Using the Ant Colony Algorithm for Real-Time Automatic Route of School Buses

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***Abstract**: Transportation and distribution systems are improving with an increasing pace with the help of current technological facilities and additionally, the complexity of those systems are increasing. Vehicle Routing Problems (VRPs) are difficult to solve with conventional techniques. Improving routes used in distribution systems provides significant savings in terms of time and costs. In this paper, current routes in school buses, which is a sub-branch of vehicle routing problems, are optimized using the Ant Colony Optimization (ACO), which is a heuristic artificial intelligence algorithm. Developed software is used for recommending the most suitable and the shortest route illustrated on a map by taking the instantaneous student wait locations online. Results of this study suggest that the current routes can be improved by using the ACO.*

Keywords: *ACO, school bus routing, vehicle routing problems, mobile software.*

Received December 30, 2013; accepted December 23, 2014; published online October 29, 2015

1. Introduction

In every period of history, people were tended to choose the shortest and the most suitable way as possible while travelling from one place to another place. Nowadays, with the increase in road transportation facilities in line with evolving technology route options increased so that, solving route problems for the selection of the most suitable and the shortest route are needed. Air pollution, losses of time and cost in transportation have made these problems more and more important. Vehicle Routing Problem (VRP) is generally defined as the problem of distribution or collection of materials in depot to customers with the transportation vehicles. Since, the beginning of the 1960s, the VRP has become a major problem in the field of distribution and logistics [5]. Transportation and distribution sectors can obtain considerable cost benefits through route solutions. In today's global market, intense competition, products with short life cycle curves and increasing expectations of the clients compel manufacturers to place extra emphasis on and invest in distribution systems [16]. With the development of portable technological devices (smart phones, tablet computers, and navigation tools) and the proliferation of their uses, not only the companies, but also the pedestrians and private vehicle owners began to widely use applications offering route solutions in their daily lives.

Creating solutions to complicated problems such as: Vehicle routing using classic methods is currently quite time-consuming and expensive. Furthermore, it is difficult to create optimum solutions by means of these methods. Different heuristic optimization techniques are used in the development of solutions for VRPs. In particular, a number of metaheuristic techniques have been successfully applied for the solution of VRP and its variants, such as: simulated annealing [13], tabu search [9, 18], genetic algorithms [19], guided local search [11], variable neighborhood search [3] and Ant Colony Optimization (ACO) [15].

It was shown that swarm-intelligence-based, simple, independent and not previously organized agents are more successful in devising solutions to completed problems compared to the human-intelligence-modeling-based, complex, central and organized approaches used in classic artificial intelligence applications [16]. Upon the conclusion of scientist's investigations regarding insect's behaviors, it was found out that ants can heuristically detect the shortest distance between food and their nests thanks to the pheromone (trace) that they release. The ant colony technique, which is an example of swarm intelligence, has been proven to be the most successful algorithm among all the others to detect the optimum route. The ant colony algorithm that was first developed by Ghafurian and Javadian [10] has been used since then to develop solutions to many problems in vehicle routing, airplane scheduling and computer network design. Ghafurian and Javadian applied ant colony algorithms to solve the multiple travelling salesman problem. In another study, Garcia *et al*. [8] used the ant colony method for the optimization of autonomous mobile robot navigation and route planning.

In the current study, the visual software that was developed using C#.NET programming language and the ACO technique to detect the most suitable and shortest route on the map for school bus services will be discussed. For this software, 18 of the school bus services' routes in the Sincan district of the capital city of Ankara in Turkey were used as case studies to apply the ant colony algorithms method. The routes that the school buses follow and the GPS locations of the stops were determined by means of mobile software and were displayed on Google Maps. The study aimed at enhancing the current routes and developing these routes online, by using students' instantaneous GPS locations and with the help of mobile software, in order to avoid current losses of time, cost and labor force.

