ORIGINAL SCIENTIFIC PAPER OPEN ACCESS

Development of optimal and cost effective bus scheduling using genetics algorithm

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ARTICLE INFO

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DOI: 10.5937/engtoday2300016S

UDC: 621(497.11) **ISSN:** 2812-9474

Article history: Received 15 September 2023; Revised 18 October 2023; Accepted 24 October 2023

ABSTRACT

Most higher institutions in Nigeria operates intra and inter campus transportation, but lack proper planning on movement schedule which contributes significantly to poor academic performance of students as it causes great fatigue due to long queue at the parks and consequently, resulting to losses of revenue to bus management. A met-heuristic algorithm, G.A and L.P model were used to optimize bus scheduling for efficient transportation. To achieve this, travel demands for peak and off-peak seasons at the two campuses of FUTMinna, Nigeria were obtained using 4 numbers of CCTV cameras located at strategic positions. Data were analyzed using the design travel times of 40, 50 and 60 minutes considering traffic and road conditions using 19 numbers of 18 seater bus, 11 numbers of 35 seater bus and 15 numbers of 60seater bus capacities buses with15 minutes departure time. It was observed that with N100/head of revenue charges, a total of N185,000/day corresponding to 231 trips would be achieved during off-peak season to convey 2,562 students, and this amount would increase by 289% at peak season with very little or no delay to move 4,411students travel demand.

KEYWORDS

Bus, Campuses, CCTV, Cost, Genetic algorithm, Travel demand

1. INTRODUCTION

Transportation involves the complex process of moving individuals, commodities, and services from one place to another. This movement can be facilitated through diverse modes of transportation, including land, air, and water. Among these modes, land transportation prevails as the most commonly utilized method owing to its numerous advantages and ease of operation. Over time, both individuals and governments have recognized the significance of embracing efficient and comfortable public transportation as the most effective means of fulfilling travel demands. This need for seamless mobility extends not only to developed nations but also permeates within educational institutions like the Federal University of Technology, Minna, which exemplifies the study area. The university's population, comprising both students and staff, has witnessed an astounding increase of 525.25% over the past six years [1].

Currently, bus management operators are experiencing financial losses, and passengers are dissatisfied due to inefficient bus scheduling. Implementing a Genetic Algorithm (GA) can enhance the transportation system, enabling the seamless transportation of a larger number of passengers while reducing delays and improving cost efficiency. Technological advancements have given rise to various solutions for transportation-related challenges, including Automatic Vehicle Location (AVL), Automatic Passenger Counting (APC), and Global Positioning System (GPS) [2]. For the purpose of this paper, Closed Circuit Television (CCTV) was employed as a means of data collection. These technologies, along with other data collection methods, fall under the purview of the Information Technology and Innovation Foundation (ITIF), which encompasses the concept of Intelligent Transportation Systems (ITS) [3]. Intelligent Transportation Systems (ITS), as elucidated by [4], constitutes a relatively new branch of Transportation Engineering that explores and applies novel technologies to resolve an array of traffic and transportation problems. Line capacity refers to the maximum number of vehicles that can be transported along a given route within a specified timeframe [5]. A bus timetable serves as crucial information provided by transportation providers to passengers, offering certainty regarding the departure and arrival times of buses [6].

Several optimization models exist for designing bus timetables, including Particle Swarm Optimization (PSO), Biogeographic-based Optimization (BBO), Gravitational Search Algorithm (GSA), and Pastoralist Optimization Algorithm (POA). However, this paper will focus on developing and solving a linear programming model utilizing a Genetic Algorithm (GA) to generate an optimal bus schedule. Genetic algorithms, categorized as evolutionary algorithms, draw inspiration from natural selection and genetics. [7] defines genetic algorithms as evolutionary and numerical techniques that utilize principles from genetic theory to ascertain the best possible solution. GA operates as a metaheuristic, a stochastic approach grounded in populations [8]. Numerous researchers have explored the development of bus timetables in related studies. Hadas and Shnaiderman (2012) addressed the minimization of costs by considering unoccupied seats and unserved demands. Li et al. (2013) incorporated stochastic parameters such as demand, arrival times, boarding/alighting times, and travel times. [9] formulated a real-time non-linear programming model incorporating GPS to provide departure information to passengers. Kidwai (2005) employed a GA to tackle bus scheduling in two phases: identifying the minimum frequency and optimizing the model for route service traffic assignment. [10] devised a GA to propose a non-linear formulation for adjusting frequency settings based on static demand, al-lowing for coordination between feeder bus lines and trunk lines in Bus Rapid Transit (BRT) corridors. [11] asserted that genetic algorithms can solve Integer Programming models. [12] employed mixed-integer programming to determine the frequency of bus rapid transit (BRT) trips, thus minimizing operational costs in the Service System of Trans Mataram Metro Bus. Deviating from the optimal condition by offering more frequent bus trips incurs high operating costs for bus operators, while fewer trips compromise the quality of service for passengers [13].

