Industrial Engineering
& Management Systems
Vol 24, No 4, December 2025, pp.624-631
ISSN 1598-7248 | EISSN 2234-6473 |
https://doi.org/10.7232/iems.2025.24.4.624

People Movement-driven Dynamic Bus Routing Problem with Route Similarity Maximization

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(Received: June 21, 2025 / Revised: September 3, 2025 / Accepted: October 7, 2025)

ABSTRACT

In the era of Industry 4.0, utilizing big data to make real-time decisions becomes possible. In the mobility and transportation area, including public transportation services, innovative practices could be incorporated to make better decisions for the system and its users. This study proposes a novel dynamic bus routing model. In the proposed mathematical formulation, previous bus routes are considered when designing new routes while minimizing the changes in the routes. Such a decision on minimizing the changes is made to provide a better experience by the bus passengers. In the numerical experiments, various data sets are solved. This study could be an initial study for the next studies to discover other potential problems to solve within the context of big data and Industry 4.0.

Keywords: Dynamic Bus Routing, Mathematical Model, Route Similarity

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1. INTRODUCTION

The advancements of big data and Internet of Things technologies enable various new possibilities, including in the field of logistics (Wang *et al*., 2016). Some interesting new ideas are the possibility to discover cargo movements and perform accurate predictions on future deliveries (Zhong *et al*., 2015; Chen *et al*., 2021). More accurate decision making can also be conducted in a real-time fashion, considering various dynamics and changes in real situations, e.g., price fluctuations and dynamic changes caused by people's behavior (Singgih and Kim, 2020; Singgih *et al*., 2024). Using the latest technology, it is possible to understand changes in people's movements, e.g., the location sensors on smartphones, etc. In fact, the fast development of sensors and big data opens great opportunities to utilize resources better and improve systems' efficiency. In other words, to take advantage of the developed technology, more methods that deal with real-time planning must be implemented to deal with the real-time data and solve actual problems (Chai *et al*., 2025).

Several studies discussed the bus routing problem, as listed in Table 1. In most cases, the static version is studied with models that only generate new bus routes, instead of considering the old and new routes simultaneously and observing the route changes. In these studies, bus routes are determined considering the given people movement demands and the bus network. The studies are divided into two subgroups based on whether all people movement demands are satisfied or not. The first subgroup (that did not consider any bus route changes and did not ensure people movement demand satisfaction) is discussed as follows. In general, the studies minimized the total bus travel times (Ma *et al*., 2023; Xiong *et al*., 2025), as normally considered in many routing studies. The studies in this subgroup did not ensure the people movement demand satisfaction. To deal with this limitation, the studies minimized the number of unsatisfied

Table 1. Comparison to earlier studies

Study	Bus route change	All people movement demand satisfaction	Objective	Proposed method
Ma *et al*. (2023)	No	No	Minimizing total bus travel times	Mathematical model, clustering and adaptive large neighborhood search
Tan *et al*. (2023)	No	No	Maximizing total passenger travels	Mathematical model
Xiong *et al*. (2025)	No	No	Minimizing total bus travel times, unsatisfied requests, violated time windows, and maximizing profit	Mathematical model, variable neighborhood search
Tong *et al*. (2017)	No	No	Maximizing number of passengers	Lagrangian decomoposition
Yuan *et al*. (2025)	No	Yes	Minimizing bus bunching and passenger waiting times	Mathematical model, branch and bound
Chow *et al*. (2024)	No	Yes	Minimizing passenger waiting and travel times and total bus operation cost	Reinforcement learning
Avila-Ordóñez *et al*. (2022)	Yes	Yes	Minimizing penalty for route change and total passenger travel times	Genetic algorithm
This study	Yes	Yes	Maximizing route similarity	Mathematical model

movement demands or maximized the number of passengers, as conducted in Ton *et al*. (2017) and Tan *et al*. (2023). Studies in the second subgroup (that did not consider any bus route changes, but ensured people movement demand satisfaction) mainly minimized the passenger waiting times (Chow *et al*., 2024; Yuan *et al*., 2025). All of the studies above proposed different solution methods (e.g., mathematical model, algorithm, and machine learning-based optimization methods).

