



Biomimicry improvement of school shuttle routing: incorporating demand balancing nodes

P. A. Ozor^{1,2*}, C. Mbohwa¹

¹ Department of Quality and Operations Management, University of Johannesburg, South Africa

² Department of Mechanical Engineering- Industrial Engineering and Management, University of Nigeria Nsukka

*Corresponding author E-mail: pozor@uj.ac.za

Abstract

Campus communities in some developing countries are predisposed to multiple modes of transport services (vehicle, motorcycle, tricycle). The security concerns in such area may lead to prohibition of one or more of the existing systems with a consequent unbearable hardship to the community. This study investigated the use of Bio-mimicking based algorithm- Ant Colony Optimization and incorporation of demand balancing nodes to determine an effective shuttle routing plan in a Campus community. The approach was applied to a specific example Campus, namely; Shuttle routing problem in a Nigeria public University. From the analysis of all the data collected for the study, five and three additional shuttle terminals were created for the hypothetical Northern and Southern zones respectively. The distances travelled by the shuttles in the new routes varied from a minimum of 1537.64m to a maximum of 3912.27m in the Northern zone. The mean route distance in the zone is 2509.25m. Similarly, the Southern zone routes have distances varying from 1932.43m to 2260.8m, with a mean route distance of 2120.42m. Comparatively, the shuttle route distances in the existing routes varied from 4134.55m to 4706.08m with a mean route distance of 4481.99m. The results show that an average distance reduction of 44% was observed for shuttle routes in the Northern zone. The results also show that average distance reduction of over 52% is obtainable for shuttle routes in southern zone.

Keywords: Ant Colony Optimization; Biomimicry; Demand Balancing Nodes; Developing Countries; Shuttle Service Improvement.

1. Introduction

The optimal course of action to follow in routing of vehicles from a depot or source to deliver customers and goods to satisfactory destinations with significant payback and probably back to the origin is a special aspect of transportation problem. In particular, it is reasonable to expect that vehicles which originate from a specified depot should be able to deliver its contents at optimal values of parameters of concern, which may range from weight, time, distance and even comfort, and then return to the place where it started. The process of determining the routes that can satisfy the expectation of all players (vehicle operators and passengers), in the light of maximum goods, shortest distance and least possible time, which in most cases translate to minimum total cost and maximum profit is classified as vehicle routing problem (VRP).

Since its application to the travelling salesman problem (TSP), following careful implementation of some of Biological Ant functionality in computerized agents (Dorigo and Gambardella, 1997), Ant colony optimization (ACO) algorithm has continued to generate VRP solutions with less computational time and effort. It has been applied in many situations with reported results of adequately mimicking wide Biophysical and industrial phenomenon. Hence, it's growing application in searching for the optimal path across processes and networks. In particular, significant reports of application of Bio-tries (Zhang and Zhang, 2017) with other search approaches (El Yakine et al., 2017) to vehicle routing problems flourished over the past decade (Bin, et al. 2009, Alves et al. 2010, Ashok and Messinger, 2012, Nogueira et al, 2014). A typi-

cal VRP solved with improved ACO is already in place (Bin et al., 2009). The presentation proposes useful techniques (ant-weight strategy) for updating pheromones while suggesting that the resulting VRP be solved by mutation operation. The improved ACO was re-parameterized to account for generation of solutions, mutation operation, local search and updating of pheromone information. The parameters were coded in visual C++ Net 2003 and executed on a Personal Computer (PC) with 512 MB of random access memory and a processor operating at 1000MHz. The improved ACO performed better than five other meta-heuristic procedures and gave the lowest average deviation under sensitive comparison. There exists a report on application of ACO algorithm to traffic dispersion routing (Alves et al, 2010). Reed et al., (2014) conducts feasibility study on the capability of Ant colony principles in solving the capacitated VRP encountered in waste collection and recycling from households. In testing the algorithm, five sets of data were selected from fourteen data sets usually employed as benchmarks in literature (Christofides et al, 1979). The authors maintain that while the approach proved effective for the capacitated VRP with unloading trips, extending the methodology used could solve vehicle multi-compartment problem with comparable efficiency.

The elaboration of ant colony technique in solving somewhat TSP, with specific emphasis on multi-depot VRP had earlier been fulfilled (Narasimha et al., 2013). The paper investigates ACO strategy that minimizes certain measures of effectiveness in arrangements that allow vehicles to visit specified cities or locations exactly once. The multi-depot VRP is essentially employed to reduce tour-length in the presentation, short of traditional time critical

problems reported in previous research efforts. Comparison of the ACO solution with other mathematical (linear programming) approaches show that the former performed better. Taxi way sequencing aimed at decreasing congestion in an airport surface has been achieved using ACO (Nogueira, et al., 2014). The Authors made use of data from Brasilia International Airport. The nodes, geographical coordinates and the distances between them were determined. The proposed solution was sub divided into five distinct steps: modeling and architecture, implementation, entry data optimization, route conclusion for each airplane as well as conflict detection and resolution. The results show that the algorithm maintains its efficiency when the aircraft flow increases within a given period of time while the simulation indicated a 32% decrease in aircraft taxiing time. Conclusively, aircraft collision was totally arrested. A research article bordering on School bus routing using ACO is available (Arias-Rojas, et al., 2012). Taking data on a private school in Bogota, the authors concerned with increasing the utilization of available buses and minimization of traveling times in a bid to take students to the school on schedule. Manhattan distance ACO method was used to establish shortest travel time/distance between each pair of points in the network resulting in asymmetric matrix of distances. The capability of the method to tackle other treatments in school shuttle routing, for instance; route alterations and decrement in available transport means was not discussed. Other issues of location differences and management attitude were conspicuously missing, though the paper fully satisfied the stated objective of reducing bus redundancy.

