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Meerkat Clan Algorithm: A New Swarm Intelligence Algorithm

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ABSTRACT

Evolutionary computation and swarm intelligence meta-heuristics are exceptional instances that environment has been a never-ending source of creativeness. The behavior of bees, bacteria, glow-worms, fireflies and other beings have stirred swarm intelligence scholars to create innovative optimization algorithms. This paper proposes the Meerkat Clan Algorithm (MCA) that is a novel swarm intelligence algorithm resulting from watchful observation of the Meerkat (Suricata suricatta) in the Kalahari Desert in southern Africa. This animal shows an exceptional intelligence, tactical organizational skills, and remarkable directional cleverness in its traversal of the desert when searching for food. A Meerkat Clan Algorithm (MCA) proposed to solve the optimization problems through reach the optimal solution by efficient way comparing with another swarm intelligence. Traveling Salesman Problem uses as a case study to measure the capacity of the proposed algorithm through comparing its results with another swarm intelligence. MCA shows its capacity to solve the Traveling Salesman's Problem. Its dived the solutions group to sub-group depend of meerkat behavior that gives a good diversity to reach an optimal solution. Paralleled with the current algorithms for resolving TSP by swarm intelligence, it has been displayed that the size of the resolved problems could be enlarged by adopting the algorithm proposed here.

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1. INTRODUCTION

Optimization practices stirred from swarm intelligence have become popular more and more throughout the previous period. They are described by a decentralized manner of working in which it imitates the performance of swarms of social insects, flocks of birds, or schools of fish. The benefit of these tactics over old-fashioned methods is their strength and flexibility. These characteristics make swarm intelligence a fruitful project paradigm for algorithms that agree with progressively complex problems. Swarm intelligence (SI) is an artificial intelligence (AI) discipline which is anxious with designing intelligent multi-agent schemes by taking stimulation from the shared conduct of social insects such as ants, termites, bees, and wasps, in addition to other animal groups such as birds or fish. Researchers have been captivated by colonies of social insects for a very long time, and the devices governing their performance stayed unidentified for a long time. Although the single associates of these colonies are uncivilized beings, but still capable of accomplishing difficult jobs in teamwork. Organized colony conduct arises from simple activities relatively or relations among the colonies' individual associates [1].

Meerkats - also known as suricates - are small (<1 kg) carnivores that belongs to the mongoose family and contains 37 species in 18 genera and two subfamilies. Meerkats are obliging breeders, living in groups of up to 50 ones. Inside the mongoose family, meerkats are one of the most very outgoing species, with other well-considered social mongooses counting the banded mongoose and dwarf mongoose. Meerkats are adapted to desert and their distribution is limited to the semi-arid areas of south-western Africa (comprising southern Angola, Namibia, Botswana and South Africa). They are not endangered and their preservation position is considered as 'least concern' by the International Union for Conservation of Nature [2].

Travelling salesman problem (TSP) is the most common routing problem. It denotes a travelling salesman that desires to call a number of nodes (cities) exactly once, and lastly returns to the initial node (city). Objective of the problem is to define a tour with the least distance. TSP is a sub-problem of several applications like transport [3].

The Traveling Salesman Problem (TSP) is debatably a maximum noticeable problem in combinatorial optimization. The humble mode where the problem is well précised in mixture with its famous effort has inspired countless exertions to discover an effective system. The TSP is a standard outing problem where a theoretical salesman is obligated to discover the utmost effective arrangement of endpoints in his land, ending only just the once at each, and finishing at the original starting locality. Owing to the combinatorial difficulty of the TSP, inexact or heuristic solution measures are nearly constantly working in preparation. Limited potential uses of TSP comprises dominating an optimized scan restraints course in a combined chip analysis, parcels collection and conveying logistic corporations, and transport course problem. Many algorithms have been presented to give period proficient keys for the problem, both precise and estimated [4].

Finally, the paper is planned as follows. Some interrelated works are revised in Section2. Section3 offers a short-term account for Meerkat behavior. The algorithm proposed here is offered in Section4. Section5 comprises the application of the case study and the experimental results. Lastly, closing remarks are offered in Section6.

This paper presents a new approach inspired from meerkat life, applied on the TSP problem to measure the efficacy of performance. This section presents some asymptotic works.

In [5] 2012, Anshul S. and Devesh N. emphasized on the Bee Colony Optimization to be used for resolving the Traveling Salesman problem with the lementary device of bees hunting conduct and its competence in resolving direct pathway between numerous routes. Neighborhood examination is advantageous once utilization is wanted. It can be practical after each bee phase to improve the quality of solutions.

