A Hybrid Methodology for Optimal Fleet Management in an Electric Vehicle Based Flexible Bus Service*

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Abstract— **The ever-increasing traffic congestion and CO_2 emission caused by rapid urbanization, calls for smarter and energy efficient transit services. Conventional public transit lacks the ability to meet these diversified needs. As a result, intelligent transit systems, influenced by the digital revolution have created a profound impact by enhancing the user-experience of transit services. Consequently, demand responsive transit (DRT) services, which operate with flexible routes and schedules have become a common option among commuters. Thus, in this work, we propose an electric vehicle (EV) based flexible bus service, a variant of DRT, that satisfies passenger demand in a given geographical zone. Next, we present a hybrid methodology to optimally manage the EV fleet minimizing the total vehicle miles travelled (VMT). Experimental results with a real map show that the proposed hybrid method achieves near-optimal results with 120x improvement in computation time. Further, the flexible bus service reduces VMT by over 70% in comparison to single occupancy vehicles, thus reducing both traffic congestion and CO_2 emissions.**

I. Introduction

Rapid urbanization coupled with diversified needs of passengers continues to challenge conventional public transit systems. These systems typically operate with fixed routes, schedules and bus-stops that makes it difficult to quickly adapt to passenger needs and demands. On the other hand, technological developments in the fields of cellular networking, mobile communication, real-time location tracking, smartphones and electronic payment has lead to intelligent transportation systems (ITS) gaining momentum [1]. Furthermore, these advances have enabled ITS to not only cater to the diversified needs but also complement conventional public transit by extending the penetration, potentially aiding to bridge the first/last mile (FM/LM) gaps [2].

To this end, advanced public transit systems, a branch of ITS, strives to increase the efficiency of transit systems and to thereby enhance user-experience. As a result, demand responsive transit (DRT) services have become a common option in the daily commute of passengers. DRT services are characterized by shared vehicles operating over flexible routes and schedules, which satisfy the point-to-point transit needs of passengers. Passengers typically request for DRT services through a smartphone application or over the Internet by providing the intended pick-up location, drop-off location and time. Subsequently, centralized or distributed agents analyse the requests and route the fleet of shared vehicles to pick-up and drop-off passengers. Hence, DRT services bridge the FM/LM gaps and also eliminate waiting times at transit stops, thus enhancing user-experience.

DRT services are broadly classified into static and dynamic modes. Static DRT services, where ride-requests are known in advance, consists of services such as para-transit (e.g. DART Paratransit Service) and shuttles (e.g. Google Bus). Dynamic DRT services, where ride-requests are received in real-time have gained traction due to its ability to serve diversified user groups while adhering to time constraints. However, most of the existing work on dynamic DRT focus on one/two ride matches (e.g. UberX, JustGrab), which connect private-hire drivers with passengers [2]. These services were first launched in 2012 in San Francisco, CA [3] and have gained widespread popularity among many commuters around the world. On the contrary, dynamic DRT with multiple ride matches, typically termed as **flexible bus services** is still an emerging area [4] [5] [6].

Further, flexible bus services also contribute to reduce traffic congestion by eliminating single occupancy vehicles (SOV). However, transit services are also a major contributor to CO_2 emissions [7] and hence efforts to reduce emissions in the form of sustainable transit have emerged in the recent past [8]. Among the many efforts undertaken in sustainable transit, zero-emission technologies such as electric vehicles (EV) have become an attractive alternative. However, most of the EV used for public transit have relatively short driving ranges [9]. This has resulted in "Range Anxiety", which is the major bottleneck for widespread adoption of EV for public transit. Furthermore, fully charging EV require nearly 10 hours and tropical climates further reduce the driving range [10]. Hence, it is imperative that the operator optimally manages the fleet while still satisfying passenger demand.

However, existing work on flexible bus services require advanced reservations to account for the significantly high computation time of the algorithms. Hence, as discussed later in Section II, we identify the need to further develop techniques in order for it to be useful in EV-based flexible bus services. Thus, our work attempts to bridge this gap by proposing a hybrid methodology for minimizing vehicle miles travelled (VMT) in a fleet of EV providing flexible services. The main contributions of this work are, (1) an optimal mixed-integer quadratically constrained programming (MIQCP) formulation, (2) A hybrid methodology combining the optimal formulation and a heuristic algorithm to rapidly prune the solution space to generate feasible solutions.

