# An Ant Colony Optimization Solution to the Optimum Travel Path Determination Problem in VANETS: A NetLogo Modelling Approach

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***Abstract*—A Dynamic Travel Path Optimization System (DTPOS) based on Ant Colony Optimization (ACO) for the prediction of the best path to a given destination is presented. The system is modeled in a multi-agent multi-purpose framework in NetLogo and experiments conducted on 100 test vehicles under different traffic scenarios. The test vehicles are released from a fixed location in the simulation environment and given a predefined destination. The route taken by the vehicles to reach the destination gives a measure of the intelligence in the system. Two variations of the system, DTPOS with ACO (DTPOS+ACO) and DTPOS without ACO (DTPOS-ACO) are investigated to establish the effect of ACO on the solution. For every vehicle which successfully makes it to the destination,the mean travel time is recorded. The results have shown that at all traffic densities the mean travel time of vehicles in DTPOS+ACO was always lower than those for DTPOS-ACO. Also it was shown that for the same percentage of vehicles arriving at the destination, DTPOS+ACO vehicles took less time than DTPOS-ACO vehicles.**

***Keywords-Intelligent Transport Systems (ITS); Vehicular Ad hoc Networks (VANETS); Swarm Intelligence (SI); Ant Colony Optimization (ACO); Dynamic Travel Path Optimization System(DTPOS)***

## I. Introduction

Traffic congestion has been a serious problem on roads around the world ever since ancient Roman times, when the streets of Rome became so congested that all non-official vehicles were prevented from entering the city [1]. In recent times, traffic congestion has been responsible for problems like long delays, wasted time, and increased pressure [2], not only to drivers, but also to passengers and even to pedestrians.

In the United States for instance, research has shown that 4.2 billion hours are wasted daily just waiting in traffic; this converts to 2.8 billion gallons of fuel [3]. Similar results have been recorded in Europe, Japan, and Australia [4][5][6]. Research has demonstrated that lower speed vehicles emit more $CO_2$, for instance, vehicles traveling at 60Kph emit 40 percent fewer carbon emissions than vehicles traveling at 20Kph and vehicles traveling at 40Kph emit 20 percent fewer emissions than the 20Kph baseline [6].

Intelligent Transport Systems (ITS) provide attractive methods for reducing congestion, which involves the use of modern electronic information systems to control, manage, and regulate traffic flows according to inputs from traffic flow status prediction systems, through dynamic signal timings [7][8].

In this paper, we propose a Dynamic Travel Path Optimization System (DTPOS) which is an ITS solution to the traffic problem based on Ant Colony Optimization techniques. Ant colony optimization is a classic example of Swarm Intelligence (SI), in which case ants using pheromone relay information from one ant to the other to enable them determine the shortest and optimum path from a new food source to the nest. Initially, the ants travel on all possible paths while depositing pheromone on their trail. After some time when more ants use the shorter paths, more pheromone is deposited to act as positive feedback which quickly results in the shortest trail being selected as a better option due to its high pheromone concentration. The ACO algorithm mimics the behavior of ants foraging for food [9][10].

The remainder of the paper is organized as follows: Section II briefly looks at some related works; Section III mathematically models the ant colony optimization solution to the traffic problem; Section IV introduces the proposed ACO inspired DTPOS model and Section V touches on the simulation of the model by NetLogo and Section VI discusses the results. Finally Section VII presents conclusions on our key research findings.

## II. Related Works

The first instance where an ant based system was used for dynamic problem solving was in [11]. Ant Colony Optimization (ACO) has been applied to dynamic path optimization in [12]. The authors in [12] have also demonstrated how the

ACO algorithm can be structured so as to adapt to changes in the initial constraints of the optimization problem. In [13] an optimum traffic system for the reduction of vehicular traffic congestion in an urban environment is proposed. The algorithm proposed in this system has the limitation of performing well only when the number of agents is above 100. A dynamic system for the avoidance of traffic jams (DSATJ) is also proposed in [14]. This system gives an alternative path whenever there is a traffic jam at any section of the road and resumes to the original route when the traffic situation gets better. An ant colony system for a dynamic vehicle routing problem has been proposed in [15], this system provides a means to route a fleet of vehicles with the objective of visiting a set of customers in minimum time. A hybrid ACO technique for dynamic vehicle routing is introduced in [16]. In [17], an improved ant colony optimization algorithm by Previous Path Replacement (PPR) which the authors term path crossover for optimal path planning is introduced.