The outline of this paper is as follows: Section 2 describes literature review of school bus routing problems and ACO. Section 3 describes ACO algorithm for dynamic school bus routing problem. Section 4 gives evaluation of software and experimental results. Finally, conclusion is drawn in section 5.

2. Literature Review

2.1. School Bus Routing Problems

The School bus routing problem relates to designing the optimum distribution/collection routes for the school buses serving geographically scattered clients from one or more storage units [2] and has been the focus of many scholars for a long time. The main aim of resolving VRPs is to provide a means for the vehicles to distribute/collect with the least expensive route under the condition that the requisite stops are made for each client/destination. In this manner, it is possible to avoid time and cost losses in transport. Milk delivery, postal delivery, solid waste collection, fuel/oil distribution, cargo/package delivery and collection, and school bus routing are all examples of VRPs [16]. All of these examples have their own limitations and criteria, such as quality of the transported material and the last stop to reach, as well as the stop from which the route will begin (for example, in the case of school bus services, the last stop in the morning and the first stop in the evening is the school), necessity to reach a certain stop before the others (cargo sent by a client to another). These limitations should be taken into consideration in the algorithms implemented to create solutions to the problems. As in network rooting problems that are mentioned in [4] VRPs can also be classified into two categories as dynamic and static routing problems. In the static VRPs, the stops/locations that the vehicle will visit are pre-specified and do not change during the distribution/collection process. In dynamic VRPs, on the other hand, new stops can be added to the planned route during the process or certain stops can be omitted. Two examples of this can be certain orders getting cancelled or new orders being taken while a water distribution vehicle is on its route, or a school bus being informed on its route that certain students will be absent from school that day. Today, dynamic school bus routing problems are more needed. Dynamic school bus routing is graphically explained in Figure 1. Within the context of this study, dynamic school bus routing will be investigated.

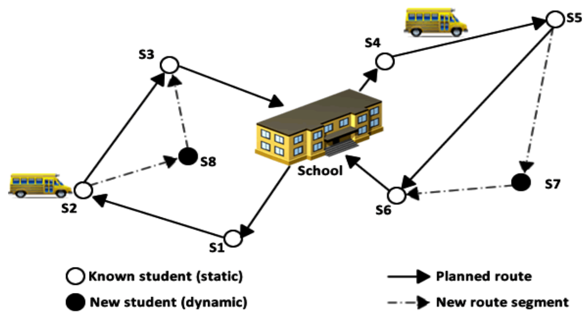


Figure 1. A dynamic school bus routing case.

The first studies regarding school bus routing were carried out by Newton and Thomas [12]. The school bus routing problem includes determining the shortest route for a school bus to pick up all the students from the pre-determined stops and to take them to school, and to pick the students up from school and leave them at the pre-determined stops. This problem consists of a number of sub-problems. The problem is solved in five steps [14].

- Data Preparation.
- Selection of Stops (assigning students to stops).
- Route Development.
- Scheduling School Bell.
- Route Planning.

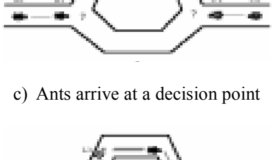
In the data preparation step, the addresses of the school and the students as well as the existing roads between these are determined. In the second step, the student addresses are assigned to different stops. In the third step, the route is planned for a single school. If the solution is to be made for more than one school, then the school bells are scheduled for each school, and in the fifth step the route is planned for all schools. In the previous section, a number of heuristic methods applicable for the VRP were mentioned. In this study, the ant colony algorithm will be used to resolve this problem.

