Determining the Number of Ants in Ant Colony Optimization

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Abstract – The goal of this contribution article is to investigate the effect of the numbers of ants on the Ant Colony Optimization (ACO) metaheuristic's obtained solution while addressing the Traveling Salesman Problem. Within a restricted number of iterations, the purpose was to see how the duration of the calculated tours varied for various numbers of ants. Three well-known ACO algorithms: Elitist Ant System (EAS), Ranked Ant System (RAS), and Min-Max Ant System (MMAS), were developed and tested in this paper. The findings revealed comparable patterns across several test instances. EAS and RAS, both of which use specialized ants, demonstrated that the number of specialists had a significant impact on the duration of solutions. Normal ants, on the other hand, had no effect on the solutions. The response differed somewhat between EAS and MMAS, with a smaller number of ants being more preferred. When working with five specialists and ants, which are the same to the smart cities, however, RAS outperformed by a considerable margin.

Keywords – Elitist Ant System (EAS), Ant Colony Optimization (ACO), Traveling Salesman Problem (TSP), Min-Max Ant System (MMAS), Ranked Ant System (RAS)

I. INTRODUCTION

Ant Colony Optimization (ACO) [1] represents a stochastic algorithm for addressing computing issues that may be simplified to discovering optimal pathways across graphs. It is used in computer programming and computational modeling. Multi-agent approaches influenced by the behaviors of actual ants are known as simulated ants. Genetic ants' neurotoxins-based correspondence is frequently used as a model. For many optimization problems requiring some type of graph, such as route selection and web networking, a blend of ant colonies and search engine engines has emerged as the preferred solution. Like numerous other techniques, the ACO metaheuristic was inspired by nature. Several disciplines of study have been devoted to it since its introduction, with the goal of discovering methods to apply it to difficult issues. Over the years, this research has spawned a slew of books, seminars, and publications, with many new discoveries as the field matures. The Traveling Salesman Problem (TSP) prompted ACO to be established [2]. However, several customized ACO variants have already been designed and evaluated against all the other complex issues ever since initial conception. The many and diversified variables that should be agreed upon are one issue that those integrating and utilizing this group of optimization techniques face. When attempting to find an optimal solution, anything from the weight of the random elements feature to neurotoxins path decay and the amount of ant colonies must be factored.

Every publication on the topic has its own take as to how to best focus and apply these criteria, which are offered to the viewer as raw facts and statistics. The number of ants employed, in particular, is nearly always a fixed quantity, and it is a topic that is seldom discussed. Trying to figure out what number is optimal or why a certain number is utilized may be a frustrating experience since there is no obvious answer. The publications on ant network methods are largely concerned with ways to enhance the method itself, such as using neurotoxins to avoid stagnating, and contrasting it to other sophisticated techniques already in use. As a result, the focus of this study is on exploring and evaluating a number of these methods, with a particular emphasis on ants.

What effect does the quantity of ants and specialty ants have on the calculated trip length? Using a restricted number of iterations, solve the problem with the Min-Max Ant System, Elitist Ant Framework, and Ranked Ant Framework. The goal is to examine how the ants react with the calculated alternatives and how many of them there are. As a result, no local optimizations or data modification will be performed for any of the techniques employed. To avoid polluting the data output and how it connects to the ants, only the raw data from the techniques themself are evaluated. In an attempt to get over the problem of standstill, all of the programs vary in how the ants engage with each other and with the neurotoxins. We used 3 distinct ant algorithms and tested them all against the first three issue scenarios to collect as much reliable information as possible. The data was then assembled and compared for various amounts of ants and for different methods to have a solid sense of how to determine the quantity of ants that would best benefit the applications chosen.

A contribution proposal cannot optimize or contribute to the subject of ACO since there is too much study, time, and effort invested in it. As a result, the research is scholarly in nature and focuses on one element of the methods. In papers regarding ACO, e.g. in [3], the researchers indicate that the quantity of ants they utilized was what they discovered to be the most ideal. The fundamental reason for this argument is because the reasons for why a certain number is selected is not explored. To achieve the rationale of the contribution, this paper has been organized as follows: Section II provides a background analysis of the paper. Section III focusses on the research methodology. Section IV presents the results' analysis. Section V presents a discussion of the results. Lastly, Section VI concludes the paper and provides directions for future research.

II. BACKGROUND ANALYSIS

The background and facts required to properly comprehend the ACO methods are discussed in this section. There's also data on the TSP, why it's so difficult to resolve, and how heuristics are employed to solve it. Terminology (section 2) To make it easier to understand this contribution, below are the acronyms and terms used in it.

- Ant Colony Optimization (ACO): Ant Colony Optimization (ACO) is a term used to describe the process of optimizing an Elitist Ant System (EAS)
- RAS is an acronym that stands for "Ranked Ant System."
- MMAS is a term that refers to a system (Min-Max Ant System) in which the TSP (Traveling Salesman Problem) that are NP-complete
- NPcomplete: Within computer engineering, there is a challenge space known as NPcomplete, with NP standing for non- deterministic polynomial-time. It is a level of intricacy used to categorize different kinds of decision-making situations. Checking if a solution is right is simple and quick, using just polynomial time.

The work of addressing choice issues and determining a solution, on the other hand, cannot be completed in polynomial time. When a solution is identified, there is no quick or easy method to determine if it is the best option. Many NP-complete issues need the discovery of all feasible solutions before determining which the best is. As shown, even with a tiny data collection, an issue of this kind will increase completion time. Because it does not measure well, this becomes an even bigger issue as the issue grows in size. Below, we'll go over the most well-known problem of this type in order to recurse on this issue even more.

Traveling Salesman Problem (TSP)

A theoretical salesperson is the center of TSP. To market their items, they must travel to all of the local towns. After completing all purchases in one location, individuals move on to a new place that they haven't yet visited and begin their business. The only thing left to do is returning to the very first town after touring every single one. As a result, the challenge is: how do you build a tour from a beginning town that visits every town and return to the beginning town in the shortest possible time? Validating that a certain tour is a legitimate response is simple and quick. The issue raised in section 2.2, nevertheless, presents itself here: How can one tell whether this is the quickest solution? There's no way to tell for sure without contrasting it to any other potential trip. This fact sparked further investigation. Heuristics are employed to address this challenge and provide a relevant response in a timely manner.