Ashok and Messinger (2012) present a variant of the conventional ACO algorithm. It is called spectral image clustering algorithm. The aim of the study was to represent the data on a 100×100 pixel of a digital globe Worldview- 28 band image as a graph and illustrate the usefulness of the proposed algorithm. The Ant colony system was found capable of identifying optimal routing paths through the validation data in the considered sphere. The resulting cluster maps as a result of the clustering algorithm showed that the developed model is not only appreciably good, but equally related well to the ability of materials to separate in the spectral domain. Generally speaking, there are several approaches to VRP in existing literature. Very recent works emphasize heuristic methodologies for generation of global solution to vehicle heterogeneity, time windows, backhaul mixed-load (Wu et al., 2016), and other variables like environmental considerations (Androutopoulos and Zografos, 2017), which were formally modeled separately. The compendium of proposed exact and heuristic approaches for major categories of VRPs is discussed elsewhere (Bulhoes et al., 2017). Variable neighborhood search techniques have been tested and proven to provide optimal solution or a near best solution for designated benchmarks (Huber and Geiger, 2017, Polat, 2017, Sevкли and Guler, 2017). The capability of ACO algorithms to handle dynamic optimization (Gao et al., 2016) and non-deterministic polynomial hard problems (Narasimha et al., 2013) has increasingly encouraged its choice in resolving emerging VRPs. Its robustness and ease of adaptation to various VRP environments has taken its constitution beyond finding optimal solutions, but also tracking it with time. Management of goods producing firms are always but not necessarily challenged with the need to increase the number of products supplied to waiting customers while minimizing the tour-time of service vehicles, which can translate to customer waiting time. The scenario presented by this objective is normally resolved as dynamic VRPs. There are instances where the basic ACO have been modified by incorporating other solution techniques to tackle the problem. One of such modifications is demonstrated in introduction of immigrant schemes where immigrants are made to replace a small portion in the existing ACO population. Mavrovouniotis and Yang (2015) is a good example of such formulation. In the presentation, three immigrants namely; memory-based, random and elitism with differences defined by the way each was generated, were introduced. The new scheme was tested on various dynamic VRP situations abstracted from dynamic benchmark generator for comparing and benchmarking

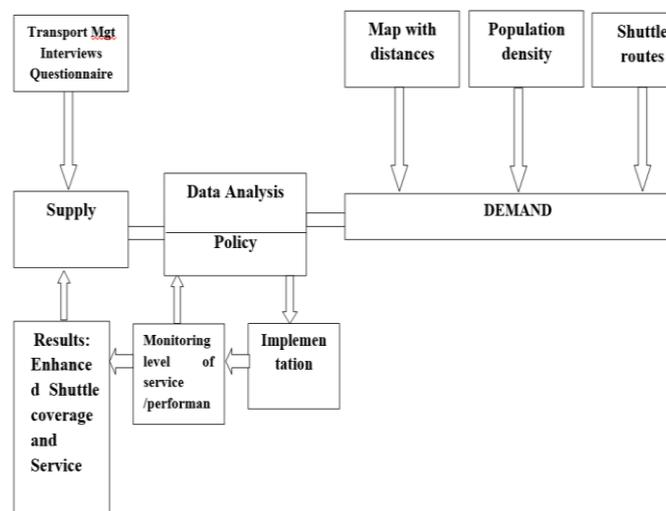
the parameters of the method. It was concluded that immigrant schemes can improve the functionality of ACO, though the underlying principles was applied to dynamic VRP. In a related development, Kuo et al., (2016) consider possible uncertainties in service time and propose a fuzzy oriented procedure that integrates another modification called cluster insertion algorithm into the original ACO algorithm. Rather than direct application to any real world situation, benchmark data sets were relied upon to validate the proposed algorithm, in line with previous authors. Insights on the applicability of the model and algorithm proposed in the work were elaborated on sensitivity analysis. The authors show that the cluster insertion made the algorithm to out-perform previous stand-alone fuzzy-ACO algorithms.

Outright ACO hybridization with other meta-heuristic models has been explored in resolving VRPs and other dynamic search situations (Ezzatneshan, 2015). In an effort to determine the optimal batch size, travelling distance and order allocation in a batch, Cheng et al (2015) propose an ACO algorithm hybridized with particle swarm optimization (PSO). The minimum total distance travelled by batch pickers together with the optimal picking strategy was decided using PSO while ACO informed the decision on the optimal traveling path per batch. The proposed algorithm was validated with generated randomized problem instances whose solutions were compared with what obtains using mathematical (linear) programming approaches. The results indicate better performance of the hybrid algorithm in solution quality as well as computational efficiency. Various industrial products can sometimes be loaded and transported in different compartments in the same vehicle due to immiscibility of the items in question. The multi-physical character of the items combines with the necessary multi-compartment structure in the vehicle to constitute a multi-compartment VRP (MCMVRP). Optimal decision on the best traveling and delivering mix in such problems can equally be made on the basis of hybridized form of the ACO algorithms. For instance; an existent version of ACO has been combined with local search heuristic algorithm to obtain different solutions to a hypothesized MCMVRP (Abdulkadera, et al., 2015). The methodology was illustrated using computer generated benchmark problem situations. Comparison of the two solutions, that is; stand-alone ACO and hybridized ACO show that the later gives better results. There is still paucity of presentations on school VRP and its exigencies for some isolated cases. Majority of the available ones relied upon artificially generated benchmark data to test the algorithm. Direct application of the ACO to real World specific locations and its peculiarities has not received the needed attention as to turn to existing methodologies in the event of deviations. In addition, most reports on VRPs are suited for cities where the destinations of the vehicles are predefined with negligible changes in the route configurations. The distances which customers must trek to the vehicle depot (vehicle nodes) remain fairly constant. Considerable study, including those listed above, has been done towards addressing the routing problems emanating from such set up. There could be some occasions where customers are already predisposed to a multiple mode of transport and prevalent regulations in the area suddenly prohibit one or more of the existing system of transport to achieve a set of new objectives. This alteration can disrupt vehicular and customers routines. Rerouting the surviving means of transportation and creation of additional nodes to ensure optimal coverage cum travel distances to both customers and vehicles can become indispensable. While such situations can be rare for fully developed cities, it is a common characteristic of developing communities still grappling with the problems of policy reversals. The severed relationship between motorcycle operators and the administration of a public University in Nigeria led to the outright ban on the former. The consequences were harsh on the Community in terms of increased trek and vehicular distances as well as asymmetrical vehicle routes. This paper seeks to apply the Biomimicry capability, in particular; ACO to real data from the Campus community to search for a set-of best tour routes which meet customers' needs as well as reduce vehicular distances. In-

corporating the proposed demand balancing nodes (DBN) is intended to provide clarity, satisfaction and regularity in the transit service.

