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Computational Model for Re-Routing and Assigning ESBs

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Abstract

Considering the necessity of electric school buses in replacement of conventional diesel school buses, this paper proposes an optimization model based on mixed integer programming to allocate electric school buses to existing and pre-determined routes where the travel paths and location sequences for each electric school bus are also be determined by this model. This model considers heterogeneous electric school buses and mixed loading of the students in the buses. Key factors including seating capacity, battery capacity, charge consumption cost, and bus price are considered in determining the best allocation of buses to different routes, to minimize overall costs. We present an illustrative example to demonstrate the applicability and effectiveness of this approach.

Keywords
Electric school bus, bus allocation, routing, mixed integer programming, and optimization.

1. Introduction
The present transportation industry is mostly controlled by vehicles that run on internal combustion engines. Most of the internal combustion engine vehicles (ICEVs) burn fossil fuels to run the vehicles, where ICEVs have a significant negative impact on the environment, especially concerning air pollution. The emissions from IC engines, including carbon monoxide, nitrogen oxides, and particulate matter, contribute to the formation of smog and respiratory problems in humans. Another harmful effect is the release of greenhouse gases, particularly carbon dioxide (CO2), which contributes to climate change and global warming. ICEVs are among the largest contributors to CO2 emissions, exacerbating the greenhouse effect and causing unpredictable weather patterns and rising sea levels. According to the United States Environmental Protection Agency's (EPA) Report on Inventory of US Greenhouse Gas Emissions and Sinks 1990-2022, Transportation activities were responsible for 38.1% of US CO_2 emissions and 28.9% of total greenhouse gas emissions in 2022 from fossil fuel combustion.

Moreover, the extraction, refining, and transportation of fossil fuels for ICEVs contribute to habitat destruction, water pollution, and ecosystem degradation. Additionally, the disposal of used motor oil and other automotive fluids poses risks to soil and water quality. Overall, the widespread use of ICEV has a profound and multifaceted negative impact on the environment, highlighting the urgent need for transitioning to cleaner and more sustainable transportation alternatives.

Electric vehicles (EVs) can be a feasible and suitable alternative to traditional internal combustion engine vehicles (ICEVs). EVs are seen as a solution to greening our transportation needs, especially when electricity is generated from renewable sources such as wind, hydro, or geothermal power. Regardless of the electricity production process, EVs prevent tailpipe emissions, thereby improving the local air quality compared to ICEVs that burn fossil fuels. Additionally, converting the wasted heat generated during braking into electricity using regenerative braking technology is yet another feature that makes EVs a smart choice (Hulagu and Celikoglu, 2022).

Electric vehicles (EVs) have a long and interesting history in the United States. In fact, the country's EV history can be traced back to the late 19th century when electric cars were among the first automobiles. However, due to primitive battery technology, range, infrastructure limitations, and high expenses, they were quickly overshadowed by internal combustion engine vehicles.

In recent years, concerns about energy security, environmental pollution, and the effects of fossil fuels on climate change have reignited interest in electric vehicles. Advancements in battery technology have resulted in greater ranges and faster charging times, and the electric vehicle (EV) market has grown in the United States. In addition, government incentives, such as tax credits and rebates, have helped make EVs more affordable for consumers. Automakers have also played a crucial role by investing heavily in developing new EV models, batteries, and infrastructure to support the growing demand. Moreover, rising gasoline prices and reduced cost of EVs contributed to attracting more middle-class consumers. All these factors combined have made EVs a viable and attractive option for people looking for a more sustainable way to travel, and the trend is only expected to continue in the future.

One of the most important areas where electric vehicles (EVs) should be implemented is in schools. School buses are among the main sources of pollution that affect students. In the United States, more than 25 million children ride over 500,000 buses to school every day. The majority of these buses run on diesel fuel, resulting in air pollution that can negatively impact the health and academic performance of children. Exposure to air pollution can worsen children's health. Diesel exhaust can cause immediate short-term adverse pulmonary effects by decreasing the membrane potential of epithelial cells in the lungs (Austin et al, 2019). On the other hand, EVs offer several benefits such as noise reduction, reduced emissions, health benefits, energy efficiency as well as low operating costs. Despite these benefits and advancements in electric vehicle (EV) technologies, they still face limitations due to their battery capacities. EV batteries are heavy, bulky, and expensive, which often results in a limited driving range. Additionally, charging infrastructure is less readily available, and charging times are longer compared to refueling diesel vehicles. This necessitates more careful route planning and allocation of buses to the routes. In assigning buses to different routes, seating capacity, battery capacity and range of the buses are critical factors.

