Optimizing University Campus Shuttle Bus Congestion Focusing on System Effectiveness and Reliability: A Combined Modeling Based-Routing Approach

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Abstract
Increased vehicular queuing inside universities has amounted to pressing concerns for staff and students, distorting their time schedules to reach classes and office buildings on time. This paper attempts to alter the traditional transportation service behavior within university campuses to reduce traffic congestions and facilitate system effectiveness and reliability through a modeling-based routing and optimization approach. A qualitative conceptual model using a system thinking approach identifies the relationships and feedback between university shuttle bus system effectiveness, service performance, and traffic congestion. A bi-objective goal programming optimization model is developed and used to select the best alternative routes for university shuttle bus services during congested peak hours considering a continuous-circulation feeder mode. Qatar University shuttle bus service network is taken as the case for model implementation. A Monte Carlo simulation was used to verify the daily bus capacity, ensuring that the chosen alternative routes met the expected demand. A sensitivity analysis was then conducted to identify the most sensitive bus stops along the best-selected routes. Results showed that the proposed alternative routes improved the system effectiveness by 75% and the alternative proposed routes satisfied the stations' daily demand.

Keywords: Bi-objective optimization; Monte Carlo simulation; sensitivity analysis, system thinking; traffic congestion.

1. Introduction
Traffic congestion is a complex dynamic problem that leads to unconventional transportation patterns and unprecedented impacts on the system life cycle and effectiveness, distorting the existing idealistic settings tranquility (Papageorgiou et al. 2009; and Cao et al. 2016). The steadily increasing enrollment rates at universities have resulted in the irrational use of transportation infrastructures around the campus, leading to traffic congestion (Bustillos et al. 2011). Eliminating hyper-congestion within the university premises to ease mobility has been the focus of debate over the past decade for transportation planners and university authorities. Apart from the high number of vehicles and weak in-house transportation service usage (Bruck et al. 2017), irrational use of road resources exacerbates traffic congestion during peak hours (Bakar et al. 2018). Pressing concerns on sustainable utilization of resources has resulted

in developing effective solutions for optimizing the transit service through dynamic approaches and simulation outcomes to overcome the traffic congestion during peak hours of the day.

Several modeling approaches have been used by researchers over the years to better understanding the congestion dynamics in the transportation sector to reach system effectiveness. Danchuk et al. (2019) modeled the Kyiv urban road traffic flows through electrical analogies aiming to increase the road capacity with congestion level redistribution in different road network sections in the city. Loubna et al. used an intelligent fuzzy graph-based control system along with multi-criteria analysis to calculate the number of vehicles on the road and the road limit by measuring the distance between two intersections aimed at optimizing the urban traffic flow. The fuzzy rule base was tested using MATLAB/SIMULINK simulation for both the fixed and dynamics inputs (Ourabah et al. 2020). Among all the studied simulation approaches, Monte Carlo simulation was found to be simple and structured enough to describe a range of algorithms based on random sampling to discover an optimal solution for congestion modeling (Du et al. 2009; Takes and Kosters 2010). A combination of Monte Carlo simulation with fuzzy logic approaches was employed by Shengda et al. to achieve an optimal delay time by simulating a smart traffic light system in order to reduce the traffic flow in a single intersection (Zeng et al. 2013).

Shuttle bus routing problems have been used broadly by transportation planners and modelers to select a set of optimal routes for a fleet of vehicles within the transit network (Toth and Vigo 2002; Bouyahia et al. 2018). Hoffmann et al. 2019 attempted a dynamic vehicle routing problem (VRP) with time windows for solving complex scenarios by means of the Athos system to simulate the effect of traffic congestion on dynamic tours. Rout et al. (2020) proposed an alternative solution through the IoT network model using fuzzy logic-based techniques for transit routing associated with emergency vehicles in terms of travel time reduction, aiming to increase patients' survival rate on board. The model was developed to inform the drivers of the forthcoming hazards along the travel route to guide service vehicles to a medical center along the shortest congested path. A sensitivity analysis was conducted to find out the impact of congestion on travel time. For a study on time-dependent VRP, Zhu et al. performed a sensitivity analysis to show that the congestion continuance negatively affects both travel duration and fuel consumption (Zhu and Hu 2019). Bus transit systems have also encountered several kinds of congestion-related issues; however, only limited studies have attempted to reduce bus congestion problems within confined regional boundaries. Huang modeled bus routing problems concerning long transit time per trip due to traffic congestion through an ant colony optimization to find the fastest and most optimal route. Further, the model's feasibility was validated through a series of simulation experiments (Huang 2011). In another study by Wang et al., the campus bus routing problem was simulated and optimized to allow the drivers to divert from the fixed route upon the customer request, especially when the density of the students is low. Such dynamic bus routes based on stochastic requests fall in favor of unnecessary traffic congestion as well as cost reduction. The validity of the model was confirmed through mixed-integer programming (Wang et al. 2009).