2. Materials and methods

The work employed analytical research design approach which involves collection of data on the population from key players in Campus shuttling. The research equally made use of Primary and secondary data. The primary data was sourced directly from the laboratory through intensive and rigorous map explorations, interpretation and development. The aim was to carefully deduce the coordinates and distances of existing shuttle bus stops (obtained as part of secondary data) and proposed nodes (DBN) idealized for the study. In particular, map of the study area showing the major routes was obtained using geographical information software (GIS). Effort was made to carry out on-site validation of some of the results obtained from maps through randomized physical measurement of few parameters. The secondary data were made up of information from scheduled interviews and opinion surveys with relevant staff in the Campus transport management. The existing Shuttle routes, though not fixed, were obtained from UNN trans-routes and the distance travelled by a shuttle in the routes estimated through extensive map reading, physical measurement and instrumentation. Semi-structured questionnaire were administered to various categories of shuttle customers inhabiting the campus to ascertain the demand for shuttle vehicles, impact of the banned motorcycles and evaluate the services rendered by the shuttle operators among others. Over seventy five percent of the respondents underscored the need for a shuttle routing that will bring the shuttle vehicles closer to customers' residences. These respondents lamented that the current routes plied by shuttle operators expose them to varying degrees of hardship, considering the total absence of motorcycles or wheel barrow operators that could convey their goods from the distant bus stops (nodes). Some twenty percent of the respondents wanted the status quo to remain. A second pass on the questionnaire revealed that respondents in this group either lived very close to the existing bus stops or made some economic fortunes with the situation on ground. That is; it accords them the opportunity to collect special and high profit fares from customers that opt to be chauffeur driven to their residences, probably because of heavy luggage. The other five percent was ready for whatever the administration thinks better and simply ticked "strongly support the administration". The datasets were vigorously analyzed to determine the best positions to incorporate DBN and enhance the existing routes in order to remediate the identified problems. In the execution, the entire campus was divided into two hypothetical zones to facilitate optimal routing of the shuttle vehicles. Additional DBNs were created in both zones according to the analytic results of the data.



Mgt = Management.

Fig. 1: Procedural Steps of the Research

The ACO algorithm was applied to the new and existing routes to obtain shortest distances for each for the shuttles. Conclusively, the result was used to propose new shuttle routes.

2.1. Existing shuttle route structure and short comings

There are four major shuttle depots in the case study Campus. These include Town depot located outside the Campus environment, Main gate depot, Ziks' flat depot and Franco hostels depot. The Town depot is essentially as a background for enhancement of transportation channels into and out of the Campus environment. Shuttles from the depot can serve as feeder to the main gate depot, but can decide to take the whole journey round the Campus. The main gate depot and Town depot are the same once the concerned shuttle arrives at the main gate. The Zik's flat depot and Franco depot tour separate routes. It will be better to define the shuttle tours under three clearly distinguishable routes, though the combined efforts of depots do not cover the nooks and crannies of the Campus community. The shuttling arrangements had been at worst satisfactory, having many transportation channels that took customers to their residences. The research only became necessary due to the eventualities in the transport scheme in the last decade. Unprecedented records of theft, car snatching and violence among others, had compelled the administration to prohibit the use of commercial motorcycles as transportation means within the institutions environment in the year 2008. This step adversely affected transport services in the Community. To palliate the situation, management decided to allow registration of private vehicles with the transportation services department. This step partly augmented existing shuttle services and attempted to bridge the gap created by motorcycle exit, but could not address the increased customer trek distances to shuttle stops. The shuttles operated without fixed routes and captured only few sectors of the Campus, leaving other parts either untouched or inadequately covered. Consequently, the cleavage of this paper in planning some level of service improvement in the school shuttle system. Direct incorporating of demand balancing nodes is proposed. The following subsections summarize the routes that can be plied by the shuttles from various depots. The areas formally accessed by motorcycles but became draught of transport medium are also recapped.

1. From Ziks' flat depot

Ziks' flat → UNN Gate → Ukuta Close → Ikejiani Junction → Fulton Junction → Christ Church → Postgraduate school → Arts/GS Building → Afrihub → Personnel/PAA → Freedom square → Social Sciences → Education → Student Affairs → St Peters → Medical Centre → Banks → Greenhouse Junction/Energy Centre/Awolowo/Vet.Junction → Carver Junction → Library → CEC junction → Arts → Staff club → Stadium → Franco → 2nd Gate → Ziks flat

2. From Franco depot

Franco → Stadium → Staff club → Arts → CEC → Library → Social Sciences → Education → St Peters → Medical Centre → Banks → Green House → Energy Centre → Vet. Junction → Carver → UNN Library → CEC → Arts → Staff club → Stadium → Franco

3. From Urban/ Main gate depot

Town → Main Gate → Ukuta close → Ikejiani junction → Fulton → Christ church → Postgraduates school → Arts/GS Building → Afrihub → Personnel/PAA → Freedom square → Social Sciences → Education → Students Affairs → St. Peters → Medical Centre → Fidelity/UBA/ECO Banks → Green House junction/Energy centre/Awolowo/Vet. Junction → Carver junction → Library → CEC junction → Arts → Staff club → Stadium → Franco → 2nd Gate → Town.

2.2. Areas not covered by shuttle services but formally accessed by motorcycles

Broadly speaking, all sections of the Campus were affected by the exit of the motorcycle operators because they take customers to their individual residences. However, this research considers mostly the areas of worst hit, that is; areas that customers trek for over 300 meters before linking to any of the shuttle routes. The areas identified include but not limited to the following:

Junior Staff quarters, Glen Taggart street, Murtala Muhammed area, Eni-Njoku street, Eze-opi Crescent, Louis Mbanefo street, Odim Street, Chief Imoke street, Odim gate residences. Others are Ikejiani Street, Magarette Cartwright, Elias Avenue, Odenigwe area, Umunkaka Street and Danfodio Street.

The existing bus stops and identified feasible domains for incorporation of DBN in the entire Campus community were identified and defined in terms of their geographical coordinates. Preliminary data analysis revealed that the Odim gate residential area had the highest potential for a demand balancing depot. Table 1 presents a sample of the 49 geographical location and definitions for most of these nodes.

