Efficient Traffic Routing using ACO

Abstract

The routing of traffic is a highly complex task which involved finding the best path for a given user, in a given space at a certain time. The problem is much harder than just find the shortest path to a destination as there are many different objectives that the user may have and factors which can affect the efficiency of the path. This report will look into the use of Ant Colony Optimisation can be used to find efficient traffic routing solutions. We will explain how ACO works, show recent examples of how ACO as a method for creating solutions to different traffic problems and give an overview of ACO in the traffic industry.

Introduction

Current traffic systems intermittently make use of research, and it may be that in future designs, Nature inspired design techniques could be employed to design road systems, to develop a transport infrastructure that could be beneficial to overall efficiency and safety.

In traffic management Ant Colony Optimisation is increasing in popularity, with its ability to find optimised solution in situation where traditional methods fail to produce any good solution. One of the large benefits of using ant colonies to assist the planning of transport systems is their ability to adapt to changes within the environment. In an ideal world all transport systems would run to schedule without delays, but in reality any scheduled transport is swarmed with a list of problems which could occur on any given day. These range from short delays given on a specific route for reasons such as road works or rush hour congestion, to larger problems such as a vehicle crash or an entire route closed for maintenance.

The de-centralised control of an ant colony allows it to easily work around problems in a network. Given a model of a working system, changes and restrictions can be applied to help simulate different styles of problems. For example, in a road network system a lane closure could be simulated through decreasing the maximum capacity of that path or by increasing the estimated time taken to traverse down it. In the case of a major road traffic collision it could be represented in a similar way or by completely removing a connection in network depending on the severity of the accident. Thinking about this in terms of nature it could be compared to placing an object such as a stick or rock along a path an ant colony is currently using between their nest and food source. The timing of this problem can occur completely at random, yet ant colonies have displayed behaviours allowing them to re-route around any obstructions.

Having placed new restrictions or changes to a previously optimised system, the simulation can be run to see how the ants adapt to the changed environment and explore different routes to find a new solution. During this, the individual ants can explore alternative routes to try and work around a given blockage in the path. Once successful new routes have been located, new pheromone trails are laid down allowing other ants to follow and strengthening the trails until a permanent new route is determined.

This style of approach can be used to deal with both expected and unexpected problems within transport systems. Expected problems can be classified as planned disturbances to a network such as closing a specific route for maintenance. In this case new routes can be planned and tested in advance to calculate the best diversion path for users to follow when the disturbances occur. This sort of
approach could also apply for known issues within a system such as an increased volume of users at a given time, for example during rush hour or around a sporting event. On the other side of the scale, ant colony optimisation can also be used to deal with unexpected events such as multiple closed paths or an unexpected build up of users in a certain area creating congestion or a bottleneck.

**How ACO Works**

Ant Colony Optimization (ACO) is a relatively new nature inspired algorithm which was originally developed by Colorni and Dorigo in 1992. [15] The method takes inspiration from how an ant colony is able to co-ordinate as a whole to locate and collect food without a central control organising and communicating with individual ants in the system. By mapping some of the ant’s behaviours to computerised agents, an ACO system can be used to replicate various different situations and assist in finding the optimal path across a network.

Whilst the individual ants do not communicate on a one to one basis, each ant is able to lay down a pheromone trail to mark a favourable path. Other ants in the system are then able to detect the level of pheromones across different trails and choose which path to follow in favour of the one with the greatest concentration. As the levels of pheromone fades over time, only routes which are regularly traversed will remain attractive to further ants in the colony.

The whole process can be broken down into a number of simple steps. Firstly, a number of foragers go out into the environment in search of food.[Fig 1.1.a] Once they have located a food source, they will return to the nest, laying down a pheromone trail as they go, to mark the path they have followed.[Fig 1.1.b] In the next stage, other ants from the colony will choose which path to follow in favour of the one with the highest concentration of pheromones. When each of these ants has located the food source it too will lay down a pheromone trail indicating its chosen path to the other ants in the colony. [Fig 1.2] As time passes, the pheromone values attached to each path will change. The routes most favoured by the ants will consistently have a high concentration of pheromones, while the infrequently used paths will become less and less attractive. In turn this encourages the ants to follow the more popular route often creating a single line of ants from the nest to the food source. [Fig 1.3]
In an investigation known as the “double bridge experiment” [Fig 2(a)] it was found that given a situation where two equally good routes were provided, the ant colony would still favour one route over the other. The factor of which route was chosen was based purely on random fluctuation of ants until one side’s pheromone values outweighed the other, resulting on convergence to a single route.

A variation of the double bridge experiment [fig2 (b)] where one of the two routes was made significantly longer than the other found consistent convergence to the shorter of the two routes. The reason behind this can be accounted for by a couple of different factors. Firstly, as the shorter route is quicker for the ants to traverse, the ants returning to the nest laying the first pheromone trail will arrive sooner than the ants following the longer route. This means that the shorter path receives initial pheromones quicker than the other increasing the probability of further ants choosing it. Equally, as the route is quicker for the ants to travel down, the pheromone trail will continue to be increased at a quicker rate than any other route, resulting in a greater build up of pheromone. These factors result in the ant colony most commonly converging to the optimal path in the system without the need to extensively explore every possible route.