Understanding the dynamics of transportation problems and congestion scenarios is often essential in identifying system effectiveness. System dynamic (SD) approaches can identify the system's nonlinear behavioral patterns by getting feedback and solving problems, which is particularly useful for complex systems such as transportation networks (Chao and Zishan 2013). Several studies in transportation systems have used causal loop diagrams and SD models to explore traffic congestion scenarios (Liu et al. 2013; Armah et al. 2010; Wan et al. 2018). The applicability of the SD model is well reflected in Suryani et al.'s work, where improving transportation systems, e.g., operational and service effectiveness as well as congestion reduction, were investigated by simulation models and different scenarios, followed by alternatives future strategies evaluation through developing an SD framework in Surabaya city. The results showed that implementing the strategies could increase the effectiveness by 80% and reduce traffic congestion by 70% (Suryani et al. 2020). Moreover, the research team analyzed the service reliability in their other study by evaluating different influential factors using the SD model, which resulted in 32% more reliable service in public transportation sectors (Suryani et al. 2019).

2. Research motivation and objectives

Since the early 21st century, service quality, reliability, and system effectiveness of shuttle bus services in university campuses are growing concerns. Achieving transportation system effectiveness requires proper planning and modeling of the transit system. This complex problem (usually NP-hard) requires a proper understanding of the transportation structure while moving through the near-optimal solution process. Thus, it is essential to use an integrated modelling approach that understands the problem variants from a system of system perspective, mathematical optimization, and random sampling approaches for proper understanding. Thus, this research aims to utilize a combinatorial approach to identify the system reliability, service effectiveness, and route-based system performance for the university shuttle bus transit network using a qualitative system thinking model, a bi-objective goal programming model, and a Monte Carlo simulation, taking the case of Qatar University, Doha-Qatar. The problem type taken into account is a many-to-one problem, where the shuttle service takes students from the different bus stops on a route to reach a desired building within the campus in the desired time. The optimization model assumes the travel pattern to be constant and uniformly distributed were; the research attempts to use the concept of university shuttle bus routing problem with a time window and accurate estimated time of arrival. The problem aims to minimize the travel time and total distance traveled to arrive at optimal routes with route capacities. The proposed modeling approach will act as a backbone for decision-makers and transportation modelers to come to the best alternatives, eliminating congestions for sustainable transportation management.

3. Model development and formulation

3.1 System Thinking Approach

A causal loop diagram (CLD) is constructed based on the authors' conceptualization and relevant literature in the area of transport planning and system modeling. The causal feedback loop diagram represents the relationship between the shuttle bus transportation system effectiveness and university traffic congestion on service reliability and quality of service. The qualitative model consists of four reinforcing (R) and six balancing (B) loops whose relationships help understand the dynamics involved in the transportation optimization problem for congestion control.

