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African Buffalo Optimization Algorithm for Collision-Avoidance in Electric Fish

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ABSTRACT

This paper presents the African Buffalo Optimization algorithm for collision avoidance among electric fishes. Collision-avoidance in electric fish finds correlation with the Travelling Salesman avoiding the cities he has earlier visited. Collision avoidance in electric is akin to collision-avoidance in modern day driverless cars being promoted by Google Incorporation and other similar companies. The concept of collision-avoidance is also very useful to persons with visual impairment as it will help them avoid collision with objects, vehicles, persons, especially other visually-impaired. After a number of experimental procedures using the concept of the travelling salesman's problem to simulate collision-avoidance in electric fish, this study concludes that the African Buffalo Optimization is a veritable tool for simulating collision-avoidance in electric fishes.

KEYWORDS: **African Buffalo Optimization, Collision-avoidance, Computational Intelligence, Electric fish, Neuroscience, Travelling Salesman's Problems.**

1 INTRODUCTION

ARTIFICIAL Intelligence has as its main thrust the exploration of the harmonious working of different creatures in our ecosystem to sustain their kind (Shepard, 2011). Nature remains the main motivating factor behind scientific and technological breakthroughs experienced since the 20th century. At the centre of the activities of man and animals is the nervous system. Needless to say that without the activities of the nervous systems, there cannot, in the real sense, be a living thing. In other words, the strength of any living thing is the capacity for and actual performance of the brain (Luria, 2012). Neuroscience is that branch of biology that is concerned with the structure and function of the nervous system in man and animals. As a field of science, of late, neuroscience has become multidisciplinary in nature comprising anatomy, molecular biology and the pharmacology of the central and peripheral nervous systems (Muldoon et al., 2013). On its own, neuroscience can be divided into three major sub-disciplines: cognitive, behavioural and computational neurosciences. Computational neuroscience, which is our focus in this paper, is the branch of neuroscience concerned with the functioning of the brain of man and animals as an information processing component of the nervous system. Computational neuroscience describes in details the physiology, information-processing functioning and brain cells' communication dynamics etc. (Byrne, Heidelberger, & Waxham, 2014)

In the last two decades, neuroscience has achieved a wider scope incorporating other scientific fields such as linguistics, genetics and chemistry as well as computer sciences. It may be important to add that it is not uncommon to hear of sub-disciplines of neurosciences such as neuro-law, neuro-psychology, neuro-education and neuro-mathematics. Some researchers rather prefer to use the term neurobiology rather than neuroscience (Cuthbert, 2014). For the purpose of this paper, the authors are rather more comfortable with the term neuroscience to refer to the broad field rather than neurobiology that tend to describe the biological components of the nervous system. In any case, a breakdown in any section of the nervous system results in disastrous consequences such as hearing-impairment, vision-impairment, total paralysis etc.(Kakooza-Mwesige & Dhossche, 2015; Kritzinger, Van der Linde, & Mosca, 2015), necessitating the need for active research efforts towards helping to ameliorate the problems of

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breakdown in any section of the nervous system (Figley & Kiser, 2013).

Of the three major sub-disciplines of neuroscience, computational neuroscience has attracted the attention of several researchers in the last two decades, possibly due to the advancement of computer technology (Bower, 2012; De Schutter, 2008; Trappenberg, 2009). Following this trend, this paper is primarily concerned with the application of the concept of the travelling salesman's problem using a recently-developed computer optimization technique, the African Buffalo Optimization, to simulate collision-avoidance among electric fishes. The effective simulation of the collision avoidance in electric fish finds practical application in collision-avoidance software for the visually-impaired using the Electronic White Cane fitted with Wi-Fi sensors.

Electronic White Canes are devices that are specifically designed to have a number of ultra sound or infrared sensors that obtain data around the user in addition to extracting important information about the environment of the user (Pallejà, Tresanchez, Teixidó, & Palacin, 2010).

