Modelling Altruistic and Selfish Behavioural Properties of Ant Colony Optimisation

C. Wickramage[#*1], D. N. Ranasinghe[*2]

[#]Department of Computer Science, Faculty of Science, University of Ruhuna, Sri Lanka.

[1]chathuridwc@gmail.com

[*]Department of Computation & Intelligent Systems, University of Colombo School of Computing, Sri Lanka.

[2]dnr@ucsc.cmb.ac.lk

Abstract— **Cooperativeness/competitiveness and altruism/selfishness are two key pairs of factors that could be adopted by natural algorithms in order to experience significant variations as well as to improve the quality of the existing solutions. Identifying the individual and social components separately and fine tuning the use of said behaviours of natural ants is worth investigating with regards to the behaviours of artificial ants in Ant Colony Optimisation. According to the experimental results of this study, it can be shown that the solutions are affected by these two key pairs of factors of ants and the colonies while their corresponding influences can make differences in the solution quality of the algorithm. This research has attempted to adapt the said behaviours of ants to solve two general issues of Evolutionary Algorithms, decreasing the delay in convergence and premature convergence. Travelling Salesman Problem is used as the reference problem.**

Keywords— **Ant Colony Optimisation, Individual component, Social component, Travelling Salesman Problem**

I. Introduction

Adapting society based interactions has been used often in the context of optimization algorithm [1]-[3]. Game theory, social theory and conflict theory are some of the examples that study the impact of social interactions among individuals through the improvements of the whole population [4]. Researchers who are interested in optimisation algorithms have already adapted Game Theory which involves the study of strategic decision making [5]-[9]. Since game theoretic approaches have been adapted with swarm intelligence in order to improve the results of original algorithms, it is worth trying to adapt these approaches in solving combinatorial problems such as Travelling Salesman Problem (TSP).

Ant Colony Optimization (ACO) is a swarm intelligence model where many individuals behave in a decentralized, self-organized and collective manner [10]. Being a well-known population based algorithm, ACO is a probabilistic technique for optimisation that was inspired through the simulation of real ant colonies. The individual ants support in improving the solution firstly by using the heuristic parameter which is the individual component of ACO, and then considers then by considering the pheromone trail information which is the social component of ACO [10].

The formal study of conflict and cooperation is the basis of Game Theory. Game theoretic concepts can be applied whenever there are number of interdependent agents. The strategic scenario for an application can be formulated, structured, analysed and understood by the language of game theoretic concepts. The interdependent agents who are involved in the game can be individuals, groups, firms, or any combination of these. Different scenarios of cooperation and conflicts among the players involved in a game are described in game theoretic approaches. Selfish players and cooperative players have also been commonly studied under the same concept [4].

Altruism and selfishness are similar important factors that could be adopted continuously by the natural algorithms in order to experience significant variations while improving the quality of the existing solutions. According to different natural algorithms and their corresponding set of parameters, it is understood that some of the parameters are completely affected and those can be classified either as altruistic or selfish.

In this study, the combinatorially hard TSP has been taken as the reference problem for the proposed approach. Several instances of symmetric TSPs have been taken to test the said approach compared to the original ACO, MAX-MIN Ant System, and with the optimum solutions of the instances.

As the main objective in this research work, it is been analysed how the cooperative/competitive and altruistic/selfish behaviours of individual ants and the colony make changes to the original ACO. Figuring out the driving force of ants' behaviour and colonies was attempted by analysing the results of well known TSP instances. Further an adaptable methodology was proposed to change and adjust the influence of parameters in individual and social components of ACO.

The rest of the paper is structured as follows. Section II describes the research background of different social theories which are of common social interactions along with the relevant researches and those theories which have been adapted in swarm intelligence domain. The basics of ACO are discussed with respect to the proposed approach in Section III. Section IV outlines the proposed new approach of this study that adapts social interactions to original ACO. Section V discusses the experimental results obtained by the proposed approach using TSP instances and conclusion is in Section VI.

II. Related Research

Real ants have different types of interactions when targeting and achieving their goal of finding food [11]. The society based interactions based on cooperative/competitive and altruistic/selfish behaviours were studied and been tried to adapt in ACO model in this research where attempt is made to solve the problems of Evolutionary Algorithms, delay in convergence and premature convergence.