The principles of this foraging behaviour can be adapted for use within a computerised system. Each ant can be represented by an agent who is given the same basic ability to make decisions based on the pheromones laid along paths. The network for the ants to explore can be represented in graphically form with each route being displayed as an edge and a node being placed at intersection points or other significant points. An artificial pheromone value can then be placed on each edge to represent its appeal to agents within the system.
As ants pass through the system the pheromone values $\tau(e)$ for each edge $e$ is updated in accordance to:

\[
\tau(e) = \begin{cases} 
(1 - \rho) & \text{if edge not traversed} \\
(1 - p) + \text{new pheromone} & \text{if edge traversed}
\end{cases}
\]

Where $\rho$ is the chosen rate of evaporation. [17]

As the system uses artificial pheromones, the rate of evaporation can be altered to change the speed at which the system converges on a route. By using a low value of $\rho$ the pheromones evaporate away slowly allowing ants to explore more of the network before the longer routes become unattractive for future ants. In contrast, a higher value of $\rho$ indicates a faster evaporation which results in a quicker solution, but may not always find the optimal route before the agents converge. This along with several other factors can be used to fine tune an ant colony to carry out a specific task.
ACO used for Timetabling Public Transport

The timetabling of public transport is a complex multi-optimisation problem due to the number of factors that should be considered. The needs of the passengers need to be balanced against the needs of the operators and the whole system needs to work within the confines of the existing infrastructure. Some of these considerations include:

Passengers:
- Frequency of transport
- Routes

Operators:
- Number of vehicles
- Number of drivers
- Routes
- Reduced idling time

Infrastructure:
- Finite possible routes
- Traffic or other obstructions
- Limited track capacity

Many of these may be directly contradictory such as frequency of transport and numbers of vehicles and drivers, the passengers want a frequent, regular service but running larger vehicles less regularly may be cheaper as fewer drivers and vehicles are required.

These problems are traditionally solved either by experts using their knowledge of the system and trial and error to find a suitable solution. They can also be solved exactly using mathematical methods although this can be expensive for large problems. Due to these restrictions nature inspired methods have proved to be useful in solving these problems.

Bus Routing Problems

The timetabling problems concerning buses usually focus on finding suitable routes as many options are available to a bus on a road network. The timing of these routes is less important as buses are able to use the same stretch of road and even the same bus stop without problems. As well as routing considerations some models also look at the number of buses and drivers required to give sufficient coverage.

Euchi and Mraihi (2012) [1] apply ant colony optimisation to the problem of buses collecting children for school. Here the aim is to cover a specified area to collect students in a limited time. The buses begin at the school at the beginning of the time period and must return to the school by the end of the time. There are a limited number of buses and each bus has a limited capacity. To reduce costs the shortest route needs to be found that can fulfil the task.

Here the obvious assignment of nodes and edges are used, the nodes are the bus stops and the school while the edges represent the roads between.
Initial solutions were found using the nearest neighbour procedure and are then optimised using a hybrid of the ant colony optimisation and the variable neighbourhood search. This method was applied to a real world example in Great Tunis. They conclude that their algorithm can provide improvements over the current system.

A similar investigation by Shi, Zhao and Zhang (2010) [3] on a public bus network in Chengguan District, Lanzhou also suggested that improvements to the system could be made using ant colony optimisation.

The bus network problems cover many of the key points such as passenger requirements and optimisation of bus and driver usage. However they are still simplified models in that the distances between nodes represent the distances between the stops and not the time. In many road networks the shortest distance is not always the quickest due to traffic levels and other road restrictions. Later in this report we will look into how ACO is used to find the quickest path between when taking into account road and traffic factors.

**Train Timetabling Problems**

Unlike the bus problems the biggest concern of the train timetabling is the limited capacity of the track and stations. Ghoseiri and Morshedsolouk [2] looked at the problem of timetabling for a single track route where trains need to run in both directions but can only cross in stations. The method used here is an extension of the Travelling Salesman problem. The travelling salesman problem is a mathematical problem where you have a set of cities (or nodes) joined together by roads (or edges). Each road has a distance and the aim of the problem is to find the shortest route that allows the salesman to visit every city [4].
The problem is very difficult to solve exactly even for small numbers of cities and therefore alternative methods such as heuristic algorithms are used to find near optimal results. Ghoseiri and Morshedsolouk [2] give an overview of the different methods that have been used to solve the problem in 2006. Ant colony optimisation is particularly suited to this type of problem and easily outperforms the other methods, finding the optimum solution on a significantly lower number of iterations. For this reason it is often used in other related problems such as timetabling.

<table>
<thead>
<tr>
<th>Problem Name</th>
<th>Simulating Annealing</th>
<th>Evolutionary Programming</th>
<th>Genetic Algorithm</th>
<th>Ant Colony</th>
<th>Optimum</th>
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<td>Iterations</td>
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In the strategy published by Ghoseiri and Morshedsolouk [2] the nodes of the travelling salesman problem are not the stations as expected but in fact the trains. The ants are paired up and each pair chooses a pair of trains to travel in opposite directions along the track. These are selected to ensure there are no collisions and the system is then optimised to reduce waiting times in the stations. They also produced a series of case studies that used a variety of track sections and trains to investigate the time difference and solution values for both solving the problem exactly and using this ant colony optimisation. A selection of results is shown below for 3 track sections.

<table>
<thead>
<tr>
<th># of Trains</th>
<th># Left Trains</th>
<th># Right Trains</th>
<th>Time</th>
<th>Solution</th>
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<td></td>
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<td>Exact</td>
<td>ACS</td>
<td>Exact</td>
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<td>2</td>
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<td>6</td>
<td>3</td>
<td>3</td>
<td>7</td>
<td>4</td>
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Philip Burrows, Kate Reed, Karen Templer, James Walker

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<td>10</td>
<td>*</td>
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<tr>
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<td>5</td>
<td>10</td>
<td>*</td>
<td>116.2</td>
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* - Indicates no solution was found within a suitable time period

Solutions and time taken to solve problems with 3 track sections using Ant Colony Systems and exact methods [2]

Other results were also given for 2 – 8 track sections. These all followed a similar pattern to the ones above.

