A Novel Traffic Routing Method Using Hybrid Ant Colony System Based on Genetic Algorithm

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Abstract—**The Ant Colony System (ACS) is a variant of Ant colony optimization algorithm. It is very famous with Traveling Salesman Problem. The parameters of ACS in tour construction, global and local updating pheromone direct effort to get the best result of this but they are often manually setting up. Beside, building the heuristic function to decide a choice next node on tour is potential research approach. Therefore, this paper present a foundation framework that propose a novel method to solve traffic routing problem by hybrid ant colony system (ACS) based on genetic algorithm, visualization online changing traffic light, it is called (GACSS). In the GACSS, We use genetic algorithm (GA) optimize ACS parameters aim to attain shortest trips and time with new functions helping them to update global and local pheromone. Our experiment with GACSS deploys in VANETsim with real map from open street map project, any vehicle kind and updating traffic light real-time able. Our framework gained higher results than A-Star and classical ACS algorithm. It is not only shorter length but also smaller time for trip**.

Keywords - Traffic routing; ant colony system; genetic algorithm.

I. INTRODUCTION

Recently, traffic congestion has become one of the most serious problems in developing countries due to the rapid development of economy and population. Hence, the traveling salesman problem (TSP) which is famous problem on finding the shortest path has attracted a lot of interest in study of optimization. A technique for solving the TSP is the ant colony optimization algorithm (ACO). There are variants of ACO such as Ant system (AS) [1], Ant Colony System (ACS) [2] which show the best efficiency on the shortest path problem. The ACS has three main ideas including tour construction, global pheromone trail update and local pheromone trail update [2]. Finding the best set of parameters for ACS is an interest approach. The performance of metaheuristics depends on the settings of their parameters that is normally well known. Finding the suitable parameters for an algorithm is a nontrivial task in practice. Therefore, the adaptation approaches on parameters setting could be divided into offline and online procedures. Offline method finds appropriate parameter values before their deployment, while online method modifies them in solving problem instances.

Thomas Stutzle at al [3] has reviewed many studies for adaptation strategy to set up ACO variants parameters. This review showed that the online method gives better results with small ant numbers, but it also introduces the fixed parameter setting method to ACS.

In practice, when the algorithm applies to different case functions, the parameter values need to be changed. Therefore, optimizing set of parameters for ACS is a potential approach. Marco Dorigo [2] built a new function local updating rule for ACS and compared to other heuristic algorithms. Their obtained results showed better than the others did. They expressed the importance of the value of ACS parameters such as the ant number to attain the good result, which requires suitable parameter values. However, they manually chose them.

Jiping Liu et al. [4] combined GA with ACS, they used GA to optimize three parameters in transfer rule of tour construction, while other parameters were fixed.

Thomas Stutzle et al [3] suggested a fixed parameter setting for ACS and Min-Max in ant system. By experiment, they compared a set of parameter values and suggested a range of values for each parameter that is meaningful to this approach.

Zhaoquan Cai et al. [5] proposed adaptive weight ACS parameters, they built new computation method for parameter heuristic information in the probability function and pheromone evaporation rate by function. The proposed ACS showed an improvement on the performance compared to other methods.

Dorian Gaertner et al. [6] used three parameters in ACS by three optional setting and analysis. They devised GMACS, which combines GA and ACS by fitness function, to produce improved solutions. Yet it did not denote relationship ant number with parameter set.

Xianmin Wei. [7] tried finding two ACS parameters of transfer rule five times by shortest path, suggested some good value setting for ant number in their figures 8.2 to 8.5 and the range of ants is from 1 to 100. Following, setting up parameter before deploying obtains stable results in any cases, online could be adaptation on solving. There are relationships between ant number with parameters and on themselves. However, there is not any manifest method to select a set of parameters homogeneously.

Hence, traffic routing may be the selected shortest path, but time and conditions of environment such as width of road, traffic time light, potential congestion information are also very important. In fact, with traffic routing problem, additional conditions of traffic light and congestion information are good factors for this. Therefore, the node on trips needs to show helping ant choose a suitable node. For this reason, we also propose GACS algorithm using GA to optimize parameters of ACS with new functions that update pheromone aim to get not only the shortest trip but also the shortest time. We simulated and visualized GACSS framework on real map, which could change the conditions online. The results obtained from our experiment are compared with other algorithms such as A-Star, classical ACS and they showed that the proposed GACS is more effective than the others. It is not only shorter length but also smaller time for trip. Because that, framework has suitable set of parameter and environment information was integrated to local and global update function.

