Prioritized Route Patterns for Autonomous Vehicles using an IoT cloud in Urban Scenarios

Anuj Abraham, Pranjal Vyas, Chetan B. Math, Justin Dauwels

Abstract — At present, one of the important challenges faced by smart cities is incorporating efficient transport/mobility and minimizing traffic congestion. Autonomous vehicles(AVs) prioritization on road networks has become much popular for the completion of specified tasks and the potential of smooth manoeuvring. This chapter deals with the design and development of high-prioritized route patterns for AVs considering the actual traffic data and using an internet-of-things(IoT) platform.

The proposed system architecture uses an IoT cloud. The real-time traffic data from the sensors on the AVs and the traffic light controller are collected in an IoT cloud using wireless communication technologies such as dedicated short-range communication(DSRC) or Cellular (4G or 5G). AVs transmit the vehicle state information and traffic signal controllers transmit the traffic signal data or phase timings to the IoT cloud. The data collected at the IoT cloud is used to compute an optimal route for the AVs.

In this study, a microscopic platform has been set up to support several attributes of traffic flow data under various scenarios such as peak time and normal hours in a week. Dynamic vehicle route accounts for traffic data (i.e., how many vehicles are in between the planned path of AVs). In the IoT cloud, traffic data is processed based on the two objectives mentioned, travel times are estimated and an optimal route for AV is determined in virtual environments. The significance of having phase timings information from traffic lights, in addition to estimated travel time, is analysed.

Whenever AV requests the IoT cloud server for the best route to reach the desired destination, at the backend, the updated traffic data is processed and acknowledges the request by sending a message to AV with an optimal route. This work enhances real-time traffic updates in an IoT context to assist AVs.

The integrated simulator combines VISSIM (Traffic simulator) and MATLAB (Application simulator) via COM interface. A road network of Ang Mo Kio (AMK) area in Singapore has been built in VISSIM for the simulations. Studies show that using an IoT platform, the travel time of AV can be reduced in reaching the specified destination.

Keywords — Dynamic vehicle routing, AV, virtual environment, IoT, travel time, urban traffic, OD matrix, VISSIM, MATLAB.

1. Introduction

In the last four decades, the significance of the vehicle routing problem(VRP) has increased due to higher traffic volumes and the advancement of AV technology. Many researchers in the area of static and dynamic vehicle routing algorithms are paying immense attention to VRP and its variants. In the static routing problem, all information is known at the time of planning the routes. Whereas, in the dynamic routing problem, the detour of vehicles happens due to the uncertainties and complexities in the real-time system that occur simultaneously to the routes being carried out. For dynamic assignment of routes, extensive research was performed in previous studies and shows that it is extremely difficult to devise one single algorithm that can cater to diverse scenarios.

A typical solution to dynamic vehicle routing is a combinatorial optimization which deals with travelling salesman problem(TSP), minimum-spanning-tree(MST), Knapsack, Bin packing problem etc. [1], [2]. In this methodology, the search space solution is finite and bounded with discrete constraints. Khouadjia et al. proposed the shortest path formulation based on heuristic algorithms, but it can lead to a sub-optimal solution and does not guarantee global optimized values for some specific scenarios [3]. Moreover, efficient vehicle routing algorithms for large-scale fleet management systems were proposed by Nagavarapu et al., where a simulator platform was developed for validation and testing in virtual environments. In general, it is seen that the main objectives considered for VRP are to minimize the total travel time and cost, the total required fleet size, overall total traveling distance, and waiting time imposed on vehicles [3].

In the past few years, efforts in intelligent transport systems show that the IoT platform can play a significant role in traffic management by connecting the sensor devices over the internet to exchange information wirelessly. An IoT application provides an added insight into both the operation and performance of all aspects of the sensor devices and has been of interest to researchers [4]. Recently, intelligent transport solutions combine mobility components with technologies. These include machine interaction, that enables transportation applications to get continuous access to connectivity platforms. Real-time information systems use IoT to connect with driver services, mobile, and online devices. For innovative urban transportation technologies, an increase of automation and road capacity, improved safety and services, optimized fuel consumption are the key factors considered [4]. Advanced wireless sensor technologies and software for Vehicle-to-Everything (V2X) environments are used to support intelligent transportation services. Various data from global positing systems(GPS), sensors, etc. from the probe vehicle can be collected using vehicle-to-infrastructure(V2I) communication. A V2I communication in semi/fully automated vehicles expands the horizon for solving VRP in the urban scenario [3]. On-board units(OBUs) and road-side units(RSUs) that broadcast their state information through DSRC use wireless access for vehicular environments(WAVE) as a wireless access technology [5]. Also, V2I communication can be performed either by using DSRC or Cellular vehicle-to-everything(C-V2X) technologies. The recent research on vehicle mobility coordination system based on a

V2I communication was developed and describes an architecture that is capable of operating either in autonomous vehicles or manual driven vehicles [6].

In view of this, several studies were also carried out to improve urban mobility for an intelligent transportation system by monitoring real-time traffic updates on traffic congestion and unusual traffic incidents via roadside units [7]. Investigation on the development of other system architectures for moving vehicles or roadside infrastructure which can dynamically connect to nearby cloudlets was performed. These are particularly relevant to smart cars and intelligent transportation for updates on accidents, safety, and other applications [8].

