Multicommodity Network Design Problem in Rail Freight Transportation Planning

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Abstract

Network Design Problem (NDP) is one of the important problems in combinatorial optimization. Among the network design problems, the Multicommodity Network Design (MCND) problem has numerous applications in transportation, logistics, telecommunication, and production systems. In general, decision making in rail freight transportation has three main levels: strategic, tactical, and operational. In the field of rail freight transportation planning, MCND occurs in all levels of decision making such as car blocking, train makeup, and empty car distribution. This paper presents a review of MCND problems modeling, their applications in rail freight transportation planning, and solution methods which have been developed to solve them.

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Keywords: multicommodity network design problem; rail transportation planning; freight transportation, logistics, operations research

1. Introduction

Network design is one of the important problems in combinatorial optimization. Network design models have numerous applications in various fields such as: transportation (Magnanti and Wong 1984, Crainic Dejax 1989), telecommunication (Minoux 1989, Minoux 2001), and distribution planning.

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(Geoffrion Graves 1974). Although in each of these applications the problem setting might be different, the underlying mathematical models are very similar to each other (Magnanti and Wong 1984).

In Multicommodity Network Design (MCND) model, multiple commodities such as goods, data, people, etc., must be routed between different points of origin and destination on the available arcs. In such network, in addition to a per unit cost (variable cost), a fixed cost can be added due to the opening cost for the first time the arc is used. MCND problem seeks a network with minimum cost which satisfies demands of commodities. This minimum cost is the sum of the fixed and variable cost (Magnanti and Wong 1984).

In general, decision making in rail freight transportation has three main levels: strategic, tactical, and operational (Assad 1980). Strategic level is associated with long term transportation planning. The aim of tactical or intermediate network design decisions is to optimal use of resources which is constructed in strategic level. Finally, operational level is the short term decision making in transportation. In the field of rail freight transportation planning, MCND problems occur in all of the decision making levels. Car blocking, train makeup planning, and empty car distribution are the examples of decision makings which can be formulated as a MCND model.

This paper surveys network design models, in particular multicommodity variant, as well as application of MCND in rail freight transportation planning. The solution methods which have been developed for MCND are also reviewed. In the next section, the steps of rail freight transportation planning are described briefly. Some of the important concepts and descriptions are also reviewed in the next section. In the other sections, the applications of MCND in rail freight transportation planning and the solution methods which have been developed for them are reviewed.

2. Rail freight transportation planning

As we mentioned, rail freight transportation planning can be classified into three strategic, tactical, and operational levels according to the planning horizon (Assad 1980). One can find good information about railroad operations in (Assad 1980, Crainic 1988). Planning steps in rail freight transportation includes demand estimation, car blocking, train makeup, train scheduling, locomotive assignment, crew scheduling and empty car distribution.

Demand estimation in rail freight transportation planning is to determine the demand of each commodity which is occurred in long term horizon. After demand estimation, car blocking is usually the first step in tactical level. Car blocking involves grouping different commodities into a car groups called blocks. In rail transportation, a commodity can pass through many classification yards from its origin to its destination. To prevent reclassification of commodities at every yard they pass through, several commodities may be grouped together in a block. After a commodity is placed in a block, it is not reclassified until it reaches the destination of that block. The aim of car blocking problem is to minimize total cost (cost of classification and movement of cars), according to the yard classification capacity and block capacity (the number of cars that can be grouped in a block) (Newton et al. 1998).

After car blocking, train makeup planning must be done. The train makeup problem is to identify number of trains, their routes and frequencies (how often the trains run in a week), and the blocks which are assigned to them, so that the total cost of transportation is the minimum possible (Ahuja et al. 2005). However, sometimes assigning blocks to trains is done in a separate step (Jha et al. 2008). Once car blocking and train makeup is done, arrival/departure times at each station must be determined in train timetabling problem.

After timetabling, locomotive assignment, crew scheduling and empty car distribution must be done. Because of the high investment costs of locomotives, it is important to maximize the utilization of these resources. The locomotive assignment problem includes assigning a set of locomotives to cover all
scheduled trains at minimum cost while satisfying some side constraints such as compatibility restrictions and maintenance requirements (Cordeau et al. 1998). Crew scheduling is to build the work schedules of crews needed to cover planned timetable (Caprara et al. 1997). Finally, empty car distribution is to assign empty cars to customers so that they can fulfill the next period orders (Dejax and Crainic 1987).

3. Multicommodity network design models

In this section the general model of network design problem is presented. This model was proposed by Magnanti and Wong (1984) as an umbrella for various network design problems. Indeed, many of the network design models can be defined as a variant of this general model.