II. Traffic Routing With GACSS Framework

A. *The Genetic Algorithm*

Genetic algorithms (GA) are search methods based on principles of natural selection and genetics [8]. The GA applied in two primary areas of research: optimization, in which GAs represent a population based optimization algorithm and the study of adaptation in complex systems. The basic principle of genetic algorithm is following these steps [9]: Step 1: Initialization, the initial population of candidate solutions is usually generated randomly across the search space. Step 2: Evaluation, once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated. Step 3: Selection, selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. Step 4: Recombination, recombination combines parts of two or more parental solutions to create new, possibly better solutions. Step 5: Mutation, while recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutation, but it usually involves one or more changes be made to an individual's trait or traits. Step 6: Replacement, the offspring population created by selection, recombination, and mutation replaces the original parental population. Step 7: Repeat steps 2-6 until a terminating condition met. Hence, we use GA for GACSS framework aim to find the best parameter value set for ACS.

B. *The Ant Colony System (ACS)*

The ACS was towards a better understanding the function of finding the shortest path. Thus, on traffic routing algorithm, we introduce it for classical example of ACO used to solve the Travelling Salesman Problem (TSP) [2]. The ACS has three main parts as follows:

Tour construction of Ant colony system: In ACS, we use the initial parameter and compute values. With randomize probability $q_0 \in [0, 1]$ be a tunable parameter, ant k in node i chose the next node j with $q<q_0$ defined as:

$$j = \begin{cases} \arg\max_{l \in N_i^k} \left\{ [\tau_{il}]^{\alpha} [\eta_{il}]^{\beta} \right\}, & \text{if } q \le q_0; \\ J, & \text{otherwise}; \end{cases} \tag{1}$$

In there, J with probability $(1-q_0)$ defined by proportional rule as:

$$p_{ij}^k(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} . \left[\eta_{ij}\right]^{\beta}}{\sum_{l \in N_i^k} \left[\tau_{il}(t)\right]^{\alpha} . \left[\eta_{il}\right]^{\beta}}, \quad \text{if } j \in N_i^k \tag{2}$$

Among them, $\eta_{ij} = 1/d_{ij}$ is a *priori* available heuristic value and d_{ij} is the distance between city *i* and city *j*, $\tau_{ij}(t)$ is the pheromone trail on arc (i, j). The parameter α, β is a parameter which determines the relative influence of the pheromone trail and the heuristic information.

Global pheromone trail update: In ACS, after each iteration, the shortest tour (global-best tour) of this iteration is determined, and arcs belonging to this tour receive extra pheromone, so only the global-best allow ant to add pheromone after each iteration by Equation 3:

$$\tau_{ij}(t+1) = (1-\rho)\, \tau_{ij}(t) + \rho\, \Delta\tau_{ij}^{gb}(t) \tag{3}$$

With $\forall (i, j) \in$ global-best tour

Where $\Delta\tau_{ij}^{gb}(t) = 1/L^{gb}$, and L^{gb} is the length of the global-best tour. It is important to note that the trail update only applies to the arcs of the global-best tour, not to all the arcs like in AS. The parameter ρ again represents the pheromone evaporation. In the ACS, only the global best solution receives feedback. Although for smaller TSP instances, the difference in solution quality between using the global-best solution or the iteration-best solution is minimal, for larger instances the use of the global-best tour gives by far better results.

Local pheromone trail update: Additionally to the global update rule, in ACS the ants use a local update rule that they apply immediately after having crossed an arc during the tour construction by below function:

$$\tau_{ij} = (1-\xi).\tau_{ij} + \xi.\tau_0 \tag{4}$$

Where ξ, $0 < \xi < 1$, and τ_0 are two parameters of ACS algorithm. In this way, the exploration of not yet visited arcs is increased. The value of τ_0 is set to be the same as the initial value for the pheromone trails while a good value for τ_0 is computed as $1/(n.L^{nn})$, where n is the number of cities in the TSP instance and L^{nn} is the length of the nearest-neighbor tour. The effect of the local updating rule is that each time one ant uses an arc (i, j) its pheromone trail τ_{ij} is reduced, so that the arc becomes less desirable for the following ants.