2.3. Demand balancing nodes, demand balancing depot and assumptions

The proposed shuttle service routes with DBN is intended to cover all the major routes including the routes not covered by the existing shuttle system due to proscribed transport modes. It was necessary to make the basic assumption that customers should be able to trek up to 300 meters to the nearest node in extreme cases. For instance, there are situations of terminal streets, where a street has no exit, and warrant the shuttle to tour the same route during the forward journey.

Table 1: Sample of Existing Shuttle Bus Stops with Specific Geographical Coordinates

S/N	Location Description	Latitude (North); Longitude (East)
1	Main gate depot	06°51'32.51"N; 07°23'52.53"E
2	Ukuta close	06°51'33.13"N; 07°24'02.77"E
3	Security/Banks	06°51'32.87"N; 07°23'55.18"E
4	Elias Junction	06°51'32.48"N; 07°24'06.72"E
5	Fulton Junction	06°51'36.67"N; 07°24'06.40"E
45	Hulder	06°51'01.2"N; 07°24'10.2"E
46	Junior Staff 1	06°52'04.69"N; 07°24'31.77"E
47	Junior Staff 2	06°52'04.77"N; 07°24'28.97"E
48	Sport Village	06°52'04.75"N; 07°24'21.83"E
49	Danfodio	06°51'59"N; 07°24'10.44"E

Apart from doubling the distance for the shuttle, it is also difficult to implement in the ACO algorithm. The algorithm requires that shuttles visit nodes just once. The affected streets have been designated as prohibited routes in this study. A prohibited route is one of extremely high cost (Sharma, 2005). The second assumption made is that customers in terminal or prohibited streets, defined earlier, should be able to arrange for (hire) shuttles for specific needs if trekking to the nearest node is not feasible. This can take care of bulky luggage, physically challenged customers and other

instances of emergency situations. On the basis of extensive map reading, consultations with school transportation services department and shuttle operators, opinion surveys with customers and trials of data on ACO algorithm as well as rigorous data analysis, the locations of the demand balancing nodes were decided.

2.3.1. Map coding

In this study, the nodes are taken to be the bus stops in the road network. The coding of the nodes was implemented from one node to the succeeding node. Demand balancing nodes are allocated on routes that shuttles do not ply currently despite significant demand for it (shuttle). The exercise followed due analysis of the population of each area and shuttle needs of residents. They are added to the authorized bus stops to help create a fully developed and effective shuttle network for the community. The choice of the proposed bus stops was partly informed by high population density in those areas and overwhelming request for them inferred from data analysis. These routes can double as alternatives during peak vehicular hours (7am-8.30am, 12pm-1.30pm and 4pm) for office work or school runs and close of work. The incorporated demand balancing nodes is also in agreement with GIS appraisal report for properly served transport service. The appraisal requires that “in a well-served or planned transport service, the distance between an urban or sub-urban unit of residence or workplace and the nearest bus stop should be between 300-500 meters. In low density or sparse area, 500 meters may be acceptable but should not exceed 1000 meters (GIS Appraisal for public transport 2013)”. The DBN was centered on the routes of most need. In the coding, a distance of not more than 300 meters was used. This roughly equals about 6 minutes’ walk at 4.0 km/h. The proposed demand balancing nodes are listed in table 2 with their geographical coordinates.

Table 2: Proposed Demand Balancing Nodes with Coordinates

DBN	Location Description	Latitude [North]; Longitude [East]
3	Ikejiani 1	06°51'30.68"N; 07°24'18.58"E
4	Ikejiani 2	06°51'30.22"N; 07°24'27.93"E
43	Nkrumah/Eni Njoku	06°52'09.33"N; 07°24'31.92"E
44	Eni Njoku/Mbanefo	06°52'09.25"N; 07°24'43.55"E
45	Mbanefo street	06°52'13.48"N; 07°24'44.38"E
47	Magarette 1	06°51'27.56"N; 07°24'06.15"E
48	Magarette 2	06°51'26.03"N; 07°24'18.27"E
49	Magarette 3	06°51'26.77"N; 07°24'27.77"E

2.4. Route separation

The road network under study was separated into two major routes, according to the imaginary two geographical zones of the community. This step was taken to make realistic application of the functions of the ACO algorithm. The community was idealized as having two existing depots in the Northern path and two depots in the Southern part. The researchers decided to analyze the shuttle service in two discrete domains called the Northern and Southern zones. There are intersecting nodes between the two zones where customers can easily switch over to shuttles plying the opposite zone. It should be noted that shuttles are not constrained to follow either of the above routes at the time of the study. Drivers are at liberty to drop off and pick up passengers irrespective of shortest base depot or route. The convenience of the driver is considered first in determining the order in which customers are dropped off or picked up. This presentation proposes a fixed depot-route system for shuttles for maximum benefit of all concerned. The proposed tour-routes of the shuttles in both zones are presented in the subsections to follow. The numbers of the bus stops are combined with the directional arrows to indicate the node-to-node movement of the shuttle in each route. As presented in Table 1, the numbers were assigned to the nodes during geographical coordinate definition to ease identification.

2.4.1. Northern zone nodes

The Northern zone area of the Campus community is made up of the bus stops presented in figure 5. The most feasible travel route is shown below:

B31 → B32 → B33 → B34 → B35 → B36 → B37 → B38 → B39 → B40 → B41 → B42 → B43 → B44 → B45 → B46 → B15 → B16 → B17 → B18 → B19 → B20 → B28 → B29 → B30.

2.4.2. Southern zone nodes

This region shown in figure 6 comprises the following bus stops and shuttle travel path:

B1 → B2 → B3 → B4 → B5 → B6 → B7 → B8 → B9 → B10 → B11 → B12 → B13 → B14 → B15 → B16 → B17 → B18 → B19 → B20 → B21 → B22 → B23 → B24 → B25 → B26 → B27 → B47 → B48 → B49

3. Data analysis using ACO algorithm

The data collected were analyzed using descriptive statistics, the conversion methods and the ACO algorithm. As presented in literature (Arias-Rojas et al., 2012), Ant Colony Optimization employs a meta-heuristic procedure which is normally actualized using the dependence of equation (1) through equation (3). The algorithm is essentially part of several Bio-mimicking analytic processes. The organism and process mimicked is the movement of Ants in search of food source. Two interesting characteristics of Ants are put to advantage in implementing the ACO algorithm: the transition and update rules.

