Impact of Variable Travel Time on the Solution of Vehicle Routing Problem: A Case Study of Bangkok

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ABSTRACT

In the logistics industry, it is essential to have optimized vehicle routes for cost-effectiveness and customer satisfaction. However, most conventional studies on vehicle routing problem (VRP) do not consider the variation in travel time, leading to nonoptimal routes. This study shows the importance of variation in travel time for different times of the day and different days of the week by comparing the optimization results of vehicle routes for constant travel time and variable travel time. Two different scenarios were considered for Bangkok city, Case-1, where customers are scattered across the city, while Case-2, where customers are concentrated on a small area. It was concluded that up to 27.59% error in travel time could be obtained with an average of 12% for Case-1. At the same time, a maximum 30.85% error in travel time can be obtained with an average of 7% for Case-2. Therefore, it is necessary to consider time-dependent travel time in urban logistics route planning in Bangkok. This study also put forward a method to collect travel time data of different origin-destination pairs for different times of the day and different days of the week that can be used by any logistics company.

KEYWORDS: *Time-Dependent VRP, Variable Travel Time, VRP Optimization*

1 INTRODUCTION

In the logistics industry, customers satisfaction and cost-effectiveness mainly depend on the optimization of vehicle routes. These optimized routes enable vehicles to full fill the customers' demands using the shortest path having minimum cost and time. This optimization of vehicle routes for a set of customers is known as the vehicle routing problem (VRP). It is essential for end-user satisfaction and the efficiency of the logistics industry as a whole.

Dantzig & Ramser (1959) were the first to introduce VRP for optimizing delivery problem for gasoline trucks. The VRP can be solved using exact methods (Adulyasak & Jaille, 2016). However, exact algorithms have very high computation time while solving large problems. Therefore, primarily heuristic algorithms are used to solve VRP. The VRP has different variants depending on the problem configuration, objectives, and constraints. Eksioglu et al (2009) performed extensive studies on the variants of VRP. One of these variants is the time-dependent VRP, also known as TDVRP, which considers "variable cost" in the objective function in tesrms of travel time instead of distance. In the real world, travel time is subjected to variations due to different times of the day and different days of the week, and many other factors. However, the data that capture the variation in travel time for different times of the day and different days of the week at the city level have not been available until recently. It is a challenging task to optimize VRP using these data.

Researchers have largely studied the TDVRP. Gendreau et al (2015) did a survey on the problem. They classified the problem in 3 categories depending on the quality and the evolution of the information related to travel times, namely: 1) Static and deterministic time-dependent VRP; 2) Static and stochastic time-dependent VRP, and 3) Dynamic time-dependent VRP. In this paper, we mainly focus on static and deterministic time-dependent VRP, in which the input is known beforehand.

Malandraki & Daskin (1992) were the first to introduce TDVRP. However, in their model of TDVRP "first in first out" (FIFO) principle was not considered when travel time was included. Step function was used by Horn (2000) with a piecewise linear continuous model to get the quadratic travel

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time model, which led to a more complicated problem framework and required some approximation and simplification of the problem. This problem was solved by Ichoua et al (2003) by using the travel speed step function to obtain the travel time function. This introduction of the travel time function helped the researchers to divide travel time into a few steps instead of considering it as a constant value. Fleischmann et al (2004) devised a framework to derive travel time data from the state-of-the-art traffic information system and used it in different algorithms for solving general VRP. An actual road network speed model was suggested by Kok et al (2012) to reflect traffic congestion. VRP instances were generated to test congestion avoidance strategies. It was concluded that the optimization would be more reliable if congestion was considered. Lecluyse et al (2013) used a method for considering time-dependent travel times that are both spatially and temporally correlated. The data were more realistic but challenging to obtain, and the VRP problem became more complicated to solve.

Xiao & Konak (2016) extended the time-dependent VRP by including a time window to further improve customer satisfaction. The time window was used to consider the available time of the customer as well as vehicle availability. Till now, the TDVRP was only considered for simple capacitated VRP; however, Sun et al (2018) and Atasagun & Karaoglan (2019) further extended TFVRP to pick-up and delivery problems. Carić &s Fosin (2020), for the first time, introduced a framework that used historical data for solving TDVRP by identifying congested areas and avoiding them using an efficient optimization algorithm. However, all these studies used a piecewise linear travel time function, in which travel time was divided only into a few intervals. Jie et al (2022) used a continuous travel time function for solving vehicle routing problem with a time window, considering variable travel time for different times of the day and different days of the week. Furthermore, their TDVRP model also included the weather effect of travel time and extended their TDVRP include time window as well.

