TRAIN SCHEDULING USING ANT COLONY OPTIMIZATION TECHNIQUE

K.Sankar Lecturer / M.E., (P.hD).,

ABSTRACT

The paper develops an algorithm for the train scheduling problem using the ant colony system metaheuristic called ACS-TS. At first, a mathematical model for a kind of train scheduling problem is developed and then the algorithm based on ACS is presented to solve the problem. The problem is considered as a traveling salesman problem (TSP) wherein cities represent the trains. ACS determines the sequence of trains dispatched on the graph of the TSP. Using the sequences obtained and removing the collisions incurred, train scheduling is determined. Numerical examples in small andmedium sizes are solved using ACS-TS and compared to exact optimum solutions to check for quality and accuracy. Comparison of the solutions shows that ACS-TS results in good quality and time savings. A case study is presented to illustrate the solution.

1. Introduction

A hierarchical process of rail transport planning is introduced and then the ant's behavior which gives inspiration for ant algorithms is presented.

Rail transport planning.

Rail transport planning is a very complex task which is carried out based on the mutual reaction among a large number of impressed components. As it was mentioned in Ghoseiri and Lindner, in respect to the complexity of rail transport planning, this process is divided into several steps. These procedures include the demand analysis, line

Ant's behavior. Special insects like ants, termites, and bees that live in a colony arecapable of solving their daily complex life problems. These behaviors which are seen ina special group of insects are called swarm intelligence. Swarm intelligence techniquesfocus on the group's behavior and study the decartelized reactions of group agents with each planning, train scheduling, rolling stock planning, and crew management. The following is a brief description on the hierarchical planning process.

In the first step, the passenger demand is analyzed. As a result, the amount of passenger's demand between certain origins and certain destinations is determined. The line planning includes decision making about routes and lines. This planning identifies which routes or lines should be exploited with what frequency. In the train scheduling phase, the arrival and departure times for all trains are determined. Determination of a timetable to separate the arrival and departure times of starting, ending, and middle stations is the product of this phase. In the next phase, the wagons and locomotives which are dedicated to the line are linked together to form a train. This phase is called rolling stock planning. The next task is the crew management. This task determines the distribution and allocation of the train's crew. This planning should be done in a way that supplies the necessary staff for each train. Crew management components include crew scheduling and crew rostering. Crew scheduling results in allocation of crews to trains and crew rostering determines their duty description. All of these phases have a close relationship.

Computing an optimal solution in one phase may restrict the feasible solution space in the next phases. other and with the environment. The swarm intelligence system includes a mixture of simple local behaviors for creating a complicated general behavior and there is no central control in it. Various types of certain ants have the ability to deposit pheromone on the ground and to follow, in probability, pheromone previously deposited by other ants.

By depositing this chemical substance, the ants leave a trace on their paths. By detecting this trace, the other ants of the colony can follow the path discovered by other ants to find food. For finding the shortest way to get food, these ants can always follow the pheromone trails. The ant algorithms based on this characteristic are inspired from Goss experiments, a laboratory colony of Argentine ants called Iridomyrmex Hmilis was placed in a closed space in which the nest was connected to food resource by a double bridge (with different length). This branched way was designed in a way that the ants could just choose one of the branches for reaching the food. After several times carrying out the experiment, the number of ants and amount of pheromone in each branch were counted and measured. It was also observed in this experiment that the possibility of choosing the shortest path increases with the length difference of two branches.

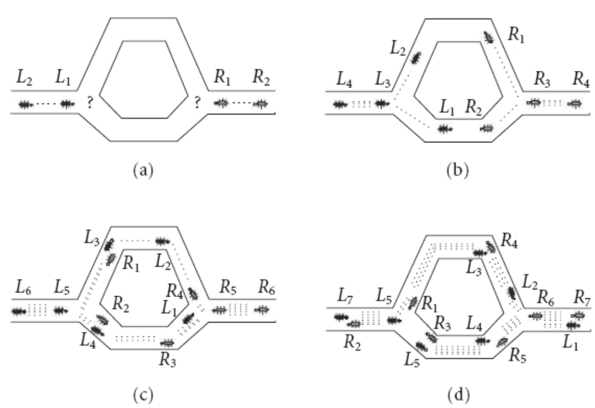

Figure 1.2. The ant's behavior: (a) the ants reach to the point of making a decision. (b) The ants choose one of the two paths randomly. (c) If the ants move with the same speed, the ants which have chosen the shorter path reach sooner to the point of making next decision. (d) The

amount of pheromone in the shorter branch increases at a higher rate.