In [18], a preference based shortest path determination using ACO is investigated. In this case, shortest path is obtained taking into consideration the preferred paths of the agents. In [19] ACO has been applied to a multi-criteria vehicle navigation problem. In this case an exact shortest path solution is not the ultimate objective but a compromised set of best solutions taking into consideration different preferences by different drivers.

ACO has been extensively applied to shortest path problems in [20]-[22]. In [23], the time for obtaining shortest path solution is shortened by using a modified version of the AntNet routing algorithm. In [24], a traffic congestion forecasting algorithm based on a pheromonal communication model is proposed. This algorithm allows vehicles to react to dynamically changing traffic situations through information disseminated in the pheromone model. A system for travel time prediction which takes into consideration past, present, and future traffic trends is presented in [25].

In our previous work in [26], we introduced a Distributed Intelligent Traffic System (DITS) which proposes a solution to the traffic problem using ACO. In that paper, we investigated how ACO reduces the global traffic situation through cooperation among the vehicles. In our recent work in [27], similar to the work proposed in this paper an optimum path prediction is proposed using ACO. The results are however limited to a single traffic density and traffic distribution. In this paper, we vary the traffic density as well as the traffic distribution and investigate the effect of ACO on the Mean Travel Time (MTT) as well as the percentage of vehicles arriving at the destination, and the time taken. To implement information relay among the vehicles in DTPOS we refer to our previous work in [28].

## III. Mathematical Modeling of the ACO Solution to the Problem

In defining the path determination problem, we consider a minimization problem $(S, f, \Omega)$, where S is the set of candidate solutions, $f$ is the objective function which assigns an objective function value *f(s,t)* to each candidate solution $s \in S$ and $\Omega(t)$ is the set of constraints. The parameter $t$ indicates that the objective function, and the constraints can be varying with time. The goal is to find a globally optimal feasible solution $s*$ which is a minimum cost feasible solution to the problem.

In determining the candidate solution set S, we begin by first defining a solution set R such that $R = \{r_1, r_2, r_3 ... r_n\}$. The constraint $\Omega$ is such that *(s,d)* is the best path given a source to destination pair *(s,d)*. In building a complete solution $S$ we begin from an empty set $\emptyset$ and then build a complete solution $S$ stepwise by adding one new component $r_i \in R$ at every step.

The step by step decision depends on a stochastic decision policy $(\Pi)$ which depends on a set of pheromone variables $\tau_{ij}$. A policy in this context is a rule which links the resultant status to an action based on given constraints. The stochastic policy $\tau_{ij}$ is characterised by a distribution probability over all the likely actions. Each feasible action is connected to a selection probability. An action is therefore taken based on the selection probability for that action. $\tau_{ij}$ therefore gives an indication of how good the decision to use a particular path is. For example $\tau_{ij}$ can represent the desirability of having $(r_i, r_j)$ in the anticipated solution sequence.

The ultimate objective is to get a good complete solution which satisfies the primary goal of having the best path from a source $s$ to a destination $d$. $\tau_{ij}$ therefore represents the desirability of moving from $s_i$ to $s_j$ in order to reach a destination $d$ such that the final path from a source $s$ to a destination $d$ is the optimum, given a list of candidate paths. The $\tau_{ij}$ values are used to calculate the selection probability $P_{ij}$ of each solution.

If $N(r_i)$ is the set of all likely components in state $r_i$, then the probability of each $r_i \in N(r_i)$ is calculated as $P_{ij}$. The road network is represented as a directed graph $G$ such that:

$$G = (N, E) \tag{1}$$

where $N$=($N_1$,$N_2$,$N_3$,$N_4$...$N_n$) is the set of $n$ nodes (i.e. junctions) and $E$ is the set of directed edges as shown in Figure 1. The objective of the model is to route vehicles so that they reach their destination in the quickest time possible while avoiding heavy traffic portions of the road. The modeling of the problem is subject to the following limitations:

Let $\psi$ represent the delay in vehicular movement and $\phi$ the congestion situation; it can clearly be seen that: $\psi \propto \phi$, however, even though other factors like road accidents and

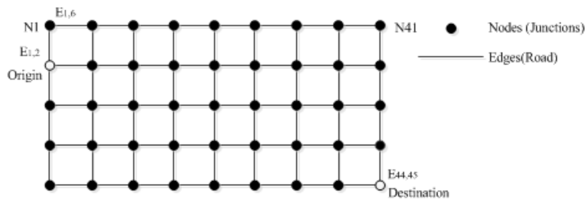


Figure 1. A typical road scenario for best path determination.

road works can also cause delays, traffic delays in this case are only limited to congestion. In this case all delays as a result of other factors are quantified in terms of congestion.