A. Real ant's behaviour

Ants communicate among each other using a class of chemicals called pheromones [11]. In foraging, when the ants

978-1-4799-7732-1/14/$31.00 ©2014 IEEE

walk from nest to food and back from food to nest, they release pheromones. The ants generally move along the path which has the highest in pheromones. Since a shorter path has a higher probability of having more pheromones, eventually the ants would find the shortest path [11].

In ant behaviour, altruism is a special attribute where the ants totally act altruistically in order to achieve their target. In some of the species within the colony they exist as neighbouring microhabitats. Though they are grouped they behave totally altruistically for the same goal [12].

Worker ants, male ants and a queen are common in an ant colony. In *Ponerine* ants when the queen get old and weak, a normal worker ant, namely *Gamergate* becomes special as the queen ant and get the control over the colony to protect the other worker ants providing guidance. Although these *Gamergates* are similar to worker ants, they fulfil the necessity of the role of the queen ant and hence appear to be someone special [13].

In the colony level, altruism of individual components strongly affects the target achieving capability of the whole ant colony. Ants, within the colony work towards a common goal acting purely in an altruistic manner. The colonies are enormous formidable feats of construction. The influence of common driving force of ants' behaviour at the colony level (i.e. altruism) is worth analysing in relation to the above discussed *Gamergate* behaviour and neighbouring microhabitats [13].

B. Game Theory

There are situations where decisions are taken knowing that the result will be governed in part by the actions of a competitor. The part of operations research that addresses this kind of situation is called Game Theory. Although clearly applicable to games as the name implies, it is appropriate in a wide variety of contexts in which one must make a decision whose outcome will be determined by the actions of one or more individuals [14].

The amount of power held by various players and the means of division of proceeds of a successful coalition in coalitional games is considered and investigated in cooperative game theory. Most naturally, this can be applied in situations where concepts such as power become the most important.

In contrast, noncooperative game theory is concerned with the analysis of strategic choices. Prisoner's Dilemma is a noncooperative game theoretic strategy which shows how two purely "rational" individuals might not cooperate even though the final result would be in their best interests [4]. It is a strategy that governs the balance between cooperation and competition in natural behaviours of any population.

C. Other Social Theories

If implications are there for both the actor and the recipient, the behaviour can be mentioned as social. The social behaviour of swarm can be classified into several different categories depending on how the actor or the recipients are benefited. Altruism, selfish, mutual beneficial and spiteful is one of those classifications [15]. If the fitness level of the actor is decreased while that of the recipient is increased after a particular action then it belongs to the altruism category. If the fitness level of the actor is increased while that of the recipient is decreased after a particular action then it belongs to the selfish category.

D. Social Behaviours based Evolutionary Algorithms

Algorithms have already used cooperative approaches coupling with game theoretical strategies and have directly modelled different styles of games such as Prisoner's Dilemma and Tic-Tac-Toe. Noncooperative approaches have been taken with the algorithms to get improved solutions for particular applications [8]. Prisoner's Dilemma is a well-known game theoretic strategy that has been adapted by several Evolutionary Algorithms recently for instance Genetic Algorithm, Particle Swarm Optimisation and Ant Colony Optimisation [7]-[9].

When applying the mentioned social theories, basically the cooperative behaviour is highly considered. When considering the ACO model, it is evident that the ants used stigmergy, the indirect means of communication and coordination by using the knowledge of previously found solutions of the ants in terms of the trail update. In application like Vehicle Routing, cooperate behaviour of ants has been tested by modifying the algorithm by introducing cooperate pheromone trails, which is an additional historical knowledge of other ants [16]. Various improvements were attempted by introducing different types of ants in the same population and introducing different methodologies for communication with each other [17].

Some of the existing approaches were separately modified when identifying the social and the individual components of the scenario before applying the above mentioned social theories. Then the identified components can be served in different flavours in improving the quality of the solution. Prisoner's Dilemma is once adapted in Particle Swarm Optimization where it was evaluated using bench mark functions such as Ackley, Griewank, Rastrigin, Rosenbrock and Sphere[8].