The existing literature shows that the travel time data that reflect the actual congestion occurring in large cities and complex road networks are complicated to obtain. No previous studies were found to compare the impact of variable travel time with constant or average travel time to the solution of VRP, especially for a large city with a complex road network like Bangkok. Lombard et al (2018) modeled the TDVRP using open data, in which they have used Google Maps, distance API matrix. The authors used a time step of 2 hours, which did not provide any promising results. This work is very relevant to our work, and our finds will be compared to the finding of this work.

In order to illustrate the variation in travel time, travel time was collected between each pair of nodes of customers with a 15-minute interval for one week. Travel time data were collected for two generalized case studies in Bangkok. Both mentioned cases were solved using the Google OR Tool (Google, 2021), which is one of the standard optimization tools, to explore further the variation in optimization of routes using different times of the day and different days of the week.

The contributions of this study are as follows: first, the variation in travel time, which reflects congestion, throughout the day and week are explored, and peak periods are identified. Second, vehicle route optimization was done for a constant value of travel time as well as for different travel times of the day and different days of the week. The importance of consideration of variation in travel time is shown by calculating the difference in total travel time of optimized routes as compared to the result obtained by constant travel time.

2 STUDY AREA AND DATA COLLECTION

In this paper, the area within Bangkok outer ring road is considered the study area, as shown in Figure 1. The area is divided into two cases, one in which the customers are scattered across the city (Case-1). This area includes the whole Bangkok province and some parts of adjacent provinces near Bangkok like Pathum Thani, Nontaburi, etc. The outer ring road plays a significant role in connecting these provinces. Furthermore, this outer ring also includes the distribution centers of many logistics companies and supermarkets. This study area also provides the freedom to select trips ranging from only a few kilometers to almost 50 kilometers. Whereas the second case study, where customers are concentrated on a small area (Case-2). The trip size in Case-2 varies from 500 meters to 5km.

For data collection, Bing map distance matrix API (Bing, 2021) is used, which provides both the travel time and distance between a set of origins and destinations. Bing map distance matric API provides users with a template for both HTML and Microsoft Excel, which can be used for data collection. For this paper, Microsoft Excel was used for data collection. The Bing map distance matric

API needs the coordinates of origin and destination, time of the day, day of the week, and travel mode as input. And provide the user with distance or travel time between the provided origin and destination based on the routes calculated by Bing maps route API. This work is mainly focused on travel time; therefore, only travel time information was collected from Bing map distance matric API. Travel time calculation is based on the predictive traffic information, depending on the start time specified in the input.

It is worth noting that the travel time matrix obtained from the Bing map is not symmetrical due to the fact that some roads are one-way as well as the congestion at different times of the day affect the selection of specific route. The triangular inequality may not be satisfied due to different levels of traffic and different types of roads. Furthermore, those roads are selected which have the least travel time rather than the least travel distance. However, the travel time, which is the cost in the objective function, will satisfy the triangular inequality as the shortest travel time between two points is used.

The travel time matrix is generated in the following steps:

- Select the location of customers and depot on the map using their coordinates.
- Select the time horizon with a number of intervals (15 minutes) and days (Monday to Sunday).
- Use the coordinates of customers and depot, with the time stamp (date and time) as an input to Bing map distance API to obtain travel time.
- Combine the output travel time into a single travel time matrix.

A similar data collection methodology was used by Lombard et al (2018). However, the authors used Google map distance API and compared the optimization results using average/constant travel time with variable travel time.

In order to investigate the peak period over the city, the variation in travel time was obtained for different times of the day for 100 origin-destination pairs, as shown in Figure 2 (Case-1) and Figure 3 (Case-2). It can be concluded from the figure that the pattern of travel time variation is similar for the different locations, with the only difference in the value of travel time. Furthermore, it can also be seen from the figure that morning peak is around 8:00 AM and evening peak is around 6:00 PM. For the sake of this work, travel time around 12:00 PM is also considered. For the constant travel time, travel time at 8:00 AM, 12:00 PM, and 6:00 PM for all days of the week were computed. Twenty-one values of travel time were obtained for the whole week. The average of those values was calculated to find the constant travel time.