2.2. Ant Colony Optimization

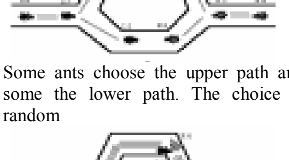
The behavioral patterns of living creatures in nature were taken as a model while developing artificial intelligence techniques. Bees, ants and even bacteria achieve their survival strategy through very complicated group behavior patterns. Today, scientists investigate these behaviors in detail and use them as models for their studies. The heuristic features of these living creatures shed light on the solution of complicated problems. Ants are one of the best examples of social insects, working together for the good of their colonies. Ants living in colonies initially send the leader ants alone to find food. These leaders scout around to find suitable food sources. If the leaders find food, they leave a trace, a special smell, on their way back to the colony. Thanks to this trace, other ants can reach the food source. Ants are capable of finding the shortest route from food sources to their nests without using their sight [17].

Ants' ability to find the shortest route between their nests and food is based on the intensity of the pheromone (trace) that they release along the way. Pheromones are chemical secretions that have an impact on other animals of the same species. Ants store a certain amount of pheromones while moving forward and prefer a certain route with more pheromone over one with less pheromone, by using a method based on probability [17]. Ants initially choose a random route and haul the food to their nest. The ant carrying the food leaves pheromones on the road, so that the other ants can follow it. The other ants in the colony decide where to pass based on the intensity of this matter. In each phase, ants are able to find a shorter route than that of the previous phase. The pheromone intensity increases on a shorter route, while it decreases on a longer route. Thanks to this pheromone updating, all ants use the shortest way between their nests and the food. Ants are able to adapt themselves based on external effects. If, due to external effects, the route that they follow is no longer the shortest route, they will find a new shortest route [17]. In case that the ants encounter an obstacle that was physically formed later on the road they passed, then they will tend to find another short route, i.e., they will adapt immediately. If they choose the wrong direction, they will recognize it as soon as possible and turn towards the shorter route.

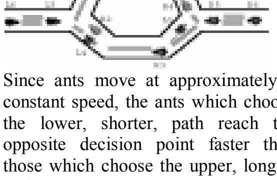
In Figure 2; a) Ants arrive at a decision point. b) Some ants choose the upper path and some the lower path. The choice is random. c) Since ants move at approximately a constant speed, the ants which choose the lower, shorter, path reach the opposite decision point faster than those which choose the upper, longer, path. d) Pheromone accumulates at a higher rate on the shorter path. The number of dashed lines is approximately proportional to the amount of pheromone deposited by ants [6]. This behavior of ants to heuristically find the shortest route while carrying food to their nests was used to develop ACO. In [17] it was first developed by Dorigo and Gambardella [6]. to develop solutions to difficult optimization problems such as: The Travelling Salesman Problem (TSP) and the Quadratic Assignment Problem (QAP).



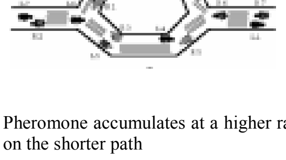
c) Ants arrive at a decision point



b) Some ants choose the upper path and some the lower path. The choice is random



c) Since ants move at approximately a constant speed, the ants which choose the lower, shorter, path reach the opposite decision point faster than those which choose the upper, longer, path



d) Pheromone accumulates at a higher rate on the shorter path

Figure 2. How real ants find a shortest path [6].

3. ACO Algorithm for Dynamic School Bus Routing Problem

While the ability of the ants to find the shortest route between their nests and food without using their sight was adapted to finding the shortest route, certain features of real ants were taken at face value and some features were added to the system later [7].

Characteristics taken at face value:

- Communication between ants through pheromones.
- Preferring routes with higher pheromone concentration over those with a lower pheromone concentration.
- Rapid increase of pheromone on short routes.

In addition, to these characteristics that were taken at face value, some features were also added to improve the results [7]:

- They live in an environment where time is calculated discretely.
- They are not completely blind and can obtain access to the details related to the problem.
- With a certain amount of memory, they can maintain the information that was formed to solve the problem.

In the ant colony algorithm, the Euclidian distance measurement method was used to calculate the distance between two nodal points. According to this method, the distance between the nodal points i and j, with certain x and y coordinates is calculated using the equation given below:

$$d(i,j)=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \quad (1)$$

A network with N number of nodal points and E number of sides is shown as $G(N, E)$.