2. Problem Statement

The objective of this study is to develop an optimization model for allocating electric school buses (ESB) to existing routes of conventional diesel school buses and sequencing bus stops and schools that will be visited by the electric school buses to transport students while minimizing procurement and electric charge consumption costs.

Various factors determine the allocation of an ESB to a particular route. These factors include the seating capacity of the bus, the number of students to be accommodated, battery capacity, distance to be traveled, availability of recharging options, school bell time, price of the bus, and charge consumption cost.

In this paper, we will develop a bus allocation model for a specific set of routes that includes fixed locations such as bus terminals, bus stops, and destination schools for each route. The model will also consider the number of students present at each location for each route as input.

3. Literature Review

Vehicle routing and scheduling is a vast area, and a lot of research has been done on this topic. Bus routing is a subtopic of the vehicle routing problem and bus routing is divided broadly into two sections public bus transportation routing and school bus routing. In this Section, we focus on reviewing the research related to school bus allocation, routing, and scheduling.

School bus routing problem (SBRP) can be categorized into several sub-problems, such as bus stop selection (BSS), bus route generation (BRG), bus route scheduling (BRS), school bell time adjustment (SBA) and strategic transportation policy (STP) (Ellegood et. al. 2020). In some research these problems are addressed separately and, in some cases, combined with different solution approaches.

In the study conducted by Sarubbi et al. (2016), a pseudo-random constructive heuristic algorithm was used to assign students to bus stops. The objective was to minimize the number of bus stops while considering the limited walking distance for students. Georeferenced data from a Brazilian city was used, and it was found that an increase in probable bus stop locations resulted in a decrease in the required number of bus stops for student assignments. Ledesma and Gonzalez (2013) used a column generation algorithm to select bus stops from a given set of potential locations and generate the route. The study considered the least number of bus stops to visit, the minimum number of students to pick up by the bus, and the maximum distance for students to travel as constraints. Chittekat et al. (2012) developed a metaheuristic model for the joint selection of bus stoppage and bus route. The model can make 3 simultaneous decisions: the set of bus stops that should be visited, which student should visit which bus stop, and which bus stop should be included in which route. Calvete et al. (2020) provided a comprehensive solution to the school bus routing problem. The solution includes bus stop selection that ensures both minimal routing cost and limited student walking distance. The proposed metaheuristic approach involves a two-stage process: first, students are partially allocated to active stops they can reach, and then routes are computed with minimum routing cost. A refining process is then applied to complete the allocation and adapt the routes, resulting in an efficient algorithm that delivers high-quality solutions within reasonable computing time. Orejuela and Hernández (2019) proposed a time-dependent school bus routing system that accounted for changes in travel time between nodes based on the start time of the journey. Ansari et al (2021) developed a mathematical model to assign special needs students to schools and organize school bus routes efficiently. Their two-phase heuristic method proves effective in generating optimal solutions, resulting in significant reductions in bus travel distance. The methodology has been tested in Fort Smith, Arkansas, demonstrating its effectiveness in improving efficiency.

Among the various subproblems of the School Bus Routing Problem (SBRP), the joint consideration of bus route selection and bus route scheduling is the most explored research area. Park et al. (2012) developed a school bus scheduling model for a given set of bus stops and destination schools within a specified time window. To develop the model, they first treated it as routing with Windows Time and then used two assignment problem-based optimization methods and heuristic methods for specific and general cases, respectively. Elgareg et al. (2017) proposed a solution for the school bus scheduling problem using a distributed ant colony optimization algorithm with a multi-agent system. The solution was designed to create a path that minimizes transportation costs while satisfying various constraints such as the distance traveled by each bus and the capacity of each vehicle. It utilized clustering strategy, metaheuristics methods, and intelligent agents to find the shortest path between schools and students. The solution can be applied to real-life cases, and they plan to apply it to more than one school in the future. (Yan et al. 2015) developed an inter-school bus routing and scheduling model based on stochastic travel time, considering real-world stochastic disturbance. The model was formulated as a special multiple commodity network flow problem using variable fixing methods and the CPLEX solver.