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The proposed hybrid methodology not only generates near-optimal results but also achieves them 120x faster.

The rest of the paper is organized as follows. In Section II, we discuss the state-of-the-art work and highlight the limitations. Next, in Section III, we present the proposed EV-based flexible bus service followed by the methodology in Section IV. Finally, we discuss the results and conclude the study in Sections V and VI respectively.

II. Related Work

Literature on DRT services focus on both passenger transit and delivery of goods. However, due to the distinctive difference in the two modes, our study is limited to work on passenger transit. Further, earliest work on DRT focus on the single vehicle problem, thus the usefulness of the proposed approaches are limited to specific scenarios. The multi-vehicle DRT problem with practical applications have been approached using exact and heuristic formulations such as column generation [11], branch-and-cut [12], tabu-search [13], sequential insertion heuristic [14], parallel insertion heuristic [15] and genetic algorithms [16]. However, it should be noted that these works consider only the static DRT services. Thus, either the impact of execution time is minimal or the systems require prior reservations.

On the other hand, we find several work, which focus on flexible bus services. Uchimura et al. [17] propose a door-to-door, dial-a-ride service similar to public taxis, provided by small buses and/or vans that connects a community to/from the transit stations. Here, the routes are optimized using a genetic algorithm. Authors present an instance with a single bus and 10 passengers in which routes are computed in 40 seconds. However, the scalability of the algorithm for multiple buses has not been validated.

Tsubouchi et al. [18] propose a flexible bus service that allows passengers to request the service over the Internet or using a mobile phone. The authors propose heuristic algorithms with linear time complexity for selection of vehicles and routing. The algorithm is tested up to 6 buses (capacity of 8) and 200 passenger requests spread across 8 hours. The authors extend this work in [19] by incorporating an end-to-end service using a cloud computing platform. This work is tested for only 5 vehicles and the shared-ride ratio in most cases is significantly low. Uehara et al. [20] [21] propose to connect people living in sub-urban areas to urban areas through complementary DRT and mass transit services. However, it requires advanced (one day prior to departure) reservations, thus not usable for flexible bus services.

Liu and Cedar [22] present a survey of demand responsive flexible bus services operating or proposed in 30 cities in China. Further, authors claim that flexible bus services reduce energy consumption and CO_2 emissions by reducing the VMT compared to SOV. Marković et al. [23] report on a dial-a-ride problem consisting of vehicles (capacity of 7) providing flexible routing and scheduling for 450 trip requests daily. Even though, most of the requests are known in advance, the work also accommodates requests in real-time. However, evaluation is only performed for advanced requests due to the claimed complexity of dynamically managing the system. Archetti et al. [24], Perera et al. [25], Tong et al. [26] discuss simulation studies of flexible bus systems. However, these works do not consider EV, thus additional constraints of limited driving ranges are not considered.

Studies by Wei et al. [27], Sebastiani et al. [28], Jing-Quan Li [29] propose optimization methods for fixed-route EV scheduling, which discuss location of bus depots, adjusting delays of buses etc. However, in a flexible bus service, depot locations are not fixed and the service operates in real-time. Kawamura and Muka [30] propose a model for an on-demand bus system using EV. They propose a meta-heuristic algorithm combining node-insertion and a genetic algorithm. Authors perform simulations with 2 vehicles and passenger requests generated every 30 minutes. Hence, using this work for flexible bus services calls for further validation.

III. Proposed EV-based Flexible Bus Service

Initially, a given geographical area is divided into several zones based on historical commuter travel patterns. Next, we assume that the proposed flexible bus service operates in each zone using a fleet of EV (supply) that satisfies the point-to-point transport requests of passengers (demand) within the zone. However, as mentioned in [31], in order to ensure the economic merits of the system, we propose to serve passengers who are traveling to/from a common destination such as a rapid transit node. In practice, the proposed work can be targeted for large industrial estates, universities etc., where public transit penetration is relatively low and a large population is traveling to/from the nearest rapid transit node. Further, the proposed service can also be used as an alternative to existing transit services during off-peak hours where the existing fixed route transit services are significantly underutilized and hence can be easily replaced by a flexible bus service.

