Application of The Spider Monkey Optimization Algorithm In A Class Of Traffic Delay Problem

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Abstract
Nature inspired algorithms have gained some level of popularity amongst researchers in recent times. They possess the ability to search and discover solutions to real-world optimization problems, which may have been difficult to solve using deterministic techniques. Spider Monkey Optimization (SMO) is in a class of such algorithm. It is one of the most recent Swarm Intelligence (SI) based algorithm, that was developed through the study of the food foraging behavior of a group of spider monkeys that mimic the Fission-Fusion Social System (FFSS) behavior. This study applies SMO to traffic delay minimization problem. Experiment includes simulation of 4-legged intersection and the result showed minimization of total travel time. This result was compared to the Artificial Bee Colony (ABC) algorithm. The SMO outperformed the ABC algorithm because of its decentralized, stochastic and self-organizational attribute that makes it suitable for the nature of traffic networks. Computer simulation results show that this method performs better when compared with conventional fully actuated control, especially under the condition of fairly saturated traffic condition.

Keywords — *Spider Monkey Optimization algorithm, Artificial Bee Colony optimization, traffic delay problem, Fission-fusion social structure.*

I. INTRODUCTION

Spider Monkey Optimization algorithm is a Swarm Intelligence (SI) algorithm that was developed and inspired by the fission-fusion social organization of spider monkeys. It is a subclass of swarm intelligence based on the intelligent forging nature of spider monkeys and was developed by J.C Bansal et al in 2014. Swarm Intelligence is a meta-heuristic technique in the field of AI that is used to find solutions to difficult optimization problems. The collective decentralized behavior of social insects, flocks of birds, swarms of bees or schools of fish in their natural habitat is being studied in this AI domain. Swarm Intelligence (SI) algorithms can be applied to find solution to real combinatorial optimization problems in different domains of engineering and science. It has been proven in earlier research that solution to real-world optimization problems could be discovered by algorithms based on swarm intelligence.

The social organization of spider monkeys is related to fission–fusion social system (FFSS) thus, the SMO algorithm can be better explained in terms of FFSS. A fission-fusion social system is one in which the size and composition of the social group or animal continuously change as time progresses and as the animals' forage for food, they merge (fusion) or split (fission) as the need arises.

The objective of optimization could either be to minimize the cost of production or to maximize the efficiency of production. An optimization algorithm is a procedure which is executed iteratively by comparing various given solutions till an optimum or a satisfactory solution is found. With the advent of computers, optimization has become a part of computer aided design activities. There are two distinct types of optimization algorithms widely used today.

1. Deterministic Algorithms: They use specific rules for moving one solution to other. These algorithms are in use today and have been successfully applied to many engineering design problems.
2. Stochastic Algorithms: The stochastic algorithms are in nature a probabilistic translation rule. They are gaining popularity due to their unique properties which deterministic algorithms does not possess.

This research presents an evaluation of the Spider Monkey Optimization Algorithm for a class of traffic delay problems.

II. RELATED WORK

We summarize in this section previous works based on swarm intelligence and adaptive traffic signal control. A repetitive algorithm was developed by Charlesworth and Charlesworth (1975) that is based on the TRANSYT8 traffic signal timing technique in order to determine the cost-traffic relationship curve through simulation and estimation of traffic delays in various traffic conditions. An effective control of signalized traffic can significantly reduce vehicle delays at busy road intersections by enhancing the operational efficiency of urban road network and also balance the rate of traffic flow

(Dafermos, 1980). In practical terms, it has been found that there is consistency between travel times distributions related to a road network that is locally affected by poor traffic signal timing and time/space spatial distributions of traffic flow on a modern road network (Aashtiani et al., 1981; SIAM, 1981). A heuristic algorithm was introduced by Marcotte (1983) in order to develop solutions for models that targets a small-scaled road network. An intersection signal optimization model was introduced by Magnanti and Wong (1984) through the adjustment of traffic signal control parameters which includes the green time splits, cycle time, phase sequences and offsets. Several optimization models that address issues between subordinate and superior about feedback and management was compared by Fisk and Schneider (1984. In the model, the signal controlling system dealing with road traffic signals and adaptive response to traffic volume changes is referred to as superior. According to Wardop's first principle, the ability of travelers to choose an optimal route convenient for them is regarded as subordinates.