Despite students leaving their residences early in the morning, they still encounter unforeseen delays and occasional denial of boarding at bus terminals (origins). These challenges contribute to fatigue and stress among students due to prolonged waiting times. These issues, along with others, stem directly from inefficient bus timetable scheduling. In many higher education institutions in Nigeria, it becomes imperative to address this perpetual problem by introducing comprehensive and efficient bus scheduling systems.

2. RESEARCH METHODOLOGY

2.1. Study Area

The study area encompasses a diverse array of transport vehicles navigating the study corridor, ranging from local school buses to privately owned cars and individually owned commercial vehicles. Specifically, this study focuses on the Bosso-Gidan-kwano stretch, which spans approximately 19.55 kilometers, with an average travel time of 38 minutes, as depicted in Figure 1. Bosso is located at the geographic coordinates of latitude 228325E and longitude 1067977N, while GK is positioned at latitude 220686E and longitude 1055014N.

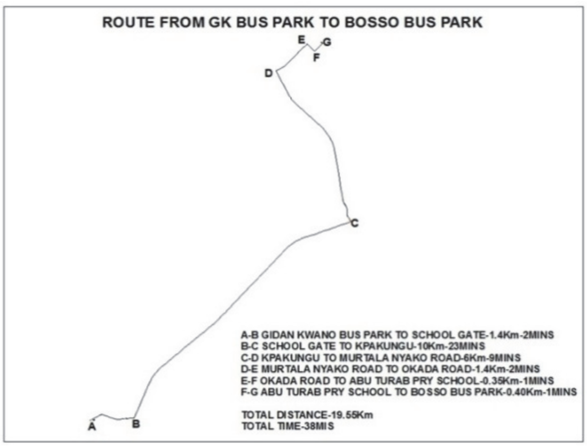

Figure1: Route map using ArcGis 10.3

2.2. Determination of Fleet Characteristics

In order to gather relevant information for the study, an interview was conducted with the bus management coordinator. The obtained information included the travel demand pattern during peak and off-peak seasons, the monthly cost of each driver, both on a daily and per trip basis, as well as the fuel and maintenance costs per trip in terms of liters. Additionally, the revenue per passenger per trip was also acquired. All the monetary values were expressed in Naira and are presented in Table 1.

2.3. Data collection

To collect the necessary data, two sets of closed-circuit television (CCTV) cameras were installed strategically at the bus parks located in both campuses. These cameras were positioned to capture the boarding of passengers, including those who had to stand during the journey. Furthermore, the cameras recorded the number of students and buses arriving at and departing from the bus parks. The data collection process was conducted continuously for 24 hours each day, while only the data from a 12-hour period, specifically from 6:00 AM to 6:00 PM, were utilized for the research. The captured videos from the CCTV cameras were exported to an external hard drive for each campus. To analyze the data, observation methods were employed, and the videos were examined at intervals of fifteen minutes. The travel demand and travel times for both campuses were computed for duration of two weeks during both peak (Exam) and off-peak (lecture) seasons. The maximum values derived from the analysis are depicted in Figure 2.

Figure 2: Exporting CCTV videos at Bosso and GK campuses bus parks.