While in operation, we assume that all passengers request the service using a smartphone application. Thus, the passenger origins along with the real-time traffic conditions (using Google Maps APIs [32]) will be logged in the back-end infrastructure of the system. Simultaneously, the proposed fleet management algorithm will be executed periodically and passengers will be allocated to the fleet. Operationally, in the proposed system the EV are considered to be initially empty. Subsequently, passengers will be picked-up and hence the scheduling will be done with passengers on-board. In both modes, passenger allocation is **constrained** by (1) capacity of each EV, (2) remaining driving range of each EV (assuming that vehicle load, air conditioning etc. does not alter the driving range), (3) EV do not need to visit charging stations when passengers are allocated, (4) all passengers request for immediate rides (advanced rides can also be accommodated with minute changes in the proposed model), (5) predefined maximum travel time (combination of waiting time and riding time) for each passenger that guarantees the service quality. The goal of the proposed methodology is to devise a set of routes and schedules in real-time to minimize the VMT while using a minimum number of EV to satisfy

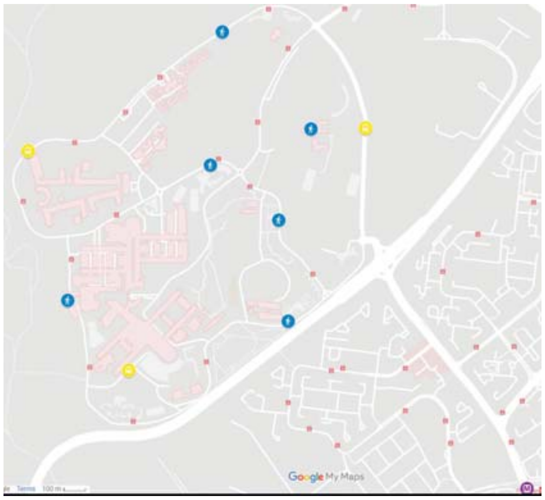

Fig. 1: Sample Locations of Passengers and EV

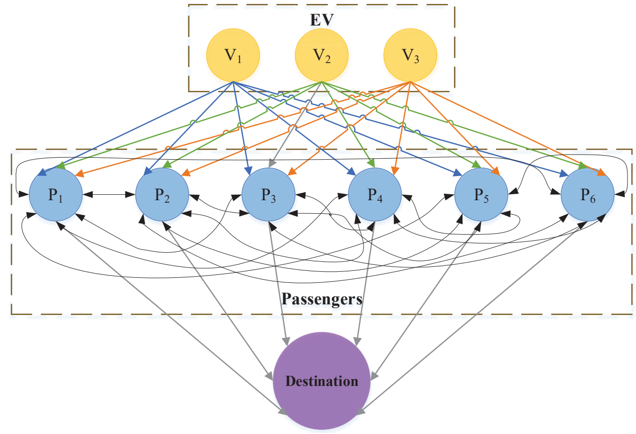

Fig. 2: Directed Graph

the full demand within the constraints.

In this paper, the study is **limited** to the following scenario; (1) transporting passengers to the common destination of the service zone from their respective origins, (2) demand and traffic conditions of a weekday off-peak period for the selected zone, (3) fleet of EV are empty and homogeneous (same capacity and driving range) at execution time of the fleet management algorithm. A snapshot of an example scenario with 3 EV and 6 passengers is given in Fig. 1. Here, yellow bus and blue walking symbols represent EV and passengers respectively. The purple metro symbol at the bottom right corner shows the common destination i.e. nearest rapid transit node.

IV. Methodology

Here, we first define the problem using a directed graph. Next, we present the optimal MIQCP formulation. Finally, we discuss the proposed hybrid methodology to solve a scenario presented in Section III.

