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SRD-LB: A Smart Route Determining algorithm with Load Balancing for Smart Cities in India

[1]Utsav Upadhyay, [2]Saurabh Maheshwari, [3]Geeta Sikka

[1]*Marwadi University, Rajkot, Gujrat, India*
[2]*Government Women Engineering College, Ajmer, Rajasthan, India*
[3]*National Institute of Technology, Jalandhar, Punjab, India*

Abstract

Traffic congestion has emerged as one of the major problems in developing countries like India. It has a very negative effect on the economy, life of the citizens and the quality of services. Traffic congestion can furthermore, increases the response time of emergency services. Some of the main reason for the emergence of this problem are due to exponential increase in number of vehicles in the past decade, lack of adequate infrastructure, insufficient parking space and inefficient law enforcement leading to traffic congestion. Researchers have been trying hard to come up with an efficient solution to the problem. This work presents a Smart Route Determining algorithm with Load Balancing (SRD-LB) based on real time traffic data analysis, road conditions and environmental factors to reduce the travel time. The simulation results proved the efficiency of SRD-LB in successfully reducing the travel time and avoiding traffic congestion.

Index Terms – traffic load balancing, smart route finding, smart traffic management, smart city, SUMO, OSM.

1. INTRODUCTION

In a developing nation like India, the transportation sector has a remarkable influence in the growth of the nation over the last decade. The number of vehicles has been increasing exponentially in the past few decades. Due to limited infrastructure, traffic congestion has emerged as a serious problem in cities. The limited infrastructure is also a chief reason for increase in environmental pollution, number of accidents [1] and delay in response of emergency services like police, ambulance, fire-brigade etc. Furthermore, traffic congestion has serious ill effects on the economic growth of the economy [2]. The Government of India (GoI) is focusing on building and developing infrastructure but due to existing conditions and limited scope in urban road infrastructure development, is not able to handle the problem of traffic congestion in cities. The existing road infrastructure is not utilized due to lack of real time traffic information and absence of centralized system to guide vehicles via a route taking smallest travel time. In this manner, the problem of traffic congestion can be handled efficiently [3].

The existing route-determining algorithms comprises of classical and dynamic route determining algorithms. The classical algorithms include algorithms like Dijkstra [4] and the A* algorithm [5], which doesn't take into consideration the dynamic nature of the route. The dynamic route-determining algorithm relies more on data analytics, machine learning and artificial intelligence for determining optimal path [6]. Dynamic route-determining algorithms are capable of handling real life situations [7-9]. However, as per our conscience, this paper first work on identifying the optimal route to minimize the travel time using real time traffic analysis while focusing on load balancing via a centralized server and Internet of Vehicles (IoV) to avoid traffic congestion. The main work in this paper are:

An algorithm that can assign weights to a path based on the real time traffic analysis, road conditions (like distance, number of lanes, condition of road, presence of divider etc.) and environmental factors (like heavy rainfall, repair in progress, etc.).

SRD-LB algorithm, navigating a driver from source to destination via optimal path (with respect to travelling time) with maintaining load balancing over the entire city's road network.

The results of simulation show that the proposed SRD-LB algorithm using optimal weight assignments, offers optimal route with lesser travel time while achieving load balancing to efficiently handle traffic congestions.

The paper organization is as follows: Section 2 deals with the literature related to route determining algorithm, Section 3 provides the insights of SRD-LB algorithm, Section 4 deals with the analysis of the simulation results and Section 5 deals gives conclusion and future scope of the work.

2. RELATED WORK

The section is sub-divided into three sub-sections: traditional route determining algorithm, dynamic route-determining algorithm and traffic prediction methods.

2.1 Classical Route Determining Algorithm

Classical Route Determining Algorithm were designed to identify the least cost route between any pair of vertices in a graph. These algorithms include Dijkstra [4], A-Star (A*) along with the work related to these algorithms.

