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Enhancing Operational Efficiency of Tourist Transportation with a Mathematical Programming Approach

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Abstract

This paper presents a mixed-integer linear programming model for the Internal Combustion Engine Bus Routing Problem with Time Windows for Tourists (ICE-BRPTWT), in which tourists from multiple flights are transported to hotels by a homogeneous fleet of ICE buses in a multiple-trip fashion. The model attempts to minimize total operating cost—including cost of routing, fleet deployment, and refueling—while honoring a wide variety set of constraints, such as route feasibility, capacity, time windows, and fuel consumption. Computational experiments demonstrate strong tractability only for small and moderate cases, in which CPLEX returns optimal solutions within seconds to under a minute. For larger instances, CPLEX, unfortunately, fails to determine the optimal solutions, due largely to the inherited ICE-BRPTWT complexity. This result suggests a need for efficient heuristics or metaheuristics in solving real-world ICE-BRPTWT instances, which is worth exploring in subsequent studies.

Keywords
Vehicle Routing Problem, Time Window, Mixed-Integer Linear Programming Model, Tourist Transportation, Internal Combustion Engine Buses.

1. Introduction
Rapid growth of urban tourism in major cities has intensified the need for transportation systems that well connect major gateways—such as airports and hotels (Iamtrakul et al. 2025; Le-Klähn et al. 2014; Pechpakdee 2024). While there are a number of transportation systems capable of transporting these tourists from airports to hotels, bus transportation is considered one of the most cost-efficient but yet flexible systems, compared to other transportation modes, like airport taxis or trains (Mehran et al. 2020).

In terms of operations, these buses are normally dispatched from airports, according to fixed-time schedules that may be changed from time to time, due to the number of scheduled flights in each season. They also follow a predefined set of routes, with a fixed number of stops (*e.g.*, hotels)—some of which may be skipped in case that stop requests are not signaled. Based on this operational setting, designing efficient bus routes could be regarded as one of the great challenges, as bus operators need to consider not only operational performance but also service quality and visitor experience at the same time (Guo et al. 2019).

Park and Kim (2010), Sarna et al. (2023) and Schittekat et al. (2013) also emphasized that bus routing for tourism must account for service reliability, accessibility, and passenger comfort—particularly in densely populated areas, where connectivity is vital to maintain cities' competitive advantages (Permana and Petchsasithon 2020). Based on these insights, this study thence focuses on the development of a mixed-integer linear programming model that helps enhance the operation of transportation buses, taking into account numbers of tourists from different arrival flights destined to different hotels. Unlike typical bus services in the literature, buses in this so-called Internal Combustion Engine Bus Routing Problem with Time Windows for Tourists (ICE-BRPTWT) could be dispatched at times they deem optimal, and their respective routes depend only on the boarded tourists, with no fixed routes to follow. In addition to time and cost of traveling, we also consider those of fuel consumption and refueling, ensuring that buses have enough fuel levels to perform services (Xiao et al. 2012).

Readers may regard the ICE-BRPTWT investigated herein as a specialized variant of the Vehicle Routing Problem (VRP) that integrates capacity, timing, fuel, and cost considerations to support efficient tourist mobility between the airport and urban destinations (*e.g.*, hotels). Similar to other complicated VRP variants (Bektaş and Elmastaş 2007; Hulagu and Celikoglu 2020; Jarumaneeroj et al. 2025; Jarumaneeroj and Sakulsom 2021; Sacramento et al. 2019), the ICE-BRPTWT could be formulated as a mixed-integer linear programming model that has been subsequently solved by a commercial optimization package (CPLEX). We assess the robustness of the proposed model by ICE-BRPTWT instances of different sizes. We find that small to moderate ICE-BRPTWT instances could be solved to optimality within a minute. But, this is not the case for large instances, as CPLEX fails to provide optimal solutions within a 60-minute time limit.

The remainder of this paper is organized as follows. Section 2 provides a thorough discussion of ICE-BRPTWT mathematical formulation. All CPLEX results to different ICE-BRPTWT instances are presented in Section 3. Finally, Section 4 summarizes the presented work, along with some suggestions for future research extensions.