2.4. Linear Programming Model and Constraint

The linear programming model, as depicted by Equation 1, seeks to optimize the multiplication of net profit/loss with the number of frequency. In this research, we focus on a single route while exploring different scheduled variations (*V*) and partitions (*P*). To calculate the net profit/loss, we determine the algebraic difference between the total revenue and total expenditure for each considered departure frequency.

$$\text{Maximize},$$

$$Z = \sum_{r\in R} \sum_{v\in V} \sum_{p\in P} C_{r,v,p} \cdot x_{r,v,p} \tag{1}$$

$$\text{where } C_{r,v,p} = inC_{r,v,p} - outC_{r,v,p} \tag{2}$$

$$\text{Subject to}:$$

$$\begin{Bmatrix} 0 \le q_{c+y} \le 60, \text{if } q_{typ} = A \\ 0 \le q_{c+y} \le 35, \text{if } q_{typ} = B \\ 0 \le q_{c+y} \le 18, \text{if } q_{typ} = C \end{Bmatrix} \tag{3}$$

$$\begin{Bmatrix} t_{r,p,A} - t_{r,p,(A-1)} \ge 90 mins, \text{if } q_{typ} = A \\ t_{r,p,B} - t_{r,p,(B-1)} \ge 85 mins, \text{if } q_{typ} = B \\ t_{r,p,C} - t_{r,p,(C-1)} \ge 80 mins, \text{if } q_{typ} = C \end{Bmatrix} \tag{4}$$

$$\frac{2T_{r,p}}{q_{bus,r}} \le 15 minutes \tag{5}$$

Equation 3 represents a constraint in the design of bus timetables for efficient transportation. It represents the relationship between the three different fleet sizes, denoted by Ai, Bi, and Ci, along with their respective capacities of 60, 35, and 18. Additionally, Constraints 4 and 5 provides essential information regarding maximum travel times and departure frequencies. In this study, genetic algorithm (G.A) was explored to generate optimal bus schedules by considering these constraints and parameters.

2.5. Genetic Algorithms input

To implement genetic algorithms, software such as MATLAB was employed. This software offers a comprehensive enviroment for developing and running the necessary codes to generate optimal bus schedules. By inputting the relevant parameters and constraints, the genetic algorithm can be executed to produce favorable timetable outcomes. The G.A input is an important parameter that facilitates the generation of optimal bus schedules. It consists of two main components: the Bmatrix and travel demand.

2.5.1. Bmatrix

The Bmatrix includes the different sizes of vehicles used in the fleet, each with specific seating capacities. For instance, the sizes may include buses with capacities of 60, 35, and 18 passengers. The factors considered when configuring the Bmatrix include maximum journey times, which take into account possible delays, revenue per passenger, and operational costs encompassing fuel, driver remuneration, and maintenance expenses. While the genetic algorithm approach offers efficient and automated results, it is also instructive to compare it with a manual approach using Excel. By manually inputting the same set of inputs and constraints, it is possible to validate the results generated by the genetic algorithm. Comparing the two approaches provides insights into the similarities and differences and allows for a comprehensive evaluation of the outcomes.

2.5.2. Travel Demand

Travel demand represents the number of passengers requiring transportation between the two campuses during different periods, such as examination and lecture seasons. By incorporating travel demand into the algorithm, it becomes possible to generate an optimal timetable that caters to the varying demands efficiently. The demand at both campuses for peak and off-peak seasons are represented in Figure 3 and Figure 4. The maximum demand during off-peak period occurs at 1:30-2:00pm for GK and 11am for Bosso campuses. Whereas, during peak period, the maximum demand falls between 6:30-7:00am for Bosso and 12pm for GK campus.