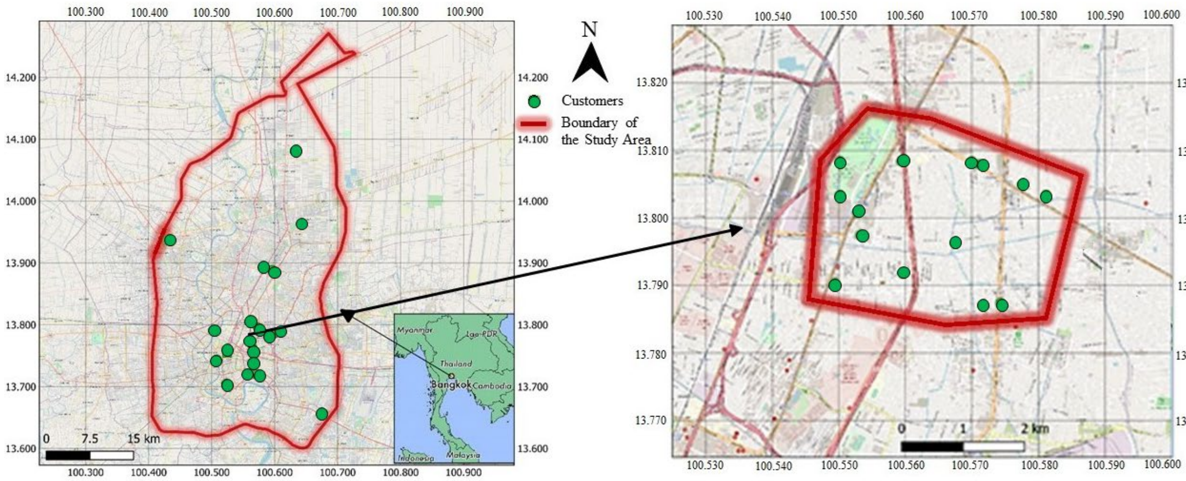
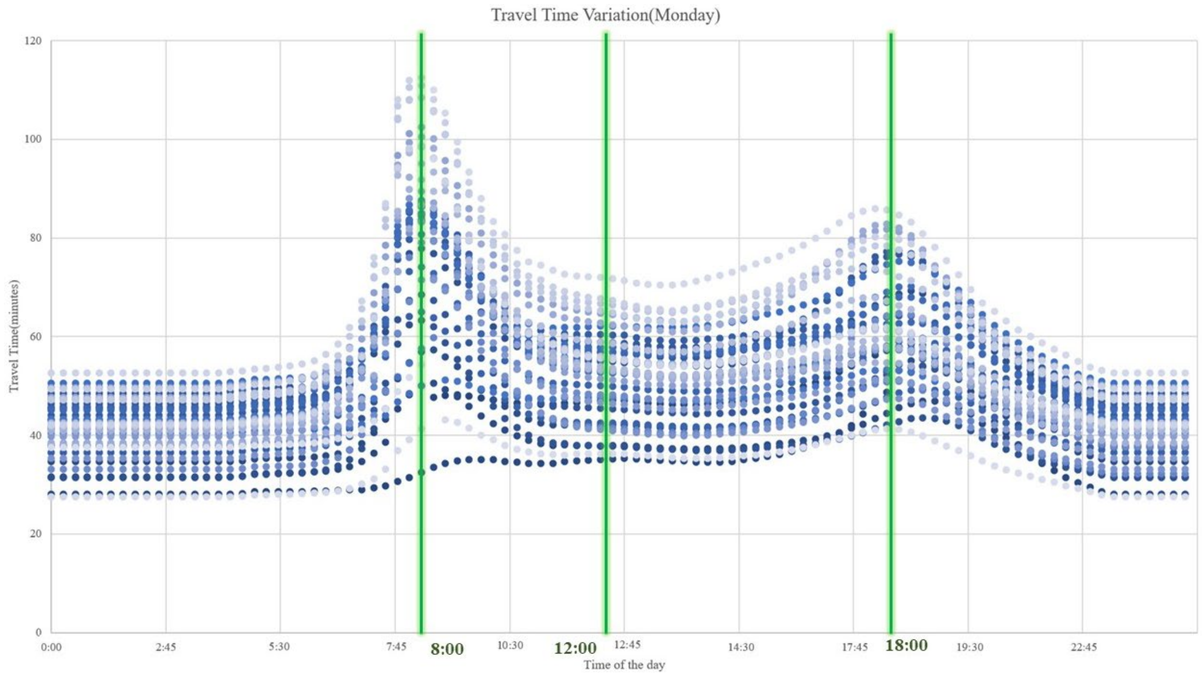


Figure 1. Study area and customers location for Case-1(left) and Case-2(right)



