Multi-objective mathematical modeling of an integrated train makeup and routing problem in an Iranian railway company

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Abstract. Train formation planning faces two types of challenges; namely, the determination of the quantity of cargo trains run known as the frequency of cargo trains and the formation of desired allocations of demands to a freight train. To investigate the issues of train makeup and train routing simultaneously, this multi-objective model optimizes the total profit, satisfaction level of customers, yard activities in terms of the total size of a shunting operation, and underutilized train capacity. It also considers the guarantee for the yard-demand balance of flow, maximum and minimum limitations for the length of trains, maximum yard limitation for train formation, maximum yard limitation for operations related to shunting, maximum limitation for the train capacity, and upper limit of the capacity of each arc in passing trains. In this paper, a goal programming approach and an $\ell_p$ norm method are applied to the problem. Furthermore, a simulated annealing (SA) algorithm is designed. Some test problems are also carried out via simulation and solved using the SA algorithm. Furthermore, a sample investigation is carried out in a railway company in Iran. The findings show the capability and performance of the proposed approach to solve the problems in a real rail network.

KEYWORDS: Train makeup and routing problem; Optimization with multiple objectives; $\ell_p$ norm; Goal-oriented optimization (GP); Simulated annealing.

1. Introduction

Dependent on a policy, sustainability and environment, transportation is considered to have a significant role in improving economic conditions of a country leading to enhanced economic indices, such as gross domestic product (GDP) \cite{1-2}. Recently, new development opportunities for various industry and service sectors have been made possible by railway transportation.

Railway enjoys significant advantages to other methods of transportation because it is able to respond to freight demand in bigger distances in terms of length as demanded with a higher safety degree \cite{3}. Empirical findings based on indicators and

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performances show the concern for the operational optimization of a railway network based on important objectives, such as economy, efficiency and customer satisfaction. Consequently, among the various studies in railway transportation, a growing body of evidence from the transportation literature shows that a train makeup problem (TMP) has a remarkable importance in academia and practitioners. Hence, the TMP has gained significance in railway transportation planning investigations. Among the various goals of optimization, an important objective has received the main attention, in which the necessary trains are formed to satisfy demand in a desired period of time. In addition, such an optimization model also considers the operational and physical constraints of the network to achieve feasible and optimal sizes, frequencies, assignments, traction, and demand profiles regarding the specific objective functions [4]. However, due to NP-hardness issues, the main challenge remains to deal with the difficulty of solving the train makeup problem in the context of a design problem of a service network.

Some new features are added to the railway planning literature in this research. In some railway transportation networks, there may be different routes from each origin to a destination. A generic routing problem tries to determine an optimal route to provide an efficient routing plan. A routing problem in the TMP is not taken into account in literature reviews; therefore, a novel optimization model with multiple objectives is considered based on integrating the makeup train and routing problems all together. In comparison to the current literature, some new constraints are added to the optimization model, which improve its validity in order to provide a better basis of reflecting real-world conditions. Following the common stream of research in multi-objective optimization, goal programming (GP) and $L_p$ norm methods are applied. In addition, a new simulated annealing algorithm is proposed to provide good solutions for the problem. Considering the application of the algorithm, ten randomly designed problems as well as a real-world problem in the context of a railway company in Iran are tested by the algorithm. To compare with the CPLEX standard software, some of the results from the algorithm, which are more pertinent, are checked for more efficiency with those obtained from the software.

Several sections contribute to the organization of the paper. Studies related to the TMP are reviewed in Section 2. Section 3 presents a model for the train makeup and routing problem based on a new approach considering new multiple objective functions. Following the main optimization research stream, Section 4 applies two important optimization methods to find a single objective function to replace with the multiple objective functions of the model. Section 5 reports the results of applying the solution method to some randomly generated test problems and provides optimality and sensitivity analysis findings. Based on a hybrid meta-heuristic, Section 6 proposes a new algorithm via developing a novel hybrid simulated annealing algorithm. Section 7 presents the computational findings of applying the algorithm to 10 randomly generated test problems and a real world problem associated with a railway company in Iran. As the final section, Section 8 concludes the paper and provides some further research remarks.
2. Literature review

A TMP has received the attention of researchers from a mathematical point of view. For example, Assad [5] presented a multi-commodity network flow model to analyze a TMP. To investigate tactical planning, in a programming model with a mixed-integer and non-linear nature solved by a heuristic method, Crainic et al. [6] minimize delay and operating costs. Based on a heuristic approach and a Lagrangian relaxation technique, Keaton [7] developed a method to deal with a programming model with a mixed-integer structure. Morlok et al. [8] developed a programming model with a mixed-integer linear structure and used a branch-and-bound technique to solve some small-sized instances. Huntley et al. [9] presented an MINLP model and used a SA algorithm to find a near-optimal solution. Adopting a hybrid approach, Yaghini et al. [4] designed a SA which is based on simplex for the TMP, in which the moves in this method are evaluated, selected and implemented. Bagheri et al. [10] proposed a method of placing hazardous material cars to minimize the derailment risk during the train assembly process. With respect to yard activities, they took into account the chance associated with derailing of railway cars with the route and the probability of extra activities.

