A SIMULATION MODEL FOR PLANNING A PUBLIC TRANSPORT USING ELECTRIC VEHICLES: A CASE OF PHETCHABUN RAJABHAT UNIVERSITY

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Abstract

The research's objective is to develop and study the behavior of public transport using electric vehicles from computer models under the conditions set by the university. The research process divides into two main parts: Part 1 is application. Metaheuristic Algorithms to find the appropriate sequence of travel routes, and part 2 is to develop and study the model. To assess the ability to assess service capability. The following indicators are observed, this includes the success of the service performance in conjunction with the waiting period, the amount of density in the queue, and the total length of time that the service recipient needs to be in the system. The model results show that the system can meet the needs of service users. However, considering the time lost on the trip, it was found that the average service time spent more than half an hour in a distance of fewer than five kilometers. The solution was to increase the frequency of service cycles. However, due to restrictions on the number of vehicles that are limited. Each round trip requires an average of 75.25 minutes. Therefore, to ensure that public transport can respond to customers effectively. The person in charge should increase the number of vehicles in line with the needs of the service users.

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However, the need for Phetchabun Rajabhat University to become a green university remains an important and challenging goal. This research demonstrates awareness of the university's environmental responsibilities and wants to stimulate activities to transform into a green university truly.

Keywords: Electric vehicles, Simulation model, Planning a public transport

Introduction

In the current era of climate change, the profound impact on humanity is becoming increasingly evident. The escalating phenomenon of global warming is unleashing catastrophic events on a worldwide scale (Shahzad, 2015). The repercussions are far-reaching, with species extinction and biodiversity loss (Alcamo et al., 2007) triggering droughts, the spread of diseases, and famine. Moreover, agricultural productivity is declining, exacerbating the challenges faced by communities. Recognizing the situation's urgency, the Thailand Greenhouse Gas Management Organization (2022) has identified greenhouse gas emissions, mainly from activities like transportation fuel combustion, as a significant contributor to global warming, intensifying the issue (Thailand Greenhouse Gas Management Organization, 2019). In response to these global challenges, countries strive to address them and prepare for the changing conditions by adopting the 17 Sustainable Development Goals (SDGs) proposed by the United Nations as a comprehensive global development framework (Kroll et al., 2019).To assess the ability to assess service capability. strategic plan for 2023-2027

Phetchabun Rajabhat University has embraced the SDGs as an integral part of its operations, guiding innovation and development. In its strategic plan for 2023-2027 (Maçin, 2019), the university emphasizes commitment, aiming to meet international standards and become a moral government agency in effectively combating carbon dioxide emissions. This commitment is aligned with the University of Indonesia's UI Green Metric World University Ranking for 2019, highlighting the importance of addressing carbon emissions.

Previous research conducted by Teannava et al. (2016) at the university explored the implementation of electric vehicles within the transportation system (Teannava et al., 2016). However, during that time, the high cost associated with electric vehicles and charging stations posed significant challenges, making it difficult to establish concrete policies. Additionally, the layout of the university changed, including upgrading the main road to accommodate four lanes, rendering the original model infeasible.

In a separate study conducted by Setsathien & Kerdphon (2018) on the public bus route system at Rampaipani Rajabhat University, it was discovered that there needed to be more fixed pick-up and drop-off points, as well as an insufficient number of Consequently, service users had to endure long waiting times (Setsathien & Kerdphon, 2018). Similar issues may arise at Phetchabun Rajabhat University without proper education and planning.

Hence, this research aims to develop and analyze the behavior of public transport using electric vehicles through computer models. The ultimate goal is to minimize service users' travel and waiting times by precisely determining pick-up and drop-off points and organizing the routes accordingly. To achieve this, the researchers will employ the Traveling Salesman Problem (TSP), a well-known problem in vehicle routing, which seeks to find the most efficient route while visiting each location only once, with the start and end points being the same (Li, 2022). It is important to note that the TSP is classified as an NP-hard problem, lacking a known algorithm that can solve every instance in less total time than the power of n (where n represents the problem size). Thus, practical search algorithms are crucial to address these challenges (Mishra et al., 2016).