Therefore, if we choose a good parameters and heuristic functions then it could be expectation results.

C. The Hybrid Ant Colony System Base on Genetic Algorithm (GACS)

In traffic routing problem, heuristic information of environment helps ants to get a tour not only shortest but also save time and congestion potential roads. Thus, we propose a novel method to solve it by hybrid ACS base on GA. The first, we define new functions to update global and local pheromone in ACS. The next, using GA choose suitable parameter set aim to finding the best trip by ACS. It is call GACS algorithm.

Following the ACS was expressed, parameter α, β, q_0 in Tour Construction direct effect to algorithm results, which the next node, ant could be chosen; in the global and local pheromone trial update part important parameters ρ , ξ decide pheromone update for arc with exactly and small values. The arc in problem is amount, thus ρ , ξ be needed more small and suitable. When ants update pheromone, the heuristic functions help them to choose the best tour. Thus, with traffic routing problem we propose functions (5) and (6) involve length on tour, average velocity, delay time of traffic time light, number traffic participant at that time denote density or congestion information.

The local pheromone updating function is defined by function below.

$$\tau_{ij} = (1-\xi).\tau_{ij} + \xi.\tau_0^j ; \tau_0^j = \left(n.L^{nn}\right)^{-1} + d_{ij} + r_{ij} + v_{ij} \quad (5)$$

In there, we define factor d_{ij} to represent density on arc from node i to node j and is computed as $d_{ij} = \frac{a_{ij}}{w_{ij}}$ with a_{ij} is ant in time on arc from node i to node j and w_{ij} as width of road from node i to node j.

The factor v_{ij} is average velocity of ants on arc from node i to node j. The factor r_{ij} represent capacity to solve congestion time and it is define by function:

$r_{ij} = \frac{a_{ij}}{t_j}$. Among them, t_j is total delay time of traffic light signal at node j and a_{ij} is ants on arc from node i to node j and L^{nn} expressed in equation (4).

In fact, base on d_{ij} , v_{ij} , r_{ij} ant could be realized traffic status on arc and the next node.

Toward, update pheromone on global-best tour, value $\Delta\tau_{ij}^{gb}(t) = 1/L^{gb}$ base on length of global best tour, proposing function to improve our traffic routing results as:

$$\Delta\tau_{ij}^{gb}(t) = \frac{1}{L^{gb}} + \frac{1}{V^{gl}} + \varphi\sum_{j=1}^{N-1} d_{jh} + \psi\sum_{j=1}^{N-1} r_{jh} \quad (6)$$

With h = j + 1, N is total node on global best tour and ψ, φ is constant weight and d_{jh} , r_{jh} was expressed in equal (5) on global - best-tour. Then V^{gb} is average velocity on global – best – tour.

When update pheromone for global best tour by equation (6), values update hidden information are length, velocity, density and traffic light status. The experiment has received higher results.

Following, we combine GA with ACS by optimizing set of parameter, building chromosome from parameters ($m, \alpha, \beta, q_0, \rho, \psi, \varphi$). The GA will choosing a best value for chromosome include $\alpha, \beta, q_0, \rho, \psi, \varphi$, which relative to each other and good results with m ants. The fitness function is computed by below equation.

$$f(c) = \frac{1}{L^{gb}} + V^{gb} + \sum_{j=1}^{N-1}(d_{jh})^{-1} + \sum_{j=1}^{N-1}(r_{jh})^{-1} + \frac{1}{t_c} \quad (7)$$

With h = j+1 and N is total node on global best tour, chromosome *c*; d_{jh} and r_{jh} express in equation (5) and t_c is total time on global best tour. The fitness function get a higher value when the fitness characteristic of the chromosome is better another.

With the end condition of genetic algorithm, we suppose the iterations of genetic algorithm is NL, then $NL_{\min} \le NL \le NL_{\max}$ with NL_{min} is the minimum iterations of genetic algorithm and NL_{max} is the maximum iterations of genetic algorithm.