$E_{ij}$ is characterized by the length $x_{ij}$ and traffic $T_{ij}$. Each route in the network is represented by (2) below:

$$R = a_{ij} \tag{2}$$

where

$$a_{ij} = \begin{cases} 1, & \text{if node } j \text{ is visited after node } i \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where *i,j=1...n* and *n* is the total number of nodes in the route *R*.

We assume that time taken to traverse $E_{ij}$ is independent of time taken to traverse other edges. Therefore the total transit time $T_m(R)$ for a route $R$ is given by:

$$T_m(R) = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_{ij} T_{ij} \tag{4}$$

The objective is to choose a path to the destination which minimizes $T_m(R)$. Every path is assigned a score and the path with the best score is attained under the condition:

$$Best\,Score(S) = Score\,at\,min(x_{ij}T_{ij}) \tag{5}$$

The shorter the route the more traffic it attracts. The relationship between distance and traffic can therefore be represented as:

$$T_{ij} \propto \frac{1}{x_{ij}^{(R)}} \tag{6}$$

The ultimate objective is to get a solution which is a trade-off between minimum distance and traffic. We play around both parameters in arriving at the best solution to the problem. In moving from node *i* to node *j* the cars make a decision based on the probability below:

$$P_{ij} = \frac{T_{ij}^{\alpha} x_{ij}^{\beta}}{\sum_{h \in Q} T_{ih}^{\alpha} x_{ih}^{\beta}} \tag{7}$$

where $\alpha$ and $\beta$ give the influence of traffic (pheromone) and distance on the solution and Q is the set of nodes not yet visited. The traffic (pheromone) update depends on the evaporation rate (the rate at which cars leave) $\rho$ and the deposition rate $\Delta_{ij}$ (the rate at which cars arrive). The pheromone or traffic update is governed by the equation:

$$T_{ij} = (1-\rho)T_{ij} + \Delta_{ij} \tag{8}$$

$\Delta_{ij}$ depends on whether a car used the edge $a_{ij}$ or not, ie whether $a_{ij}$ or $a_{ji}$ =1. The total amount of pheromone added or traffic added can be calculated as follows:

$$\Delta_{ij} = \sum_{k=1}^{N} \frac{a_{ij}^{(k)}}{t_m(k)} \tag{9}$$

$t_m(k)$ is the time taken by the car $k$ in covering that section of the road and is a function of the speed of the car $v(r)$. *N* is the total number of cars in that section of the road

$$t_m(k) = \frac{x_{ij}}{v(k)} \tag{10}$$

Substituting equation (10) into (9) and (8) yields:

$$T_{ij} = (1-\rho)T_{ij} + \sum_{k=1}^{M} \frac{a_{ij}^{(k)}}{\frac{x_{ij}}{v(k)}} \tag{11}$$

Selecting $\alpha$ and $\beta$ such that

$$\alpha + \beta = 1 \tag{12}$$

Equation (7) is reduced to:

$$P_{ij} = \frac{T_{ij}^{\alpha} x_{ij}^{(1-\alpha)}}{\sum_{h \in Q} T_{ih}^{\alpha} x_{ih}^{(1-\alpha)}} \tag{13}$$

At every junction, the car computes the probability $P_{ij}$ in (13) and selects the junction with the highest probability. It continues until it gets to the destination, after which the travel time is computed. In testing the model, it is compared with a model that computes its probability by considering only the distance of the candidate paths with no knowledge of the traffic. In that case:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{K} \sum_{j=1}^{K} x_{ij}} \tag{14}$$

where K is the number of candidate junctions. Before traffic begins to build up all other cars arriving at the junction choose their path based on (14). In that case, the path with the shortest distance to the next junction is selected, however; if the distances are the same, they all have an equal probability of being selected. Portions of the above mathematical model were introduced in [9] but the main difference between this approach and previous methods is the use of ABM techniques to investigate the effect of other agents on the global optimum path determination problem.