Based on the research conducted by Teannava et al. (2016), a comparison of the efficiency of TSP using ant colony optimization and Iterated Local Search (ILS) revealed that ILS could find the shortest distance in more minor problems with ten visiting points in fewer times (Amdee et al., 2016). Consequently, ILS was chosen as the preferred approach to find the optimal route, which will serve as the data for modeling the public bus route system at Phetchabun Rajabhat University. Computer simulation offers significant advantages in analyzing complex problems involving uncertainty, and the integration of animation aids in the decision-making process. However, it is worth noting that developing the model for computer simulation is a time-consuming endeavor compared to using mathematical models (Ransikarbum, 2020). Nevertheless, this modeling approach has been extensively analyzed in various studies, encompassing transportation (Ransikarbum et al., 2018; Pikulhom & Chaimanee, 2017), agency-level planning and management (Dias, 2022; Abdul Rasib et al., 2021), and even areas such as freight forwarding and inventory management systems (Alsolami, 2020; Doe, 2022).

Computer models have also found application in Healthcare emergency management (Modibbo & Okolo, 2018), exemplified by Modibbo & Okolo (2018) model developed in this study helped identify and address congestion in the Emergency Department by providing insights into the waiting times of patients and the service times they experienced.

Materials and Methods

1. Problem Formulation

To ensure optimal efficiency of public transportation within the university, it is imperative to consider a multitude of factors that impact the overall system. These factors encompass the volume of vehicles, availability of parking spots, and more. Equally important are considerations such as the number of users at each route pass point, bus schedule frequency, and other relevant variables, as these elements directly influence system efficiency and user satisfaction. Prolonged waiting and travel times can lead to dissatisfaction and deter individuals from utilizing the services. A study conducted by Teannava et al. (2016) demonstrated that the implementation of the ILS (Iterated Local Search) approach effectively resolves TPS (Transportation Problem Solver) issues present in university travel networks, thereby efficiently identifying the shortest travel routes. This research underscores the potential of employing computer models to comprehensively analyze the behavior of public transportation systems within university settings, thereby facilitating improved route planning, resource allocation, and optimization of pick-up and drop-off points. Furthermore, the findings of Setsathien & Kerdphon (2018) substantiate the proposition that computer models can be successfully utilized to examine and study the dynamics of public transportation systems in universities. Their research provides valuable insights into the enhanced clarity achieved in route planning, resource allocation, and the identification of optimal pick-up and drop-off points. Consequently, this research endeavor has been segmented into two distinct parts to effectively address the aforementioned considerations.

1.1 Determining the proper travel sequence This research examines the problem of restricted vehicle routing, such as the number of seats already determined by organizational policies and the changing traffic layout, according to research by Teannava et al. (2016). Traffic lanes are 4 traffic routes, so cars do not turn across the intersection immediately, and if you want to make a U-turn, you only need to drive to where there is a U-turn. However, there is still a close tour pattern, so TPS is still used as a representation of the problem, and according to research by Amdee et al. (2018), comparing the effectiveness of solving TSP problems using metaheuristics, ILS can effectively find the shortest distance in minor problems.

2.2 Develop computer models that utilize insights derived from the model studies to inform decision-making processes in designing the most efficient travel system. Operating within the constraints stipulated by the university, the system's ultimate objective is to minimize passenger waiting and travel times. This endeavor aligns with the university's commitment to fostering green initiatives, promoting environmental sustainability, and reducing carbon dioxide emissions, in line with the Sustainable Development Goals. The panel may need to disregard certain conditions that are beyond its control. Therefore, the following assumptions can be made in modeling.

1) The distance between the passing points selects the shortest distance from the route finding function in Google Maps by consideing only 10 passing points.

2) The vehicle's speed must not exceed 40 kilometers per hour. The time for getting on and off the car, including time for slowing down is a triangular distribution.

3) Vehicles can provide passengers with a maximum of 13 seats per vehicle according to the conditions of the university.

4) The car will not require a refueling break since the refueling time is incorporated into the travel time within the delay module of the computer model.

5) When the vehicle travels through all the specified passing points, it will not go back to its original direction, and will immediately move to the starting point

6) Using accidental sampling model of student behavior and personnel in the university to identify the number, arrival time, and user's destination of the service.

7) The recipient cannot select the same pickup and drop-off point.

8) The arrival time of service users is modeled as a random exponential with a rate of occurrence every 10 minutes.

9) If the service recipient wants to get off at a parking spot that the car has already passed, the recipients have to get off at the parking area in front of the

university (Point P), and then queue for the next vehicle in the next round. The recipient is not allowed to disembark from vehicles that are not at a stop.