A substantial research was conducted by Smith et al. (1985) on the assignment of traffic and the optimization of the timing of the signal. In the research, an equilibrium model for road network was developed to simulate an adaptive control system for traffic. This aided in identifying the weakness of using minimum sum of travel time as the evaluation benchmark to measure performance of the traffic control system.

A repetitive optimization model was proposed by Cascetta and Cantarella (1991) which could be applied to a wide-area road traffic. This model relies on conventional signal timing techniques such as the Webster method. The experiment from this research showed that the efficiency of operation of a road traffic network was not significantly improved. On the alternative, a performance measure of road traffic network that relies on the capacity of traffic was proposed. Yang and Yagar (1995), while considering some traffic factors like traffic delays at intersections owing to signal control and delay as a result of queuing, utilized a programming model with multi-level to find solution to the problem of traffic signal timing and assignment optimization. The identification of the optimal green time for a given cycle time was used to formulate the optimization models.

The correlation between the choice of traveller's road path behavior and road traffic signal control was studied by Allsop and Turner (1986). Knowledge that was gained from this study shows that it is possible to increase traffic signal timing plans' stability. Afterwards, the traffic signal timing equilibrium was studied. Focus of some of the studies was on the optimization of the measure of the operation performance of road signal timing system and relied on traffic flow distribution and travel route. This was then used to design an optimal signal control plan for road network intersections.

A. ABC algorithm in traffic delay problem

The Artificial Bee Colony algorithm is one of nature-inspired algorithms based on swarm intelligence. It was proposed by Lucic´ and Teodorovic´ (2001) and it has been applied effectively to a wide range of optimization problems that are real life. It is considered to be in a class of population-based algorithms that employs the random-search method. The analogy of its adopted technique relies on the strategy adopted by bees in their search for good food source and the method used by optimization algorithms to search for an optimal solution of the considered optimization problem.

A wide area modern traffic control system that is based on ABC optimization method was developed by Jovanovic et al (2017). To find the optimal cycle time, green time and offset, the algorithm was employed to minimize the total travel time of road users travelling through the considered signalized intersections. The set of numerical experiments was performed on well-known traffic benchmark network. The numerical experiments of the ABC yielded results that was evaluated with the results obtained by Simulated Annealing.

B. ACO algorithm in traffic delay problem

ACORSES is an Ant Colony Optimization (ACO) based algorithm that was proposed by Baskan, O. et al (2009) for discovering the optimum signal parameters in a co-ordinated signalized road network for a given set of fixed link flows. It is one of the most recent additions to the list of approximate optimization techniques. The interesting idea of ACO is that it uses an indirect local means to communicate with other members of the artificial ant population. The crux of the ant's behaviour is the use of chemical substance called pheromones that it leaves on it trail as a means of communication with other members of the group. This enables the ant to find the shortest possible path from its nest to food sources. This particular behaviour of real ant colonies is studied and applied in solving optimization problems. The algorithm relied on individual ants restricting their search in the neighbourhood of the best possible solution of the last iteration in a reduced search space. At the centre of modern traffic management is the optimization of the signal timing control. Factors of interest in traffic signal timing control includes rate of fuel consumption, environmental pollution, queueing method, and traffic delay. The optimization of these factors is considered multi-objective. The use of optimization methods to determine optimal signal timing for a road network with signal control has been an area of interest to researchers for decades. Owing to the complexity of Area Traffic Control

(ATC) problem, it has become necessary to introduce new techniques to enhance the efficiency of the signal timing in a road network with signal control. To enhance safety and reduce traffic congestion traffic signals are utilized to manage the movement of vehicles and also enable some traffic management strategies to reduce the pollution of the environment and minimize delays Teklu, F. et al (2007). Traffic signal timing systems that manage intersections operate based on the type of the intersection. While it is fairly easy to optimize the signal control of an isolated intersection, more research is required in the optimization of coordinated traffic network signal timing. This is owing to the "offset" factor. The Webster, F. V. (1958) method which is one of the early signal control method considered only an isolated signalized intersection.