A. Problem Definition

The problem is defined using a directed acyclic graph that represents the fleet of v EV denoted by $\{V_1, V_2, V_3, \cdots V_v\}$, set of p passengers $\{P_1, P_2, P_3, \cdots P_p\}$, and the common destination. The graph consists of $v+p+1$ nodes, where nodes $1, 2, 3, \cdots, v$ refer to the fleet of EV, nodes $v+1, v+2, v+3, \cdots, v+p$ refer to the set of passengers and node $v+p+1$ refers to the common destination. The subset of nodes in the graph are defined in Table I. Further, there are no edges ending at EV nodes or beginning from the common destination node. Also, each edge (i, j) has an associated cost, d_{ij} and t_{ij}, measured in terms of distance and travel time from node i to j respectively, where $i, j \in \Phi$ & $i \neq j$. Also, the travel time for each edge ending at a passenger node has an additional constant service time. All the constraints of the problem are given in Table II. Here, l, r, u and t_{ij} are positive integers and d_{ij} is a non-negative integer. The relevant graph for the scenario given in Section III, with 3 EV and 6 passengers is shown in Fig. 2

TABLE I: Terminology of Nodes in the Graph

Term	Description	Nodes represented in graph
Φ	set of all nodes	$1, 2, 3, \cdots, v+p+1$
ζ	subset of EV	$1, 2, 3, \cdots, v$
ρ	subset of passengers	$v+1, v+2, v+3, \cdots, v+p$
ϑ	common destination	$v+p+1$

B. Optimal Mathematical Formulation

Here, we present the optimal MIQCP formulation for the proposed EV-based flexible bus service. First, we define the two decision variables (Eq. 1 and 2) used in the model followed by the objective (Eq. 3) and finally, the constraints (Eq. 4 - 19). The binary decision variable x_{ijk}, given in Eq. 1 is defined for each edge (i, j) and each EV V_k, where $i \neq j$, $i \neq v+p+1$ & $j \neq 1, 2, 3, \cdots, v$; denotes if EV V_k travels along the edge (i, j) from i to j. Similarly, the decision variable s_{ik}, shown in Eq. 2 is defined for each node i and each EV V_k, where $i \neq 1, 2, 3, \cdots, v$ & $i \neq v+p+1$; denotes the service time of passenger P_i by EV V_k. Equation 3 shows the objective function of the mathematical formulation, which minimizes the total VMT of the fleet of EV. All constraints in the model given in Eq. 4 - 19 are further classified into routing, timing and side constraints, which are explained in detail subsequently.

Decision Variables:

$$x_{ijk} = \begin{cases} 1, & \text{vehicle } V_k \text{ travels from node } i \text{ to node } j, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

$$s_{ik} = \begin{cases} f, & \text{vehicle } V_k \text{ services node } i, \ f \epsilon z^+, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Objective:

$$minimize \sum_{i \in \rho} \sum_{j \in \Phi} \sum_{k \in \zeta} (x_{ijk} * d_{ij}); \tag{3}$$

Subject to:

* *Routing Constraints*

$$\sum_{j \in \rho} x_{ijk} = 0 \quad \forall i \in \zeta, \ \forall k \in \zeta; \quad where \quad i \neq k; \tag{4}$$

TABLE II: Constraints of the Problem

Term	Description
l	maximum capacity of an EV
r	maximum driving range of an EV
u	maximum travel time of a passenger

$$\sum_{j \in \rho} x_{kjk} \leq 1 \quad \forall k \in \zeta; \tag{5}$$

$$\sum_{i \in \rho} \sum_{k \in \zeta} x_{i\vartheta k} \geq 1 \quad \forall k \in \zeta; \tag{6}$$

$$x_{\vartheta jk} = 0 \quad \forall j \in \Phi, \ \forall k \in \zeta; \tag{7}$$

$$x_{ijk} = 0 \quad \forall i \in \rho, \ \forall j \in \zeta, \ \forall k \in \zeta; \tag{8}$$

$$\sum_{i \in \Phi} x_{ibk} - \sum_{j \in \Phi} x_{bjk} = 0 \quad \forall k \in \zeta, \forall b \in \rho; \tag{9}$$

$$x_{i\vartheta k} = 0 \quad \forall i \in \zeta, \ \forall k \in \zeta; \tag{10}$$

$$\sum_{i \in \rho} x_{i\vartheta k} \leq 1 \quad \forall k \in \zeta; \tag{11}$$

$$x_{iik} = 0 \quad \forall i \in \rho, \ \forall k \in \zeta; \tag{12}$$

$$\sum_{j \in \Phi} \sum_{k \in \zeta} x_{ijk} = 1 \quad \forall i \in \rho; \tag{13}$$