When time is equal to t, the number of ants at the nodal point i is shown by using the equation given below.

The total number of ants at the nodal points, on the other hand is calculated as follows:

$$m\sum_{i=1}^{n} b_i(t),\ bi(t)(i=1,...,n) \quad (2)$$

t_{ij} expression indicates pheromone intensity on each (i, j) side at time t. Each ant chooses the next nodal point at time t and will arrive to that nodal point at time (t+a). This means that during the interval (t, t+a)m ants carry out m moves. At the end of n iterations at the algorithm, each ant completes an iteration. At this point, the pheromone intensity is updated by using the equation given below:

$$t_{ij}(t+n)=\rho.t_{ij}(t)+\Delta t_{ij} \quad (3)$$

Where ρ represents a coefficient and $(1-\rho)$ indicates the pheromone evaporation between time t and $t+n$ $(0<\rho<1)$.

$$\Delta t_{ij}=\sum_{k=1}^{m}\Delta t_{ij}^{k} \quad (4)$$

Where Δt_{ij} shown in Equation 4 indicates the amount of trace matter left by the k^{th} ant on side (i, j) between time t and $t+n$. The possibility that the k_{th} ant passes from the ith nodal point to the j^{th} nodal point is calculated using the equation below:

$$p_{ij}^{k}(t)=\left\{\begin{matrix} \dfrac{[t_{ij}(t)]^{\alpha}.[n_{ij}]^{\beta}}{\sum k\in A_K [t_{ik}(t)]^{\alpha}.[n_{ik}]^{\beta}} & \begin{pmatrix} \textit{if } k \textit{ is an} \\ \textit{allowed} \\ \textit{selection} \end{pmatrix} \\ 0 & (\textit{else}) \end{matrix}\right\} \tag{5}$$

Where $t_{ij}(t)$ pheromone amount at sides (i, j) at time t, n_{ij} visibility values between sides (i, j). This value varies depending on the criteria considered in problem solving. α parameter indicating relative importance of pheromone trace. β parameter indicating the importance of visibility value.

$$\Delta t_{ij}^{k}=\left\{\frac{Q}{Lk}\right\} \tag{6}$$

Where Q constant, Lk, k_{th} ant's iteration length. If the ant uses the (i, j) side throughout the iteration, the amount of trace it leaves is calculated by using the Equation 6. Otherwise, the trace amount is equal to zero [1].

Clarke and Wright [5] Dorigo tested a variety of values for each parameter, by keeping the other constant. In order to obtain certain statistical information regarding the average values, only one of the parameters was changed in each experiment and more than 10 simulations were made for each arrangement. They found out the valid values for the parameters as follows: α=1, β=1.

The α value shows the importance of the pheromone amount found on a certain route. Higher α values increase the possibility of a certain route with higher pheromone intensity to be selected. The β values, on the other hand, define the effect of route lengths on the selection of the second point. The level of randomness increases with increasing β values [17].

Based on these relationships, Algorithm 1 is applied as the follows:

Algorithm 1. Ant colony.

Begin
Define number of iteration, school buses (ants).
Define the parameters α, β, ρ.
Define a random starting city for each school bus.
For each iteration.
For each school bus.
Define the next student stop by using Equation 5.
Define the iteration length.
Update pheromone by using Equation 3 *and* 4.
End.

4. Evaluation of Software and Experimental Results

School busses take the students from their houses in the morning and take them to the school, while they take the students from the school to their houses in the evening. By means of the developed application, the aim was to develop the most suitable route that the school busses should follow. The android based mobile section of the application collects the GPS coordinates of the students and the school bus to be transferred in real-time to the server, while by means of the desktop application where the ant colony algorithm runs, the most suitable route is formed on a Google map based on these coordinates and is sent to the school bus via the server. This method enables the dynamic reflection of certain factors on the route formation. These factors include any change at the initial locations of the students or the school bus, some students not attending school on a particular day and any modification to the available routes for any reasons. Figure 3 shows a block diagram demonstrating the application functionality.

