solution of population represents single route. Since a single route can contain more than one bus to fulfil all its passengers demand within the area, a solution is set of individual bus path within that route. If for route N buses are required, then solution will contain N paths depicted in Fig 6.3.

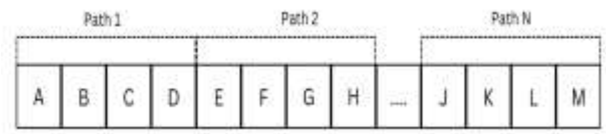

Fig. 6.3: N Paths in a Solution

Since each path is complete itinerary of bus, so it's divided into three parts I) Pickup stops II) Drop Stops III) Start Time. Pickup stops is set of stops from which passenger will board the bus while the drop stops are stops where passenger will alight from bus. Path Encoding is depicted in Fig 6.4.

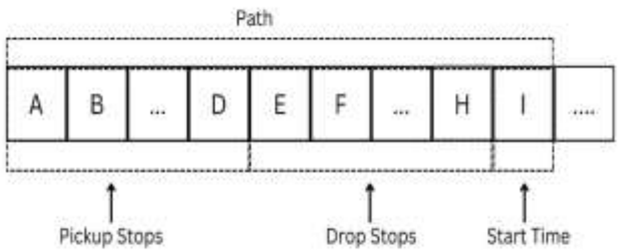

Fig. 6.4: Path Encoding

Sequence of stops defines the flow of stops that will appear during journey. Start time indicate the time at which bus will start its journey. Path defines all required constraints for a bus route withing solution. During mutation and crossover or modification of solution, the pickup stops are modified with only other pickups stop and drop stops with only drop stops.

Different phases of ABC are applied over population. Starting phase is Employee bee which generate solution neighbour by modifying solution at some extent. This modified solution fitness value is calculated which consider major factors such as cost of operating bus, passenger inconvenience and route distance. If modifies solution have less fitness value than original solution, then it is replaced. Next phase is onlooker bee which perform mutation and crossover of Differential Evolution on solution. Mutation mutates the solution by modifying the stops which is not assigned in solution. The mutated solution and original solution are passed to crossover which swap the randomly chosen segment from both solution with each other. Then all three-solution original solution and both modified solution fitness value is calculated, minimum of them is chosen and replaced with original solution. Last phase is Scout bee phase. Scout bees keep track of solution improving over iteration. If solution is not improving over period of iteration, then new solution is generated and replaced with it. This avoids solution from stagnation. This whole ABCDE process is done in single iteration and done again and again over numbers of iterations.

Step 4: With the use of algorithm, author come up with the best optimized route. Passengers are assigned to route which is best suited to their requirements and timing. Each passenger is assigned to only one route.

C. Solution Evaluation

To assess the effectiveness of author's proposed algorithm, author employed a rigorous evaluation process using established metrics relevant to the problem domain. These metrics considered factors such as passenger inconvenience, etc, enabling a comprehensive comparison with existing solutions.

P1: - This evaluation metrics evaluates the passenger assignment. If passenger is assigned it Inconvenience index is added to P1 and if passenger is not assigned, then penalty is added to P1 which is large constant number.

P2: - This evaluation metric is routing cost which is computed by total travel distance of bus by operator. This metric is related to cost concerned with space time distance of route.

P3: - It evaluates the number of stops within route. As each stop have some operating cost such as maintenance cost, construction costs, etc. So, the number of stop per route cannot be too much as it increases operating cost.

P: - Three evaluation metric namely P1, P2 and P3 are integrated to form new evaluation metric which minimize the total cost of customized bus service. The metric formulation is:

$$P = \alpha 1 * P1 + \alpha 2 * P2 + \alpha 3 * P3 \qquad (1)$$

In this formulation, α1 and α2 represent the monetary cost assigned to each unit of the two evaluation indices. This economic weighting unifies the units of measurement within the objective function P. By incorporating these costs, author can account for the relative importance of each evaluation index in financial terms. This allows us to optimize the solution not only based on technical performance but also on its real-world economic impact.