III. MATERIALS AND METHODS

Owing to the descriptive nature of this study, a qualitative research approach was adopted as the preferred methodology. Traffic and geometric data were picked at the traffic intersections of GRA junction and Waterlines junction in Portharcourt city respectively. Data of interest gathered include vehicles flow rate, capacity of each of the link, length of the road, number of vehicles crossing each of the intersection approach every hour, and the total number of lanes at each intersection. The intersection selected for the study is a typical signalized intersection (4-leg intersection or T-leg intersection). The objective is to find, using the data gathered, the optimal cycle time that will yield a minimal delay at each of these intersections. The current timing plan at each of these intersections is fixed. This means that these intersections have the same cycle length and thus the total time for each phase of the signal timing plan is the same. To address the problem of designing an adaptive signal timing control, we will find an optimal cycle time that will lead to a minimal delay at each of these intersections.

A. Traffic network model

Modelling traffic flow has been a subject of interest in the area of traffic management. Correct prediction of traffic flow behavior given an initial variable set of data, then by adjusting flow in critical areas can help maximize the general throughput of vehicular traffic along the road link. This is of particular interest in areas of high traffic density which may be caused by high volume peak time traffic or the closure of one or more lanes of adjoining roads.

The traffic network model (Fig. 1) considered in this study operates such that vehicles approach and fill the road network link by link. The number of vehicles at the upstream intersection determines the number of vehicles at the downlink intersection.

The total number of vehicles on link I4-I5 is equal to the sum of vehicles coming from the uplink intersection I4: vehicles from lane G, vehicles from shared lane B, and vehicles from shared lane D. The total number of the vehicles on the link I4-I5 is distributed among link lanes at the downlink intersection.

In computing the total travel time (TTT), the following is considered:

- Saturation flow rate
- Capacity
- v/c ratio

For the purpose of conducting an analysis for the intersections, input parameters provided include:

t_{ij}^{0} – the travel time [s] of lane (i,j) given a free flow traffic condition, which evaluates to:

I_{ij} – the actual length [m] of lane (i,j)

v_{ij} – the free flow speed [m/s] of lane (i,j)

q_{ij} – the total number of vehicles on lane (i,j) [veh/h]

c_{ij} – the design capacity of lane (i,j) [veh/h]

α - 0.15

β – 4

T – duration of analysis period [h]

PFk – the progression adjustment factor of the k-th lane or the offset

C – the cycle length [s] of the intersection

gk – length of green time of the k-th lane [s]

B. Determining saturation flow rate

When calculating delays and level of service for intersections, it is very imperative to use the correct saturation flow rates for the particular traffic condition under consideration. It describes the number of vehicles in a traffic flow that is dense for a particular group of lanes. Simply put, saturation flow rate is the total number of vehicles that passes an intersection if the traffic signal was to remain green for an hour and traffic at the intersection is heavily congested. The Highway Capacity Manual (TRB, 2000) recommends a saturation flow rate of one thousand nine hundred (1900) vehicles per hour per lane as an ideal saturation flow rate.

In order to calculate the saturation flow rate of a lane in a particular intersection, the following equation is used:

$$s = \frac{3600}{h_s}$$

where:

s= the saturation flow rate;

3600=an hour in seconds;

h_s= saturation headway i.e distance between vehicles in a road network measured in time or space.

C. Determining capacity and v/c ratio

Another variable to be determined when calculating delays is capacity and v/c ratio. Capacity of traffic is the maximum density of traffic that a road can allow at a given speed without delay. Saturation flow and saturation flow rate are the two factors that determine the capacity of signalized intersection. The following equation was used to calculate the capacity of each lane of the studied intersections.

$$c_i = s_i \frac{g_i}{C}$$

where:

$\frac{g_i}{C}$ = effective green ratio for lane group i

s_i= the saturation flow rate for the lane group i

Degree of saturation is used to describe the traffic volume to intersection capacity ratio and is represented by the symbol.

$$X_i = \left(\frac{V}{C}\right) i = \frac{V_i}{S_i\left(\frac{g_i}{C}\right)}$$

where:

vi – the design flow rate for lane group i

si – the saturation flow rate for lane group i

gi – the effective green time for lane group i

C – the intersection cycle length

When analysing an intersection, it is very important to determine the lane group with highest v/s ratio. This is the lane group that demands longer green light. This means, each phase will have one critical lane group.

