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Dynamic Travel Path Optimization System Using Ant Colony Optimization

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***Abstract*—This paper demonstrates that ant colony optimization can efficiently improve the traffic situation in an urban environment. A Dynamic Travel Path Optimization System (DTPOS) based on Ant Colony Optimization (ACO) is proposed for the prediction of the best path to a given destination. In DTPOS, traffic factors such as average travel speed, average waiting time of cars and number of stopped cars in queue are taken into consideration. The proposed method is modeled in NetLogo. The simulation results demonstrate that the DTPOS model can greatly reduce the average travel time of cars in urban cases and improves the mean travel time by 47 percent when compared to similar models where the cars select their path without ACO. It has also been shown that the results can be further improved by 56 percent when the Previous Path Replacement (PPR) method is applied to the DTPOS results.**

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

I. Introduction

In 2010 there were more than one billion motor vehicles in use in the world excluding off-road vehicles and heavy construction equipment [1]. In 2011 alone a total of 80million cars and commercial vehicles were built, with China leading the manufacturing market with 18.4 million motor vehicles manufactured [2]. This increase in vehicle population with its resulting heavy traffic causes traffic jams and in some instances accidents especially in urban cities. As a result of this, cars have to wait in queues for several hours in heavy traffic situations. In such cases, most drivers prefer to avoid heavy traffic segments of the road and use the routes with less traffic to their destinations. However; in many instances drivers have no accurate information of the traffic status of the road network before setting off and as such have a difficulty in selecting the best route to a predefined destination. It is very helpful therefore to collect real time data on traffic density and make it available to drivers to enable them determine the best path to a destination before s-tarting a journey or even change the route dynamically when necessary. Current methods used in traffic prediction such as Google maps and Windows live maps can only be accessed through the internet, however; most drivers cannot access the internet simultaneously as they drive and as such cannot fully utilize the facility. The maps are also not frequently updated and as such do not capture the most recent status of the road network which makes optimum path prediction by the use of these maps inaccurate in some situations. Google maps and Windows live map applications obtain live traffic data from drivers who voluntarily turn on their *my location* applications. They monitor to see how fast they are driving in real time and use that to predict the traffic on that section of the road. Also, the availability and accuracy of traffic data and how timely it is, depends on the number of drivers using such devices and/or applications at the time. Even though both Google maps and Windows live maps have the capability of predicting the traffic situation on the routes, only Windows live maps suggest alternative routes to a predefined destination. Though such methods have achieved some success in developed countries where many people use Google services, it may not work effectively in developing countries since only a few people use Google devices within an area. Therefore, it is important to explore other means which do not require central control but use the vehicles themselves for traffic information dissemination. We propose a Dynamic Travel Path Optimization System(DTPOS) which does not rely on maps or historical data to predict the optimum path to a given destination. This system establishes a vehicular ad hoc network and uses communication among the vehicles to relay traffic status information which is stored at storage devices at the traffic intersections. The traffic information is obtained by clustering the vehicles and using the cluster-heads to obtain the traffic density information within a particular cluster radius. The cluster-heads then relay the traffic information obtained to a nearby storage device. In proposing this method it is assumed that every car has devices installed for basic computation and wireless communication. It is also assumed that there are data storage devices at the intersections to keep and manage traffic information. The information obtained by this method takes into consideration the current state of the road which makes it more accurate than the Google map and Widows live map predictions. Unlike the other methods previously mentioned, the accuracy of the traffic information obtained also does not depend on the number of cars or the

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number of drivers using Google or Windows applications. The traffic information stored at the traffic intersections is also updated very frequently and therefore captures the most current traffic status on the road. The Dynamic Travel Path Optimization System (DTPOS) is based on Ant Colony Optimization. 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 [3,4]. The rest of this 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 model and section V touches on the simulation of the model by NetLogo and discusses the results. Finally Section VI presents conclusions on our key research findings and also highlights our future research direction.