This chapter focus on the development of a simulator platform for prioritizing AVs route patterns is performed based on actual traffic flow data via IoT cloud platforms using wireless communication technologies such as DSRC or Cellular (4G or 5G). Traffic flow data provided by Land Transport Authority(LTA), Singapore consists of vehicle counts on each lane at normal and peak hours approaching the intersection, lane speed limits, turning proposition, traffic signal phase timings, and pedestrian light activation rate at intersections. An effective way of estimating the travel times is formulated based on the gradient boosting machine(GBM) method [9]. The significance of having phase information via wireless communication technologies, in addition to estimated travel times, is addressed in this chapter. This information is provided as input for the dynamic route assignment such that an AV passes the intersections smoothly without stopping. This allows AV to reach its destination in the smallest travel time. Here, we assume that information exchange is 100% i.e., no packet drops.

The network layout for AMK area of interest(AOI) in Singapore was built in VISSIM for simulation. Firstly, the calibration and validation process are carried out for fine-tuning of specific parameters such as minimum gap time, the minimum headway, and the maximum/minimum speed of the vehicle, etc. in VISSIM. Once the calibration process is performed, the traffic flow data and signal heads are validated based on the data provided. The traffic flow data for static routing in VISSIM includes (1) Turn movements for each junction, (2) Input flow in vehicles per hour. The traffic flow data needed for static routing can be obtained from the installed detectors loops and traffic monitoring systems.

Whereas dynamic assignment parameters include: (1) origin-destination(OD) matrix, (2) Location of zones and parking lots, (3) Traffic composition, (4) Vehicle speed at free-flow (Speed limit of the road), and (5) Travel time. Obtaining the OD matrix needed for dynamic assignments is often challenging. The input of the OD matrix not only involves collected data obtained from traffic counts but also a process of determining the values according to a selected cost function. Similarly, traffic signal control includes (1) Cycle Length, (2) Green, Amber, and Red times for each traffic signal group at intersections, and (3) Pedestrian signal timing at intersections.

The rest of the chapter is organized as follows: The specific descriptions of the proposed approach to IoT system architecture are introduced in Section 2. Function modules in the simulator design platform are given in section 3. This section includes information on the traffic simulator with the real-world traffic scenarios, followed by a description on the application simulator. Section 4 deals with the vehicle routing problem followed by the implementation of prioritized route patterns for AVs in section 5. This section details the steps involved in dynamic assignment route, LTA data, OD matrix data, and learning predictor. Lastly, the paper is concluded in Section 6.

2. IoT system architecture

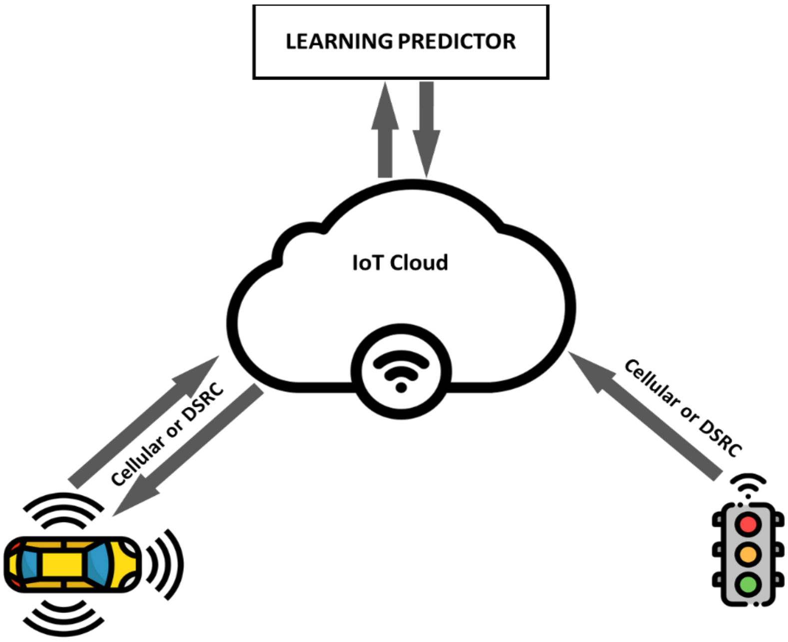


Figure 1: IoT system architecture.

The system architecture consists of an IoT cloud for data storage and data processing. The basic architecture is shown in Figure 1. The data from traffic light systems, mainly the phase timings are sent to the cloud for storage. An AV sends a route planning query to the IoT cloud using wireless communication (Cellular or DSRC). The query is handled by the learning predictor application running on the IoT cloud. The query contains information such as destination, present location, current speed and acceleration. The learning predictor uses the query, map and real-time and historical data collected by traffic light systems to find an optimal route for the AV. This route is sent to the AV vehicle as a suggestion. The route data has information such as path and travel times.

