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# A Critical Analysis of Heterogeneous Ant Colony Optimization for Combinatorial Optimization Problems

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**Abstract:** Ant Colony Optimization (ACO) is an optimization algorithm that is inspired by the foraging behavior of real ants in locating and transporting food source to their nest. It is designed as a population-based metaheuristic and have been successfully implemented on various NP-hard problems. However, majority of the studies in ACO focused on homogeneous artificial ants although biologists suggest that real ants exhibit heterogeneous behavior thus improving the overall efficiency of the ant colonies. Equally important is that most, if not all, optimization algorithms require proper parameter tuning to achieve optimal performance. However, it is well-known that parameters are problem-dependant as different problems or even different instances have different optimal parameter settings. One method to mitigate this is to introduce heterogeneity by initializing the artificial agents with individual parameters rather than colony level parameters. This allows the algorithm to either actively or passively discover good parameter settings during the search. Unfortunately, very little research has been conducted that adopts the heterogeneous approach. This paper conducts a critical review of ACO algorithms that integrates heterogeneity in their solution as well as providing a basis for our implementation.

**Keywords:** Ant Colony Optimization, Heterogeneous, Heterogeneity, Behavioral Diversity, Individual Ant Behavior

## 1. Introduction

The collective behavior of the individual agents in the biological systems has inspired a collection of computational algorithms known as swarm intelligence used to solve complex problems. These algorithms consist of artificial agents that co-operate collectively without any centralized control while solving problems in various fields such as optimization, big data analysis, robotics and many more. Some of the well-known metaheuristics algorithms are simulated annealing, particle swarm optimization (PSO), genetic algorithm, tabu search, ant colony optimization (ACO) and many more.

ACO is a population-based metaheuristic which is stochastic in nature and designed to construct solutions iteratively, also known as a constructive method [1] in order to solve combinatorial optimization problems. ACO algorithms are largely inspired by the foraging behavior of the Argentine ants [2]. The basic concept is founded on the pheromone laying mechanism of the real ants while locating and transporting the food from the source to the nest via the shortest path. The algorithm consists of a colony of artificial ants that cooperatively explores and exploits the search landscape by constructing solutions to the optimization problems. The ants then exchange information regarding the solution's quality via artificial pheromone deposition and an evaporation mechanism. This mechanism, which is an indirect communication medium called 'stigmergy', allows an individual ant to alter the environment and thus acts as a stimuli for the colony of ants [3]. In the solution construction phase, each individual ant uses two important variables to guide them towards good solutions which are the problem-specific heuristic information and the feedback from other ants via the stigmergic information. These concepts act as the fundamental framework for most ACO algorithms [2][4][5][6].

In recent years, many ACO variants have been developed and successfully applied to various problems such as vehicle routing [7], scheduling [8], image processing, assembly line, wireless sensor networks [9][10], traffic signal optimization [11] and many more.

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This shows that ACO is one of the most promising algorithms in swarm intelligence due to its robustness in solving various problems. Most ACO algorithms implement homogeneous population where all ants are initialized with colony-level parameter settings thus we term this as having similar 'behavioral traits'. However, it is also possible to initialize the swarm as a heterogeneous colony which consists of artificial agents with individual 'behavioral traits'. This concept stems from studies conducted by animal behavior researchers that found some insects such as ant colonies exhibit heterogeneous behavior where the individuals may differ in morphological characteristics as well as their function in a colony. For that instance, a soldier ant might be stronger compared to normal worker ant while worker ants might have different job scopes such as nest maintenance, foraging for food and many more. The individual 'behavioral trait' contributes to the emergent, colony-level behavior in the ant colonies that in turn allows the colony to self-organize and collectively solve problems. Correspondingly, the heterogeneous concept can also be implemented in swarm intelligence algorithms that can create a diverse population of agents with their own perspective while tackling the search landscape [3] [4].

Therefore, this paper introduces and reviews the concept of heterogeneity in ACO. Section 2 briefly discuss the inspiration behind ACO while section 3 discusses conventional ACO algorithms. This is then followed by section 4 which reviews the concept of heterogeneity and previous works related to ants with different 'behavioral traits'. The paper concludes with potential applications where heterogeneous ACO algorithms are expected to perform better.