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## IV. DTPOS DESCRIPTION

The DTPOS proposed in this section is developed within the framework of a Multi Agent Multi Purpose (MAMP) system architecture to predict the optimum path to a predefined destination. The ultimate objective of DTPOS is to reduce the travel time by intelligently selecting the best path in terms of distance and traffic. The proposed system accomplishes this task by computing a selection probability $P_{ij}$ for the best path at every traffic intersection. In this paper two variations of the DTPOS, DTPOS+ACO and DTPOS-ACO which differ only in the inclusion of ACO in one and its absence in the other are developed and simulated. The results are then discussed in later sections to get a better understanding of the effect of ACO on VANETs.

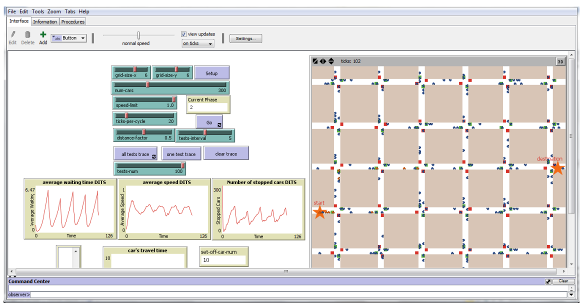

Figure 2. NetLogo GUI with 6x6 road network topology.

The use of agent-based models(ABMs) or individual based simulation models is growing rapidly in a number of fields. The Logo family of platforms is currently one of the most widely used ABMs. NetLogo is popular in this family because it offers the option of studying the behaviour of individual agents working in isolation as well as the effect of the agents working in a community.

*1) DTPOS+ACO Description:* The ACO inspired system relies on repeated sampling of multiple solutions to the optimum path determination problem. The solutions from these outcomes are used to update the value of pheromone variables in the model. The major difference between this system and ant behavior is that while ants choose the path with the highest pheromone concentration as the best path, the proposed system selects the path with the least traffic as the best path. As the traffic concentration increases, the probability of selecting a particular path reduces. Figure 2 shows the GUI of the NetLogo implementation of DTPOS+ACO.

The DTPOS+ACO mimics traffic behavior in an urban environment. The system has a control environment which permits the user to set the initial conditions for the experiment and an observation environment which gives a visual display of what is happening in the simulation environment. The system permits the number of cars, the maximum speed, the destination and the traffic controls to be set by the user. It relies on mobile agents which are vehicles in this case and stationary patches which represent the road network.

There are two breeds of vehicles in the system; these are test cars and passers. The test cars are assigned specific destinations and the time taken for them to maneuver their way through the traffic to reach their destination is recorded as the travel time. The second breed of vehicles, the passers, also travel within the study environment to create a traffic situation but they are not monitored as is done for the test vehicles. The system works in such a manner that when test cars get to the junctions and a decision has to be made as regards which path to take, the vehicles compute the probability $P_{ij}$ as indicated in equation (13). The path with the best probability at that instance is selected by the vehicle. As soon as a test car arrives at its destination the travel time is recorded, and the vehicle dies out of the simulation environment. The stopping criterion for the simulation is for all the test cars to arrive.

*2) DTPOS-ACO Description:* The DTPOS-ACO is similar to Figure 2 shown above. The major difference between the two systems is in the way the selection probability is calculated. $P_{ij}$ in this case is calculated only from the distance without taking the traffic into consideration as illustrated by (14).

## V. SIMULATION FLOW DIAGRAM

In this section, the simulation flow diagrams for the two DTPOS systems are discussed to give a better understanding of how they are simulated. As has already been mentioned the systems are implemented in NetLogo. To have a fair comparison, both systems are simulated under the same conditions, and the results obtained are analyzed. The systems are simulated based on the simulation flow diagram shown in Figure 3. The simulation is initialized by choosing the size of the grid, the number of cars, the maximum speed of cars, the pheromone evaporation rate, the traffic duty cycle, and the recording time interval. The pheromone values are initialized to give a better picture of the traffic buildup as the simulation progresses.

The simulation terminates when all the test cars have arrived at a given destination. For every traffic density selected, five separate traffic distributions are considered and the simulation run until the stopping criteria is met. The simulation parameters are as shown in TABLE I. 100 test cars are made to travel a fixed distance under different traffic densities and the mean travel times as well as the percentage of cars arriving at the predefined destination are recorded and compared.

