Concurrent Locomotive Assignment and Freight Train Scheduling

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ABSTRACT

The locomotive assignment and the freight train scheduling are important problems in railway transportation. Freight cars are coupled to form a freight rake. The freight rake becomes a train when a locomotive is coupled to it. The locomotive assignment problem assigns locomotives to a set of freight rakes in a way that, with minimum locomotive deadheading time, rake coupling delay and locomotive coupling delay all freight rakes are hauled to their destinations. Scheduling freight trains consists of sequencing and ordering freight trains during the non-usage time between passenger trains but with no interference and with minimum delay times. Solving these two problems simultaneously is of high importance and can be highly effective in decreasing costs for rail transportation. In this paper, we aim to minimize the operational costs for the locomotive assignment and the freight train scheduling by solving these two problems concurrently. To meet this objective, an efficient and effective algorithm based on the ant colony system is proposed. To evaluate the performance of the proposed solution method, twenty-five test problems, which are based on the conditions of Iran Railways, are solved and the computational results are reported.

1. Introduction

Railway transportation has a critical role in movement of freight and passengers. Due to the high cost that goes to the construction of rail infrastructures, the efficiency of railway operations is decidedly important. In Iranian

Railway, freight transportation is demand driven and the departure of freight trains occurs based on the accumulated tonnage of freight.

At the operational level, the locomotive assignment and the freight train scheduling are challenges, which planners confronted with those. Therefore, the managers are forced to plan freight transport operations on a daily basis. The locomotive assignment problem specifies that how to assign locomotives to a set of freight rakes to provide the maximum efficiency of

locomotives while the hauling of all freight rakes occur. It tries to minimize the movements of deadheading locomotives, coupling delay of freight rakes and coupling delay of locomotives.

On the other hand, scheduling of freight trains determines the departure time and sequence of freight trains during the intervals between passenger trains in the way that they do not interfere with passenger trains' schedule and the minimum delay of freight trains occurs. Passenger trains move across the network conforming to a pre-determined schedule. The necessity to enter the freight trains along with the rest of passenger trains complicates the scheduling of freight trains in the network.

The importance of locomotive assignment and freight train scheduling problems are pronounced, considering the restriction of available locomotives, the ownership costs of locomotives, high operational costs of locomotives, and the costs due to the low efficiency in locomotive utility, huge investment required for constructing new railway lines and lower priority of freight trains to move along the network than passenger trains. Addressing these issues simultaneously, especially in demand-driven freight railroads is more crucial. It is therefore necessary for railway transportation companies to manage their locomotives and freight trains movements effectively.

In this paper, an algorithm based on ant colony system is proposed to minimize the costs of locomotive assignment and scheduling of freight trains by solving these two problems simultaneously. The computational results of implementing the proposed solution for Iran Railways are presented.

We have organized the paper as follows. Section 2 reviews the related past works. Section 3 describes the compound problem of locomotive assignment and scheduling of freight trains. In addition, the proposed ant colony system algorithm for solving the compound problem of locomotive assignment and scheduling of freight trains is presented in this section. Section 4 deals with the implementation of the proposed method on an illustrative example as well as the experimental results of implementing the algorithm on several test problems in Iran Railways. The conclusions are given in Section 5.

2. Literature Review

In the last decades, many rail transportation companies have been trying for mathematical optimization and modeling of rail transportation problems, including locomotive assignment problem and scheduling of trains. Previous surveys review optimization models for the freight train scheduling and the locomotive assignment presented in [1-5] In the following three subsections, we briefly review locomotive assignment, freight train scheduling and compound models.

2-1. Locomotive assignment

One of the first models for locomotive assignment problem was formulated as a multi-commodity flow problem[6]. This was a simple version of the problem in which a single locomotive must be allocated to each train. Ziarati et al. [7] presented a solution method based on branch and cut approach for locomotive assignment problem. A mixed-integer programming formulation in the form of a multicommodity flow problem was provided for locomotive assignment in [8]. The decomposition method and very large-scale neighborhood search were used to solve this problem. The approach used in [8] was extended in [9] by adding new constraints and by developing new formulations for the locomotive planning problem to assure that the problem is more implementable. A cluster-first, route-second approach was used for a multi-depot locomotive assignment problem to a set of single depot problems in [10]. The problems were solved by using a hybrid genetic algorithm. The railway rolling stock circulation problem was considered in rapid transit networks, where resources are limited and frequencies are high [11]. A survey on optimization models for locomotive assignment was conducted by [12]. Bouzaiene-Ayari et al. [13] was presented a general optimization framework for locomotive models that captures different levels of detail. Finally, Jaumard and Tian [14] was proposed a new decomposition model and a multi-column generation algorithm for solving the locomotive assignment problem.

2-2. Train scheduling

A model, algorithms and strategies for the train pathing and timetabling in a rail network with one-way and two-way tracks were presented in [15]. A mixed integer programming model for minimizing the total train delay and fuel cost with variable train velocities in a single line track was presented in [16]. The real-time conflict resolution problem on a single-track railway was studied in [17]. A mixed integer program was used to formulate the freight scheduling problem

and a lagrangian relaxation-based heuristic was invoked to solve the problem in [18]. A compound model, which is an integer program with deterministic dynamic service network design structure for freight routing and timetabling problems, was presented in [19].

