Towards ACO Based Traffic Control System For Smart Cities

Farheen siddiqui, Tabeen Afzal, Sameena Naaz

Abstract:--- The various advents in the field of computer science and the need of technology urge the humans to find solutions to various challenges. One amongst them is solving the combinatorial optimization problems under the domain of problem solving approach. In order to meet the requirements of such stochastic problems, we need an alternative which is both optimal as well as near to being efficient. This paper gives an insight to what an ACO is, how it originated, and how ACO helps in stimulating the production of feasible solutions for day-to-day problems. The need of ACO in the trending smart city approach is analysed and discussed. A glimpse of recent research contribution towards using ACO in Traffic control justifies the selection of ACO over other algorithms. The paper concludes what methodology to incorporate to overcome the shortcomings of ACO and further its operability and utility in the development of a smart city network.

Keywords: Combinatorial optimization, meta-heuristics, Ant Colony Optimization.

1. Introduction

The dawn of the rising trends in technology and the improved standards of living has led to the emergence of urbanisation at extreme levels in many parts of the world, including India. The economy thereby poses a demand to accommodate such a growing population not just by providing them settlements but also making adequate preparation to present a city well equipped with evolving infrastructure, quality modes of communication and other innovative services that ease the way of living of its citizens. Such a city, operating with a better technological framework can be coined under the term of Smart city. It must be noted that the common modes of transport to travel all across the city still include the use of private and public vehicles that comprises of cars and buses respectively. Thereby, the larger the population- the larger the use of such vehicles and more is the traffic congestion. The smart city concept offers a solution to this by providing a better setup for transport management by introducing the concept of automated vehicles that have the path planning capabilities incorporated within them.

One of the basic criteria that an automated guided vehicle must accomplish is successful path planning and routing mechanisms i.e. encompassing both the objectives- to find a shorter and a congestion-free path and to eliminate collisions with the obstacles on the way. Path planning may be categorized under the class of NP- hard problems and the most effective way to solve such problems is by the use of meta-heuristic techniques.

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This paper portrays the applicability of one such meta-heuristic technique- The Ant Colony Optimization in the domain of vehicle routing problem, it's advantages and limitations, and a detailed study and analysis of different meta-heuristics in different scenarios especially path planning for traffic contol.Section 2 dicusses detailed analysis and application of ACO, section 3 focuses on state of art application of ACO in route planningand section 4 finally concludes the paper.

2. Ant Colony Optimization

Ant Colony Optimization is a soft computing meta-heuristic technique that is used to provide optimal solutions to combinatorial optimization problems such as the NP hard problems that can be computed in polynomial time order. It often builds a solution that is stochastic and incremental in nature. Initially proposed by Marco Dorigo in the year 1992, the ant colony is a model based search algorithm i.e. its architecture comprises of a connected, weighted graph that consists of source and destination points. The concepts of probability are then applied in order to achieve a successful graph traversal to obtain a feasible solution. Thereby, creating an environment where multi-agents are enabled to fetch and share valuable data and information by successful interaction along an optimal path.

The agents used are primitive, decentralised and self-organised in nature.

The foraging behaviour of real ants has attracted many researchers and scholars, one of them being Deneubourg et al who successfully designed the first Double Bridge Experiment to investigate the communication patterns between the ant species and their methodology to traverse from the source to the destination to procure the food by following the pheromone trails.

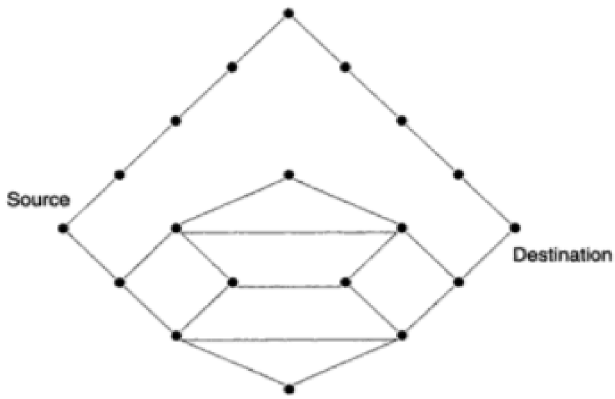

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Figure 1. An extended double bridge. An ant starting from the source node can choose to traverse between the upper or the lower parts of the graph. The upper part consists of a single path of length 8reaching directly to the destination node, whereas, the lower part has sub-paths to reach to the destination. Therefore, an ant that selects the upper path always finds a path length of 8, while the path length of the lower part could be less than 8. Regardless of this, the ants may also enter loops and may generate a long path.[3]

2.1 Basic structure of combinatorial optimization problems and the ACO:

A combinatorial optimization model can be represented as P=(S, Ω, f) where, [2,3]

- S is a search space defined over a finite set of discrete variables X_i, i=1,2,…,n.
- Ω is a set of constraints among the variables.
- f is an objective function such that

$f : S\ R^{+}_{0} \rightarrow$ has to be minimized.