D. Formulating the objective function

Based on specification of HCM 2000, the vehicle control delay dCij on the link(i,j) equals:

$$dC_{ij} = \sum_{k \in K} \alpha_{k_{ij}} . (d_{1k} . (PF_k) + d_{2k})$$

K is used to denote the total number of lanes at the considered intersection.

where

$$d_{1k} = \frac{0.5.C.(1 - \frac{g_k}{C})^2}{1 - [min(1, X_k).\frac{g_k}{C}]}$$

$$d_{2k} = 900T[(X_k - 1) + \sqrt{(X_k - 1)^2 + \frac{4.X_k}{C_k T}}]$$

where

α_{kij} = 1 if k-th lane belongs to the link(i,j), and 0 if otherwise

T – the duration of the analysis (h),

PF_k – the progression adjustment factor in the k-th lane. Adjustment factor for the effect of the progression quality in coordinated systems.

c_k – the road capacity of the k-th lane (veh/hr)

C – the intersection cycle length (s)

g_k – the length of green time in the k-th lane (s)

X_k – the degree of saturation of the k-th lane,

$d1_k$ – delay as a result of uniform arrival pattern in the k-th lane (s/veh)

$d2_k$ – delay as a result of random arrival pattern in the k-th lane (s/veh)

The uniform delay equation (d1k) gives an estimate of the delay in the signalized intersection assuming a uniform arrival pattern, stable flow, without initial traffic queue. It is based on the Webster's delay formulation and now generally accepted as an accurate representation of delay for an ideal uniform arrival.

The incremental delay equation (d2k) is used to estimate the incremental delay due to non-uniform arrival pattern and random delay as well as delay caused by sustained periods of over-saturation.

PF shows the progression quality and depends on the amount of all vehicles arriving during green time at j-th intersection. In order to calculate PF, it is necessary to determine the offset of the road link, the speed of the vehicle at the link, and the ratio of green time and cycle at the j-th intersection on the link.

The travel time of vehicles on the link(i,j) is denoted by t_{ij}. The travel time is calculated using the webster formula below:

$$t_{ij} = t_{ij}^0 [1 + \alpha (\frac{q_{ij}}{C_{ij}})^\beta]$$

where

t_{ij}^0 – the travel time [s] of lane (i,j) given a free flow traffic condition, which evaluates to:

I_{ij} – the actual length [m] of lane (i,j)

v_{ij} – the free flow speed [m/s] of lane (i,j)

q_{ij} – the total number of vehicles on lane (i,j) [veh/h]

c_{ij} – the design capacity of lane (i,j) [veh/h]

α - 0.15

β – 4

The total travel time of all network users travelling through signalized intersections is represented by the objective function and bears the following form:

$$TTT = \sum_{(i,j) \epsilon A} TTT_{ij} = \sum_{(i,j) \epsilon A} q_{ij} . d_{ij}$$

and

$$d_{ij} = dC_{ij} + d\theta_{ij} + t_{ij}$$

where

A – the total number of links in the considered traffic network,
(i,j) – the road link that connects node i to j.
dij – the total travel time of vehicle at the link (i,j) (s/Veh)
tij – the travel time at link (i,j) [s]
qij – the number of vehicles currently at link (i,j) [Veh/h]

E. The Spider Monkey Optimization (SMO) approach to travel time minimization problem

The task is to discover good solutions i.e optimal or near-optimal values of the signal control variable (cycle length) by minimizing the total travel time of all road users travelling through a signalized intersection. We assume that signal phasing is given for every road intersection under consideration.

The approach that is proposed for the Spider Monkey Optimization (SMO) is based on the improvement concept. At the beginning of the solution search, all the spider monkeys are all together in a cluster. We first generate the initial feasible solution i.e initial signal plan. The next step is to investigate the solution space in the neighborhood of the current solution and then try to improve the solution.

We need to generate a good enough initial solutions in order to speed up the optimal solution search process. The spider monkeys begin their search from the generated initial solution. The generate the initial solution, the following algorithm is followed:

1. Find the cycle time value.
2. Apportion to all the intersections phases a green time..
3. Find the value of the offset.

Firstly, the cycle time for the critical intersection is calculated by using the Webster's method below.

$$C = \frac{1.5L + 5}{1 - Y}$$

where L=total lost time per cycle, usually taken as the sum of the inter-green periods (sec).