Wang [10] suggested an improvement over Dijkstra algorithm to make it more adaptive, by introducing equivalent path instead of actual and redefining weights. However, this work is unable to form the basis of urban traffic management system. Wei et al. [11] provided an improvement over Dijkstra algorithm by introducing congestion weight functions, but its implementation doesn't adopt to real time traffic analysis performance.

Li et al. [12] suggested an improvement over A* algorithm via application of inverse search and optimizing the evaluation function, transforming it into more suitable version for larger graphs. Shi et al. [13] suggested taking into account the distance between source and destination nodes as the function of vertices and successfully improved the performance of A* algorithm.

Classical algorithms are well efficient and have large applications in graph theory for finding shortest route. However, these cannot be applied to the real-life problems like traffic congestion management.

2.2 Dynamic Route Determining Algorithm

The researchers [14-17] collected historical taxi data and proposed a route determining algorithm. Han et al. [18] suggested a route determining scheme for re-chargeable Wireless Sensor Networks for prolonging network life-time by reducing the number of dead nodes. Dai et al. [19] suggested a person-specific route determining algorithm based on needs of the vehicle drivers. Kanoh [20] suggested a dynamic route determining algorithm using last travel record and genetic algorithm for predicting future travel time.

Li et al. [21] introduced a dynamic routing algorithm, which can work with constraints. Sun et al. [22] successfully improved the worst-case performance of route determining algorithm, by assuring reliability within certain time range. Sommer et al. [23] analyzed traffic information to identify traffic congestion and suggesting optimal routes. Shang et al. [24] designed and developed a mechanism for dynamic route determination capable of adaptation based on change in external situations or parameters.

Mostly the algorithms in this section are specific to situation specific problems. Moreover, none of these take load balancing into account, while considering route determination. Therefore, the research solutions discussed in this section are infeasible in real traffic situations.

2.3 Traffic Prediction Methods

For handling traffic congestion in a more meaningful manner, analyzing the traffic in real time along with the ability of traffic prediction are crucial. Vlahogianni et al. [25] suggested multiple ideas based on parameter for predicting traffic in near future. The work [26] suggested that the prediction performance based on external factors such as rainfall, fog and other miscellaneous factors, and the problem of near future traffic prediction has some random fuzzy pattern and cannot be predicted accurately.

For near future traffic predictions, generally two types of methods are used, namely the parametric and non-parametric methods. The parametric methods rely on mathematical modelling like linear regression model, time-series model etc., while the non-parametric methods rely on domain knowledge-based prediction method.

Fontanelli et al. [27] developed a dynamic path determining strategy relying on the last known travel time and number of vehicles running on particular road to make near future predictions. Kong et al. [28] developed a TLR model based on statistical and mathematical model for predicting traffic. Guo et al. [29] presented an adaptive predictive algorithm for near future traffic flow prediction. Fei et al. [30] presented a dynamic and adaptive linear predictive model, which based on real time data, improves the prediction accuracy. However, the work presented could not account for influence of random factors and other real-life uncertainty due to its non-linear nature [31]. Based on SVM (Support Vector Machine) and PSO (Particle Swarm Optimization), Kong et al. [32] presented a strategy for predicting traffic congestion. Kang et al. [33] developed a LSTM (long short-term memory) model based on certain parameters to improve the prediction accuracy. To overcome the variation problem, Xing et al. [34] suggested the use of kernel function in place of hidden layer and presented traffic prediction algorithm. K-Nearest Neighbour is usually considered as one of the most widely accepted method for non-parametric regression. Cai [35] and Su [36] suggested the use of KNN-based methods for prediction to improve the accuracy as compared to other prediction model.

3. THE PROPOSED SRD-LB ALGORITHM

The SRD-LB Algorithm lays its foundation on Dijkstra algorithm. A network of roads in a smart city is presented in Figure 1 and is considered as weighted directed graph as presented in Figure 2. The circle represents the starting points of a Road Segment (RS), while the edges refer to the RS. The weight of an edge of the RS is represented by W (A to B). Based on the real time traffic analysis (average speed of vehicle) and other external factors (rainfall, fog, road repair, etc.), the weights are updated regularly for each time slot. The arriving number of new requests and the weights form the basis for determining the routes, to be assigned to new request. To avoid congestion on a particular RS, a load balancing scheme is also included in the proposed SRD-LB algorithm.