1. Transition rule

There are two identifiable null hypotheses associated with ants and choice of a profitable (feasible) node in searching for food. With no regards to the errors inherent in each choice, the null hypotheses can be summarized as:

H₀: The ant chooses the next feasible node with reduced travel distance and time

H₁: The ant fails to choose the next feasible node with reduced travel distance and time.

Suppose at the i – 1th and ith nodes, H₀ was accepted, then the probability that the kth ant at the ith node will choose a feasible node at the next node, j, is given by equation (1).

$$p_c\{j|i\} = \frac{\tau_{ij}^\alpha \eta_{ij}^\beta}{\sum_{l \in N_{i,c}} \tau_{il}^\alpha}, \forall j \in N_{i,c} \tag{1}$$

Where:

τ_{ij} = pheromone density of edge (i, j)

η_{ij} = visibility of the edge (i, j)

α, β are the information heuristic factor and the visibility heuristic factor respectively

2. Update rule

Ants formally at the ith node cannot determine the best route to get to jth node with certainty. In other words, Ants continue to negotiate various paths to node j until the shortest travel distance to the new node is identified. The easiest decision tool for identifying shortest route is checking the amount of pheromone concentration in all the experimented paths. The concentration of the pheromones also referred to as pheromone density on specific trails can be updated per cycle. The amount of the added information in the cycle ($\Delta\tau_{ij}$), can equally be updated. Equations (2) and (3) can be employed to effect the updates.

$$\tau_{ij}(t + 1) = \rho \times \tau_{ij}(t) + \Delta\tau_{ij} \quad \rho \in (0,1) \tag{2}$$

$$\Delta\tau_{ij} = \sum_{k=1}^p \Delta\tau_{ij}^k \tag{3}$$

Where:

ρ = the residual pheromone coefficient

$\Delta\tau_{ij}^k$ = the additional pheromone contribution of the kth Ant while on edge (i, j)

The ACO process, including the type presented in this paper, is implemented in computerized systems using the dependence presented above, to search for shortest routes. ACO has default parameters with which the algorithm runs in computerized systems. The general parametric symbols presented in Table 3 are often used in most ACO systems register. The symbols retain original significances in this study. There was no need to alter the default parameters since the results obtained with in-situ values performed better than the ones obtained after attempted parameter adjustment. Values of the parameters are displayed in Table 4.

Table 3: Parameters Used in Ant Colony Optimization Systems

Symbol	Significance	Meaning
-r	--tries	number of independent trials
-s	--tours	number of steps in each trial
-o	--optimum	stop if tour better or equal optimum is found
-m	--ants	number of ants
-a	--alpha	alpha (influence of pheromone trails)
-b	--beta	beta (influence of heuristic information)
-e	--rho	rho: pheromone trail evaporation
-q	--q_0	q_0: probability of best choice in tour construction

Table 4: Values of Parameters Used for the ACO Implementation

Symbol	Significance	Value
-r	--tries	: 10
-s	--tours	: 100
-t	--time	: 10 /* seconds */
-o	--optimum	: 1
-m	--ants	: 200
-g	--nnants	: 20
-a	--alpha	: 1
-b	--beta	: 2
-e	--rho	: 0.1
-q	--q0	: 0.9
-c	--elitistants	: 100
-f	--rasranks	: 6
-k	--nnls	: 20
-l	--localsearch	: 3 /* use 3-opt */
-d	--dlb	: 1
-u	--as	: 0
-v	--eas	: 0
-w	--ras	: 0
-x	--mmas	: 1 /* apply MAX-MIN Ant System */
-y	--bwass	: 0
-z	--acs	: 0

1. Shortest route

The ACO algorithm used in the work has the capability of determining the shortest node to node path and best route from all alternative routes. The shortest node to node path among several other paths is considered as the feasible path in this study. This corresponds to the path that minimizes the distance covered by each shuttle.

a. Implementation of ACO algorithm for the routing phase

The routing phase is solved using ACO algorithm implementable in computerized systems. Each node, including DBNs is defined quantitatively in terms of the geographical coordinate (latitudes

and longitudes). The ACO algorithm makes use of Cartesian coordinates. This warrants that the data, as measured, must be preprocessed into a form acceptable by the ant colony algorithm software. The data were transformed into Cartesian coordinates system using equations (4) and (5).

$$X = R \cos(\text{latitude}) \cdot \cos(\text{longitude}) \quad (4)$$

$$Y = R \cos(\text{latitude}) \cdot \sin(\text{longitude}) \quad (5)$$

Where R is the approximate radius of the earth, assumed to be 6371 km

The various values obtained from the transformation, that is; Cartesian coordinates (x, y) were used for the ACO procedure. Successful implementation of the algorithm demands that a node must be visited only once and that routing must start at a node and end at the same node. The procedure resulted in rearranging some parts of the nodes to reduce travel time and increase shuttle mean distance coverage. Data codes were written for all the sections generated from the map. Its default parameters and the analyzed data are coded in Java and ran using an Intel (R) Pentium (R) 2.13 GHZ Personal Computer (PC) with 4.00GB RAM. The best routes were decided on the basis of shortest distance between a set of selected nodes in each section. Five different sections were created for the northern part of the community and three for the opposite part. The purpose of these sections is to properly incorporate DBNs in the most suitable zonal spots. Sample of the nodes and their corresponding codes for the implementation of ACO are presented in Table 5 and Table 6.

Table 5: Sample Nodes and Their Corresponding Codes as Used for the Northern Zone

Node location (B)	Corresponding Data code
40	1
39	2
38	3
37	4
31	5
35	18
34	19
33	20
32	21
50	22

Table 5 presents a sample of some nodes in the first section of the northern zone. The nodes denoted by B40, B50, B33, B32, B31, B37, B38 and B39 were used to write the ACO algorithm codes. The digits 1-22 represent the selected nodes for the first schedule with their Cartesian coordinates. There are several nodes in-between the selected ones displayed in Table 5. The idea is that if the shortest route is searched out and established for any section, then shuttles can drop off and pick up at the intermediate nodes. For clarification purposes, a sample of the codes used in obtaining optimal solutions are shown only for section one (1). All other sections received the same treatment.

i) Sample codes for the ACO implementation

NAME: section1

COMMENT: 5-node problem (UNN)

TYPE: TSP

DIMENSION Z: 5

EDGE_WEIGHT_TYPE: ATT

NODE_COORD_SECTION

1 6272.554 815.035

2 6272.625 814.809

3 6272.533 815.478

4 6272.573 815.241

5 6272.476 815.635

EOF

The above data codes together with the default parameters are coded in java and executed on an Intel (R) Pentium (R) 2.13GHZ Personal computer (PC) with 4.00GB RAM. In order to define the proposed routes for the first section, the algorithm was run and the best route selected.