A double-track, uni-directional train scheduling problem considering the constraints of the station capacity and track maintenance times was studied in [3]. In [20], some exact and heuristic algorithms were proposed for train scheduling problems, based on linear relaxation methods. In [21], the implementation of a real-traffic management system was considered. In [22], the tabu search neighborhood structures and search strategies were used to investigate the effectiveness of advanced strategies to solve the compound train routing and rescheduling problem. The railway freight transportation planning problem under the mixed uncertain environment of fuzziness and randomness was studied, in which the optimal paths, the amount of commodities passing through each path and the frequency of services were determined in [23].

The optimization - based heuristics were developed for the scheduling of freight trains in [24]. An optimization method to solve the train scheduling problem for a double and single-tracked bidirectional railway network was designed in [25]. In [26], the bi-objective problem of minimizing train delays and missed connections was considered, which allowed checking feasibility and optimality at local and global networks levels, leading to a branch and bound procedure to solve the problem as quick as possible. The train scheduling problem was considered as an application of job shop scheduling in [27]. The focus was on the robust and periodic aspects of timetables for different types of trains in a single railway track. A simulated annealing algorithm was utilized to solve large-scale problems. Zahedian-Tejenaki et al. [28] were proposed fuzzy mathematical model for hazmat and freight transportation in a railway network. A genetic algorithm was proposed to solve freight train routing and block-to-train assignment problem, which tries to find a freight processing order so that the iterative dispatch subproblems leads to a lower global cost solution [29].

2-3. Compound models
In the previous subsections, the locomotive assignment problem and the train scheduling problem have been considered separately. The former problem assigns locomotives to trains with the assumption of fixed schedules of trains, and the train scheduling problem assumes that locomotives are always available for trains. Practically it is necessary to integrate these two problems together to result in an effective and efficient program [30]. There are few works integrate these two problems.

An integrated formulation of railway timetabling and rolling stock assignment problem was used in [31] to adequate the capacity and system frequencies to meet the increased passenger demand and traffic congestion around urban and suburban areas. The passenger trains follow a pre-determined schedule to move across the network. In order to compare this work with our paper, it should be noted that our proposed algorithm is used to integrate locomotive assignment and scheduling of freight trains in a network in which both freight trains and passenger trains move across the network. Kasalica et al. was presented model that enables optimization of locomotive assignment during the development of a timetable [32].

A methodology for integrated locomotive assignment and freight train scheduling problem in a passenger rail network using a two-phase genetic algorithm was developed in [30]. In the first phase, the locomotives are assigned to the freight rakes with a genetic algorithm. The output of the first phase was an input for the second one. In the second phase, another genetic algorithm was invoked to schedule the freight trains between the intervals of passenger trains. Hence, the problems were solved separately. This type of planning procedure is not cost-effective. The Ant Colony System algorithm (ACS) proposed in this paper considers the two problems simultaneously which leads to a more economical planning for the rail operators.

3. The Proposed Algorithm
3-1. Definitions and assumptions
At the operational level, the locomotive assignment problem consists of allocating a set of locomotives to the existing freight rakes with the minimum cost on a daily basis. A *freight rake* is formed by coupling cars. This freight rake becomes a *freight train* when a locomotive is coupled to it. If a locomotive is not available for a rake at a station, it must be brought from some other stations. This leads to the *deadheading of locomotives*, which is a non-value operation that is necessary to be minimized. The number and

the location of locomotives, in the other words, the availability of locomotives has a direct bearing on the deadheading time of locomotives [30].

Rake coupling delay is the waiting time of a freight rake for a locomotive. The location of the locomotives, the location of freight rakes and the passenger trains time window influence the coupling delay of freight rakes. *Locomotive coupling delay* is also the waiting time of a locomotive for a freight rake. The system cost increased due to the deadheading time, rake coupling delay and locomotive coupling delay. Thus, in the locomotive assignment, reduction of these time values must be considered.

The *time window of a passenger train* is the duration of time in which a block section is occupied by a passenger train. A freight train time window is the duration of time during which a freight train is permitted to occupy a block section [30].

The problem inputs consist of a network modeled as a graph $G = (V, E)$, where V represents the set of stations and E represents the set of block sections connecting two stations. Moreover, the hauling time of freight trains between the stations, number of locomotives, passenger and freight trains time windows, the location of locomotives in the stations, number of freight rakes, and origin, destination and ready time of freight rake are considered as the inputs of the problem.

The proposed algorithm uses some assumptions. Firstly, it is assumed that all the locomotives are the same type and can be used for all freight trains. Given the planning horizon time and freight train hauling time, each locomotive is allowed to consequently haul two freight rakes at the most. Exchanging locomotives between stations is also permitted.

In this paper, locomotive assignment and freight train scheduling are designed concurrently. The aim of locomotive assignment is to minimize deadheading time, locomotive coupling delay and rake coupling delay. In addition, the freight trains are scheduled to reduce the freight train tardiness without any interference with the passenger trains. The problem outputs are as follows:

- locomotives assignment to the freight rakes,
- the sequence of hauling freight rakes by one locomotive if the locomotive hauls more than one freight rake,
- the sequence of freight trains to the network
- the departure and arrival times of freight trains from their origins to their destinations.

To obtain the best result for the locomotive assignment and freight train timetabling, the Ant Colony Optimization algorithm (ACO) is proposed. This algorithm will be discussed in the following section.