In some instances, magnetic parts are installed on the ground of some large areas that are visited by the visually impaired in such a way that the magnetic sensors on the Electronic White Cane is able to interact with Magnetic parts on the ground to serve as a guide to the visually-impaired (Hu, Lou, Song, Gao, & Li, 2009). The problem with these methods is that they are very expensive and almost impossible to deploy on a large scale. In the real sense, most existing methods are only used for experimental purposes. This underscores the need for more research investigations, hence this study.

The rest of this paper is organised this way: section two discusses the African Buffalo Optimization and the travelling salesman's problem; section three deals with collision avoidance in electric fishes; section four examines the experimental setting, experimental parameters and discussion of results; section five draws conclusions on the study.

2 AFRICAN BUFFALO OPTIMIZATION

THE African Buffalo Optimization (ABO) is a newly-designed optimization search algorithm designed with inspiration drawn from buffalo herd management using principally two sounds: the /waaa/ call that asks the animals to move on to better grazing fields (exploration) since where the buffalos are have been over-grazed or is insecure. The next sound is the /maaa/ indicating the opposite (exploitation) (Odili & Mohmad Kahar, 2015). So far, the application areas of the ABO have been the travelling salesman's problems, proportional, integral derivative tuning of an automatic voltage regulator (Odili, Kahar, & Noraziah, 2017) and benchmark global optimization test functions (Odili, Kahar, & Noraziah, 2016; Odili, Kahar, & Anwar, 2015) etc. The algorithm is presented in Figure 1

2.1 The flow of the ABO

The ABO algorithm begins by initializing the population of buffalos. It does this by assigning locations randomly to each buffalo within the solution space. After this, it updates each buffalo's exploitation (/maaa/ values) thus, ascertaining the herd's best animal (bg) and each buffalo's best locations $(bp.\mathrm{k})$ using Equation 1:

$$\mathrm{m}'_{\mathrm{k}} = \mathrm{m}_{\mathrm{k}} + \mathrm{lp1}(bg - \mathrm{w}_{\mathrm{k}}) + \mathrm{lp2}(bp.\mathrm{k} - \mathrm{w}_{\mathrm{k}}) \quad (1)$$

In Equation 1, m'_{k} represents a new maaa (exploitation) location; m_{k}, the immediate past /maaa/ (exploitation) location, lp1 and lp2 are learning parameters that help to bias the search; bg, the best location so far found by the herd; w_{k} represents the present exploration location and $bp.\mathrm{k}$ the best location of a particular buffalo k.

In each step, the buffalos keep a memory of their coordinates. If the present fitness values are better than the individual's best fitness $(bp.\mathrm{k})$, the ABO saves the location vector for the particular buffalo as its best. Moreover, if the present fitness is better than the herd's overall best fitness, ABO saves it as the herd's maximum (bg). Furthermore, the algorithm updates the location of the entire herd of buffalos using:

$$\mathrm{w}'_{\mathrm{k}} = \frac{(\mathrm{w}_{\mathrm{k}} + \mathrm{m}_{\mathrm{k}})}{rand} \quad (2)$$

Here, w'_{k} represents a /waaa/ (exploration) call to a new location and $rand$ is a random number (0,1)

Next, the algorithm confirms the improvement or otherwise of the herd's best buffalo (bg). If there is no improvement in the status of the best buffalo (bg) in a number of iterations, the algorithm re-initializes the entire herd (that is, a return to Step 1). Otherwise, if the best buffalo is improving its location, ABO checks to see if the stopping criteria is reached and it terminates the run and outputs the location vector of the present bg as the solution to the given problem. Else, the algorithm returns to Step 2 (See Figure 1).