Suppose a network \( G = (N, A) \), in which \( N \) is the set of nodes and \( A \) is the set of directed arcs. Multiple commodities can be defined in this general model. Commodities can be distinct physical goods, or the same physical goods with different origin and destination. Let \( K \) be the set of commodities, then the amount of each commodity \( k \) which must flow from its Origin \( O(k) \) to its destination \( D(k) \) is \( d_k \). Let \( c^k_{ij} \) and \( F_{ij} \) be the per unit arc routing cost of commodity \( k \) on arc \((i, j)\), and fixed arc design cost of arc \((i, j)\), respectively. The general model can be written as follows:

\[
\min \sum_{k \in K} \sum_{(i, j) \in A} c^k_{ij} f^k_{ij} + \sum_{(i, j) \in A} F_{ij} y_{ij}
\]

subject to

\[
\sum_{j \in N} f^k_{ij} - \sum_{l \in N} f^k_{lj} = \begin{cases} 
  d_k & \text{if } i = O(k) \\
  -d_k & \text{if } i = D(k) \\
  0 & \text{otherwise}
\end{cases} \quad \forall K \in K
\]

\[
\sum_{i \in N} f^k_{ij} \leq K_{ij} y_{ij} \quad \forall (i, j) \in A
\]

\[
f^k_{ij} \geq 0, \quad y_{ij} = 0 \text{ or } 1 \quad \forall (i, j) \in A, \quad k \in K
\]

where \( y_{ij} \) and \( f^k_{ij} \) are decision variables, \( y_{ij} \) is 0 if arc \((i, j)\) is close, and 1 if it is open, and \( f^k_{ij} \) is the amount of commodity \( k \) which flow on arc \((i, j)\). Equation (1) shows the objective function of MCND model. According to this equation, the objective of the model is to minimize variable cost of commodities flows on arcs, as well as fixed cost of opened arcs. Constraint (2) is the usual balancing equations of network flow problem. Constraint (3) demonstrates that the sum of the flows on each arc \((i, j)\) must not exceed the capacity \( K_{ij} \) of the arc. The side constraints \((S)\) might be any other needed constraint.

We can classify network design models in many ways; some models are uncapacitated, whereas some of them impose shared capacity on all of commodities (equations (1) to (5)) or capacities on each commodity. When the capacities are imposed on individual commodity, the relation below must be added to the Eqs. (1) to (5):

\[
f^k_{ij} \leq u^k_{ij} y_{ij} \quad \forall (i, j) \in A \text{ and } k \in K
\]

In Eq. (6) \( u^k_{ij} \) is the capacity of each arc \((i, j)\) for each commodity \( k \). Instead of including this constraint, one can use parallel arcs with different capacity for each commodity, between each two nodes. Some of the network design models have fixed cost, and some of them have only the variable cost. In some models just one commodity must flow through the network (i.e. a single flow required between two origin and destination nodes), but in the others we might have several commodities, in this situation the problem called multicommodity network design. Furthermore, some network design models are path-based (Crainic 2000) and some of them are arc-based (Eqs. (1) to (5)). These two models are equivalent to each
other. The objective of the path-based model is similar to arc-based model, but the variable cost is the sum of flows on paths rather than arcs. For more information see Crainic 2000.

In addition to above variants of network design problem, another variant is unsplittable (or non-bifurcated) problem, in which, each commodity must follow exactly one route between origin and destination. In this situation the flow variable must be binary (0-1).

The proposed general model is the capacitated network design problem. If in this model we add
\[ K_{ij} > \sum_{t \in \mathcal{K}} d_t \]
as constraint, then the model change into uncapacitated model. One of the most important side constraints is the budget constraint:
\[ \sum_{i,j \in \mathcal{A}} e_{ij} y_{ij} \leq B \quad (7) \]

This side constraint limits the overall cost of constructing of the network by a budget B. coefficient \( e_{ij} \) is the cost of constructing arc \((i, j)\) which can be the fixed cost of the arc (Magnanti and Wong 1984).

Fig. 1 shows different classification of the network design problems.

One of the variants of MCND is multicommodity service network design model. The goal of this model is to plan services to answer demand and ensure the firm to be profitable. This model considers tradeoffs between operating costs (firm profitability) and service performance (delays or predefined performance target). This model is to some extent similar to path-based model of MCND (Crainic 2000).