School bell time is a crucial factor in school bus allocation and scheduling. Many researchers consider it as a fixed input, but some studies proposed adjusting the bell time to reduce the required number of buses and trips. For instance, Bertsimes et al. (2019) suggested adjusting school bell times, which has been implemented in the Boston school district. Qian (2023) used a multicriteria optimization model in his research to determine the optimum bell time for school.

Another factor to consider in school bus routing and planning is whether to use non-mixed or mixed loading. Non-mixed loading involves each bus carrying students from only one school, while mixed loading means a bus carries students from multiple schools and stops at multiple locations. A study by Ellegood et al. (2015) suggested that mixed loading policies are advantageous for large school districts where bus stop locations are often shared between schools. There are also some studies, Koksal et al. (2021), and Qian (2023), that employed different machine-learning algorithms for optimization in school bus routing and scheduling. A study by Prakash (2023), proposed the implementation of Vehicle-to-Grid (V2G) technology in electric school buses. The study suggested using the idle school buses as a power source to supplement the grid output during peak hours. Additionally, the study proposed several strategies to adopt V2G technology effectively.

The research mentioned earlier was focused on routing for conventional diesel-fueled school buses. However, in our study, we are taking into consideration electric school buses. We have not been able to find any prior studies on the routing, scheduling, or allocation of electric school buses. The main challenge in allocating electric school buses is their limited battery capacity, which determines their range, and the limited charging infrastructure available. This research model differs from other routing studies also because we are constrained to use the current fixed bus stops for each route to determine the bus's travel path, whereas, in most routing research, there is more flexibility in selecting any location to form the routes and even opportunities to choose where bus stops should be formed.

This paper proposes an optimization model for allocating ESB and sequencing pre-determined routes based on conventional diesel school buses. The model considers fixed routes consisting of a set of bus stops and schools to visit. However, this model determines which bus will visit which location in each pre-demined route, how many buses will be assigned for each route, and the sequence of visiting stops and schools' locations. Also, the model considers the mixed loading of students from different schools on the buses and takes into account the seating capacity and battery capacities of the buses to select the buses and minimize costs.

4. Proposed Optimization Model

To address the bus allocation and pre-determined routes sequencing problem, we develop a mixed integer programming (MIP) model that aims to minimize the overall expenses of buying buses and the expenses incurred due to the consumption of battery charges of the buses during the overall trips while satisfying a set of constraints.

The model assumes that each bus is assigned to only one route, and school bell time will not affect the allocation process. However, multiple buses can be used for a single route. The model will determine which bus will travel to which location and sequence of the travel as well, in each route. We also assume that a list of buses with specific seating capacity, battery capacity, and prices is available for selection. All buses will be fully charged at the start of the trip from the terminal and recharged only after returning to the terminal after dropping off all the students at their respective locations. Additionally, the model considers a flat rate for the cost of charge consumption during the bus trips. All the notations are introduced in Table 1.

Table 1. Notations for Bus allocation and travel path selection Model

Notation	Description	Type/use
R	Set of routes.	IP
r	Index of route.	IP
B	Set of buses.	IP
b	Index of bus.	IP
L	Set of locations.	IP
L^s	Set of schools which is a subset of L	IP
l & k	Index of location.	IP
S_b	Seating capacity of bus b.	IP
T_b	Battery capacity of bus b in kWh.	IP
$W_{r\,l}$	It is 1 if location l is included in route r and 0 otherwise.	IP
$N_{r\,l}$	The number of students in location l for route r.	IP
$D_{l\,k}$	Distance between location l and k.	IP
P_b	Price of bus b.	IP
C	Cost of charge consumption per kWh	IP
E	Required battery capacity to travel per mile.	IP
M	Big number	IP
$X_{b\,r}$	Binary variable is 1 if bus b is allocated to route r and 0 otherwise	DV
A_b	Binary variable is 1 if bus b is allocated to any route and 0 otherwise.	DV
$Y_{b\,r\,l}$	Binary variable is 1 if bus b is visiting location l which is included in route r and 0 otherwise.	DV
$V_{b\,r\,k\,l}$	Binary variable is 1 if bus b in route r is going to location k from location l and 0 otherwise.	DV

IP= Input Parameter DV = Decision Variable

Objective function:

$$\text{Min } \left(\sum_{b=1}^{B} P_{b*} A_b\right) + \left(2 * C * \left(\left(\sum_{b=1}^{B}\sum_{r=1}^{R}\sum_{l=1}^{L}\sum_{k=1}^{L} V_{b\,r\,l\,k} * D_{l\,k}\right) * E\right)\right) \tag{1}$$