Shafia et al. [11] developed a novel robust model with a mixed-integer nature for a TMP with uncertain input data, in which a heuristic method is designed because of the difficulty of finding an optimal solution. Based on the train scheduling and focusing on the average travel duration time, Sun et al. [12] considered the user’s satisfaction and energy consumption to present an optimization model with multiple objective functions for the train routing on a railway network supporting high-speed, which is able to provide an important basis for planning of train to provide a good service. For implementation purposes, an enhanced genetic algorithm (GA) is developed and implemented. Yaghini et al. [3] developed a hybrid technique to solve a mathematical model for train makeup planning with fuzzy costs in an Iranian railway system. In fact, they developed a network design model that considers a fixed-charge situation with capacity limitations and multiple commodities. In an operational setting on a railway network, Masek et al. [13] mathematically investigated the transportation of single wagon consignments. Borondofer et al. [14] analyzed a problem that considers the freight train routing. Considering both passenger and cargo, they investigated a transport network, in which routes of trains are fixed. Taking into account all running times and all expected delays for each freight train, they found feasible and optimal routes. Boysen et al. [15] introduced and discussed the train formation problem in its basic setting. They analyzed the status of its complexity and designed both heuristic and exact solution methods. They also tested their solution method in a wide-ranging computational experiment. Cheng et al. [16] proposed a methodology to assess risk. Adopting a mathematical approach, they modelled the train formation and the location of railcars of a hazmat kind in a predefined transport passage. A sample study was
considered and analyzed to gain managerial insights with four different sets of conditions related to an American network.

Based programming with a mixed-integer nature, Bahrami et al. [17] investigated by integrating hub location and vehicle routing problems in order to provide door-to-door parcel delivery services. A simulated annealing approach helps them to propose a novel technique that has multiple steps based on an algorithm with local search capability. They used the technique to solve a real case in Iran. Gallardo-Bobadilla et al. [18] apply a linear programming approach to optimize the railway blocking problem efficiently and find the optimal allocation of shipments to blocks and their routing plan with an acceptable level of error. Yaghini et al. [19] proposed a modified specific method of a train makeup problem. This is an exact approach in real life of the railway network. This method is proposed to modify the behavior of a standard solver to deal with a mixed-integer programming problem.

Jamili [20] focused on trip duration and expected deferrals and presented a novel periodic train-scheduling mathematical model under uncertainty. He proposed simulated annealing (SA) and electromagnetism-like method (EM) as well as a hybrid of these two metaheuristics for solving the problem. To deal with an integer-linear setting, Tavakkoli-Moghaddam et al. [21] designed a programming model for a cell formation problem in an environment that is dynamic with a multi-cycle scheming vision. This problem is categorized as an NP-hard problem, thus they took into account an SA algorithm to solve their model. Furthermore, Alikhani-Kooshkak et al. [22] presented a multi-objective model for the train makeup problem with locomotive limitations. They considered seven different objectives (e.g., minimizing the total lost demand, the transfer time of trains, and the total consumed fuel) and proposed a hybrid firefly algorithm to solve the problem in a real-word application.

Despite its multi-dimensional nature, the literature review reveals that the multi-objective optimization of the TMP is understudied. Some examples are offered here. First, maximization of the profit is possible via mathematical focus on incomes and expenses. Second, maximization of the customers’ satisfaction level is attainable by considering frequencies of trains. This results in the decrease of the time demands spend in yards for shunting activities. Thus, one criteria to the maximization of the customers’ satisfaction level and minimization of the costs is to assume maximizing trains in terms of the total frequencies, minimizing yard activities in terms of the total quantity of the action of shunting kind, and minimizing the train underutilization.

This is currently missing from the literature (see for example [3-4]); basically, minimization of variable and fixed costs is common in the current literature. In addition, all the required constraints associated with train formation problem is not considered in the current stream of research. Focusing on the length of train, Yaghini et al. [19] models merely the biggest train considering the size of station with respect to the quantity of trains and the quantity of action of a shunting kind. In other words, they do not consider the vital concepts such as the determined minimum limitation related to the least length of each train which is formed, train tonnage, the capacity of
yard in terms of tonnage, the time available and upper limit of the capacity of each arc in passing trains for different routes in the railway network.

3. Mathematical model

In this section, we optimize the fixed and variable costs of transportation. In doing so, we assume the transportation of goods with a specific origin and destination for each based on available information (e.g., [19]). Here, the origin and destination define each train. We also assume that there exists a balance of the flow for each yard-demand pair. Furthermore, we consider there is an upper limit for the length of train constraining the amount of demands allowed to be allocated to an arbitrary train. Each yard faces a maximum limitation in the number of trains it can form and another maximum limitation in the size of demands put together for train formation in an operation with a classification or shunting nature. We extend the current literature by adding some new features. First, we assume a routing problem with the train makeup in railway networks. In some railway transportation networks, there may be different routes from each origin to a destination. Each route of a network consists of some tracks (i.e., arcs), in which each track has a specific capacity (i.e., a number of trains passing through the track in a specific time period). Additionally, one of the main contributions of this presented model is to transfer the demands from an origin to a destination via different routes consisting of tracks (i.e., arcs) with the limited capacity. It is worth noting that decision for train’s route is based on the objectives of our integrated train makeup and routing problem and related limitations. In fact, this model determines the trains and relevant routes in order to transport dedicated demand. Notably, the proposed model specifies that each demand must be transferred by which trains. It is worth noting that the basic model [19] does not cover this topic. It may not be economical to form a train to carry almost nothing due to a very low volume of demands. In addition, the capacity of routes in terms of tonnage and the arcs capacity in terms of the size of frequencies of passing trains via arcs are constrained. Therefore, this paper considers some new constraints to supplement the original model to improve its validity by considering previously ignored important real life conditions. In particular, we assume a minimum limitation for the length of train to constrain the least amount of demands that can be allocated to a train. We consider a maximum limit in terms of tonnage for the capacity of yard operations of a shunting type. We also assume a maximum limitation for the number of trains that is allowed to pass an arbitrary arc of the network.

Second, in the basic model, all the requests for transportation are accepted. In contrast, we allow for the lost demand property in our model and compare the costs and benefits of accepting a request. This leads to denial of some demands due to their uneconomical nature. These directions are not considered in the previous literature.

In this paper, we consider four objective functions by optimizing the profit and the customers’ satisfaction level to its maximum possible and yard activity in terms of the
total quantity of the operation of a shunting kind and the underutilized trains in terms of tonnage to its minimum possible.

Based on the above points, we adopt a mathematical approach to formulate a novel model as follows.