2. Problem Description

The Internal Combustion Engine Bus Routing Problem with Time Windows for Tourists (ICE-BRPTWT) is a variant of the Vehicle Routing Problem (VRP), in which tourists from different arrival flights are transported to the designated hotels—according to their check-in times (*i.e.*, time window constraints)—by buses at the least cost. Similar to other bus-routing applications, these ICE buses are operated in a multiple-trip manner. Yet, there are no fixed-time schedules or predefined routes for them to follow. Instead, buses could leave the airport at times they deem optimal, with enough fuel levels. Furthermore, their respective bus routes depend largely on the boarded tourists.

While there are a number of evaluation metrics to be considered, the underlying ICE-BRPTWT focuses more on the operational cost of ICE bus fleet—derived from traveling and bus-deployment costs. Service quality, on the other hand, is treated as a part of model constraints, ensuring that all tourists are successfully transported to the hotels with no violations on their time-window requirements.

Sets

- $G = (N, E)$ is a transportation network.
  - $N = \emptyset \cup I$ is a set of nodes, where $\emptyset$ denotes an airport and I is a set of hotels.
  - $E = \{(i, j) \mid i, j \in N, i \neq j\}$ is a set of edges connecting nodes in N.
- K is a set of transportation buses.
- R is a set of trips performed by buses (*i.e.*, each bus may perform several trips daily).
- T is a set of flights.

Parameters

- c_{ij} denotes the traveling cost between hotel $i \in N$ and hotel $j \in N$.
- c_k denotes the fixed cost of operated bus $k \in K$.
- ω is the cost of refueling (per liter).
- $time_t$ denotes the time that tourists from flight $t \in T$ arrive at the bus stop.
- θ denotes the loading (unloading) times for tourists to get on (off) the bus.
- M is a large integer number.

- q_{jt} is the number of tourists from flight $t \in T$ visiting hotel $j \in I$.
- Q denotes the capacity of each bus.
- τ_{ij} denotes the traveling time from $i \in N$ to $j \in N$.
- δ_{ij} denotes the traveling distance from $i \in N$ to $j \in N$.
- $e_{\emptyset}$ is the starting time of the planning horizon.
- $l_{\emptyset}$ is the ending time of the planning horizon.
- e_j is the earliest time that tourists could visit hotel $j \in I$ (i.e., check-in time).
- l_j is the latest time that tourists could visit hotel $i \in I$.
- γ is the remaining fuel level of bus $k \in K$ prior to its first trip.
- g is the hourly refueling rate.
- C_{tank} represents the capacity of each bus's fuel tank.
- W denotes the fuel consumption rate of buses.

Decision Variables
- x_{ij}^{kr} is a binary decision variable indicating whether bus $k \in K$ traverses on edge $(i,j) \in E$ in trip $r \in R$.
- $Z_{\emptyset}^{kr}$ is a binary decision variable indicating whether trip $r \in R$ of bus $k \in K$ departs the airport.
- $d_{\emptyset}^{kr}$ is the ready time for trip $r \in R$ of bus $k \in K$ to start loading tourists at the airport.
- d_i^{kr} is the arrival time at hotel $i \in I$ by trip $r \in R$ of bus $k \in K$.
- b_i^{kr} is the departure time at node $i \in N$ by trip $r \in R$ of bus $k \in K$.
- y_{it}^{kr} denotes the number of tourists from flight $t \in T$ destined to hotel $j \in I$ on trip $r \in R$ of bus $k \in K$.
- A_t^{kr} is a binary decision variable indicating whether trip $r \in R$ of bus $k \in K$ departs the airport before the arrival of tourists from flight $t \in T$.
- $u_{\emptyset}^{kr}$ represents the fuel level of bus $k \in K$ at the end of trip $r-1 \in R$ (i.e., prior to the refueling).
- $v_{\emptyset}^{kr}$ is the fuel level of bus $k \in K$ prior to the start of trip $r \in R$ (i.e., after refueling).
- v_i^{kr} is the remaining fuel levels of bus $k \in K$ upon the arrival at hotel $i \in I$ in trip $r \in R$.
- $m_{refueling}^{kr}$ is the refueling time of bus $k \in K$ prior to the start of trip $r \in R$.
- μ^{kr} is an auxiliary variable representing $max\left(m_{refueling}^{kr}, \theta \cdot \sum_{i\in I}\sum_{t\in T} y_{it}^{kr}\right)$.