2.2 The Travelling Salesman's Problems

The history of the Travelling Salesman's Problem (TSP), which is one of the most studied combinatorial problems dates back to 1930 (Tüű-Szabó, Földesi, & Kóczy, 2016). Basically, the Travelling Salesman's Problem is a minimization problem which involves an anonymous salesman that has to visit his customers in different geographical locations within a large city or in a number of cities. His goal is to visit each of their locations, using the shortest/cheapest possible route and then returns to the starting city/location. This problem utilizes a graph as its data structure. The complete weighted graph G= N, E. Here N is a set of n nodes/locations and E represents the fully

Step1.	Initialization: randomly place buffalos *to* nodes at the solution space;
Step2.	Update the buffalos' exploitation using equation: $$\mathrm{m}'_\mathrm{k} = \mathrm{m_k} + \mathrm{lp1}(\mathrm{bg} - \mathrm{w_k}) + \mathrm{lp2}(\mathrm{bp.k} - \mathrm{w_k})$$ where $\mathrm{m_k}$ and $\mathrm{w_k}$ represents the exploitation and exploration moves respectively of the $\mathrm{k^{th}}$ buffalo (k=1, 2………...N); lp1 and lp2 are learning factors; bg is the herd's best fitness and bp. k, the individual buffalo's best location.
Step3.	Update the location of buffalos using: $$\mathrm{w}'_\mathrm{k} = \frac{(\mathrm{w_k} + \mathrm{m_k})}{\mathrm{rand}}$$
Step4.	Is $\mathrm{bg_{max}}$ updating? Yes, go to 6. If No, go to 1
Step5.	If the stopping criteria is not met, go back to algorithm step 2, else go to 6
Step6.	Output best solution.

Figure 1: ABO algorithm.

interconnected edges (routes) to the different nodes in the graph G. To help clarify the problem, each edge is weighted by a given weight, d_{jk}, which is the cost/distance between nodes 'j' and 'k.' An example of a weighted graph is presented in Figure 2

In this graph, it can be seen that the weight of route AB is 5, BD is 6, CD is 7, AC is 8 etc. Also, the longitude and latitude of each node, location or city is attached. For instance, city A is located at longitude 5, latitude 5, while city B is at longitude 4, latitude 5 etc. It is important to observe that the routes/paths taken by the Travelling Salesman could be symmetric (in which case the distances between locations 'j' to 'k' is the same as that between 'k' and 'j'). In other instances, the paths/routes could be asymmetric where distances/cost between city 'j' to 'k' may not be same as city, 'k' to 'j' in at least one edge in the travelling graph. Asymmetric cases could result from one-way traffic routes, differences in transportation costs, differences in road tolls, blockage of roads or other civil engineering, commercial or administrative considerations (Kefi, Rokbani, & Alimi, 2016).
Mathematically, since the TSP is a minimization problem, the minimization equation could be formulated thus: given k cities and their x, y coordinates, find an integer permutation:

$$\pi = (d_1\ d_2\ d_1\ d_3 \dots \dots\ d_k) \tag{3}$$

where d_k represents location/city 'k', with the minimization function:

$$f(\pi) = \sum_{i=1}^{k-1} d\big(d_{1,}\ d_1 + 1\big) + c(d_k, d_1) \tag{4}$$

Here $d_{1,} d_1 + 1$ represents the transition between location, $d_{1,}$ and $d_1 + 1$, whereas $\mathrm{c}(d_{k},, d_1)$ represents the cost/distance of city 'k' and city '1'.

The TSP is about the most studied optimization problem and a number of metaheuristics have been applied to solving the TSP. Some of the algorithms that have successfully solved the TSP are the Artificial Bee Colony (ABC) (Nozohour-leilabady & Fazelabdolabadi, 2015), Particle Swarm Optimization (PSO) (Kefi, Rokbani, Krömer, & Alimi, 2015), Genetic Algorithm (GA) (Chang, 2015) etc.