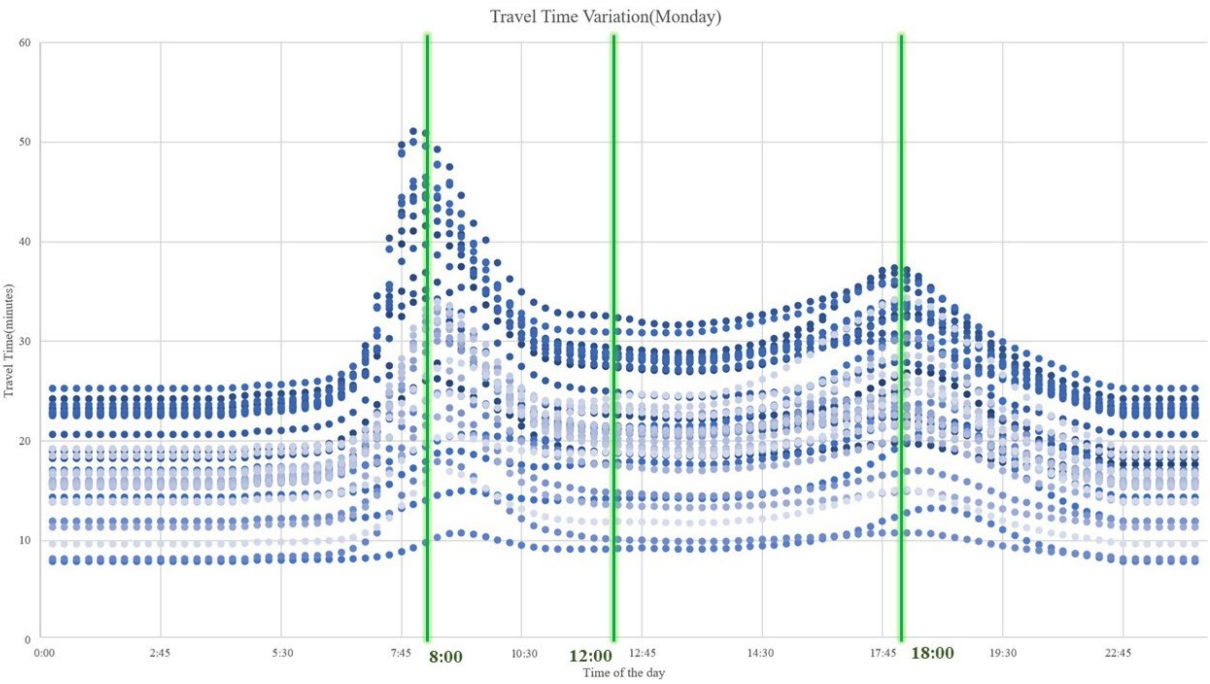


Figure 3. Travel time variation between different pairs of origin-destination (Case-2)

Similarly, Figure 4 shows the variation in travel time for different days of the week. It can be seen from this figure that the pattern of travel time variation from Monday to Friday is similar, with high intensity specifically for Friday. At the same time, the pattern on weekends is different as the peak occurs at different times. For this paper, travel time matrices for 8:00 AM, 12:00 PM, 6:00 PM, and an average of these three (constant/average travel time) were generated.

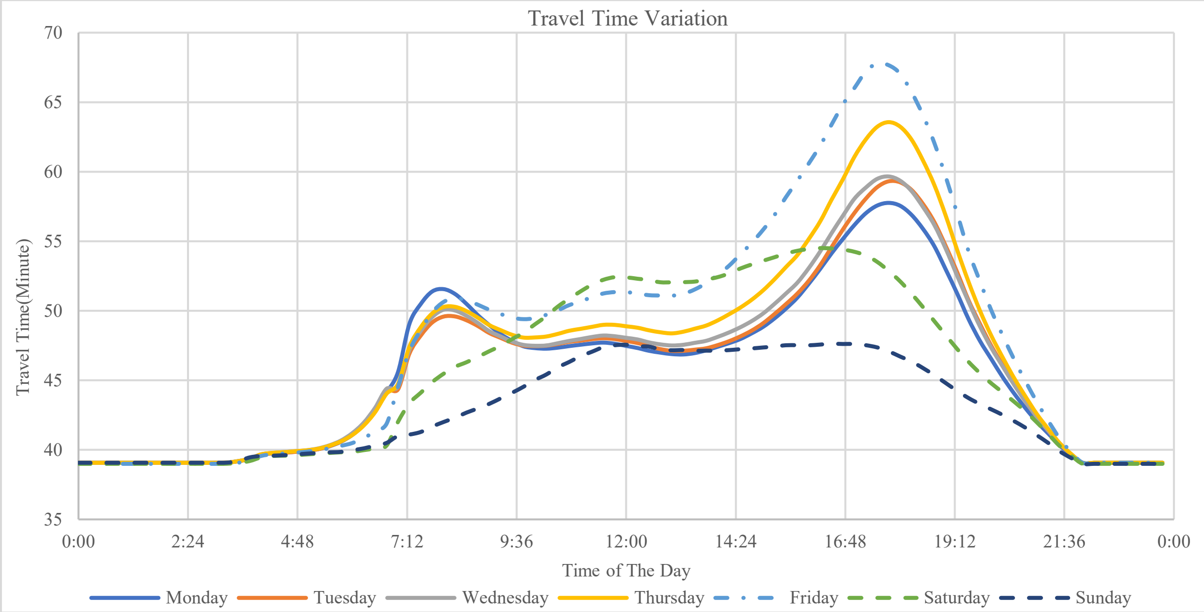


Figure 4. Travel time variation for different days of the week (Case-1)