## VI. SIMULATION RESULTS AND ANALYSIS

Let the time taken by a vehicle *i* to arrive at the predefined destination be $t_i$. Given that N vehicles successfully arrived at the destination, the mean travel time given N vehicles is given by:

$$t_t = \frac{\sum_{i=1}^{N} t_i}{N} \tag{15}$$

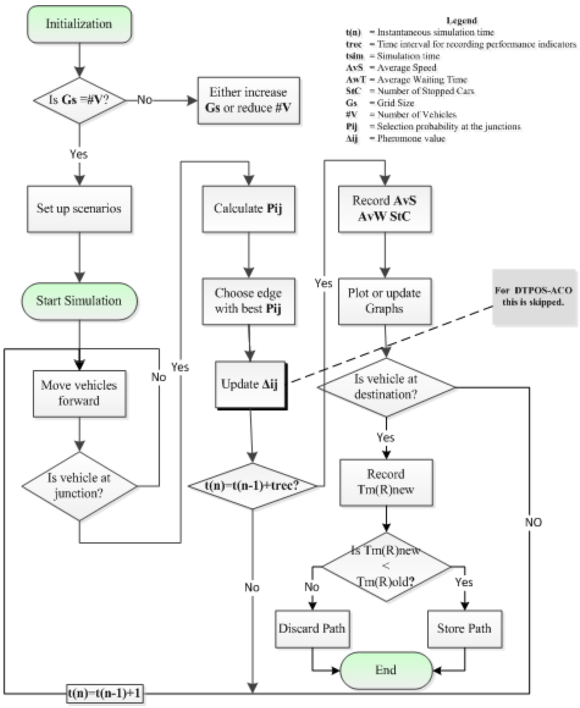


Figure 3. Simulation Flow Diagram for DTPOS.

TABLE I
SIMULATION PARAMETERS.

| PARAMETER | SPECIFICATION |
|---|---|
| Model Simulator | NetLogoV4.1RC5 |
| Total number of vehicles | 200, 300 and 400 |
| Total number of test vehicles | 100 |
| Road Topology | 6x6 |
| Maximum Speed | 1.0(50Km/h) |
| Trace volatility rate($\rho$) | 8 percent |
| $\alpha$ | 0.5 |
| $\beta$ | 0.5 |
| Terminating Criteria | All test cars to arrive |

Also let the number of vehicles arriving at the destination be K and let $T_K$ be the time taken for all the vehicles to arrive at the predefined destination. The time taken for all vehicles to arrive is calculated as a sum of the individual times. Hence the total time is given by:

$$T_K = \sum_{i=1}^{K} t_i \qquad (16)$$

In the experiment, 100 test vehicles are set off and the mean travel time for every N vehicles arriving is computed using equation (15). The time taken for a percentage of the vehicles to arrive at the predefined destination is also recorded. Three different cases are defined for the experiment as follows:

- Case 1: 200 Vehicles in 6x6 topology;
- Case 2: 300 Vehicles in 6x6 topology;
- Case 3: 400 Vehicles in 6x6 topology.

The experiment is conducted for DTPOS+ACO and DTPOS-ACO to obtain $t_t$ and $T_K$ for three different traffic densities. $t_t$ and $T_K$ are measured in ticks which translates to seconds in the simulation. 1tick is equivalent to 1second in this simulation.

### A. Case1: 200 Vehicles

Figure 4 shows the mean travel time comparison for DTPOS+ACO and DTPOS-ACO for a traffic density of 200 vehicles. It is evident that vehicles in the DTPOS+ACO case have shorter mean travel times than those in the DTPOS-ACO case. What this means is that vehicles in the DT-POS+ACO case spend less time reaching their destination compared to those in the DTPOS-ACO case travelling to a common destination. Figure 5 also shows the percentage of vehicles arriving at the specified destination and the cumulative time taken. As can be seen from the figure it takes about 50ticks for 50 percent of the vehicles to arrive in the DTPOS+ACO case and vehicles take 100ticks which is twice that time to get 50 percent of the vehicles arriving in the DTPOS-ACO case. The figures double in both cases to have 100 percent of the vehicles arriving.