Table 1. Causal feedback loops and relationship

Loops	Components and Feedback Relations
B1	Degree of traffic congestion – Total travel time – Pressure to meet bus service daily demand – Shuttle bus trip frequency – coverage rate of passengers by the shuttle bus at stops – passenger flow – waiting interval - Degree of traffic congestion.
B2	Service quality level – Time per commute trip – Total travel time – Pressure to meet the bus service daily demand – shuttle bus trip frequency – service reliability as the impact of adequacy in shuttle service – Demand based system reliability – service quality level.
B3	Service quality level – Time per commute trip – Total travel time – Pressure to meet the bus service daily demand – shuttle bus trip frequency– coverage rate of passengers by the shuttle bus at stops – passenger flow – waiting interval - Degree of traffic congestion – Service quality level.
B4	Shuttle bus trip frequency – Road network average speed – Road traffic status – Route based system performance – Total travel time - Pressure to meet the bus service daily demand – shuttle bus trip frequency
B5	Total travel time – Choice on the mode of transportation – Impact of daily traffic – Daily traffic – Shuttle bus trip frequency – Road network average speed – Road traffic status – Route based system performance – Total travel time.
B6	Transportation system effectiveness – Total travel time – Pressure to meet the bus service daily demand – shuttle bus trip frequency –Transportation system effectiveness.
R1	Service based system effectiveness – Waiting interval – Degree of traffic congestion – Service quality level - Service level effectiveness.
R2	Transportation system effectiveness – Time per commute trip – Transportation system effectiveness.
R3	Transportation system effectiveness – Total travel time – Choice on the mode of transportation – Impact of daily traffic – Daily traffic – Shuttle bus trip frequency – Transportation system effectiveness.
R4	Service quality level – Selection of optimal travel route – Impact of daily traffic – Daily traffic – Shuttle bus trip frequency – service reliability as the impact of adequacy in shuttle service – Demand based system reliability – service quality level

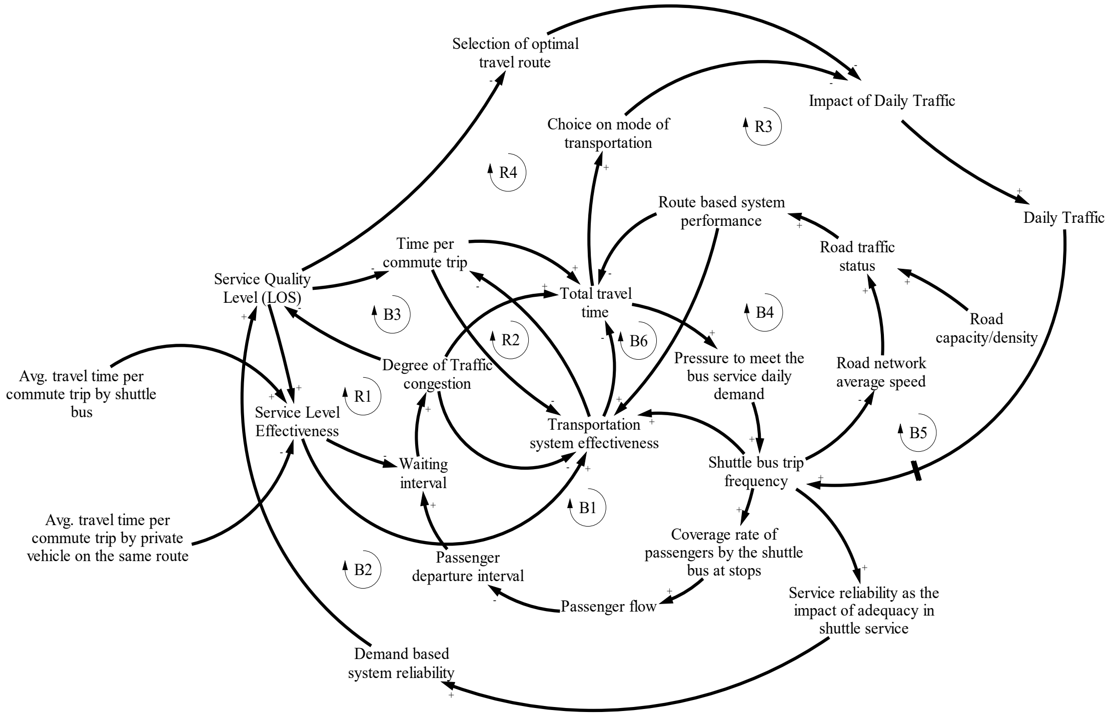

Figure 1. A conceptual model for shuttle bus system effectiveness with congestion dynamics

3.2 Mixed-integer Optimization

A mixed-integer optimization model is used to identify the route-based service performance and thus the effectiveness by analyzing multiple alternative routes that effectively provide service to reach the destination on time along the shortest possible path. These alternative routes eliminate hyper-congestion and ensure the timely arrival of passengers at the destination without unexpected delays. Reducing passenger queuing times ensures addressing the actual priority of shuttle bus users within the campus, thus enhancing the service reliability and passenger satisfaction.