3-2. The overall structure of the proposed algorithm

ACO is used to solve the compound problem of locomotive assignment and freight train scheduling. The ACO consists of a wide range of algorithms applied for solving various optimization problems [33-35]. One of the successful ACO algorithms is the Ant Colony System (ACS). This paper applies ACS for solving the compound problem of locomotive assignment and freight train scheduling. In order to solve the problem using the ACS, firstly it is necessary to describe how a graph of the ant movement can be created. Due to the dynamic nature of the problem, this graph will change as the solving time of the problem moves forward.

The nodes of the ant movement graph are divided into two groups: (1) nodes indicating locomotives (shown as squares in the graph), and (2) nodes indicating freight rakes (shown as circles in the graph). As an example, Figure 1 represents a graph for the ant movement. In this graph, there are two locomotives and three freight rakes. An ant selects a locomotive node followed by selecting a freight rake node.
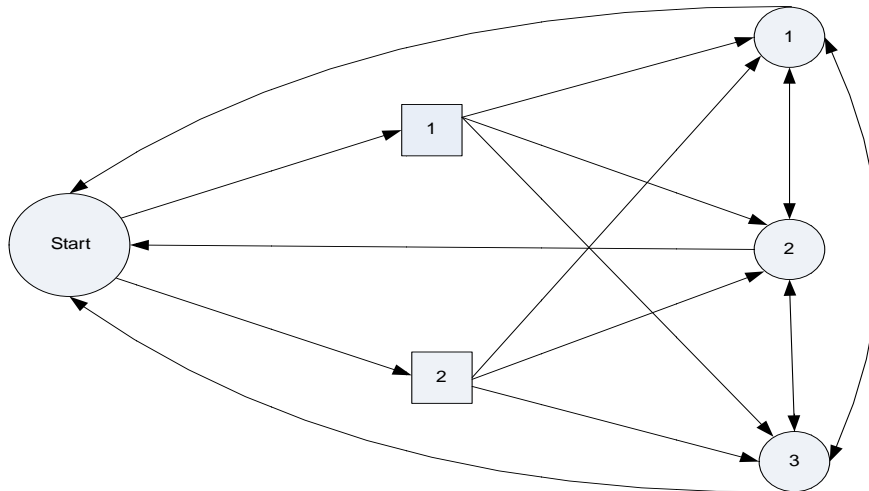
Fig. 1. An example for the ant movement graph

The ants select a locomotive node randomly whereas a freight rake node is chosen based on the heuristic and pheromone values. The algorithm checks whether the selected locomotive is allowed to haul another freight rake or not. If the locomotive can select another freight rake, then the set of selectable rakes is determined. Naturally, if this set is empty, two conditions occur: (1) there is no more freight rake in the problem and the solution is completed, and

(2) there is at least one rake in the problem but the selected locomotive cannot choose it. Therefore, the ant will go back to the start node to select another locomotive.

Figure 2 summarizes the construction of a solution by an ant in a flowchart. In this flowchart, SR, SL and SR^k_i indicate the set of selectable rakes, the set of selectable locomotives and the set of selectable rakes for ant k which is in arc i, respectively.
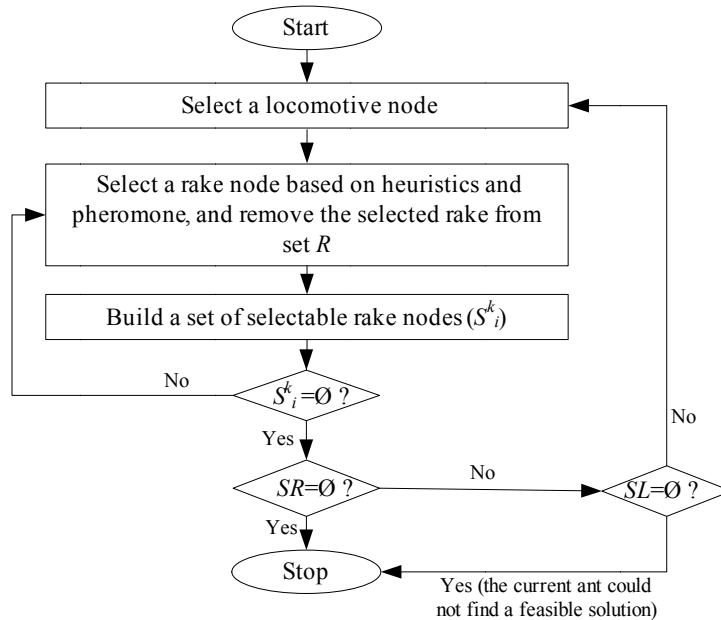

Fig. 2. Flowchart for construction of a solution by an ant

As it was mentioned previously, each ant selects a freight rake based on the values of heuristic and pheromone. In the proposed algorithm, when located at locomotive node i, ant k selects a freight rake represented by node j according to the *pseudorandom proportional rule*, given by Equations (1) and (2) [33]:

$$
j = \begin{cases} \arg\max_{l \in N_i^k} \{ \tau_{il}[\eta_{il}]^\beta \}, & if \quad q \le q_0 \quad (1) \\[2ex] P_{ij}^k = \dfrac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, & j \in N_i^k \quad else. \quad (2) \end{cases}
$$

Where q is a random variable uniformly distributed in $[0,1]$, $0 \le q_0 \le 1$ is a parameter and P_{ij}^k is a random variable to decide which freight rake to select next. In other words, with probability q_0, the ant makes the best possible move as indicated by the learned pheromone trails and the heuristic value, while with probability $(1 - q_0)$ it explores the arcs. Tuning the parameter q_0 allows modulation of the degree of exploration and the choice of whether to concentrate the search of the system around the best-so-far solution or to explore the solution space [33].