3. Simulator design

A. *Traffic Simulator*

A traffic simulator is required to create an accurate urban traffic model that matches with the real-world traffic scenarios. VISSIM is chosen because of the following reasons: (1) It precisely replicates the trajectories of any vehicle in the simulation. (2) It simulates the right and left hand side movements (3) It fulfils the advanced transit and traffic signal requirements; (4) It produces the vehicular and infrastructure (e.g. signals) information at high resolution interval as little as 100 ms; (5) It provides real-time data exchange with external programs; and

(6) It manipulates infrastructure components in a traffic network (e.g. cars dynamics and routes) as a response to stimuli obtained from external programs. Though the traffic simulator known as Simulation of Urban MObility(SUMO) satisfies most of these conditions, it does not possess the capability of simulating left-hand driving. Since, the simulations are done majorly for Singapore road networks, VISSIM is chosen over SUMO.

B. Application Simulator

There are a number of applications that can be designed to solve traffic problems. These may be broadly classified as information exchange, safety applications or vehicle re-routing. In this work, we chose MATLAB for application simulation. The application simulator also contains the logic of the V2I application that is being tested. It should seamlessly interact with traffic simulators. Multiple choices are available that satisfy this criterion. However, for the integrated simulator MATLAB was chosen because of its mature and convenient communication interface with VISSIM.

The basic block diagram of functional modules used in the simulator design is shown in Figure 2. The combination of the software has been carried out in a manner that allows an online exchange of data amongst them [5]. The COM interface helps in communication between MATLAB and VISSIM [5][10]. Traffic data can be fetched in MATLAB and control signals (the optimal route for vehicles) or the infrastructure (change in phase timings of traffic signals) can be given to VISSIM using the component object module(COM) interface.

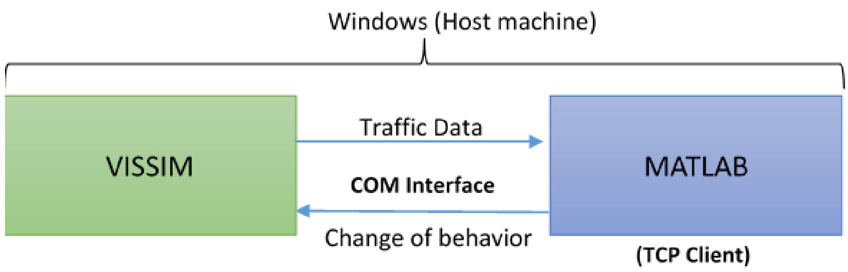


Figure 2: Function modules in Simulator design platform.

The vehicles, traffic scenarios, and traffic signals are simulated using VISSIM. The data from VISSIM is collected by MATLAB. The collected data is used by the learning predictor (Random Forest (RF) algorithm) running on MATLAB to find the optimal route. Similar to an IoT architecture the data from the traffic light system is collected at MATLAB and the RF algorithms run in MATLAB to find the optimal route. The optimal route is later suggested to the vehicles in VISSIM where it generates the origin-destination matrix for selection. Note that we assume ideal wireless communication and IoT cloud with very high reliability and low delays.

4. Vehicle Routing Problem

The VRP is one of the most popular challenge in modern day transportation as it generalizes Travelling Salesman Problem (TSP) and solves real-life scenarios. VRP defines a set of vehicles at a depot and delivers to a set of customers where all the customers are served only once.

In VRP, the main objective is to determine an optimal route by improving the travel time or some other cost. There are many constraints influencing the problem at different conditions such as vehicle load, the time interval between each customer that has to be delivered, backhauls, the time frame within each customer needs to be serviced, a route is designed for door to door mobility and users uncertainty [11]. These are classified into capacitated VRP(CVRP), VRP with time windows(VRPTW), VRP with backhauls(VRPB), VRP with pick-up & delivery(VRPPD), dial-a-ride-problem(DARP) and dynamic VRP(DVRP) respectively [12]. Figure 3 shows the different variants of VRP according to a survey study.