3.1. Notations

\( k \) Demand \( k \) belongs to the set \( K \)

\( t \) Train \( t \) belongs to the set \( T \)

\( s \) Yard \( s \) belongs to the set \( S \)

\( r \) Route \( r \) belongs to the set \( R \)

\( i \) Arc \( i \) belongs to the set \( I \)

\( K \) Set \( K \) denotes demands originating an arbitrary node called \( \text{orig}(k) \) and destined to \( \text{dest}(k) \)

\( T \) Set \( T \) denotes trains carrying demands. Each train starts at its origin and ends at its destination in a setting where its origin and destination are set before. The train does not load or unload any demand in the midway; but, it is allowed to take many paths in its entire trip.

\( S \) Set \( S \) denotes yards. Each yard receives trains, breaks them up, blocks their cars, assembles their demand and forms the train. After these activities, the train is ready to depart the station.

\( R \) Set \( R \) denotes the routes between the origin and destination (O-D) of trains. Each route contains a number of arcs

\( I \) Set \( I \) denotes the arcs in the related railway network

\( \text{orig}(k) \) Demand \( k \) originates from node \( \text{orig}(k) \)

\( \text{dest}(k) \) Demand \( k \) is destined to node to \( \text{dest}(k) \)

\( G_k \) One unit of demand \( k \) has the weight \( G_k \)

\( b_k \) If the rail company ships demand \( k \), it gains \( b_k \) for each unit of demand

\( d_k \) Amount of flow \( d_k \) from its origin \( \text{orig}(k) \) to its destination \( \text{dest}(k) \)

\( c_{kt}^k \) Shipping one unit of demand \( k \) on train \( t \) has the cost \( c_{kt}^k \)

\( f_t^r \) Forming train \( t \) on route \( r \) has the fixed cost \( f_t^r \)

\( U_t^r \) Train \( t \) on route \( r \) has a maximum \( U_t^r \) of units of demand allocated to it. This concept helps to define the biggest train in terms of length.

\( L_t^r \) Train \( t \) on route \( r \) has a minimum \( L_t^r \) of units of demand allocated to it. This concept helps to define the smallest train in terms of length.

\( P_t^r \) Train \( t \) on route \( r \) has the capacity \( P_t^r \) in terms of tonnage

\( Q_s \) Shunting operation in yard \( s \) has the capacity \( Q_s \) in terms of tonnage

\( H_s \) Trains formed in yard \( s \) have the maximum number \( H_s \)

\( N_s \) Shunting operations operated in yard \( s \) have the maximum number \( N_s \)

\( A_i \) For a desired period of planning, trains passing through arc \( i \) have the maximum number \( A_i \)

\( c_k \) Rail company loses \( c_k \) for each unit of demand if it rejects demand \( k \)

\( a \) Planner is allowed to reject the fraction \( a \) of demands as lost sale ratio
3.2. Decision variables

- $x_t^k$: Demand $k$ on train $t$ has the flow amount of $x_t^k$
- $y_t^r$: Train $t$ on route $r$ has the number of frequencies $y_t^r$
- $w_k$: Demand $k$ has the amount $w_k$ as the number of lost units from transporting.

In assessing a request, the rail company compares both benefits and costs of accepting a request.

3.3. Mathematical model

3.3.1. Objective functions

In this section, we explain the objective functions of our model. The first objective function optimizes the profit. It attempts to maximize the incomes. In addition, it tries to minimize the costs. Variable, fixed and lost demand costs are considered in the model. The second objective function optimizes the customers’ satisfaction level. It attempts to maximize the total train frequencies. If we increase the total train frequencies, a decrease in demands waiting in yards of a shunting type prepared to transfer from an origin to a destination is expected; consequently, one criteria to the improvement of the customers’ satisfaction level may be considered as maximizing the total train frequencies. The third function targets the minimum of the yard activities in terms of the total number of operations of a shunting type. Putting differently, the main objective here is to minimize the unnecessary disassembly of wagons (i.e., demands) in intermediate stations before arriving the destination targeted by the demand. In fact, this approach leads to minimization of demands transportation via trains with mismatching origins and destinations. The best scenario occurs when two conditions are satisfied: a) the origin of demand and the origin of train carrying the demand coincide, b) the destination of demand and the destination of train carrying the demand coincide. This implies that the optimal plan to transport a demand which avoids the unnecessary shunting costs and operations requires a single train which carries the demand throughout its journey from its origin to its destination. The fourth objective function targets the minimum of underutilized trains. It tries to find the minimum of the difference of the trains in terms of tonnage able to carry and the demands, which are transferred.

\[
\begin{align*}
\text{Max } Z_1 & = \sum_k b_k (d_k - w_k) - \sum_k \sum_t c_t^k x_t^k - \sum_t \sum_r f_t^r y_t^r - \sum_k c_k w_k \quad (1) \\
\text{Max } Z_2 & = \sum_t \sum_r y_t^r \quad (2) \\
\text{Min } Z_3 & = \sum_s \sum_{k} \sum_{t} x_t^k \\
& \quad \text{subject to } \text{dest}(k) \neq \text{dest}(t) \text{ and } \text{dest}(t) = s \quad (3)
\end{align*}
\]
Min $Z_4 = \sum_t \sum_r P_t^r y_t^r - \sum_k \sum_t G_k x_t^k \quad (4)$

