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Research paper

Metro bus transit frequency regulation system for a smart city using an optimization algorithm

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Abstract

Background: The increase in passengers with inadequate number of buses available results in an overcrowded bus. This is accompanied by a cramped experience for the passengers.
Objectives: To facilitate the passengers and to ease their travel, by automating bus and route allocation.
Methods: In this work, a Metro Bus Transit Frequency Regulation System Using Nelder-Mead Optimization Algorithm is presented. This system allows the Metropolitan Transport Corporation to allot buses in specified routes according to the demands and eases the ordeal that daily commuters face. Additionally, it aims to reduce the fuel expenses incurred by the Metropolitan Transport Corporation by optimizing the allocation of the number of buses in a particular route. It not only assuages the distresses of the passengers but also looks to reduce the woes of the workers of the Transport Corporation in allocation of buses. The vision of the proposed work is to produce a smart automated bus transit system which paves the way for a technologically improved city.
Results: The simulation of the system resulted in 95% of requirements satisfaction by the passengers by using an average resource of 70% during the peak hours in the morning.
Conclusions: From the results, it is inferred that developing a transit frequency regulation system will definitely ease the commutation of passengers and also reduces the fuel expenses. Indirectly the system can be used to reduce air pollution by reducing the number of private vehicles on road.

Keywords: *Bus Allocation; Bus Transit System; Frequency Regulation; Nelder-Mead Optimization; Route Analysis.*

1. Introduction

With the increase in population and inadequate transportation facilities in a metropolitan city, there is a need for a transport system that satisfies the passengers' needs [1]. A passenger's major need is to travel without any difficulties like congestion and delay [2]. Passengers wish to travel in a comfortable manner. The transport system must be designed in a way to cater to the needs of the passengers.
The proposed system aims to reduce the waiting time of passengers. It also ensures that most of the passengers get a seat in the bus they board [3]. The application also aims to reduce the fuel expenses incurred by the Metropolitan Transport Corporation by optimizing the allocation of the number of buses plying in a particular route. This system attempts to eliminate shuttling of buses in which a vast number of seats are empty. This system also reduces the frequency of the buses through the routes that incorporates bus stands that are often sparsely populated. The system employs machine learning in determining the average number of people travelling through a route so that the bus allocation can be optimized. During peak hours, adequate number of buses is not available which results in overcrowded buses and discomfort for passengers [4]. During off-peak hours, more number of buses is present which will lead to wastage of fuel and several other resources. Hence the transport system must involve flexibility in the allocation of its buses.
The proposed system aims to optimize the number of buses in a fixed route without changing the routes but dynamically allocating the buses. Also, while most of the other systems use expensive hardware to account the commuters waiting for the vehicle in a bus stop, the proposed system works economically in that all it requires is the historic data and this data is used to predict the number of passengers in a bus stop considering time and the day. This system seems to best fit the needs of passengers of a metropolitan, addressing their daily needs preventing the rush, especially during peak hours.
The daily commuters and people who often travel by bus are greatly benefited by this proposed work as the bus routes that are more frequently travelled are allocated more number of buses, thereby optimizing the frequency of buses. Besides being of much use to the common people, it also eases the burden of the Transport Corporation workers by automating most of the complicated tasks leaving behind only the trivial tasks to be worked on. Because of the optimization of the buses, manpower deficit is considerably reduced particularly during emergency times or festive occasions. It also reduces the fuel consumption of the buses since the frequency of bus services to sparsely populated areas are cut down.

This work is organized as follows: Section II presents a review on the existing methods for allocation of buses. Section III gives the system framework of the proposed system. Section IV discusses the results and Section V presents the conclusions of the proposed system and the future works.

2. Existing literature review

The works related to transport allocation and frequency regulation and optimization are discussed in this section.

Fang et al. [5] proposed a quick response approach in two phase for efficient dynamic bus routing system that routes buses based on demand. The model makes a trade-off between the solution accuracy and computational cost and thus, it is highly time-complex. In this work, a scheduling method for assigning immediate request that works in real time is used, which also allows variable route. The authors constructed a multi-objective model for the real-time scheduling problem taking into account the cost, commuters on bus and waiting at stops. A numerical experiment based on the real-world case has been designed to test the effectiveness of the proposed method.