* *Timing Constraints*

$$s_{kk} = 0 \quad \forall k \in \zeta; \tag{14}$$

$$x_{ijk}(s_{ik}+t_{ij}-s_{jk}) \leq 0 \quad \forall i \in (\Phi \backslash \vartheta), \forall j \in \Phi, \forall k \in \zeta; \tag{15}$$

$$s_{\vartheta k} \geq 0 \quad \forall k \in \zeta; \tag{16}$$

$$s_{\vartheta k} \leq u \quad \forall k \in \zeta; \tag{17}$$

* *Side Constraints*

$$\sum_{i \in \rho} \sum_{j \in \Phi} x_{ijk} \leq l \quad \forall k \in \zeta; \tag{18}$$

$$\sum_{i \in \Phi} \sum_{j \in \Phi} x_{ijk} * d_{ij} \leq r \quad \forall k \in \zeta; \tag{19}$$

The first routing constraint in Eq. 4 initiates the origin of a route to the respective node of the EV. Equation 5 ensures that minimum number of EV are used to serve passengers. Similarly, Eq. 6 enforces that EV reaches the common destination. Equation 7 and 8 prevent routes from originating at the common destination and ending at EV nodes respectively. Similarly, Eq. 9 eliminates routes from ending at a passenger node. Equation 10 prevents EV travelling directly from the origin to the common destination, while Eq. 11 ensure that they reach the common destination through a passenger node. Equation 12 forbids loops in the route and Eq. 13 ensures that each customer is serviced by only one EV.

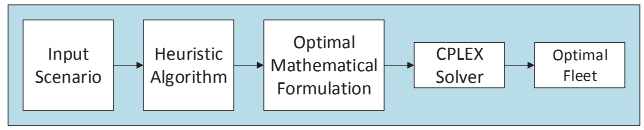

Fig. 3: Proposed Hybrid Methodology

Equation 14 - 17 deal with the timing constraints of the model. Equation 14 initializes the service time of each EV. The travel time between nodes is modelled in Eq. 15. Equation 16 sets the lower bound for the service time of the EV at the common destination. Thus, for EV that do not transport passengers, the respective service time at the common destination will be zero. In Eq. 17, we set the upper bound on the travel time constraint for all the passengers. Finally, the side constraints in terms of capacity and the maximum driving range of the EV are modelled in Eq. 18 and 19 respectively. Here, as mentioned in Section III, we assume that factors such as loading and air-conditioning does not alter the driving range of the EV. Hence, in Eq. 19, VMT is compared with the maximum allowable driving range.

C. Hybrid Methodology

The MIQCP formulation proposed in Section IV-B solves the given scenario optimally. However, as we show later in Section V, finding a feasible solution even for a relatively small problem consumes considerable time when a solver works independently. Thus, we propose to use the hybrid method given in Fig. 3 to eliminate portions of the search space and thus rapidly find a solution. Initially, the given scenario is solved using a heuristic algorithm to obtain a feasible solution. This results in a reduced search space for the optimal formulation which in turn yields a significant reduction of time to obtain results. Thus, the main goal of the heuristic algorithm is to rapidly find a feasible solution, which can be used to initialize the solver. Thus, we propose to use the local search heuristic algorithm in [25]. Even though complex heuristic algorithms with better accuracy that consumes a considerable amount of time have been proposed to solve similar problems, we use the algorithm proposed in [25] as it provides a solution within a few micro-seconds. However, we further modify this algorithm by incorporating the EV driving range and the maximum travel time constraints of passengers to ensure solution feasibility.