Considering the probabilistic rule (Equation (2)), the probability of selecting a particular freight rake (j) by an ant which has chosen locomotive i increases with the value of the associated pheromone trail τ_{ij} and of the heuristic information value η_{ij}. Heuristic value for this problem is based on four parameters, namely, locomotive deadheading time, rake coupling delay, locomotive coupling delay and train tardiness. It is calculated using Equation (3).

Heuristic value (η) = 1/ [1+((2*deadheading time) +rake coupling delay+ locomotive coupling delay+(2*train tardiness))] (3)

In fact, the parameter η influences the selection of the freight rake j by locomotive i. Defining the parameter η, the ants will select a route in which the minimum deadheading time, coupling delays and train tardiness occur. As illustrated in Equation (3), due to the higher effects of the two parameters, deadheading time and train tardiness, on the system costs, they are multiplied by 2 in the heuristic.

The parameters α and β determine the proportional effect of the pheromone trail and the heuristic value. The N_i^k is the feasible neighborhood of ant k when being at node i, that is, the set of freight rakes that ant k has not visited yet (the probability of choosing a freight rake outside N_i^k is 0). As it was mentioned before, after random selection of a locomotive by an ant, it must select a freight rake to be hauled by the chosen locomotive using the selection rule of the ACS. Assume both the locomotive and the freight rake are at the same station, if the freight rake will be coupled to the locomotive, a freight train is formed and it is scheduled based on the passenger train time window.

However, if the locomotive and freight rake are not at the same station, the locomotive must deadhead in the network as a dummy train to reach the station in which the freight rake is located. Then it is necessary for the ant to move to the starting node of the graph, and select a new locomotive. The procedure for providing a solution will be iterated. After selecting a freight rake to be hauled by a locomotive, it is necessary to update the movement graph of the ants by deleting the corresponding freight rake node and its entire links to the other nodes. Furthermore, it must be checked whether the selected locomotive is permitted to haul another freight rake considering the planning horizon or not. If it is not possible for the locomotive to haul another freight rake, the node representing the corresponding locomotive is deleted from the graph and the graph will be updated one more time. It is also necessary to update the location-time graph for the movement of the freight trains. The time windows occupied by the scheduled freight trains should be excluded from the available time windows, and a new timetable is generated to use in the next stage of the planning.

Initial solution

The quantity of freight rakes multiplies by locomotives specifies the quantity of ants for each colony. Each ant in the colony produces a solution using the explained procedure. Due to

the equal amount of initial pheromone for all the links at the beginning of the problem, the freight rakes are selected just by considering the heuristic values.

Pheromone trial update
There are two types of local and global updates in the proposed ACS algorithm. The ants use a local pheromone update rule that they apply immediately after having crossed the arc (i, j) during the path construction. In this paper, local pheromone trial update takes place by a 2-5% reduction in the value of pheromone on the visited arcs by each ant using Equation (4):

$$\tau_{ij} \leftarrow (1 - \xi)\tau_{ij} + \xi\tau_0 \qquad (4)$$

The parameter ξ is the local evaporation assumed between $0.02 \leq \xi \leq 0.05$. The value of τ_0 is set as the initial value for the pheromone trails. The effect of the local updating rule is that each time an ant uses an arc (i, j) its pheromone trail τ_{ij} is reduced, so that the arc becomes less desirable for the following ants. In other words, this allows an increase in the exploration of arcs that have not been visited yet and, in practice, has the effect that the algorithm does not show a stagnation behavior [33].

When all ants in a colony constructed their paths, the pheromone level will be updated at the end of an iteration, which is known as global updating. In the proposed ACS algorithm, only one ant (the best-so-far ant) is allowed to add pheromone after each iteration. Thus, the update in the proposed algorithm is implemented by the Equation (5) [33].

$$(1 - \rho)\tau_{ij} + \rho\Delta\tau_{ij}^{bs}, \qquad \forall (i, j) \in T^{bs} \quad (5)$$

In our problem, $\Delta\tau_{ij} = 1 / (total\ tardiness)^{bs}$ and T^{bs} contains all the arcs on the best-so-far solution. The deposited pheromone is discounted by a parameter ρ $(0 < \rho < 1)$.

Evaluation of the solution constructed by each colony

$$Fitness = C \times \left(\frac{1}{1 + Total\ Tardiness} \right)$$

$$C = \begin{cases} 0.8 \ \ if \ \ \max \ tardiness > 3 \times \dfrac{Total\ tardiness}{Number\ of\ tardy\ trains} \\ 1 \qquad otherwise \end{cases}$$

To evaluate the solutions constructed by the ants, it is necessary to calculate the fitness of each solution to compare their quality. As freight trains do not have a pre-scheduled arrival time at their destinations, we have applied a lower bound on the arrival time of the freight trains at their destination based on a method presented by [30], given as follows.