2. Literature review

In this section, first there is a review on the literature of the train scheduling problem and then the manner of creating, developing, and applying the ant algorithms is put forward. The literature review of the train scheduling problem and the ant algorithms show that ant colony optimization algorithms currently are not used for solving the train schedule problem.

Train scheduling. The train schedule problem is one of the difficult problems in rail transport planning. This planning has been carried out manually and by trial and error methods for over a century. In a manual method, the train arrival and departure times from each station are identified based on the individual's experience and information. The solution quality and building time in this method are closely related to the individual's experience and ideas. (For a further study refer to Chiang. Mathematical programming, simulation, expert systems, heuristic and metaheuristic methods, and combinational methods are other techniques for train scheduling.

Mathematical methods give exact or optimal solutions. Although these techniques consistently find solutions with high quality, the time and memory used in these methods for solving realistically sized problems is very high. For these reasons, simulation, heuristic, metaheuristic methods and expert systems are typically used for solving these problems. The application of simulation during the 1970s faced failure when solving the train scheduling problem. In these years, simulation had impractical application because of extra calculations and informational necessities. However, today computers can implement the simulation models much easier. Databases can be combined with other programs and this leads to a considerable improvement in simulation technology. There are several researches using simulations in the rail network literature; Heuristic methods are not always able to give good solutions to problems but these algorithms may solve the problem in a shorter time. This property makes these algorithms play a more constructive part of the primary solutions for other algorithms. These algorithms are made based on the problem structure and have a different structure for each problem. These algorithms' applications to railway problems can be noted in Cai and Goh, Carey and Lockwood, and Higgins. Knowledge-based systems (expert systems) have typically been used to solve problems that are either too complex for amathematical formulation or too difficult to be solved optimization approaches. Some examples of application of the knowledge-based systems in railway transportation are Cury et al. These algorithms are considered subgroup of heuristic algorithms. (For a further study refer to Chiang et al. [20].)

Historical development of ant colony optimization.

Ant algorithms are a population- based approach which has been successfully applied to several NP-hard combinatorial optimization problems. As the name suggests, ant algorithms have been inspired by the behavior of real ant colonies. One of the main ideas of ant algorithms is the indirect communication of a colony of agents, called (artificial) ants, based on pheromone trails (pheromones are also used by real ants for communication). The (artificial) pheromone trails are a kind of distributed numeric information which is modified by the ants to reflect their experience while solving a particular problem. The first ACO algorithm, called ant system (AS) has been applied to the traveling salesman problem (TSP). In spite of hopeful results, the algorithm results were not comparable to the other advanced algorithms which were already applied to solve this problem. Despite the fact, this algorithm built important principles in creating more advanced algorithms. At the present time, many algorithms have been suggested based on the improvement of AS algorithm and used for solving various problems. A comprehensive list of ACO algorithms and their applications are shown in Table 2.2.

Ant colony system (ACS)

ACS was suggested as a new heuristic method to solve optimization problems by Dorigo and Gambardella. The reformed form of the AS algorithm and functions is as follows. Each ant generates a complete solution by choosing the nodes according to a probabilistic state transition rule. The state transition rule given in (3.1) and (3.2) is called a pseudorandom-proportional rule:

$$s = \begin{cases} \arg\left[\mathrm{Max}_{j \in N_i^k}\{[\tau_{ij}][\eta_{ij}]^{\beta}\}\right] & \text{if } q \le q_0, \\ S & \text{if } q > q_0, \end{cases} \tag{3.1}$$

$$p_{ij}^k = \frac{[\tau_{ij}][\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k}[\tau_{ij}][\eta_{ij}]^{\beta}}, \tag{3.2}$$

where q is a random number uniformly distributed in [0 ⋯ 1], $q0$ is a parameter between 0 and 1, S is a random variable selected according to the probability distribution given in (3.2), $\tau i\, j$ is the amount of pheromone in edge $i\, j$, $\eta i\, j = 1/\delta i\, j$ where $\delta i\, j$ is the cost of edge $i\, j$, β is a parameter that determines the relative importance of η versus τ, and

```
Procedure Ant colony system
Set pheromone trails to small constant
While (termination condition not met) do
        Place each ant on initial node
        For i = 1 to n do (# ants)
            For k = 1 to m do (#locations)
                Apply State Transition Rule (pseudorandom proportional)
                Apply Local Update pheromone
            End for (build one route)
        End for (run one set)
        Apply Global Update
End while
End Ant colony system
```

ALGORITHM 3.1. ACS algorithm procedure.