It is understood that individual and social components which are been used in the original evolutionary models, the individual component behaves partially selfishly while social component behaves altruistically. It is worth studying how the above described social and individual components can be fine-tuned to be cooperative or competitive in the natural algorithm models.

III. Ant Colony Optimization

The inspiration for ant algorithm was due to the observation of real ant colonies. Ants living in colonies would like to see the survival of the colony as a whole rather than thinking in terms of single individual components. These ant colonies get the attention of scientists, especially on their foraging behaviour, and the way how they find the shortest path between food sources and their nest. When it is modelled as an algorithm, artificial ants are taken as probabilistic solutions with artificial pheromones and heuristic information [18]. In the solution construction process, the heuristic information is derived from a problem instance to guide the ants. Pheromones that are represented as numerical information, iteratively modified towards good quality solutions [18].

ACO is introduced by Dorigo et al. [10] in 1999 as a multi agent approach that search for solutions to instances of TSP and other combinatorial optimization problems. Not only in TSP, it has been extensively applied to a variety of discrete combinatorial optimization problems such as the Quadratic Assignment Problem[19], [20] and the Network Routing

Problem [21] where it was applied to continuous search domains as well [22].

The original ACO model and most of the improved ACO versions were designed to use both social and individual components when deciding the solution. The Ţ and Ŋ are the two social and individual components respectively in ACO. An ant (or agent) is randomly planted in a particular node i in the TSP instance and traverse the graph using the random-proportional rule with a selection of the next node j with probability,

$$P_{ij}^{k} = \frac{(\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})}{\sum_{l \in N_i^k} (\tau_{il}^{\alpha})(\eta_{il}^{\beta})}, \qquad \text{if } j \in N_i^k \qquad (1)$$

where N_i^k is the feasible neighbourhood of ant k at node i, τ_{ij}^{α} is the amount of pheromone on an edge, $\eta_{ij}^{\beta} = 1/d_{ij}$ is a heuristic value known a priori of the algorithm execution (with d being the Euclidean distance between node i and node j as the length of the edge) [23]. The parameter α, $0 \leq \alpha$ is a parameter to control the influence τ while β, $\beta \geq 1$ is a parameter to control the influence of η.

When taken pheromone evaporation as negative feedback and the pheromone update from the ants as positive feedback the solution construction will slowly converge to the better quality tours. Combined in one function, this rule is,

$$\tau_{ij} = (1-\rho).(\tau_{ij}) + \sum_{k=1}^{m} \Delta\tau_{ij}^{\alpha}, \forall (i,j) \in L \qquad (2)$$

where *L* is the set of all edges, ρ is the evaporation rate, *m* the number of ants [23].

The amount of pheromone dropped on *(i, j)* by ant *k*, denoted with $\Delta\tau_{ij}^{k}$, can be computed as:

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L^k \\ 0 \end{cases} \qquad (3)$$

where *Q* is a constant (often 1) and L_k is the length of the constructed tour of ant *k* [23].

As far as the history of the trails is available, the ant selects the best path considering the distance and the trails (the results of the previous ants). The approach discussed here was to analyze the effect of the ant behavior and the corresponding components of the ACO model given in Table I.

TABLE I
COOPERATIVE COMPETITIVE COMPONENTS OF ACO

Ant Behaviour	Component in the ACO Model	Parameter	Influence
Cooperate/Altruism	Social	Trails Ŋ	α
Compete/Selfish	Individual	Distance Ţ	β

IV. PROPOSED SOCIAL APPROACH IN ACO MODEL

It is worth studying and analysing the driving force behind the activities at the colony level of ants. Ants are individuals, who support the well-being of the community. Altruism, the influence of common driving force at the colony level, was tested with a different approach in this research *Gamergate* behaviour (discussed in Section II A) was applied to smaller groups of ants similar to neighbouring microhabitats of a large ant population attempting to adapt to the original ACO model. Further, the influence of the individual and social components were separately analysed with relation to the altruistic behaviour.