L=2n+R

where

n = number of phases
R = all red time
Y = V/s = Ratio of the design flow rate to the saturation flow rate for the critical approach or lane in each phase.

In the second step we calculate the green time for all the phases at all the intersections under consideration by using the Webster's method. Signal setting for effective green periods (g) should be in proportion to the y values on each approach, with an allowance for lost time.

$$\frac{g1}{g2} = \frac{y1}{y2}$$

$$g = \frac{y(c - L)}{Y}$$

where

g = effective green period
y = flow factor i.e ratio of design flow rate to saturation flow rate
c = cycle time
L = total lost time
Y = sum of y flow factors
c-L = total effective green time

Therefore:

$$g1 = \frac{y1(c - L)}{Y}$$

$$g2 = \frac{y2(c - L)}{Y}$$

In step 3, we calculate offset with relation to the Performance Index (PI) of the link under consideration. The performance index PIij of the link (i,j) represents product of the link flow qij and the link travel time tij.

$$PI_{ij} = q_{ij}.t_{ij}$$

where

t_{ij} = travel time at the link (i,j)
q_{ij}= number of vehicles at the link (i,j)

Algorithm 1: The SMO algorithm

1. Initialize the population.
2. Calculate the fitness, that is, how far each spider monkey is from the food sources.
3. Using the greedy selection method, select global and local leaders.

while (criteria for loop termination is not met) do

(i) To find the objective i.e the Food Source, generate for all the group members a new position by employing the use of self-experience, the local leader experience and the experience of the group members.

(ii) Based on the fitness of the group members, apply a greedy selection process.

(iii) Calculate the probability for all the group members.

(iv) Using self-experience of group members and global leader, generate new positions for all the group members.

(v) Apply greedy selection on the groups to update the position of local and global leaders.

(vi) If for a predefined number of times (LocalLeaderLimit) any Local leader in the group is not updating its position then all the members of that group should be re-directed for foraging.

(vii) If for a predefined number of times (GlobalLeaderLimit) the global Leader is not updating its position then the group is divided into smaller groups with a minimum size of 4 for each group.

end while

F. Testing the SMO algorithm on traffic network

The SMO algorithm was tested on the traffic network model in Fig.1. The traffic network consists of two (2) intersections and 7 links. The saturation flow and design vehicle flow in all lanes for each intersection in the network is given in Table 1. The lanes are denoted by capital letters A,B,C,D…. The first column holds the values for the vehicle flows [veh./h], while the second column holds data related to the saturation flow [veh./h]. Other values for the test are as below:

- The allowed cycle time as expressed in the optimization constraint i.e the minimum Cmin and maximum Cmax cycle length allowed. Values for Cmin and Cmax are 45s and 120s respectively.
- The Lost time within a cycle at all the intersections is 9s.
- Traffic link capacity is 2500 veh per hour per link.
- The free flow speed is 20m/s or 72km/h.
- Length of each lane is 500m
- Saturation flow rate is 2500 veh/hr for each link
- Design flow rate is 2000 veh/hr for each link

Table 1 shows the values for traffic volume and link capacity used for the test. Traffic volume is the number of vehicles crossing a section of the signalized intersection per unit time at any selected period. Capacity of a link on the other hand is the maximum hourly rate at which vehicles can move in a reasonable order of a lane of road, during a period of time under a particular traffic condition.

To determine the parameters of the SMO and ABC during the optimization, the test was performed as presented in Table 2. Four values of the number of spider monkeys/bees (10,20,40,80) was used respectively. Number of runs per test was set at 10 and number of iterations was set at 30 iterations per run. Each of the combinations of the parameters was tested three (3) times and the best value of the objective function obtained among all combinations was chosen and shown in the Table 2. The total CPU time for all the tests was 2.5min. As can be observed, the best solution was acquired in the case of 80 spider monkeys and bees respectively. This value for the SMO parameter was used as the objective function value for further tests.

The results of the experiment are as given in Table 3. The best SMO solution has an objective function value of 122.5570595, while the best ABC solution has an objective function value of 123.9190656. The SMO solution is clearly better than the ABC solution. It has a difference of 1.3620061 (1.11%).