II. Related Work

The first instance where an ant based system was used for dynamic problem solving was in [5]. Ant Colony Optimization (ACO) has been applied to dynamic path optimization in [6]. The authors in [6] 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 [7]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 [8]. 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 [9], 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 [10]. The problem is expressed as a bi-criterion optimization problem with the aim of minimizing both the total mean transit time and the total variance in transit time. The paper introduces a hybrid dynamic programming ant colony optimization technique to solve this problem. The hybrid technique uses the principle of dynamic programming to first solve simple problems using ACO by routing from each adjacent node to the end node, and then builds on this to eventually provide solutions for routing between each node

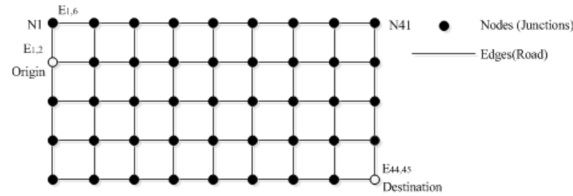

Figure 1. A typical road scenario for best path determination

in the network and the destination node. This method focuses on all possible routes from a given origin to a destination. This method also uses hybrid parameters of mean transit time and variance of the mean transit time to determine the best route. In [11] an improved ant colony optimization algorithm by previous path replacement (PPR) which the authors term path crossover for optimal path planning is introduced. The study solves the path determination problem by using the ACO algorithm improved by the PPR scheme. The PPR scheme is a two-point crossover of paths found by ants. The best path is stored and is compared with a new path every time. The best path replaces the one already stored in memory. This method considers all paths as candidate paths. The search space in this method is therefore bigger and takes a longer time in arriving at a solution. At least two paths must be known before they can be compared. This slows down the search, since at any time there must be two solutions to compare. This method does not consider the traffic which is very crucial in optimum path determination in a traffic environment. In developing our proposed model we improve upon the traditional ACO results further using a modified version of the PPR concept proposed by previous researchers. In the previous application of the PPR, the best path among all the possible paths from a given origin to a destination is chosen, in our proposed model however; we narrow the search by considering only best traffic routes. All routes are therefore not candidate routes which narrows the search space and search time.

III. Mathematical Modeling of the Ant Colony Optimization Solution to the Optimum Travel Path Determination Problem

The road network is modeled as a connected graph G as shown in Fig1 above such that

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

Where N=(N_1,N_2,N_3,N_4...N_n) is the set of nodes n (i.e. junctions) and E is the set of directed edges. 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 uncertainties:

1) Traffic congestion can cause delays but traffic cannot easily be predicted

2) Road works or accidents can also cause delays but the assumption is that delays are mainly caused by traffic.

The edge E_{ij} cannot easily be characterized in terms of the distance between i and j, E_{ij} is characterized by the distance x_{ij} and traffic T_{ij}. Each route in the network

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

Where

$$a_{ij} = \{1 \quad if\, node\, j\, is\, visited\, after\, node\, i\, and\, 0\, if\, otherwise \tag{3}$$

Where *i,j=1...n*. 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 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:

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

The relationship is as shown in Fig2 below:

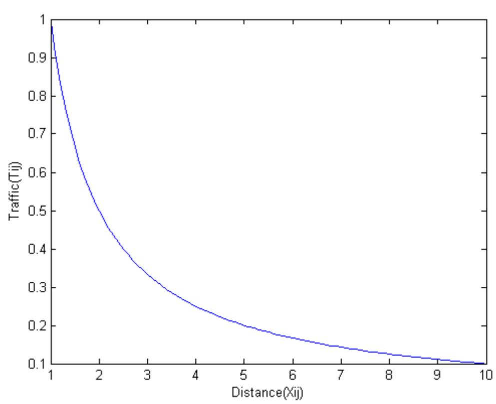

Figure 2. A graph of traffic against inter-nodal distance

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 for 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 α and β 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) ρ and the deposition rate Δ_{ij} (the rate at which cars arrive). The pheromone or traffic update is governed by the equation:

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

Δ_{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:

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

Selecting α and β such that

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

Equation (7) is reduced to:

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

IV. An ACO Inspired Dynamic Travel Path Optimization System (DTPOS) Model

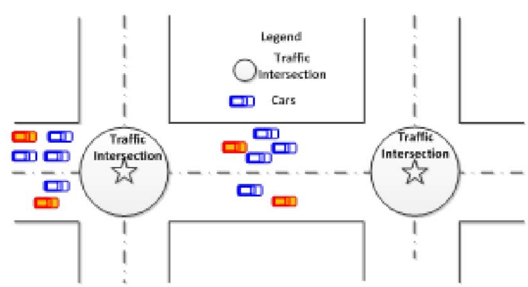

Figure 3. Junction Scenario

The ACO inspired DTPOS model relies on a 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 the model and ant

TABLE I
SIMULATION PARAMETERS

PARAMETER	SPECIFICATION
Model Simulator	NetLogoV4.1RC5
Total number of vehicles	300
Total number of test cars set off	100
Road Topology	6 by 6 square
Maximum Speed	1.0
Trace volatility rate(ρ)	8 percent
α	0.5
β	0.5
Terminating criteria	All test cars

behaviour is that while ants select the path with the highest pheromone concentration as the best path, the DTPOS selects the path with the least traffic as the best path. As the traffic concentration increases, the probability of selecting a particular path reduces. Fig3 shows a junction scenario of the DTPOS model. It is based on the assumption that the cars are installed with sensors with the ability to sense the traffic upon arriving at the intersection and are able to avoid the dense traffic routes using V2V communication.