This study's bi-objective goal programming model can help achieve the required goals to reduce passenger travel time and distance and identify the most effective route within the transit network. The goal objectives need to be assigned to all the routes (the congested route and the alternative paths) within the transit network and formulated using the following model. We assign,

α_{ij} : The binary variable that takes the value 1, if the sub-route *i* (route between two bus stops) is assigned to the alternative route *j*, otherwise 0.

D_{ij} : The distance variable for the sub-route *i* to the alternative route *j*.

T_{ij} : The travel time variable for the sub-route *i* to the alternative route *j*.

To minimize

a) Distance traveled by the bus along each sub-route

$$\sum_{i=1}^{n} \sum_{j=1}^{n} D_{ij}\alpha_{ij} \qquad (1)$$

b) T time is taken by the bus to travel along each sub-route

$$\sum_{i=1}^{n} \sum_{j=1}^{n} T_{ij}\alpha_{ij} \qquad (2)$$

Subject to:

$\sum_{j=1}^{n} \alpha_{ij}=1$, i=1,.….n

$\sum_{i=1}^{n} \alpha_{ij}=1$, j=1,…..n ; $\alpha_{ij} \in \{0,1\}$, i, j=1,…n.

$$\text{To minimize } \frac{\delta_1^+}{\beta_D} + \frac{\delta_2^+}{\beta_T} \text{ (Sum of relative deviations)} \qquad (3)$$

Subject to:
$\sum_{j=1}^{n} \alpha_{ij}=1$, i=1….n
$\sum_{i=1}^{n} \alpha_{ij}=1$, j=1….n
$\sum_{i=1}^{n} \sum_{j=1}^{n} D_{ij}\alpha_{ij} - \delta_1^{+}= \beta_D$
$\sum_{i=1}^{n} \sum_{j=1}^{n} T_{ij}\alpha_{ij}- \delta_2^{+}= \beta_T$
$\alpha_{ij} \in \{0,1\}$, i,j=1….n
$\delta_1^{+}, \delta_2^{+} \geq 0$

The service effectiveness is calculated using the following formula adopted from;

$$\text{Service effectiveness} = \frac{\gamma_o}{\gamma} \text{ x } \omega_{LOS} \qquad (4)$$

where,
γ_o : Average travel time per commute trip by private car along the same route.
γ : Average travel time per commute trip by shuttle bus.
ω_{LOS} : Calculated weight for the Level of Service (LOS).

$$\omega_{LOS} = \frac{\text{Vehicle Speed}}{\text{Road Density}} \qquad (5)$$

The LOS classifications as per Transportation Research Record (Roess 1984) for the transit segments are shown in Table 2.

Table 2. Level of services classifications

LOS	LOS Performance Critiera	
	Speed (Km/h)	**Density (PC/Km/LN)**
C	≥ 64	≤ 21.9
D	≥ 56	≤ 29.4
E	≥ 48	≤ 41.9
F	< 48	> 41.9

C is the best LOS for this category, and F is the worst

3.3 Monte-Carlo Simulation

The outcome of the bi-objective goal programming model was validated using a Monte-Carlo simulation to ensure that the chosen alternative route meets the expected demand to ensure the system's reliability based on demand satisfaction. The input variables for the simulation model were represented as a triangular distribution with minimum, maximum, and most likely demand values at each bus stop. The total daily demand, which is the sum of all the demands at each bus stop, is compared with the alternative route's total daily capacity using the following formula;

$$\text{Daily Total Demand}= \sum_{w=1}^{m} D_w \qquad (6)$$

where,
D_w : The daily demand (D) at bus stop (w).
m : Total number of bus stops along the selected alternative route.

Total Daily Capacity = Bus seat capacity x No. of buses assigned to the route x No. of commute trips (cycles) per hour x No. of bus operating hours. (7)

This step is essential to identify if the selected alternative routes meet the required demand at each stop from a probabilistic perspective. A sensitivity analysis was then conducted to determine the most sensitive bus stops among all of the stops along the selected route.