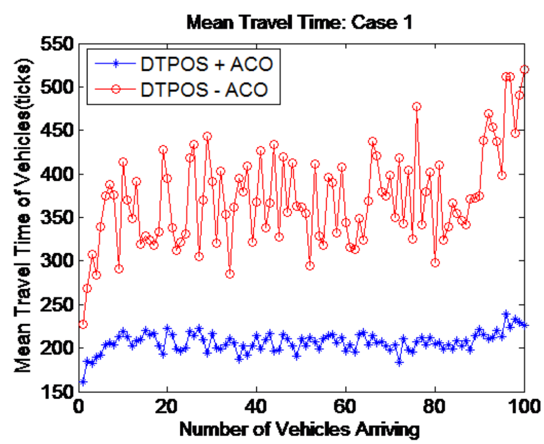


Figure 4. Mean Travel Time of Vehicles: Case 1.

### B. Case 2: 300 Vehicles

Figure 6 shows a similar trend to what has been previously discussed with DTPOS+ACO showing lower mean travel times than DTPOS-ACO. The mean travel time figures however are much higher for the 300 vehicles traffic density than for the 200 vehicles.

Figure 7 also shows the percentage of vehicles arriving at the predefined destination and the time taken for all of them to reach their destination. For the case of 300 vehicles, it takes 100ticks for 50percent of the vehicles to arrive at the destination in the DTPOS+ACO situation and 200ticks for the same percentage to arrive at the destination in the

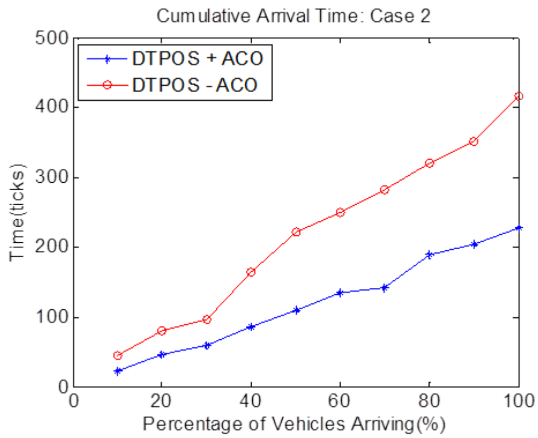


Figure 5. Percentage of Vehicles Arriving Vs Time: Case 1.

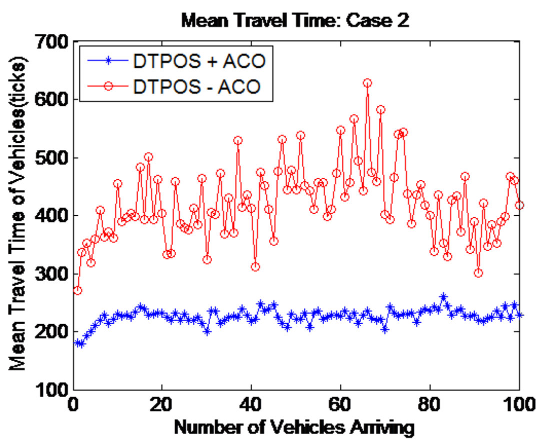


Figure 6. Mean Travel Time of Vehicles: Case 2.

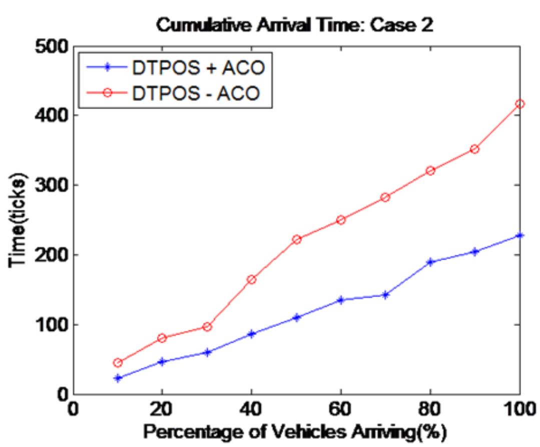


Figure 7. Percentage of Vehicles Arriving Vs Time: Case 2.

DTPOS-ACO situation. It takes twice as much time in both systems for all the vehicles to arrive. Once again it has been shown that vehicles in the DTPOS+ACO case use less time than those in DTPOS-ACO.