Not like in the ordinary ACO that use the whole population as it is, the approach is to segregate the population into separate individual ant sets. Then the ants in each and every ant set work individually, without considering the history results, i.e. the social component (the trails- Ţ), of the other ants in the same ant set. However the separate sets work cooperatively altogether to get the final solution iteratively, depending on both distance (Ŋ) i.e. the individual component and the social component. The goal is to make use of stronger individuals who improve the whole population. Thus, initially the individual component is kept stronger while the individuals eventually improve the social component.

The ants in the proposed approach behave in two identical ways. Since the population is divided into separate smaller groups within the population, the ants can be further considered as Social ants and Individual ants. The two ant types are defined based on the content of information exchanged within the population. The content of the information is defined by the usage of history trails of the population. Then, interaction behaviours are introduced for the whole colony as well as the ants within the smaller groups in the colony separately. Thus the interaction is defined through the manner which the history of the trails is used within and outside of the smaller groups. In this approach, the ordinary method of updating the pheromone information and the way how the updated information is used has been deviated by maintaining the effect and the influence of the individual and social behaviours of the ants.

The two ant categories behave differently from each other influencing the social and individual components. Within a divided smaller group there exists a special ant named Social Ant who behaves social as *Gamergate*. Social Ant considers the total effect of the whole population regardless of the smaller groups and read the pheromones that is been updated by every ant who has been active so far when the Social Ant chooses his tour.

Every ant except the Social Ant, within a particular smaller group behaves partially individually to a certain extent. They are called Individual Ants. Soon after Social Ant chooses the tour, he updates the pheromone accordingly, using the trails been used by all other individual ants in the smaller groups. Every single Individual Ant in the smaller groups read the updated pheromone of their Social Ant along with its own individual influence when selecting the tour. Even though the Individual Ants do not read the updated information of the whole population over and over again, every ant updates the pheromone trails accordingly to maintain the cooperative effect that can be adapted by the Social Ants in the smaller groups. Ultimately the Individual Ants behave competitively within the smaller groups of ants according to their Social Ant's trail updates. However the Social Ants behave cooperatively capturing the complete trail effect of the whole colony when selecting the tour.

To deal with the above explained approach, a new parameter is introduced and applied to the standard ACO algorithm named ANTSET. Modified algorithm is given in Fig. 1.

In the proposed approach where the individual and social components of Ant Colony Optimization model were analyzed, two separate behaviors have been introduced for the two types of ants.

```
Select TSP-Instance
Create construction graph
Initialize cooperate set of ants ANTSET
while not stop-condition do
   Create all ants solutions
      For all ϵ in colony ANTSET
         For all ϵ in colony
            Perform local search
            Read pheromone
            Update pheromone values
   Update oldPheromone values
end while
```

Fig. 1 Pseudo code for the proposed algorithm

A. Adaptive Social Ants

The artificial ants construct the solution with the use of heuristic parameter and the pheromone trails. When considering the heuristic parameter (individual component) and the pheromone trails (social component), influences of the parameters vary according to the stage of the algorithm runs. The smaller the influences of both the parameters the solution supposed to be less significant [24]. In the early stage of learning, influence of the heuristic parameter should be large since ants do not have much information. In the later stages, the influence of the heuristic parameter can be maintained at a low value as the pheromone trails keep on collecting information since the heuristic parameter would misinform the solution thus result in premature convergence. Same way in early stage there is no pheromone trail information to learn. When the algorithm runs the pheromone trail information can be collected. Thus keeping the influence of pheromone trail lesser in earlier stages and increasing while information is collected in later stages influence is better for good performances while the information is collected in later stages, the influence should be increased.

According to the above explanation, the behavior of the two parameters is also worth applying. The new approach defines a different parameter set which is not assigned to be constant in the initial stage as in original ACO. With the above mentioned ANTSET variable, the two influences were tested accordingly. The Social Ants were given an adaptive set of parameters. The Social Ant s in a smaller group g_x is planted in a particular node i in the TSP instance, who traverses the graph using the random-proportional rule with a selection of the next node j with the same probability in equation (1) above. The pheromone evaporation of τ_{ij}^{s} is also same as in equation (2).