3 COLLISION AVOIDANCE IN ELECTRIC FISH

ELECTRIC fish refers to a kind of fish that are able to generate electric currents as well as detect electric currents in the water (MacIver, Fontaine, & Burdick, 2004). They are common in fresh and ocean waters of Africa and Latin America. It is important to emphasize that the mere capacity to detect electric currents in water does not qualify a fish to be described as an electric fish. Fishes like ray, shark and catfishes which can detect electric currents, therefore, do not qualify to be categorized as electric fishes (Nelson, Grande, & Wilson, 2016). An electric fish must be able to both generate and detects electromagnetic fields. A good example of an electric fish is the electric eel which generates up to 900 volts of electricity at a time (Sun, Fu, Xie, Jiang, & Peng, 2016). There have been recorded instances of electric fishes killing other electric fishes, crocodiles and even humans (Arnegard & Carlson, 2005)

The electric fish navigates the waterways through careful use of the electromagnetic (EM) field that a particular component of its tail called the Electric Organ generates (Feulner, Plath, Engelmann, Kirschbaum, & Tiedemann, 2008; Heiligenberg, 2012). Using the electroreceptors situated all over the electric fish's outer skin to trap the electromagnetic field, the fish is able to distinguish between objects as it navigates the waterways (Hollmann, Engelmann, & Von Der Emde, 2008). Sometimes, however, some objects, including electromagnetic fields from other electric fishes could act as noise elements to the fish's