3 VRP MODEL

VRP is a route optimization problem with some constraints. VRP model is a complete graph G = (V, E). The related sets, decision variables, and parameters are defined as follow:

Sets:

V = {0, 1, 2, …, *n*} represents customers, where 0 represents the origin(depot).

E = {(*i,j*) ϵ *V*, $i \neq j$} edges represents routes.

K = {0, 1, 2, …, *k*} set of the vehicles.

Decision Variables:

s_i: variable used for optimization priority

x_{ijk}: variable indicating the vehicle kth traveling from node *i* to *j*.

Parameters:

M: number of vehicles

R: Vehicle range (length of one shift).

v_{ij}: travel cost by vehicle k traveling across route (*i,j*) as x_{ijk}.

n: number of nodes, including depot.

As far as this paper is concerned, the main focus is on the effect of variation of travel time on vehicle route optimization. Therefore, to simplify the model demand of the customers as well as the capacity of the vehicles are neglected. Therefore, the optimization is done based on using the minimum number of vehicles to obtain the minimum overall travel time. The first objective of the VRP model is to minimize the number of vehicles, and the second objective is to minimize the travel cost. The objection function F(x) is shown as:

$$F(x) = s_1 M + s_2 \sum_{k=1}^{M} \sum_{i=0}^{n} \sum_{j=0}^{n} v_{ij} x_{ijk} \tag{1}$$

Where s1 >> s2 to ensure the priority in optimization is given to minimizing the number of vehicles. Equation (1) is subjected to:

$$\sum_{i=0}^{n} \sum_{k=1}^{M} x_{ijk} = 1, \forall j = 1,2, \dots, n \tag{2}$$

$$\sum_{j=0}^{n}\sum_{k=1}^{M} x_{ijk} = 1, \forall i = 1,2, \dots, n \tag{3}$$

$$\sum_{k=1}^{M}\sum_{i=1}^{n} x_{i0k} = \sum_{k=1}^{M}\sum_{j=1}^{n} x_{0jk} = M \tag{4}$$

$$\sum_{i\in K}\sum_{j\in K} x_{ijk} \geq 1 \tag{5}$$

Where M is the number of vehicles, n-1 is the number of customers. Constraints (2) and (3) ensure that each customer is served by one vehicle only once. Constraint (4) is for every vehicle to leave the depot and return to the depot. Constraint (5) eliminates secondary paths. Travel time variation will not make any changes to the model as the same model will be applied to the problem but at a different time of the day. Furthermore, R was used as vehicle range constraint selected as 210 minutes for Case-1 and 80 minutes for Case-2. In the standard VRP model shown above, it can be seen that objectives, vehicles, depots, customers, and roads are the main elements of the problem. Roads are the means of delivery, whereas customers are the nodes of the road network. The customers should be visited once and only once. Similarly, depots are the origin and destination for the vehicles which are responsible for picking up goods from depots and delivering goods to the customers. (Zheng, 2019)

4 PROBLEM-SOLVING METHOD

The problem considered in this work is a standard VRP problem. For the study area, twenty random points (one depot and 19 customers) were generated, and four vehicles were considered to fulfill the demands of those customers for Case-1. In comparison, fifteen random points (one depot and 14 customers) and four vehicles were considered for Case-2. For both cases, small four wheels trucks and delivery vehicles were considered as in Bangkok, more than four wheels trucks are not allowed during peak hours (Thailand, 2017). However, this ban is only limited to inner Bangkok, which includes Case-2 of the study area.

For solving the problem, Google OR Tool (Google, 2021) was used. Google OR Tool is one of the standard open-source combinatorial optimization tools. It consists of many libraries for different problems like bin packing, vehicle routing, scheduling, etc. The specialized library related to routing consists of many generalized VRP problems. It provides the user with the code based on some standard programming languages such as python, java, etc. The user must input their desired distance or travel time matrix and other inputs of the VRP problem. For metaheuristics, i.e., local search, OR Tool is set to automatic by default. This means the solver will select the best metaheuristic in terms of computation time to find the solution. However, the user has a choice of choosing the metaheuristic among greedy descent, guided local search, simulated annealing, tabu search, and objective tabu search.