The generic variable Xi takes values in Di = $\{v^1_i, ..., v^{|Di|}i\}$. A feasible solution s ∈ S is a complete assignment of values to variables that satisfies all constraints in Ω. A solution s*∈S is called a global optimum if and only if: f(s*) ≤ f(s) ∀ s∈S.

The model of a combinatorial optimization problem is analogous to that of the pheromone model of ACO. A pheromone value is associated with each possible solution component; that is, with each possible assignment of a value to a variable. Formally, the pheromone value τ_{ij} is associated with the solution component c_{ij}, which consists in the assignment $X_i = v^j_i$. The set of all possible solution components is denoted by C. [2,3]

Corresponding to the above stated structure of the combinatorial optimization problem, can be constructed an ant optimization model that can be represented as G=(C,L,T) where,

- G is a connected, weighted construction graph as stated earlier that the ant traverses upon.
- C is a set of all the components $\{c_1, c_2, \ldots c_{Nc}\}$ where N_c is the total number of components.
- L is the length of the path between the vertices of the graph.
- T is the vector set of all the pheromone trails τ_{ij} laid on different solution paths.

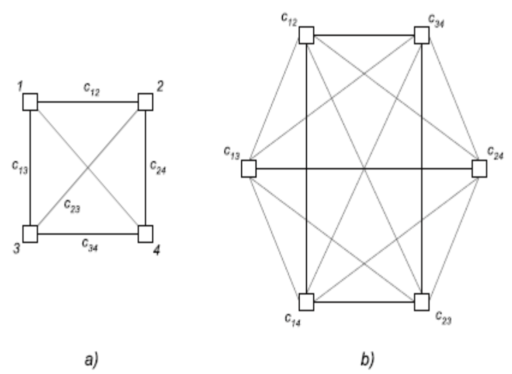

Figure 2. Example of possible construction graphs for a four-city TSP where components are associated with (a) the edges or with (b) the vertices of the graph.[2]

The two major steps involved in the ACO are:

1. Building a set of candidate solutions using a parameterized probabilistic model over the search space.
2. To modify the candidate solutions in such a way that the low cost and optimal paths are identified.

2.2 Genralised ACO Algorithm

The generalised ACO algorithm is given by: [2,3,12]

```
Set parameters, initialize pheromone trails
while termination condition not met do
ConstructAntSolutions
ApplyLocalSearch (optional)
UpdatePheromones
end while
```

The probabilistic parameters are given by the following:

a. Construction of ant solutions: When ant k is in city i and has so far constructed the partial solution s^p, the probability of going to city j is given by: [2,3,12]

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \cdot \eta^{\beta}_{ij}}{\sum c_{il} \in N(s^p) \tau^{\alpha}_{il} \cdot \eta^{\beta}_{il}}, & \forall c_{ij} \in N(s^p), \\ 0 & \text{, otherwise} \end{cases}$$

where $N(s^p)$ is the set of feasible components; that is, edges (i,l) where l is a city not yet visited by the ant k. The parameters α and β control the relative importance of the pheromone versus the heuristic information η_{ij}, which is given by: [2,3,12]

$$\eta_{ij} = \frac{1}{d_{ij}}$$

b. Local Search Algorithm: Here Daemon actions may be applied in order to meet the situations where a single ant is unable to operate. Also it is decided which pheromone values are suitable for updation. This step however is optional.

c. Update pheromones: This step mainly focuses on forgetting the pheromone values that are associated with the bad solution, by simple pheromone evaporation method, and by enhancing the pheromone values associated with a path that forms a good quality solution.

$$\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij} + \sum_{k=1}^{m} \Delta\tau^{k}_{ij}, \quad [2,3,12]$$

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- where, τ_{ij}, is the pheromone associated with the edge joining cities i and j, to be updated.
- where ρ is the evaporation rate, m is the number of ants, and
- $\Delta \tau^k_{ij}$ is the quantity of pheromone laid on edge (i, j) by ant k.

$$\Delta \tau^k_{ij} = \begin{cases} Q/L_k & \text{if ant k used edge (i, j) in its tour,.} \\ 0 , & \text{otherwise} \end{cases}$$

[2,3,12]

Where, Q is a constant, and L_k is the length of the tour constructed by ant k.