## 2. Motivations for Heterogeneous ACO

**Begin**
Load the problem instance;
Initialization;
**While** termination criterion not met **do**
    Ants construct solution;
    Local search procedure (optional);
    Pheromone trail update;
**End**
**End**

Algorithm 1: ACO General Framework

ACO is specially designed to solve NP-hard combinatorial optimization problems [12]. The general ACO framework consists of four main phases with one optional phase as shown in Algorithm 1. Once the problem instance has been loaded into the algorithm and the main parameters are initialized, a population of ants construct their solutions and pheromone trails are updated until the stopping criterion is met. The additional step is applying the local search procedure which is usually used to improve the solution found. This step is optional as it is best used especially when to solve large instances as it can further improve the solution found by performing neighbourhood search. Each ant starts with an empty solution and constructs the solution by adding nodes or components that it has traversed until all nodes have been visited. The choice of the node to be visited is based on the probabilistic rule that consists of pheromone trail and heuristic information. Each information component has a coefficient to create a bias toward pheromone or heuristic during the decision-making. Each variant of ACO has its own choice of the coefficient values. These values are usually set during the initialization phase either based on recommendations by other researchers or one's expertise by performing parameter tuning. It is well known that the behavior and performance of an ACO algorithm strongly depend on the parameters initialized during the start-up [13][14][15][16][17]. Dorigo et al [5] analysed and summarised three categories of parameter values which are the good parameters, poor parameters that will not cause stagnation and lastly, poor parameters which will lead the colony to stagnation behavior. This suggestion has acted as a guide for many ACO algorithms where the parameter values are set during initialization and kept constant throughout the search process. However, various studies and analyses both empirically and theoretically have shown that the optimal parameter settings are very much dependant on the problem being solved, the problem instances or even a particular stage of the search process [18][19][20][21][22][23]. As an example, parameter values in job shop scheduling [8] did not corroborate to any of the parameter suggestions by Dorigo and Stützle [2, p. 71].

Generally, parameter tuning may enhance the performance of the algorithm if tuned carefully. However, it is trivial and computationally expensive as it requires a considerable amount of time and processing power. In addition to this, a deep understanding of the algorithm's behavior and the problem being tackled is also important during parameter tuning. On top of that, the trial-and-error method is practically ineffective because it is a computationally exhaustive process to tune the parameters for every problem or problem instance. The tuning of the parameter values before the optimization process does not guarantee optimal performance in the ACO algorithms [24]. In essence, little research has been reported on parameter tuning in ACO [25]. Lack of population diversity is a key reason for premature convergence to local optima, especially in ACO algorithms. As most of the ACO algorithms deploy a homogeneous concept, where all ants in the colony have similar 'behavioral traits', the algorithm is unable to escape from this phenomenon due to stagnation behavior of which all ants construct the same tours repeatedly. It is also down to the nature of the ACO algorithm that is unable to switch between the exploration and exploitation phase hence stuck in local optima. As most of the ACO algorithms with the aforementioned drawbacks deploy a homogeneous population, one of the possible approaches to overcome the problems is to maintain diversity in a population-based algorithm such as ACO by implementing a heterogeneous single population approach where the ants are initialized with individual ‘behavioral traits’. This will allow the algorithm to switch between exploration and exploitation as the search progresses due to the inclusion of explorative and exploitative ants. The proposed framework will then be able to promote a self-adaptive approach by taking advantage of the specific strengths of each individual ant in different stages of the search process. Both of these approaches will be able to mitigate the aforementioned drawbacks of the ACO algorithm by removing the need for tedious optimal parameter tuning process and create a more robust and scalable ACO algorithm.

Lastly, heterogeneity is omnipresent in nature. Several biological studies have shown that real ant colonies are in fact heterogeneous where the ants are known to have individual ‘behavioral traits’ or personalities [26][27][28][29]. The ant colonies with higher variation between nest members are more productive and more efficient in nest maintenance and division of labor [27]. In another study, animal behavior scientists have also found that the ant colonies do have individual personalities similar to that of humans where the colony consists of ants with different levels of aggressive behavior [30]. In conclusion, instead of heterogeneity, conventional ACO algorithms deploy the homogeneous concept mainly due to the algorithmic simplicity in implementation. Therefore, the heterogeneous approach, which is proven to be effective from the biological aspect point of view, will be explored in this study.