After presenting MCND models, here, a brief review of solutions methods which have been developed to solve MCND problem will be presented. One can classify solution methods of MCND into two categories: exact and approximate. Network design problems can be easy stated but solving them is too difficult (Balakrishnan et al. 1997). There are effective exact solution methods for uncapacitated network design problem. In exact algorithms, finding optimal solution is guaranteed. Decomposition methods and branch-and-bound have been the two most effective methods for this type of problem (Magnanti and Wong 1984). Decomposition methods involve Dantzig-Wolf decomposition (column generation) (Dantzig, P. Wolfe 1960), Benders partitioning (Benders 1962) and Lagrangian relaxation technique (Bazaraa et al. 2009). Adding capacity to the arcs of network design problem adds more complexity to this problem (Balakrishnan et al. 1997). Furthermore, large scale network design problems which occur in real world applications are very difficult to solve (Magnanti and Wong 1984). Clearly, capacitated network design problem is one of the most difficult problems in combinatorial optimization.

![Fig. 1. Different classification of network design models](image-url)
There are theoretical and empirical evidence that capacitated network design problems are NP-hard. As a result, the researchers proposed approximate methods to solve them (Magnanti and Wong 1984, Balakrishnan et al. 1997). However, this type of solution methods cannot guarantee the optimality of solutions. Heuristics and metaheuristics are the two classes of approximate methods (Talbi 2009). The most popular metaheuristics which is used for MCND in the field of rail freight transportation planning include Genetic Algorithm (GA) (Holland 1975, Goldberg 1989), Tabu Search (TS) (Glover 1986), and Simulated Annealing (SA) (Kirkpatrick 1983), Scatter Search (SS) (Glover 1997), and Variable Neighbourhood Search (VNS) (Mladenovic and Hansen 1997). Some of recent works on MCND problem and main characteristics of the model are summarized in Table 1.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Model structure</th>
<th>Solution method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crainic &amp; Gendreau (2002)</td>
<td>capacitated</td>
<td>tabu search</td>
</tr>
<tr>
<td>Ghamlouche et al. (2003)</td>
<td>capacitated</td>
<td>tabu search</td>
</tr>
<tr>
<td>Crainic et al. (2004)</td>
<td>capacitated</td>
<td>heuristic</td>
</tr>
<tr>
<td>Alvarez et al. (2005)</td>
<td>capacitated</td>
<td>scatter search</td>
</tr>
<tr>
<td>Crainic &amp; Toulouse (2006)</td>
<td>capacitated</td>
<td>tabu search</td>
</tr>
<tr>
<td>Crainic &amp; Gendreau (2007)</td>
<td>capacitated</td>
<td>scatter search</td>
</tr>
<tr>
<td>Frangioni &amp; Gendron (2008)</td>
<td>capacitated</td>
<td>cutting-plane</td>
</tr>
<tr>
<td>Pedersen et al. (2009)</td>
<td>capacitated</td>
<td>tabu search</td>
</tr>
<tr>
<td>Katayama et al. (2009)</td>
<td>capacitated</td>
<td>heuristic</td>
</tr>
<tr>
<td>Chouman &amp; Crainic (2010)</td>
<td>capacitated</td>
<td>tabu search</td>
</tr>
<tr>
<td>Hoff et al. (2010)</td>
<td>capacitated</td>
<td>VNS</td>
</tr>
<tr>
<td>Martin &amp; Gonzalez (2010)</td>
<td>capacitated</td>
<td>heuristic</td>
</tr>
</tbody>
</table>

4. MCND in rail freight transportation planning

In this section we review applications of MCND in rail freight transportation planning. Recent surveys about optimization models of railway operations can be found in (Ahuja et al. 2005, Cordeau et al. 1998, Crainic 2003 a, Crainic 2003 b, Newman et al. 2002, Crainic 2009).

4.1. Blocking problem

As we mentioned in section 2, car blocking is usually the first step in railway freight transportation planning. Newton (1996) used a general path-based network design problem (NDP) with budget constraints on nodes for car blocking problem. In this network, the blocks and yards were presented as arcs and nodes, respectively. The aim of the model is to determine the optimal built blocks and optimal assigning of commodities to these blocks. The budget constraint is used for each node to ensure that the number of blocks which may be built in each yard must not be more than the number of classification track of it. The costs which must be minimized in objective function include travelling costs of cars and delay costs because of classification and block swap. A branch-and-price algorithm to solve the model
was also proposed. Newton et al. (1998) proposed a model and solution method for blocking problem which was similar to Newton 1996. They showed the robustness of their solution on 19 test instances.

Barnhart et al. (1992) use the same formulation as Newton et al. (1996) and proposed a Lagrangian relaxation heuristic to solve proposed model. The proposed solution procedure decomposes the problem into two simple sub-problems and as a result, in contrast with branch-and-price, the storage requirement and computational effort are reduced. Ahuja et al. (2007) proposed an arc-based MCND model and a new heuristic algorithm for blocking problem. Similar to the model of Newton (1996), in this model, the blocks and yards were presented as arcs and nodes, respectively. The model determines which block must be built and which commodity must be assigned to these blocks. Their solution method, named very large-scale neighborhood (VLSN) search, starts with a feasible solution to the blocking problem and iteratively improves the current blocking solution by replacing it with its neighbor solution until the solution can no longer be improved. Their proposed model and solution method have been applied for blocking plan of 3 major railroad companies of US. Table 2 summarized research works on blocking problem which have been used MCND models.