3.1 Parameters of the Model

In our work, we have incorporated a multi-layered, feedforward and non-linear sigmoid perceptron model of Artificial Neural Network. As the model is well suited in function approximation problems [36], it is well suited for the scenario and the experimental results also proves the same. The model is based on supervised and gradient descent is used as the learning algorithm. Table 1 provides the details of input parameters required for identifying the weight of a RS. Table 2 provides the detail insights of parameters for training the model.

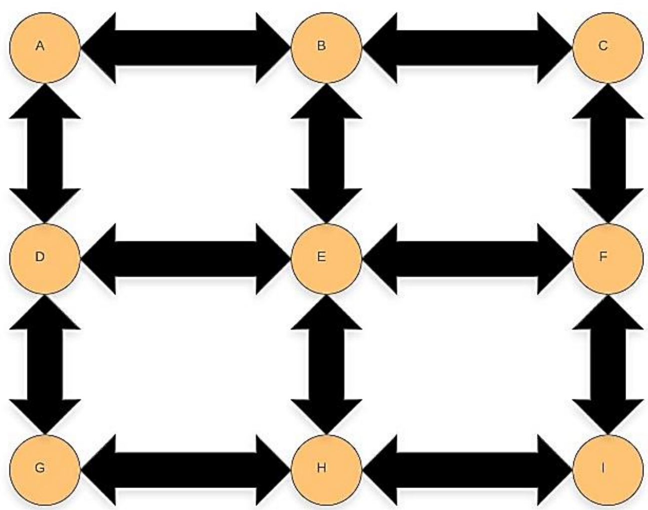

Fig 1. Sample Network of Roads

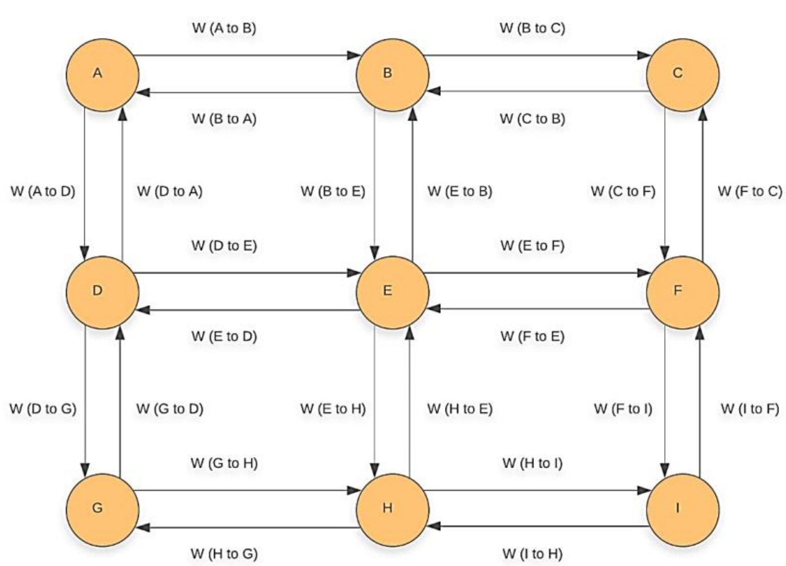

Fig. 2. Sample Network of Roads transformed as Weighted Directed Graph

3.2 The Algorithm

This section presents the pseudo-code of the SRD-LB algorithm along with the detailed description of the modules used in the algorithm. The SRD-LB algorithm begins execution by estimating the weight of each road segment and is capable of identifying possible paths between source and destination.

```
The SRD-LB Algorithm
Begin
        For each Road Segment
                Call Identify_weight
        End for
        For each vehicle requesting path from source to destination
                For each vehicle at the start of road segment
                Call Indentify_Candidate_List
                Call Path_Selector from candidate list
                Call Update_Weight of RS selected by Path_Selector
                Repeat For until destination is reached
                End For
        End For
End
```