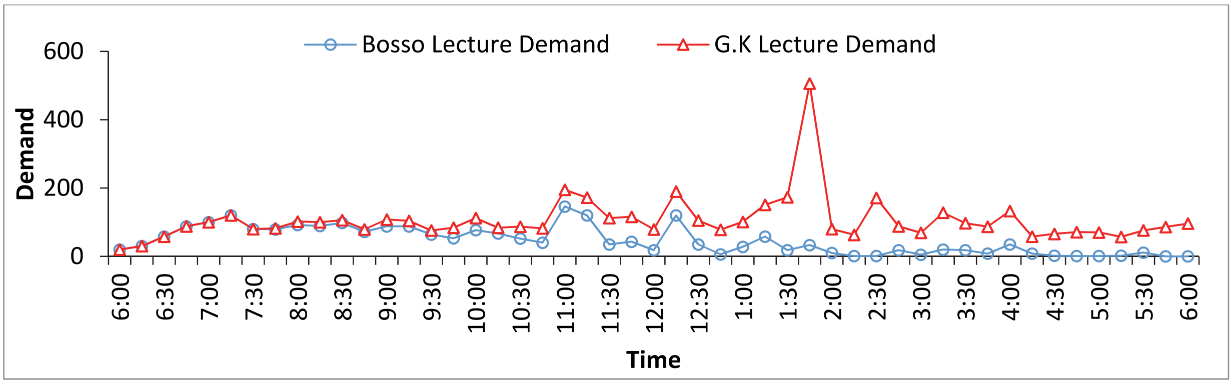

Figure 3: Design travel demand at off-peak season

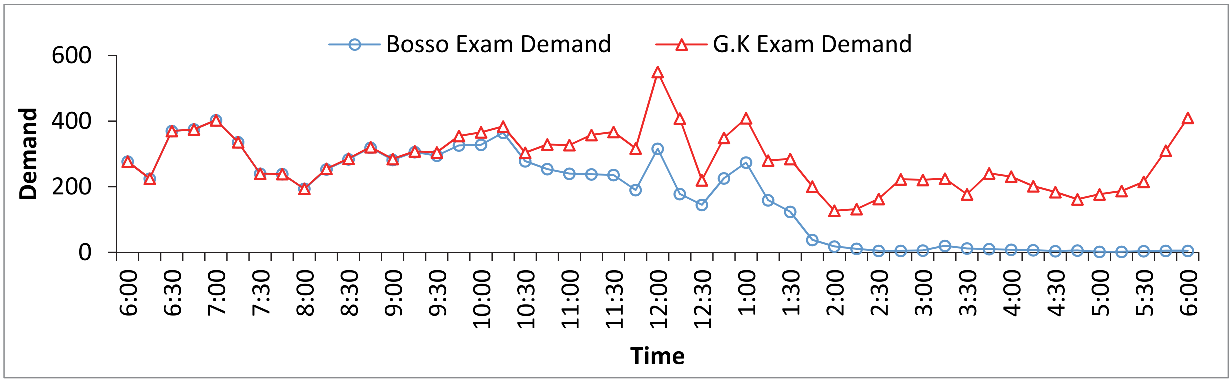

Figure 4: Design travel demand at peak season

2.5.3. Numbers of chromosomes, Iterations and Extermination Criterion

The number of chromosomes, which represents the population size or search agents ranged from 200 to 1000, incrementing by 200 at each interval. Simultaneously, the number of iterations was fixed at 1000, ensuring a consistent evaluation process. To identify the optimal solution, extermination criterion was selected based on the iteration with the maximum best cost and minimum violations. This criterion allowed progressive refinement in the results by iteratively running the program 20 times for each chromosome until the best cost was achieved.

2.6. Genetic Algorithms output

The Genetic Algorithm outputs were presented in the following categories;

2.6.1. Best Solution

(i) Position matrix: This matrix, denoted as nxm, reflects the number of buses (n) and their corresponding departure times (m). In this study, total of 38 buses was considered, with each bus scheduled to depart at 49 different time intervals ranging from 6:00 am to 6:00 pm at 15-minute intervals.

(ii) Cost: represented as an integer, this parameter indicates the maximum cost reached after 1000 iterations, facilitating cost comparison and evaluation across different scenarios.

(iii) Violations: This vector, of size 1xn, serves as a binary indicator for violations in the departure schedule. A value of 1 indicates a scheduled violation, while 0 signifies no violations.

2.6.2. Best Cost

It is represented as a vector illustrating the number of iterations and the corresponding costs. Specifically, it takes the form of a 1000x1 (double) vector. The best cost is computed iteratively after each trial with a different number of chromosomes until the optimum chromosome configuration is attained.

2.6.3. Number of Violations

This is another crucial parameter generated for each chromosome. This integer value plays a significant role in the selection of optimal chromosomes with the least violations. Interestingly, a higher violation value reduces the likelihood of selecting the corresponding chromosomes, indicating the influence of violations on the overall optimization process.