Objective Function

$$\min \sum_{r\in R}\sum_{k\in K}\sum_{(i,j)\in E} c_{ij}x_{ij}^{kr} + \sum_{k\in K} c_k Z_{\emptyset}^{k1} + \sum_{r\in R}\sum_{k\in K} \omega \cdot g \cdot m_{refueling}^{kr} \tag{1}$$

Eq. (1) defines the ICE-BRPTWT objective function aiming to minimize total cost of transporting tourists to hotels. This objective function is comprised of three cost components: (*i*) total traveling cost incurred when bus $k \in K$ performs trip $r \in R$, (*ii*) total fleet cost incurred by the dispatched buses, and (*iii*) total refueling cost incurred when bus $k \in K$ requires refueling prior to the start of trip $r \in R$.

Constraints

Constraints (2) – (4) are flow conservation constraints that help control the movement of bus $k \in K$ in performing their r^{th} trip. In particular, if trip $r \in R$ of bus $k \in K$ is dispatched (*i.e.*, $Z_{\emptyset}^{kr}$= 1), it must visit some hotels in I before returning to the airport. Else, when $Z_{\emptyset}^{kr}$= 0, no hotels would be visited by trip $r \in R$ of bus $k \in K$.

$$\sum_{i\in I} x_{\emptyset i}^{kr} = Z_{\emptyset}^{kr}; \forall k \in K, \forall r \in R \tag{2}$$

$$\sum_{i\in I, i\neq h, h\neq\emptyset} x_{ih}^{kr} = \sum_{j\in I, h\neq j, h\neq\emptyset} x_{hj}^{kr}; \forall h \in I, \forall k \in K, \forall r \in R \tag{3}$$

$$\sum_{j\in I} x_{j\emptyset}^{kr} = Z_{\emptyset}^{kr}; \forall k \in K, \forall r \in R \tag{4}$$

Constraint (5) stipulates that each hotel can be visited multiple times by different bus trips; but, in each trip, each hotel could be visited only once.

$$\sum_{i \in I, i \neq j, j \neq \emptyset} x_{ij}^{kr} \leq 1; \forall j \in I, \forall k \in K, \forall r \in R \tag{5}$$

Constraint (6) ensures that trip $r+1 \in R$ of bus $k \in K$ could be dispatched only when trip $r \in R$ of bus $k \in K$ has already been dispatched.

$$Z_{\emptyset}^{k,r+1} \leq Z_{\emptyset}^{kr}; \forall k \in K, \forall r \in R \tag{6}$$

Constraints (7) and (8) link the arrival time of tourists from flight $t \in T$ at the bus stop with the departure time of trip $r \in R$ of bus $k \in K$ via the logical decision variable A_t^{kr}. In this regard, A_t^{kr} will be set to one if tourists from flight $t \in T$ arrive before the departure of trip $r \in R$ of bus $k \in K$ by Constraints (7) and (8). And, in such a case, tourists from flight $t \in T$ destined to hotel $j \in I$ may board the bus according to Constraint (9). Conversely, $A_t^{kr}= 0$ implies that tourists from flight $t \in T$ arrive after the departure of trip $r \in R$ of bus $k \in K$. As such, no tourists from such flights could board the bus ($y_{jt}^{kr}= 0$).

$$b_{\emptyset}^{kr} - time_t - \theta \cdot \sum_{i \in I} y_{it}^{kr} \leq M A_t^{kr}; \forall k \in K, \forall r \in R, \forall t \in T \tag{7}$$

$$b_{\emptyset}^{kr} - time_t - \theta \cdot \sum_{i \in I} y_{it}^{kr} \geq M(A_t^{kr} - 1); \forall k \in K, \forall r \in R, \forall t \in T \tag{8}$$

$$y_{jt}^{kr} \leq M A_t^{kr}; \forall j \in I, j \neq \emptyset, \forall t \in T, \forall k \in K, \forall r \in R \tag{9}$$

Regarding the demand constraint, Constraint (10) ensures that the number of tourists from flight $t \in T$ destined to hotel $j \in I$ has been properly transported to such a hotel via multiple bus trips.

$$\sum_{r \in R} \sum_{k \in K} y_{jt}^{kr} = q_{jt}; \forall j \in I, \forall t \in T \tag{10}$$

Constraints (11) and (12), on the other hand, are capacity constraints ensuring that, in each bus trip, a maximum of Q tourists could be on board. Note that these constraints also serve as logical constraints that link boarded tourists with destined hotels in trip $r \in R$ of bus $k \in K$. In particular, Constraint (11) states that tourists destined to hotel $j \in I$ from various flights could be transported by a bus trip that indeed visits hotel $j \in I$. Likewise, these tourists could be on board only when the underlying bus trip exists, by Constraint (12).