In [6] 2012, Krishna H., Ravindra K., and Gajendra S. confirmed that the Ant Colony Optimization (ACO) is a meta heuristic algorithm that has been verified as a effective method and practical to many Combinatorial Optimization (CO) problems. There are numerous motives for choosing the TSP problem to clarify the functioning of ACO algorithms it is simply reasonable, so as the algorithm conduct is not hidden by too lots of procedures. It is a normal test bed for innovative algorithmic thoughts as a worthy performance on the TSP is frequently taken as an evidence of their practicality. They offered a method for resolving traveling salesman problem centered on better-quality ant colony algorithm.

In [7] 2014, Sonam Khattar and Dr. Puneet Gosawmi has come up in their paper with how Genetic Algorithm can be used for resolving the Traveling Salesman Problem. Genetic Algorithm catches the upright solution for the TSP, depending on the method of how the problem is encoded and the categories of crossover and transformation approaches are used. A plenty of genetic algorithm practices were examined and measured for resolving TSP.

In [8] 2012, Ahmed T. Sadiq AlObaidi and Amaal G. Hamad proposed a new Bees algorithm framework. This new approach is highly general and can be modified to suit any application area. Results of experiments with the selected problems show the applicability of the proposed methods.

In [9] 2013, Ahmed T. Sadiq Al-Obaidi improve Scatter Examine with haphazard consideration to search the space of problem and more of variety and amplification for hopeful solutions centered on the Harmony search algorithm.

In [10] 2014, Sonam K. and Dr. Puneet G. has concluded in this work how Genetic Algorithm (GA) solve the TSP. GA finds the best-solution for the TSP, depend upon problem description, crossover type and mutation approaches. GA techniques have been surveyed and analyzed to solve TSP.

2. MEERKAT BEHAVIOUR

Meerkats are searching animals, living in great open networks with numerous entrances in which they leave only throughout the day. They are considered as social and up to forty can live in colonies. Animals of the similar group frequently prepare each other to reinforce social bonds. The alpha pair will often trace scratch for the group to express their power, and such actions are commonly tracked by the subordinates licking the faces of and grooming the alphas. These actions are also frequently trained when members of the group are reunified after a short dated time. Most meerkats within the same group are all siblings and offspring of the alpha pair [11].

2.1. Sentry Behaviour

Meerkats establish altruistic conduct within their colonies; one or more meerkats will attitude sentry (lookout) while the others hunt or play in order to inform them if anything dangerous happens. The meerkat performs as sentry if a hunter is found, and gives a notice bark, and the others running and hiding in one of the numerous bolt holes and they ought to range across their land. The sentry meerkat is the first one to return from the hole and look for hunters, and keep barking to have the others underground. If the danger is gone, the sentry meerkat will stop barking and the others will be harmless to go. Meerkats will also watch any young one in the group. Females that have not made their own broods will often nurse the alpha pair's young while the leading female is absent with the others left in the group. They will also defend the young from any risk, frequently jeopardizing their own lives to do so. In case of a danger, the babysitter will either take the young to a safe place underground and be ready to support them if the threat is there, or gather all the young and lie on top of them if going underground is not possible [2].

2.2. Foraging Behaviour

Foraging behavior is usual of social mongooses, where animals extent out and forage separately while upholding visual and vocal contact. Systematically a pack forages and carefully within its home range, taking a different rout each day and typically letting at least a week for an area to restart its food supply between visits. Hidden prey are located by small and dug out with the forefeet. Adult readily share food with youngsters in the pack [12].

2.3. Baby-sitter Behaviour

Meerkats contribute in a numeral of supportive actions. The key assistances to supportive upkeep are baby-watching, and helpers persist at the burrow with pups 25 whereas the rest of the group is absent for foraging, and pup feeding where helpers offer an amount of their food stuffs to pups while foraging. Both baby-watching and pup-feeding go along with by substantial energetic costs to the helper: baby-sitters forgo feeding is up to 24 hours, and leads to insignificant weight loss, and pup-feeders lose their own forage items in favor of delivering them to pups [11].