Heuristics are a kind of algorithm that is used to solve problems. TSP may be solved in a few different methods. Traveling down a greedy road is a simple method to accomplish this. That is, choose the town closest to the present town as the next segment of the route, and repeat until the list of unvisited towns is exhausted, before resuming to the beginning town. One of the simplest ways to explain what a heuristic is to say that it is a shortcut. In other words, a relatively good enough estimate of the best solution to a problem. Because the NP-complete issue space lacks solutions that can be calculated in polynomial time, several ways have been developed to circumvent this constraint. It is quite simple to construct a legitimate, greedy tour.

Moreover, fine-tuning the tour and performing local optimizations will provide a resolution that is a reasonable sufficient estimation of the optimal solution. Because of the widespread use of heuristics, a broad range of metaheuristics have been developed to address these issues. Such heuristics are designed in such a manner that they are easily adaptable, requiring little modification when applied to a variety of issues. ACO is a metaheuristic that belongs to this group. It's possible that the final calculated trip will be the shortest, but this isn't a given. The objective is to arrive at a reasonable answer as quickly as possible. A near optimal trip would be useless if it took several days to compute.

Ant Colony Optimization (ACO)

ACO was initially mentioned and presented to the public in a PHD contribution titled " Efficiently solving the thief orienteering problem with a max–min ant colony optimization approach " published in [4]. Three methods based on ants were included in his work. The study' concepts drew an increasing amount of attention over time. Only one of the techniques receives attention and effort in recent times. As the two previous methods faded away, the one that remained became recognized as ACO. When ants go foraging for food, they radiate out from the colony to gather food to return back to the colony. Every ant leaves a little quantity of neurotoxins behind on the trail they walk. The neurotoxins shall draw near other ants, who will therefore be more inclined to follow in the footsteps of previous ants. They carry food back to the colony or move back and forth among the colony and the nearest food supply when they find it.

Every moment an ant makes this journey, the neurotoxins trail is strengthened, becoming stronger and more appealing, guaranteeing that more ants engage in the duty of obtaining food from the origin. The ants cannot solve difficult issues or do anything on their own. In bigger groups, though, they can determine the quickest route to food and ensure that individuals are more prone to follow it, opening the way for a mechanism that can solve difficult problems. Ghariani and Furnon [5] contribution was inspired by the way ants collaborate and is the foundation for the concept of ant colonies as a powerful metaheuristic. Artificial ants, like natural ants, can work together to solve complicated issues in polynomial time. The ants explore the issue space after choosing a starting point, taking into account neurotoxins as well as many other problem-specific weights when selecting their remedies.

The distances between the next available towns, for example, would logically constitute a weight in the TSP. When a remedy is identified, the ants leave neurotoxins behind, making it more likely that additional ants will investigate it in the future. Neurotoxins will gradually build up on excellent, shorter pathways, whereas they will gradually deteriorate along less favourable paths. As the process approaches stagnation, ants will move closer to the potential remedies in the issue area, searching for even better ideas.

```
Procedure: The ACO algorithm
        Initialization of neurotoxins
                        While Terminating conditions not considered do
                Establish Ant remedies
                Apply the Local Search % optional
                Update Pherome
        end
end
```

Fig 1. General pseudo-code for the ACO algorithm.

Construct Ant Solution implementations will be greatly influenced by the issue being addressed, while Updated Neurotoxins will be influenced by the kind of Ant System being utilized [6]. Downturn is an issue with this technique. When a large number of ants wander around the issue space, they leave a multitude of neurotoxins behind, but as they all gravitate to the ideal option they discover, other sections of the dataset get starved. This implies that, at a certain point, most ants will eventually wind up on roughly the same route since the chance of veering from it becomes insignificant. This is because neurotoxins decay with time and only travelled pathways are replaced, resulting in circumstances where no alternative treatments can be identified, even if one exists. When this occurs, genuine downturn occurs, making further improvement difficult. To tackle this, a variety of sophisticated programs have been developed, each of which addresses the issue of stagnation in a unique manner. The three ant platforms that we chose and developed for this work are listed below.

Elitist Ant System (EAS)

When Elitist Ant System (EAS) [7] was established, the most significant alteration was the addition of a new ant species. In comparison to their regular counterparts, these specialized ants have a distinct role. After all, ants usually leave a trail of neurotoxins along the pathways they have discovered. Nevertheless, with EAS, additional neurotoxins are awarded to the best discovered solution, thereby doubling the quantity of neurotoxins provided by the volume of expert ants. Every time a good answer is discovered, a flood of neurotoxins is released, making it more relevant for longer. Normal roads decay quickly and are forgotten, whereas elite paths have sufficient neurotoxins concentration to remain viable possibilities. As a result, only one diverging good route is sufficient to divert from the problem area presently being explored, so avoiding stalemate.

Rank-based Ant System (RAS)

Rank-based Ant System (RAS) [8] also uses a kind of specialized ant, but instead of providing all of the neurotoxins to the best route detected, they split them out among numerous excellent pathways. Every road is graded based on its distance, with the right approach receiving far more neurotoxins and the poorest receiving the fewest. Another feature of RAS is if there are less specialists than typical ants, the lowest-ranked pathways will get no neurotoxins. With three experts and ten regular ants, for instance, the ten ants each would discover their own way, while the experts would rate the trails and choose the three finest to distribute the neurotoxins to.