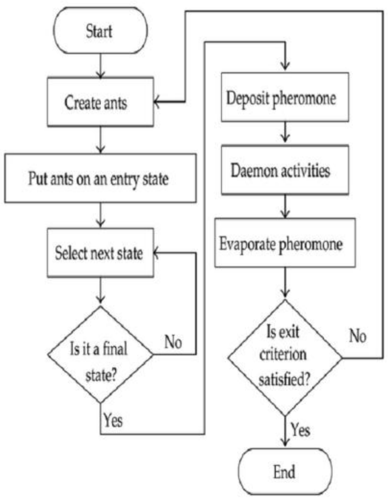

Figure 3 :Flow chart of ACO[13]

A selection of ACO variants

ACO variant	Authors
Elitist AS (EAS)	Dorigo Dorigo, Maniezzo, and Colorni
Rank-based AS (RAS)	Bullnheimer, Hartl, and Strauss
MAX–MIN Ant System (MMAS)	Stützle and Hoos
Ant Colony System (ACS)	Dorigo and Gambardella
Hyper-Cube Framework (HCF)	Blum and Dorigo

Figure 4: Depiction of major ACO variants[1]

The concept of smart cities has acquired the thoughts of citizens of different nations now. One of the prime components that this upcoming project encompasses is the upgradation of the congested transport system.The problem statement in this paper incorporates the fact that to what extent the Ant Colony Optimisation justifies its applicability in traffic control system and it's success in the smart city paradigm when compared to other algorithms like the Genetic Algorithm, the Dijkistra's algorithm, The Particle Swarm Optimisation, Neural Networks etc. Through the literature survey we also get a glimpse of how the limitations of ACO can be overcome by hybridising it with the above mentioned algorithms in order to achieve better results.

2.3 Advantages of ACO:

1. The algorithm follows the foraging behaviour of the real ants and its mechanism is based on storing the information of the trails with the large amount of pheromone values. After each construction of solution, this information is shared and necessary changes are made to the solution set. The goal is to ensure the collection of solutions with a range of higher probabilities and thus in turn a - **positive feedback loop.**
2. **Distributed Computation:** It eludes preterm convergence by deploying multi-agents into the network.
3. **Greedy Heuristic:** This indicates the success rate of finding the optimal solution in the prior levels of the search algorithm.

Selection of ACO over other meta-heuristics:

I) The ACO approach is easily relatable to the optimization problem solving strategy and experiments result into effective implementation in such scenarios.

II) The algorithm has gained extensive popularity in all fields of computational research in comparison to other meta-heuristics and that too with a maximum number of articles being published in renowned journals.

III) Ant Colony Optimization presents problem specific solutions by proposing it's successful variants.

IV) The convergence of ACO has been methodologically and mathematically been proved, whereas other meta-heuristics still lag behind in terms of mathematical models. Their end results are yet based upon the experimentation results.

2.4 Limitations of ACO:

a. Number of required agents(ants)

The optimal number of these agents varies with the problem size. ACO implementation model for the Travelling Salesman Problem could not estimate the fact that increasing number of ants give efficient results.

It is also true that decreasing the number of ants below a certain level resulted in no optimum solution being found.

Therefore, there is no precise description of how many minimum number of ants would be required to obtain a feasible solution i.e. for converging to an optimal solution.

b. The stopping criteria.

Literature survey shows that most of the times, the stopping criteria revolves around the number of iterations. Sometimes to cover the search space a greater iteration value has also been used e.g in Dorigo's paper 200 cycles or so have been specified to accomplish the target. The stopping criteria should be more tangible as proposed in other articles like time etc.

Also, in case the algorithm encounters a plateau, no optimal solution would be discovered and the algorithm is terminated.