3. RESULTS AND DISCUSSION

3.1 Fleet Characteristics

Table 1 presents a comprehensive overview of the fleet characteristics, specifically focusing on three types of buses: 43-seater, 54-seater, and 60-seater. The operational costs associated with these buses, including fuel expenses, maintenance costs, and driver remuneration per trip, exhibit remarkable similarity. Notably, the 60-seater bus holds the advantage of accommodating a larger number of passengers, consequently leading to potential higher revenue generation. Thus, for the purpose of developing an optimized timetable, the 60-seater bus was chosen as the preferred option. This rationale also holds true for the 30-seater and 35-seater buses, as they exhibit comparable operational cost dynamics and revenue potential.

Table 1: Bus and drivers information

Type of Bus	Maximum Allowable Standee	Revenue/run (₦)	Fuel Cost/run (₦)	Driver Cost (₦)	Maintenance Cost (₦)
18	N. A	1800	330.00	100.00	52.27
30	N. A	3500	660.00	100.00	65.33
35	N.A	3500	660.00	100.00	65.33
43	20	6000	1237.50	100.00	326.67
54	25	6000	1237.50	100.00	326.67
60	10	6000	1237.50	100.00	326.67

3.2 Travel Time

The travel duration between the two campuses for the chosen bus capacities was calculated and displayed in Table 2. The total time taken for the journey was determined, taking into account potential delays caused by refueling, passenger arrivals/departures, and traffic congestion. However, to account for the worst-case scenario, the journey duration representing the overall travel time was considered.

Table 2: Maximum design travel time

Bus Capacity	Range of Travel time	Maximum Travel Time
18	34-40mins	40mins
35	39-50mins	50mins
60	43-60mins	60mins

3.3 Travel Demand

Figure 5 presents an analysis of maximum travel demand based on CCTV data during the two weeks of the exam and lecture period at two different campuses, Bosso and GK. During the exam period, it was noticed that in the early hours of the day, the maximum demand at Bosso exceeded 200, while there was no significant demand at GK until around 11:30 am. This timing coincides with the completion of early morning exams, suggesting that students were ready to return to Bosso at that time. On the other hand, during the lecture period, there was minimal demand in the early hours at both Bosso and GK campuses. However, at approximately 1:30 pm, there was a sharp increase in demand at GK campus. This surge aligns with the possibility that first-year students (100 level) intended to travel to Bosso for laboratory practical sessions. These findings indicate a fluctuation in travel demand patterns during the exam and lecture periods, highlighting the complexity and unpredictability of student movements between the two campuses.