The results are;

t_avgbest = 0.0

t_avgtotal = 3.0050000000000000

Best tour:

5

[3, 0, 4, 2, 1, 3]

From table 5, the best route is B33-B31-B37-B40-B33

The result of the first section showed that the algorithm took a total average time of 3.0050000000000000secs and an average best time of 0.0secs in moving round the selected nodes. The first shuttle terminal is B33.

4. Results and discussion

The results indicate that incorporating DBNs did not raise the cumulative distance traveled as would have been expected. It shows that the ACO algorithm is a powerful tool for use in searching for shortest routes amidst multiple competing alternative routes. The total distance travelled by shuttles in the existing trial and error combined with unplanned stoppages approach was seen to be higher than ACO with demand balancing nodes in all the depots and nodes. The summary of results obtained for both existing and proposed shuttle routing have been delineated and presented in figures 3 through figure 5.

4.1. Comparison of distances covered by both existing and proposed Shuttle route

1. Existing routes

The four different shuttle depots in the study area have been introduced. Shuttles starting from any of the depots visit the nodes in the routes without regards to any order. The individual nodal distances are summed progressively to arrive at the total travel distance in a particular route. The starting point is normally zero and the summation starts from the distance between the i^{th} node and $i + 1^{\text{th}}$ node and end with the distance at the origin which is zero. This method was used because each shuttle must start from a depot, visit each node once and come back to its starting point. There is no fixed depot for any shuttle in the existing model as any shuttle can cross carpet between depots and routes. The total distances covered by each shuttle starting from each of these depots are captured in figure 2. The Zik's flat depot route appears to be equal in length with the Franco depot route. The difference of 18.5m that separates them in figure 2 is a pointer that Franco depot route is not as short as might be thought. The two depots are separated by over 500 m in practice and shuttles from Zik's flat must cover the distance first before getting to Franco depot, where each brakes into separate routes. The Town depot route is the longest. It is located outside the school environment. The main gate depot has the shortest traveling distance. It is difficult to state categorically the route which shuttles from this depot will follow. Therefore, an average was obtained from all the possible routes during descriptive statistical analysis of the data.

2. Proposed demand balancing depot, nodes and routes

The tour order proposed for the shuttle with the DBNs incorporated was obtained using the ACO algorithm. The total distance involved in all the proposed routes were determined. Accordingly, the ACO results were corroborated with on-site measurements for the different routes in the zones. The node-to-node distances in both zones are presented in figure 3. Figure 3 is not a comparative

tool whereby the reader can be tempted to match the bars in the individual depots. The figure is only showing cumulative distances between arrays of nodes connected by a line (route). For instance, the Northern and Southern zone nodes are located in somewhat opposite areas of the school but are also related closely along the line of divide.

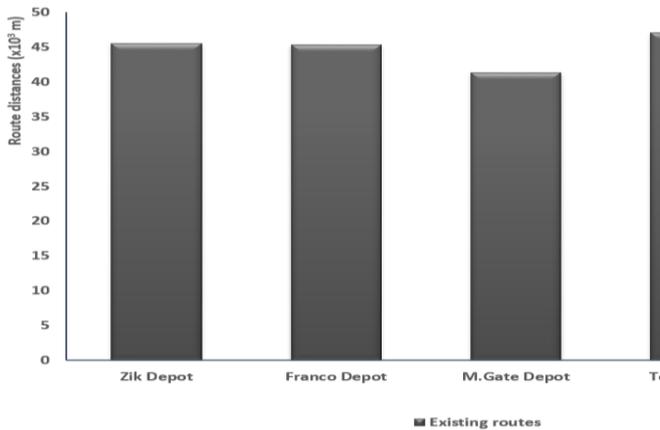


Fig. 2: Distances Covered by the Shuttle in the Existing Depots.

In particular, the two zones share common nodes in certain routes. It can be observed that the Southern zone route does not appear in Town and proposed Odim gate depots. This is a design strategy to reduce the complexities of modeling the traffic situations outside the school. For example, motorcycles still operate in the Municipality but stops customers outside the campus main gate. Other commercial vehicles in the Town can also drop off customers at the main gate. Customers can trek into the main gate depot to board shuttles into the Campus community. The main gate depot is like a shuttle hub where customers are most likely to spend minimum waiting time for boarding a shuttle. The researchers are of the view that guiding shuttles and customers outside the school by a monosyllabic route (Northern zone route or Southern zone route) can increase the waiting time and affect customer goodwill. It is recommended that the Town depot should primarily be a feeder depot to the main gate depot, where customers can break into guided routes. At the same time, customers from the Campus community should exit at the main gate depot and join the Town shuttles back to town. However, this category of shuttles (from Town depot) should be free to use any of the routes inside the Campus at no extra cost to the customers from Town. The same rule should apply to shuttles from the Campus depot that wishes to ply the Town depot. The fixed route with penalty of zero cost to shuttles on deliberate extension of scheduled distances will make the application of the results of this research seamless and effective. The brand new demand balancing depot, otherwise called Odim gate depot in figure 4 is proposed for improving the school shuttle system. The depot is an off-shoot of the study. Although, successful application of the results will cover the shuttle needs of customers from the area, as adequate DBN is now proposed. It should be stated that this will not necessarily eliminate the problem. Residents will still be subjected to waiting for passing shuttles from other depots which might not have needed to stop at the specific nodes. A fully loaded shuttle continues moving until a customer indicates exit interest. It is only when such exit happens at a node with a waiting customer that the new customer would board the shuttle.