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c. Stagnation in the Local Optima:

Other shortcoming faced by Dorigo et al [3] proposed work is that it tends to stagnate in the local optimum.Therefore to address this problem Dorigo himself felt the need to introduce an improved algorithm called the 3-opt local search [4]mechanism. Infact, even the variants of ACO including Max–Min, Elitist and Rank Based approaches face this problem of getting stuck into the local optima. The problem however, persists to a relatively smaller extent. According to Deneubourg et al. (1983), a highly stochastic implementation which will lead to errors in path selection will provide better exploration of the search space and hence will overcome the problem of getting stuck in local optima [3]. But the overall effectiveness of this algorithm has been proven by taking a deeper look into the convergence results, where most of the times the algorithm succeeds to find the optimal path in minimal time.

d. Metrics Evaluation:

In order to provide results that are successful in terms of feasibility and optimality, most of the parameterized metrics inclusive of the trail intensity*(α)*, importance of the visibility criteria *(β)*, Evaporation Parameter *(ρ)*, Trail Intensity *(τ)*, Visibility *(η)* etc. are manipulated in terms of their values.

A range of values for these parameters is proposed by each author in order to justify his/her implementation results but there still has not been defined a concrete methodology that will be able predict to what extent, and how these values must be changed to accommodate beneficial results.

3. ACO based Traffic control

As per recent contributions and analysis of various subsets of the traffic control systems for smart city concept, the followed broad areas needs to be addressed:

- The path planning mechanism for AGV's.
- Vehicle traffic congestion.
- Traffic light management.

3.1 Resolving vehicle congestion by applying the Ant System

Mohammad Rzea et al [5] have chosen to brief us about a bio-inspired algorithm i.e. ACO over the primitive statistical algorithms like the A* and the Dijkistra. The extract also lays emphasis on the behavioural aspects of ants which has been proven to be a favourable strategy to resolve the traffic congestion in vehicular networks. According to [5] aspects like the average travel speed of the vehicles corresponding to a map that defines the dynamic environment and gives an overview of the plot of vehicles at different levels of the city. The shortest and the least congested routes are first identified and then neglected by the vehicles for the purpose of travelling, thus favouring congestion avoidance over congestion redemption.

The purpose of AVCAS is to accumulate all real-time traffic data from various agents (here, cars) and various other components that lay on the travel route to envisage parameters like average travel speed, travel distance, etc. different types of multi-agents have been designed to accomplish the formerly stated objective and further caching the valuable information which is ideal to circumvent congestion.

Simulation results conducted on various vehicle densities show that the proposed system outperforms the existing systems in terms of average travel time, which decreased by an average of 11.5%,and average travel speed which increased by an average of 13%. In addition, AVCAS handles accident conditions in a more efficient way and decreases congestion by using alternative paths. Comparison of AVCAS with the Dijkistra's can be done by considering following parameters into account:

a) Average Travel Time: The vehicle's average travel time and the vehicle density on the path redirectly proportional to each other i.e. as the no. of vehicles increase, the travel time increases. ACO is used to divulge this factor.

However,the Dijkistra algorithm distincts its working by guiding all the vehicles through the same path without keeping in consideration the vehicle congestion and collisions.

The ant system decreased the travel time by 19%.

b) Average Travel Speed: AVCAS obtained the best average speed rate at all vehicle densities by avoiding congestion and providing alternative paths before congestion occurred. By increasing the vehicle density, the average speed decreased smoothly from 25 to 17.7 m/s in AVCAS.

c) Average Travel Distance: AVCAS may propose longer paths with less congestion instead of shorter paths with more congestion.

3.2 Global path planning by using a hybridized ACO-GA algorithm.

Imen et al [6] have selected the two most effective algorithms from a bunch of algorithms- the Ant Colony optimization and the Genetic Algorithm approach and their features to resolve the path planning problem in an environment-static in nature.The selective advantages of ACO and GA and hybridized them to maximize the probability to find an optimal path after the application of real-time constraints. The proposed hybrid algorithm, smartPath and has two main components- An improved version of ACO for systematized and quick path selection and a modified cross-over operator to avoid stagnating into the local minimum. Comparative study between the independently run classical ACO, GA and the Dijkistra's methodology for extensive graph surroundings shows that:

Besides incorporating the best features of ACO and GA, the paper contributes towards finding mechanisms that would efficiently prune the search space, reduce the search time complexity and all in all improve the quality of the solution. Heuristic distance information probability and its description that leads to the selection of more suitable paths in the very beginning of the algorithm, therefore, converging to paths satisfying the optimality criterion. Modified transition rule probability focus on the lower-bound estimation of the remaining distance to the destination, thereby, eliminating the exorbitant paths.