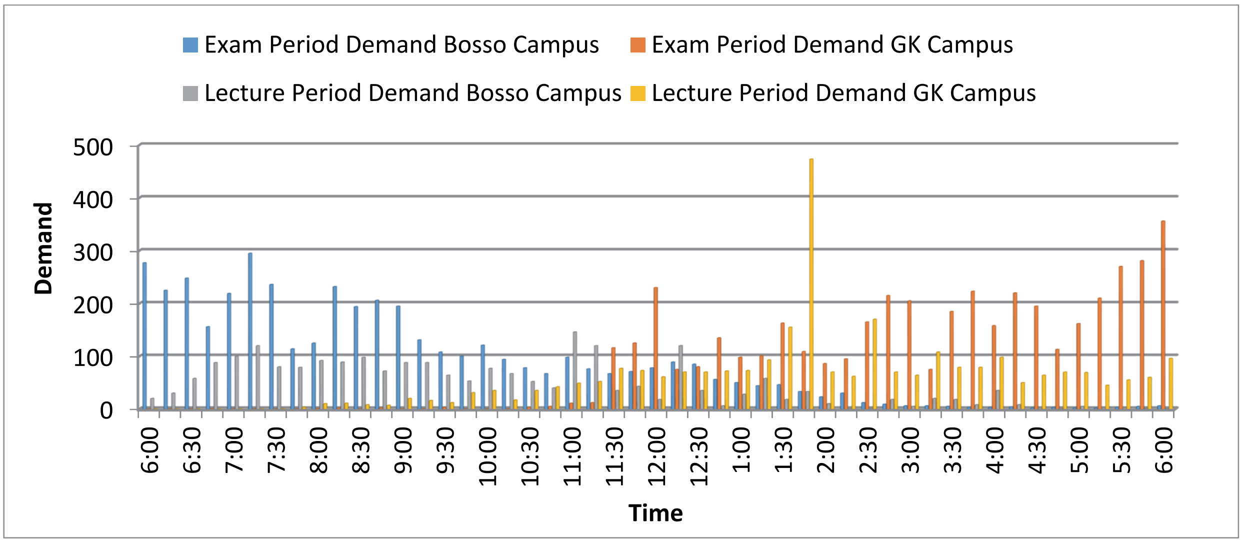

Figure 5: Maximum travel demand of both campuses at different period

3.4 Genetic Algorithms Result

Table 3 provides a summarized representation of the outcome derived from the application of genetic algorithms (GA). By subjecting the code to 1000 iterations and progressively adjusting the chromosome sizes in increments of 200, a comprehensive evaluation was conducted for each campus and associated conditions. Notably, as the chromosome size increased, the execution time also exhibited a corresponding rise, amounting to approximately 20 minutes for a value of 1000. To visualize the fluctuations in net cost across iterations, Figure 6 graphically presents the comparative analysis of different campus locations and conditions

Table 3: Summary of G.A results

Conditions	Bus Capacities	Available Number	Campuses	Periods	Net Cost (₦)	Violations due to delay
	18	20		Exam	258,885.00	15
	35	7	Bosso	Lecture	61,324.47	4
				Exam	275,963.00	12
Design Time Table	60	8	Gidan Kwano	Lecture	125,045.68	5
	18	15		Exam	314,234.81	22
	30	Nil				
	35	3	Bosso	Leture	112,631.33	14
	43	2		Exam	330,926.16	19
	54	2				
Existing Time Table	60	2	Gidan Kwano	Lecture	177,953.28	10