Most studies, including the studies mentioned above, did not consider bus route changes. As stated in the introduction section, the development of information technology enables dynamic and real-time bus routing, which would ultimately reduce bus operational costs while providing better passenger satisfaction. Most existing studies ignore the initial routes and design any new routes from scratch, which is not practical, considering that a lot of changes in the routes would make the passengers much less comfortable because understanding and adapting to the route changes would be difficult. It is necessary to deal with changes in the real system appropriately (Gu *et al*., 2022) to ensure people's satisfaction. Making real-time decisions would not only improve the performance of the system but also attract more positive responses from the service users (passengers) (Larsen *et al*., 2023).

The dynamic bus routing considers route changes from old (current) routes to new set of routes that must occur as a response to changes in people flows (Avila-Ordóñez *et al*., 2022). Avila-Ordóñez *et al*. (2022) considered such a dynamic bus routing problem and solved the problem using a genetic algorithm method. Their study minimized the penalty of route change and total passenger travel times. Given the nature of the genetic algorithm, there is no guarantee of producing optimal solutions for the problem. To enrich the studies in this field, our study proposes a novel way to deal with the dynamic bus routing problem. Our study proposes a mathematical model to define the dynamic bus routing problem and solves the problem optimally. Such a study typically introduces a novel problem formally using a mathematical model representation and solves the problem optimally using a mathematical solver, e.g., Gurobi in this study (Doan *et al*., 2018; Anthara *et al*., 2024). The research question is: "How can we revise current bus routes when the demand for passengers' movements is changed while ensuring the least possible changes in the routes? The route similarity is maximized as a way to allow a smooth adaptation of the passengers due to the possible frequent route changes. Such similar routes are required especially to assist a certain number of passengers who are still not that familiar with using technology that allows real-time bus route sharing. To ensure the minimization of the total bus travel times, our study introduces a maximum threshold that limits the increase of total bus travel times, when the new routes are applied.

The rest of the study is as follows. Section 2 defines the discussed dynamic bus routing optimization problem. Section 3 proposes the mathematical model. Section 4 presents the numerical experiments. Section 5 concludes the study and list some potential future research topics.

2. PROBLEM DEFINITION

The dynamic bus routing problem is solved anytime it is considered necessary to provide better services to the passengers by the decision makers, e.g., when a response to the demand changes is required (Su *et al*., 2024). When to trigger the bus rerouting itself could be solved as another optimization problem and requires further experiments and data analysis. This triggering period could differ based on the passenger flow density (e.g., whether peak hours are considered or not; Bie *et al*., 2020). This situation fits a short-term (intra-city or inter-city) bus route adjustment, instead of a long-term bus route planning.

The studied dynamic bus routing problem considers a complete bus network that consists of one bus depot 0 and several stations (1, 2, 3, …, $|N|$). Times required to travel (1) from depot 0 to each bus station i and (2) between stations are provided. A set of bus routes is given (k=1,2,…,$|K|$). The indices are used to identify old and new routes simultaneously. In this study, initially, information on old routes is given. After solving the problem, new routes are designed that might replace the old routes depending on the passengers' travel requirements. Nodes that are travelled in each old route k are recorded by using a_{ik} parameter. Each bus route k has its fleet size f_k. With a same capacity c for all buses, the buses must be deployed to satisfy all people group movement demands. The people group movements (origins, destinations, and number of passengers) are identified as follows:

Each group p consists of a number of passengers q_p and travels from an original station o_p to a designated station d_p. The purpose of the travels can be for leisure, business (work), education (school), personal activities, etc (Yang and Gao, 2025). The origin-destination information for each type of passenger can be extracted from the smart card transactions (historical data), which have been proven to be reliable and cost-effective (Rahmani *et al*., 2025). When the people group movement changes, the bus routes must be updated. New bus routes must be determined by using decision variables x_{ijk} and w_{ik}, which represent pairs of nodes connected on each route and nodes passed by each route, respectively. In this study, considering that the total number of passengers remains the same, the required total bus route capacity is the same, and the new routes are considered as a refinement of the existing bus routes.