## 3. HETEROGENEOUS ACO FRAMEWORK

Homogeneity or homogeneous population consists of individuals with the same traits or little variation physically or behaviorally. On the contrary, heterogeneity or heterogeneous population comprises of individuals with variation among them. The most obvious is the variation in human beings where generally, we differ in height, weight, skin colour and other traits. It is well known that heterogeneity is ubiquitous in natural systems. Behavioral variation has been observed in social insects by animal behavior researchers who have been studying the relationship between heterogeneity and population diversity in social insects and how this behavioral variation, especially in social insects, is beneficial to the colony. Recent studies have shown that intra-colony variations do exist in ant colonies where the ants differ in ‘behavioral traits’ within the colony [31][27][26][32][33][34][35]. This can be divided into two categories which are variation due to the age and size of the ants [36] and secondly, the behavioral variations such as aggressiveness or choosiness of the ants concerning nest maintenance [35]. Behavioral variation also has been attributed to an increase in colony efficiency and higher colony fitness compared to homogeneous swarm or colony with less behavioral variations [27]. One example of behavioral variation found in ants is the variation in the exploratory behavior of the workers where some ants might exhibit a higher preference toward exploration compared to others. Both the aggressiveness and exploratory behavior of the colony are important traits in determining the evolution and efficiency of the colony [37]. The diversity in the population introduced by the intra-colony behavioral variation allows a more efficient task allocation in the division of labor thus indirectly increasing the productivity of the colony.

The hypothesis is that with heterogeneity, a mixture of ants (exploratory, exploitative or random walkers) creates a balance in the search process. This creates a co-existence of search strategies as different strategies are required at different stages of the search process. The conventional ACO with static homogeneous parameter settings will not be able to interchange between exploration and exploitation strategies due to the fixed search behavior where normally the algorithm starts with exploration before exploiting the solutions found. However, this search strategy of conventional ACO might hinder the performance of the algorithm especially when the algorithm is stuck in local optima. In addition to that, the performance of these algorithms is dependent on the parameter settings. The proposed heterogeneous approach is capable of overcoming this drawback due to the behaviors of the ants of which are randomly initialized either to be more inclined towards exploration or exploitation.

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha^k}[\eta_{ij}]^{\beta^k}}{\sum_{(l \in N_i^k)}[\tau_{il}]^{\alpha^k}[\eta_{il}]^{\beta^k}} \; if \; j \in N_i^k \tag{1}$$

Or

$$P_{ij}^{k} = 0 \; if \; j \notin N_i^k \tag{2}$$

The concept of heterogeneity is proposed by modifying the probability rule (Equation 1) to incorporate individual $\alpha$ and $\beta$ values during the initialization phase which are two relative parameters that determine the weight of the pheromone trail and heuristic information respectively. This probability rule is chosen as the basis for the introduction of the proposed approach as it is used in most of the conventional ACO algorithms except with slight modification in Ant Colony System. Figure 2 illustrates the heterogeneous approach proposed in this study. This rule governs the ant's decision-making to move to cities based on edges with high amount of pheromone or short edges [38] represented by pheromone trail intensity on edge (i, j) ($\tau_{ij}$) and heuristic information of edge (i, j) ($\eta_{ij} = 1/d_{ij}$) respectively. The idea of this study is that although ants are governed by the probabilistic rule but their preferences can be controlled by the heterogeneous elements that allow each ant to have a different perspective while exploring or exploiting the search space by introducing ants with individual behavioral traits ($\alpha^k$ and $\beta^k$).

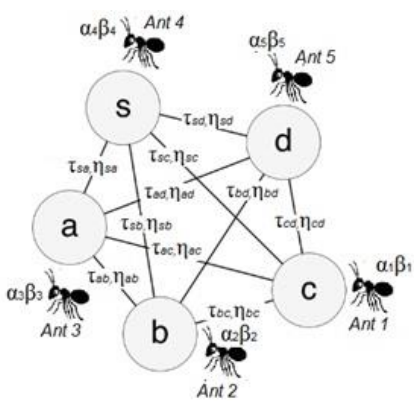


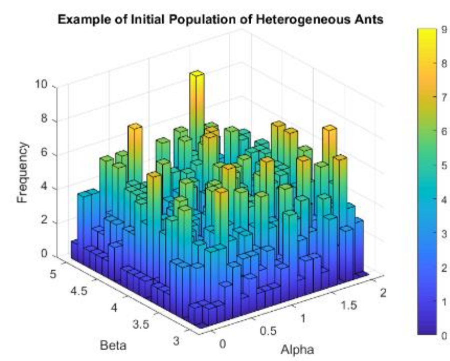

Figure 2: The principle of heterogeneity in ACO.