3.3.2. Limitations considered in the model

Allowing for the lost demand for transportation. Constraint (5) establishes the balance of flows for all the yard-demand pairs. Constraint (6) requires the predetermined maximum limit for the trains that are formed in terms of its length to constrain the uppermost quantity of the demands allocated to trains. The inequality (7) requires the predetermined maximum limit for the quantity of trains formed in all the yards. Constraint (8) requires the predetermined maximum limit for the yard activity in terms of the number of the operations of shunting type. Constraint (9) examines the predetermined minimum limit for each formed train in terms of its length. Constraint (10) demonstrates the capacity of train in tonnage as a maximum limit. It models the maximum weight the train is allowed to carry. The inequality (11) ensures that each yard shunts demands as much as its shunting capability in terms of tonnage. For a desired period of planning, the inequality (12) necessitates the predetermined maximum limit for the overall frequencies of trains passing each track. Constraint (13) defines the magnitude of demands permitted to be lost since they are rejected and will not be transported. Since variables $x, y$ and $w$ are required to be integer, Constraint (14) imposes this requirement.

\[
\sum_{\text{orig}(t)=i} x_{t}^{k} - \sum_{\text{dest}(t)=i} x_{t}^{k} = \begin{cases} 
  d_k - w_k & \text{orig}(k) = i \\
  -d_k + w_k & \text{dest}(k) = i \\
  0 & \text{otherwise} \end{cases} \quad \forall i \in S, k \in K \quad (5)
\]

\[
\sum_k x_t^k \leq \sum_r U_t^r y_t^r \quad \forall t \in T \quad (6)
\]

\[
\sum_t \sum_{r\in \text{Orig}(t)=s} y_t^r \leq H_s \quad \forall s \in S \quad (7)
\]

\[
\sum_k \sum_{\text{dest}(k)\neq\text{dest}(t)} \sum_t x_t^k \leq N_s \quad \forall s \in S \quad (8)
\]

\[
\sum_k x_t^k \geq \sum_r L_t^r y_t^r \quad \forall t \in T \quad (9)
\]

\[
\sum_k G_k x_t^{k} \leq \sum_r P_t^r y_t^r \quad \forall t \in T \quad (10)
\]

\[
\sum_{\text{dest}(k)\neq\text{dest}(t)} \sum_t G_k x_t^k \leq N_s Q_s \quad \forall s \in S \quad (11)
\]
\[
\sum_{i \in r} y_t^r \leq A_i \quad \forall i \in I \tag{12}
\]
\[
w_k \leq a_k d_k \quad \forall k \in K \tag{13}
\]
\[
x_t^k, y_t^r, w_k \in \text{Integer} \tag{14}
\]

4. Multi-objective decision making approaches

It is well-known that there are three main well-known methods to solve a multi-objective optimization problem, namely (1) a priori articulation of preferences, in which before running the optimization algorithm, the user is able to determine the relative importance of the objective functions or desired goals, (2) a posteriori articulation of preferences, in which a single solution is selected out of the various possible solutions that are equivalent from a mathematical point of view, and (3) no articulation of preferences where the decision maker is not able to determine any preference.

Based on our discussions with managers of the Iranian railway network, we find that although the managers understand the importance of considering multiple objectives in this decision making, they are not able to determine any preference over the objectives. This is the first time they are to introduce such an approach to the network. Consistent with the literature discussed above, we consider goal programming and \( L_p \) norm approaches to solve our problem, in which all the weights are set to one. This is because, these approaches are basic methods that are belongs to the category of “a priori articulation of preferences” and the category of “no articulation of preferences”. It is indeed a simplified version of the a priori category, in which all the weights are considered to be equal to one (see for example [23]).

In this section and for aggregation purposes, we adopt two common aggregating approaches, namely goal programming and \( L_p \) norm, to convert a mathematical model with multiple objectives to a model with one objective.

4.1. Goal programming approach

In the goal programming aggregation method (see, for example [22]), the objective function is defined by:

\[
\text{Min } Z = \theta_1 v_1^+ + \theta_2 v_2^+ + \theta_3 v_3^- + \theta_4 (v_4^+ + v_4^-) \tag{15}
\]

In addition, the constraints below are supplemented to the above developed model.

\[
\sum_k b_k (d_k - w_k) - \sum_k \sum_t c_t^k x_t^k - \sum_r \sum_t f_t^r y_t^r - \sum_k c_k w_k - (v_1^+ - v_1^-) = M_1 \tag{16}
\]
\[
\sum_t \sum_r y_t^r - (v_2^+ - v_2^-) = M_2 \tag{17}
\]
\[ \sum_{s} \sum_{k}^{ \text{dest}(k) \neq \text{dest}(t) } \sum_{t} (x^k_t - (v^+_s - v^-_s)) = M_3 \] 
\[ \sum_{t} \sum_{r} P^r_t y^r_t - \sum_{k} G_k x^k_t - (v^+_4 - v^-_4) = M_4 \]
\[ v^+_i, v^-_i \geq 0 \ \forall i \in Z \]

where \( \theta_i \) denotes the coefficient, \( v^+_i \) denotes the slack variables, and \( v^-_i \) denotes the surplus variables of objective function \( i \). \( M_i \) symbolizes the desired level (target value) for the individual objective function \( i \) (i.e., IOF \( i \)). Here, this parameter may be assumed as the optimal objective function value (OFV) as the same is done here.

With regard to the following issues, the sum of deviation of individual objective functions from the related desired level is minimized in objective function (15):

- Orientation aimed individually by each objective function (e.g., max and min).
- Individual importance factor of each objective function.

The inequalities (16) to (19) are associated with objective functions (1) to (4) by regarding their related individual level, which is desired. Constraint (20) shows that the variables of surplus and slack \( (v^+_i \text{ and } v^-_i) \) are positive.

4.2. \( L_p \) norm method

Concerning the \( L_p \) norm technique, the aggregated mathematical goal is as below:

\[ \text{Min } L - P = \left[ \Delta_1 \left( \frac{Z^*_1 - Z_1}{Z^*_1} \right)^p + \Delta_2 \left( \frac{Z^*_2 - Z_2}{Z^*_2} \right)^p + \Delta_3 \left( \frac{Z^*_3 - Z_3}{Z^*_3} \right)^p + \Delta_4 \left( \frac{Z^*_4 - Z_4}{Z^*_4} \right)^p \right]^{1/p} \]

where \( \Delta_i \) symbolizes the multiplier of mathematical goal \( i \), \( Z_i \) symbolizes mathematical goal \( i \), and the \( Z^*_i \) stands for the optimal OFV \( i \). Objective function (21) tries to minimize the sum of normalized deviation of individual objective functions from a related solution, which is optimal, taking into account the following issues:

- Kind of the deviation calculation \( (P) \).
- Fraction of deviation by taking into account the related individual OFV, which is optimal.