An et al. [6] combined bus-holding and stop-skipping strategies and proposed a mixed integer programming model which can improve the service with minimal cost. This system looks to minimize passenger's waiting at stations for a long time, time between two buses of same route and the negative effects caused due to holding buses and skipping the stops. The departure time of two buses in the same route often deviates from the planned departure frequency because of external factors such as traffic conditions and public transport demand. This in turn leads to inefficient usage of transit resources thereby reducing the quality of service. In view of these existing shortcomings, the authors suggested this model so that the transit service can be improved.

Kim et al. suggested an approach by analysing the real-time traffic information used to route the vehicles to their corresponding destinations [7]. Their approach used a Markov decision process to determine the optimal values for the parameters such as driver attendance time, departure time and routing policies under time-varying traffic flows. It combined this information with historical data to minimize cost and increase productivity. The approach suggested changing the routes of the vehicles dynamically to obtain the shortest and optimal path using a stochastic shortest path algorithm. Real-time traffic information was considered in optimal vehicle routing in a non-stationary stochastic network.

Kirci proposed a method using tabu search and Hopfield neural network to solve the traditional capacitated Vehicle Routing Problem (VRP) [8]. The algorithm focussed to minimize repetitions such as the same vehicle plying on the same route over and over even though there is no demand and penalizes the repetitions. They tried their approach as a real-world application on google maps.

Schittekat et al. suggested an approach to solve the School bus routing problem [9] similar to a VRP except that only a subset of the stops are visited by the buses where each student can walk to from his/her station[10]. The solution to the problem is the least number of buses to accommodate all the students. Their work used a set of decision variables to reduce the travelling distance by bus, to ensure all vehicles start from the depot and that all stops in the subset are visited. The authors used a commercial integer programming solver to solve this problem.

Chandurkar et al. proposed a system to track the bus' current location [11] and send it to a server which then broadcasts it to all the passengers. Their approach predicted the ETA which is very valuable information to a passenger. The system used GPS trackers installed on the buses to track their location. The location details are transferred to a centralized control unit and represented symbolically in the route map in their geographic positions approximately.

Barbucha proposed a multi-agent paradigm [12] to solve concurrent vehicle routing problems which is more or less the same scenario of routing buses in a Metropolitan city. They consider the routes as a directed graph and apply various shortest path algorithms considering various factors such as time, distance, traffic etc. Pavone et al. solved a dynamic as well as a stochastic Vehicle Routing Problem [13] using time slots called as windows. They assumed that the demand for service actually enters according to a Poisson distribution with rate λ to a bounded region Q with area |Q| in the Euclidean service space. After the arrival, the demand is considered to be independent and uniformly distributed in location Q.

From the survey carried out, a system is proposed which involves pre-fixing the bus route timings based on demand by the passengers. This system predicts the adequate number of buses to satisfy the actual demand without incurring any wastage of resources. Dynamic allocation of buses in a route improves the customer comfort and reduces the unnecessary usage of assets [14]. Although, many similar works exist, they tend to modify the bus routes based on requirement.

Compared to the other existing works, this system reduces the wastage of resources such as fuel, manpower, etc. Additionally it improves the experience of travel for every passenger. It ensures that every passenger travels in a comfortable manner even during peak hours.

3. Methods

The proposed system involves allocating the buses in a metropolitan city. Finite Stock Optimization involves allocation of buses in a route provided there is a limitation on the stock of the bus. Initially the model is developed by considered the stock of the system to be infinite. The Infinite Stock Optimization model is analyzed to develop Finite Stock Optimization. This system is optimized using Nelder Mead Optimization.

3.1. Infinite stock optimization

The stock of the buses is considered to be infinite. Each route will have an unlimited supply of buses. Hence the allocation of buses must satisfy the user requirements. The architecture of Infinite Stock Optimization is presented in Fig 1.

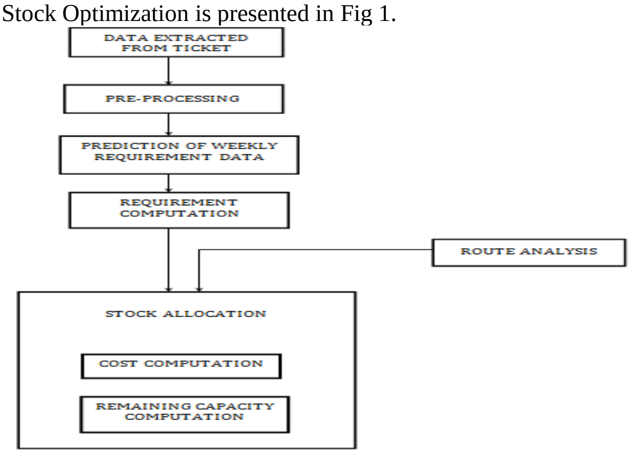

Fig.1: Infinite Stock Optimization Framework.