G. Evaluation of results

From the result obtained from the SMO procedure as shown in Table 3 where the objective function value obtained from SMO was compared to that obtained from ABC, it clearly shows that as far as traffic congestion travel time minimization is concerned the SMO algorithm is better than the ABC. The best SMO solution has an objective function value of 122.5570595, while the best ABC solution has an objective function value of 123.9190656. It has a difference of 1.3620061 (1.11%). However, as seen in Table 3, the ABC algorithm is faster in execution compared to SMO. For the same set of traffic data, ABC can execute in 33.3% of time taken by SMO to execute. The time reduction was so negligible and thus was not considered as worth the effort. This is left for further research and improvement.

The result of the research also shows a better mean error and standard deviation for SMO when compared to ABC. The reason for this could be deduced from Table 2 where the best objective function value for SMO and ABC were obtained for different population sizes (10,20,40,80). While SMO achieve a better and more consistent reduction in the objective function value, the ABC is less consistent with regards to objective value reduction. This also proves the reliability of SMO when applied to traffic congestion problem management especially in reduction of travel time.

In order to obtain the optimum cycle time for any given set of traffic data, the Webster's method was used to obtain the cycle time. As shown in Table 3, the obtained optimum cycle time for the given traffic data is 61s. These values are consistent for the two different optimization methods used. This implies that for the given set of traffic data, 61s is the optimum cycle time required to ensure that delay is reduced. Therefore, if a cycle time of 61s is applied to each of the intersections under study, the maximum delay for each vehicle at each of these intersections will be equivalent to 122.5s for SMO and 123.9s for ABC respectively

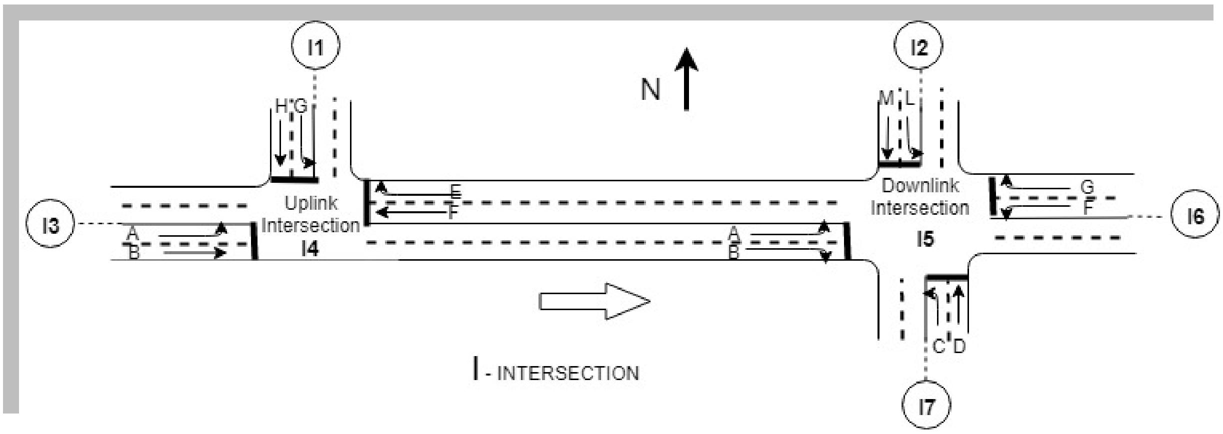

Fig 1: Traffic network model

Table 1: Traffic volume and lane capacity in the traffic network

GRA JUNCTION

i	A		B		C		D		G		F		M		L	
q_i/s_i	2050	2500	1900	2500	1950	2500	2000	2500	2100	2500	1900	2500	1980	2500	2030	2500

WATERLINES JUNCTION

i	A		B		E		F		H		G	
q_i/s_i	1750	2500	1800	2500	2000	2500	1820	2500	1900	2500	1900	2500

Table 2: Analysis of the SMO and ABC optimization parameters

Population Size	*Best Result (SMO)*	*Best Result (ABC)*
10	123.06669791544	124.320424448
20	122.83716207641	124.12001795523
40	122.64029193859	124.12658738872
80	122.5525202365	124.033786368