In this study, the standard vehicle routing problem was considered with an asymmetric travel time matrix and with a default setting of OR Tool.

5 RESULTS

Before the optimization of the VRP problem a paired t-test was used to check whether the difference in the constant travel time and variable travel time is significant or not. The travel time of each pair of origin destination for each day of the week at 8:00, 12:00, and 18:00 o clock was compared with the constant travel time. The results of the t-test are summarized in Table 1 and Table 2 for Case-1 and Case-2 respectively. These tables show that for all of the case the difference is significant except for Case-1 on Sunday at 8:00 AM.

Table 1. Result of t-test (Case-1)

Day of the week	Time of the day	Mean	S.D.	t Stat	P-value
Constant	-	34.43	14.61	-	-
Monday	08:00	35.80	15.50	15.95	0
	12:00	38.79	16.43	25.40	0
	18:00	27.42	11.77	-42.65	0
Tuesday	08:00	37.37	15.98	23.67	0
	12:00	40.86	16.92	30.67	0
	18:00	27.42	11.77	-42.67	0
Wednesday	08:00	39.15	16.30	25.74	0
	12:00	41.26	16.98	32.24	0
	18:00	27.41	11.77	-42.70	0
Thursday	08:00	38.46	16.49	25.57	0
	12:00	41.33	17.07	33.43	0
	18:00	27.42	11.77	-42.63	0
Friday	08:00	42.76	19.08	28.18	0
	12:00	45.19	19.12	33.55	0
	18:00	27.34	11.80	-43.33	0
Saturday	08:00	39.91	18.17	23.79	0
	12:00	35.67	15.42	16.73	0
	18:00	27.36	11.79	-42.97	0
Sunday	08:00	34.47	15.95	0.27	0.79
	12:00	32.99	14.73	-13.02	0
	18:00	27.42	11.77	-42.71	0

Table 2. Result of t-test (Case-2)

Day of the week	Time of the day	Mean	S.D.	t Stat	P-value
Constant	-	47.63	12.50	-	-
Monday	08:00	47.88	13.01	2.60	0.01
	12:00	54.53	13.47	44.13	0
	18:00	38.75	11.29	-57.62	0
Tuesday	08:00	48.80	12.91	9.16	0
	12:00	56.11	13.40	44.21	0
	18:00	38.75	11.29	-57.60	0
Wednesday	08:00	49.61	13.03	13.44	0
	12:00	56.45	13.28	43.98	0
	18:00	38.75	11.29	-57.60	0
Thursday	08:00	49.58	12.93	11.17	0
	12:00	56.91	13.55	46.47	0
	18:00	38.75	11.29	-57.58	0
Friday	08:00	54.25	14.01	24.49	0
	12:00	63.07	14.87	63.07	0
	18:00	38.76	11.33	-57.60	0
Saturday	08:00	52.60	14.73	19.82	0
	12:00	49.32	13.53	12.56	0
	18:00	38.76	11.33	-57.69	0
Sunday	08:00	45.14	12.91	-19.12	0
	12:00	44.66	12.30	-35.10	0
	18:00	38.79	11.32	-57.41	0

The optimization was done using constant travel time and, for each day of the week at 8:00, 12:00, and 18:00 o clock. The results are summarized in Table 3 and Table 4. These tables show the travel time of the trips for vehicle 1 to vehicle four after optimization, as well as the total travel time of the trip. The total travel time of trip of constant travel time compared with variable travel time and the difference is calculated.

Table 3. Travel time for different vehicles after optimization (Case-1)

Day of the week	Time of the day	Vehicle 1 (minute)	Vehicle 2 (minute)	Vehicle 3 (minute)	Vehicle 4 (minute)	Total (minute)	Difference from constant travel time (%)
	Constant	173	172	167	155	667	-
Monday	08:00	160	158	157	147	622	-6.75
	12:00	141	136	133	125	535	-19.79
	18:00	206	203	200	182	791	18.59
Tuesday	08:00	177	162	156	125	620	-7.05
	12:00	139	138	133	130	540	-19.04
	18:00	188	187	182	172	729	9.29
Wednesday	08:00	166	166	160	158	650	-2.55
	12:00	138	139	133	130	540	-19.04
	18:00	195	194	193	149	731	9.60
Thursday	08:00	167	167	164	159	657	-1.50
	12:00	141	136	133	125	535	-19.79
	18:00	202	188	181	147	718	7.65
Friday	08:00	178	171	166	161	676	1.35
	12:00	142	142	135	133	552	-17.24
	18:00	190	189	186	180	745	11.69
Saturday	08:00	168	89	161	168	586	-12.14
	12:00	127	126	122	108	483	-27.59
	18:00	162	160	160	158	640	-4.05
Sunday	08:00	160	160	154	153	627	-6.00
	12:00	141	136	133	125	535	-19.79
	18:00	150	147	147	145	589	-11.69