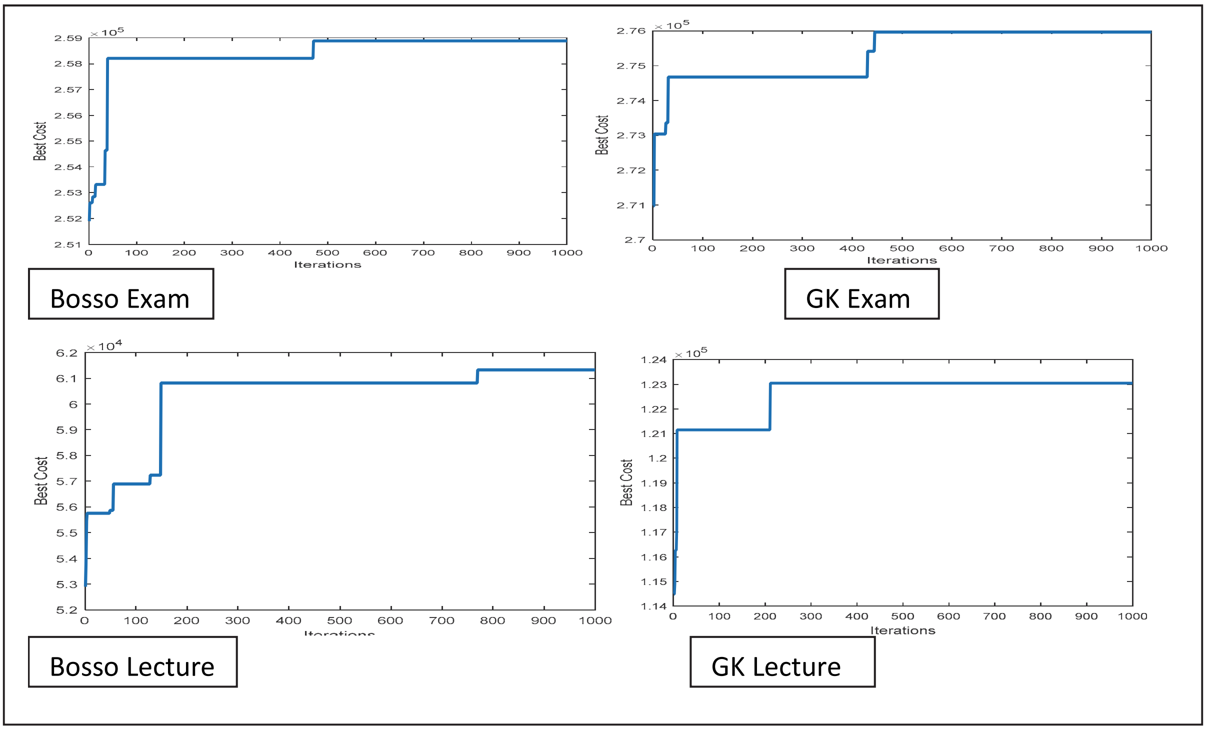

Figure 6: Variation of best cost with iterations

Table 4 displays an analysis of the total trips generated during specific 15-minute intervals for bus departures at different campuses and during different seasons (peak and off-peak). The study reveals intriguing patterns, showcasing increased complexity and unpredictability in the data. Across both seasons and campuses, it was observed that the utilization of 18-seater buses resulted in a significantly higher number of trips. In fact, the trips generated by these 18-seater buses were approximately 3-4 times greater than those generated by 35-seater buses and 4-6 times greater than those generated by 60-seater buses. This substantial disparity can be attributed to the higher number of 18-seater buses available, as well as their shorter journey times compared to buses with other seating capacities. Furthermore, the data indicates variations in the total trips generated during peak and off-peak seasons. Specifically, during the peak season, Bosso campus recorded 231 trips, while GK campus recorded 232 trips. In contrast, during the off-peak season, Bosso campus saw 223 trips, while GK campus witnessed 222 trips. These fluctuations further contribute to the increased complexity and unpredictability observed in the data analysis.

Table 4: Trip generation from scheduled buses

Periods	Campus	Bus Types	Total Trips
Exam	Bosso	18	161
		35	41
		60	29
	GK	18	147
		35	47
		60	38
Lecture	Bosso	18	149
		35	42
		60	32
	GK	18	155
		35	40
		60	27

4. CONCLUSION

The study employed the journey time of buses as the basis for designing travel times, specifically considering 40, 50, and 60 minutes for 18, 35, and 60-seater buses respectively with a departure interval of 15 minutes. By utilizing a total of 35 buses, significantly more than the typical 22, the generated GA bus time table resulted on daily revenue of approximately ☒ 290,224.61 during off-peak periods across the two campuses. Remarkably, during peak seasons, this amount surged by a factor of over two, reaching an amplified total of revenue.