2. Traveling Salesman Problem

Finding the optimal path in this research relied on the results of solving a salesperson's journey problem. This can be explained by having the network represented by the graph G= (V, A) where V is the set of all nodes. It consists of a salesperson and a customer, where A is a line between nodes called arcs (Arc), where A={i,j} with the distance C_{ij} in each path (i,j) of A can be written as matrix $C=C_{ij}$, where each round trip must always begin and end at the starting node, each round must pass through all nodes i ; i = 1,..., n only once. Raff et al. (1983) describes a mathematical model for solving this problem as follows:

Minimize

$$MinZ \;= \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}x_{ij} \tag{1}$$

Subject to

$$\sum_{i=1}^{n} x_{ij} = 1 \;\; (j = 1,2,...n) \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \;\; (j = 1,2,...n) \tag{3}$$

$$\sum_{i=1}\sum_{j=1} x_{ij} \le |S| - 1 \;\;\; i \in s, j \in s \tag{4}$$

$$x_{ij} = 0 \;\; or \;\; 1 \;\;\; for \;\;\; all \;\;\; i, j \tag{5}$$

Equation (4) checks the sub tour may be written in another form as follows:

$u_i - u_j + Nx_{ij} \le N - 1$ ($for \;\; i \ne j; i == 2,3,...N; j = 2,3...N$)

Variables definition

n = number of nodes

x_{ij} = distance traveled from i to j

$$x_{ij} = \begin{cases} 1 & \text{If there is a journey from i to j} \\ 0 & \text{Otherwise} \end{cases}$$

S = The set of nodes in a sub tour means a sequence of travel that does not go through all of the points and completes it

$|S|$ = Number of nodes in the sub tour

u_i, u_j = Tour's position

N = Number of nodes in the sub tour

Equation (1) is the shortest path, Equation (2) and Equation (3) departing from any city i must be equal to 1 (a city can only depart once in Where there is only one journey into town j, Equation (4) is an equation preventing the occurrence of a sub tour. The journey starts from a particular city but does not complete the journey, resulting in a sub-tour. Equation (5) is the decision variable.

3. Iterated Local Search Algorithm

Results from the research conducted by Teannava et al. (2016) and Amdee et al. (2018) provide valuable insights into the effectiveness of Iterated Local Search (ILS) in finding the shortest distance in more minor problems with 10 visiting points, accomplishing this task in less time. Given these findings, ILS was selected as the preferred approach for determining the optimal route to be utilized in modeling the public bus route system at Phetchabun Rajabhat University. Therefore, to determine the outcomes, the researchers chose an ILS that has a strategy for enabling LS to avoid getting the answer value stuck to the best answer value in the neighborhood (Raff, 1983), with the following steps:

Initialization

Selection of the set neighborhood structures $N(x)$ for $l = 1...l_{\max}$ and $n = 1...n_{\max}$

Find an initial Solution x

Current step (Repeat)

1) Set $l \leftarrow 1$ and $n \leftarrow 1$

2) Repeat the following step until $l = l_{\max}$ and $n = n_{\max}$

a) Find the solution $x' \in (N(x))$:

b) If $f(x') < f(x), x \leftarrow x'$ and iterate (a) otherwise iterate (a) set $n \leftarrow n+1$

c) If $n = n_{\max}$ $Random$ $N(x) \leftarrow N(x'')$ and set $l \leftarrow 1+1$

3) If the solution of $l = l_{\max}$ have been considered, stop.

4. Case Study and Results

Since the university never used a public transport system, the model input relies on data from the regular time that users start entering the university from 7.05 AM.

to 17.05 AM. There will be issued every interval according to the frequency specified by the experimenter in the first round. For the next lap, the frequency will be automatically determined based on the travel time of each lap of each car. Therefore, the next lap will start from the starting point after the vehicle can run through all 9 points to receive service recipients and only return to the starting point. The study uses a 13-seater electric landscape car that does not stretch the driver's seat. The vehicle's speed must not exceed 40 kilometers per hour and time for getting on and off the car, including time for slowing down with a triangular distribution. From the preliminary experiment, it was found that the input data could be defined as the time traveled between nodes plus the time with the triangular distribution pattern. The expected case duration is 30 seconds, the best-case time (optimistic time) 15 seconds, and the pessimistic time 45 seconds, and there are three special conditions. Firstly, vehicles can run for 8 hours without stopping to refuel. Secondly, vehicles need to pass through every passing point. When all points are complete, they will not go back to the original direction and will move to the starting point immediately in front of the university.