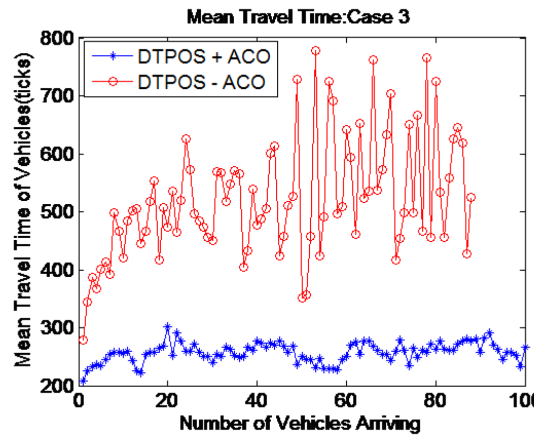


Figure 8. Mean Travel Time of Vehicles: Case 3.

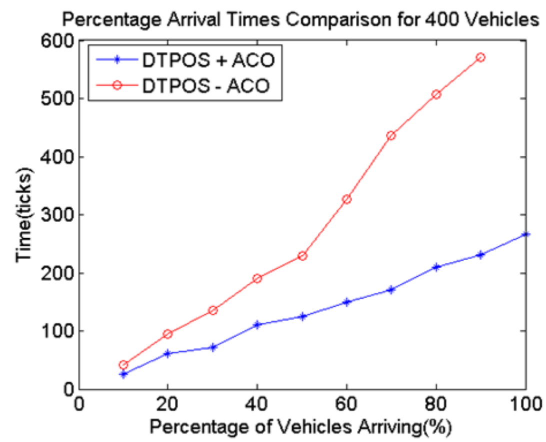


Figure 9. Percentage of Vehicles Arriving Vs Time: Case 3.

### *C. Case 3: 400 Vehicles*

Figure 8 shows the mean travel time comparison of vehicles for the two systems with a traffic density of 400 vehicles. The trend remains the same with higher values of travel time as a result of the increased traffic density. Figure 9 however, shows an interesting trend when the percentage of vehicles arriving and their cumulative times are studied. It was realised that as the traffic density increases it becomes almost impossible for all the vehicles to arrive in the DTPOS-ACO case. For the 400 vehicles traffic density, it was realised that while it took about 220ticks for all the vehicles to arrive in the DTPOS+ACO case, it took almost 600ticks which is almost thrice the time for all the vehicles to arrive in the DTPOS-ACO case.

## VII. Conclusion

In this paper, a dynamic travel path optimization system has been proposed. The system is implemented in NetLogo. Two cases of the DTPOS have been developed, one with ACO and the other without ACO. The two systems were simulated, and the results analyzed for comparison of performance. The performance indicators studied have shown that the DTPOS with ACO always gives results which are better than the case without ACO. At all traffic densities, the mean travel time of vehicles was always lower for the DTPOS+ACO than the DTPOS-ACO. Also, the percentage of vehicles arriving at the destination and their cumulative time were compared, and it was evident that DTPOS+ACO took less time for all the vehicles to arrive than DTPOS-ACO. It can therefore be inferred that Ant Colony Optimization solves the vehicular traffic problem by substantially reducing the travel time.

## REFERENCES


[1] R. Salter and N. Hounsell, Highway Traffic Analysis and Design, Third ed. Palgrave: Macmillan, 1996.

[2] United Kingdom, Department for Transport, Perceptions of congestion: report on qualitative research findings, London, UK, 2001.

[3] RITA, Intelligent Transportation Systems (ITS) Strategic Plan: Background and Processes, January 8, 2010, pp. 18-19.

[4] E. Thielman, Head of Division for ITS, European Union, keynote speech at the 15th ITS World Congress, New York City, November 17, 2008.

[5] S. Ezell,Report by The Information Technology and Innovation Foundation, "Explaining International Leadership: Intelligent Transportation Systems"; January, 2010.

[6] Japan Highway Industry Development Organization, ITS Handbook Japan 2007-2008 pp. 89-90.

[7] L. Rao, L. Owen, and D. Goldsman, "Development and application of a validation framework for traffic simulation models" presented at the 30th conference on Winter simulation, WSC '98, Washington, DC, USA, 1998, pp.1079-1086.

[8] M. Slinn, P. Mathews, and P. Guest, Traffic Engineering:Design, Principles and Practice, Second ed Butterworth-Heinemann, 1998.

[9] M. Dorigo and G. Di Caro, "Ant Colony Optimization: A new meta-heuristic" Congress on Evolutionary Computation, 1999, pp. 1470-1477.

[10] K. Jones, "Comparison of genetic algorithm with particle swarm optimization" Journal of International Conference on Computer Systems and Technologies, vol. IIIA, pp. 1-6 2005.

