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ANT COLONY ALGORITHM IN TRAFFIC FLOW CONTROL

Andrii Danyliuk, Oleksandr Muliarevych

Lviv Polytechnic National University, 12, Bandera Str, Lviv, 79013, Ukraine.
Authors' e-mailis*: andrii.h.danyliuk@lpnu.ua, oleksandr.v.muliarevych@lpnu.ua*

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***Abstract*: The relevance of the research is determined by the need to optimize traffic light control at intersections to reduce congestion and delays and increase the capacity of intersections. A practical solution to this problem is using intelligent transport systems and specific decision-making subsystems. However, automating such tasks requires scientific research to develop effective algorithms suitable for practical use.**

This work proposes an approach to optimizing traffic light control at intersections that considers the traffic flow parameters at a specific intersection and those at adjacent intersections, utilizing an ant colony optimization algorithm to optimize traffic light control at neighboring intersections.

The results obtained show that this approach is more effective compared to existing methods and has the potential to reduce delays by 10% and increase intersection capacity by 15% and more.

Index Terms: Traffic, congestion, intersection, traffic light controller, adaptive traffic control, cyber-physical system.

I. INTRODUCTION

In recent years, increasing road congestion has led to increased traffic accidents and significant transportation issues [1]. During their initial planning phases, many major cities needed to account for the rapid increase in vehicle numbers [2], resulting in urban road designs that only addressed the traffic levels of that time [3]. Due to the increasing in the number of cars and developing industry, finding optimal traffic signal parameters has been an important task in order to use the network capacity optimally. Through the last decade, developments in communications and information technologies have improved the classical methods for optimising the traffic signal timings toward the intelligent ones [4].

Recently, the most significant interest has been shown in approximate algorithms. In the early 60s of the 20th century, heuristic methods, ours, received active development days called classics. In the last twenty years, the primary efforts were directed at developing the so-called metaheuristic methods [5]. Mitigation of urban road congestion can be considered from three aspects: widening the road, reducing the intersection and optimizing the traffic signal control system at the intersection. The investment in road broaden is huge and the effect is not obvious in a short time [6]. The establishment of the viaduct can reduce road intersection to achieve effective shunt, but the cost is high [7]. Therefore, optimizing the traffic signal control system is the most effective approach. Real-time traffic flow can be obtained through monitoring facilities [8]. Adjusting the traffic signal period, according to the traffic flow to reduce the stopping time of road intersection and alleviate the traffic congestion effectively [9]. At present, more and more attention has been received to the traffic signal timing method.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

A wide range of solution methods to traffic control problem have been discussed in the literature.

One method of finding optimal traffic control signal timings is the Ant Colony Algorithm [10]. It uses graphs and simulates behaviour of real-world ants to find best possible routes [11]. Sophia Liu et al. presented an ACO-based algorithm for traffic signal optimization at intersections, in their study "Ant Colony Optimization for Multi-phase Traffic Signal Control" [12]. The study showed that the algorithm could dynamically adjust green light durations based on real-time traffic density data, decreasing waiting times and enhancing traffic throughput [13].

Another approach was introduced by Yulianto, B. in their study "Adaptive Traffic Signal Control Using Fuzzy Logic Under Mixed Traffic Conditions" [14]. Yulianto B. introduced a fuzzy logic controller for adaptive traffic signal control. In their study, the Fuzzy Logic Traffic Signal Control (FLTSC) algorithm on the VISSIM simulation model was evaluated for an isolated four-way intersection with two-stage signal type 42 and compared its performance with the optimized FTC under different traffic conditions [15].

Ant colony optimization-based traffic routing with intersection negotiation for connected vehicles was introduced by Tri-Hai Nguen in their study "Ant colony optimization-based traffic routing with intersection negotiation for connected vehicles" [16], where a decentralized traffic management system that integrates dynamic traffic routing and signal-free intersection traffic control for connected vehicles was presented. They applied the ant colony optimization algorithm and the proposed concept of colored CV to solve the dynamic traffic routing problem with multi-source multi-destination traffic flows [17].

III. SCOPE OF WORK AND OBJECTIVES

This work aims to examine algorithms used for signal timing regulation, review basic parameters for traffic signal timing processing, and prepare ACO-based algorithms for related intersections to address the problem of traffic flow regulation. Based on the prepared algorithm, demonstrate a block diagram of the algorithm and develop an experimental system that uses the associated number of intersections represented as a graph that has the potential to reduce traffic delays by up to 10% and more.