Table 4. Travel time for different vehicles after optimization (Case-2)

Day of the week	Time of the day	Vehicle 1 (minute)	Vehicle 2 (minute)	Vehicle 3 (minute)	Vehicle 4 (minute)	Total (minute)	Difference from constant travel time (%)
	Constant	55	53	42	38	188	-
Monday	08:00	63	59	55	37	214	13.83
	12:00	51	48	40	34	173	-7.98
	18:00	78	74	65	-	217	15.43
Tuesday	08:00	65	58	52	45	220	17.02
	12:00	51	48	40	34	173	-7.98
	18:00	77	76	70	-	223	18.62
Wednesday	08:00	66	59	54	45	224	19.15
	12:00	51	48	40	34	173	-7.98
	18:00	75	70	51	43	239	27.13
Thursday	08:00	65	58	51	44	218	15.96
	12:00	51	48	45	30	174	-7.45
	18:00	75	75	68	-	218	15.96
Friday	08:00	67	67	66	46	246	30.85
	12:00	34	46	51	40	171	-9.04
	18:00	75	74	68	-	217	15.43
Saturday	08:00	60	57	53	33	203	7.98
	12:00	51	46	40	34	171	-9.04

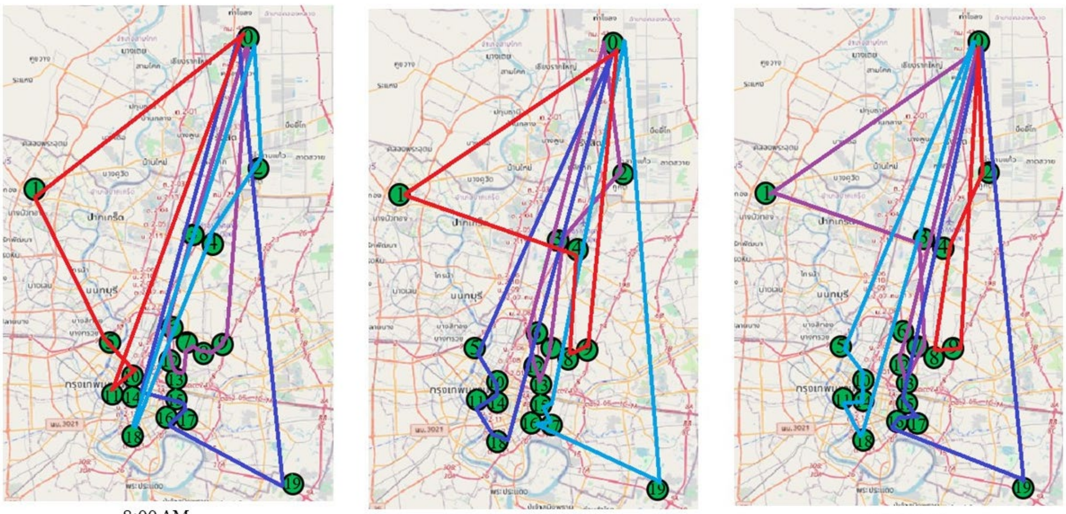
	18:00	57	56	43	40	196	4.26
Sunday	08:00	57	56	43	40	196	4.26
	12:00	51	48	40	34	173	-7.98
	18:00	54	54	40	36	184	-2.13

It can be seen from the results that the difference in the travel time calculated using constant travel time and the variable time is considerable. In the case of overestimation, the constant travel time can lead to 27.59% error for Case-1 and 9.04% error for Case-2. Similarly, in the case of underestimation, the constant travel time can lead to an 18.59% error for Case-1 and a 30.85% error for Case-2. On average, the error can be up to 12.5%. This huge percentage of error is a clear indication of the importance of considering different travel times for different times of the day as well as the different days of the week. These results can be compared with the Lombard et al (2018) work; however, the authors used 2 hours' time step instead of 15 minutes as in our case. Their results show that if variable travel time is used instead of constant travel time can lead to 4.3% savings. This further favors our side that using variable travel time with small intervals can improve our ressults.

Furthermore, it is also worth noting that routing at a different time of the day and different days of the week can also lead to different route sequences, which is illustrated in the tables below. For illustration purposes, the route sequence for only one day is shown in figure 5 and figure 6.