Therefore, we propose GACS algorithm as Fig 1 below:

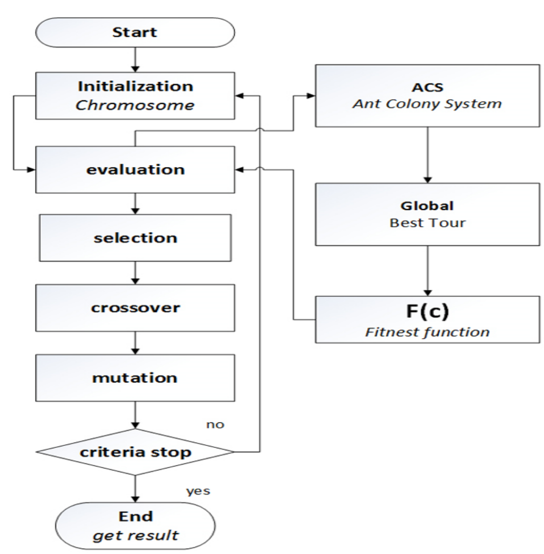

Fig. 1. The GACS algorithm

D. *The Monitoring Traffic Light Online*

The traffic light system is very important in traffic routing. In fact, it is an useful factor on controlling traffic system in everywhere. Thus, we design GACSS framework base on GACS algorithm, this could change online by condition of traffic light such as adding a light or changing delay time light. After we vary this, GACSS framework is online updated new status by update pheromone functions (5) and (6). The traffic light controlling problem is really challenges, there are any intelligent traffic light introduction [10] and potential approaches.

III. EXPERIMENT AND RESULTS

A. *The Simulation GACSS with VANET simulator*

1) *VANET simulator*

The VANET simulators was developed aim to drivers must be provided with precise traffic and road conditional [11, 12]. It could be classifying as microscopic or macroscopic. Microscopic traffic simulators emphasize local behavior of individual vehicles by representing the velocity and position of each vehicle at a given moment [13] and most of research was applied microscopic. VANET simulator has two main components as a network component, capable of simulating the behavior of a wireless network, and a vehicular traffic component, able to provide an accurate mobility model for the nodes.

Mobility models represent the velocity and position of each vehicle at a given moment. This type of simulation is especially helpful for traffic routing problem.

2) *Simulation GACSS framework*

The traffic routing problem in VANET simulator with microscopic could be communicated and shared traffic density, speed, direction of vehicles, road and traffic light information. When deploy simulation GACSS framework on VANET, we separate to four module as Fig. 2

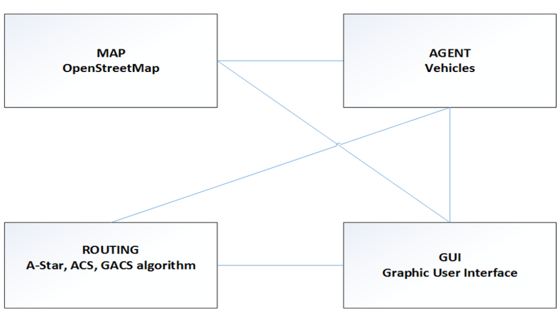

Fig. 2. Simulation system with VANET

Following Fig.2, the MAP module processing map problem to get and transform map from an open street map project, loading and visualization agent activity. It also establishes online changing traffic conditional as traffic light, road and environment attributed. The next, the AGENT module construct agents from traffic vehicles kind with attributes on system, controlling agent behaviors and traffic conditionals. Continuously, the GUI module solves visualization graphic information and provides interaction ability between user and system. Finally, the Routing module process algorithms and respond results to system.

B. *The Encoding and Experimentation*

As stated above, the best result is responded from system corresponding to appropriate set of parameter value and the range of them have remark achievements [3, 7, 14, 15]. With chromosome $(m,\alpha,\beta,q_0,\rho,\psi,\varphi)$ of GACS algorithm, via experiment was shown that, appropriate range for α,ρ,q_0 are from 0 to 1, and β is between 1 and 5, and ψ,φ is between 1 and 10. At last, value m is initial ant number of system between 1 and 500. With the fitness function computed by equation (7), and the stop criteria NLmin= 10 and NLmax = 55.

The experimentation was deployed on Windows 7 OS, Intel Core i7-6700 (3.4Ghz , 8M Cache) processor, 16GB DDR3L. The vehicles kind are motorbike, bicycle, bus, total of them between 10 and 100. We used Open JDK Java 8 environment and VANETsim version 1.3.