4. Results and discussion

4.1 System Effectiveness through System Thinking

Based on the causal loop diagram constructed (see Fig.1), we can see that the degree of traffic congestion saturates the transit network and constrains the maneuverability of the shuttle bus service along the route, distorting the service quality level. An increased travel time calls vigilance to meet the daily demand, thus resulting in improved service frequency. The increased transit service enhances the transportation system's overall performance and effectiveness, thus reducing the total travel time, as shown in loop **B6**. Service frequency measures hold a significant impact on the service reliability as a result of adequacy in the shuttle service. This satisfies the daily demand ensuring the transportation system is reliable, resulting in a higher level of service (loop **B2**). An increased trip frequency generates more travel, thus meeting the daily demand at each bus stop along the service lane. This causes an increase in the passenger flow that is sensitive towards passenger departure intervals. Longer departure intervals result in prolonged waiting time by passengers at each bus stop along the service lane. This results in the operational instability of the shuttle service, resulting in chronic traffic congestion as depicted through the balancing loop **B1**. The degree of congestion deteriorates the service quality and service-based system effectiveness (loop **R1**). The impact of chronic congestion holds pressing concerns on the level of service, resulting in an increased time per commute trip by the shuttle bus service. This will cause a delay in the trip travel time, thus balancing the loop **B3**. The increased travel time leaves concerns about choosing an alternative transportation mode to reach the destination on time, as shown in **R3**. This will decrease the traffic flow due to the increased number of vehicles passing through the route, causing an increase in the daily traffic. As daily traffic increases, people tend to navigate more using shuttle service offered within the campus than their private owned vehicle, as a prolonged effect. This increases the shuttle bus trip frequency to meet the growing demand, increasing overall transportation system effectiveness (loop **R3**). An increase in the number of trips will decrease the road network average speed. This will hold a negative impact on the traffic flow and traffic congestion. An increased network average speed represents a condition where the traffic flow is increased without any delay along the route, leading to performance efficiency, thus reducing the total travel time as depicted through the loop **B5.** The use of transit lanes based on the design capacity can help understand the rate of road traffic service, thus impacting the route-based system performance, seen through the loop **B4**. From the service provider perspective, a decreased level of service leaves concerns in choosing an optimal path to meet the daily travel demand to reach the destination on time without any delay. The alternative routes will have a better traffic flow decreasing the daily traffic. This ensures that the shuttle service system is reliable, thus achieving the desired service quality level (loop **R4**).

4.2 Route-based performance evaluation

The Qatar University campus shuttle bus service system was chosen as the case study to implement and validate the proposed model, where two highly demanded bus services were selected. The details of the bus stops and sub-routes for each selected service are shown in Tables 3, 4, and 5.

Table 3. Sub-route details and service demand

Sub - Route	Bus Stops / Stations	Corresponding Travel Demand
1	Station a to Station b	High to Low
2	Station b to Station c	Low to High
3	Station c to station a	High to High
4	Station d to Station e	High to High
5	Station e to Station c	High to High
6	Station c to station d	High to High

Table 4. Travel distance and time for **Bus Service A**

Route	Sub – route 1		Sub – route 2		Sub – route 3	
	D (m)	T (Min)	D (m)	T (Min)	D (m)	T (Min)
Orig.	603	10.60	693	10.69	563	10.56
Alt. 1	430	0.43	2,150	2.15	4,280	4.28
Alt. 2	430	0.43	2,150	2.15	2,390	2.39

Table 5. Travel distance and time for **Bus Service B**

Route	Sub – route 4		Sub – route 5		Sub – route 6	
	D (m)	T (Min)	D (m)	T (Min)	D (m)	T (Min)
Orig.	554	10.60	693	10.69	697	10.70
Alt. 1	668	0.67	2,100	2.10	3,760	3.76
Alt. 2	668	0.67	2,100	2.10	2,720	2.39

The original route (Orig.) for bus service A and bus service B is the shortest in the distance and the one chosen by Qatar University to meet the daily demand. However, due to the traffic congestion along these routes, there is a travel time delay compared to the other alternatives (Alt.) that have long distances but have shorter travel time due to zero net congestion. The proposed bi-objective goal programming model is used to select the best alternative route with shortest travel time and distance. The travel time must be less than 15 minutes (min), to allow the students to transfer to the respective buildings for attending their next lectures without delay. Using Excel solver, the following results were obtained for the bi-objective problem.

Bus Service A

The results show that Alternative route 2 (Alt.2) meets the objective function with sub-route 1, and Alternative route 1 (Alt.1) meets the objective function with sub-route 2, and the original route meets the objective function with sub-route 1, as shown in Table 6. A detailed investigation was conducted that resulted in tagging Alt.2 route as the best route meeting both the objectives (shortest travel time and distance). As sub-route 2 is the same for Alt.1 and Alt.2, as shown in Table 4, choosing any of them will not significantly affect the system performance. Moreover, as the Orginal route needs to be avoided due to the road congestion, the Alt.2 route is selected as the best performing route for sub-route 3 as it has the second shortest distance and the shortest travel time.