[11] E. Bonabeau, Dorigo, M, and Theraulaz, G., Ed.,"Swarm Intelligence:From Natural to Artificial Systems", Santa Fe Institute Studies in Science of Complexity, Oxford University Press, 1999.

[12] D. Angus and T. Hendtlass, "Dynamic ant colony optimization" Applied Intelligence vol. 23 pp.33-38 2005.

[13] S. Nahar and F. Hashim, "Modelling and analysis of an efficient traffic network using ant colony optimization algorithm" Third International Conference on Computational Intelligence, Communication Systems and Networks, 2011, pp. 32-36.

[14] P. Bedi, N. Mediratta, S. Dhand, and A. Singhal, "Avoiding traffic jam using ant colony optimization-A novel approach" International Conference on Computational Intelligence and Multimedia Applications, 2007, pp. 61-67.

[15] R. Montemanni, L. M. Gambardella, A. E. Rizzoli, and A. V. Donati, "Ant Colony System for a Dynamic Vehicle Routing Problem" Journal of Combinatorial Optimization, vol. 10, 2005, pp. 327-343.

[16] Darren M. Chitty and Marcel L. Hernandez, "A Hybrid Ant Colony Optimization Technique for Dynamic Vehicle Routing", Lecture Notes in Computer Science, vol. 3102, 2004, pp. 48-59.

[17] L. Joon-Woo, K. Jeong-Jung, and L. Ju-Jang, "Improved Ant Colony Optimization algorithm by path crossover for optimal path planning" Industrial Electronics, 2009. ISIE 2009. IEEE International Symposium, 2009, pp.1996-2000.

[18] S. Ok, W. Seo, and J. Ahn, "An Ant Colony Optimization Approach for the Preference-based Shortest Path Search" Journal of the Chinese Institute of Engineers, Vol 34, Issue 2,2011, pp.181-196.

[19] M. Boryczka and W. Bura, "Ant Colony Optimization for the Multi-criteria Vehicle Navigation Problem" Studies in Computational Intelligence, Volume 456, 2013, pp. 29-53.

[20] M. Glabowski, B. Musznicki, P. Nowak and P. Zwierzykowski, "Shortest Path Problem Solving Based on Ant Colony Optimization Metaheuristic" Image Processing and Communication, Volume 17, Issue 1-2, 2013, pp.7-17.

[21] L. Andrei, "Analysis of Ant Colony Optimization for Dynamic Shortest Path Problems", 2012.

[22] Y. Jiang, W. Wang and Y. Zhao, "Solving the Shortest Path Problem in Vehicle Navigation Systems by Ant" Proceedings of 7th WSEAS International Conference on Signal Processing,Computational Geometry and Artificial Vision,2007,pp. 188-192.

[23] A. M. Ghazy, F. EL-Licy, and H. A. Hefny, "Threshold Based AntNet Algorithm for Dynamic Traffic Routing of Road Networks", Egyptian Informatics Journal, Volume 13, Issue 2,2012, pp. 111-121.

[24] S. Kurihara , Traffic Congestion forecating Algorithm Based on Pheromone Communication Model, Ant Colony Optimization - Techniques and Applications, Dr. Helio Barbosa (Ed.), ISBN 978-95351-1001-9, 2013.

[25] B. Tatomir, L.J.M Rothkrantz, and A.C Suson, "Travel Time Prediction for Dynamic Routing Using Ant Based Control", presented at Conference on Winter Simulation (WSC), Austin, TX, 2009, pp. 1069 - 1078.

[26] J.J Kponyo, Y. Kuang, Z. Li, "Real Time Status Collection and Vehicular Traffic Control Using Ant Colony Optimization", International Conference on Computational Problem-Solving (ICCP), 2012, pp. 69 - 72.

[27] J. Kponyo, Y. Kuang, and E. Zhang, "Dynamic Travel Path Optimization System Using Ant Colony Optimization", Proceedings of the 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation. IEEE Computer Society, 2014, pp.141-147.

[28] J Kponyo, Y Kuang, E Zhang, K Domenic, "VANET cluster-on-Demand Minimum Spanning Tree (MST) Prim Clustering Algorithm", in 2013 International Conference on Computational Problem-solving (ICCP), Jiuzhai, 26-28, October 2013,pp. 101-104.