Subject to:

$$\sum_{b=1}^{B} X_{b\,r} \geq 1 \qquad for\ \forall r. \tag{2}$$

$$\sum_{r=1}^{R} X_{b\,r} \leq A_b \qquad for\ \forall b. \tag{3}$$

$$\sum_{b=1}^{B} Y_{b\,r\,l} = W_{rl} \qquad for\ \forall r\ and\ l, l \neq 1. \tag{4}$$

$$\sum_{b=1}^{B} Y_{b\,r\,l1} = \sum_{b=1}^{B} X_{b\,r} \qquad for\ \forall r. \tag{5}$$
$$\sum_{l=1}^{L} N_{r\,l} * Y_{b\,r\,l} \leq S_b * X_{b\,r} \qquad for\ \forall b\ and\ r. \tag{6}$$
$$\sum_{l=1}^{L} Y_{b\,r\,l} \leq M * X_{b\,r} \qquad for\ \forall b\ and\ r. \tag{7}$$
$$2 * E * \left(\sum_{l=1}^{L}\sum_{k=1}^{L} V_{b\,r\,l\,k} * D_{l\,k}\right) \leq T_b * X_{b\,r} \qquad for\ \forall b\ and\ r,\ l \neq k. \tag{8}$$
$$\sum_{k=1}^{L} V_{b\,r\,l\,k} * W_{r\,l} * W_{r\,k} \leq Y_{b\,r\,l} \qquad for\ \forall b, r, and\ l,\ l \neq k \tag{9}$$
$$\sum_{l=1}^{L} V_{b\,r\,l\,k} W_{r\,l} * W_{r\,k} \leq Y_{b\,r\,k} \qquad for\ \forall b, r, and\ k,\ k \neq l. \tag{10}$$
$$\sum_{r=1}^{R} V_{b\,r\,l\,k} + \sum_{r=1}^{R} V_{b\,r\,k\,l} \leq 1 \qquad for\ \forall b, l, and\ k,\ l \neq k. \tag{11}$$
$$\sum_{l^s=1}^{L^S} V_{b\,r\,l^s\,l1} = X_{b\,r} \qquad for\ \forall b\ and\ r. \tag{12}$$
$$Y_{b\,r\,l^s} = X_{b\,r} * W_{r\,l^s} \qquad for\ \forall b, r,\ and\ l^s. \tag{13}$$

Constraint (2) specifies that at least one bus will be assigned to each route. Constraint (3) ensures that when any bus is assigned to any route that will be marked as selected bus and it also ensures that a bus can't be assigned to more than one route. Constraint (4) specifies that other than location l1, which is considered a bus terminal, all other locations included in a route won't be visited by more than one bus. Constraint (5) ensures that all the assigned bus will start their trip from location l1, the bus terminal. Constraint (6) specifies the seating capacity constraint which ensures that the total number of students served by any bus in any route should not be more than the seating capacity of the bus. Constraint (7) ensures that any bus allocated for a specific route will not be able to visit the locations not included in the route. Constraint (8) specifies battery capacity constraint which restricts a bus from traveling more than its battery capacity permits. Constraints (9) and (10) indicate that a bus selected for a route will travel from one location to another by only one path. Constraint (11) ensures the flow of the direction. Constraint (12) ensures that after dropping students off at school, it will return to the bus terminal. Constraint (13) ensures that a bus assigned for any specific route will visit all the schools included in the route.

5. Illustrative Example

In this example, we have considered 8 electric school buses of different prices and specifications from which we must select suitable buses to allocate for different routes. Table 2 shows the list and specifications of the buses, Table 3 shows the distance between each location, and Table 4 shows which locations are included in which route.