5. Modeling the Input Data

5.1 Modeling

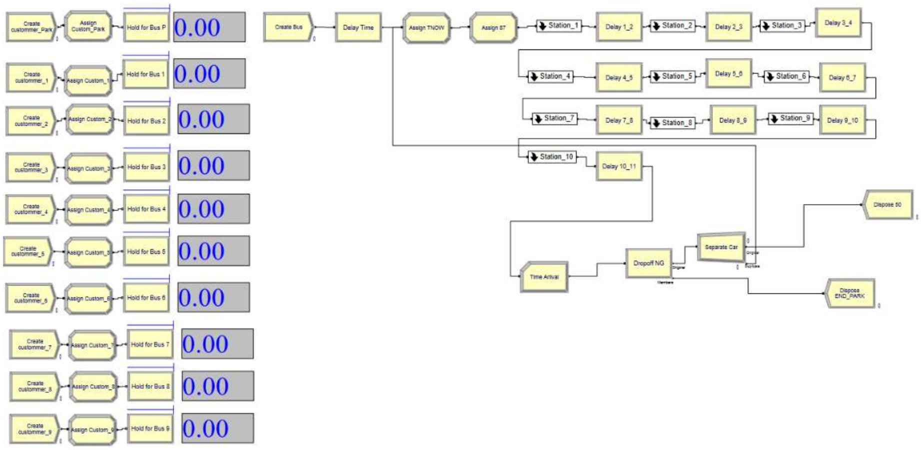

Figure 1 Main model

5.1.1 The left-hand side of Figure 1 depicts a group of modules responsible for importing user entities, utilizing data from 10% of the total demographics as outlined in Table 1. For pick-up and drop-off points, random exponential arrivals occur at intervals of 10 minutes, except for stops with a frequency of 6 minutes due to their higher density. On the right-hand side, the module group on the correct imports vehicle entities into the system. The first car enters at the 5th minute, followed by subsequent cars every 10 minutes until three cars have been processed. Each car enters the pick-up and drop-off point within a sub-module and passes through a delay module. This delay module adjusts the scheduled route speed from 40 km/h to accommodate the minimum triangular dispersed passenger boarding and unloading times. The median and maximum values for these times are 15, 30, and 60, respectively.

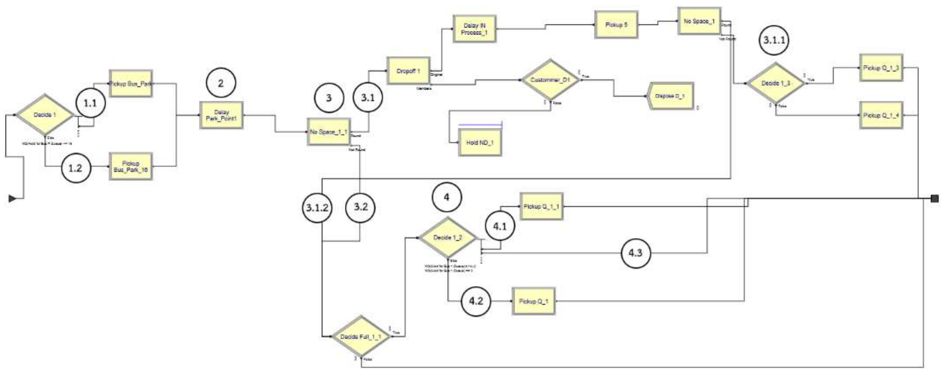

Figure 2 Sub-model

Since the sub-model has quite complex characteristics and processes, as shown in Figure 2, the explanation is divided into the following sub-topics:

5.1.2 Sub-model

To align with the arrangement typically found in academic papers by MIT professors, I have revised and reorganized the provided subsections while addressing grammar and coherence. Here is the revised version:

1) Pick-up Module:

1.1) Module 1.1 serves to receive from the entire queue if the number of people in the queue is less than 13. Module 1.2 will be selected when 13 or more people are in the queue. However, only 13 people will be accepted to align with the available seating capacity in the car.

1.2) Module 1.2 is selected when the queue contains 13 or more people. However, only 13 people will be accepted to reflect the available seats.

2) Delay Module:

The delay module functions when the vehicle is routed from the previous stop to Pick-up and Drop-off Point 1.

3) Search Module:

The search module verifies if there are users on the vehicle.