**For** k 1:max_ants
// uniform distribution
alpha (k) = rand(1).*(b-a) + a;
beta (k) = rand(1).*(d-c) + c;

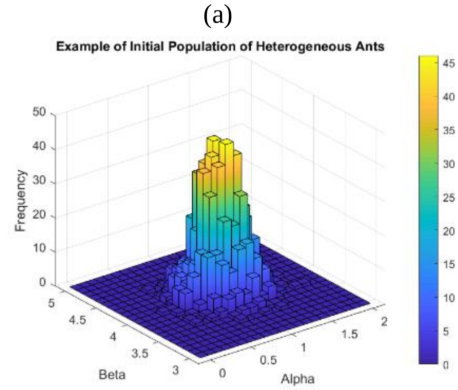
// normal distribution
alpha (k) = normrand(mean alpha, standard deviation alpha);
beta (k) = normrand(mean beta, standard deviation beta);
**End**

Algorithm 2: Initialization phase of heterogeneous approach

Algorithm 2 shows the initialization phase of the heterogeneous ants via uniform and gaussian distributions. Pre-defined values (a,b for alpha and c,d for beta) is centered around parameter values close to those suggested by Dorigo [5] at the inception of the ACO technique. The proposed approach highlights the $\alpha$ and $\beta$ values for each ant can be randomly drawn from different distributions (i.e uniform, continuous) within a pre-defined range based on parameter suggestions by Dorigo [5]. In a continuous uniform distribution with the interval of [a,b], each ant has an equal probability of being assigned to a value within the range of the interval while in a continuous normal distribution, each ant has a higher probability of being assigned to a value close to the central value known as the mean value, μ. The normal distribution or also known as the Gaussian distribution is commonly used because most of the phenomenon in nature such as height and weight of the human population can be represented by the normal distributions hence the tendency to be used in a study. Figure 3(a) illustrates the example of the initial population of the colony drawn from a uniform distribution while Figure 3(b) depicts the initial population of the colony drawn from a Gaussian distribution.




(a)




(b)

Figure 3: Example of the initial population of a single trial drawn from (a) uniform distribution and (b) normal distribution.

## 4. RELATED WORK

Various mechanisms can be used to introduce the heterogeneous approach in ACO. Tsutsui [38] implemented a colony of ants that consist of both donor ants and cunning ants. A partial solution from the donor ant is used by the cunning ant in the next iteration to build its solution. The main reason for deploying this is to speed up convergence and escape from premature convergence. However, determining the right amount of information shared in the solution construction can prove decisive in the performance of the algorithm. In addition to that, over-exploration or exploitation may still exist in the algorithm especially if too little or too much of the partial solution is shared between the solutions. More importantly, the idea of varying the population's parameters was suggested in [39] where the $\alpha$ and $\beta$ values for the whole colony change at every iteration. The values were randomly sampled from a uniform distribution at every iteration. Furthermore, the authors also modified the pheromone deposition and evaporation mechanism to further improve the algorithm in order to escape from local optima. This method introduces heterogeneity into ACO, but the concept lacks an explanation on why and how the parameters change every iteration and how this can improve the performance of the algorithm as well as relation towards the real ant colony. Lee et al [40] introduced heterogeneous individual ants with different sight, speed and function behaviours for obstacle avoidance in a robotic environment. Although the authors stated that the performance of the proposed approach is better when compared to conventional ACO, they also stressed that there is room for improvement in the proposed approach especially when the main ACO parameters are varied during execution rather than being kept constant. Nugulescu et al [41] reviewed the idea of synthetic genes for artificial ants similar to that of a Genetic Algorithm (GA) approach. The authors suggested several parameters that can be converted from global to local parameters to incorporate the idea. However, the authors did not follow up on their initial idea as there are no published results of a working concept. Chira et al [42][43] discussed the effects of deploying artificial ants with different sensitivity levels to the pheromone trail. The parameter that influences the relative weight of the pheromone trail, α is randomly sampled from a normal distribution with a pre-defined range of 0 to 1. Ants with a low level of pheromone sensitivity (closer to 0) will act as an explorer thus will conduct a random search on the solution landscape while ants with high sensitivity level (closer to 1) will exploit solutions found in order to strongly follow the pheromone trail. This Sensitive Ant Model (SAM) improvised and extends the ACS approach by optimizing the properties which are responsible for inducing heterogeneity in each agent of model which leads to the sustainable search intensification. A similar approach was conducted by Yoshikawa et al [44] who used a cranky ants approach that explores paths with a low level of pheromone as opposed to the normal behaviour of standard ACO. This involves modifying the probability rule to include the reciprocal of the pheromone level rather than the pheromone level itself. Nevertheless, Stützle et al [45] suggested that both α and β, should be considered while implementing the parameter variation or adaptation mechanism as they are responsible for controlling the influence of heuristics.