7. RESULT AND ANALYSIS

For measuring the effectiveness of the proposed optimization model, a solution is implemented using Python [10] in Google Colab. Passenger requests data created based on the real-world passenger traffic data which was obtained from the Mumbai 'BEST' services [11]. The results are compared with the results of the base model which is based on Genetic Algorithm with VNS (Variable Neighbourhood Search) [4]. For this comparison author are using Mira-Bhayander zone of Mumbai region, where author are considering the passenger traffic data between 7:00 AM and 12:00 AM. traffic data or initial data created here is based on the data, which was obtained from Mumbai 'BEST' services [11]. There are 315 such requests, so there are same number of home destinations. Same number stops are considered in every route for both ABC-DE and Genetic-VNS models. The number of routes considered for the test is 4. Maximum time gap between a passenger request and the bus arrival time is considered to be 15 minutes. And service time at each stop is considered to be 1 minute. The values for route cost and passenger cost assumed as ₹ 20 /Km and ₹ 4 /Km respectively, which was referenced from the past BEST statistics [11] Variable mutation and crossover rates are used for genetic operations in both the models. When the total number of requests full filled are less than 70% for a solution, the mutation rate is 0.85 and crossover rate is 0.6. Mutation and crossover rates are 0.65 and 0.9 when total request full filled are greater than 70%. This is done so that the solution is not good it can be mutated, and when solution is somewhat good the exploration via crossover can be focused. For ABC-DE the maximum number of trials with no improvement in solution after which the solution can be replaced is 8 for 50 iterations and 12 for 100 and a greater number of iterations. The test is conducted 10 times for both the optimization models. In ABC-DE are the solution can be replaced with the new solution, the best solution can be on any iteration, not necessarily on the final iteration. Therefore, the best solution throughout all the iterations is considered.

Table 7.1: Parameter Values

Parameter	Value
Total number of iterations	100
Max trials for ABC-DE	12
Penalty for unassigned requests	100
Route cost	₹ 20 /Km
Passenger cost	₹ 4 / Km
Maximum walking distance	400 m
Maximum time gap	15 minutes
Passenger inconvenience coefficient (α1)	0.1
Total distance coefficient (α2)	1
Total stops coefficient (α3)	5

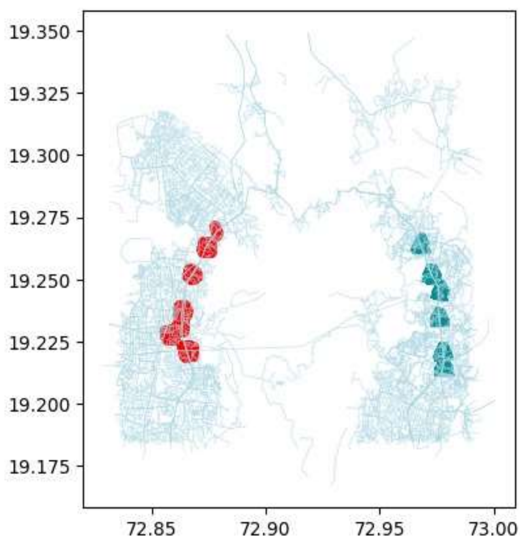

Fig 7.1: Request Distribution

In Fig.7.1 the home and destination zones are plotted on map using osmnx [9] and networkx [8]. On the left side of the map the pickup locations are represented in red and on the right side the destination.

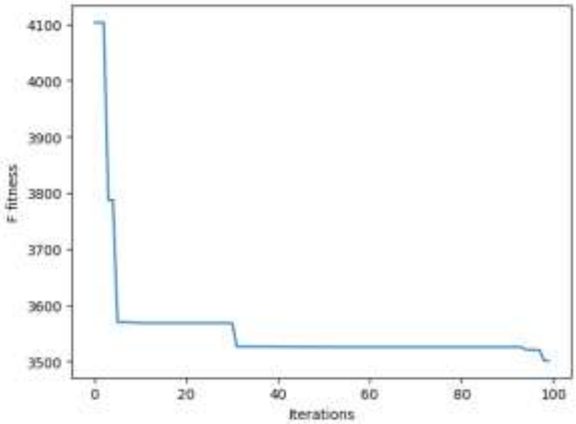

Fig 7.2: Fitness Graph for Genetic-VNS

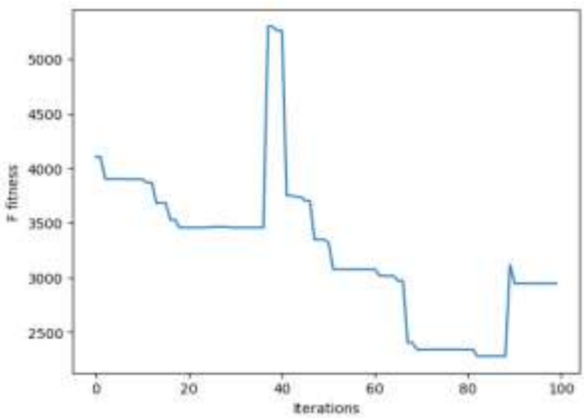

Fig 7.3: Fitness Graph for ABC-DE

The results of the test, the graph for fitness value over every iteration are obtained for both ABC-DE and Genetic-VNS optimization models and the optimized solution which is also visualized on the map. For the Genetic-VNS model, from the graph of fitness over iteration as shown in Fig 7.2, it is observed that the solution improvement is rapid in the beginning but after some iterations the improvement slows down and there is no major improvement from iteration 30 to iteration 90. The total passenger assignment for this method is 169. For ABC-DE the fitness for the initial population is 4153 as shown in Fig 7.3, with iterations increasing the fitness value is decreasing. Between iteration 20 and 38 the stagnation occurs, therefore after maximum trials the solution is replaced, which results in the fitness value increasing as the solution is not optimized yet. The replaced solution has better improvement as it reached fitness of around 2300. The fitness value again increases after iteration 85 as max trial value is reached. As the solution around iteration 85 is best with 288 requests full filled out of 315, it is selected. Similar results are observed for all the tests conducted. In the Genetic-VNS method the optimized solution is not guaranteed, as it suffers from stagnation. This problem in ABC-DE is solved by the scout bee phase where the solution is replaced after certain number of iteration if there is no improvement.