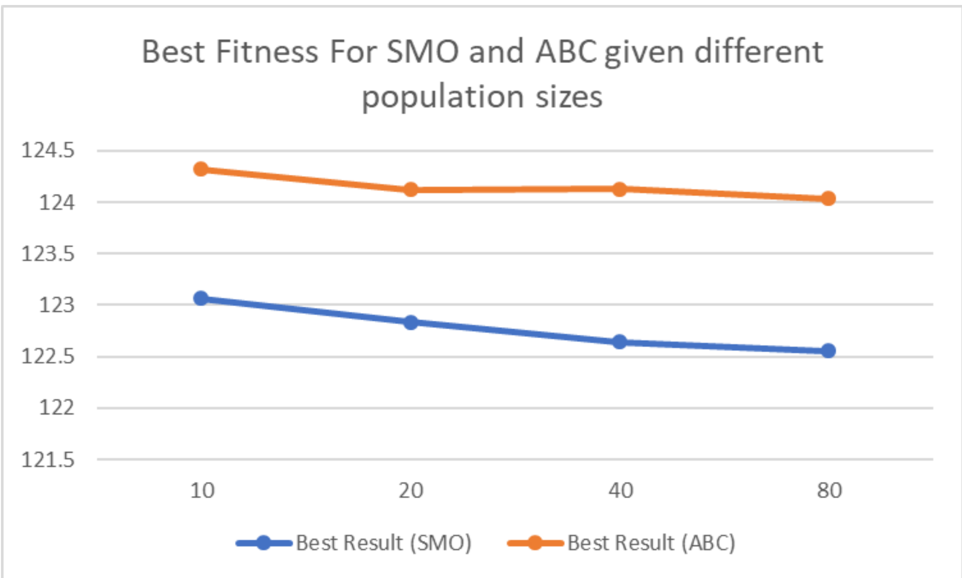

Fig 2: Best fitness comparison between SMO and ABC

Table 3: Result after running the SMO and ABC algorithms on traffic data

Run No	Best Fitness (SMO)	Best Fitness (ABC)
1	122.6591084	124.1989043
2	122.5925378	124.1802266
3	122.6093061	124.2115456
4	122.6342482	124.2886886
5	122.5584312	123.9190656
6	122.7455782	124.2585912
7	122.5570595	124.1841797
8	122.6203088	124.2722227
9	122.6013131	124.39217
10	122.6752218	124.339266
Execution Time	17.16462302	5.756736994
Cycle Time	61	61
Overall Best	122.5570595	123.9190656
Mean	122.6253113	124.224486
Objective function value	122.5525202365	124.033786368
Variance	0.002923977	0.014654331
Standard Deviation	0.054073813	0.121055075

IV. CONCLUSIONS

Most intersections in Port-harcourt city still use the fixed-time signal control strategy where control is not adaptive and so more often than not, results to traffic congestion. In this study, the offline area-wide traffic control system was considered. It was assumed in this work that the signal phasing was given for the two considered intersections. It is known that area-wide traffic control problem is combinatorial in nature and thus require a stochastic optimization technique. The optimal cycle length is determined by minimizing the total travel time of all road users travelling through the studied signalized intersections. The SMO heuristic algorithm was applied to solve the area-wide traffic control delay problem. The SMO algorithm is a meta-heuristic method that utilize the concept of collective intelligence. This method was created by the analogy with the food foraging nature of Spider Monkeys. The SMO algorithm approach proposed in this paper is based on the self-improvement concept. The initial feasible solution i.e initial signal's plan was first generated. In the next step, the Spider monkeys investigated the solution space and attempted to improve the solution.

The SMO algorithm was tested on the traffic network model on Figure 1. The tested network consists of two intersections (1 4-legged and 1 3-legged) and 7 links (14 lanes). In order to measure or evaluate the quality of the solutions obtained by the proposed approach, the result of SMO algorithm was compared with the ABC algorithm. To run the experiment, traffic data was fed to the developed SMO App and initial solution was obtained. The obtained best objective/fitness value was used as the subsequent test objective value. The SMO App uses the algorithms and equations in this study to generate initial/optimal solution.

It can be concluded, based on the results obtained, that the SMO algorithm is capable of delivering high quality solutions within significantly small CPU times. The result obtained from the SMO algorithm was compared with that of ABC and it shows that the SMO algorithm when applied to traffic delay optimization problem is significantly better than ABC algorithm. This is so because the objective function value for each of the runs of SMO is closer to each other when compared to ABC, making it a very reliable and stable optimization algorithm.

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