Firstly, consider a solution, i.e. locomotive assignment and freight train scheduling. Then the corrected rake ready time is calculated as the maximum of locomotive assignment time and rake ready time. Finally, considering the corrected rake/train ready time of the freight rakes/trains, the lower bound on arrival time of freight trains is the expected arrival time of freight rakes/trains at their destinations. The lower bound on arrival time of freight trains to their destination will be used as the due date of freight trains for evaluating tardiness-based objectives [30].

Minimization of total tardiness (Equation 6) is used as the primary objective for evaluating a freight train schedule in each colony. In this minimization, f is index of freight trains, DD_f illustrates the lower bound on the arrival time of freight train f at its destination, and AT_f indicates the actual arrival time of freight train f at its destination [30].

$$Total\ Tardiness = \sum_f (AT_f - DD_f) \qquad (6)$$

We use maximum tardiness (Equation 7) as the secondary objective to penalize the fitness value. The number of tardy trains is calculated in Equation (8) to obtain complete information on the quality of the freight train schedule.

$$Max\ Tardiness = Max\left\{ 0, Max\left| AT_f - DD_f \right| \right\} \qquad (7)$$

$$Number\ of\ tardy\ trains = \sum_f n_f \quad where \qquad (8)$$

$$n_f = \begin{cases} 1 \ \ if \ \ (AT_f - DD_f) > 0 \\ 0 \ \ otherwise \end{cases}$$

The fitness of an ant is calculated using Equation (9)[30]:

$$(9)$$

When a colony comes to the end, the fitness of all ants is computed using Equation (9). The ant with the highest fitness is known as the best ant of the colony, i.e. the best solution in the colony.

Having determined the best solution in the colony, the pheromone should be updated in the graph. The parameters used in the ACS algorithm is shown in Table 1.

Tab. 1. The final values of the parameters for the ACS

Parameter	Value
α	1
β	2
Quantity of ants	M= quantity of locomotives*quantity of freight rakes
Primary pheromone	$\tau_0 = 1$
Increasing value of global pheromone	$\Delta\tau_{ij} = \dfrac{1}{(Total\ Tardiness)^{bs}}$
Decreasing value of local pheromone	$\Delta\tau_{ij} = \tau_{ij} \times \xi \quad , 0.02 \le \xi \le 0.05$
pseudorandom proportional rule parameter	q_0=0.9

Termination criteria
The ACS captures the knowledge generated while solving the problem based on the fitness values of the ants, pheromone trials and heuristic, and it produces the solutions that generate a better locomotive assignment and freight train schedule. After a certain number of colonies, the best-so-far solution may not have any improvement. If the ACS algorithm does not improve the best-so-far solution for 20 consecutive colonies, it is terminated.
Solution ranking

The ACS gives a set of solutions for locomotive assignment and freight train scheduling. A decision maker can select one of them. This subsection describes a method for ranking the solutions to aid the decision makers for selecting an appropriate solution.
Firstly, the solution values need to be scaled between 0 and 1 before calculating the weight for each solution. The scaling method for minimization objectives is calculated using Equations (10) [30].

$$Scaled\ value\ for\ objective\ k\ in\ solution\ j = \frac{Minimum\ value\ of\ objective\ k\ in\ the\ solution\ set}{value\ of\ objective\ k\ in\ solution\ j} \qquad (10)$$

The ranking method is used when a decision maker gives Equal priority to all the objectives. The weight for a solution is the product of scaled objective values as shown in Equation (11).

$$W_j = \prod_k S_j^k \qquad (11)$$

Where j and k are the indices of solutions and objectives, respectively. s_j^k is the scaled value of objective k in solution j which is calculated in Equation (10), and W_j represents the weight for solution j. The solution with the higher value of

W will be selected as the final solution of the problem.

4. Experimental Results
4-1. A simple test problem
To demonstrate the procedure for the proposed solution method, a simple test problem is presented in this section. This simple example consists of a network with three stations 1, 2 and3 as shown in Figure 3.
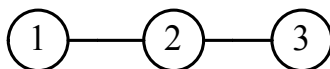
Fig. 3. The network for the simple test problem

The hauling time of the freight trains in blocks 1-2 and 2-3 are 20 and 30 minutes accordingly. A minimum headway of five-minutes is assumed for entering a new train to the block. It is also assumed that coupling a freight rake to a locomotive, which has been deadhead to the station, takes 5 minutes. In this example there are three freight rakes which originate from stations 1, 3 and 2 and they terminate at stations 3, 1 and 1, respectively. In addition, the planning time is considered to be 4 hours and the ready time for all freight rakes is assumed to be zero. For hauling the freight rakes to their destination, two locomotives are available which are located in stations 1 and 2. As it is necessary to consider the passenger train schedule to insert the freight trains into the network, the location-time of the passenger trains should also be available as an input of the problem (Figure 4).
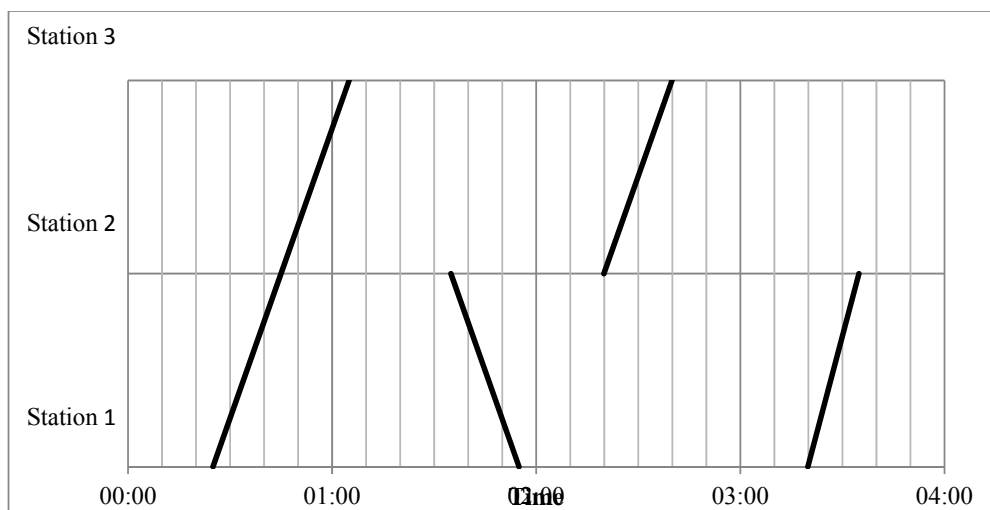