Min-Max Ant System (MMAS)

There are no specialized ants in the most recent system we deployed, reverting to the previous approach of employing just regular ants. The major difference in MMAS is how neurotoxins levels are managed, which now includes upper and lower limits [9]. The maximum or lowest neurotoxins quantity on a route cannot be exceeded. Because there is a limit on both ends, a path's neurotoxins can never go below the point where it is no longer useful. A road will ultimately become saturated to the point that it overpowers all others. There's also a softening mechanism. The neurotoxins values are smoothed whenever one or more pathways are near maximum intensity. This has the effect of heavily supporting low-neurotoxins pathways while keeping the rankings between them intact. Finally, neurotoxins are only used on the best route, with the rest of the paths being ignored. All of these enhancements to the original ant system result in powerful, efficient algorithms.

III. METHODOLOGY

We discuss the formulae on which the techniques are built in this part, rather than the actual computer code. We also discuss why we chose to test the methods in the first place.

Problem Scope

Only two parameters influence the TSP alternative: the number of towns in the TSP example and the intervals among them. A few judgments were taken to ensure that the data collected was diverse and accurately reflected the quality of the replies. To begin, all of the TSP examples picked were problems having known optimized solutions, allowing for a comparative of the obtained solution to the optimum. Second, only symmetric TSP examples were chosen, which means that the distance among town A and town B remains constant irrespective of which directions an ant travel. To avoid ants from being fooled into walking an edging that is only useful from the other way, asymmetric TSP would need two levels of neurotoxins, further aggravating the situation. eil101 had 101 towns, tsp225 had 225 towns, and att532 had 532 towns.

Ant System Implementations

The ant networks all function in the same manner and have the same general framework. The only thing that separated them was how neurotoxins worked, specifically how they were modified and preserved with each iteration. Every ant present and contributing towards the solutions in all the ant networks will begin each iteration in a random selection town. When deciding on another town to visit, the probability of each town is determined by the number of neurotoxins connecting to it as well as its proximity, as calculated by the formula below.

$$C_{ij}(t) = \left|T_{ij}(t)\right|^{\alpha}\left(\cap_{ij}\right) \quad (1)$$

$$P_{ij}^{k}(t) = \frac{C_{ij}(t)}{\sum_{J\epsilon N_i^k} C_{ij}(t)} \quad (2)$$

Eq. 1 focusses on the manner in which the heuristics values are established for edge (i and j). The strength of the neurotoxins trails denoted by $T_{ij}(t)$ on the edge at the (t) iteration, whereas $\cap_{ij}$ represents the heuristics dataset. As foR tsp, $\cap_{ij}$ is the same as $\frac{1}{C_{ij}}$whereby dij represents the existing distance between different towns noted by (i and j). The metrics β and α decide the influences, which neurotoxins trails and heuristics datasets ought to have α equals to zero would imply that the heuristics datasets are used, whereas β equals to zero would imply the opposite. Eq. 2 utilizes the heuristics value from Eq. 1 to evaluate the probability, which ant “k” could select “j” town when presently found in “i”town. In this case N_i^k holds towns, which ant “k” yet has to prevail. Researchers consider a minimum a minimization of neurotoxins in every iteration. Ants in actual life will only embrace a fresher trail structured by peers whereas neurotoxins on scarcely utilized paths gradually disappear within a few moments.

$$T_{ij}(t+1) = \rho T_{ij}(t) + f(t) \quad (3)$$

An analogue to this based on the ACO algorithms is the “ρ” constant, the available numbers between 0 and 1. Every form of iteration, the neurotoxins value are multiplied by the factors before a novel additional neurotoxins level are integrated to the routes. This makes sure that the initial routes not a segment of the better remedy are gradually disregarded. The $f(t)$ function in Eq. 3 denotes to particular neurotoxins update approaches of every ant system, further illustrated in the subsections below.

Elitist Ant System (EAS)

Elitist Ant System (EAS) represents the first of the dual ant systems we have selected, which depends on the secondary, expert ants to functions. The availability of the expert ants is essential to enforce the elastic approach. Neurotoxins upgrades for EAS is illustrated as:

$$T_{ij}(t+1) = \rho T_{ij}(t) + \sum_{k=1}^{m} \Delta T_{ij}^{k} + \sigma \Delta\, T_{ij}^{best} \quad (4)$$

$$\text{Whereby } \Delta T_{ij}^{k} = \begin{cases} \frac{Q}{L_k} & incase\ ant\ k\ can\ traven\ on\ the\ edge\ (i\ and\ j)\ tourinng \\ 0 & otherwise \end{cases} \quad (5)$$

$$\text{And } \Delta T_{ij}^{best} = \begin{bmatrix} \frac{Q}{L_{best}} & incase\ \ edge\ (i\ and\ j)\ is\ a\ segment\ of\ the\ short\ tour\ identified \\ 0 & otherwise \end{bmatrix} \tag{6}$$

whereby "m" denotes the number of the typical ants, and "σ" the elitist ant (specialist) number. Lk represents the overall length of the tours structured by L and k Best represents the overall length of the shorter tour identified in the entire iterations. Q represents the constant multiplier, which simply defines the neurotoxins number ought to be placed down on the various ants. Eq. 5 defines how typical ants alters neurotoxins whereas Eq. 6 defines the elitist ants. Eq. 4 therefore integrates together the results of the typical ants whereas multiplying the elitists ant.

Rank-based Ant System (RAS)

Normal ants do not actively contribute neurotoxins, which is the most significant distinction among RAS and EAS. RAS has also altered the behavior of specialised ants. Unlike the elite ants, the ranking ants classify all tours, assigning each one a rating before adding neurotoxins. The shortest tour is the highest rated, while the others become longer as you go down the list. Outside the amount of potential remedies detected, alternatives do not get any extra neurotoxins, but they do decay. The following is a formula:

$$T_{ij}(t+1) = \rho T_{ij}(t) + \textstyle\sum_{\mu=1}^{\sigma} \Delta T_{ij}^{\mu} \tag{7}$$

$$whereby\ \Delta\ T_{ij}^{\mu} \begin{bmatrix} (\sigma - \mu + 1)\frac{Q}{L_{\mu}} & incase\ ants\ with\ \mu\ rank\ travels\ on\ edges\ i\ and\ j \\ 0 & otherwise \end{bmatrix} \tag{8}$$

Eq. 8 defines the manner in which the ranked ant affects neurotoxins, which $\Delta\ T_{ij}^{\mu}$ considered the transitions in neurotoxins by ants with ranks μ. A real ranking of the tour is not illustrated. $(\sigma - \mu + 1)\frac{Q}{L_{\mu}}$ makes sure that the ant with high ranks (next to 1) provides more neurotoxins compared to low ranked ant. Because Eq. 7 provides a summation of the ranked ants to "σ", in the instances where "σ" is less than "m", the tours will be disregarded.