Nk i is the remaining node set of ant *k* based on moving from node *i* to build a feasible solution. In ACS, only the globally best ant which has built the best solution deposits pheromone in the graph. At the end of an iteration of the algorithm, once all the ants have built a solution, pheromone is added to the arcs used by the ant that found the best tour from the beginning of the trial. This updating rule is called the global updating rule of pheromone:

$$\tau_{ij} \longleftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij},$$

where $0 < \rho < 1$ is a pheromone decay parameter and $\Delta\tau i$ j equals to

$$\Delta\tau_{ij} = \begin{cases} \dfrac{1}{\cos t_{\text{gb}}} & \text{if } (i,j) \in \psi^{\text{gb}}, \\ 0 & \text{if } (i,j) \notin \psi^{\text{gb}}, \end{cases}$$

ψgb is the best solution which was built and cos *t*gb is the cost of the best solution. In ACS, ants perform step-by-step pheromone updates using local updating rule of pheromone. These updates are performed to favor the emergence of other solutions than the best so far. The updates result in step-by-step reduction of the pheromone level of the visiting edges by each ant. The local updating rule of pheromone is performed by applying the rule

$$\tau_{ij} \longleftarrow (1-\xi)\tau_{ij} + \xi\tau_0,$$

τ0 is a small fixed value and $0 < \xi < 1$ is the local evaporation coefficient of pheromone.

The proposed mathematical model of train scheduling.

In this section a mathematical model for train scheduling on a single track line is presented. This model is the work done by Higgins and Kozan [56] with minor changes in order to account for the assumptions of the model. In this model it is supposed that the trains are only dispatched from the first and last station. After preparation, the trains in the beginning or end stations should be dispatched immediately. In the case that the prepared trains to dispatch are stopped in the stations with unpermitted time stop and go over the allowed time, we undergo some cost. In this model, the speed and trip times in each track section for each train are assumed to be fixed. Also, a train can travel in two directions, but it is not permitted to overtake another train.

Notations

R: the group of trains that should be dispatched from right station to left.
L: the group of trains that should be dispatched from left station to right. *T*: the group of total trains ($i, j \in R$ or L or T and $T = R \cup L$).
S: set of stations ($k \in S$), track sections and stations are indexed in numerical orderfrom left to right.
Track section *k* is a section of track that connects two stations *k* and *k* +1.
D: the set of permitted stop times in the station ($dik \in D$).
AD: the set of arrival and departure times from a station ($Xa(i,k), Xd(i,k) \in$ AD).
M: a big positive number.

Parameters

Trip time: the time that train *i* needs to pass track section *k*·(*tik*).
Dwell time: this time indicates the permitted dwell time of train *i* in station *k* · (*dik*).
Headway: minimum time interval between trains *i* and *j* to arrive/depart from track section *k* · (*hi jk*).
Train importance weight: (*Wi*).

Binary variables

ai j =1 if train $j \in R$ enters the track section after train $i \in R$, 0 otherwise,
bi j =1 if train $j \in L$ enters the track section after train $i \in L$, 0 otherwise,
ci jk = 1 if train $j \in L$ enters the track section *k* after train $i \in R$,
0 otherwise (i.e., train $i \in R$ enters the track section *k* after train $j \in L$).

Continuous variables.

Xa(i, k): the arrival time of train *i* to station k.
Xd(i, k): the departure time of train *i* from station k.

Objective function.

Objective function in this model is to minimize the total train delays in the stations. The delay equals the time difference between the amounts of time a train is stopped and its permitted dwell time in the station

Conclusion

This paper developed an algorithm for the train scheduling problem using the ant colony system metaheuristic called ACS-TS. At first, a mathematical model for a kind of train scheduling problem was developed and then the algorithm based on ACS was presented to solve the problem. The problem was considered as a traveling salesman problem wherein cities in the TSP represent the trains. ACS determined the sequence of trains dispatched on the graph of the TSP. Using the sequences obtained and removing for collisions incurred, train scheduling was determined. Numerical examples in small and medium sizes were solved using ACS-TS and compared to exact optimum solutions to check for quality and accuracy. Comparison of the solutions showed that ACS-TS results in good quality and time savings. A case study was presented to illustrate the solution.

References

Adriaans, P. (2002). Backgrounds and general trends. In J. Meij (Ed.), *Dealing with the dataflood, mining data,text and multimedia* (pp. 16–25). STT

Beweton, The Hague, Netherlands. Adriaans, P. (2002a). Production control. In W. Kl¨osgen, & J. M. Zytkow (Eds.), *Handbook of data mining and knowledge discovery*. Oxford University Press.

Adriaans, P., & Zantinge, D. (1996). *Data mining*. Addison-Wesley

K.Sankar M.E., (P.hD)., / Lecturer
K.S.R College of Engineering
Tiruchengode, Namakkal
Tamil Nadu, India
Email : san_kri_78@rediffmail.com