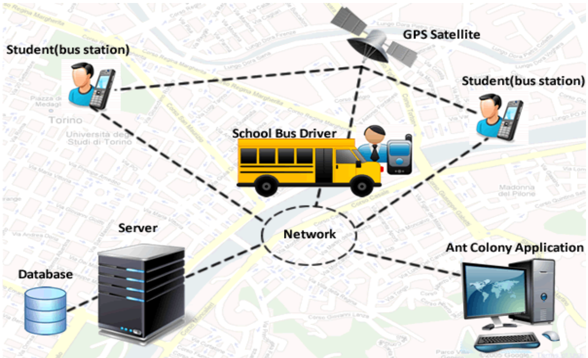


Figure 3. Block diagram of developed application.

For this study, the school bus routes within the Sincan district in the capital city of Ankara were used as case studies. The school bus routes were recorded by using the Android application and instantaneous GPS monitoring method. The home address of each student was taken as a stopping point. At the end of each route, the distances between the beginning and end points were recorded. After transferring the obtained route data into the database, the ill-adapted points were eliminated.

This application aimed to draw the shortest and the most suitable route on a Google Map based on the stop locations using the ant colony algorithm. The application was developed using C#.NET programming language. In order to store the planned route and points at the route, on the other hand, a SQLite database was used. In this application, GMap.NET was added to locate the routes on Google Maps. The coordinates, as well as latitude and longitude values of each point on the route, were recorded in the database. Figure 4 explains how the routes were formed in the application and how the algorithm was applied.

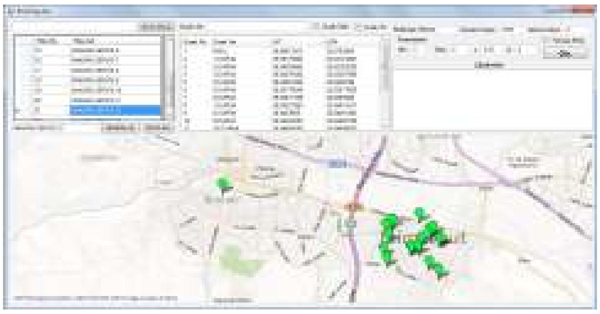


Figure 4. Main application form.

The points selected on the route selection made by using the "load route" combo box object were added with the coordinate information. The points can be seen with their instantaneous or pre-loaded locations. The locations of the points belonging to a certain route record can be seen at the right hand side of the form, while the window where all the algorithm parameters are entered is found below that. In the classic ant colony method, initially a random point is selected. However, because this study focuses on the school bus services, the route beginning point will be "school" or the desired student stop. For this reason, the user is given the opportunity to define the beginning point. If the beginning point is kept constant, the first point to take into consideration for the solution will be the beginning point. After selecting parameters and number of trials, the "solve" button is pressed and the ant colony algorithm starts to run on the points located on the selected route for the selected parameters and for the defined number of trials. The algorithm will add all the solutions to the list titled "Solutions" together with the route information. If the obtained solution is better, i.e., shorter than the previous solutions, it is added to the list.

In the application, in order to calculate the distance between two points, the route length was taken into account instead of calculating the direct air distance by means of the classic Euclidian method. To calculate the length of the route, the characteristics of the roads such as one-way roads or those appropriate for pedestrian passage were taken into consideration.

The points whose GPS (latitude, longitude) coordinates were taken were placed in Google Maps and while the distance between nodal points i and j, $d(i, j)$ was calculated, the real road distances between these two points were considered by means of the GMap.net add. In the Euclidian distance method, the distance between the nodal points i and j, $d(i, j)$ is equal to the distance between the nodal points i and j, $d(i, j)$. On the other hand, because real roads were used in this study, the routes from i to j and j to i were calculated separately for a variety of reasons (for instance, one-way or not allowing turns at junctions).