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Performance analysis of smartPATH points out its effectiveness in comparison to the classical ACO, the classical GA and the Dijkstra algorithms. The study clearly depicts the fact that smartPath clearly surpasses the the above stated approaches and improves on the solution quality up to 57% in comparison with the classical ACO. In the vast, denser and extensive environments also, the smartPath proves to be a better option than the classical Dijikstra's method of route finding.A successful experimental and implementation strategy that depicts the attainability of good convergence results and its triumphant applicability in the real –world automated guided vehicles.The improved ACO hybridised with Genetic Algorithm avoids the algorithm from falling into the local optimum by the successful application of the cross-over operator.The Execution Rate is improved by 48.3% in comparison to the classical ACO.To summarize, the efficiency three major parameters taken into account are:

a) Path length: For default values of ants m=10, the hybrid algorithm generates same optimal path as generated by the Bellmann Ford Algorithm. However for an environment with higher complexity of obstacles, the number of agents has to be increased to achieve same optimal path as generated by the Bellmann Ford Algorithm.
b) Execution Time & No. of Iterations: The algorithm is robust and time-efficient in terms of time complexity. The hybrid algorithm provides better solutions but in lager amount of time and more number of iterations in comparison to separate algorithms that consume less time and less iterations but the solution may not be an optimal one in this scenario.
c) Environment: The hybrid algorithm guarantees to find the optimal solution in all four environments which are small-scale, medium-scale, large- scale and highly-complex. Whereas, ACO and GA if taken separately fail to do so in medium and large scale environments.
d) Scalability: The Algorithm is scalable when the values of the pheromone factor α, the number of ants used m, the heuristic factor β, and the evaporation rate are extended.
e) Platform: 2-D maps have been used to reduce the search space complexity.

3.3 Comparative study of ACO Vs. PSO In the field of Path Planning

Walid Elloumia et al [10] presents a comparative study between the particle swarm optimisation and the ant colony optimization algorithm in the field of path planning activity [7]. It also gives an overview of the PSO and the ACO algorithms and uses CPU time to differentiate between the results of the two algorithms. The graphical comparison between the ACO and the PSO algorithms can be shown by plotting CPU times against the no. of iterations as shown in the figure.

RESULTS & DISCUSSIONS

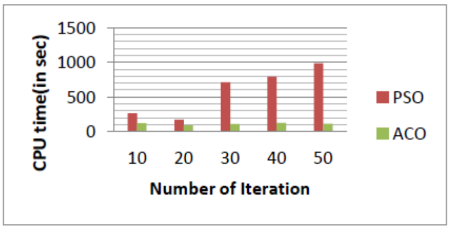

Figure 5: Performance of PSO and ACO algorithm on path planning problem[10]

3.4 Implementation of ACO with the Evolving Graph Model in the field of VANET's

Xueyang et al [8] use hybridized methodology of the ACO and the EG to portray the evolution of communication between vehicles in VANETs when most of the MANET algorithms fail to do so.

The approach is influenced by major parameters that form the basics of a network topology like the routing capabilities and rate of data transfer through various nodes of the network, the quality of service provided by the network including other computational capabilities that determine the performance of the network topology. Such metrics can also involve a better use of the GPS systems that are incorporated within the car systems. Proper routing calculations and optimization strategies have been incorporated to demarcate its feasibility in the VANETs. The author proposes routing mechanisms that are able to adapt even in the dynamic network topologies and also the mechanisms for congestion avoidance and control via the deployment of hybridised ACO and EG models. The simulation models are then presented and the effectiveness of the algorithm is corroborated by suggesting parameters like end-to-end delay, routing reply ratio, route discovery time and delivery ratio. The hybrid ACO-EG is compared with AODV and the DSR routing protocols on the basis of.

a. Average package delivery ratio
b. Average routing reply ratio
c. Average route discovery time.
d. Average end-to-end delay.

ACO-EG provides lower values and a comparatively stable end-to-end delay than AODV for the same route discovery time. Also, this value of DSR is the lowest, with the lowest package delivery ratio. Considering the behaviour of ACO-EG, some packets may wait for a long time in transmit queue until the link with specific nodes emerges, and the wasted time will be counted into the metric.