Many changes in the bus routes could cause inconvenience for the passengers, e.g., those who expect to visit the same destinations. To ensure better satisfaction for the passengers, the similarity between the old and the new routes is maximized. Even though this study considers the total bus travel times in the constraints, different from Avila-Ordóñez *et al.* (2022) that minimized the total travel times, this study still somehow minimizes the total travel times by limiting the increase in the total travel times. This study proposes a better approach by limiting the total travel times to ensure the passengers' satisfaction better than Avila-Ordóñez *et al.* (2022) that allowed having any longer bus routes than the initial routes. The route similarity is assessed based on the number of same bus stations in the old and new routes, considering that passengers who initially travel through the old routes would expect to still travel on the same bus route to visit the same designated stations.

This study assumes that the fleet size for each route k (f_k) remains the same. Even though the proposed model can generate new bus routes when any changes in the people group movements occur, the proposed model would fit better in cases with fewer group movement changes that do not require changes in the fleet sizes.

The dynamic bus routing problem in this study is summarized as follows:

1. Input (given parameters):
    a. Bus network that consists of one depot and several bus stations.
    b. A set of current bus routes with their fleet sizes and list of nodes travelled through the routes. All buses have the same capacity.
    c. A set of passenger groups with the number of passengers per group, their origin and designated bus stations.
2. Output (decisions):
    a. New bus routes with the list of new nodes travelled through the routes.
    b. Allocation of passenger groups to the new routes.
3. Objective:
    Maximizing the similarity between the old and new bus routes.

3. MATHEMATICAL MODEL

The mathematical model of the truck appointment scheduling is presented below.

Sets

K	: Set of routes (k = 1, 2, …, $\|K\|$)
N	: Set of stations (i,j = 1, 2, …, $\|N\|$)
N'	: Set of stations and depot (i,j = 0, 1, 2, …, $\|N\|$)
P	: Set of passenger groups (p = 1, 2, …, $\|P\|$)

Parameters

a_{ik}	: 1, if station i was traveled in the old version of route k; otherwise, 0
c	: Capacity of each bus
d_p	: Designated station of passenger group p
e	: Percentage of allowed travel time increase for each route
f_k	: Fleet size for route k
g_k	: Total travel time of the old version of route k
o_p	: Origin station of passenger group p
q_p	: Number of passengers in group p
t_{ij}	: Bus travel time required from station i to station j

Decision variables

v_{ik} : 1, if station i is traveled in the new and old versions of route k; otherwise, 0

w_{ik} : 1, if station i is traveled through the new version of route k; otherwise, 0

x_{ijk} : 1, if the new version of route k includes a direct movement from station i to station j; otherwise, 0

y_{pk} : 1, if passengers in group p travel on the new version of route k; otherwise

z_{ik} : 0 auxiliary variable for subtour elimination

$$\max \sum_{i\in N}\sum_{k\in K} v_{ik} \tag{1}$$

$$\sum_{j\in N'} x_{0jk} = 1 \quad \forall k \in K \tag{2}$$

$$\sum_{i\in N'} x_{i0k} = 1 \quad \forall k \in K \tag{3}$$

$$\sum_{j\in N'} x_{ijk} = \sum_{j\in N'} x_{jik} \quad \forall i\in N, k\in K \tag{4}$$

$$z_{jk} \ge z_{ik} + 1 - M(1 - x_{ijk}) \quad \forall i, j\in N, k\in K \tag{5}$$

$$z_{ik} \le |N| - 1 \quad \forall i\in N, k\in K \tag{6}$$

$$w_{ik} \le \sum_{j\in N'} x_{ijk} \quad \forall i\in N, k\in K \tag{7}$$

$$x_{ijk} \le w_{ik} \quad \forall i\in N, j\in N', k\in K \tag{8}$$

$$w_{o_p k} + w_{d_p k} \ge 2y_{pk} \quad \forall p\in P, k\in K \tag{9}$$

$$\sum_{k\in K} y_{pk} = 1 \quad \forall p\in P \tag{10}$$

$$cf_k \ge \sum_{p\in P} y_{pk} q_p \quad \forall k\in K \tag{11}$$

$$\sum_{i\in N'}\sum_{j\in N'} x_{ijk} t_{ij} - g_k \le g_k e \quad \forall k\in K \tag{12}$$