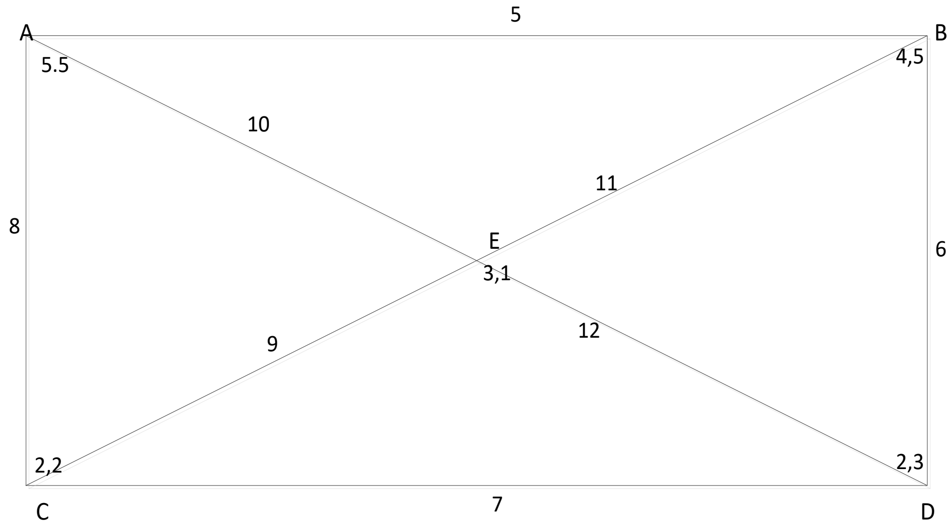

Figure 2: **A five-node TSP instance.**

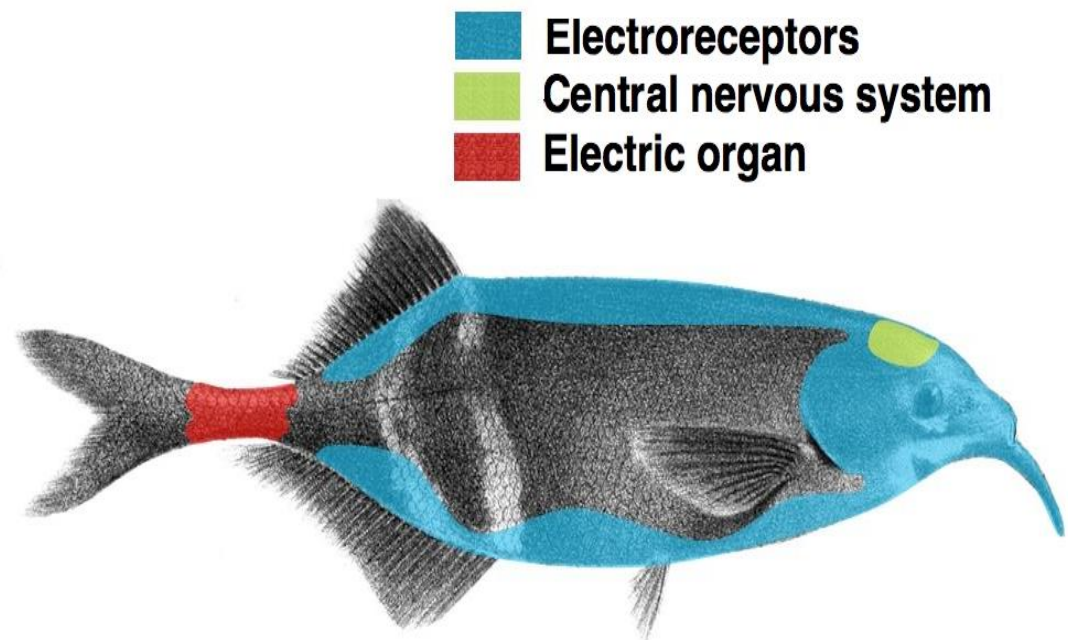

Figure 3: **Major navigational tools of an electric fish (Von der Emde, 1999).**

electric flow thereby confusing the electric fish (Heiligenberg, 2012; von der Emde, 2006). To handle this noisy situation, the particular electric fish may need to generate discharge signals (DS) to avoid collision (Feulner et al., 2008). An electric fish with its major navigational components are presented in Figure 3.

Studies have shown that when two electric fishes release discharge DS that are on the same frequency, the situation results in signal distortion (SD) that could endanger the two electric fishes concerned (Mendes-Junior, Sá-Oliveira, & Ferrari, 2016; Zakon, Zwickl, Lu, & Hillis, 2008). To ensure efficient and effective navigation, therefore, it is required that the fishes generate EMs and SDs that are on different frequencies (Leblanc, 2005). This situation is akin to the exploration /waaa/ and exploitation /maaa/ coefficients of the African Buffalo Optimization algorithm. So appropriate simulation of the ABO's exploration and exploitation parameters could bring about effective collision avoidance mechanism in electric fishes.

The collision avoidance scenario in electric fish is akin to the concept of the travelling salesman's problem in computer science where a particular salesman is required to visit all his customers in different locations across a given geographical area in such a manner that he should avoid visiting any location more than once before returning to his initial starting city/location. This is the motivation for the choice of electric fish in this study. For the purpose of illustration, see the movement of the fishes presented in Figure 4. Each fish swims in a position parallel to the other in order to avoid electromagnetic fields collision.

Similarly, in a TSP problem, the salesman moves in a way to avoid an already visited in order to not to violate the TSP constraint of visiting a node/city only once. For instance, the movement of the salesman in Figure 5 where he has to visit 60 cities/nodes illustrates deliberate attempt to avoid already-visited cities/nodes, just like the electric fish does to other electric fishes with electromagnetic fields that are on the same frequency.

4 EXPERIMENTAL SETTING

THE experiments were done on a desktop computer running windows 7 Intel Duo Core ™ i7-3770 CPU, 3.40 GHz with 4GB RAM. It was necessary to investigate the performance of the ABO with other heuristics in solving the ATSP. To do this, experiments were carried out on 15 out of the 19 benchmark optimization problems available on TSPLIB95 (Reinelt, 1991). The choice of the datasets is informed by their complexity and popularity in literature. The results obtained from this exercise were compared with those obtained from three other heuristic algorithms available in Tsp-solve (Hurwitz & Craig) . The comparative algorithms are Addition heuristics, Assign heuristics, Loss and Patching heuristics (Rocha, Fernandes, & Soares, 2004). The Addition Heuristics employs the construction method in its search and tour development; the Loss Heuristics uses a technique described in (Van der Cruyssen & Rijckaert, 1978) and the Patching Heuristics engages in solving an assignment problem and later integrates the sub-tours into one tour using the patching technique (Karp & Steele, 1985).