Here, we consider objective function (21) with \( p=1 \) (i.e., linear) and \( p=2 \) (i.e., nonlinear). The set of constraints is identical with no difference.

5. Results and analysis for sensitivity

5.1. Experimentation of our model

Here, we consider ten random problems. Our computer has Intel Core 2 Duo 2.53 GHz CPU and 4.00 GB of RAM. We use the standard solver CPLEX version 12.4. The
incoming value $b_k$ is two times the value of demand loss cost $c_k$. The multipliers of all objectives are identical in all the techniques. When weights of the objectives are not pre-specified, considering identical importance values for them is not a strange task in the literature [24]. Thus, we allocate importance values (weights) that are equal to 1 to all the goals before being aware of the importance values for the objective functions. We define the test problems in Table 1.

{Please Insert Table 1 about here.}

At first, the test problems are dealt with by taking into account each objective function individually. Table 2 demonstrates the outcomes of our numerical experiments. Here, GP as well as $L_p$ norm techniques solve these problems. Table 2 shows the values of the IOFs that are optimal. As shown in this table, the data related to column IOF 3 are all zero. In other words, in all the test problems 1 to 10 the total number of shunting operations is zero which indicates that there is no unnecessary disassembly and assembly operations (shunting operation) in the network in the optimal solution for two reasons. First, the high variety of trains to transport demands of the problem with common origins and destination. Second, there exist demands with origin and destination different from the origin and destinations of available trains which are rejected from transportation by the lost sale constraint (i.e., Constraint (13)). Finally, the results of the IOF 3 seem to be an ideal solution with respect to the data of this problem.

{Please Insert Table 2 about here.}

Table 3 shows the outcome of our numerical experiment. The standard solver software does not find any solution in 10 hours. The findings indicate the suitability of CPLEX in terms of time resource when $p=1$ and for GP. Therefore, they are almost similar since they demonstrate the same performance. However, based on the solving time reported in Table 3, the $L_1$ norm method always outperforms the goal programming method as reported in all the cases of Table 3, the solving time related to the $L_1$ norm method is less than the solving time related to the goal programming method (see Figure 1). However, due to the non-linearity for the case $p=2$, even a feasible solution cannot be found in 10 hours of time for problems with a considerable size. It is worth noting that deviation of individual objective functions in goal programming methods doesn’t normalized, therefore the optimal value of this method is different from $L_p$ norm method.

We consider two cases: $p=1$ and $p=2$ for the $L_p$ norm technique. Because of the the non-linearity of the case $p=2$, the technique for $p=2$ is able to effectively discover better solutions in the related solution space [25]. Because of the compatibility of non-linear models with real life conditions and their capability to attain the suitable quality in solution finding, the $L_2$ norm method is applied. In the $L_p$ norm method with $p = 2$, the solver has to examine much more points in solution space, which calls for much
more time for discovery of no-dominated solution. The outcomes in Table 3 demonstrate this argument. Regarding this issue, Figures 2 (a) and (b) demonstrate the $L_p$ norm method in discovery of a solution for $p=1$ and $p=2$, individually. In addition $L_p$ norm with $p=1$ was merely used for testing the model and sensitivity analysis.

5.2. Sensitivity investigation

In order to investigate the sensitivity of our model, we use problem No. 3 in this section. This model contains multiple objective functions with different characteristics. Since each function has a different impact on the solutions, their multipliers and the target value of each individual are examined in our sensitivity analysis [26-27]. Four different aspects described below are very important, because some of the aspects are the basic factors in converting the model with multiple objectives into a single combined objective one.

5.2.1. Impact of cost of losing demands on IOF (1)

Figure 3 demonstrates that increasing the cost of losing demands ($c_k$) leads to a significant reduction in the value of the IOF (1). As shown in Figure 2, increasing the cost of the losing demands is caused by decreasing the IOF (1) indicating a great impact on the objective function by this parameter. Figure 4 demonstrates that increasing in the cost of the losing demands leads to more demands coverage.

5.2.2. Impact of varying the multiplier of IOFs in the $L_1$ norm method

The importance factors of all IOFs are fixed as 1. The output of the mathematical objective for the $L_1$ norm technique is examined by varying the importance factor of each IOF and assuming the rest are unchanged. Additionally, the importance factor of the selected IOF is fixed as 100. Figure 5 exhibits the impact of changing the importance factor of IOFs on the mathematical objective for the $L_1$ norm method. The outcomes demonstrates the great importance of the IOF (1).

5.2.3. Impact of varying the multiplier of IOFs in the GP method
To solve the problems by the GP method, the importance factors of all IOFs are fixed as 1. The output of the mathematical objective is examined by varying the importance factor of each IOF and considering the rest are unchanged. The importance factor of the chosen IOF is fixed as 5. Figure 6 shows the effect of varying the importance factor of IOFs on the mathematical objective by in the GP method. The findings indicate significant importance of IOF (1) compared to other IOFs.

5.2.4. Impact of changing the target value of IOFs in the GP method

To solve the problems in the GP technique, the target values of all IOFs are set to their best values. The output of the mathematical objective is studied by varying the target value of each IOF and assuming the rest are unchanged. Figure 7 shows the impact of varying the target value of IOFs (i.e., ±20%) on the mathematical goal in the GP method. The related results illustrate the more important role of IOF (1) over other IOFs in contributing to the best output of the mathematical goal.