3.5 Comparative study of SA, GA and ACO when applied to TSP

Hosam et al [9] presents a comparative study on the above stated algorithms in the domain of TSP. The paper also states the applications of TSP in real world in the field of transportation planning mechanisms like a school bus traversing through nodes to pick-up students through different depots, home delivery of items in minimum span of time when online ordering is implied, cab scheduling for

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pickups and dropping schedules, etc.The comparison of different meta-heuristics can be done on the basis of benchmarks of changing size & execution time. The ACO easily accommodates the changing size of the problem size and works efficiently in large size problems though it takes more execution time. Whereas, Genetic Algorithm is fast and easy to run.However, the hybridized ACO-SA outclasses the two in terms of convergence. Taking ACO, SA, and GA into into account, the 2 comparable benchmarks –shortest path and execution time when simulations are performed on JAVA platform:

Based on the simulation results it is observed that:

- GA is ranked to be second in order in both finding the shortest path and execution time. Therefore, it is not exactly optimal to solve TSP.
- ACO is ranked to be first in order in finding the shortest path, but it takes a longer time to execute when compared to other algorithms. So it could be considered suitable algorithm in finding optimal shortest distance solution between cities.
- SA has a time execution of < 1s and presents the average shortest distance results between GA and ACO.

Therefore, to accommodate problems of large sizes a hybridised algorithm ACO-SA can be taken into account for efficient results in terms of shortest path, time of execution and the size of problem.

3.6 Study demonstrating the use of hybridised ACO-PSO for the TSP problem

The concept presented by Walid et al [10] revolves around the problems that have complex structure including the shortest route finding with the help of TSP; and the author presents the fact that conventional mechanisms may not be able to do justice to the set benchmarks in comparison to the hybrid methods.The experimental results and the parameters of comparison were

- The execution time i.e. the best time (as stated in the paper itself),
- the best length i.e. minimum optimal path,
- and the size of the population, i.e. no of agents used.

It is observed that:

1. The best time parameter is considered to be modified to yield better results by the hybridised algorithm.
2. The best length path is also optimised due to the new variant.
3. As the size of population increases, the execution time decreases and so does the distance of travel.

✓ PSO is faster and therefore executes in less time than ACO, but for the length of the shortest path converse is true where ACO converges to better results.

✓ The results are successful when compared to those of genetic algorithms, fuzzy algorithms classical ACO.

3.7 Modified Ant algorithm for path planning

Mohammad et al [11] proposes a new modified version of the ant colony algorithm called the Green Ant algorithm that improvises the path planning mechanisms implemented in the automated guided vehicles. The author presents a low power/energy consumption model which finds a collision-free shortest path. The author gives an analogous study of ACO, GA, PSO and the G-Ant algorithm [12]

Platform: A planning Graph developed using MATLAB.

The effectiveness of the G-Ant algorithm has been tested by taking into consideration the three basic parameters that are:

- No. of iterations,
- Travel length (distance),
- Computation time.

✓ With an increase in the number of iterations, all approaches retrieve a better path [13].

✓ The ACO and the PSO tend to stagnate in the local optimum, whereas, the G-Ant has no such issues.

Moreover, the algorithms are employed in different configuration spaces like moderate and complex. The G-Ant outshines over the other two inclusive of Genetic Algorithm, in terms of travel time, travel speed and travel distance

4. Summary and Conclusion:

The paper summarises all the aspects of Ant Colony Optimization algorithm from its basic definition to the variants, from advantages to limitations, and is even inclusive of a comparative study that depicts ACO as a solo unit to ACO hybridised with other heuristics to achieve feasible and optimal results.

The conclusion of the paper is that ACO may have certain limitations which can easily be curbed when used in collaboration with other algorithms like the genetic algorithm, the particle swarm optimization and simulated annealing etc. or by presenting a modified ACO like the G-Ant, AVCAS etc. The results yielded after combining ACO with other algorithms have proven to be streamlined as well as productive in comparison to the classical algorithms.

Also, the research suggests that ACO can successfully be incorporated to design a smart traffic control system by devising the minor components of such a diverse system like the automated guided vehicles, smart traffic light systems, lane detection, load shedding and much more and further find its application in design and development of smart cities.

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