The performance of the system is evaluated by criteria such as total length of vehicle from starting point to destination, time for this trip and time that is used for algorithm processing.

C. *Results and Analysis*

In the first scenario, we evaluated on Berlin, German map, which real loaded from open street map then randomized starting point coordinate A as x = 582858 and y = 353950 on Holzmarktstrabe road and destination B on Littenstrabe with coordinate as x = 550418, y = 320967. The GACSS framework deployed by trip from A to B in Fig 3.

Fig. 3. Simulation GACCS framework in Berlin Map

In the Fig.3, when vehicle realize congestion in intersection between StralauerStrabe and Littenstrabe, it updates information and chooses Direksenstrabe road direction to their trip. Experiment is evaluated in three kind of values included such as Length (length of the global best tour), Time (time of best tour), Processed time (interval system processing). Results expressed in Table 1.

Table 1. Simulation A-star, ACS, GACS algorithm results on Berlin map

Algorithm	Length (meter)	Time (seconds)	Processed Time (milliseconds)
A-Star	1060	58.56	25
ACS	950	56.38	45
GACS	545	51.80	156

In Table 1 shown that, with GACS algorithm, the Length is shorter than A-Star 515 meters and ACS 405 meters. The time for global best tour of GACS is smaller than A-Star 6.76 seconds and 4.58 seconds with ACS. Because that, environment information is integrated to node and ants could be recognized suitable node on their tour. However, processing time was higher. Cause, ACS algorithm has repeated computing on GA. It is simple acceptant when using GA to optimize and with capability hardware in recently, it could be solved and applied on real life.

In second scenario, framework is deployed the same method on Hanoi, Vietnam Map with starting point in Tran Thai Tong street at coordinate A as x = 12971115, y = 10755648 and destination point B in Tho Thap street as x = 12991416, y = 10810560. The comparison results when deploy on algorithm in Fig.4 and expressed on Table 2.

Fig. 4. Simulation GACCS framework in Hanoi Map

Table 2. Simulation A-star, ACS, GACS algorithm results on Ha Noi map

Algorithm	Length (meter)	Time (seconds)	Processed Time (milliseconds)
A-Star	1150	64.12	18
ACS	802	60.88	31
GACS	601	58	162

Therefore, in Table 2, the length on GACS is shorter A-star (549 meter), ACS (201 meter). However, The Time is higher than Table 1. Because that, the conditionals of Berlin map are better than Hanoi map.

In the thirst scenario, framework is deployed online monitoring setting traffic light conditional. It showed in Fig.5.

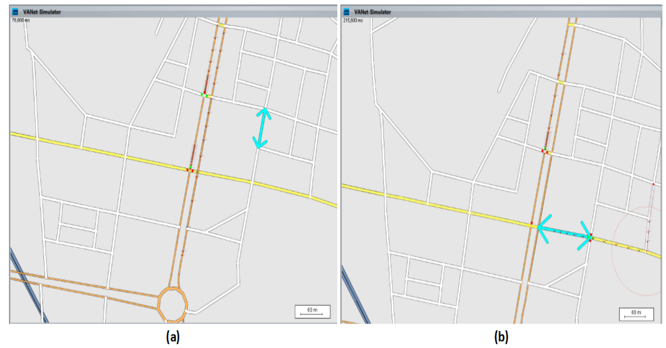

Fig. 5. Online monitoring traffic light

The Fig.5 (a) expressed ability updating traffic light on Caugiay district in Hanoi Map. The traffic light had been added, changed delay time light. The GACSS was updated online information and processing. The ants had chosen new suitable tour and expressed in Fig.5 (b). It is meaningful with our framework in some case need to change traffic conditional solving congestion etc.

IV. Conclusions

In this paper, we proposed a framework, called GACSS, for solving traffic routing problem in shortest path and time. We also demonstrated a novel method to build new GACS algorithm by using GA optimization parameter set of ACS, and to achieve better results in terms of length and time than A-star, ACS classical algorithms. However, it has longer processing time than the other algorithms. The GACSS framework provides ability for monitoring the condition of traffic light. In the future, we are planning to further improve the current framework to ability of dynamic changing the traffic light and reduce the processing time

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