V. Results

Here, we present the results of the computational experiments. IBM ILOG CPLEX Optimization Studio 12.7.1 [33] and its in-built cplex solver is used to implement and solve the optimal formulation in Section IV-B. The hybrid methodology in Section IV-C is implemented in C++ and the Java API in [33] is used to initialize the optimal formulation. An Intel Xeon E5-2670V2 CPU at 2.6 GHz with 20 GB RAM running windows 7 is used in runtime measurements.

A. Experimental Setup

We select a zone surrounding a university for the experiments. In all experiments, vehicles and passengers are randomly dispersed within this zone. However, for clarity

TABLE III: Performance of the Proposed Hybrid Methodology

Parameters				VMT (m)				
Experiment Number	EV	Passengers	Instance	Local Search Heuristic Algorithm	Proposed Hybrid Methodology	Optimal Formulation	Deviation (%)	Runtime of Optimal Formulation (s)
1	5	10	1	14054	8835	8835	0.00	54
			2	20281	9429	9429	0.00	52
			3	22394	10509	10509	0.00	113
2	5	15	1	24655	12242	12105	1.13	1423
			2	20805	11605	10850	6.96	3600
			3	24672	12113	11513	5.21	3600
3	6	18	1	28040	16398	16026	2.32	3600
			2	28403	14999	14160	5.93	3600
			3	23737	15024	14539	3.34	3600
4	6	14	1	24572	10224	10224	0.00	580
			2	21891	9988	9988	0.00	278
			3	27143	11499	11375	1.09	3600
5	7	17	1	29222	15965	15662	1.93	3600
			2	29617	14534	14095	3.11	3600
			3	30329	16041	14050	14.17	3600
6	7	30	1	34660	26752	21503	24.41	3600
			2	36327	23711	21074	12.51	3600
			3	32670	29985	22755	31.77	3600
7	8	36	1	39972	33690	27700	21.62	3600
			2	39166	35395	29541	19.82	3600
			3	39364	33657	28034	20.06	3600
8	9	33	1	37314	33998	25954	30.99	3600
			2	40276	32684	25808	26.64	3600
			3	42042	31846	27964	13.88	3600
9	10	30	1	40173	29600	23050	28.42	3600
			2	42255	27334	23918	14.28	3600
			3	41504	27292	25797	5.80	3600
10	10	40	1	46385	36062	28218	27.80	3600
			2	48177	35700	31621	12.90	3600
			3	45862	35134	33487	4.92	3600

TABLE IV: Difference of VMT of the Proposed Hybrid Methodology and SOV

		Experiment Number									
		1	2	3	4	5	6	7	8	9	10
VMT (m)	Proposed Hybrid Method	10460	12661	15637	11228	14677	26971	36353	31962	27910	35094
	Single Occupany Vehicle	32912	50337	60656	45669	53219	96725	118277	108814	97586	130046
	Reduction %	68	75	74	75	72	72	69	71	71	73

we restrict the origins of passengers to a set of 40 selected locations. However, the methods proposed in this work are independent of the number of locations. Also, it is noteworthy that there may be multiple passengers in a single location in a given experiment. Further, the nearest mass rapid transit node is selected as the common destination.

B. Experiments

We consider scenarios with a fleet of 10 EV having a maximum capacity (l) and driving range (r) of 8 and 30 km respectively. Further, based on off-peak travel demand, maximum number of passenger requests is set to 40. Maximum travel time (u) of passengers is set to 40 minutes. Also, in each experiment, we control the supply (available seats) to be equal or greater than the demand (number of passengers). Further, each experiment is repeated 3 times and for each instance the origins of demand (among 40 locations) and supply are selected randomly. Further, travel time (t_{ij}) and distance (d_{ij}) between EV, passengers and the common destination are obtained from Google maps APIs [32].