Min-Max Ant System (MMAS)

Min-Max Ant System (MMAS) contrasts from RAS and EAS because it does not use specialists' ants. Otherwise, its concentration lies a maximum and minimum value for the concentration of neurotoxins. The upgrading of neurotoxins for MMAS is illustrated as:

$$T_{ij}(t+1) = \rho T_{ij}(t) + \Delta\ T_{ij}^{best} \tag{9}$$

$$whereby\ \Delta\ T_{ij}^{best} = \begin{Bmatrix} \dfrac{Q}{L_{best}} & incase\ \ edge\ (i\ and\ j)\ is\ a\ segment\ of\ the\ short\ tour\ identified \\ 0 & otherwise \end{Bmatrix} \tag{10}$$

Eq. 10 is the same to the elitist approach indicated as Eq. 6 with the variation considered that there are not specialists ant in Eq. 9, which amplifies the results. The aspect of amplification is not required since only the most effective tours are considered in the process of upgrading. In EAS, the Lest was illustrated as the overall length of the shorter tour identified in the entire iteration. Following our application of MMAS, nonetheless, we utilize the integration of the Lgb (global best) and the Lib (length of iteration best). Particularly, we utilize L_{gb} each 10th iterations. This is to generate the ant some directions, stopping them from searching the iteration best remedy, which could have been bent away from the global best remedy. Each time L_{gb} (whenever a novel best remedy is identified), the $T_{maximum}$ (maximum) and $T_{minimum}$ (minimum) neurotoxins level is upgraded to:

$$T_{maximum} = \left\{\frac{1}{1-\rho}\frac{Q}{L_{gb}}\right\} \tag{11}$$

$$T_{minimum} = \left\{\frac{T_{maximum}\ (1 - \sqrt[n]{P_{best}}}{mean - 1\sqrt[n]{P_{best}}}\right\} \tag{12}$$

where "n" represents the towns and the mean equals $n/2$, which represents the mean number of towns ant colonies have to select during every phase of tour creation. An estimation of $T_{maximum}$ potential value determined from the neurotoxins upgrade method (in case L_{gb} was the optimum tour length, it could not be an approximation). In Eq. 12, $\sqrt[n]{P_{best}}$ represents the probabilities of selecting the edge segment of a better remedy after attaining the aspect of stagnation. As such, P_{best} represents the probability of establishing the present remedy after stagnations. Pbest represents constant parameters, which needs resetting, with lower values considered since this will enhance the differences between $T_{minimum}$ and $T_{maximum}$. As for MMAS, we identify stagnation as a condition in which edges of the best tour has attained $T_{minimum}$, and the edges not a segment of the tour fallen to the $T_{minimum}$. In this condition, it is unlikely for ant colonies to select edges not a segment of the best tour (event though there is a high chance because $T_{minimum}$ is greater than 0, amounting to ant colonies structuring similar tour, therefore stagnating. Based on this, we could determine γ (stagnation) as:

$$\gamma = \frac{\sum_{T_{ij} \epsilon T} minimum\ (T_{maximum} - T_{ij}, T_{ij} - T_{minimum}}{n^2} \quad (13)$$

where represents a segment of neurotoxins trail and “n” represents the number of towns. Particularly, numerators will be closer to 0 as the traits are closer to $T_{maximum}$ and $T_{minimum}$. Because γ tasks time to compute and varies less from a single iteration to the other, we typically evaluate stagnation in every iteration. This implies that an operation of smoothing will sometimes be illustrated by a single that is insignificant. Whenever “γ” is closer to 0 and MMAS therefore has significantly stagnated, the neurotoxins trail is smoothed based on:

$$T_{ij}^{\times}(t) = T_{ij}(t) + \delta\left[(T_{maximum}(t) - T_{ij}(t)\right] \quad (14)$$

where $T_{ij}^{\times}(t)$ is a neurotoxins concentration following smoothing (still considered a segment of similar iteration), and δ represents the parameter of smoothing. In case δ equals to zero, smoothing could have a minimal impact, and in case δ is greater or equals to one, each neurotoxins trail could be reset to maximum. Nonetheless, by setting δ to zero or one, it is potential to significant enhance the neurotoxins concentrations on minimally utilized paths, whereas still maintaining the collected maintaining the collected heuristics data from the past iteration intact to one another. The edge, which has lesser neurotoxins compared to another edge will have a lesser neurotoxin after smoothing and vice versa.

Testing methodology

During testing, we focused on results, which were granular to visualize the condition of an algorithm, whereas being significantly faster during computation. Therefore, the ant colonies were divided into segments of 1% to 100% (with intervals of 10%) of the towns’ amount. The specialist’s ant colonies were otherwise split into segments of 1% to 100% (with intervals of 25%) of the amounts of standard ant colonies. Five different experiments are conducted for every integration of ant colonies, TSP cases and specialists. The five experiments were therefore integrated to evaluate the mean number for every integration. Moreover, similar predetermined seeds were utilized over the various integrations. The simplified tests ensure that algorithms encounter similar degrees of randomness whereby the various input datasets did not have a significant impact.