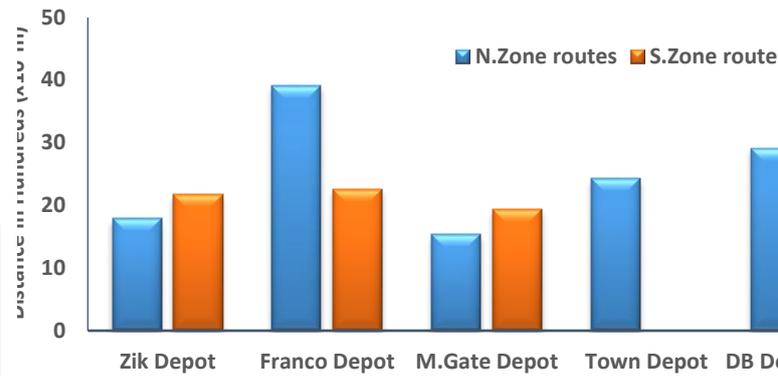


Fig. 3: Distances Covered by the Shuttle in the Proposed Model.

To ensure robust and efficient shuttle service that would account for such probabilistic instances, the researchers recommend the creation of the Odim gate depot as a feeder to the library node. It was observed that many customers from the other depots exit the shuttle at the library node. Secondly, the node is shared by shuttles from both main gate and Franco and Zik’s flat depots. The Odim gate customers can aboard the most suitable shuttle at the library node. Figure 4 presents the existing depots and routes alongside those from the research realities. From figure 4, the existing routes offer the longest distances in every depot, yet the allowable fares charged by the shuttle operators are the same. This implies that the new shuttle service model proposed in this research can reduce travel distance of the shuttles appreciably. It can equally increase shuttle value and reduce the hardship imposed on some sections of the Campus community by the proscription of all transport modes that has less than four wheels.

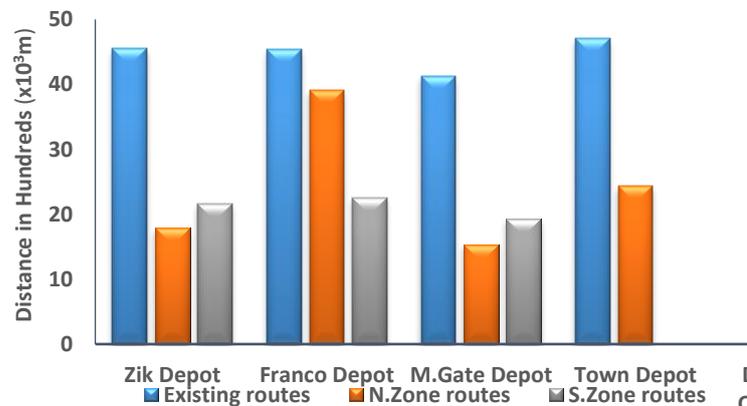


Fig. 4: Distances Covered by the Shuttle in All Three Scenarios.

From the foregoing, five demand balancing nodes were created for the Northern zone, namely; B33, B18, B20, B50 and B43. The Southern zone had three which include B49, B14 and B7. The research revealed the need for an additional shuttle depot for the studied area. This depot referred to as demand balancing depot have been proposed for the Odim gate end of the Campus community. The outcomes of the research make near uniformly distributed shuttles coverage of the Campus community possible. Most of the customers now have shuttle bus stops at strategic locations close to their area of concern. It is noteworthy that the demand balancing nodes did not increase the total transportation distance previously obtained for shuttles in each depot, rather the distances diminished. This can easily be translated to cost reduction on the part of the shuttles as well as quality service to the Campus community.

5. Conclusion

Campus communities in some developing countries are predisposed to multiple modes of transport services (vehicle, motorcycle, tricycle). The security concerns in such area can lead to prohibition of one or more of the existing systems with a consequent unbearable hardship to the community. A typical case where motorcycles and tricycles were banned from entering the campus is studied. A Biomimicry descent widely known as Ant colony optimization have been explored to propose new shuttle routing system, which palliates the harsh effects of the ban on motor cycles that carried passengers from shuttle stops to residences. It was possible to locate shortest distance nodes nearer to residences with the methodology used in the work. A wider coverage of customer-shuttle needs have been guaranteed by the success of the study. The study has also satisfied its cleavage of providing a good shuttle routing plan for the Campus with the aid of Ant Colony Optimization and demand balancing nodes. The approach have been applied to a specific example namely; Shuttle routing problem in a Nigeria public University Community. From the analysis of all the data collected for the study, five and three additional shuttle terminals were created for the hypothetical Northern and Southern zones of the Campus respectively. The distances travelled by the shuttles in the new routes varied from a minimum of 1537.64m to a maximum of 3912.27m in the Northern zone. The mean route distance in the zone is 2509.25m. Similarly, the Southern zone routes have its distances varying from 1932.43m to a maximum of 2260.8m, with a mean route distance of 2120.42m. Comparatively, the shuttle route distances in the existing routes varied from a minimum of 4134.55m to a maximum of 4706.08m with a mean route distance of 4481.99m. The results show that an average distance reduction of 44% was observed for shuttle routes in the Northern zone. The results also show that average distance reduction of over 52% is obtainable for shuttle routes in southern zone. The results of this study, apart from being capable of streamlining shuttle service in the studied location, also provided wider coverage of all customers needing shuttle service. Every area of the campus have been provided with optimum shuttle vehicle coverage and efficient transport service. It can be seen that provision of demand balancing nodes and use of ant colony optimization algorithm are very good means of service improvement for school shuttle services under stochastic transport modes.

This paper opens the avenue to the following concerns that were not considered in the research. Other variants of Biomimicry VRP with time windows and removal of the prohibited routes can be explored, and the results compared to what obtains in this study. A model with time windows which can provide efficient shuttle service on intermediate routes to reduce passenger waiting time, especially during peak hours of the day can equally be labored upon.

Acknowledgement

The material and financial assistance of the TWAS-NRF fellowship: award number PD-TWAS160531166951; UID: 105554, towards this research are hereby acknowledged. The support of University of Nigeria Nsukka towards the completion of the work cannot be overemphasized. However, opinions expressed and conclusions arrived at, are those of the authors and are not necessarily to be attributed to the acknowledged bodies.