C. Evaluation

1) Solution Quality Variation with Time: The efficacy of the proposed hybrid method is evaluated by the convergence rate of the solution in comparison to the optimal formulation. Thus, we conduct an experiment by executing both the optimal formulation and the proposed hybrid method with a time limit of 30 minutes and observe the VMT variation with time. Figure 4 shows results for an experiment with 10 EV and 20 passengers. Here, the vertical axis shows VMT and the horizontal axis shows time. The blue continuous line shows results of the optimal formulation while the orange dotted line shows the same of the proposed hybrid method. In Fig. 4, we notice that the proposed hybrid method converges quickly in contrast to the optimal formulation. Furthermore, the feasible solution obtained at 30 minutes from the proposed hybrid method is 4.2% better compared to the optimal formulation. However, in the proposed hybrid method, we observe that the solution has only improved by 2.6% after 30 seconds. Hence, in the rest of the experiments, results of the proposed hybrid method is obtained with a time limit of **30 seconds**.

2) Performance: Suitability of the proposed hybrid method for the flexible bus service in different scenarios is validated using 10 experiments with parameters as given in Table III. Here, we present the results (for all 3 instances of an experiment) in terms of VMT of the local search heuristic

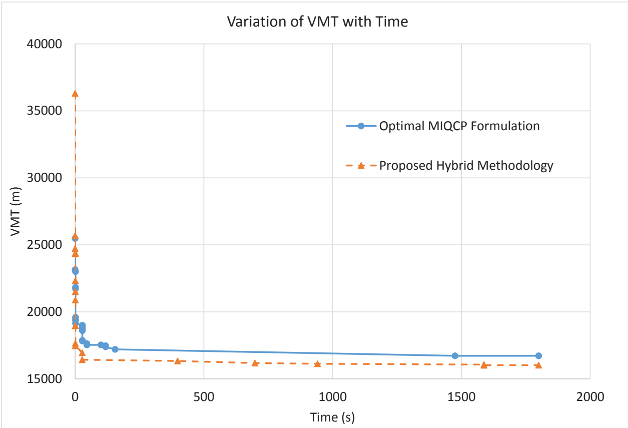

Fig. 4: Variation of VMT with Time

algorithm [25], proposed hybrid method and the optimal formulation. It should be noted that we have set a time limit of 30 seconds and 1 hour for the proposed hybrid method and the optimal formulation respectively. Results show that the proposed hybrid method provides optimal results for small problems and near-optimal results for other instances. The average deviation of VMT of the proposed hybrid method compared to the optimal formulation for all experiments is **11.4%**. However, the near-optimal results are achieved **120x** faster. Further, we observe that based on the runtime of the optimal formulation in Table III, optimally solving a problem is only feasible while the demand is significantly low.

3) Reduction of VMT compared to SOV: An additional benefit of flexible bus systems is the reduction of VMT in comparison to SOV, which helps to reduce traffic congestion. Thus, we analyse VMT reduction for the same set of experiments given in Table III. Results of the experiments are given in Table IV. Here, we observe that the proposed EV-based flexible bus service on average reduces VMT by **72%** compared to SOV. However, this is achieved at a cost of increased travel time compared to SOV, thus justifying the requirement to impose a maximum travel time (u) constraint. Overall, VMT reduction affirms the suitability of EV-based flexible bus services for reducing traffic congestion.

VI. Conclusion

This work proposes an EV-based flexible bus system, which is an application of ITS in the domain of advanced public transit systems. We provide a practical implementation for the proposed flexible bus system and present a hybrid methodology for the optimal management of the fleet of EV. Experimental results using real-data show that the proposed hybrid method achieves considerable accuracy in a relatively short time. Further, compared to SOV, the proposed system reduces the total VMT aiding to reduce traffic congestion. In future, we plan to explore the impact of varying the maximum passenger travel time and EV capacity constraints on the performance and recommend suitable EV configurations for different scenarios.

References

[1] A. Jarašūnienė, "Research into intelligent transport systems (ITS) technologies and efficiency," 2006.

[2] S. Logan *et al.*, "First and Last Mile Connections: New Mobility," http://on.nrdc.org/2utPxUd, 2016.

[3] S. Shaheen *et al.*, "Shared Mobility: Current Practices and Guiding Principles," https://bit.ly/2v5LZtx, 2016.

[4] J. Alonso-Mora *et al.*, "On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment," *PNAS*, 2017.

[5] Land Transport Authority, Singapore, "LTA awards first phase of tender for on-demand bus service trial," https://bit.ly/2GUD2EG, 2018.