3.1.1. Data extracted from ticket

The data extracted from ticket is the input data that has the details with respect to the ticket for passengers. The ticket represented in Table 1 has details regarding ‘From station (F)’, ‘To Station (T)’, ‘Epoch Time (Et)’. Epoch time is a specific date and time that is represented in seconds. The parameters ‘From Station’ and ‘To Station’ represent the bus stops in a route. The system assumes the stations to be some numerical values for training purposes. Epoch Time represents the time at which a passenger boarded the bus. This is a raw form of data which requires a pre-processing step.

3.1.2. Pre-processing

Pre-processing involves counting the number of passengers travelling from one station to another at a particular time slot and at a particular day slot. It involves the process of extracting time and day slots from the epoch time in the original dataset. Additionally, the number of passengers boarding the bus is counted from the dataset. The pre-processed dataset represented in Table 2 contains information about the number of passengers in a particular at a specific day and time slot.

Table 1: Initial Data

Epoch Time	From	To
1480572000	0	1
1480572000	0	1
1480572000	0	1
1480572000	0	1
1480572000	0	1
1480572000	0	1
1480572000	0	1

Table 2: Pre-Processed Data

From	To	Day	Timeslot
0	1	3	0
0	2	3	0
1	2	3	8
0	1	3	30
0	2	3	30
1	2	3	38

3.1.3. Prediction of weekly requirement data

The pre-processed data is the input for the regression model. The training and testing ratio of the data is 75:25 [15]. The regression technique used for this model is Support Vector Regression (SVR) similar in principle to Support Vector Machine (SVM). Support Vector Regression kernel functions transform the data to a higher dimensional feature space and perform the linear separation process. This model predicts the number of passengers for every time and day slot pair. The pre-processing and prediction of weekly requirement data is presented in Algorithm 1.

Algorithm 1: Prediction Model Construction (F, T, Et)
F: From station
T: To station
Et: Epoch time

1) Calculate Time slot (Ts) and Day slot (Ds) from Epoch time.
2) Calculate the number of records for a particular epoch time which is the number of passengers (Np).
3) Develop a regression model and generate a regression vector (Rv) which has the number of passengers boarding the bus at a particular time period.
4) Return (F, T, Ds, Ts, Np, Rv).

3.1.4. Route analysis

Station data(S) consists of all bus stops in the city. From station data and ticket data, the routes are analyzed. Each route is represented as an object with three members. The three member data are: Start Station, Destination Station, Route Matrix.The route matrix contains information on the stations along a route. Additionally, the approximate time taken to reach these stations in a route is present in the route matrix.

3.1.5. Requirement computation

The weekly requirement data along with route analysis is used to build a 4D matrix consisting of the requirements for each time slot from each source to each destination for all the 7 days of the week. This 4D requirement matrix is then reduced to a zero matrix (all the elements are zero) by calculating the number of buses needed to serve the requirements, taking into consideration the time required for the bus to travel from one pick up point to another such that once a bus is used it is never used again which is later optimized using 'Finite Stock Optimization'. The outcome from this step consists of the number of buses needed and the excess seats available for each time slot of each day of the week. Requirement computation is presented in algorithm 2.

Algorithm 2: Requirement Computation (F, T, Ts, Ds, Np)
F: From station
T: To station
Ts: Time slot
Ds: Day slot
Np: Number of passengers

1) Convert regression vector into a 4D Matrix format (Requirement Matrix)
2) Generate Sub route matrix from Bus Route Data
3) Initialize the bus allocation matrix with infinite stock to 0
4) Return (BA_i, Rm)

3.1.6. Stock allocation

The stock of the bus is considered to be infinite without any constraints. The buses are allocated as if there is unlimited supply of buses.The number of buses required at each [day | time | route] is predicted from the preprocessed and analyzed data. The optimal number of buses required are calculated via a cost function which determines which [day | time | route] satisfies maximum requirement.Buses are allocated considering that the number of buses is not limited. The Stock Allocation algorithm with Infinite Stock available is presented in Algorithm 3.