The results show that although the ant colony optimisation cannot always achieve the optimum solution it is capable of achieving very similar results. However the time difference between the methods becomes very noticeable as the number of trains increases and the exact methods was unable to solve the problem for 8 trains in a reasonable time period. This is further demonstrated in the following graphs that show the running times as the track sections and number of trains increase.

Graphs showing the running time of exact methods vs ACS algorithm – [2]

The final solution can be represented as a time-distance graph such as the one below. This was the solution for 30 trains on 4 pieces of track. The total waiting time in the stations was 2492.1. The solid lines represent the trains running in one direction while the dashed lines represent trains running in the other. It can be seen that no trains collide, that is none of the lines cross except in stations.
This is a solution of a single problem in train scheduling, that of a single track line. Real train networks are much more complicated with double tracks, other branching lines and trains that will not stop at every station. Also this model does not consider the requirements of the passengers such as more trains at rush hour or regularly spaced trains for convenience. There are also train and driver issues as the trains do not return to their point of origin.

Some of these issues were covered by Jau-Ming and Jen-Yu (2006) [5] in their train timetable solution. Their problem had a double line, allowing trains to cross between stations. It also used depots where the trains could be stored and therefore removed from the system; this allows more trains to be dispatched at peak times. It was also required that the trains should return to their point of origin at the end of the day. Although this method does cover many other considerations it is still solving a very simple problem compared to real world train networks.

The research done so far on ant colony optimisation of transport networks covers many but not all of the considerations required when planning a system. The bus networks are more complete, they have been applied to real world networks and take the passenger requirements into account. The train networks have focussed on simplified problems concerning capacity on the tracks and have not yet been implemented into full real world models. Both sets of models also assume that the network is capable of running at full capacity at all times. This does not take into account the problems caused by overcrowding at rush hour or unpredictable events such as accidents or broken network systems.
ACO for London Underground Management

One transport system where the use of ant colony optimisation has been explored to assist with problems in the transport network is the London Underground. The network consists of 270 stations linked together with a combined total of 250 miles of track and each year transports approximately 1,107 million people across London. With this size and volume of users, disturbances to specific areas can have a large impact on the whole network. [6] Therefore finding an efficient diversion around any given problem in a short amount of time is vital to prevent congestion spreading throughout the whole system.

Fig. 1. Map of the London Underground

In the paper [6] covering the use of ants to explore alternative routes across the London Underground several assumptions had to be made to allow for the network to be simplified for use with an ant colony. One such assumption was the fact ants can only follow existing routes within a network. Whereas in real life an ant may be able to find a route around an object blocking the path simply by exploring whether they can go over or around it on the same path, this style of solution isn’t useful within a fixed rail network. If a train breaks down on a track then other trains can’t simply leapfrog or sidestep it to work around the problem. Instead the ants must navigate back through the system and find an alternative path around. Equally it was assumed that the ants can’t deviate from a specified route between nodes. Whilst at certain stations in the Underground system several different paths meet allowing passengers to transfer from one to another, it is physically impossible for passengers to swap trains mid-journey. Therefore any randomness applied within the system can only cover the choice of edges to choose from rather than how to travel along a specific edge.

Another assumption made covered the fact that a given passenger will only be travelling to one destination at a time. Taking users into account, this seems like a realistic restriction as in general they will wish to get to a specific end destination rather than one out of several options. However this differs from the real ant colonies where there may be several different food sources for the ants within an area surrounding the ant’s nest which may alter the colonies behaviour when discovering the optimum route.

The structure of the network allowed for it to easily be translated in to a graph with each station represented by a node and each track creating a connection between the corresponding stations. The testing of the system was applied to small clusters of stations given short routes between them. This choice was taken to allow the author of the paper to thoroughly test the system under different
parameters and examples before scaling the network up to work with the whole London Underground system. Real data gathered by the London Underground on estimated travel times between two nodes was used to populate the graph with initial travel times which could later be adapted during the simulations.

The investigation focuses predominately on calculating real time solutions to problems occurring within the London Underground. Up to date information on the status of each path could be obtained from the Transport of London website to be used to update the network’s values. Using interpretations of short and severe delays along with part or complete closures the model could then be adapted to represent the current status of the network. Allowing the ant colony to investigate the modified model it could then work to determine an optimum route for a user to use given a specified start and end destination in the network. The program also allowed for external modifications to be applied by the user in case they knew of additional problems in the network, or wished to apply added restrictions to the system.

The quality of the solutions was then tested against the optimum paths found from several other route planning algorithms. It could therefore be asked why ant colonies should be used to help solve these problems if other algorithms are able to calculate the optimum with higher reliability. The answer to this lies in the scalability of the system. Whereas the alternative algorithms were able to find solutions quickly over the small clusters, when applied to the whole network the time taken to compute a route vastly increases. In comparison, the ant colony is easily able to scale up to far larger system as it doesn’t have to exhaustively search the entire network for the optimum route.

Using a graph structure allowed for the real time delays to easily be applied to the network. If for example a station was closed, then the system could easily represent this by preventing any of the ants from travelling down path connecting in and out of that node. If some sort of delay occurred then the travel time for the journey would be adjusted based on the estimated delay provided with the travel information.

Having tested the system both with and without using the estimated journey times, it was that the time component was important for the system to accurately produce the optimum solution. A lack of the time component would cause some issues where an ant would still choose a delayed path as the pheromone value was high enough to suggest it was still the optimum path. By taking the estimated times into account the overall performance of the system improved with the shortest route often being found using the ants.

The results of the experiments indicated that it is possible to use ants to find alternative optimum routes through the London Underground when delays and obstructions are applied to the network. There was the occasional case where a new route wasn’t correctly found, however across zones 1 and 2 (the most populated sections of the Underground) an accuracy of 97% was obtained when problems across the network were introduced.