3.1) If users are found (Case 3.1), the Drop-off Module separates the user from the vehicle. Users who wish to disembark at Stop 1 use Dispose 1, while the remaining entities are placed in Module Hold ND1. The vehicle entity then enters the Pick-up Module to integrate with the users not served by the Stop 1 service. If no users are found, proceed to Case 3.2.

3.2) Case 3.2 occurs when the Search Module finds no users on the vehicle. In this case, or Case 3.1.2, a decision is made to determine if the number of users in the vehicle is less than 13. If it is less, proceed to Decision 4. Otherwise, the bus proceeds to the next pick-up point as the seating capacity is total.

4) Decision-Making Module:

The decision-making module utilizes a conditional decision-making model with three scenarios:

4.1) In the first scenario, if Pick-up Point *1* has more users than or equal to the remaining seats on the bus.

4.2) If the number of remaining seats at Pick-up Point *1* is less than the remaining seats on the bus, the number of remaining seats on the bus is adjusted accordingly.

4.3) If there are no users at Pick-up Point 1, the vehicle can proceed directly to Pick-up Point *2* without stopping.

5.2 Input Data

Since it is in the early stages of the system development process, at present, the demand for electric vehicles has not yet been explored. Most of the population uses personal vehicles mainly. Therefore, preliminary operations rely on estimating the frequency of the recipient's arrival from random sampling at the beginning in front of the university as a reference point (the densest point) as it is a starting point of the journey. Other points density is estimated from 10% based on the classroom schedule of the total population nearby by specifying an exponential arrival pattern, the frequency of arrival of service users is different according to the population density at each transit point. As for the selection of the destination of the population at various transit points, the service provider decision has a discrete distribution format (Table 1).

5.3 Verification and validation

Model verification and model validation are two distinct processes within simulation model development. Verification processes ensure that computer programs and implementations accurately represent conceptual models. Their primary focus is confirming that the model is programmed correctly and functions as intended. Conversely, validation is the process of confirming whether a model generates results that closely align with real-world observations. Its purpose is to assess the model's predictability and verify its ability to effectively find answers and represent the system under study (Sargent, 2020). Therefore, this model may only be applicable for verification since the implementation is currently in the policy planning stage and has yet to be executed in the real world. The verification process is as follows:

1) Test the accuracy of the distribution of user data imports.

1.1) Import data on the number of users, consisting of 100 users at each point.

1.2) Assign a drop-off point to the representative entity of the service user. Each drop-off point should provide an equal opportunity for users to disembark, with the number of opportunities equal to 10% of the total number of users.

1.3) Verify the accuracy of the logged-out entity count.

2) Test the accuracy of user transportation at various points.

2.1) Import data on the number of users, consisting of 100 users at each point.

2.2) Assign a distinct drop-off point for the representative entity of the service user. The assigned drop-off point should remain constant and verifiable.

2.3) Observe the behavior through animation in all scenarios. Check if the combined waiting lines' quantity does not exceed the vehicle's capacity to accommodate passengers. In the event that the vehicle is empty, observe if the waiting line decreases to a capacity that the vehicle can handle.

3) Verify the input and output data, ensuring that the number of entities entering the system is less than or equal to the number of entities leaving the system, and not greater.

6. The Computerized Model

The research equipment divides into two parts: hardware and software. Hardware: Personal computer, 21.1-inch screen, 16 GB primary memory (Ram), Intel(R) i5-9400 @ 2.90 GHz central processing unit (CPU), 256 GB solid-state drive. The software includes the Arena Simulation version 15.0 for modeling and python 3.8.5 to develop Metaheuristic Algorithms and troubleshoot salesperson journeys.

Table 1 The arrivals of 10% of the total population

Points	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	364	249	275	296	216	53	49
2	6	3	3	5	3	2	1
3	22	10	23	20	15	0	0
4	47	38	34	41	33	10	7
5	52	65	58	63	42	12	14
6	6	7	5	5	4	2	2
7	84	66	81	78	71	8	3
8	86	1	23	24	21	10	5
9	8	6	6	4	4	2	2
10	53	53	42	55	24	8	14

Remark * The frequency distribution of service recipients uses the Exponential model.

Results

To assess the system's capabilities focused on the satisfaction of service recipients. Therefore, considering the following indicators.