Five ranked ant colonies’ constants provided better results with experiments of RAS. Resultantly, extra 6th segment of specialists was evaluated particularly for RAS, whereby σ is equals to 5. In Fig. 2, a while-loop with conditions, which regulate the numbers of ant colonies to determine the optimum route. In our experiments, were focused on looping 20,000/m iterations, whereby “m” represents the ant colonies utilized. Because “m” paths are structured in every iteration, this implies that about 20,000 routes are established in general for every test that ought to provide a better contrast. Because the main purpose of this paper was to identify how the number of ant colonies transformed the duration of remedies, the other parameters were maintained between the different tests. Moreover, values are considered to be similar proposed in other literatures, to avoid spending more time optimization. The net parameters utilized in ant systems were considered to be: $\alpha = 1$; $\beta = 5$; $\rho = 0.5$; $Q = 100$. The metrics different from MMAS were otherwise established as δ = 1; $P_{best} = 0.01$. In addition, during the checks for stagnation, neurotoxins were thereby smoothed when the value of stagnation “γ” is below 10 to 12.

IV. RESULTS

The findings of all EAS, RAS, and MMAS examinations are displayed in this chapter. The divergence from the ideal fluctuates with the number of ant colonies employed in each of the images. The y-axis should have a smaller value.

The System of Elitist Ants

The number of experts has a significant influence on the solutions, as can be observed in all three charts but especially so in **Fig 1**. The solution is poorer relative to the known optimal the fewer experts there are. The number of regular ant colonies, on the other hand, has less of an impact on the solution. With 100 percent elitist ant colonies and roughly 10 percent regular ant colonies, the optimal answer is determined in all three sample situations.

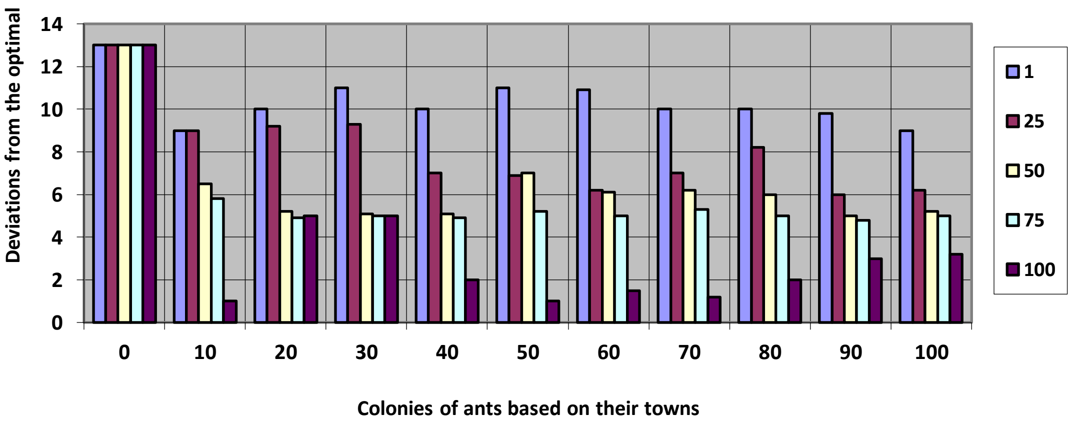

Fig 1. Average deviation from optimum using EAS solving eil101.

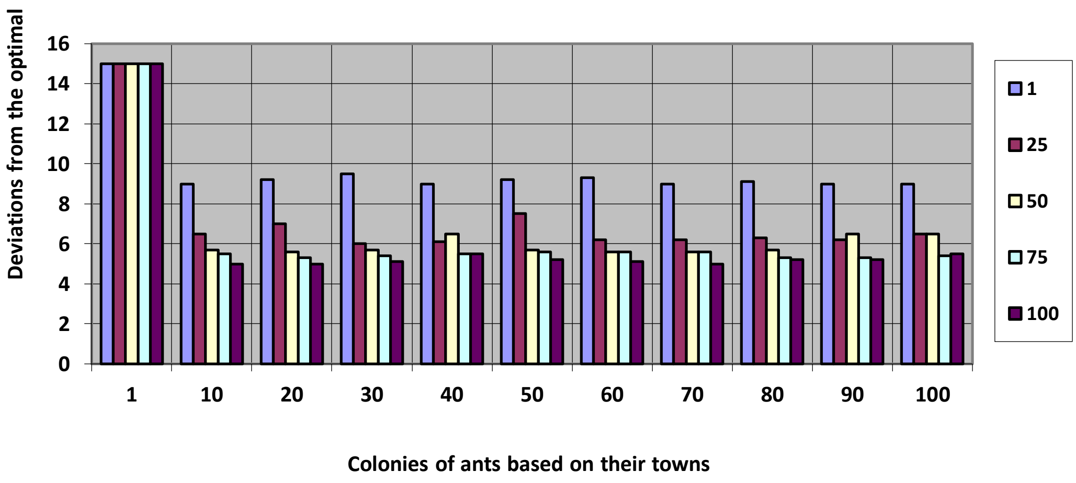

Fig 2. Average deviation from optimum using EAS solving tsp225

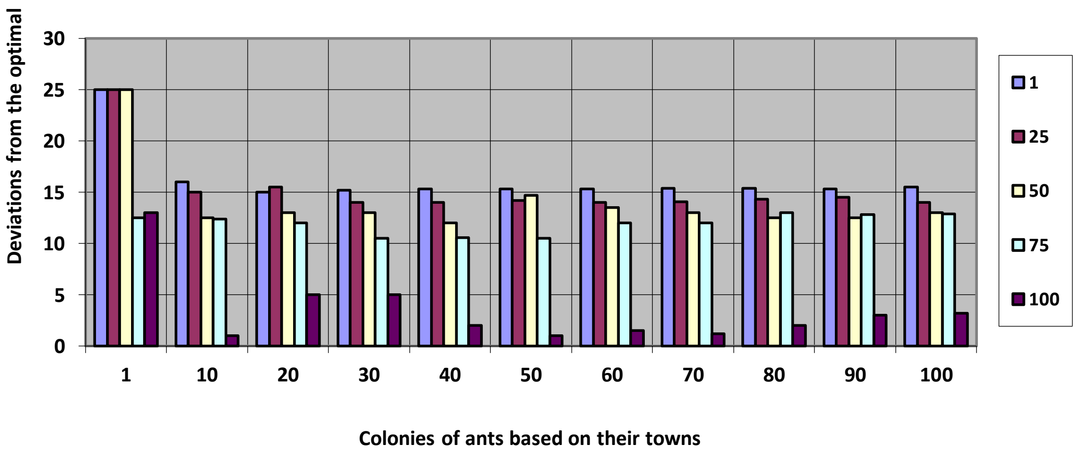

Fig 3. Average deviation from optimum using EAS solving att532.