Fig. 4. The location-time graph of passenger trains in the assumed network

The initial graph for the ant movement is as it is in figure 1. Each colony in this problem includes six ants. Having moved on the graph, an ant generates a solution. A single ant is selected as an example to explain the process of generating a solution.

Firstly, the ant selects the first locomotive randomly. Assume it selects locomotive 1. Then the ant has a set of selectable rakes. The probability of each freight rake to be selected by the ant is calculated based on the related heuristic values. Considering the calculated probability for selecting the freight rakes, locomotive 1 was assigned to haul freight rake 1. The origin of locomotive 1 and freight rake 1 is the same and no deadheading would occur in the network. Hence, freight train 1 is the first train, which is planned to move toward its destination through the network with the minimum delay (Figure 5). The graph of the ant movement is also updated as shown in figure 6.
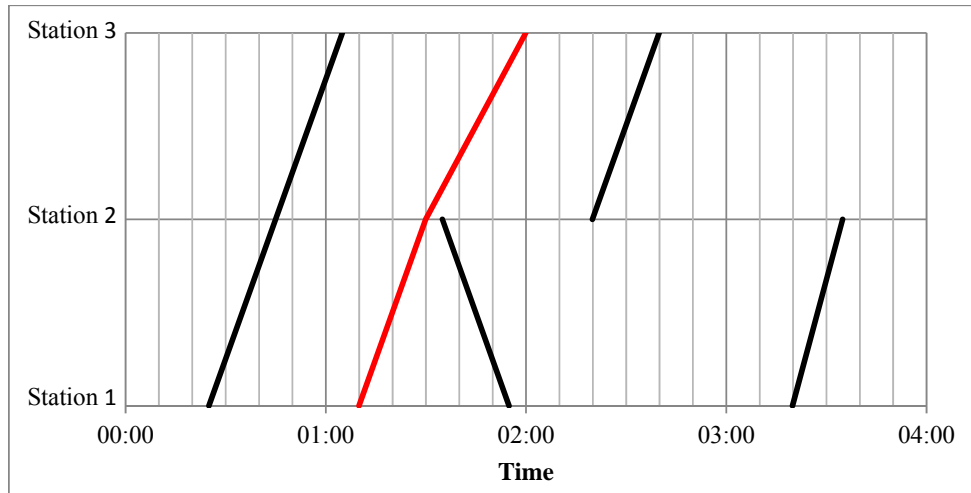
Fig. 5. The location-time graph for hauling freight rake 1 by locomotive
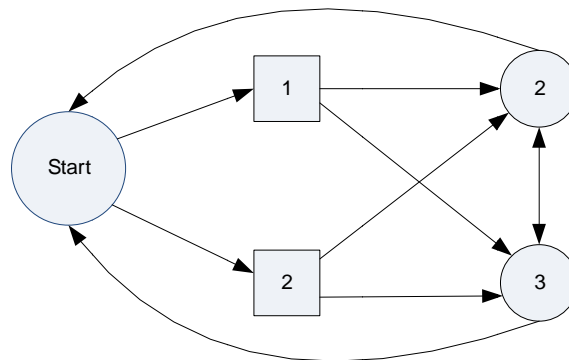