6. Proposed hybrid algorithm design

We adopt a meta-heuristic approach here to solve the model in case \( p=2 \) for the \( L_p \) norm technique. The rationale behind our effort is the nonlinearity of the model in this case which leads to unacceptable requirement for time resource for computational purposes. Specifically, we design a hybrid algorithm considering the SA and branch-and-cut algorithms.

SA as a well-known meta-heuristics was first introduced by Kirkpatrick et al. [28]. The main steps of SA are as follows. Starting with an initial solution, SA moves to other alternative neighboring solutions iteratively. If the alternative solution outperforms the current solution, it is chosen as the new solution. If, however, the performance of the alternative solution is worse than the current solution, it is still accepted by the probability \( \exp(-\frac{\Delta E}{T}) \), where \( \Delta E \) denotes the difference of the OFV between the current and alternative neighboring solutions, and \( T \) is a parameter called temperature to control the exploration process of the SA algorithm. Many iterations are executed at each temperature. Then, gradually, the temperature is decreased. While, initially, the temperature is selected to be at its highest value to increase the probability of accepting undesirable solutions in terms of the OFV, the temperature has its lowest value at the end of search to decrease the probability of accepting undesirable solutions. Subsequently, we explain the structure of our hybrid algorithm and its building blocks.

In our meta-heuristic method, SA specifies the lost demand \( w_k \) and the exact method solves for other unknows of the model. In Figure 7, a pseudo code for our meta-
heuristic algorithm used in the problems with \( p=2 \) of presented model is shown. In this pseudo code, \( \textit{currentSolution} \) denotes the current solution, \( \textit{initialSolution} \) denotes the initial solution, \( \textit{neighborSolution} \) denotes the neighborhood solution and \( \textit{bestSolution} \) denotes the best solution. In addition, \( \textit{Cycle} \) denotes the number of moves needed to generate neighboring solutions. When this number reaches the defined value \( (\textit{MAX\_CYCLE}) \), the internal loop of the algorithm terminates to start the new iteration with the new temperature. Afterward, the building blocks of our pseudo code are explained.

6.1. Generating initial solution

To generate an initial solution, we apply the \( L_1 \) norm technique in the standard solver. In so doing, we temporarily assume a full coverage of all demands and all of \( w_k \) variables are set to zero. We then plug the solution from the \( L_1 \) norm technique into \( L_2 \) norm and consider its value as \( \textit{initialSolution} \) (See Figure 8). Since the \( L_1 \) norm technique is much more efficient compared to the \( L_2 \) norm technique, we apply it to find initial feasible solutions in a fast manner.

6.2. Generating the neighbor solutions

The initial solution generation step leads to another step, in which a move is required to search the solution space. Figure 9 shows the pseudo code of the procedure for generating a neighbor solution. In each cycle of move, this process should be done. In this pseudo code, \( \textit{MAX\_TEMP} \) is a parameter that shows the initial temperature in SA.

6.3. Terminating criteria

In the proposed algorithm, two terminating criteria are considered, namely reaching to initial temperature and \( m \) numbers of reducing the temperature without any improvement.

7. Experimental results

For experimental purposes, we test our algorithm on ten test cases. These test cases are already introduced in Table 1. The comparison of the behavior of the standard solver and the proposed algorithm is tabulated in Table 4. In fact, in comparison to the standard solver, our algorithm is able to provide a better solution method in terms of both problem size and speed.
Figure 10 depicts our sample investigation of a star type railway network in Iran. This network has 60 yards. In addition, 200 origin-destination pairs demonstrate its demand pattern. Tehran plays the role of a hub in the center of the network. The yards of the network order the trains and classify them for incoming and outgoing trains, respectively.

The parameters of our sample investigation is tabulated in Table 5. Tables 6 to 8 present the results, which are similar to the results of 10 test cases presented before (see Table 4). Once again, in comparison to the standard solver, our algorithm is able to provide a better solution method in terms of both the problem size and speed.

Table 9 defines the demands associated with Figure 10. Here we consider the lower bound of the demand for each train to be 10. In addition, the upper bound of the demand for each train is assumed to be 45.

Figure 12 show the best plan for train formation. Here, lines show the paths passed by trains. Moreover, circles show the yards. In addition, arrows show the route of trains. The findings indicate that 17 trains are required to be formed. As shown in Table 9, these trains will carry 20 origin-destination pairs. It should be noted in Figure 11, for example, train 8 travels through Bandar Abbas – Bafgh – Yazd – Ardakan – Arzhang – Sistan – Isfahan route that ships demands 3 and train 12 travels through Chadormalo – Ardakan – Yazd route that carries demands 8. It is worth noting there are some loops associated with Figure 10 in the network, for this reason, these issues cannot be shown in Figure 11. The answer shows that some of the demands are not covered (the demand of 6, 7, 13-18 and 20) and all the covered demands are transferred by direct trains.

It is noteworthy the implementation of the proposed model for the Iranian railway network shows that the model is completely practical and can be used for different rail networks in the world. The results reveal the capability of the proposed model.
We considered a mathematical model with multiple objectives for the TMP integrated routing problem. The mathematical objectives maximize the total profit, maximize the customers’ satisfaction level, minimize the total quantity of the operations in the yards of shunting type, and minimize the underutilized trains. To combine these objectives into only one objective, GP and $L_p$ norm techniques were applied. In addition, we recommended a hybrid simulated annealing (SA) algorithm to solve the problem. Based on the standard and proposed techniques and for experimental purposes, we solved ten random test problems. Furthermore, a sample investigation in a railway company in Iran was performed. Our algorithm was able to show nice behavior in all test cases and the sample investigation with a reasonable requirement for time resource while the standard software could not find feasible solutions for some test cases and the sample investigation in 10 hours of time. Our findings show provide significant evidence for the effectiveness of our model as well as the efficiency our solution technique. This paper has also taken into account the customer satisfaction as one of the key issue that will be discussed in more depth and provided more accurate parameters to measure it as the future study. Furthermore, the presented model can be extended in a routing problem by considering the time travel of trains, scheduling and certain restrictions (e.g., safety, cost and benefit).