$$v_{ik} \le a_{ik} \quad \forall i\in N, k\in K \tag{13}$$

$$v_{ik} \le w_{ik} \quad \forall i\in N, k\in K \tag{14}$$

$$x_{ijk} = \{0,1\} \quad \forall i, j\in N', k\in K \tag{15}$$

$$y_{pk} = \{0,1\} \quad \forall p\in P, k\in K \tag{16}$$

$$v_{ik}, w_{ik} = \{0,1\} \quad \forall i\in N, k\in K \tag{17}$$

$$z_{ik} = \text{integer} \quad \forall i\in N, k\in K \tag{18}$$

Objective (1) maximizes the similarity between the old and new versions of bus routes. Constraints (2) and (3) restrict each route k to start from and end at depot 0. Constraints (4) guarantee the flow conservation for each route k. Constraints (5) and (6) are the subtour elimination constraints. Suppose that a bus moves through route k directly from station i to station j, these constraints ensure that the value of variable z_{jk} is larger than the value of variable z_{ik}. In each route, the value of variable z would be equal to 1 on the first visited station, and the value would be at most equal to $|N|$-1 on the last visited station. Similar subtour elimination constraints are presented in Campuzano *et al.* (2020) and Zeng *et al.* (2022). The constraints ensure that no subtour (that starts and ends at any bus station) exists because the buses must start and end their travels at the depot. Constraints (7)-(9) allow each passenger group p to be assigned to route k if route k passes through the origin and destination of passenger group p. Constraints (7) set the value of variable w_{ik} to be equal to 0 when station i is not visited at all on route k. On the other hand, constraints (8) restrict the value of any variable x related to station i and route k to be equal to 1 when the value of variable w_{ik} equals 0. Constraints (9) ensure that when the movement of passenger group p is satisfied through route k (y_{pk}=1), then the route must pass the origin (o_p) and designated stations (d_p) of the group by setting the values of both related variables w to be equal to 1. Constraints (10) ensure each passenger group p is served by a route. Constraints (11) limit the total number of passengers assigned to route k to be less than the total available capacity in the fleet of route k. Constraints (12) ensure the increase in total travel time of each route k to be less than e percent of its old total travel time. Constraints (13) and (14) calculate the similarity indices between the old and new versions of routes. Constraints (15)-(17) are the binary and integer constraints. Constraints (12) are set to simultaneously reduce the inconvenience experienced by the passengers (Avila-Ordóñez *et al.*, 2022) and the service provider that is caused by the too large increase in the total bus travel times, when compared with the initial routes. The increase in total travel times must is limited to ensure less disturbance in the whole bus operation (Esquivel-González *et al.*, 2023). Such a constraint would restrict the set of feasible routes during the search. When the problem becomes infeasible, the value of e can be increased, and the problem can be solved again. Such a strategy would ensure an efficient search by focusing the search on a limited search space. This study prioritizes the passengers' convenience, which is reflected in the objective function, more than the service providers (in Constraints (12)).

4. NUMERICAL EXPERIMENTS

The mathematical model is written in Python programming language and solved on Google Colab using Gurobi Optimizer version 12.0.1 with the activated presolving procedure. The processor used for the computations is Intel® Xeon® CPU at 2.20GHz. The code and data are provided in the following link: https://github.com/ivanksinggih/dynamic_bus_routing_math_model and are freely available for use, provided that this paper is properly cited.