Algorithm 3: Stock Allocation (F, T, Ts, Ds, Np, BA_i)
F: From station
T: To station
Ts: Time slot
Ds: Day slot
Np: Number of passengers
BA_i: Bus Allocation Matrix (Infinite Stock)

1) For everyday slot, while Requirement Matrix is not completely zero.
2) Find the route which satisfies maximum requirement with maximum cost.
3) Add the route to Bus Allocation Matrix with finite stock.
4) Return the current Bus Allocation Matrix.

The Bus Allocation Matrix contains the optimal number of buses needed and the remaining capacity.

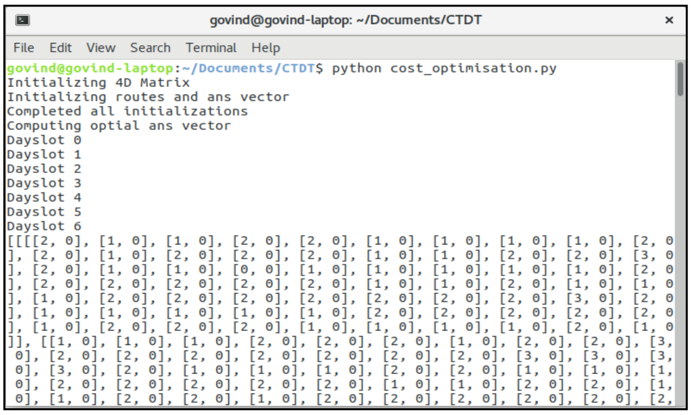

Fig.2: Stock Allocation.

Fig.2 represents the intermediate output of the infinite stock optimization which presents the minimum number of resources or stock required to satisfy all the requirements. It can be inferred that when the stock is infinite all the requirements are being satisfied; however this is not possible in real time. Hence finite stock optimization technique is used in this system.

3.2. Finite stock optimization

The stock of the buses is considered to be finite with certain constraints. Each route will have a limited supply of buses. Hence the allocation of buses must satisfy the user requirements and could not exceed the maximum limit of available buses. The architecture of Finite Stock Optimization is presented in Fig.3.

3.2.1. Stock data

The Stock Data contains information about the number of buses available in a Bus Terminus at the start of a day – that is, the stock available at initial time.

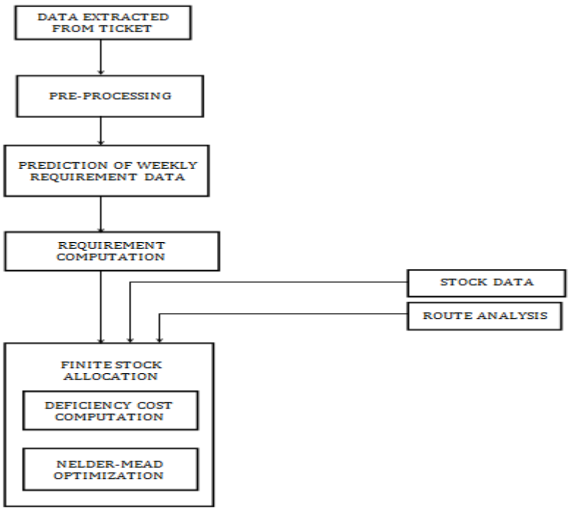

Fig.3: Finite Stock Optimization Framework.

3.2.2. Finite stock allocation

Deficiency Cost Computation: Deficiency cost is computed by sum of squares of all the requirement fields in the requirement matrix.

4. Nelder-mead optimization

Nelder-Mead is an optimization algorithm which maximizes or minimizes objective function [16]. It is a heuristic search technique that can converge to non-stationary points. It is used for multi-dimensional unconstrained optimization with no derivatives. It refers to the problem of finding points with optimal value for an objective function. It is briefly outlined in Algorithm 4.

Algorithm 4: Nelder-Mead (f, v_1, v_2……, vn)

f – function to be optimized

v_1, v_2…, v_n– Initial values of the optimized parameters

1) Construct a n+1-dimensional simplex in an n-dimensional space
2) Repeat the following steps until the function is optimized
   i) Order the vertices v_1, v_2..., vn in increasing order of their function values and re-number them accordingly.
   ii) Assign $h=v_n$, $s=v_{n-1}$ and $l=v_1$.
   iii) Calculate centroid c of the vertex l.
   iv) Try to replace the vertex h, by finding the best replacement vertex using the most optimal value yielded by one of the transformations – reflection, expansion and contraction, of vertex h.
   v) If none of the above-mentioned transformations yield an optimized functional value, calculate a whole new set of candidate vertices v_1, v_2….v_n by shrinking the simplex towards vertex v_1.
3) Return the values v1, v2…, vn.