IV. TRAFFIC CONTROL PRINCIPLES AND ALGORITHMS

The article aims to manage traffic lights in real time to optimize the overall waiting time of vehicles at intersections and maximize the flow of vehicles crossing the intersection. Thus, the real-time management approach involves using traffic state data for each lane at the intersection, collected by a traffic monitoring system through an optimization algorithm. This allows for the development of a phased traffic light plan based on real-time observed traffic conditions.

Fundamental parameters used in traffic flow regulation are:

Phase: At the signal control intersection, each control state, which is the combination of different light colors shown in different directions of each inlet, is called a signal phase.

Timing period: The combined time of red, green, and yellow lights in one intersection.

Effective green time: The total period minus the red light time and the time lost when the vehicle starts. (4) Green ratio: Green ratio refers to the proportion of vehicle passing time and period in the traffic signal period.

Traffic flow: The sum of all vehicles passed by a specific section of a unit of time.

Queue length: Queue length refers to the total length of vehicles parked within the actual line of a specific phase intersection.

Delay time: Delay time is the time difference between the actual time taken to cross the intersection and the time that should be taken when crossing the intersection.

Parking rate: Parking rate is the number of times a car has been parked from one intersection to another.

Traffic capacity refers to the maximum number of vehicles that pass at one intersection within a unit of time.

Green wave belt: According to the time the vehicle needs to pass a particular section and coordinates the traffic signals at each intersection, the vehicle can continuously obtain the green light when passing.

As traffic flow control is a critical aspect of urban planning and management, various algorithms have emerged to enhance traffic regulation. There are three notable algorithms: Webster algorithm, Ant Colony Optimization and Fuzzy Logic Control.

Webster algorithm. Webster's Method, developed by the engineer William Webster in the 1950s, is one of the foundational algorithms for traffic signal timing. It provides a systematic way to determine the optimal cycle length and green time allocations for traffic signals. This algorithm takes the minimum traffic flow delay as the standard and reasonably sets the green time. Webster algorithm has the advantage that when the arterial road is in a heavy traffic flow situation, and the secondary road is in a less traffic flow situation, this algorithm can guarantee the arterial road traffic and avoids wasting the green time of the secondary road. The basic formula used in Webster's Method is:

$$C = \frac{1.5\mathrm{L} + 5}{1 - \mathrm{Y}}, \tag{1}$$

where C = cycle length (seconds); L = total lost time (seconds); Y = sum of traffic flow ratios (demand divided by capacity).

Ant colony optimization algorithm. The foraging behavior of ants inspires Ant Colony Optimization (ACO). This algorithm employs a swarm intelligence approach to solve complex optimization problems, including traffic flow management. This article proposes the enhanced model of the ant colony algorithm to optimize the signal timing of associated intersections. ACO uses a population of artificial ants that simulate the behavior of real ants searching for food. These ants deposit pheromones on paths, influencing the probability of other ants following the same route. The algorithm dynamically adjusts to changing traffic conditions, allowing for real-time optimization of traffic flows. ACO effectively finds optimal vehicle paths, reducing congestion and travel time by adapting to real-time traffic data.

Fuzzy control method. Fuzzy Logic Control (FLC) is based on fuzzy set theory and allows for decision-making in uncertain and imprecise environments. It is particularly suitable for traffic control systems that require nuanced responses to varying traffic conditions. FLC can process vague input data, such as "heavy traffic" or "moderate waiting time," allowing for more flexible and adaptive traffic signal control. FLC operates on a set of rules defining how the system should respond to traffic conditions. Experts create these rules based on experience and data analysis. Based on the detected real-time traffic flow data of intersections, the fuzzy control theory can dynamically optimize the traffic signal timing method, which is better than the Webster algorithm. The system adjusts real-time traffic signals, optimizing green and red light durations based on current conditions.

V. ANT COLONY OPTIMIZATION ALGORITHM IMPLEMENTATION IN TRAFFIC FLOW CONTROL

The ant algorithm belongs to the swarm intelligence algorithms category and models an ant colony's behavior. Ants are social insects capable of forming groups (colonies). The collective system makes it possible to effectively solve problems of a dynamic nature that could not be completed by individual elements of the system without appropriate external control and coordination.

At the heart of an ant colony's behavior lies the power of self-organization. This innate ability enables the colony to swiftly adapt to changing environmental conditions and successfully pursue the collective goals of the colony through low-level interactions.

Interaction within the ant colony is facilitated by pheromones, which individual ants use to mark the paths they have traveled. The concentration of pheromones on a trail indicates its frequency of use, thereby signifying its optimal length.