There are however areas that weren’t covered by the research. It was assumed that the time to make any connections between two different trains was set at a standard 2 minutes. This however isn’t always accurate as in reality as some connections taking far longer. It also relies on the passenger being able to transfer directly from one train to another without any additional problems such as missing the next train. Equally the maximum capacity of a station wasn’t taken into account. It was assumed that any station was large enough to quickly and efficiently transfer passengers on and off of trains at any time of day. However it is common for bottlenecks to appear at some stations such that the speed at which passengers can get on and off of trains is hindered causing delays for passengers who aren’t able to get on a train even if they are waiting at the platform.

Another problem not fully explored by the investigation is how accurate the model of delays was against the real world. Using information sent via the internet of how the London Underground feel the system is running could cause for some inaccuracies when translating this to real values for the
system to use. For example, a minor delay was expressed as 2 minutes whilst a severe delay was noted by 8 minutes. In reality there is far more variance in the delays experienced by users which could be better represented when transferring them to the model.

One interesting addition that could have been made to this system is the use of real data feeding back into the system. By somehow tracking how actual users pass through the real London Underground using specified routes, more accurate information could have been feedback to the system in real time. However, the large problem with this concept is the ability to gather this information without imposing on the users being tracked. There are a couple of concepts which could be introduced. First is the use of Oyster cards – prepaid swipe cards which can be used across the London Underground network instead of purchasing tickets. As user have to swipe on when using their first train in a journey and swipe off when exiting the system for their fare to be correctly calculated, information on the timings between these could be fed back into the system to give an indication of how long journeys took. This data could however have anomalies where users may perhaps pause on their journey resulting in an inaccurate time being calculated. Equally a user may swipe on some period before actually boarding their first train, adding additional time to their journey. However, having filtered out problematic data, it would provide a more accurate idea of how long each journey takes both between adjacent stations and across larger journeys.

The second concept is the use of smart phones. When the paper was produced, routes were calculated by a user using a computer. With the constant increase of smart phone users it opens up the idea of creating some sort of app allowing users to both access and update the information provided by the system. Whilst this data may be slightly less reliable, it may offer faster feedback to the system on delays and bottlenecks than that provided through the Transport of London website. This could be done via tracking phones through the system or relying on the users actually inputting valid information as in the modern era of online communities, people may be open to offering feedback to the system if it helps other members access more up to date information when the ant colony is used to calculate their route.

**ACO for Road Traffic Routing**

In 1991, the first algorithm called ‘Ant System (AS)’ was developed by Dorigo. It became a common benchmark for several other successful variants including Ant Colony System (ACS), Max-Min Ant System (MMAS) and Rank-based Ant System for solving static problems in which the number of nodes/cities and the distance between the cities do not change during the execution. [12] This section of the report will explain the approach of ACO in solving traffic routing problems and look into detailed examples of recent implementations from some of the most recent published papers in the field.

**The Problem**

The dynamic basis of Ant Colony Optimisation makes it well suited to optimising road traffic networks which are continuously changing and unpredictable. Knowing the route from one place to another is not enough on its own to provide good navigation and management of a road network. This is because there numerous factors which can affect the journey time and efficiency on a given section of road. Such factors include: road accidents and break downs, adverse weather conditions, speed limits, and slow moving vehicles. The variance and unpredictability of traffic means that a dynamic system is needed to manage it.
Traffic routing is a complex task and can have several objectives that can be in conflict with each other. Each road user is interested in travelling the shortest and quickest route to their destination with minimum route changes. This goal is known as User Equilibrium. From the interest of managing the road network as a whole, the goal is to maximise the traffic flow, this could be for certain important sections of the road network or for the entire network as a whole. This goal is called the System Optimum and aims to minimize the average travel time in the network, which may mean that some users travel along suboptimal routes or at suboptimal speeds for that user’s interest. These two contrasting objectives are hard to reach separately in its dynamic environment and the choosing the right balance between them is also difficult; when a good balance is used between the two objectives the network will be more stable.

Why use ACO?
Modern algorithms tend to use much precompiled data, which leads to determine their usage for static route planning. Application in dynamic networks is inefficient, because of the need to recalculate at least the part of pre-processed information. [8] ACO may not always find the most optimal solution, but is very good at quickly producing good solutions.

ACO is stochastic which makes it good at modelling impulsive and sometimes random behaviours of real drivers. ACO as an adaptive algorithm can cope very well with the dynamic nature of the traffic networks. Basic ACO can be extended to use more intelligent ants, with features such as memory of paths and individual behaviour, to create agents which better simulation real life drivers.
In General how ACO is used for Traffic Routing

Basic route planning is based on solving the shortest path problem for a road network. When ACO is used for traffic planning a graph is used to represent the road network and this graph is used to find the shortest paths between points. The edges in the graph represent different roads and the vertices represent turning, crossings and other important road features, which separate the sections of road. The weighting of the edges are usually the length of the edge and is always positive. Basic graphs are static and do not model changes in the network such as closure of a road or reduction in the maximum speed limit. A dynamic road network is almost always be more accurate provide that enough information about the roads it is modelling is collected and used correctly. For finding the shortest path in static graphs ACO work by depositing pheromones based on how many ants traverse an edge, thus this edge will become be attractive as more pheromones are add. However, when managing traffic flow the amount of pheromone deposited could be used to represent congestions so edges become less attractive with increasing pheromones. Also as there are many objectives that a system may be trying to achieve the function for pheromone depositing will be much more complicated than just the amount of ants which traversed the edge. Such functions for pheromone depositing will need to take into account the dynamic features of the road network.