3. MEERKAT CLAN ALGORITHM

The thoughtful observing of the conduct of some living beings can show us the way they plan their natural behavior into algorithmic routines. That is why the new meta-heuristics debated in this work are nature-stimulated algorithms. These novel methods are global optimization meta-heuristics and they are essentially collected by choosing the best structure and by a randomization structure. The former guides, the algorithm merging to the optimality (utilization) and the far ahead evades both the loss of variety and the algorithm to get bordered in local optima (examination). A good stability between utilization and investigation may lead to the global optimality achievement.

Meerkats are animals that live socially in colonies of 5 – 30 individuals. Being sociable beings, they exchange both toilet and parental care duties. Each mob has a leading alpha male and leading alpha female. Each mob has its own land where they occasionally transfer if food is not found or when obliged by a tougher mob. If the latter happens, the weaker mob will then attempt to increase in another way or stay till they become tougher and recover their lost burrow.

Each mob has also what is called a ‘sentry’ which means someone who guards over the mob and when to spot risk and notify the other members if danger is there. The sentry either watches from the ground or from climbing a tree or in the bushes. The sentry watches over both the burrow scheme and when the other members of the mob are foraging for food. The sentry will give a sound of a loud bark when a risk is observed and the mob will then bolt rapidly to their hiding holes.

From the prior explanation about Meerkat animal inspired MCA, below is the general steps for MCA, these steps are can be change depend upon problem encoded.

a. Initialization: create clan of individuals' randomly and set the other parameters' clan size, foraging size, care size and worst foraging and care rate.
b. Compute the fitness for the clan
c. Chose the best one as 'sentry'
d. Divide the clan into two groups (foraging & care)
e. Generate neighbors for foraging group
f. Chose the worst individuals in foraging group and swap with the best individuals in care group
g. Drop the worst individuals in care group and generate another individual randomly
h. Replace the best individual in foraging with sentry if its best.

The pseudocode algorithm shown in the Figure 1.

```
Parameter
        n       clan size
        m       foraging size     where m < n
        c       care size         n-m-1
        Fr      worst foraging rate
        Cr      worst care rate
        k       neighbor solution

Begin
        Generate random clan of solutions clan(n)
        Compute fitness for clan solutions
        Sentry = best solution of clan
        Divide the clan into two groups (foraging & care)
        While not termination condition Do
                For i=1 to m
                        Generate k neighbors from foraging set
                        foraging(i)= best one from k neighbor
                end for
                Swap the worst for Fr solution in foraging group with best ones solution in care
                group;
                Drop the worst Cr solution from care group and generate ones solution randomly;
                Select the best one of foraging call it best_forg
                If best_forg <= Sentry then
                        Sentry ←→ best_forg
                end if
        end while
End
```

Figure 1. Meerkat Clan Algorithm Pseudocode.

4. MEERKAT CLAN ALGORITHM TO SOLVE TSP

A routing solution in the TSP can be signified as a graph G= (V,E), in which, V= {1,2,...,n} is the set of all nodes (cities) within the problem graph, and E = {(i, j)|i, j ϵ V} is the set of all possible edges among the nodes. More specifically, each node represents the position of a city, whereas each edge corresponds to a joining path between two cities. The distance dij which is associated with edge (i, j), represents the Euclidean distance from city i to city j, and is calculated according to Eq. 1. Before employing the SI algorithms at offline step the heuristic information is calculated. As a result, the distances of all edges were saved.

$$dij = \sqrt{(xi - xj)^2 + (yi - yj)^2} \quad (1)\ [3]$$

In all SI algorithms, after constructing the solutions, the qualities of the collected solutions are assessed by the defined objective function, which is same for all SI algorithms. It can be evaluated for each solution (a chromosome, a particle, an ant, or a bee) by simply calculating the sum of Euclidean distances of the consecutive edges inside the tour as follows:

$$Cost = \sum_{l=1}^{n} dl \quad (2)\ [3]$$

To solve TSP by SI algorithms, at the first, an initial population is generated to search among N-dimension search space according to get an optimum tour. In order to generate the initial solutions, at first, a city is selected randomly as the initial node (e.g., city i). Then, the remained cities are consecutively added to the tour, until all cities will be selected. At each step, the next city is chosen according to a defined chance which corresponds to the reverse of its distances from the current city [3].

For the sets of experiments parameters involving Meerkat Clan Algorithm (MCA), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Practical Swarm Optimization (PSO) and Artificial Bee Colony (ABC). Table 1 covers the information of the parameters used.