TABLE 1. PARAMETERS USED AS INPUT TO IDENTIFY THE WEIGHT OF A RS

S. No.	Parameter	Type	Description of the Parameter	Proportionality
1.	Distance	Float	This parameter presents the actual length of the RS.	Directly
2.	Lanes	Integer	This parameter presents the number of active lanes in RS.	Directly
3.	Vehicles	Categorical	This parameter presents the type of Vehicles running on the RS at the given interval. The vehicles can be Heavy, medium and light.	Inversely
4.	Average Speed	Float	This parameter presents the average speed of Vehicles running on the RS (category-wise) and this parameter is based on historical data.	Directly
5.	Number of Vehicle	Integer	This parameter presents the number of Vehicles running category-wise on the RS at the given interval.	Inversely
6.	Visibility Condition	Categorical	This parameter presents the visibility condition on the RS at the given interval. The visibility can be High, Normal Low and No.	Directly

7.	Water Logging	Categorical	This parameter presents the water logging condition on the RS at the given interval. The condition of water logging can be High, Normal, Low and No.	Directly
8	Maintenance Work	Categorical	This parameter presents the situation of maintenance work on the RS at the given interval. The situation of maintenance work can be High, Normal, Low and No.	Directly

TABLE 2. PARAMETERS USED FOR TRAINING THE MODEL

S. No.	Parameter Name	Value	Description
1	NNIL	14	The number of inputs provided to the model. The parameter Vehicles, Average Speed and Number of Vehicles contribute to 9 parameters, being category wise and remaining 5 contributes as single.
2	NNHL	20	The no. of neurons in one hidden Layers.
3	NHL	5	The no. of Hidden Layers
4	NNOL	2	The output provided by the model (weight of the RS and expected travel time).
5	Epochs	2000	Max. no. of epochs to train
6	Goal	0	Performance Goal of the model
7	Lr	0.9	The Learning rate of the model
8	Max fail	50	Max. validation failures of the model
9	Mc	.95	Momentum constant of the model
10	Min grad	e-10	Min. performance gradient of the model

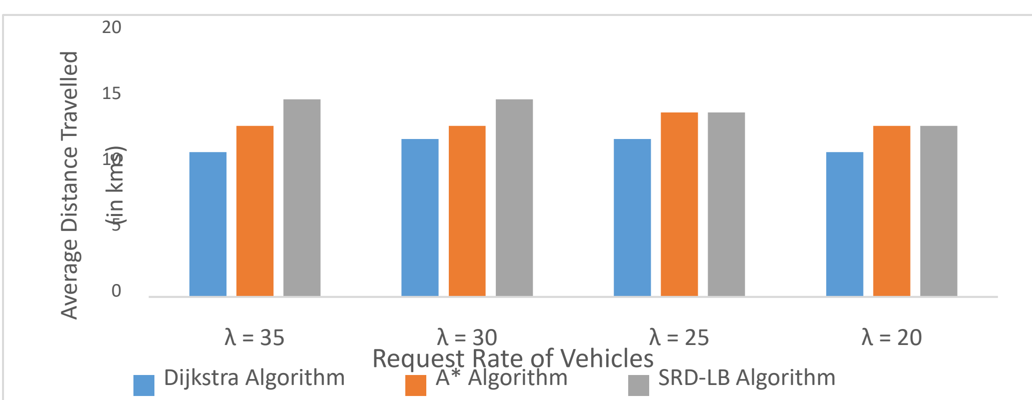

Fig 3. The Simulation Results of Average Distance Travelled by Vehicle at different Request Arrival Rate of Vehicle on Dijkstra, A* and SRD-LB Algorithm.