$$\sum_{t \in T} y_{jt}^{kr} \leq Q \sum_{i \in I} x_{ij}^{kr}; \forall j \in I, j \neq \emptyset, \forall k \in K, \forall r \in R \tag{11}$$

$$\sum_{j \in I} \sum_{t \in T} y_{jt}^{kr} \leq Q Z_{\emptyset}^{kr}; \forall k \in K, \forall r \in R \tag{12}$$

Constraints (13) – (16) are time window constraints for the departure of buses. Note that decision variable $d_{\emptyset}^{kr}$ presents the ready time for trip $r \in R$ of bus $k \in K$ at the airport—or equivalently its arrival time at the airport. Based on this definition, Constraint (13) states that all buses are initially ready at the airport at time $e_{\emptyset}$.

$$d_{\emptyset}^{k1} = e_{\emptyset}; \forall k \in K \tag{13}$$

$$\mu^{kr} := max\left(m_{refueling}^{kr}, \theta \cdot \sum_{i \in I} \sum_{t \in T} y_{it}^{kr}\right); \forall k \in K, \forall r \in R \tag{14}$$

According to Eq. (14), the auxiliary variable μ^{kr} is introduced to represent the duration of service at the airport for bus $k \in K$ prior to the start of trip $r \in R$, where refueling and tourist boarding can occur at the same time. Based on this equation, μ^{kr} would capture only the largest term between the two activities.

$$b_{\emptyset}^{kr} \geq d_{\emptyset}^{kr} + \mu^{kr}; \forall k \in K, \forall r \in R \tag{15}$$
$$b_{\emptyset}^{kr} + \tau_{\emptyset j} x_{\emptyset j}^{kr} - M\left(1 - x_{\emptyset j}^{kr}\right) \leq d_j^{kr}; \forall j \in I, \forall k \in K, \forall r \in R \tag{16}$$

Regarding Constraints (15), for any trip $r \in R$ of bus $k \in K$, tourists must complete boarding by time $b_{\emptyset}^{kr}$. And, once the bus departs, it will visit the first hotel $j \in I$, with the arrival time d_j^{kr}, as controlled by Constraint (16).

The arrival and departure times at other hotel $i \in I$ in trip $r \in R$ of bus $k \in K$ are preserved by Constraints (17) – (19), which could be regarded as another set of time window constraints for each hotel.

$$b_i^{kr} \geq d_i^{kr} + \theta \cdot \sum_{t \in T} y_{it}^{kr}; \forall i \in I, \forall k \in K, \forall r \in R \tag{17}$$
$$b_i^{kr} + \tau_{ij} x_{ij}^{kr} - M\left(1 - x_{ij}^{kr}\right) \leq d_j^{kr}; \forall i, j \in I, i \neq j, \forall k \in K, \forall r \in R \tag{18}$$
$$b_j^{kr} + \tau_{j\emptyset} x_{j\emptyset}^{kr} - M\left(1 - x_{j\emptyset}^{kr}\right) \leq d_{\emptyset}^{k,r+1}; \forall j \in I, \forall k \in K, \forall r \in R \tag{19}$$

To make sure that all buses return to the airport before its closure time, Constraint (20) is, thus, needed. Likewise, trip $r \in R$ of bus $k \in K$ should visit hotel $j \in I$ during its operational times, which is mandated by Constraints (21) and (22).

$$b_j^{kr} + \tau_{j\emptyset} \leq l_{\emptyset}; \forall j \in I, \forall k \in K, \forall r \in R \tag{20}$$
$$d_j^{kr} \geq e_j; \forall j \in I, \forall k \in K, \forall r \in R \tag{21}$$
$$b_j^{kr} \leq l_j; \forall j \in I, \forall k \in K, \forall r \in R \tag{22}$$

Next, Constraints (23) – (25) are introduced to keep track of fuel levels, ensuring that each bus trip has enough fuel to perform service. To this end, decision variable $u_{\emptyset}^{kr}$ represents the initial fuel level of bus $k \in K$ at the end of trip $r - 1 \in R$ (*e.g.*, the remaining fuel level after the completion of its previous trip). According to this definition, Constraint (23) states that all buses begin with a predefined initial fuel level, denoted by γ, before undergoing their first refueling process. To determine an efficient refueling amount/duration for trip $r \in R$ of bus $k \in K$, we do need Constraint (24), along with Constraint (25) to prevent over refueling.