Rank-based Ant System (RAS)

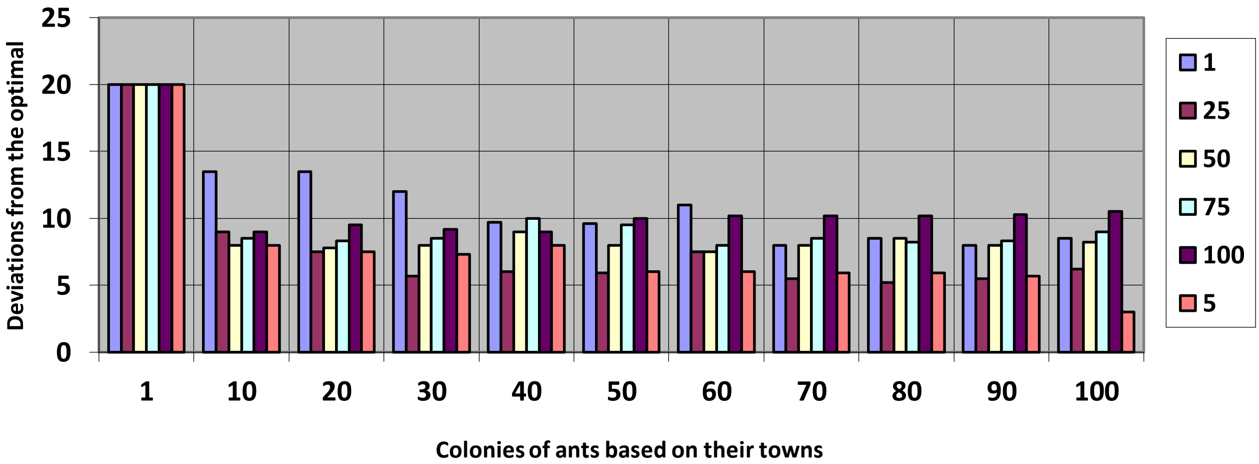

Fig 4. Average deviation from optimum using RAS solving eil101

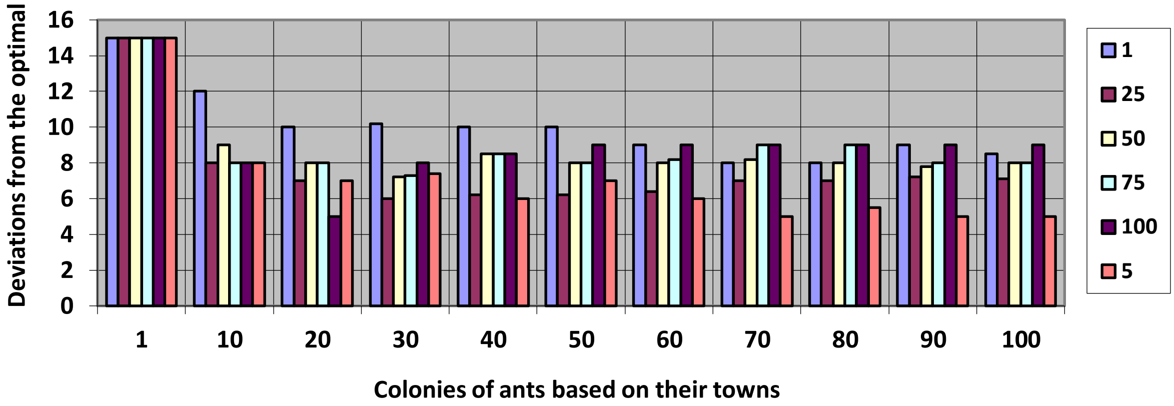

Fig 5. Average deviation from optimum using RAS solving tsp225.

RAS's outcomes are the polar opposite of EAS's. The presence of a significant number of specialised ant colonies exacerbates the problem. When utilizing 5 rated ant colonies, the number of regular ant colonies has an influence, and not when using so much. In terms of towns, the optimum option is determined with five experts and 100 percent regular ant colonies. **Fig 6**, on the other hand, shows a variation in which utilizing more than 50 percent typical ant colonies makes the solutions worse.

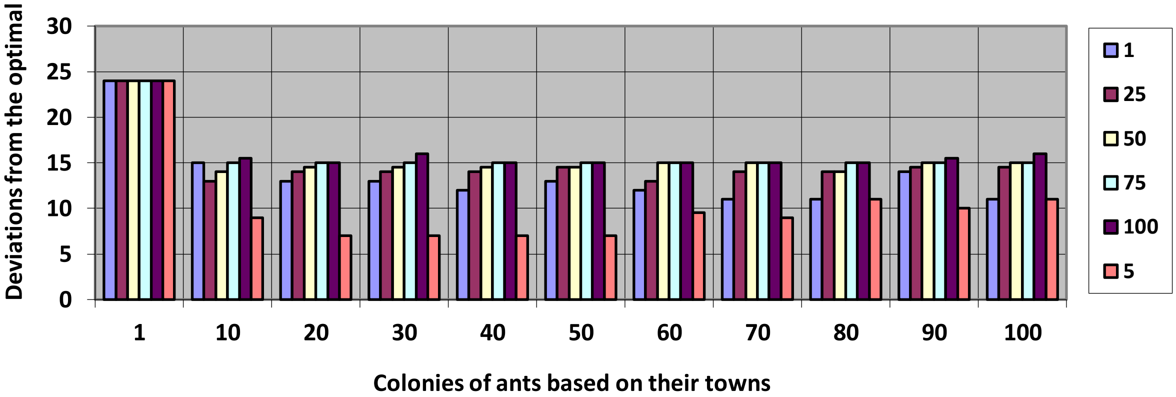

Fig 6. Mean deviation from the optimal employing RAS for TSP 532

Min-Max Ant Systems (MMASs)
MMAS, the ultimate ant system, doesn't need specialised ant colonies. Rather than displaying the many specialized ant groups, the blue region in the charts highlights the variation in the answers (as mentioned in Section 3.3, five tests are performed for each test case).