B. Stronger Individual Ants

Soon after the Social Ant of any smaller group is planted accordingly, then the other Individual Ants run with the same set of parameters that was copied by their Social Ant in their smaller group. They all read the final trail that was updated by its Social Ant of the group without considering the other ants in the same group when selecting the next tour. However they update the trails as they progress, since the Social Ants take the advantage of the pheromone trail updates of the whole ant population. However the Individual Ants behave competitively without capturing the complete trail effect of the whole colony but use their individual capacity for the well-being of the whole population, when selecting the tour.

The probability of selecting the next tour of an Individual Ant is changed according to the concept. Now the Individual Ant is planted in a particular node i of a smaller group x in the TSP instance who traverse the graph using the random-proportional rule and the trail information taken from their Social Ant in their group as τ^{s} with a selection of the next node j with probability,

$$P_{ij}^{k} = \frac{(\tau^{s\alpha})(\eta_{ij}^{\beta})}{\sum_{l\in N_i^k}(\tau_{il}^{s})(\eta_{il}^{\beta})}, \qquad \text{if } j \in N_i^k \tag{4}$$

Here τ^{s} is not going to be changed for every ant in the group.

C. Adaptive changes of influence parameters

As with the original ACO model, the parameters, α, β, Q, q_0 and $p$are initially set in the same manner. The ANTS (number of ants) has to be defined same as in the original ACO. The variable ANTSET (the number of smaller groups of ants) is then defined as to follow the new approach. Further the influence of the social and individual components, α and β are changed throughout the program. When the ANTSET variable is increased, the value of α is decreased and the value of β is decreased.

Continuously, two values are been changed in several phases. The phases are declared by a second variable introduced as PHASE in the algorithm. According to the number of ANTS in the population the number of PHASEs could be varied. The decreasing and increasing properties of the parameters are given in Table II.

TABLE II
SOCIAL/ INDIVIDUAL INFLUENCE LIMITATIONS

Parameter	Lower Bound (lb)	Upper Bound (ub)
α	0	0.7
β	1	12
PHASE	2	5

The two influence parameters are changed adaptively while the program is been executed as follow.

$$\alpha = \alpha - \left\{\frac{(\alpha_{ub} - \alpha_{lb})}{PHASE}\right\} \tag{5}$$

$$\beta = \beta - \left\{\frac{(\beta_{ub} - \beta_{lb})}{PHASE}\right\} \tag{6}$$

Since the Social Ants consider the updated trails of every member in each smaller group, it can be stated that they behave cooperatively. The Individual Ants consider only the trails updated by their Social Ant of the group, thus it can be stated that they behave competitively. Stronger individuals who competitively work for the well-being of their own population who in turn support the cooperate leaders who work for the well-being of the whole population is modeled in the said approach.

Most of the Evolutionary Algorithms suffer from the problem of premature convergence and various suggestions are introduced as improvements. The issue of premature convergence of the Evolutionary Algorithms has been solved in the proposed approach to a certain extent. The agents in the original ACO start positioning randomly and then select the next path considering the historical results of the other ants, the pheromone trails. Since the history knowledge is taken from the beginning, this may result in premature convergence. This was addressed in the proposed approach while improving the convergence speed of the algorithm as well.

V. EXPERIMENTAL RESULTS

TSP instances were chosen as the benchmark in order to test the proposed approach. Eleven (11) different TSP instances in TSPLIB [25] were used to test the individual and social behaviour of the ant model. The same instance is tested with different set of agents and corresponding different ANTSETs accordingly. The best result of the proposed approach was then compared with the original ACO solution, Max-Min Ant System and with the optimum result of the problem instance as mentioned in Table III. Then the error with the optimum solution was calculated. The error was calculated according to the following formula.

$$Error = \frac{\left(\begin{matrix}\text{Best solution of} \\ \text{proposed approach}\end{matrix} - \begin{matrix}\text{Optimum} \\ \text{solution}\end{matrix}\right)}{\text{Optimum Solution}} \times 100$$

TABLE III
DISTANCE COMPARISON OF SMALL SCALE INSTANCES

TSP Instance	Proposed approach	ACO	Max-Min Ant System	Optimum	Error
Bayg29	9148	9234	9078	9074	0.82
att48	34518	34351	33523	33522	2.97
Eil51	440	433	427.6	426	3.29
Berlin52	7670	7544	7544	7542	1.70
KroA100	21912	21420	21291	21282	2.96
Bier127	121573	120279	118710	118282	2.78
Lin318	43325	44058	42346	42029	3.08
pcb442	52140	51690	51515	50778	2.68

Three (03) middle scale TSPLIB instances vm1084, pr2392 and pcb3038 were tested with the proposed approach and the best result was compared with the optimum solution of the corresponding instance. The error with the optimum answer is then calculated. The results are given in Table IV.