5. Results and discussion

The proposed system is tested based on the data generated by considering the bus routes, passenger count and congestion. The dataset has 60000 records containing the information relating to four bus routes. The output of the proposed work is the optimal number of buses to be sent along a route based on levels of demands from historical data and also the optimal number of buses to be sent along a route based on levels of demands from historical data, when there is limited number of buses. The output is represented as the optimal number of bus on a particular day and time slot.

Considering a simulation of a part of the Chennai metropolitan city, the demands of the population is satisfied to an extent of 60% with limited amount of resources. In addition to the allocation of resources from real time requirements, optimal number of buses required to satisfy the need is estimated. This can be further used to manage resources based on those requirements. The proposed work mainly focuses on the allocation of resources based on the needs and requirements of the passengers. The proposed model is trained only on weekly basis. This does not include special occurrences. The bus timings are dynamic according to the number of stoppages at various stations and it needs to be regularized in weekly basis.These will pose as a limitation to the proposed work

$$\text{Requirement Satisfied} = \frac{\text{Initial Requirement} - \text{Final Requirement}}{\text{Initial Requirement}} \quad (1)$$

Requirement Satisfied (RS) as mentioned in equation (1) represents the requirement satisfied for a time period with the available resources.Initial Requirement (IR) refers to the demands posed by the passengers which are to be satisfied. Final Requirement (FR) refers to the requirements left unsatisfied after the allocated buses service the initial requirements.

$$\text{Resources Used} = \frac{\text{Maximum Resources Utilized}}{\text{Available Resources}} \quad (2)$$

Resources Used (RU) as mentioned in equation (2) represents the resources utilized in a time period. Maximum Resources Utilized (MRU) refers to the maximum number of allocated buses used to service the requirements in any timeslot in a given time period. Available Resources (AR) refers to the allocated number of buses.

Table 3: Requirement Satisfied and Resources Used in the Morning

Timings	IR	FR	MRU	AR	RS	RU
6 – 6:30	17	0	1	2	1	0.5
6:30 – 7	52	2	1	1	0.96	1
7 – 7:30	108	11	2	2	0.9	1
7:30 - 8	167	0	3	7	1	0.42
8 – 8:30	198	32	4	4	0.84	1
8:30 - 9	159	0	4	14	1	0.29
Average					0.95	0.70

Table 3 presents the requirements satisfied and the resources used in the morning from 6:00 – 09:00 a.m. The average requirements satisfied is 95% and the average resources used is 70%. Table 4 represents the average requirements satisfied and resources used in various time periods of a day.

Table 4: Performance Metrics

	Allocation by Predictive Requirement Learning	
	Requirement Satisfied	Resources Used
Morning(06:00 - 09:00)	95%	70%
Before Noon(09:00 - 12:00)	90%	55%
After Noon(12:00 - 17:00)	98%	55%
Evening(12:00-20:00)	80%	100%
Night(20:00-24:00)	86%	80%

From the intermediate unprocessed output in Fig.2, the final result about the required number of buses for a time and day slot is derived. Table 5 represents the optimal number of buses to be allocated on the day slot 3 which is a Tuesday and at the time slot 4 which is of time 06:04 a.m.

Table 5: Resources (Bus) to Be Allocated

From/To	0	1	2	3
0	0	6	30	38
1	27	0	29	37

2	33	6	0	31
3	29	35	37	0

6. Conclusion and future work

The smart bus transit system for a metropolitan city predicts the optimal number of buses to be sent along a route based on levels of demands from historical data and also predicts the optimal number of buses to be sent along a route based on levels of demands from historical data, when there is limited number of buses. This system allocates bus services to localities based on demand. Bus services to sparsely populated or rarely used bus stops will be shortened down. Bus services to popular areas or highly populated bus stands are increased. It simplifies the overall process and reduces the burden of Metropolitan Transport Corporation workers. The proposed system attempts to eliminate bus journeys in which a vast number of seats are empty, except during night services or any emergencies. This system tends to reduce the work of MTC employees and reduce the probability of a passenger not receiving the right service at the right time. This certainly will be a useful asset to MTC or any other transport corporation for that matter.

This work can be extended to employ smart ticketing devices which transmit the data to a centralized server as and when a ticket is being issued to a passenger during his/her journey. This data can be used to enhance the proposed model by considering contemporary requirements rather than entirely relying on historic data.

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