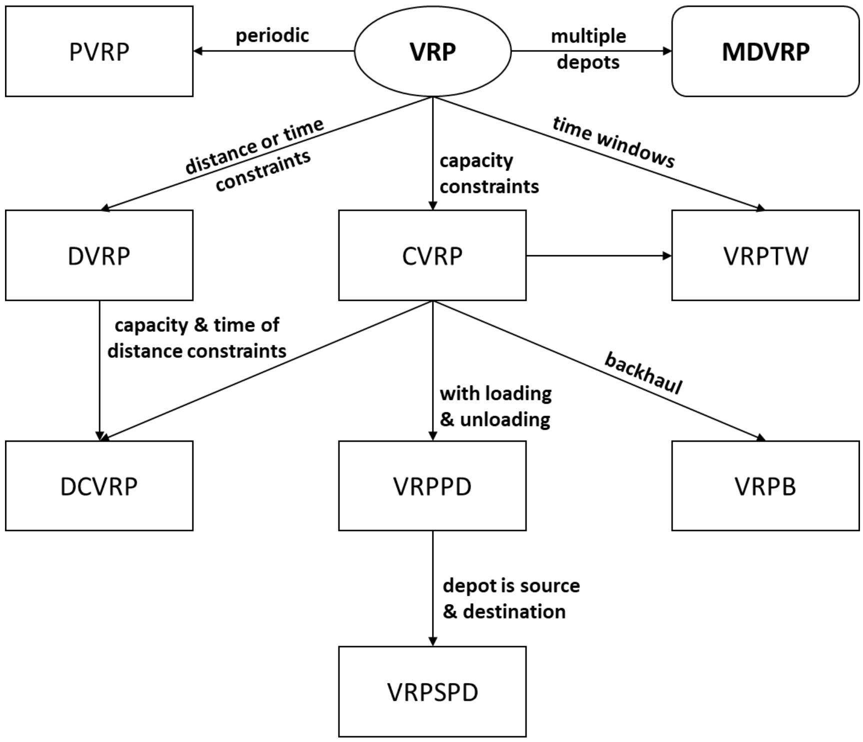


Figure 3: Different types of VRP [12] .

In this chapter, DVRP yields an optimal path between a set of OD matrix with variance in signal phase timing between junctions and vehicle volumes. Figure 4 represents the concept of DVRP.

Figure 4 explains the execution of single vehicle entry. Initially, the route is defined as A,B,C,D,E after two new dynamic requests as time constraint a new route has been designed such as A,B,C,D,Y,E,X. This example reveals the optimal path for dynamic vehicle routing and real-time communication is necessary between the vehicles [13]. The proposed work develops a simulator platform for prioritizing AVs route pattern based on real data.

With reference to static elements, dynamic routing problem faces some challenges such as congestion due to emergency vehicle affecting the cost factor of travel time and uncertainty of traffic conditions such as peak and normal hours within a week.

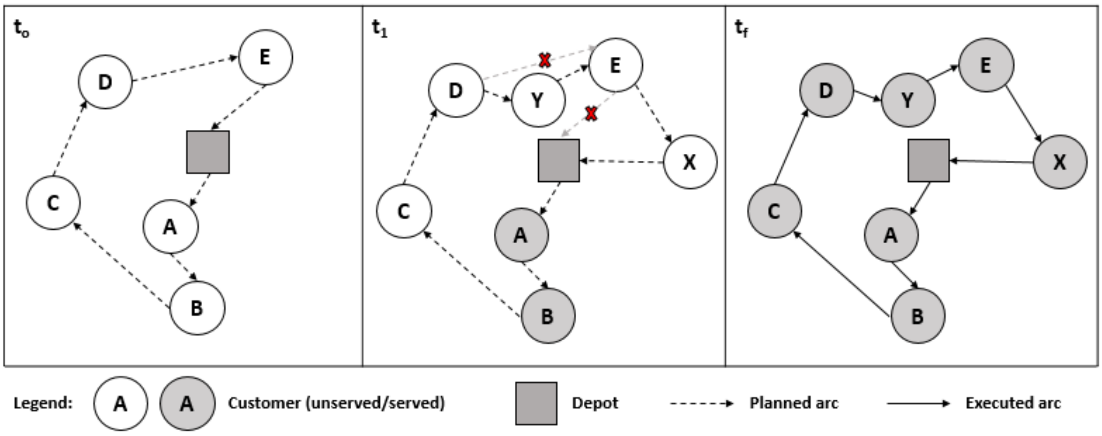


Figure 4: Dynamic VRP [13].

5. Implementation of Prioritized Route Patterns

This work uses VISSIM 11 for the dynamic route assignment and generates travel cost for different zones combinations. The main inputs to dynamic route assignment depend on the generation of OD matrix, vehicle composition and its cost function.

A. *Steps involved in dynamic assignement route.*

In VISSIM, dynamic assignment/route builds a model according to route choice behaviour, avoiding the static routes and using the OD matrix as flow input. Origin-destination matrix contains information such as the number of trips flows where each cell represents the travel demand between each origin (row) and destination (column) zone. This is represented as a matrix column according to the number of zones and parking lot in each zone. In this chapter, we consider the parking lot as zone connector. Parking lot defines the point where the vehicle actually appear or leave the road network and there are three types:

1) Zone connector
2) Abstract parking
3) Real parking lot

Each zone can have only one parking lot, which is placed in between two nodes. Nodes placed in the junctions or path where it could diverge and edges are route sequences or links. Some parameters considered for dynamic route assignment in VISSIM are Kirchhoff assignment (defines the polarisation of path distribution), logit function (defines parking lot choice model), correction of overlapping paths (affects the vehicle distribution on paths that are partially identical), travel time on paths & edges and volume on edges. The flow chart representing the Steps involved in dynamic vehicle route is described in Figure 5.