[6] Transit Systems: Next Generation Transport, "Demand Responsive bus services to be launched," https://bit.ly/2GQsmLn, 2017.

[7] United States Environmental Protection Agency, "Sources of Greenhouse Gas Emissions," https://bit.ly/2ecDrVc, 2014.

[8] C. Lin *et al.*, "Survey of green vehicle routing problem: Past and future trends," *Expert Systems with Applications*, 2014.

[9] Z. Chao and C. Xiaohong, "Optimizing battery electric bus transit vehicle scheduling with battery exchanging: Model and case study," *Procedia - Social and Behavioral Sciences*, 2013.

[10] Land Transport Guru, Singapore, "Electric Buses in Singapore," https://bit.ly/2GTCi2A, 2018.

[11] J. Desrosiers *et al.*, "A dynamic programming solution of the large-scale single-vehicle dial-a-ride problem with time windows," *Amer. J. Math. Management Sci*, 1986.

[12] J. F. Cordeau, "A branch-and-cut algorithm for the dial-a-ride problem," *Operations Research*, 2006.

[13] J. Cordeau and G. Laporte, "A tabu search heuristic for the static multi-vehicle dial-a-ride problem," *Transp Res Part B: Methodological*, 2003.

[14] J. J. Jaw *et al.*, "A heuristic algorithm for the multi-vehicle advance request dial-a-ride problem with time windows," *Transp Res Part B: Methodological*, 1986.

[15] M. Diana and M. M. Dessouky, "A new regret insertion heuristic for solving large-scale dial-a-ride problems with time windows," *Transp Res Part B: Methodological*, 2004.

[16] R. M. Jorgensen *et al.*, "Solving the dial-a-ride problem using genetic algorithms," *J. Oper. Res. Soc.*, 2007.

[17] K. Uchimura *et al.*, "Demand responsive services in hierarchical public transportation system," *IEEE TVT*, 2002.

[18] K. Tsubouchi *et al.*, "Scheduling algorithm for on-demand bus system," in *ITNG*, 2009.

[19] K. Tsubouchi *et al.*, "Innovative on-demand bus system in japan," *IET Intelligent Transport Systems*, 2010.

[20] K. Uehara *et al.*, "A proposal of a transport system connecting demand responsive bus with mass transit," in *ICCE*, 2014.

[21] K. Uehara *et al.*, "Evaluation of a hierarchical cooperative transport system using demand responsive bus on a dynamic simulation," *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, 2016.

[22] T. Liu and A. Ceder, "Analysis of a new public-transport-service concept: Customized bus in china," *Transport Policy*, 2015.

[23] N. Marković *et al.*, "Optimizing dial-a-ride services in maryland: Benefits of computerized routing and scheduling," *Transp Res Part C: Emerging Technologies*, 2015.

[24] C. Archetti *et al.*, "A simulation study of an on-demand transportation system," *Int Transactions in Operational Research*, 2018.

[25] T. Perera *et al.*, "A scalable heuristic algorithm for demand responsive transportation for first mile transit," in *INES*, 2017.

[26] L. Tong *et al.*, "Customized bus service design for jointly optimizing passenger-to-vehicle assignment and vehicle routing," *Transp Res Part C: Emerging Technologies*, 2017.

[27] R. Wei *et al.*, "Optimizing the spatio-temporal deployment of battery electric bus system," *Journal of Transport Geography*, 2018.

[28] M. T. Sebastiani *et al.*, "Evaluating electric bus operation for a real-world brt public transportation using simulation optimization," *IEEE ITS*, 2016.

[29] J.-Q. Li, "Transit bus scheduling with limited energy," *Transportation Science*, 2014.

[30] K. Kawamura and N. Mukai, "Optimization of transport plan for on-demand bus system using electrical vehicles," in *Knowledge-Based and Intelligent Information and Engineering Systems*, 2009.

[31] MIT, "Welcome to MIT "Real-Time" Rideshare Research," https://bit.ly/2tGJaxT, 2010.

[32] "Google Maps APIs: Build the next generation of location experiences," https://developers.google.com/maps/.

[33] "IBM ILOG CPLEX Optimization Studio," https://ibm.co/2vXgzRC.