A crucial layer in the ACO approach for traffic modelling is data layer. For important features of roads to be represented sufficient information about it needs to be collected and embody within the system. This background information is needed to design a dynamic system and can include the road capacity, speed limitations, times when the road is busy and weather. However, it is challenging and time consuming to gather all of the necessary information because there are so many variables which can effect traffic flow, and data is often geographically and quantitative limited. There are approaches that involve tracker user movement for gathering traffic flow data. TomTom navigation systems offers the IQ Routes technology, which calculates routes based on the real average speeds measured on roads every day compared to speed limits using historical data provided by other users. [9]

Specific Cases and How ACO is used in Detail

In a paper published by the Technical University of Ostrava in 2011 uses a probability threshold to divert traffic around congested routes. [8] The more ants traverse edges, the more pheromone which is deposited and the probability of an ant choosing an edge increases with higher pheromone deposit on the edge been considered. The modified ACO algorithm is used for traffic routing my making edges less attractive when the pheromone level reaches a set threshold. The routing will prefer the most efficient paths that are not crowded. Once more efficient paths become less crowded (the probability that an ant chooses them falls below the threshold), the algorithm will ants will immediately be routed towards such paths.
This shows the solution generated using a pure ACO approach.

The thickness of the edges represents the amount of pheromone deposited. The thicker the edge the more pheromones it has.

A hierarchical approach to network routing using ACO was introduced by Tatomir and Rothkranz in 2006. [10] In this method, the road system is split in smaller less complex areas interconnected into a hierarchy of roads. Three kinds of ants are used to route the traffic in the network. Local ants are used to maintain routes within a sector. Backward ants are used to update routing tables which are being kept at each node. These ants take the same path as the corresponding local ant, but in the opposite direction. Exploring ants are used to find and maintain routes between sectors. The local ants are not allowed to travel out of their current sector and the exploring ants must travel to a node within another sector. The model is good for characterising the inner and outer sections of city routing.

A recent paper in 2010 [12] shows how ACO can also be used to dynamically control network equilibrium and to optimise traffic flow through the network. This uses a multipath approach, where a fitness function has been designed that targets the conflicting goals of user equilibrium and system
optimum with the help of three partial objectives: to keep the flows below known capacity, to keep
the difference between fastest and slowest route below given threshold, and to utilise the fastest route
fully.

This algorithm is composed of two separate main steps; network pruning and flow optimisation. The
network pruning step consists of a normal ant-based routing algorithm that finds multiple paths with
less travel time costs than other paths, based on the present traffic conditions. Next, the flow
optimisation step consists of determining the correct distribution of flows on these paths such that the
overall network conditions (expressed in function of the travel time costs) are optimised. When we
want to optimise the distribution of flows that leads to a better usage of the network as opposed to
finding one single optimal route the pheromone deposit function in cannot be based on the number of
ants using it. Instead, the pheromone deposits should be based on the aggregated solutions of all ants
and this function with take into account the conditions for each partial objective.

De-centralized Control of Traffic Systems and
Research Expansion into Swarm Intelligence

In comparison there is also systems for traffic routing which have no central management. Traffic
environments such as those in India, which includes a large number of road users, road planners may
well have great difficulty in implementing a traffic lighting system in the future, both in cost, logistics
and in getting drivers to comply with new laws. The study of these kinds of systems can give other
countries insights into the problems with their traffic systems. It may offer distinct advantages coming
from decentralized control, where many agents have the intelligence to alter their actions accordingly
rather than a single entity controlling many agents. Studies have shown that de-centralized traffic can
become much more efficient than those with some form of centralized control, such as the method of
traffic lighting.

Methods found to increase traffic efficiency is often a goal for traffic designers, in road or air
systems with varying amounts of traffic control. The safety aspect is also considered to be an
important goal, as this is the main reason for having centralized control. Comparing the accidents of a
road system such as those in India, with other more centralized systems; can often show correlations
that are due to other reasons other than their use of decentralized control. This may be due to the
inherent differences with safety that are not present in many centralized traffic systems. For example,
there is a high proportion of road users that use bikes, scooters, rickshaws and motorbikes, which
would likely increase the likelihood of injury to drivers. There is also the matter of lowered safety
regulations, and higher use of less safe vehicles. However it has been shown that safety is increased
with these kind of systems, however the trust in these kinds of methods may be diminished by these
current traffic scenarios.

When using swarm intelligence to simulate traffic, the method employed normally involves building
traffic models to represent a large collection of agents, to explore what emergent patterns can be
observed. The uses of this could expand to include evacuation of transport or to study an environment
and scenario. Evacuation of transport can be useful when catering for high volumes of traffic
intending to exit a populated area. This area studies on agents could be experimented with by
adjusting their cares and their concerns, which will often give a different outcome or group
movement. For example, when a swarm agent cares about another swarm agent, it may move towards
that object. The environment could be adjusted also. The fitness would be the amount of cars that are
able to pass by a junction in a certain amount of time.
Partial De-Centralised Control within Traffic Junctions

There may be a way to suggest an efficient formation for traffic at each junction, depending on the agents destination, and the situation that the driver is presented. A graphical overlay of suggested attempts to reach and travel through a junction could be given. However it is difficult to see how this would implemented without having some kind of centralized control (or suggestion); at least in some form. This could be a possible area of study to explore the efficiency and safety of such a technique. Examples of this kind of traffic prediction are shown in some papers, which use ACO to predict urban traffic flow [24].

De-centralized Control of Automobile Junctions

Swarm intelligence has been shown to be a more efficient and safer way to navigate a junction for the whole, when no centralized control is used. This is in comparison to using traffic lighted systems. The use of traffic lights are designed to reduce traffic accidents, however they still occur due to a disobedience of the rules and an over trust on the instruction of these essentially automated switches. The intelligence of road users is obviously much higher than this, however due to the conflicting goals of each agent, the likelihood of traffic accidents is often presumed to be heightened without some form of centralized control.