Table 6. Bi-objective outputs for **Bus Service A**

Route	Sub-route1	Sub-route2	Sub-route3
Orig.	0	0	1
Alt. 1	0	1	0
Alt. 2	1	0	0

Bus Service B

The results show that the Alt.2 route meets the objective function with sub-route 1, and Alt.1 route meets the objective function with sub-route 2, and the original route meets the objective function with sub-route 1, as shown in Table 7. After the additional investigation, the Alt.2 route was found to be the best route, meeting both the objectives (shortest travel time and distance). Since sub-route 2 is the same for Alt.1 route and Alt.2 route as shown in Table 5, choosing any of them will not significantly affect the system performance. Moreover, as the Orginal route needs to be avoided due to hyper congestion, the Alt.2 route is selected as the best performing alternative for sub-route 3. It has the second shortest distance and the shortest travel time.

Table 7. Bi-objective outputs for **Bus Service B**

Route	Sub-route4	Sub-route5	Sub-route6
Orig.	0	0	1
Alt. 1	0	1	0
Alt. 2	1	0	0

4.3 Service Effectiveness

LOS weight is calculated to identify the system effectiveness based on the service offered for the selected alternative routes for the original route and the two new alternative routes, as shown in Table 8.

Table 8. LOS and ω_{los}

Service	Route	Avg. Speed (km/h)	Road Density (PC/km/LN)	ω_{LOS}	LOS
A	Original	10	50	0.20	F

	Alt. 2	60	29	2.1	D
B	Original	10	50	0.20	F
	Alt. 2	60	29	2.1	D

Table 8 shows the details needed to calculate the LOS weight (ω_{LOS}), where the average speed is gathered for each route along with the road density - which represents the congestion level. Service A and Service B use the congestion-free road (low road density) for Alt.2 route. This helps buses drive faster, ensuring better traffic flow and decreased daily traffic; on the other hand, the original congested route (high road density) reduces the bus speed, delaying the passengers from reaching their destinations on time. The values presented for the LOS weights are higher for the Alt.2 route than the original one.

The service effectiveness for the best-selected route compared to the original route is as shown in Table 9.

Table 9. Service effectiveness for the proposed system

Route	γ_0 (km/h)	γ (km/h)	ω_{LOS}	Service Effectiveness
Original	60	10	0.2	1.2
Alt. 2 (Service A or B)	60	60	2.1	2.1

From Table 9, it can be seen that the Alt.2 route is better than the original route for both the bus services (A and B); then, the percentage of improvement on the effectiveness of the proposed routes was calculated and showed improved service effectiveness by 75%.

4.4 Demand-based System Reliability

After identifying the route-based performance and service effectiveness, computing the demand-based system reliability is essential to ensure whether the newly proposed routes fulfill the daily demand for each bus service. For the same, the Monte-Carlo simulation was used to identify the daily demand for each bus service probabilistically. Average-based or maximum-based daily demand calculations do not represent the actual scenario because the bus stops/stations will not have constant demand throughout the day, nor will they reach the maximum demand all together at the same time. The daily demand details for each station are as shown in Table 10.

Table 10. Daily demand at each station for each service (passenger)

Station	Max.	Most likely	Min.	Service	Service Daily Capacity
a	2,225	451	236		
b	167	100	34	A	2,922
c	1,055	212	114		
d	3,860	503	256	B	4,630
e	1,364	345	154		

The two services (A&B) were simulated for 50,000 hours to obtain a stable output; the simulation results for service A are shown in Figure 2.

The simulation results for Bus Service A showed that for about 95% certainty, the forecasted daily demand for the service is 2,421 passengers per day, which is less than the service capacity 2,922 passengers per day. This implies that the selected alternative route serves the station's daily demand on service A route and will still have a buffer of 501 passengers per day whose demand can be met if needed. Moreover, the results also showed that station (a) is 82% sensitive than other stations, which will require close attention to this station's demand behavior if changes in a specific time will affect the system reliability based on the demand.