Fig. 6. The updated graph of ant movement after hauling rake 1 by locomotive 1

After hauling freight rake 1, the node represents rake 1 in figure 2 is omitted and the ant gets back to the start point of the graph and selects the second locomotive randomly (assume locomotive 2 is selected). Considering the procedure of selecting a freight rake, the ant selects freight rake 3 to be hauled by locomotive 2. Then this train is scheduled on the network as shown in figure7. In this picture, it is also shown that freight train 1, which was scheduled in the former step is considered as an input for the location-time graph in the current step. Moreover, the graph movement of the ant is updated by omitting freight rake 3 as shown in figure 8.
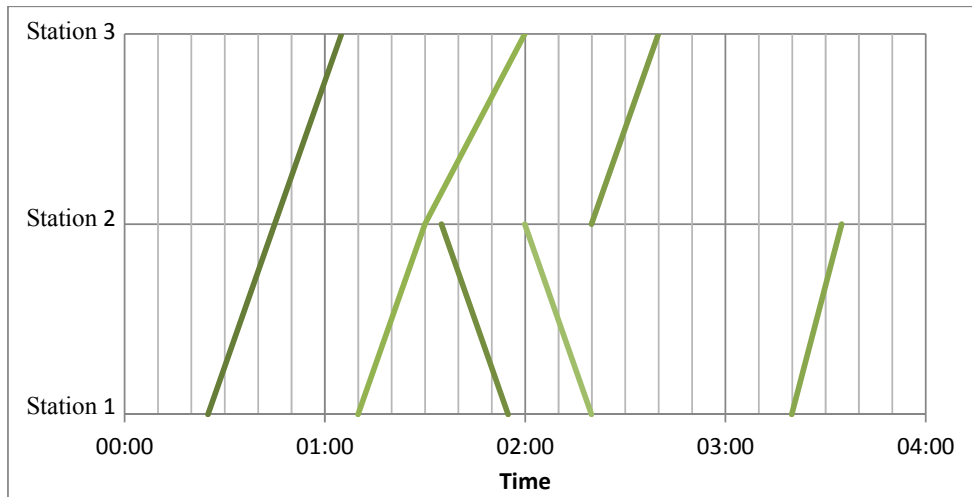
Fig. 7. The location- time graph for hauling freight rake 3 by locomotive 2
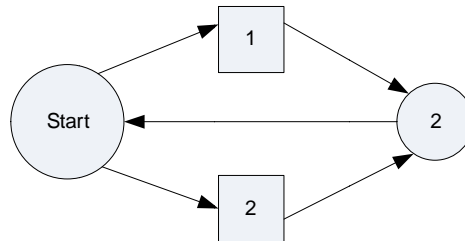

Fig. 8. The updated graph of ant movement after hauling rake 3 by locomotive 2

The ant goes back to the start point, selecting the next locomotive randomly. Assume it selects locomotive 1which is now located in station 3. As the planning horizon time of the locomotive 1 is not completed yet, the ant is allowed to select this locomotive one more time. As the freight rake 2 is the only remained rake, the locomotive selects it. Therefore, the third freight train is also scheduled to move across the network as shown in figure 9.
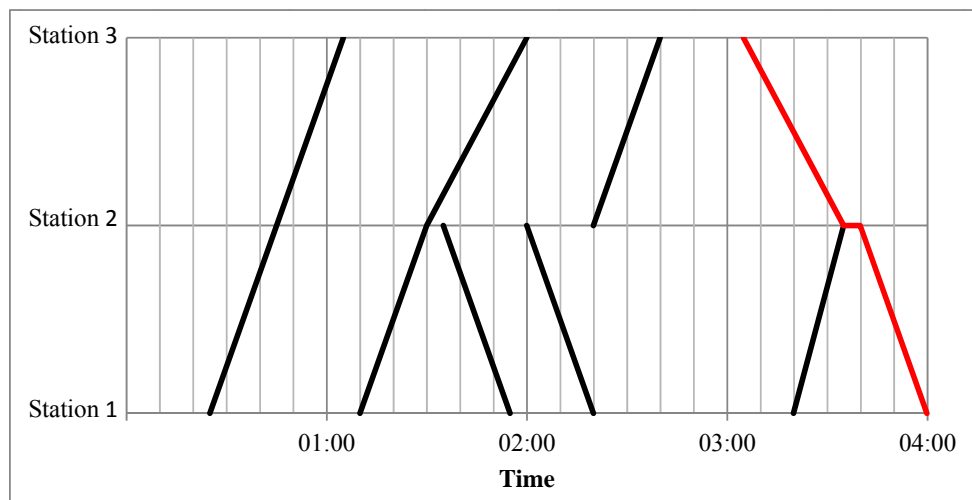

Fig. 9.The location- time graph for hauling freight rake 3 by locomotive 1

The fitness value for this ant is calculated using Equation (9). The other ants also follow the same procedure and the fitness value is calculated for them as well. When the colony comes to the end, the ant with the highest fitness value implies as the best solution of the colony. A reduction of 2% occurs for the pheromone value of the arcs on which the best ant of the colony moves. So the

pheromone is updated locally according to the Equation (4). The global update occurs as well by the best-so-far solution using Equation (5). Then the second colony starts to generate new solutions.

Considering the small-scale of the current test problem, the selected ant in the first colony is chosen as the best solution for the second colony as well, that is the best solution of the problem. The fitness value, weight and the average of tardiness for this ant is calculated as 0.028, 1 and 12 minutes accordingly. It should be noted that the ACS and the other metaheuristic algorithms are appropriate algorithms for the large-scale problems. Applying this algorithm for this small example is just to explain the proposed algorithm.

4-2. Applying proposed algorithm for the Iran Railways

To evaluate the efficiency of the proposed algorithm for solving the compound problem of locomotive assignment and freight train scheduling for real world problems, it was employed for Iran Railways network.