This does however require that each agent behaves a certain way (as is always true with agent based findings), which is something that is never fully guaranteed and can only be shown to be likely due to empirical research. These agent behaviors could be incorrect, and could result in incorrect conclusions being made. To reduce this possibility and to increase the safety and efficiency of the system, agents or drivers could be encouraged to behave a certain way. This could be accomplished by ensuring that users (agents) of a traffic system adhere to certain rules, as much as is possible; through the use of education or through some kind of real-time encouragement or guidance at each junction situation.

The use of encouragement could use ACO to suggest the most used method for navigating a junction, considering the amount of agents using a path to get across the junction by looking into the pheromone buildup of certain areas of the junction. These areas could then be suggested to new road users, encouraging them to take this path rather than disrupting the learned path. The agent being guided could have otherwise taken a different route, slowing down the main flow of other routes. However, it is also possible that the new agent could take a more efficient route, which could then be suggested afterwards to the other agents entering the junction.

These kinds of systems could be adopted in other traffic systems such as air traffic routing, which is much less populated and could offer increased efficiency even when considering it is within a 3D space with much more variables to influence the system. These areas will be explored in later paragraphs. There may also be a benefit in employing these techniques to help in the speed of evacuation of traffic, which could concentrate on different loads and stresses on a transport systems considering certain situations.

Review of Road Traffic Planning Using ACO

Current traffic systems as a whole intermittently make use of research, and it may be that in future designs, Nature inspired design techniques could be employed to design road systems, to develop a transport infrastructure that could be beneficial to overall efficiency and safety. ACO will be most
likely temporary, in road systems without any centralised control [22], giving that the planned routes of agents will change frequently. However, some emergent patterns may be demonstrated over time, which may give suggestions on how to lay out traffic junctions or other influencing factors. This is the power of ACO, as well as all Nature Inspired Design techniques, in that it is able to adapt uniquely to difficult problems that are highly complex. Due to the varying degrees of stability of many traffic systems, ACO can provide many advantages, in guidance and in the recommendation of designing traffic environments.

When observing behaviour of individual vehicles and their reaction times, it is important to have accurate agents. If agents do not behave as true to a scenario as possible, the simulations usefulness is reduced. This is difficult when simulating traffic, which is controlled by individuals that are all different in their nature, and their reaction to different problems.

ACO for Air Traffic Control and Other Aircraft Mapping

In ACO, Ant colony optimisation is different as it involves examining paths that are within a three-dimensional space, rather than a rather two-dimensional space of other traffic systems. Aircraft trajectories involve several factors, however they do have rather predictable and highly trained agents, with few alterations between aircraft other than major types and sizes. Any ACO would have to take into account continuous alterations in weather patterns if it were to successfully guide aircraft in real-time. Weather does not seem as crucial in other areas, where weather does not constantly effect the vehicles position unless in extreme situations. The consideration of weather when creating this kind of optimisation for aircraft control would be paramount in the formation of popularised paths for aircraft to take, and would not be dependent on any specific and physically constrained path such as those existing within the common use of road vehicles. Aircraft do normally travel at a much higher speed, and factors such as wind speed, weight and drag can all effect the route that an aircraft can possibly make. Within the study of these kinds of systems, it seems that these considerations are lessened by the high level nature of the methods and algorithms, making such factors a possible problem rather than a constant consideration.

Areas in which there is little air control, in smaller airports for example, may benefit from a suggestion of each aircraft’s position. Research that discuss this, suggests possible avenues of advancement in this field that may benefit the congestion and delays of air traffic. These could provide opportunities for implementing practical technologies such as on-board systems that communicate with neighbor aircraft, or a storage of previous routes taken by planes. More prominent routes could be shown on the instrument displays in comparison to the aircraft’s current position. These practical applications are only made plausible when they are shown to be effective through empirical or exploratory research.

Air traffic has long been controlled either by a centralized human controller, or by a pilot within small airports. This approach has much to do with the trust that must be placed in a system that is so very complicated. The continued updating of an aircraft position and the occasional need for two-way communication makes replacing this system with full automation very difficult. Some attempts have been made to control aircraft trajectory and the overall organization of airports, however they are currently only theoretical, with some not been tested against meta-heuristics.

The current attempts involve using ACO to alter and adjust paths within the surrounding areas of an airport in order to make landings more efficient. They use numerical calculations that take around 1 to 4 seconds to organize a situation and the most efficient and safe path to be taken.

A paper describing an efficient ‘Ant Colony system based on receding horizon control for aircraft
Arrival Sequencing and Scheduling Problem [13] demonstrated that ACO can be employed using a given algorithm to assist in an efficient method for Arrival sequencing and scheduling of aircraft using ACO. Essentially, this paper demonstrated an efficient algorithm that had real benefits in the aiding of landings. The algorithm uses ACO to look at the surrounding horizon, and works out their paths. It then schedules the aircraft in the standard time. It then constructs a landing sequence, and uses the historical best to use for all following aircraft.

There are several suggestions that using ACO within air traffic control could be beneficial. Methods that employ a replacement of aircraft control and landing depending only on ACO must be defined within safe limits, and must be robust. It seems likely that the most beneficial methods are those that guide current methods rather than those that replace the human controller. This may offer an error checking ability that could reduce accidents.

Other more practical and grounded persist include the use of ACO to implement an efficient route for taxiing aircraft [18]. This paper produced as a response to increasing aircraft density shows how ACO can be beneficial in the predictable and repetitive routes taken in taxiing aircraft.