TABLE IV
DISTANCE COMPARISON OF MEDIUM SCALE INSTANCES

TSP Instance	Best Solution from proposed approach	Optimum Solution	Error
Vm1084	244297	239297	2.08
Pr2392	387837	378032	2.59
Pcb3038	142553	137694	3.52

The following figures (Fig. 02, Fig. 03, Fig. 04) show the convergence comparison of three (03) best tuned TSP instances of new approach Bayg29, att48 and Berlinn52. The dashed lines stand for the proposed approach's convergence trail while the solid lines stand for the original Ant Colony Optimisation Algorithm's convergence trail. Ten (10) best solutions of each instance of the new proposed approach and the original ACO model were taken to generate the graphs.

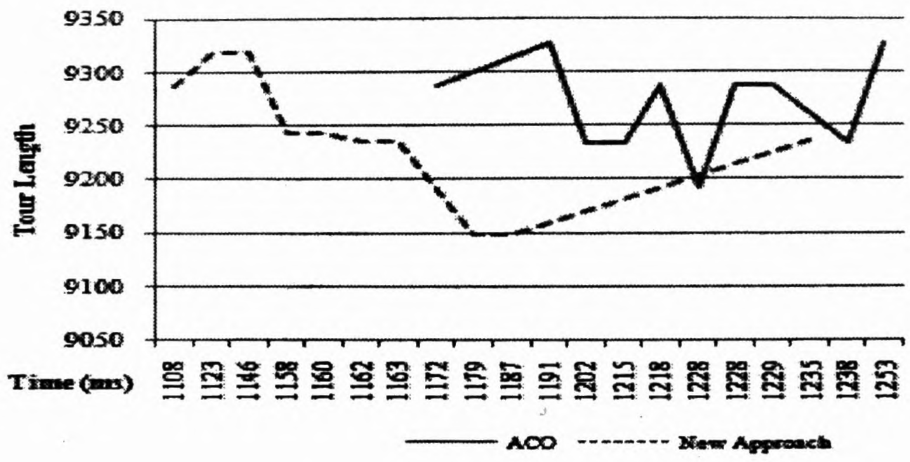

Fig. 02 Convergence speed of Bayg29

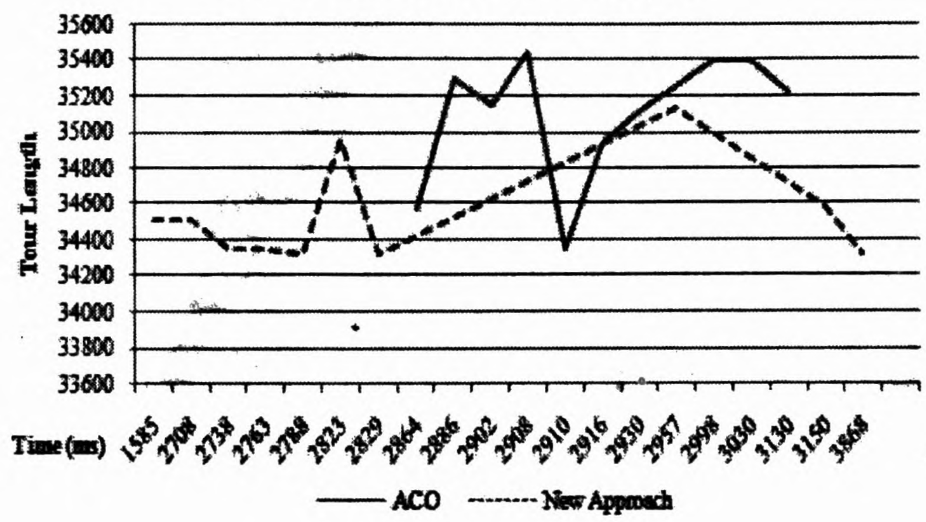

Fig. 03 Convergence speed of att48

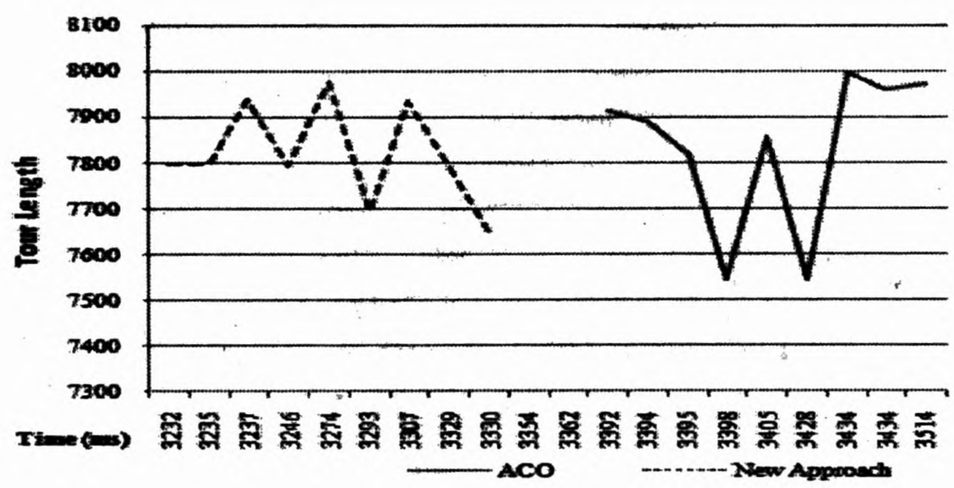

Fig. 04 Convergence speed of Berlin52

The experiment shows that the proposed approach has faster convergence in finding solutions for the three TSP instances. The approach has been carried out as a solution to the two issues premature convergence and delay of convergence. However even though the proposed approach does not give the respective optimum solutions for the TSP instances tested, the approach is effective in reaching convergence faster for large scale problems. Since this is an ongoing research the same approach could be fine-tuned further to obtain optimum solutions while addressing the issue of convergence of very large scale problems.

VI. CONCLUSION

In this research two natural ANT behaviors, cooperative/ competitive as well as altruistic/ selfish properties have been studied and adopted in original ACO, in order to observe important variations to improve the quality of existing solutions. The study shows that the solutions of ACO are affected