V. DTPOS Model Algorithm and Simulation

A. The DTPOS Model Simulation Flow Diagram

The model is simulated based on the simulation flow diagram shown in Fig4 below:

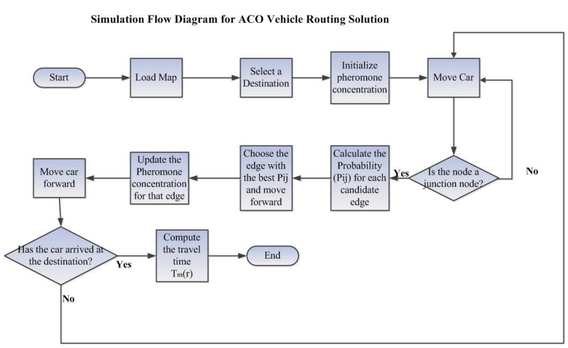

Figure 4. Simulation Flow Diagram for ACO Vehicle Routing Solution

B. Simulation Results and Analysis

In order to evaluate the performance of the DTPOS, two NetLogo models were developed, one emulating the behaviour of DTPOS and the other with the cars selecting the best path from a maximum of three possible paths based on the candidate route with no knowledge of the traffic situation. The shortest among the candidate routes is selected in the *without ACO* case. A bidirectional road scenario was used with the model simulation parameters as shown in Table 1 above:

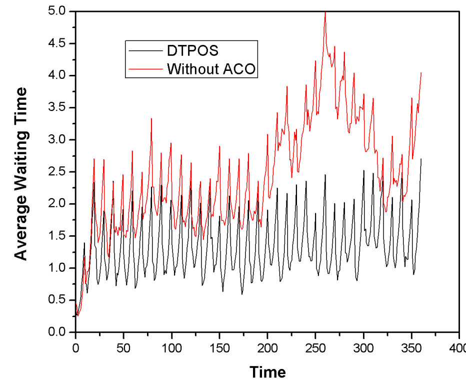

Figure 5. Average waiting time for the two scenarios

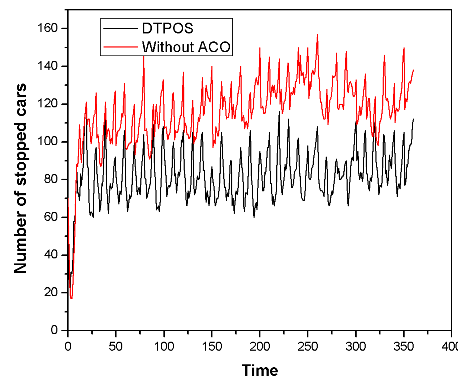

Figure 6. Number of stopped cars at a traffic intersection for the two cases

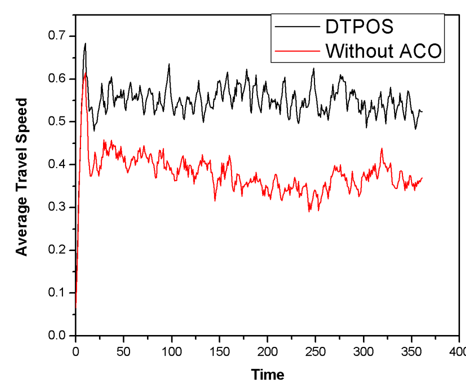

Figure 7. Average speed of cars for the two cases

Each simulation was run for a total of 300 cars with 100

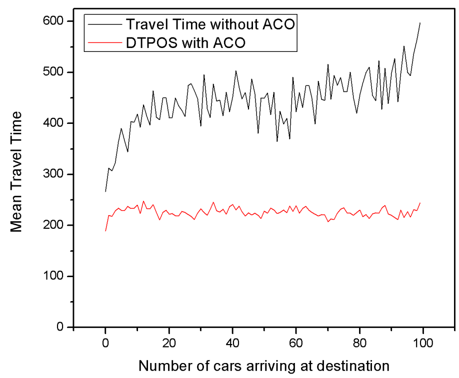

Figure 8. Mean Travel Time comparison for the two scenarios

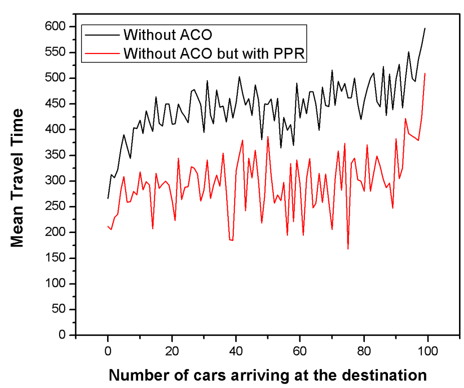

Figure 9. Mean Travel Time improvement of without ACO case using PPR method

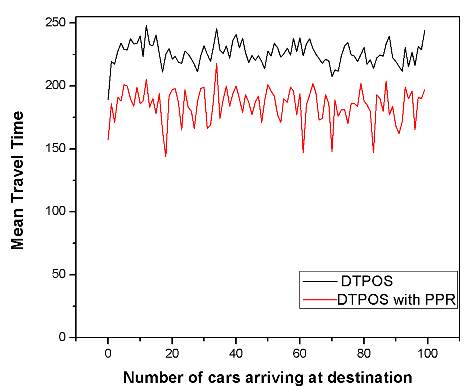

Figure 10. Mean Travel Time improvement of DTPOS result using PPR method

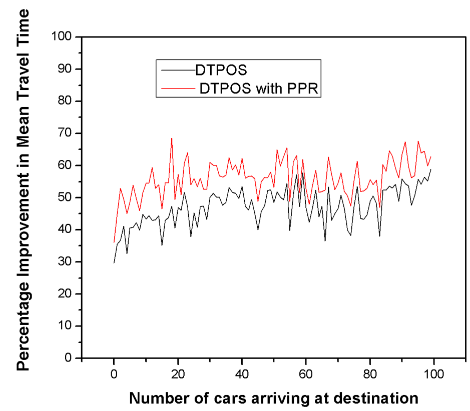

Figure 11. Percentage Mean Travel Time improvement

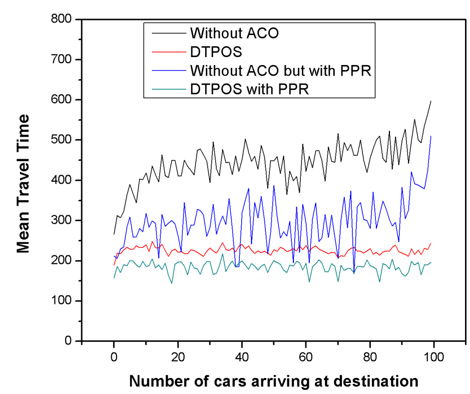

Figure 12. Mean Travel Time comparison for the four separate scenarios

of them being test cars. The simulation terminates only when all the test cars have arrived at the destination and the mean travel time is recorded. PPR was applied to the results of the DTPOS model for best results. In analyzing the performance of the model, the following performance measures: average speed of cars, average waiting time of cars, the number of stopped cars in the queue and the mean travel time were considered. The average waiting time of cars in a queue for the two different scenarios is shown in Fig5. It can clearly be seen that cars using ACO spend shorter time in queues than those which do not employ ACO. This is the result of the intelligent selection of least traffic segments of the road at the junctions. In Fig6 a graph of the number of stopped cars in both scenarios is shown. As can be seen from the graph, there are more stopped cars at the traffic intersections in the case without ACO than in the ACO case. As a result of the increased traffic in the case without ACO, the average speed of cars is lower in that scenario than in the scenario with ACO as shown in Fig7. Fig8 shows a graph of the mean travel time for a number of cars arriving at a common destination for both cases. It is evident from the graph that cars which use the DTPOS model take much less time in arriving at the destination compared to cars which do not use ACO. To further improve the mean travel time, the PPR method is applied to the two models and the improved results are depicted in Fig9 and Fig10. Fig11 shows a graph which compares the percentage mean travel time improvement for the DTPOS case with the DTPOS running the PPR scheme. The average percentage improvement in the DTPOS case is 47percent and the average percentage improvement applying the PPR to the DTPOS results is 56percent. Fig12 compares the results in the four separate scenarios and shows that the best path is obtained by running the PPR method with the DTPOS.

VI. Conclusion and Future Work

In this paper we have demonstrated that a DTPOS which is based on ACO can be used to predict the best path to a predefined destination and improves the mean travel time by 47percent. We have also demonstrated that there is a 56percent improvement in the results when we apply the PPR method to the DTPOS results. Further research will focus on developing a data dissemination scheme through which the traffic information collected by the cluster-heads could be relayed to the traffic information storage devices at the junctions.

Acknowledgment

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