References

- [1] Abdulkadera, M.M.S., Gajpalb, Y., ElMekkawy, T.Y., (2015), Hybridized Ant colony algorithm for the multi compartment vehicle routing problem, *Applied Soft Computing*, 37, 196–203. <https://doi.org/10.1016/j.asoc.2015.08.020>.
- [2] Alves, D., Van, J., Cong, Z., Shutter, B., Babuska, R., (2010), Ant colony optimization for traffic dispersion routing, *Proceedings of the 13th International IEEE conference on Intelligent Transportation systems*, 683–688. <https://doi.org/10.1109/ITSC.2010.5625146>.
- [3] Androutsopoulos, K.N., Zografos, K.G., (2017), An integrated modeling approach for the bicriterion vehicle routing and scheduling problem with environmental considerations, *Transport research part C, Emerging Technologies*, 82, 180–209. <https://doi.org/10.1016/j.trc.2017.06.013>.
- [4] Arias-Rojas, Fernando, J., Montoya, J., (2012), Solving of School Bus Routing problem using Ant colony Optimization, *EIA*, 17, 193–208.
- [5] Ashok, L., Messinger, W., (2012). A spectral image clustering algorithm based on Ant colony optimization, In Shen, S. S., Lewis, P. E. (Ed.) *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultra spectral Imagery XVIII*, In *Proceeding of SPIE 2012 Vol. 8390, 83901P* CCC code: 0277-786X/12/\$18 <https://doi.org/10.1117/12.919082>.
- [6] Bin, Y., Zhong-Zhen, Y., Baozhen, Y., (2009), An improved Ant colony optimization for vehicle routing problem, *European Journal of Operational Research* 196, 171–176. <https://doi.org/10.1016/j.ejor.2008.02.028>.
- [7] Bulhoes, T., Ha, M.H., Martinelli, R., Vida, T., (2017), the vehicle routing problem with service level constraints, *Production, manufacturing and logistics, European journal of operational research*, 000 (article in press), 1–15, <http://dx.doi.org/10.1016/j.ejor.2017.08.027>.
- [8] Cheng, C-Y., Chen, Y.Y., Chen, T.L., Yoo, J.J-W., (2015), Using a hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem, *Int. J. Production Economics*, 170, 805–814. <https://doi.org/10.1016/j.ejor.2017.08.027>.
- [9] Christofides, N., Mingozzi, A., Toth, P., (1979), the vehicle routing problem, in: N.Christofides, A. Mingozzi, P. Toth, C. Sandi (Eds.), *Combinatorial Optimization*, Wiley, Chichester, 1979, 315–338. <https://doi.org/10.1016/j.jipe.2015.03.021>.
- [10] Dorigo, M. and Gambardella, L. (1997), Ant colonies for the traveling salesman problem, *BioSystems*, vol.43, no.2, pp.73–81.
- [11] El Yakine, K.N., Mena, M., Hasni, M., Boudour M., (2017), Using differential search algorithm for solving optimal frequency regulation problem in interconnected power system, *International Journal of Bio-Inspired Computation* 9, (3), 182, [https://doi.org/10.1016/S0303-2647\(97\)01708-5](https://doi.org/10.1016/S0303-2647(97)01708-5).
- [12] Ezzatneshan A., (2015), Vehicle routing optimization using spanning tree and Ant colony, *Visi journal Akademik*, 6, 107–115. <https://doi.org/10.1504/IJBIC.2017.083719>.
- [13] Gao, S., Wang, Y., Cheng, J., Inazumi, Y., Tang, Z., (2016), Ant colony optimization with clustering for solving the dynamic location routing problem, *Applied Mathematics and computation* 285, 149–173.
- [14] Huber, S., Geiger, M.J., (2017), Order matters - A variable neighborhood search for the swap-body vehicle routing problem, *European journal of operational research*, 263, (2), 419–445. <https://doi.org/10.1016/j.amc.2016.03.035>.
- [15] Kuo, R.J., Wibowo, B.S., Zulvia, F.E., (2016), Application of a fuzzy ant colony system to solve the dynamic vehicle routing problem with uncertain service time, *Applied Mathematical modeling*, 40, 9990–10001. <https://doi.org/10.1016/j.ejor.2017.04.046>.
- [16] Mavrovouniotis, M., Yang S., (2015), Ant algorithms with immigrants schemes for the dynamic vehicle routing problem, *Information Sciences* 294 (2015) 456–477. <https://doi.org/10.1016/j.apm.2016.06.025>.
- [17] Narasimha, K.V., Kivelevitch, E., Sharma, B, Kumar, M., (2013), an ant colony optimization technique for solving min–max multi-depot vehicle routing problem, *Swarm and evolutionary computation*, 13, 63–73. <https://doi.org/10.1016/j.ins.2014.10.002>.
- [18] Nogueira, K., Aquiar, P., Weigang, L., (2014), Using Ant algorithm to arrange Taxiway sequencing in Airport, *International journal of computer theory and engineering*, 6, (4) 357–361. <https://doi.org/10.1016/j.swevo.2013.05.005>.
- [19] Polat, O., (2017), A parallel variable neighborhood search for the vehicle routing problem with divisible deliveries and pickups, *Computers & Operations research*, 85, 71–86.
- [20] Reed, M., Yiannakou, A., Evering, R., (2014), An Ant colony algorithm for the multi-compartment vehicle routing problem, *Applied soft computing*, 15, 169–176. <https://doi.org/10.1016/j.cor.2017.03.009>.
- [21] Sevkli A.Z., Guler, B., (2017), A multi-phase oscillated variable neighbourhood search algorithm for a real-world open vehicle routing problem, *Applied soft computing*, 58, 128–144. <https://doi.org/10.1016/j.asoc.2013.10.017>.

- [21] Sharma, J.K. (2005) Operations Research: Theory and Applications, 2nd ed., Macmillan India Ltd., Rajiv Beri, 2/10 Ansari road, Dar-yanganj, New Delhi. <https://doi.org/10.1016/j.asoc.2017.04.045>.
- [22] Wu, W., Tian, Y., Jin, T., (2016), A label based Ant colony algo-rithm for heterogeneous vehicle routing with mixed backhaul, *Ap-plied soft computing*, 47, 224-234.
- [23] Zhang, M., Zhang, Y., (2017), Ant colonial-based approach for the minimal full trie problem, *International Journal of Bio-Inspired Computation* 9(4):235. <https://doi.org/10.1016/j.asoc.2016.05.011>.
- [24] Zhang, M., Zhang, Y., (2017), Ant colonial-based approach for the minimal full trie problem, *International Journal of Bio-Inspired Computation* 9(4):235 <https://doi.org/10.1504/IJBIC.2017.10005264>.