by the said pair of properties of natural ants and the colonies while their corresponding influences can change the solution quality of the algorithm. This study shows a path in adapting the same approach in other improved ACO variations as well due to its simplicity. Most important aspect in this approach is the adaptation of the newly introduced individual ANTSET, allowing the decrease of the delay in convergence and the premature convergence of ACO algorithms. Moreover, the present experiment opens a path to adapt society based interactions in swarm intelligence algorithms such as that of game theoretic approaches in order to solve large scale combinatorial problems.

ACKNOWLEDGMENT

It is a pleasure to acknowledge W. A. T. Lakmali for her programming support and R. R. Fernando, C. I. Kithulgoda and W. A. Indika for comments that greatly improved the manuscript.

REFERENCES

[1] Chen, Hanning, Y. Zhu and K. Hu. "Cooperative bacterial foraging algorithm for global optimization," *Control and Decision Conference-CCDC'09*. Chinese. IEEE, 2009.

[2] V. den Bergh, Frans and A. P. Engelbrecht. "A cooperative approach to particle swarm optimization," in *Evolutionary Computation, IEEE Transactions*, pp. 225-239, 2004.

[3] Goh, C. Keong, K. C. Tan, D. S. Liu and S. C. Chiam, "A competitive and cooperative co-evolutionary approach to multi-objective particle swarm optimization algorithm design," *European Journal of Operational Research*, 202.1, pp. 42-54, 2010.

[4] D. Fudenberg and J. Tirole, *Noncooperative Game Theory For Industrial Organization: An Introduction and Overview*, Handbook of industrial Organization , vol. 1, 1989, Pages 259–327 1987

[5] I. A. Ismail, N. A. El Ramly, M. M. El Kafrawy and M. M. Nasef, "Game Theory Using Genetic Algorithms," *in Proceedings of the World Congress on Engineering*, 2007.