Another heterogeneous ACO was introduced by Hara et al [46] where initially α value is set to constant and give-up ants were introduced that construct partial solutions consisting of nodes where the distance from the current node to the next node does not exceed a pre-defined distance, d. When the give-up ants encounter a situation where the distance of all possible nodes exceeds d, then the tour construction will be terminated immediately yielding partial solutions. Then, all partial solutions from the give-up ants will be merged to produce one complete tour. As the performance was not satisfactory, the authors then varied the α parameter of the give-up ants from 0 to 1 with a step size of 0.005 for every iteration. Although improvement in performance was noted, the authors indicated that important parameters are problem-dependent hence better performance can be achieved if parameters are varied as the search progresses. Abdelbar et al [47] also implemented a slightly similar approach by introducing stubborn ants where these ants have the ability to implement its solution from the previous iteration on the next iteration. The authors introduced a stubbornness parameter to determine the biases of each ant in using the previous solution. This approach enhanced the exploitation of previous tours where a single ant in every iteration will have a higher probability of choosing its previous solution rather than exploring a new path. This somehow reduces the diversity of the colony by limiting the exploration of new search areas. In the meantime, Zufferey et al [48] implemented pre-determined a colony of ants which is categorized into the normal ants, follower ants, moody ants and innovative ants. Follower ants have a higher probability of choosing the previous tour with the highest pheromone trail while moody ants can interchange its decision-making by choosing a tour with high in pheromone or inverse to the pheromone value and lastly, innovative ants can alternate between the exploration or exploitation phase. The main contribution of this paper was to categorize the ants with different personalities and then vehicle routing problem is being implemented. Although result reported was not according to the state-of-the-art, however, the performance of the better metaheuristic approach of ant personalities is encouraging.

The most recent study of heterogeneous ACO was conducted by Sueoka et al [49] in which both hard-working and lazy ants were introduced and allowed to interchange between each other in the colony. The hard-working ants prefer the path with a high concentration of pheromone level while lazy ants perform a random walk on the search landscape. The authors concluded that lazy ants play an important role in exploring the search landscape in order to locate the global optimum. Again, this study only focused on exploration and exploitation in context of the parameter that influences the pheromone trail, $\alpha$ while did not take into consideration of the parameter that influences the heuristics, $\beta$. This is a key parameter in ACO that can improve the performance as suggested in [45] that should be considered when introducing parameter adaptation method.

In a nutshell, it can be seen that there is a modest amount of research conducted in the heterogeneous ACO field unlike that of PSO although the concept has been proven to improve the performance of optimization algorithms. Secondly, the algorithms reviewed mostly adopt static or constant parameter settings or vary only a single ACO parameter even though it is known that both $\alpha$ and $\beta$ should be taken into account for parameter adaptation. The algorithms discussed above, approach the principle of heterogeneity from a different standpoint, either using different ant roles or through the implementation of problem-specific heterogeneity. The approach taken in this paper is one of biological plausibility for ants with similar roles, but differing behavioural traits, which are being drawn from a mathematical distribution. Therefore, this study analyses the heterogeneity in the ACO approach by randomly sampling the $\alpha$ and $\beta$ parameters from two different distributions (explained later) within a pre-defined range. This allows each ant to have distinctive 'behavioural traits' in relation to a pair of $\alpha$ and $\beta$ values that remain constant throughout the search process. In order to measure the effectiveness of the proposed approach in this study, both static (parameters do not change over time) and dynamic approach (the parameter changes over time via adaptive approach) is implemented as most of the heterogeneous ACO approaches presented above are static which put restriction while analysing the efficiency of an approach.

## 5. CONCLUSION

Interestingly, individually simple agent, ants as a whole are capable of complex behaviours such as nest building and maintenance, nest defence, foraging for food and many more. These are only possible due to what is known as the 'emergent behaviour' where the colony does not require any centralized control in solving complex problems. This review also primarily focused on the biological explanation of the foraging behaviour of real ants that acts as the main inspiration for the ACO algorithms. More importantly, biological researchers suggest the existence of heterogeneity in real ants and how an individual ant has its own preferences or behaviour especially in solving problems such as choosing a nest. Hence, this acts as an inspiration for the proposed approach.

Moreover, the ACO field has seen tremendous growth since the introduction of AS both in terms of new variants and applications that have been solved by ACO. However, it has been reported in several studies that the performance of heuristics, in general, is highly dependent on the parameter settings hence can easily deteriorate if not well-tune. However, tuning the optimal parameter of ACO for every problem or problem instance is tedious and almost impossible. Therefore, this paper reviewed in detail the heterogeneous ACO possible approaches to overcome the aforementioned problem. This then provides a basis for the realization of the proposed approach. In general, previous works indicate that heterogeneity is able to improve the performance of the main ACO algorithm via introducing individual 'behavioral trait' for each artificial ant. This allows for the ants to collaboratively explore and exploit the search landscape to locate better solutions iteratively. The review also suggests that the heterogeneity approach is able to overcome the tedious parameter tuning approach by assigning the ants with random parameters within a suitable range of values.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