$$u_{\emptyset}^{k1} = \gamma; \forall k \in K \tag{23}$$
$$u_{\emptyset}^{kr} + g \cdot m_{refueling}^{kr} = v_{\emptyset}^{kr}; \forall k \in K, \forall r \in R \tag{24}$$
$$v_{\emptyset}^{kr} \leq C_{tank}; \forall k \in K, \forall r \in R \tag{25}$$

In additional to the boundary constraints, Constraints (26) – (28) form the last set of constraints governing the dynamic of fuel level throughout the bus route. In particular, the fuel level of bus $k \in K$ at the beginning of trip $r \in R$—denoted as $v_{\emptyset}^{kr}$—incrementally decreases along the route, until it reaches the final destination, that is, the airport. The rationale behind this set of constraints is similar to that of time window constraints, except for the reduction in fuel level at each visit.

$$v_{\emptyset}^{kr} - W\delta_{\emptyset j} x_{\emptyset j}^{kr} + M\left(1 - x_{\emptyset j}^{kr}\right) \geq v_j^{kr}; \forall j \in I, \forall k \in K, \forall r \in R \tag{26}$$
$$v_i^{kr} - W\delta_{ij} x_{ij}^{kr} + M\left(1 - x_{ij}^{kr}\right) \geq v_j^{kr}; \forall i, j \in I, i \neq j, \forall k \in K, \forall r \in R \tag{27}$$
$$v_j^{kr} - W\delta_{j\emptyset} x_{j\emptyset}^{kr} + M\left(1 - x_{j\emptyset}^{kr}\right) \geq u_{\emptyset}^{k,r+1}; \forall j \in I, \forall k \in K, \forall r \in R \tag{28}$$

3. Results

The proposed ICE-BRPTWT mathematical model has been assessed based on randomly generated ICE-BRPTWT instances of different sizes. For each instance sizes, ICE-BRPTWT instances of different characteristics are also created, such as balanced scenario—representing the case in which the number of tourists destined to each hotel is comparable—or that with tight time windows—representing the case in which tourist's time windows are relatively short compared to the airport's operational time window. Based on these varying ICE-BRPTWT instances, we can comprehensively examine model performance and its respective scalability under different scenarios.

For ease of computational comparability, all experiments are conducted on high-performance computing infrastructure (Intel Core i7-14700K processor and 64 GB of DDR5 RAM) using IBM ILOG CPLEX Optimization Studio V12.10.0.

3.1 Small ICE-BRPTWT Instances

The computational results to all 15 small ICE-BRPTWT instances are reported in Table 1. From Table 1, it could be seen that CPLEX could solve all 15 small ICE-BRPTWT instances to optimality within fractions of a minute—as low as 0.00 to 0.01 minute in multiple scenarios. Optimal objective values, however, vary greatly according to different spatial and temporal characteristics—confirming the model's sensitivity to different instance structures.

Table 1. CPLEX results to 15 small ICE-BRPTWT instances

Instance Number	**Number of**							**Optimal Objective Value**	**CPLEX Runtime (min)**	**Instance Characteristic**
	Hotels	**buses**	**Trips**	**Flights**	**Tourists**	**Airport Opening Hour**	**Airport Closing Hour**			
1	3	2	2	5	52	0	24	288.6	00.44	Balanced scenario
2	3	2	2	5	57	0	24	5,645.90	00.00	Clustered hotels
3	3	2	2	5	61	0	24	1,278	00.32	Early rush scenario
4	3	2	2	5	10	0	24	1,946.70	00.13	Tight time windows
5	3	2	2	5	54	0	24	380.5	00.19	Uneven distribution
6	3	2	2	5	53	0	24	13,731.50	00.40	Long distances
7	3	2	2	3	13	0	24	128.2	00.12	Minimal scenario
8	3	2	2	5	55	0	24	947.7	00.27	Late arrivals
9	3	2	2	5	52	0	24	3,850	00.29	Linear configuration
10	3	2	2	5	53	0	24	3,352	00.22	Spread-out hotels
11	3	2	2	7	148	0	24	3,711	00.36	Capacity stress test
12	3	2	2	5	53	0	24	2,496	00.01	Asymmetric distances
13	3	2	2	5	52	0	24	834.7	00.00	Mixed time windows
14	3	2	2	5	61	0	24	254.6	00.00	Quick turnaround
15	3	2	2	5	50	0	24	8,358	00.01	Fuel-critical scenario

3.2 Moderate ICE-BRPTWT Instances

Similar to small ICE-BRPTWT instances, nine moderate ICE-BRPTWT instances of different characteristics have been generated and solved by CPLEX, whose results are reported in Table 2.