[6] Z. Cui, X. Cai, J. Zeng and G. Sun, "Predicted-velocity particle swarm optimization using game-theoretic approach," in *Computational Intelligence and Bioinformatics*, pp. 145-154, Springer Berlin Heidelberg, 2006.

[7] M. A. Bharathi and B. P. V. Kumar, "Reverse Game Theory Approach for Aggregator Nodes Selection with Ant Colony Optimization Based Routing in Wireless Sensor Network," *International Journal of Computer Science*, 2012.

[8] W. Liu and X. Wang, "An evolutionary game based particle swarm optimization algorithm," *Journal of Computational and Applied Mathematics*, vol. 214, pp. 30–35, April 2008.

[9] H. B. Ammar, K. Tuyls and M. Kaisers, "Evolutionary Dynamics of Ant Colony Optimization," Lecture Notes in Computer Science, Trier, Germany: Springer, 2012, vol. 7598, pp 40-52.

[10] M. Dorigo, G. D. Caro and L. M. Gambardella, *Ant algorithms for discrete optimization*, Artificial Life, vol. 5, pp.137–172, 1999.

[11] Poulsen, Michael and J. J. Boomsma, "Mutualistic fungi control crop diversity in fungus-growing ants," *Science 307.5710*, pp.741-744, 2005.

[12] A. Narendra, and S. M. Kumar, *On a Trail with Ants: A Handbook of the Ants of the Peninsular India*, 2006.

[13] C. Peeters, J. Liebig and B. Hölldobler, "Sexual reproduction by both queens and workers in the ponerine ant Harpegnathos saltator. Insectes Sociaux 47," pp. 325-332, 2000.

[14] R. J. Aumann, *The New Palgrave Dictionary of Economics*, 2nd ed., Ed. Lawrence Blume. Palgram Macmillan, 2008.

[15] W. D. Hamilton, "Selection of selfishness and altruistic behaviour in some extreme models'" In *Man and Beast: Comparative Social Behaviour* (J.F. Eisenberg & W.S. Dillon, eds), pp. 57–91. Smithsonian Press, Washington, DC.1971.

[16] J. Liu., L. Yuan, X Wang, Y. Wen and T. Zhou, "A Two-phase Methodology Heuristic Insertion Algorithm for TSP," *Transactions on Computer Science and Technology*, vol. 2, pp.62-68, December 2013.

[17] F. Liu, "A dual population parallel ant colony optimisation algorithm for solving the travelling salesman problem," *Journal of Convergence Information Technology*, vol. 7, pp. 66-74, March 2012.

[18] T. Stutzle and H. H. Hoos, "MAX-MIN ant system," *Journal of Future Generation Computer Systems*, 16, pp. 889–914, 2000.

[19] L. M. Gambardella, E. Taillard and M. Dorigo. "Ant colonies for the QAP", *Journal of the Operational Research Society*, 1998.

[20] V. Maniezzo and A. Colorni, "The Ant System applied to the Quadratic Assignment Problem," *IEEE Transaction on Knowledge and Data Engineering*, vol. 11, pp. 769–778, 1999.

[21] G. D. Caro and M. Dorigo, "AntNet: Distributed stigmergic control for communications networks," *Journal of Artificial Intelligence Research*, vol. 9, pp.317–365, 1998.

[22] K. Socha, "ACO for continuous and mixed-variable optimization," *In ANTS Workshop*, pp. 25–36, 2004.

[23] T. Stützle, M. López-Ibánez, P. Pellegrini, M. Maur, M. M. de Oca, M. Birattari, M. and M. Dorigo, "Parameter adaptation in ant colony optimization. In *Autonomous Search*," pp. 191-215. Springer Berlin Heidelberg, 2012.

[24] Z. C. S. S. Hlaing and M. A. Khine. "Solving traveling salesman problem by using improved ant colony optimization algorithm," *International Journal of Information and Education Technology* vol. 1, pp. 404-409, 2011.

[25] G. Reinelt, "TSPLIB—A travelling salesman problem library", ORSA *Journal on Computing*, vol. 3, pp. 376-384, 1991.