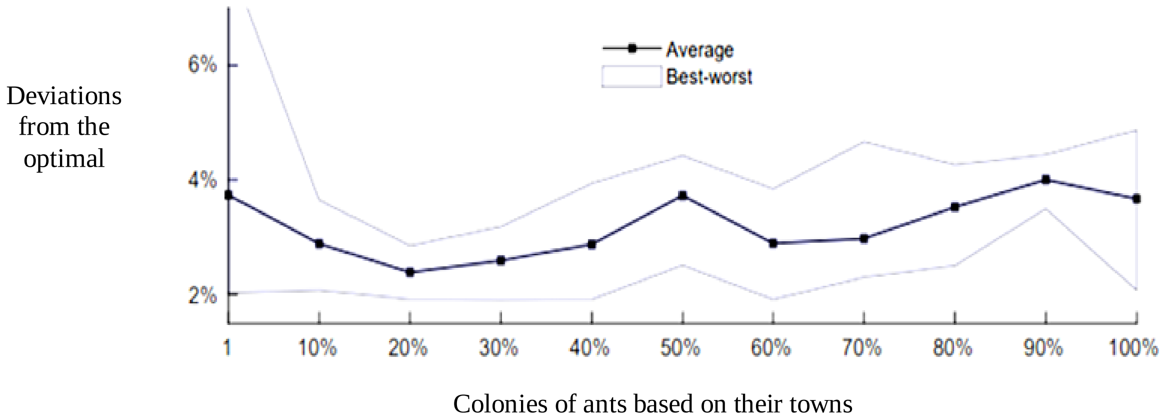

Fig 7. Average deviation from optimum using MMAS solving eil101.

Fig 8 and **Fig 9** vary between 2 and 4 percent while they vary between 6 and 11 percent in **Fig 10.** The best solutions are found within the span of 10% to 30% ant colonies in relation to towns across all three test cases.

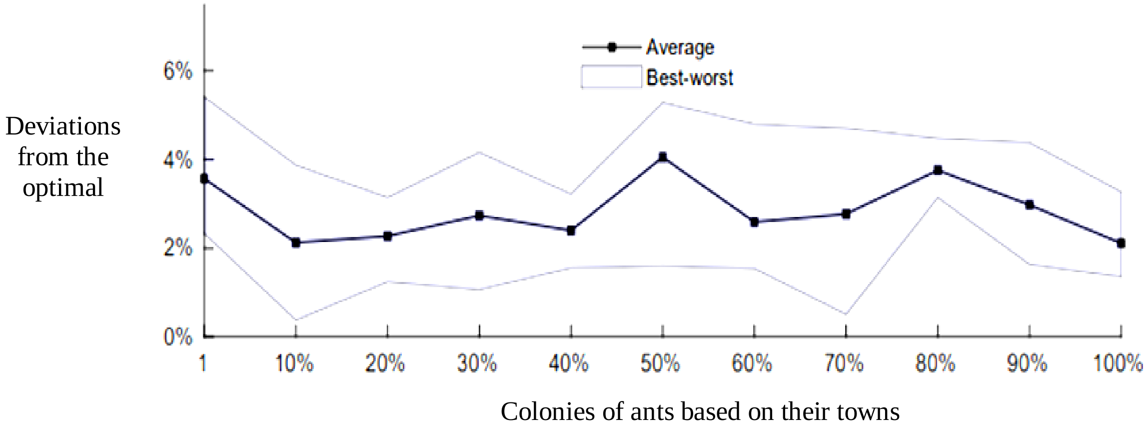

Fig 8. Average deviation from optimum using MMAS solving tsp225.

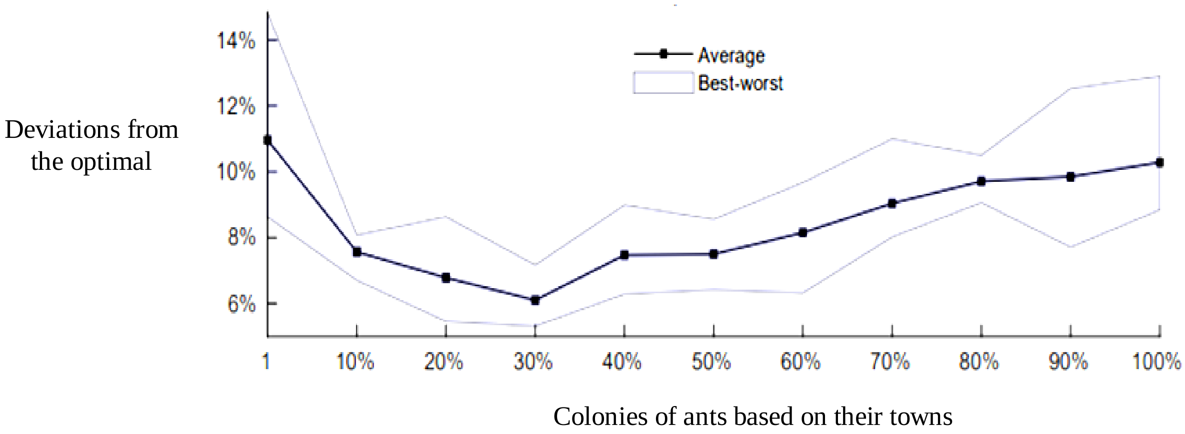

Fig 9. Average deviation from optimum using MMAS solving att532.