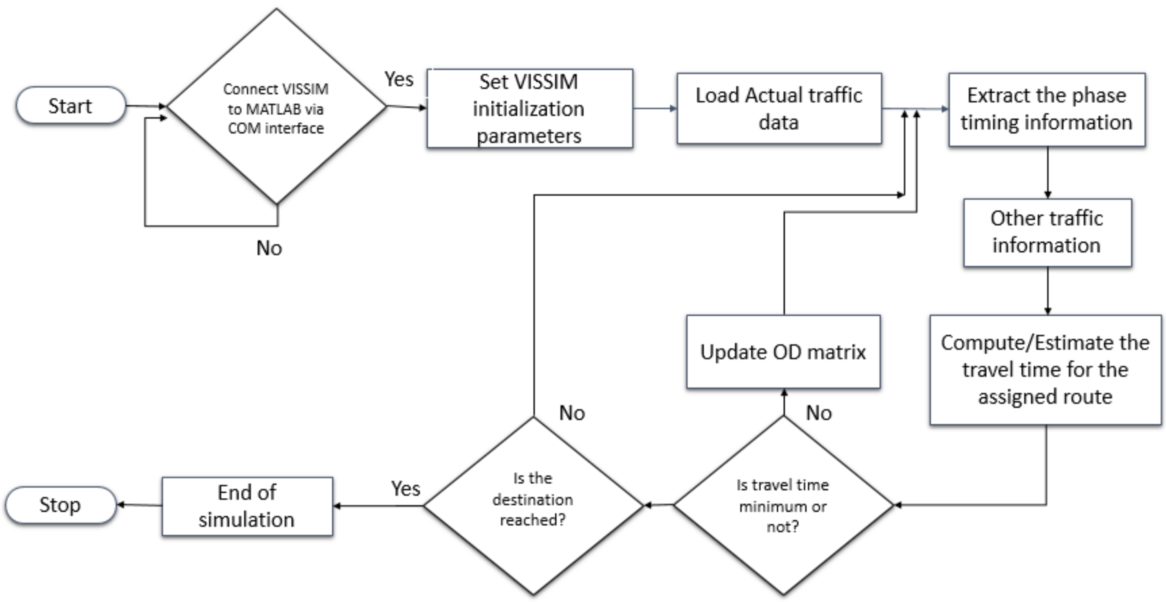


Figure 5: Steps involved in dynamic vehicle route.

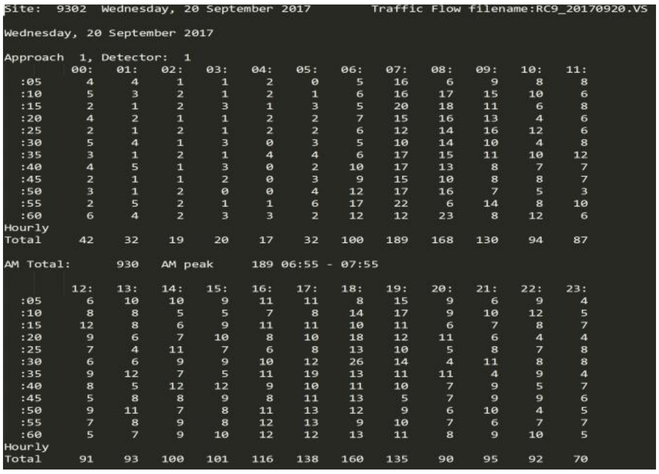
B. LTA Data

In this work, the AMK road network is considered where five signal junctions are used for the study of a high prioritized route pattern. The traffic flow data [14] contains information such as:

1) Traffic light and pedestrian signal timing.
2) Pedestrian light activation rate at intersections.
3) Turning proportions at intersections
4) Vehicle counts for each lane at normal and peak hours.

Figure 6(a) shows lane marking and signal phase timings for a particular intersection in AMK road section. The signal phases are represented according to the ring-and-barrier diagram [14]. Figure 6(b) shows the vehicle counts data for traffic control signal TCS 9302 intersection in AMK road section.

(a)



```
Site:  9302  Wednesday, 20 September 2017         Traffic Flow filename:RC9_20170920.VS

Wednesday, 20 September 2017

Approach  1, Detector:  1
          00:   01:   02:   03:   04:   05:   06:   07:   08:   09:   10:   11:
  :05       4     4     1     1     2     0     5    16     6     9     8     8
  :10       5     3     2     1     2     1     6    16    17    15    10     6
  :15       2     1     2     3     1     3     5    20    18    11     6     8
  :20       4     2     1     1     2     2     7    15    16    13     4     6
  :25       2     1     2     1     2     2     6    12    14    16    12     6
  :30       5     4     1     3     0     3     5    10    14    10     4     8
  :35       3     1     2     1     4     4     6    17    15    11    10    12
  :40       4     5     1     3     0     2    10    17    13     8     7     7
  :45       2     1     1     2     0     3     9    15    10     8     8     7
  :50       3     1     2     0     0     4    12    17    16     7     5     3
  :55       2     5     2     1     1     6    17    22     6    14     8    10
  :60       6     4     2     3     3     2    12    12    23     8    12     6
Hourly
Total      42    32    19    20    17    32   100   189   168   130    94    87

AM Total:       930   AM peak     189 06:55 - 07:55

          12:   13:   14:   15:   16:   17:   18:   19:   20:   21:   22:   23:
  :05       6    10    10     9    11    11     8    15     9     6     9     4
  :10       8     8     5     5     7     8    14    17     9    10    12     5
  :15      12     8     6     9    11    11    10    11     6     7     8     7
  :20       9     6     7    10     8    10    18    12    11     6     4     4
  :25       7     4    11     7     6     8    13    10     5     8     7     8
  :30       6     6     9     9    10    12    26    14     4    11     8     8
  :35       9    12     7     5    11    19    13    11    11     4     9     4
  :40       8     5    12    12     9    10    11    10     7     9     5     7
  :45       5     8     8     9     8    11    13     5     7     9     9     6
  :50       9    11     7     8    11    13    12     9     6    10     4     5
  :55       7     8     9     8    12    13     9    10     7     6     7     7
  :60       5     7     9    10    12    12    13    11     8     9    10     5
Hourly
Total      91    93   100   101   116   138   160   135    90    95    92    70
```

(b)

Figure 6: (a) Lane markings Signal phase timing at intersections in AMK road section and (b) Vehicle count data.