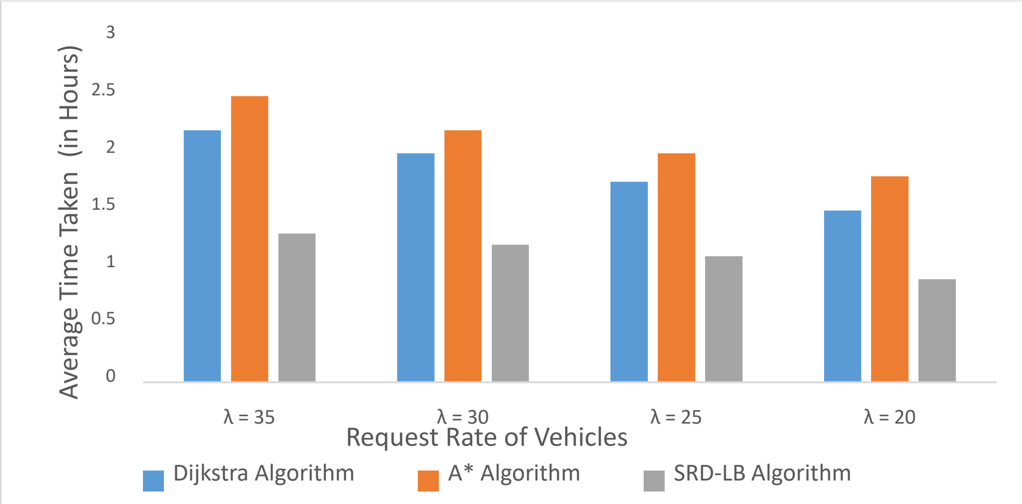

Fig 4. The Simulation Results of Average Time Taken by Vehicle at different Request Arrival Rate of Vehicle on Dijkstra, A* and SRD-LB Algorithm.

The Identify_weight module is designed for calculating the weight of a road segment based on the model presented in Section 3.1. The weights of each RS are recorded in the database, which are later used for determining optimal route. The Indentify_Candidate_List module is used for the process of determining the next possible candidates of optimal routes (the next RS to be used). The Path_Selector module selects the RS which will result in the least travel time based on the current traffic weight state. The Update_Weight module is called for each RS which is selected by the Path_Selector module.

4. RESULTS AND DISCUSSIONS

This section presents the results of the proposed SRD-LB algorithm. The simulations were conducted on SUMO (Simulation of Urban MObility), to provide a more realistic picture of traffic simulation, using OSM (Open Street Map) of New Delhi.

The Poisson process is used to generate request arrival rate (λ), which is defined as the number of requests arriving per minute. The experiments are conducted on different values of λ. The source to destination, along with the category of vehicle are generated randomly. To show the effectiveness of the simulation, same seed are provided to Dijkstra and A* algorithm as well. The results are compared on the basis of the average distance travelled and average time taken by the vehicles during the simulation. The values of λ are kept higher to ensure that the simulation results present the real picture. Multiple simulations (More than 100) were run at each request arrival rate and each simulation generated an analysis on the time frame of nearly 10 hours. The simulations were allowed to run for some time before starting the analysis since at the start of simulation, there is no traffic in the road network. Figure 3 presents the simulation results for average distance travelled by the vehicles with respect to different values of λ. Figure 4 presents the results for average time taken by the vehicles with respect to different values of λ.

5. CONCLUSION AND FUTURE SCOPE

This work presents a route determining algorithm with load balancing based on real time traffic data analysis and other external factors. The main goal of this work is to reduce the travel time within the smart city. The SRD-LB algorithm is furthermore capable of identifying and managing the state of traffic at particular time and avoiding traffic congestion by balancing the traffic between different routes. The SRD-LB algorithm is capable of handling the concurrent requests. The simulation results show that SRD-LB algorithm is capable of determining the route with shortest travel time while ensuring the traffic load balancing in the smart city road network. The SRD-LB algorithm, however increased the average distance travelled by the vehicles but considerably reduced the average travel time, which concludes better and efficient traffic management and congestion control. The future scope of this work is to integrate a mechanism which can reduce the response time of emergency services like ambulance, fire brigade, police, etc. within the city and provide support for centralized traffic policing.

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