Table 2. CPLEX results to nine moderate ICE-BRPTWT instances

Instance Number	Number of							Optimal Objective Value	CPLEX Runtime (min)	Instance Characteristic
	Hotels	buses	Trips	Flights	Tourists	Airport Opening Hour	Airport Closing Hour			
1	4	3	2	6	84	0	24	2,052.80	00.01	Balanced distribution
2	4	3	2	6	107	0	24	3,622.00	00.12	Clustered demand
3	4	3	2	6	120	0	24	3,434	00.10	Rush hour scenario
4	4	3	2	6	95	0	24	2,009.00	00.80	Tight time windows
5	4	3	2	6	84	0	24	10,205.90	00.10	Long distance scenario
6	4	3	2	6	96	0	24	1,697.30	00.04	Early morning flights
7	4	3	2	6	135	0	24	3,453	00.01	Single dominant hotel
8	4	3	2	6	108	0	24	2,722	00.04	Triangular layout
9	4	3	2	6	133	0	24	6,024	00.10	Mixed complexity

From Table 2, CPLEX can determine the optimal solutions to these instances within one minute. Yet, total operational cost varies substantially—ranging from 2,052.80 to 6,024.00—reflecting the influence of spatial configurations, demand patterns, and temporal constraints on routing efficiency. Notably, instances with tight time windows or long traveling distances typically results in higher operational costs, whereas balanced or clustered distributions generally lead to more efficient solutions.

3.3 Large ICE-BRPTWT Instances

The results to all nine large ICE-BRPTWT instances of different characteristics are reported in Table 3.

Table 3. CPLEX results to nine large ICE-BRPTWT instances

Instance Number	Number of							Optimal Objective Value	CPLEX Runtime (min)	Instance Characteristic
	Hotels	buses	Trips	Flights	Tourists	Airport Opening Hour	Airport Closing Hour			
1	5	4	2	7	123	0	24	Unknown	>60.00	Balanced distribution
2	5	4	2	7	149	0	24	Unknown	>60.00	Clustered demand
3	5	4	2	7	210	0	24	Unknown	>60.00	Rush hour scenario
4	5	4	2	7	139	0	24	3,390.40	6.16	Tight time windows
5	5	4	2	7	135	0	24	Unknown	>60.00	Long distance scenario
6	5	4	2	7	166	0	24	2,920.20	5.02	Early morning flights
7	5	4	2	7	193	0	24	Unknown	>60.00	Single dominant hotel
8	5	4	2	7	169	0	24	Unknown	>60.00	Hub-and-Spoke layout
9	5	4	2	7	223	0	24	Unknown	>60.00	Mixed complexity

From Table 3, it could be seen that a slight increase in instance sizes substantially impacts CPLEX performance in both terms of solution quality and computational time. To be precise, CPLEX runtimes exceed 60 minutes in almost all cases, except for “Tight time windows” and “Early morning flight” scenarios with substantially increases in computational times from fractions of one minute.

These findings infer that, while the ICE-BRPTWT model performs quite well on small to moderate ICE-BRPTWT instances, large-scale operational settings are far more complex, thereby requiring advanced heuristics which is worth exploring in sub-sequent studies.

4. Conclusion

This paper introduces a new variant of Vehicle Routing Problem (VRP), called the Internal Combustion Engine Bus Routing Problem with Time Windows for Tourists (ICE-BRPTWT), in which tourists from multiple flights are transported to hotels by a homogeneous fleet of ICE buses in a multiple-trip fashion. Unlike typical bus routing problems, buses in the ICE-BRPTWT setting could leave the airport if the timing deems right. Furthermore, each bus route depends largely on the destinations of boarded tourists, with no fixed routes to follow. To ensure that buses could perform services properly, fuel consumption—and so refueling—is also embedded as a part of the model.