V. DISCUSSION

The outcomes are discussed in this part, as well as how the various ant technologies relate to each other. We also talk about how we can enhance the data we've gathered and any shortcomings in the methodology we employed. The quantity of normal ant colonies utilized had less of an effect than expected, according to the findings. This outcome, however, is not wholly unexpected. What distinguishes the ant system is how neurotoxins are developed and modified among iterations. As a result, it's not surprising that neurotoxins and the factors that influence them, notably experts, have the greatest effect on tour duration. When EAS changes the neurotoxins, there are several little adjustments, one for each built tour, with the optimal option being compounded by each elitist ant. When this multiplication is tiny or around 1, the best option receives hardly little attention. In that instance, the ant colonies have no reason to search around in the best discovered route rather than either of the other trips in subsequent iterations. This is reflected in the statistics, where more professionals result in the better answers, resulting in a greater multiplier. With a big number of experts, the quantity of additional neurotoxins is so great that dissipating the condensed neurotoxins takes a long time, making the route tractive much longer. Non-optimal tours fade far more quickly than the greatest tours from prior iterations, resulting in just a few excursions gaining traction. As a result, without the need for a large number of ordinary ant colonies to discover answers since their individual contribution is minimal in comparison to the professionals.

According to the findings of our testing, 10 percent of ant colonies in respect to towns and as many professionals as ant colonies provide excellent EAS outcomes. Similarly, MMAS showed a similar pattern. Except for Fig. 10, which exhibited the most changes in solution length, the quantity of ant colonies presents in the sample had no effect on the ultimate outcome. MMAS always outperformed its peers in all test instances, even when there was variation. The addition of lower and higher neurotoxins boundaries reduces the possibility of stagnation, guaranteeing that no edges genuinely die off. Even though the edges get stagnant, neurotoxins smoothing rejuvenates them all while maintaining the data collected in prior cycles. After smoothing, the ant colonies are more likely to target edges that are near to the optimal solution but were not previously examined. However, the fact that just one tour influences the neurotoxins per iteration is the fundamental explanation why several ant colonies do not execute better. The amount of ant colonies has a significant impact on the numbers of iteration in our approach; the more ant colonies, the less iterations. As a result, having a high number of ant colonies provides no practical advantage since it takes MMAS longer to converge on the optimum solution. The range of 10-30 percent ant colonies in proximity to towns typically produces excellent findings, despite slight changes in the information.

The number of observations and the amount of ant colonies are well balanced during that time range. The same tendencies were seen with RAS as they were with the other ant programs. The quantity of ant colonies had a little effect on general effectiveness in several situations. Nevertheless, the results were the polar opposite of EAS whenever it came to experts. As more experts were deployed in RAS, the outcome deteriorated significantly, mimicking EAS's trend. The specific test scenario with five ranking ant colonies was the most distinguishing feature. When a large number of ant colonies were combined with five ranking ant colonies, the outcomes were improved, with 100 percent ant colonies producing the best findings. This is most likely due to the fact that the number of rated ant colonies has a direct correlation with the number of excursions shown in the neurotoxin's updates. Edges in alternatives may overlap when there are numerous ranking ant colonies. Even if sub-optimal tours are modified with fewer neurotoxins than ideal tours, the overlap might result in a neurotoxins concentration. This concentration affects the probabilistic selection of towns, lowering the quality of high-probability towns. When just a few ranking ant colonies are deployed, on the other hand, having a large number of normal ant colonies working on the problem is beneficial.

The chance of finding excellent tours improves as the number of regular ant colonies grows. As a result, better tours will be available to higher-ranked ant colonies. This gives the following iteration a good and vast search space, improving the likelihood of discovering near-optimal options. Fig. 7, however, provided a different outcome with the final test scenario. The tendency of better outcomes for a higher number of ant colonies containing five experts was not fulfilled in this situation, instead demonstrating the opposite. This kind of information seemed unexpected at the time, but it's not so unusual now. As previously stated, the number of observations is limited, and the number of repetitions is reduced as the number of ant colonies increases. Because the ant colonies do not have the time to correctly calculate the response, the accuracy of the result suffers. In Fig. 6, with 225 towns, the best answer was provided by 100percent ant colonies, which was only marginally better than 90 percent. Fig. 7 shows that 40 percent and 50 percent of the ant colonies in 532 towns provided nearly the same response, with more ant colonies yielding increasingly poorer findings. This indicates that our application of RAS reaches a tipping point at about 225 ant colonies.

VI. CONCLUSION AND FUTURE RESEARCH

We investigated the influence of the number of colonies on calculated outcomes after adopting three variants of the ACO algorithms, particularly EAS, RAS, and MMAS. The amount of normal ant colonies had a little influence on overall performance, albeit the effect was very constant across test cases. When RAS utilized five professionals, for instance, there was a significant boost in productivity with 100 percent ant colonies in comparison to the regions utilized. This is in contrasts to EAS and MMAS, where a smaller number of ant colonies (1030%) resulted in superior results. The implication is that the best number of ants is very contingent on the implementations, and there is no one-size-fits-all solution. In the case of specialized ants, EAS continuously generated positive outcomes with a significant number of elitism ants, but RAS gave good results with fewer ranked individuals, with 5 ants becoming the optimum. This demonstrates that the appropriate number of ants differs depending on the method. Additional experimentation of various ACO algorithm variants is required, and this contribution will serve as a useful starting point for future study.

The fact that efforts and funds were restricted posed a barrier while assembling information for this research. Concessions would have to be undertaken to ensure that schedules were fulfilled and that days were not wasted testing unnecessarily. To prevent excessive execution times, the most natural and practical option was to limit the amount of repetitions the ants would have to create solutions. Even with the limits in place, computing all of the information took more than a day, requiring numerous machines and many iterations of the test application. Limiting iterations produced certain unintended consequences, which were visible in the final results, particularly in the instance of RAS, which had five rated ants and a significant number of ants. We think that, given sufficient time to calculate, bigger datasets will perform similarly to their 101 and 225 town equivalents. Another point worth mentioning is that the estimates for the methods' parameters were taken at face value from previous works. If there had been more time to explore to observe how variables other than ants impact calculated outcomes, the functionality of the implementation created for this research may possibly increase. Future research that allows the ACO methods to fully converge even without time limits imposed in this contribution will provide greater findings, as well as the ability to identify more optimum values for various data input.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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