To test the model, thirty data sets of various sizes are generated. Testing the model on various problem sizes is necessary to verify the model, understand how the solution method solves different cases, and becomes a reference for the next research, as conducted by many studies (Singgih *et al*., 2020; Dahimi *et al*., 2025). Information on the instances and the experiment results is shown in Table 2. For each instance, a complete network is generated that satisfies the triangular inequality condition between any of three connected stations/depot. Each row in Table 2 for each of the small, medium, or large instance sets has a difference in the specific capacity per route (e.g., as shown in Figure 1) and the number of passengers for each origin-destination pair (e.g., as shown in Figure 2). For the same category (small, medium, or large), the bus networks can be the same or different. In all of the instances, optimal solutions are obtained, shown by the gaps between upper and lower bounds that are equal to 0% in the Gurobi results. Table 2 shows that the percentages of the increase of total travel times on the new routes, when contrasted to the old routes, are less than the set threshold. It ensures the new routes are not much longer than the old ones.

Table 2. Instances for numerical experiment and the experiment results

Data	# of stations	# of routes & total bus capa-city	# of passenger groups & total number of passengers	Solving time (s)	(Maxi-mized) route similarity value	Average increase in travel times of the routes = (new-old)/old	Total travel time increase threshold (%)
small_1	3	2 & 40	2 & 30	0.03	4	5.3%	10%
small_2				0.04	3	3.8%	10%
small_3				0.03	4	-9.6%	10%
small_4				0.05	4	3.7%	10%
small_5				0.03	4	-1.9%	10%
small_6				0.02	2	2.1%	10%
small_7				0.03	2	0.0%	10%
small_8				0.03	4	-6.5%	10%
small_9				0.04	5	-5.0%	10%
small_10				0.04	3	-7.0%	10%
medium_1	4	3 & 70	4 & 60	0.05	5	7.3%	15%
medium_2				0.09	6	8.0%	15%
medium_3				0.12	5	-9.5%	15%
medium_4				0.05	6	10.8%	15%
medium_5				0.18	5	4.2%	15%
medium_6				0.06	6	0.0%	15%
medium_7				0.04	6	2.1%	15%
medium_8				0.13	5	11.9%	15%
medium_9				0.13	4	12.2%	15%
medium_10				0.03	6	3.9%	15%
large_1	5	4 & 110	6 & 100	0.05	10	8.2%	20%
large_2				0.05	8	8.2%	20%
large_3				0.05	12	11.5%	20%
large_4				0.13	10	11.0%	20%
large_5				0.07	9	9.0%	20%
large_6				0.05	9	-11.4%	20%
large_7				0.47	7	9.1%	20%
large_8				0.19	7	11.5%	20%
large_9				0.27	7	6.4%	20%
large_10				0.42	5	17.4%	20%

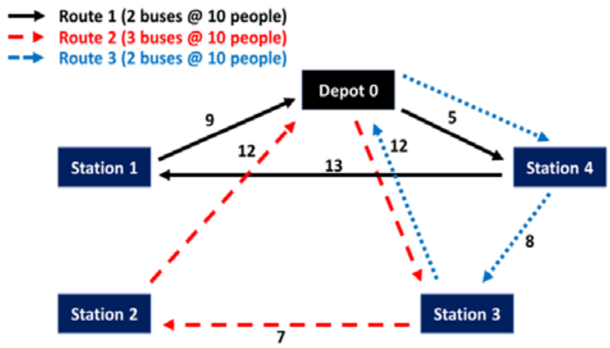


Figure 1. Bus network and route information in medium_9 instance.

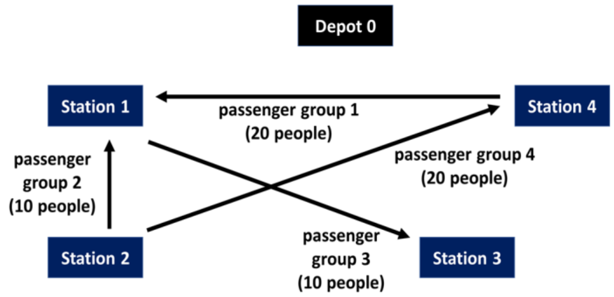


Figure 2. Passenger group movements in medium_9 instance.