Regarding model assessment, we find that—similar to other complicated VRP variants—small to moderate ICE-BRPTWT instances could be solved to optimality by commercial optimization packages, like CPLEX. Yet, when the instance size further grows, CPLEX tends to terminate with no solutions, due largely to the inherited problem complexity.

We also find that CPLEX solutions tend to consolidate arriving tourists from different flights, destined to the same destination, into the same trip. While these solutions are genuinely cost-effective, they are, however, less preferable from the passengers’ point of view, as passengers arriving early may need to wait longer so that each bus trip is cost-justified.

Another extension worth exploring is to consider environmental-related objectives, along with cost and quality objectives. Note that the ICE-BRPTWT currently captures the amount of fuel consumed and used by the buses. As the amount of fuel used could be directly transformed into CO2 emissions (Jarumaneeroj et al., 2025). It is therefore possible to set up and thoroughly explore the multi-objective ICE-BRPTWT that focuses on operational cost, service quality, and CO2 emissions all at once. With richer problem settings, their respective results would be more meaningful not only for this particular routing application but also for those with similar characteristics, worth exploring in the future.

References

Bektaş, T. and Elmastaş, S., Solving school bus routing problems through integer programming, *Journal of the Operational Research Society*, vol. 58, no. 12, pp. 1599-1604, 2007.

Guo, R., Guan, W., Zhang, W., Meng, F. and Zhang, Z., Customized bus routing problem with time window restrictions: model and case study, *Transportmetrica A: Transport Science*, vol. 15, no. 2, pp. 1804-1824, 2019.

Hulagu, S. and Celikoglu, H. B., Environment-friendly school bus routing problem with heterogeneous fleet: A large-scale real case, *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 4, pp. 3461-3471, 2020.

Iamtrakul, P., Chayphong, S., Seo, D. and Trinh, T. A., Promoting accessibility for sustainable tourism: a spatial analysis of tourist attractions and public transportation networks in Bangkok, *City, Territory and Architecture*, vol. 12, no. 1, pp. 13, 2025.

Jarumaneeroj, P., Krairiksh, S., Dusadeerungsikul, P. O., Li, D. and Iris, Ç., Eco-friendly long-haul perishable product transportation with multi-compartment vehicles, *Computers & Industrial Engineering*, vol. 202, pp. 110934, 2025.

Jarumaneeroj, P. and Sakulsom, N., An adaptive large neighborhood search for the multiple-day music rehearsal problems, *Computers & Industrial Engineering*, vol. 157, pp. 107279, 2021.

Le-Klähn, D. T., Hall, C. M. and Gerike, R., Promoting public transport use in tourism, *Understanding and Governing Sustainable Tourism Mobility*, Routledge, pp. 208-222, 2014.

Mehran, B., Yang, Y. and Mishra, S., Analytical models for comparing operational costs of regular bus and semi-flexible transit services, *Public Transport*, vol. 12, no. 1, pp. 147-169, 2020.

Park, J. and Kim, B. I., The school bus routing problem: A review, *European Journal of Operational Research*, vol. 202, no. 2, pp. 311-319, 2010.

Pechpakdee, P., Enhancing urban tourism in Bangkok: Challenges and opportunities, *Asian Review*, vol. 53.

Permana, A. S. and Petchsasithon, A., Assessing the seamlessness of Bangkok metropolitan public transport by using modified quantitative gap analysis, *International Journal of Built Environment and Sustainability*, vol. 7, no. 1, pp. 81-97, 2020.

Sacramento, D., Pisinger, D. and Ropke, S., An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones, *Transportation Research Part C: Emerging Technologies*, vol. 102, pp. 289-315, 2019.

Sarna, N. J., Ahmed, M., Rithen, F. A. and Islam, M. M., A framework of vehicle usage optimization for tour purposes, *Applied Sciences*, vol. 13, no. 19, pp. 10973, 2023.

Schittekat, P., Kinable, J., Sörensen, K., Sevaux, M., Spieksma, F. and Springael, J., A metaheuristic for the school bus routing problem with bus stop selection, *European Journal of Operational Research*, vol. 229, no. 2, pp. 518-528, 2013.

Xiao, Y., Zhao, Q., Kaku, I. and Xu, Y., Development of a fuel consumption optimization model for the capacitated vehicle routing problem, *Computers & Operations Research*, vol. 39, no. 7, pp. 1419-1431, 2012.

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