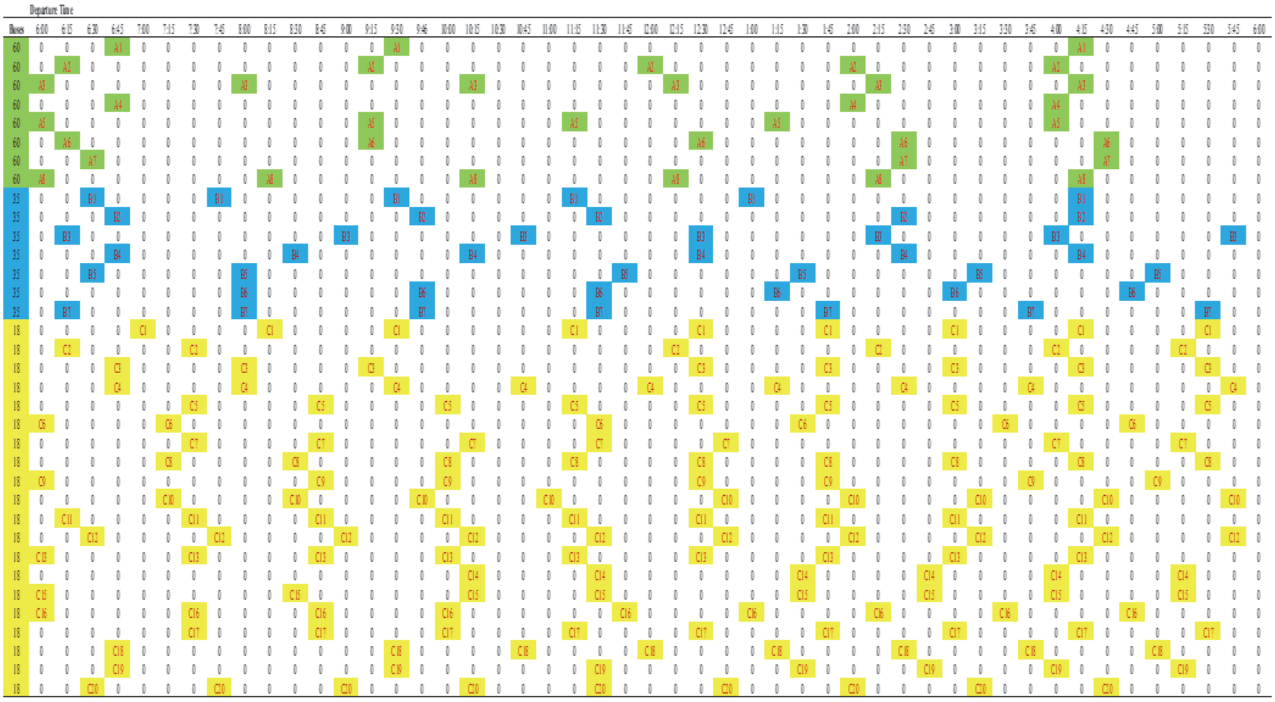

Figure 7: Genetic algorithm bus time table for Bosso peak season

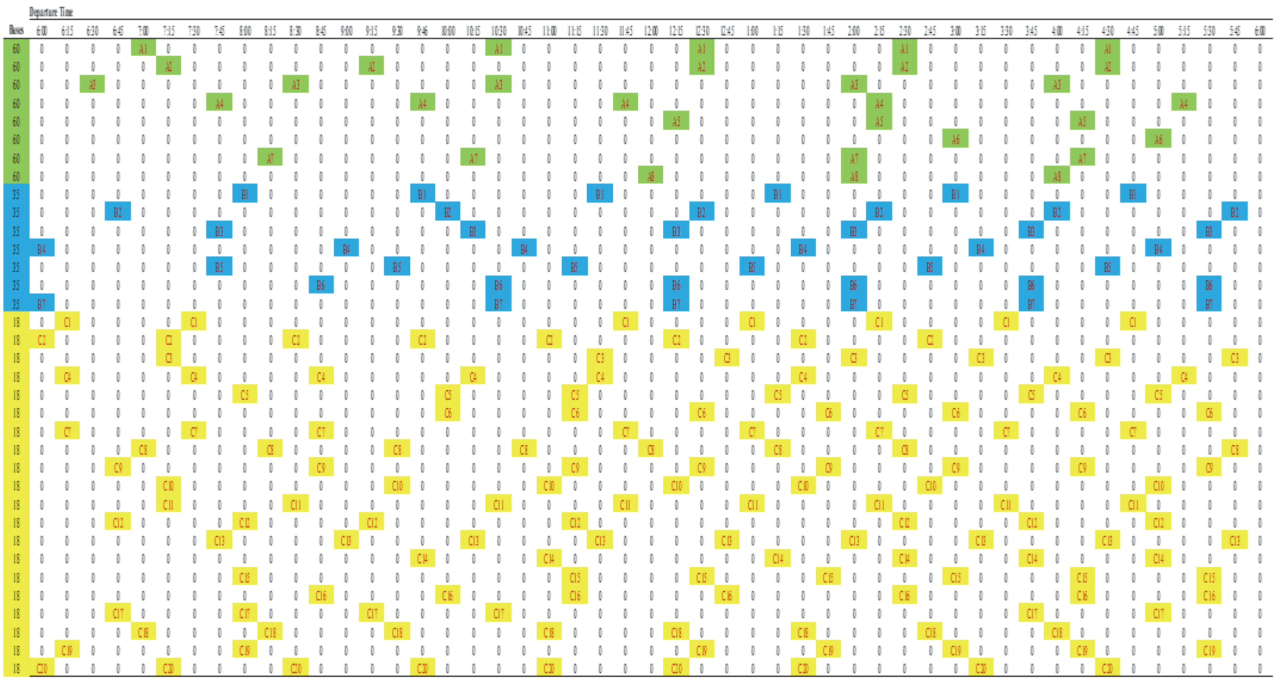

Figure 8: GA bus timetable for Bosso off-peak season

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