Figure 4: Movement of fishes to avoid electromagnetic field collision (Freud, 2013).

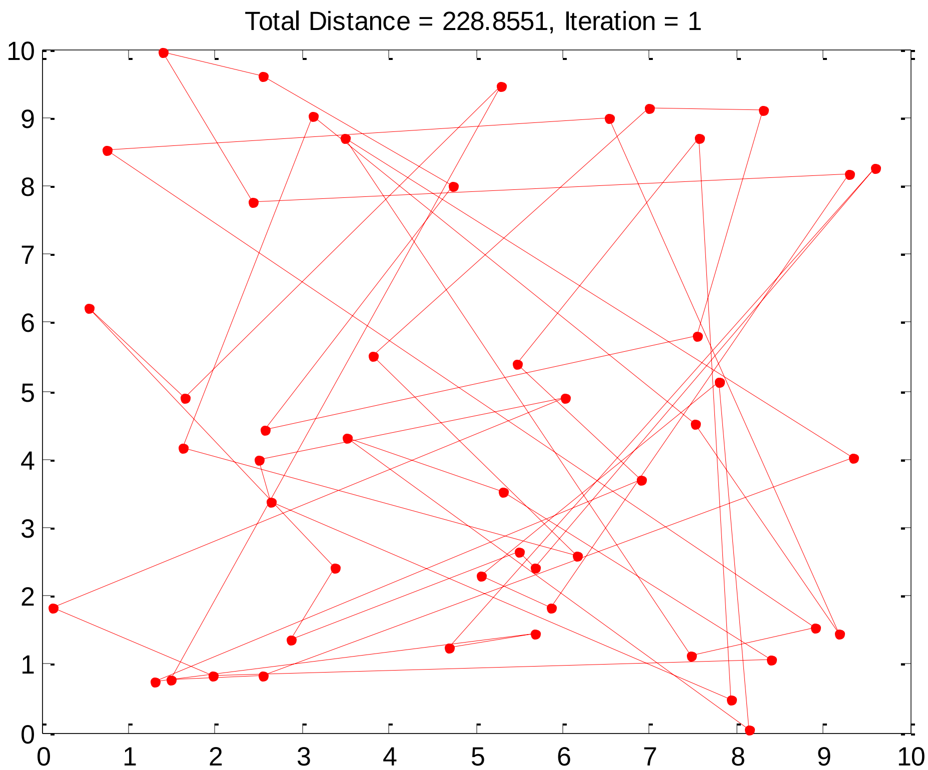

Figure 5: 60-node TSP instance.

This comparison is relevant because there are three basic methods of solving Travelling Salesman's Problem (whether symmetric or asymmetric) in literature and these are the Constructive method, the Improvement method and the Composite method that uses a combination of the first two (Helsgaun, 2000). The ABO solves the Travelling Salesman's Problems using the composite method. It starts by using the constructive method, especially for problems involving less than 100 nodes but turns to improve upon the construction as the number of nodes increases. This coupled with the ABO's use of very few parameters enables the ABO to arrive at solutions faster than many other methods. Basically, tour construction method builds a tour by simply adding a new node that has not been added or visited at each step/iteration. When the tour has been constructed, the buffalos return to the starting node, avoiding any already visited. An example of a method that uses strict Construction technique is the nearest neighbourhood algorithm (Sarwar, Karypis, Konstan, & Riedl, 2002). Meanwhile, the tour improvement method gets a tour improved through making improvements/exchanges on the already existing tours. Examples are the 2-opt algorithm and the Lin-Kernighan algorithm (Helsgaun, 2000). The composite method, on the hand, as in ABO, starts solving the problem by constructing a tour through the addition of unvisited nodes and then performs improvement exchanges depending on the location of the best buffalo. This helps the algorithm to arrive at better solutions. The simulation results obtained from this study are presented in Table 1 and Figure 6.