Further could be expanded in order to guide aircraft in a complete three-dimensional space, using a matrix to represent the area and using this space to represent pheromones as the paths of aircraft. These pheromones could be increased in events where actual air traffic control has similar methods. This could then be used to create a learned method that could offer some degree of automation. Alternatively an ACO method could be used to popularize certain routes that offer the most efficient
and safe path for aircraft as a whole, however this kind of unsupervised air traffic control is very unlikely to be trusted as a real world method.

Some attempts have also been made to use a graph which represents a series of trajectories within this kind of 3D space, and instead use ACO not to directly search for a path but to find the preferred trajectories, given a fitness [19]. These methods are then more commonly used when their pheromones are strongest, given the amount of weather problems and other properties of a node that could lower the preference of that route. The method suggests that each node relates to a neighboring node, in that it is a set of ‘weather avoidance trajectories’, which presumably means that the trajectory can be continually adjusted to adjust for differing weather conditions throughout a flight.

Global Flight Path efficiency

In a global aircraft system, where there are known destinations for several aircraft, there may be a method to improve routes taken by so many aircraft daily. I will report on the methods used currently for these or similar systems using mainly Ant Colony Optimization or perhaps other swarm intelligence. This could offer an apparent but previously unseen route, in cases where the average route taken is not visible to the aircraft or vehicle. As a result, the routes suggested by road signs, or perhaps on standard aircraft routes (and their internationally agreed charts) could be altered.

The effect of weather in air traffic control is sometimes substantial. The amount of flights altered due to weather conditions is detrimental to the long term scheduling of the aircraft industry, and can often cost a great deal to flight companies as well as the countries affected. This difficulty coupled with the amount of traffic volume globally, suggest the need for greater adaptation in an area that has greater amounts of alteration given the different situations that are presented at each point in time. A study by the University of Queensland (Australia) and the University of New South Wales (Australia) by Alam Abbas and Barlow, suggest that Ant colony optimization in the trajectories of aircraft is a possible solution to be explored. This technique can take into account weather conditions that influence aircraft and the concept of Free Flight.

Further Work

Conclusion

The exploration of these techniques has illuminated the advantages and weaknesses of ACO in traffic improvement techniques. Most notably, the power of the ACO to adapt to new situations and the impressive ability of this optimization technique to find solutions that can be popularized over time quickly because of its specialized method.

Nature Inspired Techniques are shown to be continually useful in finding solutions that would not have normally been considered by experts or normal people. This is due to some solutions appearing as if they are not appropriate, when they are actually very effective. ACO has shown to be effective in areas where the solution is not clear, specifically relating to the traveling salesman problem, or any routing task involving a network. There are apparent conflicts in the goals of ACO, when applied to traffic. These goals need to be carefully selected as many have conflicts. These goals could range from reducing traffic congestion, increasing efficiency, limiting speed and increasing safety and lowering emissions of internal
combustion vehicles. There are obvious conflicts between reducing emissions and increasing safety and increasing traffic efficiency, in that the latter can be accomplished with increased speed and emissions.

ACO can have multiple hard constraints which can offer a wide variety of solutions, however these solutions could increase the likelihood of a failed solution being given. A small number of soft constraints would be more sensible, however this would still increase the search space and make it more difficult to find a possible solution. In comparison, a small number of hard constraints could be applied, which would decrease the search space, but reduce the possibility of an efficient solution being found.

From examining the papers for the creation of Timetables through the use of ACO, timetables can most likely be implemented quickly, with information on all possible paths being devised quickly and efficiently. It seems that timetabling using ACO as a method is quick enough for implementation for real world problems therefore, and it can find optimal results in a fraction of the time when compared to other methods. However, a major problem with this application is the amount of trust that must be placed onto a system which is after-all solving a non-deterministic polynomial, and an incorrect decision could cause serious accidents.

Overall it seems that control may be difficult in terms of trust when ACO techniques are applied to areas where the decisions made could create increased danger for any person. This is true to most systems, but it is normally justified, due to the boundaries or limitations on decisions that can be put in place. However, when a method is implemented to direct traffic, these boundaries are less obvious. This is because problems can occur in ways that may not be noticed from an increase in some variable, but instead in ways that may occur when an unconsidered variable occurs within what is most likely a complex system.

For example, consider a timetabling system that takes into account the speed limit of 50mph of a Subway track, and many other variables are also included in a simulation. If two trains are scheduled to pass an intersection, one after the other, could result in a collision, even when both drivers are following the instruction of the timetable determined to be safe. The reason for this being that the track had been incorrectly laid out, making part of the track shorter in the calculation of the ACO timetable when compared with the real track.

The possibility of this kind of occurrence has its origins the use of a simulated space, which can never be exact in it's portrayal of the real system. This is a problem that occurs in all techniques that use simulations to calculate the appropriate action. This is required by ACO because of the need for looking ahead, in using data that does not exist; examining possible situations to solve the existing situation. For example, in the solving of a congested junction, a simulation must be created in order to train the Ant Colony. This would require many assumptions to be included in this model, which should be minimized, but will always need to exist in order for an ACO technique to calculate solutions.

The difficulties mentioned above can be applied to all traffic routing solutions using ACO. These problems can be reduced, however because of their possibility, ACO cannot be completely assured in its safety. This means that for engineers of solutions for new and existing traffic systems have to justify this increase in danger. If this danger can be reduced to such a degree, that it can been shown to cause no collisions given several randomized erred
situations, then it may be explained that in this situation the creation of a traffic problem given ACO decisions is very unlikely.

These problems are increased when attempting to predict the optimal routing solutions for traffic agents; with greater amounts change. This increase in disparity could occur through the range of behavior seen in agents, or through an increase in the possible paths or locations that an agent can move to.