C. OD Matrix Data

In this chapter, OD matrix considers four zones in Ang Mo Kio region which are simulated in traffic simulator. The OD matrix that represents the number of trips between the zones is tabulated in Table 1. The total matrix travel time considered is 5 minutes.

TABLE 1: OD MATRIX

	Zone 1	Zone 2	Zone 3	Zone 4
Zone 1	0	20	40	59
Zone 2	77	0	56	44
Zone 3	56	56	0	23
Zone 4	78	89	32	0
Total	**211**	**165**	**128**	**126**

For example, a scenario is considered where AV is prioritized based on the traffic data, mainly at peak traffic and normal traffic periods in the road network. Similarly, another scenario is analysed where both the traffic flow data and signal flow control for smooth movement of AV is illustrated in Figure 7. For both the scenario, the objective is to minimize the travel time and determine an optimal route for AV in virtual environments.

D. Learning Predictor

Random forest (RF) is a well-known supervised collective learning method and is used to do travel time prediction [15]. A real-time traffic data set for an urban road network of AMK road networks in Singapore is considered to perform this simulation. Traffic data can be updated periodically in real-time to estimate the shortest travel time/path. RF learning predictor is one of the best travel time prediction techniques which uses tree-based classifiers [16]. In training phase, RF creates multiple classification and regression trees (CART)-like trees [17][18], each trained on the original training data and searches only across the randomly selected subset of the input variables to determine a split. Keywords related to RF are:

1) *Bagging*: In bagging or bootstrap aggregation, each base model is trained with the training data.
2) *Decision Tree*: A decision tree is a hierarchical data structure with nodes and branches. The entry point of a decision tree, which is at the top of the hierarchy is called the root node. The root node will have child nodes, which in turn may have their successors.

By limiting the number of trees, the computational complexity of the algorithm is controlled and the correlation between trees is decreased. As a result, RF can easily handle high-dimensional data by using large number of trees. The main advantages of using RF in traffic prediction are: (1) it runs efficiently on large datasets such as traffic data; (2) gives predictions with very low prediction errors; (3) it is relatively robust to noise; and (4) it has less computational complexity. Defining mathematically, the variance of a RF, (σ_{RF}^2) can be given as shown in equation 1,

$$\sigma_{RF}^2 = \rho_i \sigma_i^2 + \frac{1-\rho_i}{m} \sigma_i^2 \ (1)$$

where, m is the total number of trees, ρ_i is the correlation between the individual trees and σ_i^2 is the variance of the individual trees.

Recent studies on forecasting methods [20] prove that the travel time and traffic condition predictions that are based on data-driven approaches are appropriate to determine the shortest travel time. To achieve improved accuracy, the random forest is trained with a fixed value of 500 trees [16]. But irrespective of the problem, the number of trees is to be varied such that we get better accuracy with an objective of RF variance minimize to zero. To find the optimum number of trees for training one can perform sensitivity analysis. In this paper, the number of trees in RF was determined by 10-fold cross-validation, which is between 50 to 1000. In our study, the number of trees is taken as 200 (best threshold value), as smaller the trees computational cost is lesser. Also, it was seen that for a higher value of trees chosen it gives the same minimum test error of 5% with additional computation cost. Thus, a trade-off is created between the accuracy and complexity.

The two important tuning parameters of RF are: the number of trees *m* and the random independent variables σ_i^2 considered at each split. In our work, the prediction accuracy is represented in terms of mean absolute percentage error (MAPE). At each split, the tree only considers some randomly selected variables and average the predicted values to get the new forecast. All models were trained with 3 independent variables to generate a forecasting result by using historical data, *i.e.*, the 3 most recent travel times observed (*t*-3, *t*-2, & *t*-1) in the network are used to predict travel time for the next interval (*t*). Thus, MAPE which is used as the evaluation criteria is given in equation 2,

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t} \ (2)$$

where, n is the total number of samples, A_t is the actual value of the travel time and F_t is the forecasted value of travel time.

It is observed that, MAPE is reducing with increase in number of trees m. The RF supervised ensemble learning method is built using the 'TreeBagger' class which create a bag of decision trees, as used in MATLAB [19], is involved in this paper. Also, 'TreeBagger' selects a random subset of predictors to use at each decision split as in RF. For regression problems, the class 'TreeBagger' supports mean and quantile regression forest.