As can be seen in Table 1, the ABO outperformed the other methods in obtaining the optimal solutions. The ABO obtained optimal solution in three ATSP instances: Ftv38, Ft53 and Ftv64 in addition to obtaining over 99.5% accuracy in the remaining instances. Meanwhile the other methods were only able to obtain optimal result in one instance each and that is Br17. Their performances in other instances were rather not encouraging (see Fig.2). For instance, the cumulative relative error percentage of the ABO in all ATSP instances is 1.53% to Addition Heuristics 102.52%; Loss Heuristics 59.43% and Patching Heuristics 67.68%. From this analysis, it is obvious that the ABO outperformed other methods. The above results are further highlighted in Figure 2.

In all, it took ABO a cumulative iteration of 1070 to obtain best results to all the problems. This is less than the needed iterations required to solve a particular ATSP instance in the other competing algorithms. This clearly marks out ABO as being one of the fastest optimization algorithms in literature presently.

Table 1. **ABO and some heuristics on ATSP**

***TSP* Cases**	***Opt***	***ABO***			***Addition* Heuristics**			***Loss* Heuristics**			***Patching* Heuristics**		
		Best	PDB. (%)	Iter	Best	PDB (%)	Iter	Best	PDB (%)	Iter	Best	PDB (%)	Iter
Br17	39	39.17	0.43	17	39	0	100	39	0	100	39	0	100
Ry48p	14422	14440	0.12	186	14939	3.65	200	15254	5.77	100	14857	3.02	100
Ftv33	1286	1287	0.08	79	1482	15.24	200	1372	6.69	600	1409	9.56	200
Ftv35	1473	1474	0.07	107	1491	1.22	100	1508	2.38	300	1489	1.09	200
Ftv38	1530	1530	0	126	1634	6.79	200	1547	1.11	700	1546	0.98	100
Ftv44	1613	1614	0.06	58	1733	7.44	3400	1673	3.72	300	1699	5.33	100
Ftv47	1776	1777	0.06	6	1793	0.96	700	1787	0.56	1600	1846	14.45	300
Ftv55	1608	1610	0.12	117	1781	10.76	3400	1747	8.64	200	1657	3.05	100
Ftv64	1839	1839	0	10	2054	11.69	500	1890	2.77	500	1871	1.74	900
Ftv70	1950	1955	0.26	46	2168	10.9	400	2074	6.36	100	2004	2.77	600
Kro124p	36230	36275	0.12	13	40524	11.85	200	41121	13.5	500	40106	10.7	100
Ft53	6905	6905	0	126	8088	17.13	300	7383	6.92	500	7847	13.64	100
Ft70	38673	38753	0.21	179	40566	4.89	500	39065	1.01	1900	39197	1.35	100
			1.53%			**102.52%**			59.43%			67.68%	