Table 1. Experimental Algorithms parameter

MCA		GA		ACO		PSO		ABC	
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
Max Iteration	500	Max Iteration	500	Max Iteration	500	Max Iteration	500	Max Iteration	200
No. of Meerkats	100	No. of Chromosome	100	Number of Ants	100	No. of Particles	100	No. of Employed Bees	100
Foraging size	60	Selection Type	Elitism Selection	No. of Candida ants	2	Type of Combination of pbest and gbest to Generate the Velocity	PMX Operator	No. of Scout Bees	5
Care size	39	No. of Selected Parents	5	Initial Pheromone of All Edges	0.5			Probability of applying NS operator	20%
Worst foraging rate	13%	Crossover Operation	MOX	Evaporation Factor λ	15%	Type of Combination the Particle with its Velocity	MOX Operator	Probability of applying NSC operator	30%
Worst Care rate	20%	No. of Point for Crossover	3 points	Deposition amount (D)	0.5			Probability of applying NC operator	50%
Neighbor solution	20	Mutation Operation	NC	A	2	N/A	-	β	-20
N/A	-	Mutation Probability	0.5/ No. of cities	N/A	-	N/A	-	ϒ	32
N/A	-	N/A	-	N/A	-	N/A	-	H	5
N/A	-	N/A	-	N/A	-	N/A	-	α	2

The best achievement solution for each algorithm with runs 10 times can be shown in Table 2. The first column is the problem names; the second, third, fourth, fifth and sixth columns are consisting of the best error rate found, respectively using MCA with GA, ACO, PSO, and ABC [3]. The Error Rate (ER) is calculated as follows:

$$ER = \frac{(Best\ value\ for\ algorthm - Best\ value)}{Best\ Value} \quad (3)$$

Table 2. Comparison of the Bet Error Rate for 10 Runs (in Percentage)

Problem	MCA	GA	ACO	PSO	ABC
att48	1.14	1.23	0.72	0.67	0.31
eil51	0.12	1.71	0.43	0.2	0
berlin52	0.22	1.62	0	1.03	0.27
eil76	0.2	2.03	0	0	0
kroA100	0.76	1.92	1.25	1.37	1.08
lin105	0.76	2.67	1.08	0.93	0.36
beir127	0.57	3.04	2.12	1.25	1.25
kroA200	1.86	4.33	2.45	1.87	1.37

The difference between GA, ACO, PSO, ABC, and the proposed algorithm to finding the best value was clearly shown in Figure 2.

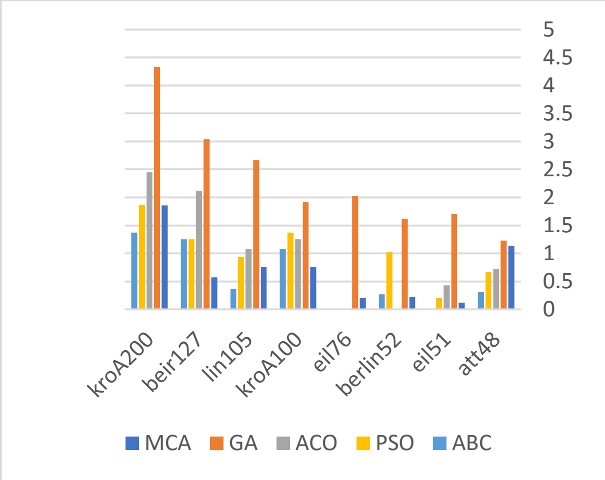

Figure 2. Difference between Strategies

5. CONCLUSION

Generally speaking, this paper presents the Meerkat Clan Algorithm, and displays its capability to solve the Traveling Salesman's Problem. The results of MCA gained through divide the solution set into two sets (foraging & care). most the operations performed on foraging set and the worst solutions replaced with the best ones in care solution. The worst solution in care set are dropped and add another solution created randomly. These results show the amazing performance of the algorithm's capacity to obtain optimal or near-optimal solutions at an incredibly fast rate.

Now a days the community of computer science have learned about the significance of growing behaviors for complex problem solving. As exposed in this study, getting to learn about the collective behavior of living beings can offer motivating and valuable swarm-based meta-heuristics. The work that have been done to date show the potential of these new methods to successfully find effectual solutions to numerous kinds of applied optimization problems. In fact, there is no 'best' method, individually of specific context. Different applications will be more acceptable for different problems, either leading to better solutions, or enhanced speed. Furthermore, the suitability of a specific method does not rest only on the problem: diverse procedures will be more suitable for different people, counting on their knowledge and capability.

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