After running the algorithm at the desired step, when the desired solution is double clicked in the relevant list, the route to follow is drawn between selected points, as shown in Figure 5. If the route is ordered from the school bus, then the route thus formed is transferred to the school bus.

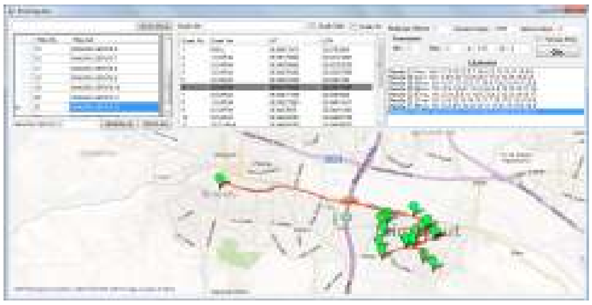


Figure 5. Drawing of the selected route.

This study attempted to resolve the school bus routing problem, which is a specific type of VRP. For the solution, a type of software was developed by using a heuristic technique, the ACO method. With the mentioned software, the aim was to avoid current time and cost losses and to enhance existing routes. The software, being mobile-supported and online, allows instantaneous modifications to the routes to be reflected directly in the problem solving process. In addition, it suggests feasible routes, thanks to the real map and GPS location features. The software enables route and student stop recording in a database. Any selected route can be solved on the basis of desired parameters and the obtained results can be visually presented to the user.

In this study, the school bus routes used in the Sincan district of the city of Ankara were taken as study cases. The routes that the school bus follows as well as the locations of the stops were recorded by means of the Android application that was developed within the framework of this study and ill-fitting points were eliminated and then transferred to the database. The classic ACO algorithm and developed ACO algorithm was used in the software developed for this routing process. All of the obtained solutions are shown in Table 1.

Table 1. The obtained solutions.

Route			Developed ACO			Classic ACO		
No	Distance (km)	Bus Stop Count	Best Solution (km)	Iteration	Optimization Rate	Best Solution (km)	Iteration	Optimization Rate
1	12	5	8,86	8	26,17 %	9,87	22	17,75 %
2	6,73	11	4,57	373	32,1 %	5,27	8450	21,69 %
3	9,82	6	9,26	33	5,7 %	9,38	84	4,48 %
4	17	13	12,98	4890	23,65 %	14,82	5495	12,82 %
5	15	13	12,69	1197	15,4 %	14,49	5304	3,4 %
6	6,8	6	5,9	8	13,24 %	6,8	10	0 %
7	4,1	7	3,47	431	15,37 %	3,98	742	2,93 %
8	22,8	17	19,96	9579	12,46 %	22,55	7498	1,1 %

5. Conclusions

The obtained results demonstrated that the ant colony algorithm can enhance the existing routes. A higher number of stops results in better solutions. It was also, observed that more alternative routes are suggested in the case that the number of ants is equal to the number of stops. Many scholars have attempted to solve the

VRP for quite some time. It is a complicated problem that is difficult to solve by classic techniques. This problem is becoming even more important due to today's transportation and technological means. An optimum routing may considerably reduce losses in cost and workforce, as well as environmental pollution.

We have developed this software by using ant colony algorithm to optimize routes of school buses. Developed ACO algorithm has reached more efficient results than the classic ACO algorithm. Thanks to the mobile support of this developed software, successful results were obtained for the dynamic routes as well as fixed routes. In this study, a single school and a single school bus route were considered. Routing for more than one school and school bus by using the ACO is considered for future studies.

References

[1] Alaykıran K., and Engin O., "Ant Colony Metaheuristic and an Application on Traveling Salesman Problem," *J. Fac. Eng. Arch. Gazi Univ.*, vol. 20, no. 1, pp. 69-76, 2005.