The behavior of ants in finding the optimal path is shown in Fig. 1. The challenge is to find the optimal path from the nest (N) to the goal (food source, F). Vectors a and b represent the direction of movement of a single ant, from F to N and from N to F, respectively.

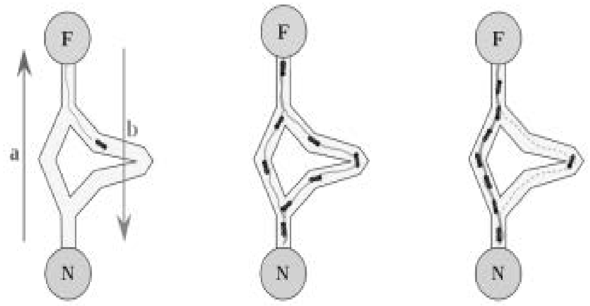

Fig. 1. Scheme of finding the most optimal path.

It is logical to assume that initially, the ants will go around the obstacle on the left and on the right with equal probability. However, those representatives of the colony who accidentally choose the shortest path cover the distance from the starting point to the goal and back in a shorter period of time, which means that in several movements, this path is more enriched with pheromones.

Since the pheromone serves as a reference point for ants when moving, the remaining colonies will choose the path with a higher concentration.

The following sequence of actions can describe the ant algorithm:

Creation of ants. The method of placing ants is decisive and depends on the problem's conditions: all ants can be placed at one point or different. Also, when creating ants, it is necessary to set the initial level of pheromone, characterized by some small positive number. This is necessary to ensure a non-zero transition probability to the next point at the initial step.

Finding a solution. A route is a collection of graph vertices. The probability of transition from node i to node j is shown in (1) :

$$Pij = \begin{cases} \dfrac{{\tau_{ij}}^{\alpha} * {\eta_{ij}}^{\beta}}{\sum {\tau_{ih}}^{\alpha} * {\eta_{ih}}^{\beta}}, & j \notin tabu_k, \\ 0 \end{cases} \quad (1)$$

where τ_{ij} – is the amount of pheromone on the edge (i, j), the ant's "sense of smell"; η_{ij} – attractiveness of edge (i, j), $\eta_{ij}= 1/d_{ij}$, d_{ij} – distance between vertices i and j, "vision" of the ant; α, β – adjustable parameters that determine the importance of components (edge weight and pheromone level) when choosing a path; $tabu_k$ – list of already visited nodes, ant's "memory".

When α = 0, the algorithm degenerates into a greedy one because the nearest vertex is selected without considering the amount of pheromone. When β = 0, the choice is based only on the pheromone value; the path length is not considered.

A greedy algorithm is an approach to solving optimization problems by making a series of choices, each of which looks best. The algorithm makes a locally optimal choice at each step, hoping that these local solutions will lead to a global optimum.

Pheromone update. After all the ants have finished their journey, the number of pheromones should be updated. This process consists of two stages: firstly, where there is need to reduce the pheromone value on all arcs by a specific constant value, then increase the pheromone level on those ribs the ants visited. Imitation of pheromone evaporation is carried out according to the formula:

$$\tau_{ij} = (1 - \rho)\, \tau_{ij}, \quad (2)$$

where ρ is a parameter that controls the intensity of pheromone evaporation.

The ρ parameter allows us to avoid the endless accumulation of pheromones on the edges of the path, leading to the fact that the algorithm will not "forget" bad decisions obtained earlier. If the ants did not choose the edge, then the pheromone level associated with it will decrease exponentially with each iteration.

After evaporation, all ants change the pheromone level on the edges they visit. For edge (i, j), the amount of deposited pheromone is given as:

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \quad (3)$$

where $\Delta\tau_{ij}^{k}$ – the amount of pheromone deposited by the kth ant on the edge it visited.

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L, & if\ (i,j) \notin L \\ 0 \end{cases}, \quad (4)$$

where Q is a constant that artificially adds pheromone; L – total length of the traveled path.

According to (4), the better the path, the more pheromones will belong to the edges of this way. This means they are used by more ants that are part of the shortest path, receiving more pheromones and, therefore, will most often be chosen by ants in subsequent iterations.

This iterative process will continue until a particular condition is completed: the specified number of iterations has been completed, all specified numbers of ants have completed the search, the required quality of the solution has been achieved, or the CPU time quantum has expired.