The average execution time for the ABC-DE is around 10 minutes with average passenger assignment of 90%, and for Genetic-VNS average execution time is around 12 minutes with average passenger assignment of 84%.

Table 7.2: Comparison of Results

	Genetic-VNS	**ABC-DE**
P (fitness value)	3540	2450
P1 (unassignment measure)	3360	2581
P2 (routing cost measure)	2340	1956
P3 (total stops measure)	12	12
Assigned Passengers	253	288
Average Passenger Cost	₹ 134.2	₹ 112.7
Average Route Cost	₹ 2340 per route	₹ 1956 per route
Total Stops	12	12
Avg. Execution time	12 minutes	10 minutes

The comparison of effectiveness of both models is carried out comparing P, P1, P2, P3, total assigned passengers, average passenger cost, route cost and total stops, which is shown in table 7.2. The total number of assigned passengers are higher for ABC-DE. Therefore, passenger inconvenience and unassignment penalty (P1) for Genetic is higher. The average routing cost (P2) of ABC-DE is also lower than the results of Genetic-VNS solution, which shows that the route length is better optimized. Solution form both the methods have same number of stops. The average fitness (P) for the best solution is less for ABC-DE with faster execution time. The best solution for both the models are marked on the interactive map using folium [7]. The circles with yellow center represents pickup stops and the circle with white center represents drop stops. The route for the base model is much more unordered than proposed model as the solution improvement rate for it is low.

Fig 7.4: Route 1 of Genetic-VNS

Fig 7.5: Route 1 of ABC-DE

The results from multiple tests and all the different parameters shows that the proposed optimization model demonstrates the superior optimization in total passenger assignment, average passenger cost and average route cost. The average passenger assignment for the proposed model is 90% which is higher than the base model. This is due the scout bee phase of the proposed model as it prevents stagnation by replacing solutions. Thus, author concluded that the ABC-DE algorithm is better for CB problem as it is much faster and gives better optimized solutions.

8. CONCLUSION

The study introduces an improved approach to optimizing Customized Bus Stop Deployment problem (CBSDP) for Indian crowded cities like Mumbai. It integrates various aspects including passenger assignment, stop deployment, route design, and timetable development. The goal is to minimize passenger inconvenience, reduce the total number of stops, and decrease the total running distance. Ultimately, striking a balance between service quality and operating cost. To tackle this multilevel optimization problem, the study proposes a heuristic approach that combines Differential_Evolution (DE) operators with the Artificial- Bee-Colony approach (ABC algo.). By leveraging the strengths of these algorithms, the proposed approach aims to efficiently explore the solution space and find high-quality solutions.

To assess the effectiveness of the proposed approach, extensive experimentation is conducted. Initially, a real-world instance based on Mira-Bhayander zone in Mumbai is implemented to compare the solutions derived from the ABC-DE approach with those obtained from the Genetic algorithm with Variable- Neighborhood search approach i.e. Genetic-VNS algo . The evaluation revealed interesting performance differences between the ABC-DE and Genetic-VNS algorithms. The ABC-DE algorithm achieved an average passenger assignment rate of 90%, with a relatively fast execution time of around 10 minutes. In contrast, the Genetic-VNS algorithm exhibited a slightly longer average execution time of 12 minutes and achieved an average passenger assignment rate of 84%. This evaluation shows that proposed algorithm can provide more reliable results with relatively less computational time. This comparison shows the improved performance and efficiency of the proposed method. In conclusion, the proposed approach offers an improved and comprehensive methodology to optimize CBSDP for Indian cities, effectively addressing the complex interplay between service quality and operating cost and shows promising results in enhancing the efficiency and effectiveness of CBSDP optimization.

For the future studies, going ahead author can integrate the real time traffic data in the optimization process, for getting more accurate results. Also the CB service can be incorporated with the existing transportation systems like trains and metros.

ACKNOWLEDGEMENT

Author would like to express sincere gratitude to Mumbai “BEST” service for their invaluable input to this project. Their willingness to share real-time data was instrumental in enabling us to understand and create input data to understand real time routes. The detailing of their data played a crucial role in achieving results, making significant advancements. author are thankful for their commitment to open data initiatives and sharing helpful information. This has paved the way for future advancements in Customized Bus System in India.

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