[2] Bowerman R., Hall B., and Calamai P., "A Multi-Objective Optimization Approach to Urban School Bus Routing: Formulation and Solution Method," *Transportation Research Part A: Policy and Practice*, vol. 29, no. 2, pp. 107-123, 1993.

[3] Bräysy O., "A Reactive Variable Neighborhood Search for the Vehicle Routing Problem with Time Windows," *INFORMS Journal on Computing*, vol. 15, no. 4, pp. 347-368, 2003.

[4] Chin T., Abbou F., and Tat E., "Simulation Study of a Heuristic Near-Maximum Ant-Based Dynamic Routing," *The International Arab Journal of Information Technology*, vol. 5, no. 3, pp. 230-233, 2008.

[5] Clarke G. and Wright J., "Scheduling of Vehicles from a Central Depot to a Number of Delivery Points," *Operations Research*, vol. 12, no. 4, pp. 568-581, 1964.

[6] Dorigo M. and Gambardella L., "Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 53-66, 1997.

[7] Ekin E., and Yakhno T., "A Case Study of Adopting Ant System to Optimization Problems," *the Tenth Turkish Symposium on Artificial Intelligence and Neural Networks, TAINN2001*, Gazimagusa, T.R.N.C., pp. 20-25 2001.

[8] Garcia M., Montiel O., Castillo O., Sepúlveda R., and Melin P., "Path Planning for Autonomous Mobile Robot Navigation with Ant Colony Optimization and Fuzzy Cost Function Evaluation," *Applied Soft Computing*, vol. 9, no. 3, pp. 1102-1110, 2009.

[9] Gendreau M., Hertz A., and Laporte G., "A Tabu Search Heuristic for the Vehicle Routing Problem," *Management Science*, vol. 40, no. 10, pp. 1276-1290, 1994.

[10] Ghafurian S. and Javadian N., "An Ant Colony Algorithm for Solving Fixed Destination Multi-Depot Multiple Traveling Salesmen Problems," *Applied Soft Computing*, vol. 11, no. 1, pp. 1256-1262, 2011.

[11] Kilby P., Prosser P., and Shaw P., "Guided Local Search for the Vehicle Routing Problem," available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.11.689&rep=rep1&type=pdf, last visited 1999.

[12] Newton R. and Thomas W., "Design of School Bus Routes by Computer," *Socio-Economic Planning Sciences*, vol. 3, no. 1, pp. 75-85, 1969.

[13] Osman I., "Metastrategy Simulated Annealing and Tabu Search Algorithms for the Vehicle Routing Problem," *Annals of Operations Research*, vol. 41, no. 4, pp. 421-451, 1993.

[14] Park J. and Kim B., "The School Bus Routing Problem: A Review," *European Journal of Operational Research*, vol. 202, no. 2, pp. 311-319, 2010.

[15] Reimann M., Doerner K., and Hartl R., "D-ants: Savings based Ants Divide and Conquer the Vehicle Routing Problem," *Computers and Operations Research*, vol. 31, no. 4, pp. 563-591, 2004.

[16] Rizzoli A., Montemanni R., Lucibello E., and Gambardella L., "Ant Colony Optimization for Real-World Vehicle Routing Problems," *Swarm Intelligence*, vol. 1, no. 2, pp. 135-151, 2007.

[17] Soyler H. and Keskinturk T., "Global Ant Colony Optimization," *J. Fac. Eng. Arch. Gazi Univ.*, vol. 21, no. 4, pp. 689-698, 2006.

[18] Taillard È., Badeau P., Gendreau M., Guertin F., and Potvin J., "A Tabu Search Heuristic for the Vehicle Routing Problem with Soft Time Windows," *Transportation Science*, vol. 31, no. 2, pp. 170-186, 1997.

[19] Van Breedam A., "An Analysis of the Effect of Local Improvement Operators in Genetic Algorithms and Simulated Annealing for the Vehicle Routing Problem," *RUCA Working Paper 96/14*, University of Antwerp, Belgium, 1996.

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