References


Biographies

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Address: Department of Industrial Engineering, College of Engineering, Karaj Branch, Islamic Azad University, Alborz, Iran  
Postal Code: -  
Phone: -
Captions

Table 1. Test problems

Table 2. Outcomes of each individual mathematical goal to be considered as input for GP and $L_p$ norm approaches employed as optimal solution (i.e., $Z^*_i$) or desired level (i.e., $M_i$)

Table 3. Outcomes of $L_p$ norm and GP techniques

Figure 1. Comparison of the performance of GP and $L_1$ norm techniques, in which the $L_1$ norm method always outperforms the goal programming method.

Figure 2. $L_p$ norm method in discovering a solution for (a) $p=1$ and (b) $p=2$

Figure 3. Impact of increasing the cost of losing the demand (i.e., $c_k$) on the value of the IOF (1)

Figure 4. Impact of the incremental changing rate of the cost of losing the demand (i.e., $c_k$) on the quantity of covered demands

Figure 5. Impact of varying the multiplier of IOFs on the mathematical objective in the $L_1$ norm method

Figure 6. Impact of varying the multiplier of IOFs on the mathematical objective in a GP technique

Figure 7. Impact of variations of the target value of IOFs on the best mathematical objective value in the GP technique

Figure 8. Pseudo code of our hybrid algorithm

Figure 9. Pseudo code of generating the neighbor solutions

Table 4. $L_2$ norm method results (i.e., $p=2$) by using the proposed algorithm obtained by solving test problems

Table 5. Specifications of the Iranian Railway

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Table 7. Results of the $L_p$ norm and GP methods for an Iranian railway network
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Figure 10. Network of the Iranian railway

Figure 11. Part of the network to provide a more detailed illustration

Table 9. Demands related to Figure 10

Figure 12. Train makeup and routing plan for a part of the network by the proposed algorithm.
Table 1. Test problems

<table>
<thead>
<tr>
<th>No.</th>
<th>No. of yards</th>
<th>No. of demands</th>
<th>No. of potential trains</th>
<th>No. of constraints</th>
<th>No. of variables</th>
<th>Ratio of trains to demands</th>
</tr>
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<tbody>
<tr>
<td>1</td>
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<td>25</td>
<td>427</td>
<td>2251</td>
<td>21375</td>
<td>17</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
<td>30</td>
<td>466</td>
<td>2688</td>
<td>27990</td>
<td>16</td>
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<tr>
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<td>40</td>
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<td>583</td>
<td>2999</td>
<td>29175</td>
<td>23</td>
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<td>75</td>
<td>1380</td>
<td>9759</td>
<td>207075</td>
<td>18</td>
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</table>

Table 2. Outcomes of each individual mathematical goal $n$ to be considered as input for GP and $L_p$ norm approaches employed as optimal solution (i.e., $Z^*_i$) or desired level (i.e., $M_i$)

<table>
<thead>
<tr>
<th>Problem No.</th>
<th>IOF (1) ($\text{IOF } (i)$)</th>
<th>IOF (2) (No. of trains)</th>
<th>IOF (3) (No. of shunting operations)</th>
<th>IOF (4) (Tonnage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>649.0</td>
<td>0.0</td>
<td>227533.0</td>
</tr>
<tr>
<td>2</td>
<td>346586.1</td>
<td>800.0</td>
<td>0.0</td>
<td>286855.0</td>
</tr>
<tr>
<td>3</td>
<td>179625.9</td>
<td>896.0</td>
<td>0.0</td>
<td>247304.0</td>
</tr>
<tr>
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<td>756824.6</td>
<td>839.0</td>
<td>0.0</td>
<td>533449.0</td>
</tr>
<tr>
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<td>411148.9</td>
<td>570.0</td>
<td>0.0</td>
<td>885869.0</td>
</tr>
<tr>
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<td>591.0</td>
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<td>573.0</td>
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<td>1373561.0</td>
</tr>
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<tr>
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</table>

Table 3. Outcomes of $L_p$ norm and GP techniques

<table>
<thead>
<tr>
<th>No.</th>
<th>$L_1$ norm</th>
<th>$L_2$ norm</th>
<th>Goal programming</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Optimal value</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Solving time (sec.)</td>
</tr>
<tr>
<td>1</td>
<td>1.80</td>
<td>1.17</td>
<td>3.24</td>
</tr>
<tr>
<td>2</td>
<td>1.74</td>
<td>1.12</td>
<td>4.68</td>
</tr>
<tr>
<td>3</td>
<td>1.75</td>
<td>1.13</td>
<td>36000.00</td>
</tr>
<tr>
<td>4</td>
<td>1.50</td>
<td>N/A**</td>
<td>73.26</td>
</tr>
<tr>
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<td>1.71</td>
<td>N/A</td>
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<td>1.86</td>
<td>N/A</td>
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</tr>
<tr>
<td>7</td>
<td>1.53</td>
<td>1.09</td>
<td>21648.00</td>
</tr>
<tr>
<td>8</td>
<td>1.67</td>
<td>1.09</td>
<td>2929.00</td>
</tr>
<tr>
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<td>1.83</td>
<td>1.09</td>
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</tr>
<tr>
<td>10</td>
<td>1.50</td>
<td>1.09</td>
<td>11948.00</td>
</tr>
</tbody>
</table>

* Optimal value = The sum of deviation of individual objective functions from the related desired level ($IOF(i)$).

** N/A = Not available (i.e., no feasible solution is found in 10 hours of time)
Figure 1. Comparison of the performance of GP and $L_1$ norm techniques, in which the $L_1$ norm method always outperforms the goal programming method.