This study focuses on planar intersections, where all roads meet at the same level without involving multiple layers of pathways. Typical planar intersections include crossroads, T-junctions, Y-junctions, and roundabouts. The various directions of traffic at these intersections create points where conflicts are likely to occur, known as conflict points. To minimize those, many junctions are designed as roundabouts. Initially, roundabouts can eliminate conflict points when traffic volume is low. Generally, they work well for intersections with lower traffic flow; however, roundabouts can reveal their drawbacks as vehicle numbers increase, such as occupying a large area while providing limited traffic capacity. This study examines crossroads and conflict points, explicitly focusing on motor vehicles, noting that a typical crossroad can present around 16 conflict points.

VI. APPLICATION OF ANT COLONY OPTIMIZATION ALGORITHM IN TRAFFIC FLOW CONTROL

A hybrid approach is proposed to address congestion. The key feature is to address multiple intersections and associated ones and interchange traffic flow parameter data between different intersections to adjust signal control timings to avoid a situation where dynamic control creates another congestion at the nearest intersection.

The ACO-based algorithm is proposed to manage multiple intersections. This algorithm's key features are that intersections are nodes and roads are edges on a graph. Each node navigates this graph to find optimal routes for vehicles, taking into account the traffic conditions at various intersections.

Proposed algorithm combines next steps:

Modeling the Road Network. A road network is represented as a graph using the following elements: vertices, edges and weights. Vertices represent intersections, road junctions or locations. Edges represent roads connecting these locations. Weights represent attributes of the roads, such as distance, travel time, or congestion levels. Example of simple road network with three intersections: A, B and C where weights are assigned based on distance and congestion levels is shown in Fig. 2.

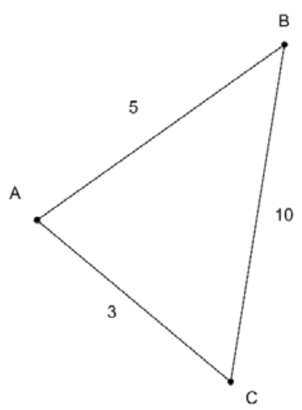

Fig. 2. Graph representation of intersection connections.

Nodes A, B, and C represent different intersections, and weights 5, 10, and 3 represent weights based on distance and current congestion levels.

Initialization of Pheromone Trails

In a road network represented as a graph, if there are multiple routes between two locations, uniform initialization would assign the same pheromone value to each route. This could result in ants randomly exploring all routes, potentially leading to suboptimal solutions.

If a road network contains both short and long routes, randomly initializing pheromone levels could unintentionally prioritize longer, less efficient routes, leading to inefficient traffic management.

Adaptive initialization is used as it provides more dynamic pheromone adjusting process based on real-time data for the optimization process comparing to uniform initialization and random initialization which could often lead to sub-optimal approaches.

Ant Behavior and Route Selection

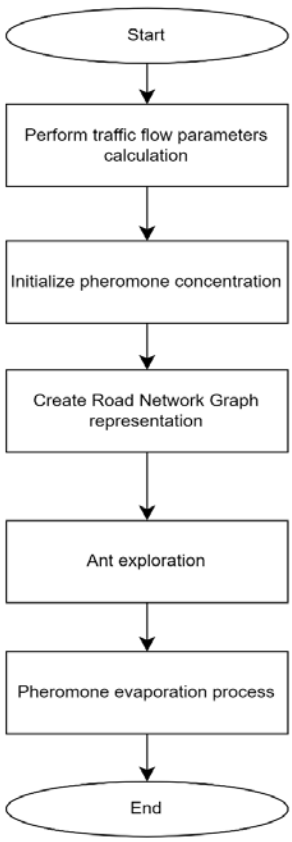

Fig. 3. General ACO algorithm application to road traffic distribution issue.

Ants exhibit swarm intelligence, where the collective behavior of individual ants leads to optimal solutions. Fundamental dynamics include a positive feedback loop and a negative feedback loop. In the positive feedback loop, frequently used paths become more attractive as they accumulate pheromones, leading to more ants choosing those paths. On the other hand, in the negative feedback loop, less traveled paths lose pheromones due to evaporation, making them less attractive over time.

Iterative Search Process

A predetermined number of ants from various starting points are deployed in the network during each iteration. Each ant explores the network and completes its route, collecting data on travel time and congestion levels. After all ants have completed their routes, update the pheromone levels on all edges using (2). The algorithm continues iterating until a stopping criterion is met. A diagram illustrating general algorithm is shown in Fig. 3.