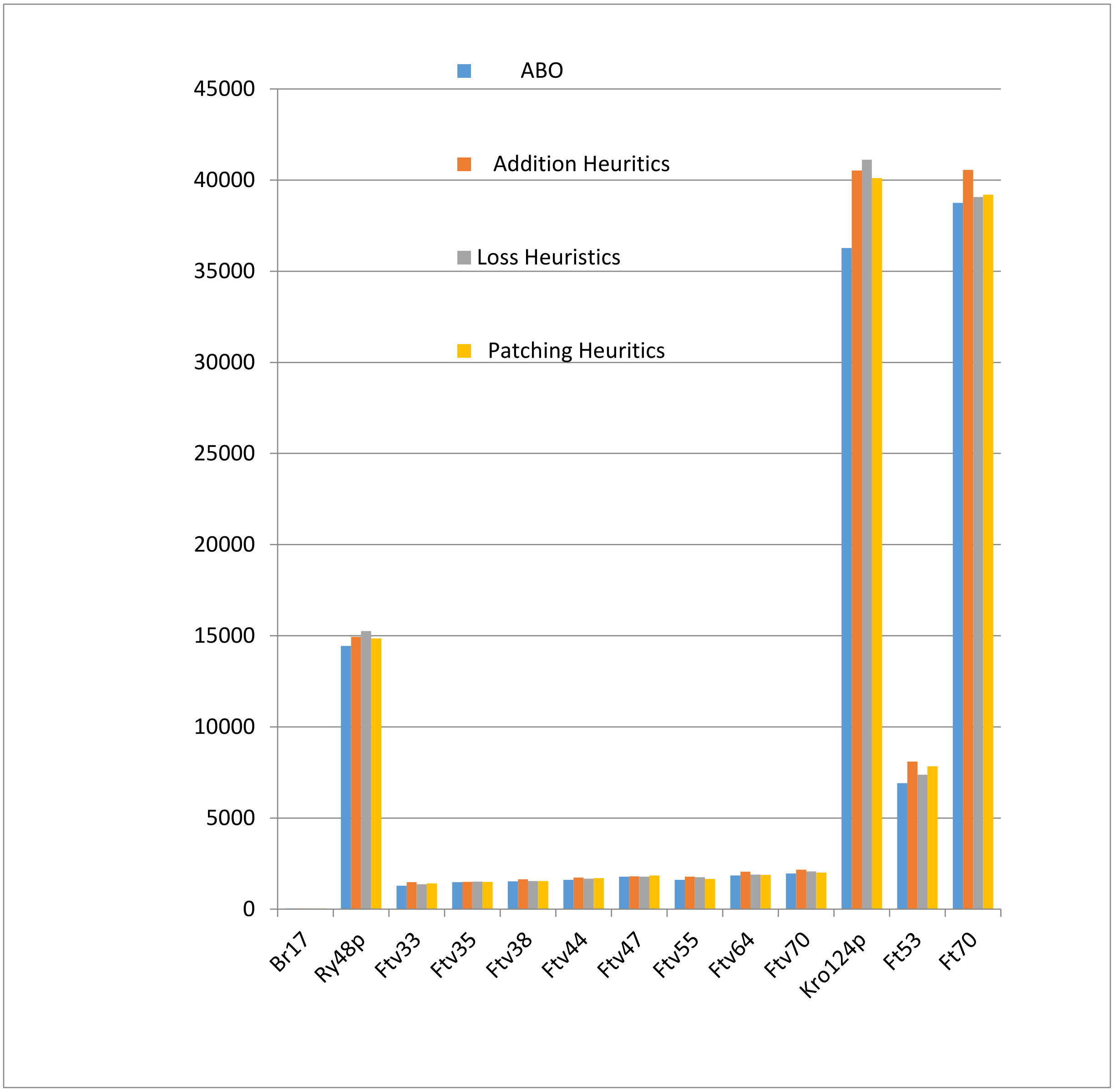

Figure 6: ATSP and other Heuristics.

5 CONCLUSION

SCIENTISTS are still exploring the capacity of the spongy 1.36-kilogramme substance called the brain with the aim of fully understanding its working and then developing systems and models that can assist those who have some nervous breakdowns (Lee, 2016). The continuous investigation by researchers and neuroscientists in particular into the workings of the brain and the entire nervous systems inspired this study which is aimed at developing collision-avoidance models to assist those with visual impairments as well help in further enhancing the capabilities of the recently introduced driverless cars. Drawing inspiration from the travelling salesman's problems in simulating collision-avoidance in electric fishes in number of experimental procedures, this study concludes that the ABO is a veritable tool developing models and systems to assist the visually-impaired, mechanical robots and driverless cars in collision-avoidance. It is hoped that this study will open a new research direction towards exploring heuristics and metaheuristics in neuroscience research. Further studies in developing electronic white canes for the visually-impaired using a combination of the visited-nodes avoidance mechanism of the TSP coupled the collision-avoidance strategy of the electric fish is recommended.

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