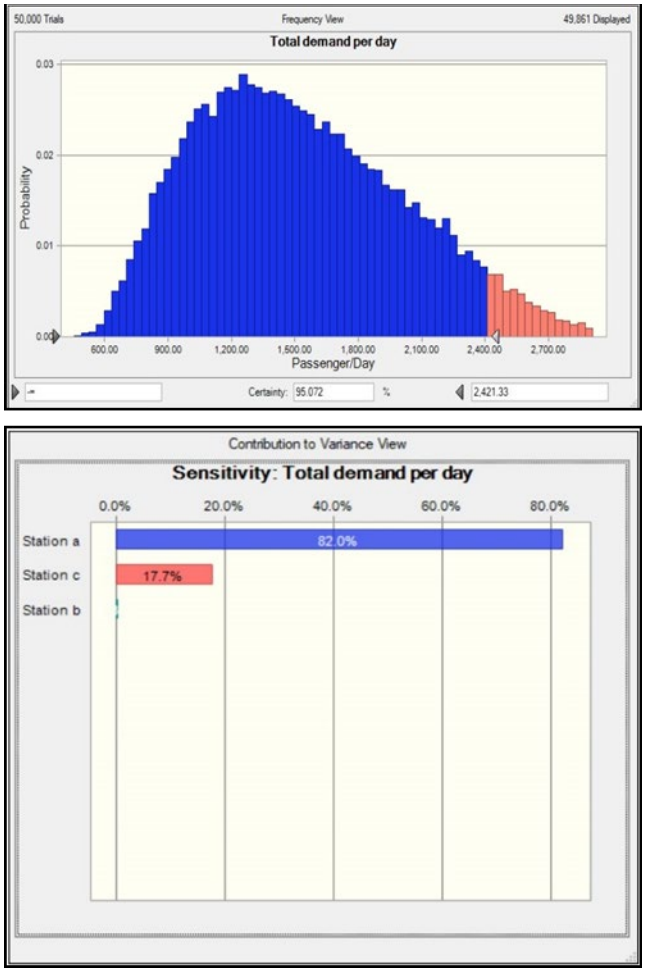

Figure 2. Bus Service A simulation outputs for system reliability assessment

On the other hand, for Bus Service B, the simulation results as per Figure 3 showed that for about 95% certainty, the forecasted daily demand for the service is 4,024 passengers per day. Which, indicates that the selected alternative route serves the station's daily demand on the service B route and will still buffer 606 passengers per day. Thus, indicating that the proposed system is reliable in meeting the daily demand of passengers at the station along the selected route. Additionally, the results showed that station (d) is 83.2% sensitive than other stations, which will require close attention to this station's demand behavior if changes in a specific time will affect the system reliability for the service based on fluctuations on demand.