Iran Railways network has the form of star type networks where Tehran is located in the central area of network as a hub and other regions are connected to it. Iran Railways network is depicted in figure 10. The current Iran Railways network contains 170 yards, where demands are shipped from about 50 origin yards; about 90 yards have the facilities of classifying blocks and origin-destination demands received in 100 destination yards. Since the problem has been considered at the operational level, the data for the number of freight rakes and the available locomotives are needed at the real time, which is not available for Iranian Railway. Therefore, we generate some simulated data as well as using the real data for Iranian railway. The real data of Iran Railways used in this study contains main yards of the Iran Railways, the distance between the yards, the hauling time of the freight trains through block sections, and the passenger train time window. In addition, we simulate some data consists of the number of freight rakes, the origin and destination of the freight rakes, the number of available locomotives, and the location of the locomotives.
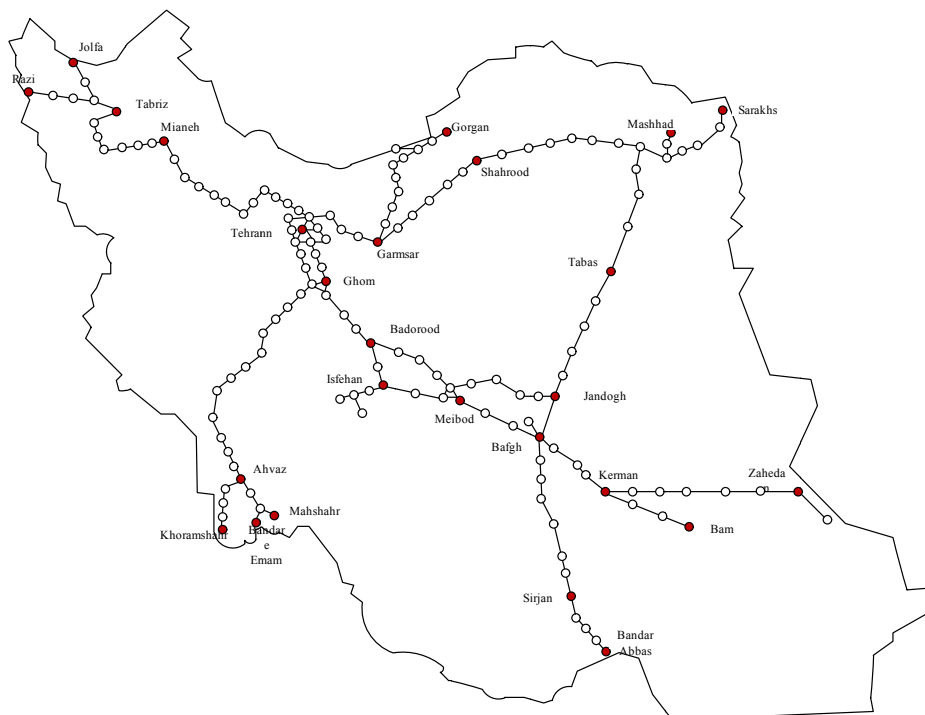

Fig. 10. The physical network of Iran Railways

The solution results of the proposed algorithm for the compound problem of the locomotive assignment and the freight train scheduling in Iran Railways network is illustrated in Table 2. Twenty-five test problems are generated based on the real and simulated data of Iran Railways.

Tab. 2. Results for 25 test problems implemented for Iran Railways using Ant Colony System

Test Problem	Number of Locomotives	Number of Freight Rakes	Number of Tardy Trains	Fitness for the best Ant	W for the best Ant	Average of Tardiness
1	5	5	1	0.00777	0.93432	72.28
2	5	5	2	0.00017	0.87243	125.65
3	5	5	1	0.00467	0.94573	77.67
4	5	5	1	0.00513	0.90243	81.59
5	5	5	2	0.00536	0.95826	141.70
6	5	10	3	0.00068	0.91573	79.16
7	5	10	3	0.00670	0.87538	91.14
8	5	10	2	0.00195	0.89405	68.49
9	5	10	3	0.00446	0.89247	95.06
10	5	10	2	0.00300	0.89206	69.80
11	10	15	3	0.00400	0.91022	64.05
12	10	15	3	0.00023	1.00000	62.37
13	10	15	4	0.00528	0.83786	88.34
14	10	15	3	0.00298	0.93640	65.17
15	10	15	5	0.00481	0.80305	100.81
16	10	20	4	0.00167	0.87406	67.10
17	10	20	5	0.00743	0.82277	75.77
18	10	20	5	0.00528	0.79922	77.47
19	10	20	5	0.00008	0.79277	76.90
20	10	20	4	0.00173	0.85001	66.18
21	15	20	5	0.00395	0.84856	78.45
22	15	20	4	0.00691	0.70265	72.83
23	15	20	5	0.00618	0.72053	97.59
24	15	20	5	0.00387	0.82064	89.18
25	15	20	4	0.00999	0.94161	83.97

In Table 2, the second and third columns show the quantity of the available locomotives, which are 5, 10 and 15 locomotives, and the quantity of the freight rakes, which are 5, 10, 15 and 20 rakes. In the latter columns of the table, the fitness value of the best solution, the value of *W* for the best ant and the average tardiness is calculated for each test problem using the proposed algorithm.

5. Conclusion

In this paper, the locomotive assignment and scheduling of freight trains were solved simultaneously using the ASC algorithm. The tuned parameters of the proposed algorithm was reported in Table 1. The different simulated test problems based on the conditions of Iran Railways were solved by implementing the proposed algorithm. The results showed in Table 2 illustrates the quantity of the available locomotives and the quantity of the freight rakes. The deadheading locomotives and tardy trains impose high operational costs on the systems. Therefore, it is crucial for railway companies to plan the locomotives and freight trains to attain the minimum deadheading time and the minimum train tardiness. Using the proposed algorithm

specifically for the railways in which trains do not follow a pre-determined schedule decreases the high operational costs of the locomotives and freight trains on the system.

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