1. Troubleshooting TPS results with ILS for optimal routing.

The search results have revealed that ILS could find the shortest trip's distance, equal to 4,380 meters or approximately 4.38 kilometers, in just one round. The journey starts from points 0, then proceeds to 8, 7, 6, 3, 5, 4, 2, and finally 1, before returning to 0, as shown in Figure 3. The remarkable aspect is that ILS achieved this result in a mere 9.20 seconds. This rapid computation showcases the efficiency and effectiveness of the algorithm.

2. Results from studying the behavior of the system using computer models.

The study analyzed four indicators that influence service receiver satisfaction consists of service success percentage Average waiting time Volume density in the queue and Total duration in the system to assess these indicators, the simulation was run 100 times, and the following results were obtained.

Figure 3 Sequence of pick-up points with the shortest distance

Table 2 The arrivals of 10% of the total population

Reported topics	Number in	Number out	Success Rate
Number of Trips	22.00	22.00	100.00
Park	199.50	178.67	89.56
Stop 1	6.00	6.00	100.00
Stop 2	22.00	22.00	100.00
Stop 3	46.91	46.64	99.42
Stop 4	51.68	51.02	98.72
Stop 5	6.00	6.00	100.00
Stop 6	59.41	56.19	94.58
Stop 7	61.09	56.71	92.83
Stop 8	8.00	8.00	100.00
Stop 9	52.96	52.42	98.98
average	48.69	45.97	97.64

2.1 Service success percentage

An investigation into systemic behavior determined that the system was specifically designed to cater to 10% of the total population, exhibiting an impressive average success rate of 95.52%. Daily, the system facilitates an average of 22 bus trips. Table 2 exemplifies a report table that succinctly summarizes the system's success rate. Remarkably, despite the presence of only three cars, the service manages to accommodate an average of 299 users. Additionally, Figure 4a presents a comprehensive overview of the overall success percentage throughout the entire week.

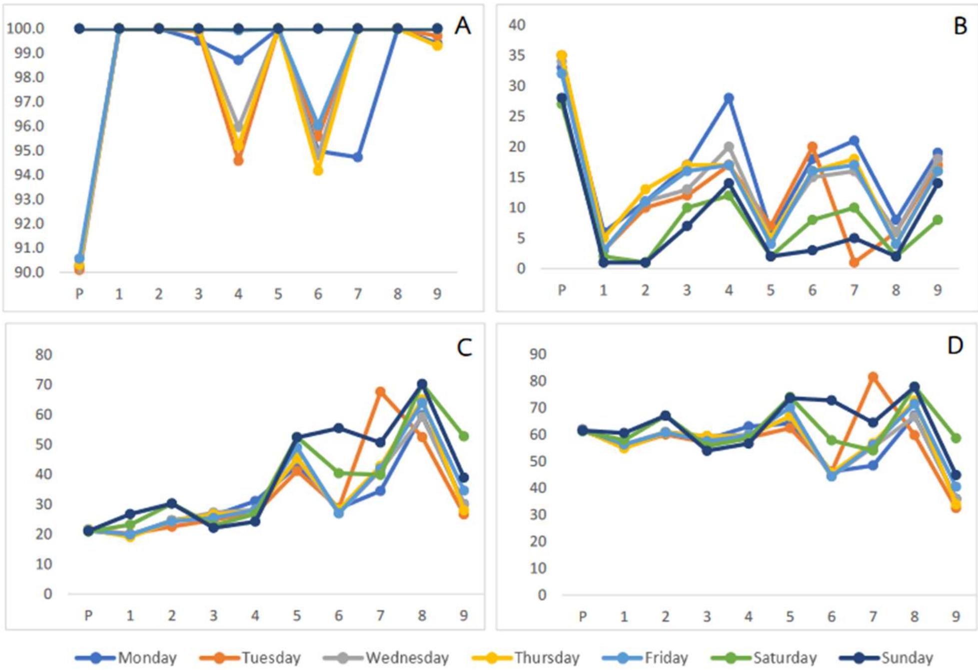

Figure 4 The result of total models

A) Percentage of success daily service B) Average daily waiting time

C) Average daily density and D) Total duration in the system

2.2 Average Waiting Time

The results of the system capability assessment in Figure 4b shows that at the beginning, the overall waiting time was minimal, then gradually increased at the next passing point depending on the number of service recipients accumulated within the system. The minimum average waiting time at the entry point was 21.17 minutes on Monday, with the highest average of 70.16 minutes at point 8 on Sunday. The waiting period is at most 10 minutes.