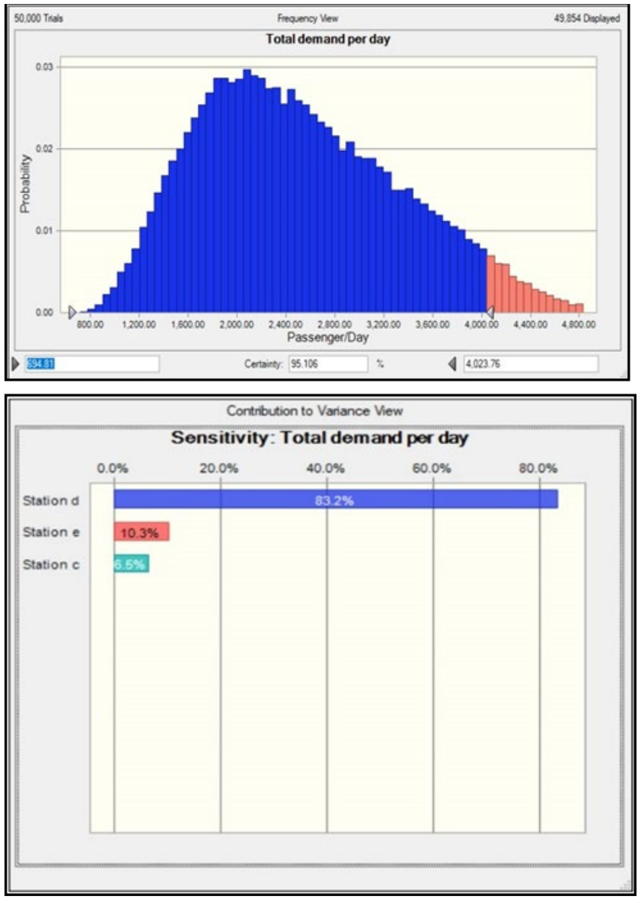

Figure 3. Bus Service B simulation outputs for system reliability assessment

5. Conclusion

Complexity characterizes an issue in many research disciplines. The systems thinking approach as a qualitative tool helps understand the dynamic interactions existing within the system, eliminating complexities. Simple optimization models like mixed-integer optimization with multi-criteria analysis targeted at specific objectives and goals can rule out system unreliability to achieve full performance and system effectiveness. This research attempted to bring novel contributions to relationships between several variables, modeling dynamic congestion behavior of shuttle bus transit networks and constructing scenario models to improve mobility and reduce traffic congestion in the shuttle bus network. Qatar University, as a case, was investigated for possible solutions to the current unreliability of the shuttle bus transportation systems during congestion hours. The proposed goal programming model selects the best possible routes with the least travel time and shortest travel distance to reach the desired bus stops within the university campus. The case study showed that Alternative 2 on both bus services is the best-performing route based on the Level of Service (LOS) with the shortest possible distance and travel time. The proposed alternative paths improved the service effectiveness by 75%. The outcomes from the goal programming model were validated by a Monte-Carlo simulation, ensuring that the chosen alternative route met the expected demand to achieve demand-based system reliability. Moreover, the sensitivity analysis showed that (Service A - Station a) and (Service B - Station d) are the most sensitive stations, which will require the campus service operators close attention to these stations if any unexpected variation of demand during the day.

The authors have provided a blueprint of recommendations for an enhanced level of shuttle bus services within university premises based on the research study outcomes. In order to attain the Meta goal of perceived service level quality, service effectiveness, and system reliability, the university transportation section can adopt the following short-term guidelines, namely:

1. Enhance the service frequency of shuttle bus services where routes can be split into multiple service points covering the same area. The too-frequent stopping of buses at various service points can cause students to reach late at their respective destinations.
2. Re-allocate the resources to meet the intra-campus service needs based on latent demand and identify the under-served stops or areas within the university campus.
3. Improve the on-time service performance by downsizing the number of bus stops along the planned bus routes. For the same, universities can conduct a survey to know the willingness of students to commute on foot and then re-allocate the bus stops.
4. Re-design process of the routes can be done to shift the current existing pattern of loop routes in the campuses like Qatar University to either of the following pattern of routes, namely; a) Split routes b) Linear routes c) Express routes and, d) Through routes, which can possibly reduce the congestion within the university campus.
5. Use of Internet of things (IoT) technology to enhance internal transportation services. Bus drivers will only stop in stations to drop off or pick up students based on their request (student request will be sent as a signal to the bus drivers) to avoid delays or unnecessary stops.
6. Determine prominent route measurement parameters that can be used for computing the shuttle service performance on a timely basis. These measures include;
   a) Student trips per service miles (per student trips and route service miles)
   b) Student trips per service hours (per student trips with route service hours)
   c) Real-time performance (student entry and exit data from each stop)
   d) Number of service-related complaints (create a channel to accept transportation-related complaints from students).

For future research, the authors suggest using several machine intelligent tools for shuttle bus service design and development related problems such as the time-optimal speed setting design model developed by Bae et al., for improving the service reliability during unlikely events for self-driving university shuttle bus services (Bae et al. 2019). Similarly, an Artificial Intelligence (AI) based visualization map with Satellite Navigation (SatNav) system that measures the headcount of students using bus services based on course enrollment as developed by Somsuphaprungyos et al., can be used (Somsuphaprungyos et al. 2015). This technology supports the shuttle bus management system in accordance with the student movement within the university premises. Decision support systems with fuzzy architectures like the "Trans Jakarta Fuzzy Interface Systems (TJFIS)" developed by Samosir et al., reduce considerable amount of uncertainties in fleet management for shuttle bus services (Samosir et al. 2017). Despite the fact that numerous methods and techniques exist till date, the service system design problems are of a class of NP-hard problem. In real time situations, several scenarios need to be run to obtain a near optimal, optimal or sub-optimal result. There might be unrealistic scenarios that might result in computational delays. In addition, scenarios such as change in conditions like road closures, service breakdowns etc. can make daily operations more complex and proper planning a complex task.

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