Table 3. Vehicle Routing Sequence (Case-1)

	Monday (Case-1)		
	08:00	12:00	18:00
Veh1	0→3→6→12→13→7→8→9→0	0→6→12→13→7→3→2→0	0→6→12→13→7→3→1→0
Veh2	0→14→15→17→16→19→0	0→18→11→14→10→5→0	0→15→17→16→19→0
Veh3	0→18→4→2→0	0→15→17→16→19→0	0→5→10→14→11→18→0
Veh4	0→11→10→5→1→0	0→1→4→8→9→0	0→2→4→8→9→0



8:00 AM 12:00 PM 18:00 PM

Figure 5 Vehicle route sequence (Case-1)

Table 4 Vehicle Routing Sequence (Case-2)

	Monday (Case-2)		
	08:00	12:00	18:00
Veh1	0→2→3→5→6→14→12→0	0→1→7→9→8→10→11 →0	0→2→3→5→6→13→14→12→ 0
Veh2	0→1→4→8→0	0→4→0	0→1→7→8→9→10→11→0
Veh3	0→7→9→10→0	0→2→3→5→6→0	-
Veh4	0→13→0	0→12→14→13→0	0→4→0

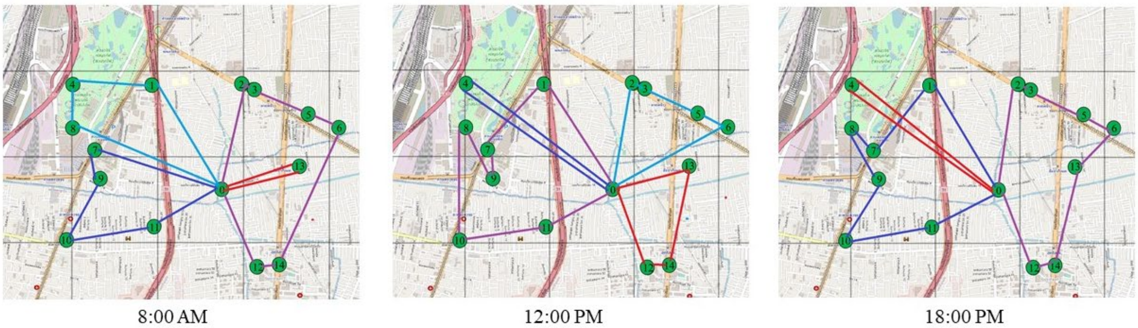


Figure 6 Vehicle route sequence (Case-2)

It can be seen from table 3, table 4, figure 5, and figure 6 above that for different times of the day, due to the variation in congestion, the vehicle routing sequence also changes. The main reason is that the algorithm will try to optimize in such a way by selecting the sequence of the customer to minimize the total travel time. In other words, we can say that the algorithm will take into effect the congestion and will try to avoid the congested routes during peak hours. The same is true for a different day of the week. This further clarifies the importance of considering the different travel times for the different times of the day and different days of the week. Consideration of this variation in travel time becomes more critical for other variants of VRP like VRP with time window. In which the delivery to the customer should be made in a specific time window.

6 CONCLUSION

This study shows the importance of considering different travel times for different times of the day and different days of the week. Bing Map API was used for travel time data collection over a period of one week and 15-minute intervals for 24 hours. Study periods were identified at 8:00 PM, 12:00 PM, and 6:00 PM, and average travel times were calculated, which is later on used as constant travel time. Optimization was done based on the constant travel time as well as variable travel time, and results were compared. It was found that a maximum of up to 30.85% error in the estimation of travel time can be observed if constant travel time is considered as compared to variable travel time. On average, a 12% error in travel time is observed. This study has also shown that it does not matter if the customers are scattered across the whole city or concentrated on a small area. In both, cases using constant travel time will lead to error in estimation and will give us nonoptimal routes. Furthermore, this study has also shown that the sequence of customers is also changed with the variable travel time, which further indicates its importance if the VRP with time window is considered.

7 RECOMMENDATION AND FUTURE WORK

In this study, the travel time is divided into three periods for illustration. However, the actual road network is more dynamic, and there is more uncertainty associated with travel time. Furthermore, the customers are usually requesting the delivery in a certain time window. However, this will further increase the complexity and size of the problem to the extent that it is beyond the capacity of existing algorithms.

In the future, state-of-the-art algorithms will be used to solve time-dependent VRP with a time window with at least 15-minute travel time intervals. One of the possible algorithms can be reinforcement learning with Monte Carlo Tree Search. Which is already used to solve alpha go zero, having state-space greater than 4.5*10^12 (Li, 2019).

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