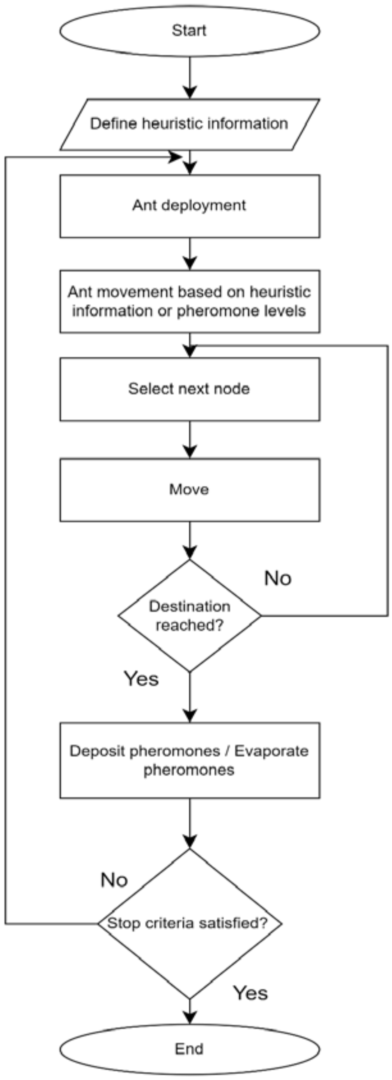

Fig 4. Block diagram illustrating the exploration sub-step.

Fig. 3 shows a general algorithm for applying ACO to solve road traffic distribution. It includes several steps: traffic flow parameters calculation, initializing of pheromones, graph representation of road network, exploration, and pheromone evaporation.

Ant exploration step contains several sub-steps and covers activities such as definition of heuristic information, ant deployment, ant movement based on heuristic information or pheromone levels, node selection and movement. Heuristic information in current approach includes traffic flow information and distance between nodes. A diagram illustrating the Ant exploration sub-step is shown in Fig. 4.

Base on suggested algorithm, an experimental system is built and experimental calculations were made with following parameters: associated intersections 5, minimum green time 5s, maximum green time 30s, all red time 2s, minimum headway 2s, extension time 1s, average queue from 4-8 vehicles. Different traffic situations with light (S1), medium (S2) and heavy(S3) are presented (see Table).

Comparison between different traffic scenarios

Density	Average queue, vehicles	Green time, sec	Green ratio, sec	Delay time, sec	Traffic capacity, vehicles
Default	5	17	0.2	26	3800
S1	4	19	0.2	20	4100
S2	6	23	0.19	21	4500
S3	8	29	0.19	23	5234

By analyzing experimental calculations, it is discovered that traffic control systems that use Ant Colony Optimization for traffic signal regulation decrease average delay time and improve traffic capacity. When the traffic is heavy, the algorithm significantly affects the traffic distribution at the intersection. By using the Ant colony algorithm in adaptive traffic control systems we can expect a reduction in the number of stops vehicles experience at intersections, leading to smoother traffic flow and decreased travel time.

VII. CONCLUSION

The work examined algorithms and approaches used for traffic signal timing regulation. The growth of cities and the improvement in the quality of life of the population led to an increase in the level of motorization. These factors indicated the need for spontaneous optimization the existing urban transport system, which did not meet the requirements of modern society.

Work also reviewed basic parameters used for traffic signal timing calculation and comparison, examined algorithms used for traffic signal timing regulation.

ACO-based algorithm for set of associated intersections was prepared to address the problem of traffic flow regulation. Prepared algorithm represented associated intersections as nodes on the grapth which had edges and weights. Weights were calculated based on traffic flow parameters and current congestion indexes. Based on the prepared algorithm, a block diagram of the algorithm was demonstrated and an experimental system was developed.

Experimental calculations showed that developed system had possibility to decrease average delay time and increase traffic capacity more that 10%.

Future studies could also explore application of different variations of Ant colony optimization algorithm in the field of adaptive traffic control systems.

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Andrii Danyliuk received the B. S. degree in computer engineering at Lviv Polytechnic National University, Ukraine, in 2020 and the M. S. degree in system programming at Lviv Polytechnic National University, Ukraine, in 2021. Since 2021, is a postgraduate student of Computer Engineering Department. His research interests include “smart home”, traffic light control optimization, calculation optimization and methods.

Oleksandr Muliarevych Is an Assistant Professor at the Computer Engineering Department at Lviv Polytechnic National University. His research interests include distributed highly scalable microservice systems, swarm intelligence, IoT, cloud computing, parallel computing technologies, computer vision, machine learning and multi-agent systems applications.