In respect to the application of automobile traffic improvement, it is known that people always drive differently, which means that ACO will always have difficulty predicting all situations. Without knowing the personality of each and every agent that effects the traffic system would need to be known for accurate simulations to occur. The use of averaging agents behavior could help to reduce this problem, and may help generalize all agents as a whole for use in many future situations. It is apparent that a single driver may decide to act in a way that was not predicted by a simulations' solution, however if this unpredictability can be reduced, and made workable for many solutions then it may prove to be helpful. The application of ACO in these sporadic situations must have limitations in that it cannot be made solely responsible for any situation that may cause an accident. It may be that real applications can be provided for aircraft and automobile traffic in the suggestion, but not reliance of solutions; for this kind of route finding.

Another possible application could be the completion of adaptations made by ACO by human knowledge. This could allow for a confirmation of solutions that can help reduce the risk of dangerous decisions being made only by blindly following ACO findings. Natural computation techniques are supposed to find interesting and unique solutions, but it is not designed to create safe, or sensible solutions. These must be confirmed through the use of limitations and confirmations put into a system, and it is possible that human knowledge could offer a reliable section in this kind of method.

Reducing the size of the model may increase the usefulness of ACO in many situations. Traffic routing may not work well in massive scenarios, with a large amount of agents and large amounts of variables. But if this sporadic model is reduced to only a few hundred agents and a small number of junctions for example, the optimal solution could be found more successfully. This is in essence a division of the problem, but it does not remove the problem of disparity, but rather reduces it - for use in short term solutions. This would be compared to large simulations that could easily find an incorrect solution given an incorrect assumption of some variable. This could be applicable to creating solutions for short distance traffic routing, in getting data from one point to another in a faster time.

There are different ways to use ACO. For example, ACO can be used in realtime, or it could analyze previous situations. ACO can also be used in finding a route to the Fitness of a specific solution, and not the Destination itself. The method would use other methods to find a solution, and only then use ACO not to search for the solutions in traffic, but to search the search space for the most optimal solution.

Perhaps problems need to be imbedded into the physical network, meaning that the ACO takes into account most of the variables. However, road systems could be automated, removing the most random element of the network; the driver. If this is put forth, the ACO can control the network because it is more predicable, and without the agents there is less of a random element.
Problems that occur in perfectly optimized models, could cause a complete break in the efficiency of the system. For example a single delayed plane could disrupt the most efficient system completely. This could occur in cases where the most efficient solution is extremely vital to conditions being exact, and if they are changed even slightly; the system could become very inefficient. For example, in a solution that requires that each aircraft on a runway line up and take a specific route with few junctions. In a case where the front aircraft must return to the airport, the entire trail of aircraft would become halted. It is perhaps improbable that this may occur; as it is more likely that a slight change in a variable (i.e. a shift in the search space) will only give a slightly less efficient solution. It may be however, in noisy search spaces, that a slight change may completely destroy the efficacy of a solution.

ACO in Global Positioning System (GPS) route planning has constantly arisen as an effective application during the creation of this report. It has been shown to have real applications. For route planning, ACO can continually adjust routes given new information and situations. However it may be that this is difficult to trust in all situations of congestion, given a persons everyday experience and logic. The ACO may suggest some route that seems really counter intuitive; for example planning routes in the opposite direction to the intended destination to travel faster and avoid a problem area.

Possible explorations into ACO in future experiments could include adapting the network in different degrees, for example increasing the strength of pheromones in cases where problems occur, and decreasing them otherwise. The storage of ACO methods previously produced in specific scenarios could also be compared with other scenarios within the system itself, and applied to a route instantly, therefore adjusting the route; rather than having a unique solution been gradually constructed for each individual situation.

When comparing ACO to other techniques, Evolutionary computation as a whole is less specialized. Evolutionary computation is more aimed towards game theory, or situations with a specific set of variables for change. Although this is true for traffic routing, evolutionary methods will not take into account the overall goal of routing. Evolutionary computation is useful for creating unique techniques where the layout of the solution is less known. Though fewer assumptions can be made, it is possible that Evolutionary computation could be applied to traffic improvement. However, it is possible that due to the apparent randomness of the method, that several more solutions will be found that will not be useful. Where ACO is specifically designed for route finding, evolutionary computation can apply to many fields. If an effective genotype is to be devised, the situation must be considered fully.

Perhaps this could be a list of roads that must be taken for a route to complete. These paths should then be combined and mutated. However this kind of representation would require that any paths must be connected. This would make it rather similar to ACO, but without the logic available in the path finding ability of the ants. Perhaps for route planning All of these considerations will most likely make Evolutionary Computation much slower than ACO.

It seems that the major advantage of ACO is the specific nature of the representation. It involves a search within a network, that is excellent for any increase in a network. This does not only include traffic, but also computer networking traffic, which is very similar. ACO is perhaps then most useful because of it's specific and well devised design when compared to other more general methods such as evolutionary computation. Neural networks are a specific problem solver in the most popular sense of the method, used to classify noisy data. This
technique will most likely be difficult to apply in traffic efficiency, again because of the general nature of the technique.

It may be that for many situations, humans are the best for adapting to new and unique situations. This is most likely because of the high intelligence and general adaptability of people. However it does remain a problem that people continually use techniques for travel that are not helpful. It is perhaps not possible that ACO can provide a complete flight system, capable of adapting in real time. It could not, for example, calculate the best actions for landing a plane in the river, which has never been attempted by previous optimization techniques. The question still remains whether these techniques will ever be a total replacement for a human controlled network. It may be that high intelligence systems must only rely on it as a form of guidance for the correct choice; but not as the final word of any critical action.

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