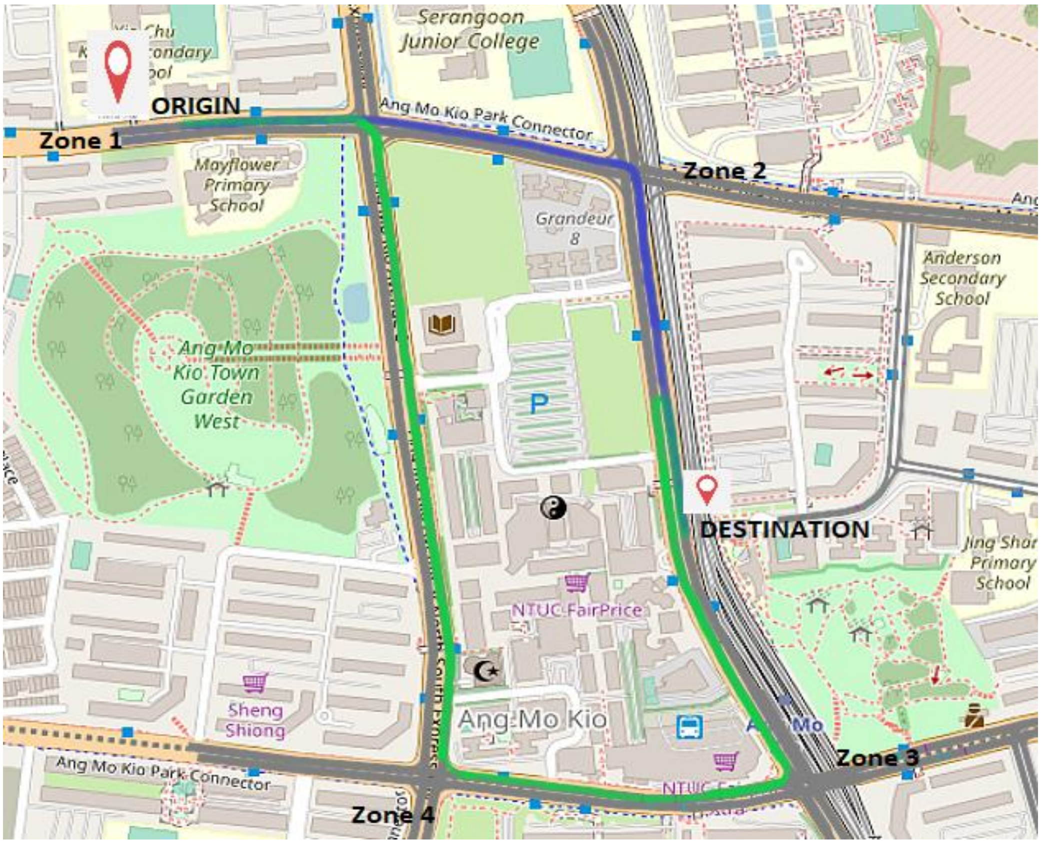


Figure 7: Dynamic vehicle routing scenario in AMK section based on traffic flow data and traffic signal control in VISSIM.

From Figure 7, it is seen that the four zones, parking lots at each zone connector and origin-destination information are predefined in VISSIM. The initial static route is represented in blue colour based on the shortest path algorithm. The routing cost obtained from the shortest path is 1.2km. The sequence of the served zones is: **Origin** ⟶ **zone 2** ⟶ **Destination**.

Then, the prioritized AV route pattern is determined dynamically based on traffic volume and signal heads. It is observed from the vehicle flow data that congestion occurs at the intersection near to zone 1 and zone 2 in a certain time instant. Therefore, the estimated travel time while incorporating the traffic data and phase timing information at the intersection is 350s. Whereas, the optimal dynamic route sequence determined with a minimal travel time of 276s is: **Origin** ⟶ **zone 4** ⟶ **zone 3** ⟶ **Destination**.

The dynamic path assignment is performed through zone 1, zone 4 and zone 3 respectively, (indicated in green colour) to minimize the travel time rather than the shortest path. Hence, it is observed that the total travel times are minimal when the phase information is considered using wireless communication in IoT platform and the optimal route is determined.

6. Conclusions

A simulation platform has been developed to test, validate and illustrate prioritized route patterns of AVs in virtual environments using an IoT platform. The network layout for AMK region in Singapore was built in VISSIM. The travel time of AV is estimated from actual traffic data and optimised through traffic light controller in an IoT cloud using wireless communication technologies such as DSRC or Cellular (4G or 5G). The primary objective of smallest travel time of AV incorporating other traffic condition in reaching the specified destination is performed and analysed. Hence, it is observed that the total travel time is minimal when the phase information are considered via IoT cloud using wireless communication and optimal route is determined.

Future work involves investigating the other techniques to include more constraints such as real-time delays, road conditions, weather/climatic data, routing policies, time windows for pick-up and drop-off, battery management and fleet optimization of AVs into the simulation platform to illustrate more realistic vehicle routing scenarios. Also, an attempt will be performed to understand the influence of passenger comfort under traffic congestions.