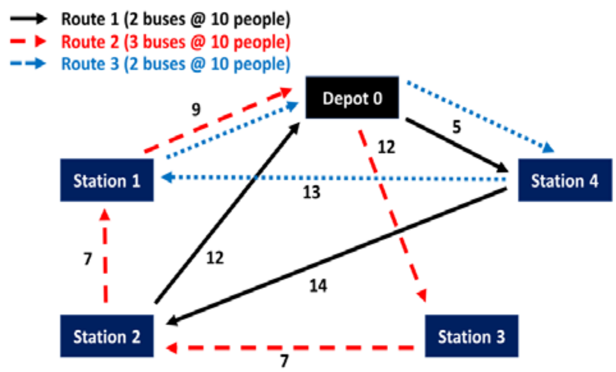


Figure 3. New bus routes in medium_9 instance.

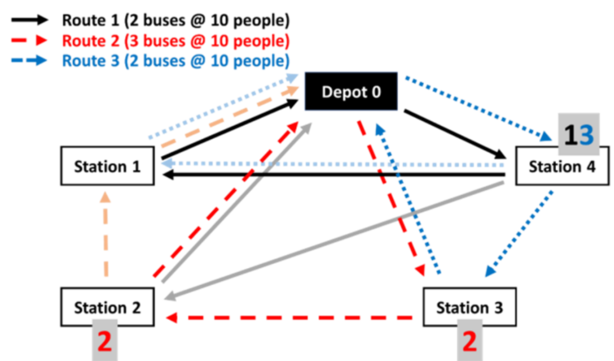
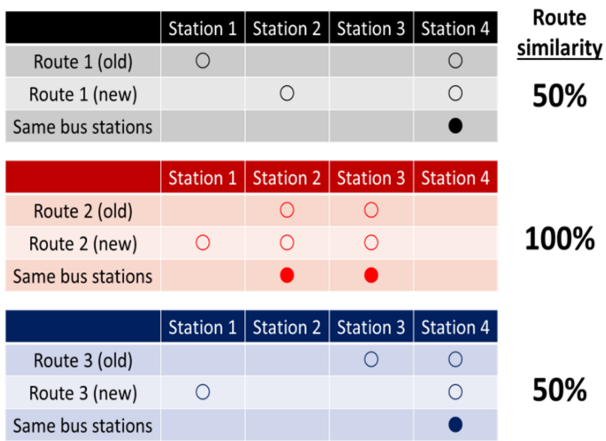


Figure 4. Passenger group movements in medium_9 instance.



	Station 1	Station 2	Station 3	Station 4	Route similarity
Route 1 (old)	○			○	
Route 1 (new)		○		○	50%
Same bus stations				●	

	Station 1	Station 2	Station 3	Station 4	
Route 2 (old)		○	○		
Route 2 (new)	○	○	○		100%
Same bus stations		●	●		

	Station 1	Station 2	Station 3	Station 4	
Route 3 (old)			○	○	
Route 3 (new)	○			○	50%
Same bus stations				●	

Figure 5. Route similarity in medium_9 instance.

An illustration of the results is provided based on medium_9 instance. The initial bus route is presented in Figure 1. The results show the updated bus routes (Figure 3) that satisfy all people group movement demands (Figure 2). Figure 4 and Figure 5 identifies the similar stations on the old and new bus routes. In Figure 4, old and new routes are shown (both routes are overlapped when they are exactly the same with each other). Numbers close to the stations represent the indices of the (old and new) routes that travel through the stations together. The information is summarized in Figure 5. Considering the limit for the increase in the total travel times, the number of the same stations on the old and new routes has been maximized (the route similarity percentage is measured when contrasted with the stations in the old routes).

5. CONCLUSIONS

This study discussed a bus routing problem that considered previous bus routes when designing new routes while minimizing the changes in the routes to provide a better experience by the bus passengers. The problem was formulated mathematically to solve larger data effectively. It is shown that the proposed mathematical model obtains optimal solutions for problems up to five number of stations, four number of routes, 110 of bus capacity, six passenger groups, and a total of 100 passengers.

Future research could explore (1) the incorporation of real data for setting the parameter values, e.g., the allowed percentage in the increase of the total travel times per bus route (which would be highly related to qualitative research results as well), (2) various variants on the dynamic bus routing problems and solution approaches, and (3) a comprehensive framework that integrates data collection and analysis through machine learning techniques, thereby enhancing the outcomes of the optimization process.

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