2.3 Volume Density in the Queue

The queue density significantly impacts the waiting time, as illustrated in Figure 4c, displaying the daily pass density. System behavior analysis reveals that high-density points typically correspond to areas with many users. During peak hours, the waiting line is projected to reach a maximum capacity of approximately 20-35 individuals. Such congestion exceeds the seating capacity of the vehicles. In situations where the queue becomes excessively crowded, it may be necessary to consider alternative modes of transportation.

2.4 Total Duration in the System

The duration of the car's presence within the system significantly affects the car's trip volume. Since only three cars are available, if a car remains in the system for an extended period, it can impact waiting times. Experimental results revealed that the average waiting time ranged from a minimum of 32.02 minutes on Tuesday to a maximum of 81.5 minutes on Thursday, as depicted in Figure 4d. Such considerable time spent on travel can be considered excessive, as longer travel durations often lead to wasted time. Consequently, ensuring that the car does not remain in the system for more than an hour is crucial, including the time required for service delivery and retrieval. Therefore, based on the conditions of this research, it is evident that system optimization efforts are necessary to ensure efficient and punctual transportation, resulting in an enhanced customer experience.

Discussions

The assessment of the system's ability to meet user satisfaction under various conditions and limitations has revealed insightful findings. The experiments conducted align with the research of Teannava et al. (2016) and effectively demonstrate the utility of models in evaluating the system's initial capabilities. Notably, when operating with three vehicles, the service success rate reached an impressive range of 95.52%, indicating a commendable level of performance.

However, upon considering factors such as wait times, queue congestion, and overall user experience within the system, it becomes evident that the system falls short in responding promptly to user needs. Users face significant time wastage during their journeys, with travel times exceeding half an hour for distances of fewer than 5 kilometers. This issue primarily stems from insufficient traffic capacity to meet the growing demand. As the number of users increases, it leads to user accumulation within the system, resulting in heightened queue density at each point and ultimately prolonging the total trip duration. The average daily wait time chart, as depicted in Figure 2b, effectively demonstrates the escalating waiting times at pick-up and drop-off points, exacerbating the accumulation of users within the system. Consequently, users at these points often encounter service unavailability, leading to a gradual increase in waiting times. However, as users continue to disembark at their desired destinations, the waiting time gradually decreases.

To enhance user satisfaction, one potential solution is to increase the frequency of service cycles. However, this is limited by the number of available vehicles, resulting in each round trip currently taking an average of 75.25 minutes. Consequently, the most effective solution lies in expanding the fleet size. Nevertheless, such an expansion requires a higher budget allocation. In conclusion, while the system demonstrates a commendable level of service success percentage, it faces challenges in effectively addressing wait times, queue congestion, and overall trip durations. Increasing the fleet size and thereby improving service frequency emerges as a promising solution to enhance user satisfaction. However, it is important to note that this expansion would necessitate a higher budget allocation.

In the future, as the university receives the required number of electric trains, there is an opportunity to gather additional information and enhance the model to achieve a more realistic representation. It is crucial to research student behavior and decision-making processes when utilizing the public transport system service. This research study will provide valuable insights into factors influencing their choices and enable the implementation of effective strategies to promote green activities, foster environmental sustainability, and reduce carbon emissions within the university. By aligning with these goals, the university can establish itself as a leader in sustainable transportation and contribute to a greener and more sustainable campus environment.

Conclusions

The study focused on assessing the capacity of the public transport system based on indicators that influence operator satisfaction. Four indicators, namely service success, average wait time, queue volume, and total duration, were examined. The results revealed an average service success rate of 95.25%, indicating a commendable level of performance. However, the system exhibited long waiting times and travel durations, leading to considerable time wastage for service recipients. The average time spent by service recipients within the system was found to be significantly prolonged, highlighting the inefficiencies in travel time. Furthermore, when considering queue density, certain points within the system experienced high congestion, particularly during peak hours when the service had to accommodate up to 20-35 passengers in the waiting line. In conclusion, although the public transport system demonstrated a commendable service success rate, it fell short in addressing waiting and travel times issues. The extended duration experienced by service recipients can be considered a significant waste of time. Additionally, the density of queues at certain points, particularly during peak hours, led to congestion and potential service unavailability. To improve service recipient satisfaction, it is crucial to optimize waiting and travel times, as well as alleviate queue congestion at densely populated service points.

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Information and details of policies for promoting the use of public transport by electric vehicles from Phetchabun Rajabhat University

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