Acknowledgements

The authors gratefully acknowledge the contributions of Ms. Rajashree A. Sundaram, Ms. Priyanka R. Mehta and Mr. Usman Muhammad of Energy Research Institute@ NTU, Nanyang Technological University, Singapore for their timely support. This material is based on research/work supported by National Research Foundation under Virtual Singapore Program Award No. NRF2017VSG-AT3DCM001-018. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of National Research Foundation.

References

[1] Christian Prins. 2004. A simple and effective evolutionary algorithm for the vehicle routing problem, *Computer & Operations Research*. 13(12):1985 -2002.

[2] Nagavarapu, S.C., Tripathy, T., and Dauwels, J. 2017. Development of a Simulation Platform to Implement Vehicle Routing Algorithms for Large Scale Fleet Management Systems. *Proceedings of the 20th IEEE International Conference on Intelligent Transportation Systems (ITSC)*, Yokohama, Japan: 124-129.

[3] Khouadjia, M. R., Sarasola, B., Alba, E., Jourdan, L., and Talbi, E.G. 2012. A comparative study between dynamic adapted PSO and VNS for the vehicle routing problem with dynamic requests. *Applied Soft Computing*, 12(4):1426–1439.

[4] Alshehri and Sandhu, R. 2016. Access control models for cloud-enabled internet of things: A proposed architecture and research agenda. *Proceedings of the IEEE International Conference on Collaboration and Internet Computing (CIC),* Pittsburgh, PA, USA. 530–538.

[5] V. Milanés, Godoy, J., Pérez, J., Vinagre, B., González, C., Onieva, E. and Alonso, J. 2010. V2I-Based Architecture for Information Exchange among Vehicles. *IFAC Proceedings Volumes*. 43(16):85-90.

[6] Mohammed Sarrab, Supriya Pulparambil, and Medhat Awadalla. 2020. Development of an IoT based real-time traffic monitoring system for city governance. *Global Transitions*. 2:230-245.

[7] Gupta, M., Benson, J., Patwa, F., and Sandhu, R. 2020. Secure V2V and V2I Communication in Intelligent Transportation using Cloudlets. *IEEE Transactions on services computing*. 1-12.

[8] Tangirala, N.T., Anuj Abraham, Apratim Choudhury, Pranjal Vyas, Rongkai Zhang, and Dauwels, J. 2018. Analysis of Packet drops and Channel Crowding in Vehicle Platooning using V2X communication. *Proceedings of the IEEE Symposium Series on Computational Intelligence (SSCI-2018)*, Bangalore, India, November 18-21. 281-286.

[9] Mason L., Baxter J., Bartlett P. L., and Frean, Marcus. 1999. Boosting algorithms as Gradient Descent. *Proceedings of the 12th International Conference on Neural Information Processing Systems*. 512–518.

[10] Apratim Choudhury, Maszczyk, T., Asif, M.T., Mitrovic, N., Math, C.B., Li, H. and Dauwels, J. 2016. An integrated V2X simulator with applications in vehicle platooning. *Proceedings of the IEEE International Conference on Intelligent Transportation Systems (ITSC)*. 1017–1022.

[11] Ghannadpour, S. F., Noori, S., Tavakkoli-Moghaddam, R., and Ghoseiri, K. 2014. A multi-objective dynamic vehicle routing problem with fuzzy time windows: model, solution and application. *Applied Soft Computing*, 14(1): 504–527.

[12] Jairo, R. Montoya-Torres, Julián López Franco, Santiago Nieto Isaza, Heriberto Felizzola Jiménez, and Nilson Herazo-Padilla. 2015. A literature review on the vehicle routing problem with multiple depots. *Computer & Industrial Engineering*. 79:115-129.

[13] Pillac, V., Gendreau, M., Guéret, C. and Medaglia, A. L. 2013. A Review of Dynamic Vehicle Routing Problems. *European Journal of Operational Research*. 1-11.

[14] Traffic Signal Timing Manual. 2017. [*LTA data*]
https://ops.fhwa.dot.gov/publications/fhwahop08024/chapter4.htm

[15] Vladimir Svetnik, Andy Liaw, Christopher Tong, Christopher Culberson J., Robert Sheridan P., and Bradley Feuston P. 2003. Random forest: a classification and regression tool for compound classification and qsar modeling. *Journal of chemical information and computer sciences*. 43(6):1947–1958.

[16] Narayanan, A. K., Pranesh, C., Nagavarapu, S. C., Kumar, B. A. and Dauwels, J. 2019. Data-driven Models for Short-term Travel Time Predictio," *Proceedings of the IEEE*

International Conference on Intelligent Transportation Systems (ITSC), Auckland, New Zealand. 1941-1946.

[17] Breiman, L. 2001. Random forests. *Machine learning*, 45:5–32.

[18] Breiman, L., Jerome Friedman, Charles J. Stone, and Richard A. Olshen. 1984. *Classification and regression trees*. CRC press.

[19] MATLAB. *Treebagger*. 2019. https://www.mathworks.com/help/stats/treebagger.html.

[20] Simon Oh, Young-Ji Byon, Kitae Jang, and Hwasoo Yeo. 2015. Short-term Travel-time Prediction on Highway: A Review of the Data-driven Approach. *Transport Reviews.* 35(1):4-32.