Table 2. List of available buses and their specifications

Bus No.	Seating Capacity (person)	Battery Capacity (kWh)	Price of Bus ($)
1	40	88	150000
2	50	120	200000
3	50	100	190000
4	60	110	240000
5	70	145	260000
6	40	80	155000
7	50	90	210000
8	80	145	275000

Table 3. $D_{l\,k}$ Matrix

Location no.	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	l_9	l_{10}
l_1	0	5	9	10	13	9	11	14	18	19
l_2	5	0	8	7	9	5	8	11	14	13
l_3	9	8	0	6	5	7	10	10	12	10
l_4	10	7	6	0	4	8	10	7	10	11
l_5	13	9	5	4	0	5	7	11	10	10
l_6	9	5	7	8	5	0	4	6	8	9
l_7	11	8	10	10	7	4	0	5	7	8
l_8	14	11	10	7	11	6	5	0	6	7
l_9	18	14	12	10	10	8	7	6	0	3
l_{10}	19	13	10	11	10	9	8	7	3	0

Table 4. $W_{r\,l}$ Matrix

routes, locations	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	l_9	l_{10}
r_1	1	1	0	1	0	1	0	0	1	1
r_2	1	0	1	1	0	0	0	0	0	1
r_3	1	0	0	0	1	1	1	0	1	1
r_4	1	0	0	1	0	0	1	1	1	0
r_5	1	1	1	0	0	0	0	0	1	1

Location l_1 is bus terminal, l_2 to l_8 indicates bus stops and l_9 and l_{10} are schools. The bus/ buses selected for any route will cover all the locations in that route alone/combined and in which pathway they will travel these locations will be determined by this optimization model. In addition, the total number of students to pick from each location in each route is given in Table 5. In this example, we have also considered the cost of charge consumption c = 1.2 USD/ KWh and the battery capacity of a bus required to travel per mile, CR= .4 kwh.

Table 5. $N_{r\,l}$ Matrix

routes, locations	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	l_9	l_{10}
r_1	0	30	0	10	0	32	0	0	0	0
r_2	0	0	30	20	0	0	0	0	0	0
r_3	0	0	0	0	20	15	12	0	0	0
r_4	0	0	0	20	0	0	30	35	0	0
r_5	0	18	25	0	0	0	0	0	0	0

These inputs have been used to optimize the model, which has been solved using GAMS software with CPLEX solver. The results of the model are displayed in Table 6. The solution reveals that a total of 6 buses have been assigned to 5 routes. Let's take Route 1 as an example: Bus No. 8 is assigned to this route, beginning at Terminal l_1, picking up students at locations l_2, L_4, and l_6. The bus will then drop off the students at School l_{10} and School l_9, respectively. After dropping off students, the bus will return to Terminal l_1. The results in the table only display the one-way direction because the bus will follow the same path in the opposite direction when returning. This means that the bus will travel from Terminal l_1 to School l_9 and then to School l_{10}, pick up the students, and drop them off at their respective bus stops at l_6, l_4, and l_2 before returning to Terminal l_1. Therefore, since the distance traveled in both directions is the same, we multiplied the total distance by 2 in the objective function. In addition, the main goal of this optimization model is to minimize the total cost and the minimum cost for this example is USD 1265255.360.

Table 6. Results from the optimization model of bus allocation and travel path selection

Route	Allocated Bus	Locations traveled by bus	The sequence of one-way travel
r_1	b_8	l_1, l_2, l_4, l_6, l_9, l_{10}	l_1 -l_2 -l_4 -l_6 -l_{10} -l_9 -l_1
r_2	b_3	l_1, l_3, l_4, l_{10}	l_1 -l_4 -l_3 -l_{10} -l_1
r_3	b_2	l_1, l_5, l_6, l_7, l_9, l_{10}	l_1- l_6- l_5 -l_7 -l_{10} -l_9 -l_1
r_4	b_1 b_4	l_1, l_7, l_9 l_1, l_4, l_8, l_9	l_1- l_7- l_9- l_1 l_1- l_4- l_8- l_9-l_1
r_5	b_7	l_1, l_2, l_3, l_9, l_{10}	l_1-l_2-l_3-l_{10}-l_9-l_1

6. Conclusion

This paper described the formulation of an optimization model for the allocation of electric school buses to pre-determined routes as well as for determining the travel path and sequence of bus stops and schools in each path at minimum cost. These two factors, bus allocation, and travel path determination, are very crucial if school authorities plan to replace the current diesel school buses with ESBs and operate ESBs on the same existing and pre-determined routes considering students' health benefits and the government's initiatives.

In this paper, we demonstrated the proposed optimization model using a few routes and buses hence heuristic and metaheuristic methods may also be considered for larger applications. For future research, we may consider allocating buses in more than one route then scheduling of the buses will be necessary where school bell times will come into play. Furthermore, intermediate charging options and charging schedules may also be determined by taking into account existing charging infrastructures or proposing new charging infrastructures as well.

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