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Figure 3. Impact of increasing the cost of losing the demand (i.e., $c_k$) on the value of the IOF (1)
Figure 4. Impact of the incremental changing rate of the cost of losing the demand (i.e., $c_k$) on the quantity of covered demands

Figure 5. Impact of varying the multiplier of IOFs on the mathematical objective in the $L_1$ norm method

Figure 6. Impact of varying the multiplier of IOFs on the mathematical objective in a GP technique
Input parameters;
Generate Initial Solution; // generate initialSolution
Set \( T = T_{\text{max}} \);
Set currentSolution = initialSolution;
Set bestSolution = currentSolution;
Repeat
Set Cycle = 0;
Repeat
Generate neighborSolution;
Set Cycle = Cycle + 1;
Until Cycle < MAX_CYCLE
If (neighborSolution < currentSolution)
Set currentSolution = neighborSolution;
If (neighborSolution < bestSolution)
Set bestSolution = currentSolution;
EndIf
Else // neighborSolution >= currentSolution
If (acceptance criteria of the SA met)
Set currentSolution = neighborSolution;
EndIf
EndElse
Update T;
Until the terminating criteria is satisfied;

Figure 8. Pseudo code of our hybrid algorithm
The pseudocode of generating neighbor solution

Input current solution and parameters;
Select a demand;
If (value of the demand is greater than zero in current solution)
  If (T > MAX_TEMP)
    Set value of the demand in neighbor solution to value of the demand in current solution minus 10% amount of the commodity;
  Else // T <= MAX_TEMP
    Set value of the demand in neighbor solution to value of the demand in current solution plus 50% amount of the demand;
Else // value of the demand is equal to zero in current solution
    Set value of the demand in neighbor solution to value of the demand in current solution plus 50% amount of the demand;
EndElse

Figure 9. Pseudo code of generating the neighbor solutions

Table 4. $L_2$ norm method results (i.e., $p=2$) by using the proposed algorithm obtained by solving test problems

<table>
<thead>
<tr>
<th>No.</th>
<th>CPLEX software</th>
<th>Proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimal value*</td>
<td>Solving time (sec.)</td>
</tr>
<tr>
<td>1</td>
<td>1.17</td>
<td>81.43</td>
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<tr>
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<td>1.12</td>
<td>124.31</td>
</tr>
<tr>
<td>3</td>
<td>1.13</td>
<td>267.87</td>
</tr>
<tr>
<td>4</td>
<td>N/A**</td>
<td>36000.00</td>
</tr>
<tr>
<td>5</td>
<td>1.13</td>
<td>572.80</td>
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<tr>
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<td>N/A</td>
<td>36000.00</td>
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<tr>
<td>7</td>
<td>1.09</td>
<td>36000.00</td>
</tr>
<tr>
<td>8</td>
<td>N/A</td>
<td>36000.00</td>
</tr>
<tr>
<td>9</td>
<td>N/A</td>
<td>36000.00</td>
</tr>
<tr>
<td>10</td>
<td>N/A</td>
<td>36000.00</td>
</tr>
</tbody>
</table>

*Optimal value = The sum of deviation of individual OFVs from the related desired level (IOF(i)).
**N/A = Not available (i.e., no feasible solution is found in 10 hours of time)

Table 5. Specifications of the Iranian Railway

<table>
<thead>
<tr>
<th>No. of yards</th>
<th>No. of demands</th>
<th>No. of potential trains</th>
<th>No. of constraints</th>
<th>No. of variables</th>
<th>The ratio of trains to demands</th>
</tr>
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<tr>
<td>56</td>
<td>197</td>
<td>1089</td>
<td>14534</td>
<td>429263</td>
<td>6</td>
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</tbody>
</table>

Table 6. Outcomes of each mathematical objective to be used for GP and $L_p$ norm techniques employed as the optimal solution (i.e., $Z^*$) or desired level (i.e., $M_i$)

<table>
<thead>
<tr>
<th>IOF (1) ($)$</th>
<th>IOF (2) (Number of train)</th>
<th>IOF (3) (Number of shunting operations)</th>
<th>IOF (4) (Tonnage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>281656.29</td>
<td>211.00</td>
<td>0.00</td>
<td>2529437.00</td>
</tr>
</tbody>
</table>
Table 7. Results of the $L_p$ norm and GP methods for an Iranian railway network

<table>
<thead>
<tr>
<th></th>
<th>$L_1$ norm (i.e., $p$=1)</th>
<th>$L_2$ norm (i.e., $p$=2)</th>
<th>Goal programming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal value</td>
<td>1.80</td>
<td>N/A</td>
<td>496668.00</td>
</tr>
<tr>
<td>Solving time (sec.)</td>
<td>179.21</td>
<td>36000.00</td>
<td>691.32</td>
</tr>
</tbody>
</table>

Table 8. Computational results of $L_2$ norm method (i.e., $p$=2) by using the proposed algorithm obtained by solving an Iranian railway case study

<table>
<thead>
<tr>
<th></th>
<th>CPLEX software</th>
<th>Proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal value</td>
<td>N/A</td>
<td>1.12</td>
</tr>
<tr>
<td>Solving time (sec.)</td>
<td>36000.00</td>
<td>4411.29</td>
</tr>
</tbody>
</table>

Figure 10. Network of the Iranian railway

Figure 11. Part of the network to provide a more detailed illustration
Table 9. Demands related to Figure 10

<table>
<thead>
<tr>
<th>Demand No.</th>
<th>Origin</th>
<th>Destination</th>
<th>Demand volume</th>
<th>Demand No.</th>
<th>Origin</th>
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<tr>
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<td>Chadormalo</td>
<td>Isfehan</td>
<td>161</td>
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<td>Kerman</td>
<td>Bafgh</td>
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Figure 12. Train makeup and routing plan for a part of the network by the proposed algorithm.