Table 2. Characteristics of MCND which is applied in different papers for blocking problem

<table>
<thead>
<tr>
<th>Authors</th>
<th>Planning horizon</th>
<th>Capacitated/uncapacitated</th>
<th>Path/arc-based</th>
<th>Splittable/unsplittable</th>
<th>Budget constraint</th>
<th>Solution method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newton (1996)</td>
<td>tactical</td>
<td>capacitated</td>
<td>path-based</td>
<td>splittable</td>
<td>yes</td>
<td>column generation</td>
</tr>
<tr>
<td>Newton et al. (1998)</td>
<td>tactical</td>
<td>capacitated</td>
<td>path-based</td>
<td>splittable</td>
<td>yes</td>
<td>branch-and-price</td>
</tr>
<tr>
<td>Barnhart et al. (2000)</td>
<td>tactical</td>
<td>capacitated</td>
<td>path-based</td>
<td>splittable</td>
<td>yes</td>
<td>Lagrangian relaxation</td>
</tr>
<tr>
<td>Ahuja et al. (2007)</td>
<td>tactical</td>
<td>capacitated</td>
<td>arc-based</td>
<td>unsplittable</td>
<td>yes</td>
<td>VLSN</td>
</tr>
</tbody>
</table>

4.2. Makeup and routing problem

In 1986, Crainic et al. (1986) proposed a general multicommodity service network design model that in the case of railway transportation can determine different types of trains (direct and indirect) and their frequencies. The objective function of the model is to minimize operating and delay cost of transporting flows by services (variable cost), and operating and delay cost of each service (fixed cost). The objective function has also an additional term which modeled capacity constraints of services as penalty of delays and costs. They also proposed a column generation approach for solving their model.

Keaton (1989) proposed a model to determine origin and destination and frequencies of trains, assigning demands to blocks, and assigning blocks to trains. Indeed, the proposed model combines blocking problem with train makeup and routing problem. The objective function of the model is to minimize variable and fixed costs. Variable costs include car time and classification costs. Car time consists of waiting for departure in the origin yard, moving in trains, classification in intermediate terminals, and waiting for delivery to customers in destination yard. Fixed cost is the costs of providing a train. Main constraints of the model are car capacity of train, block capacity of yard, and maximum transit time of each commodity. He also proposed a Lagrangian relaxation to solve the proposed model. In 1992, he also proposed a Lagrangian relaxation solution approach with dual adjustment procedure to implement relaxation for solving previous model (Keaton 1992). The proposed solution method could find near optimal solution for real life scale instances.

Marin and Salmeron (1996a) proposed and analyzed three heuristics for the tactical planning of rail freight networks. The model is based on a service network design in which each demand is defined by
origin and destination yards and freight type. The objective function of the model has three parts: two variable cost of cars flow on each route and service, and a fixed cost that is an investment cost that added to objective function when there is not enough train service. There were two capacity constraints in the model: yard and train capacity. They proposed three heuristic methods involved descent method, simulated annealing, and tabu search. They compared proposed heuristics with branch-and-bound method. Computational tests on four generated networks showed that simulated annealing obtained the best solutions but required more time than the other heuristics. In another research work, again in 1996, they solved largest instance and perform statistical analysis for proposed solution method in previous paper (Marin and Salmeron 1996b).

Gorman (1998a) proposed a hybrid metaheuristic of genetic algorithm and tabu search approach for model which had been proposed in Keaton (1992). Tabu search has applied to improve the performance of genetic algorithm. Furthermore, again Gorman (1998b) successfully applied his proposed solution method for a major US railroad. Newman and Yano (2000) propose a model for train schedules and freight route. The aim of the model is to choose train schedules and car routes. The objective function of the model includes fixed cost of direct and indirect trains, the storage cost of cars, and handling cost of cars. The main constraints of the model are train capacity, yard capacity, and freight due dates. In the model, the demands are varied in different times, but the transit times are fixed. A heuristic solution method based on Lagrangian relaxation and benders decomposition was also proposed.

Sometimes block to train assignment was done in separate step. This problem, known as the block-to-train assignment problem, is considered by Jha et al. (2008). They provided two formulations for this problem: an arc-based and a path-based formulation. The objective of the model is to minimize cost of flowing blocks on train arcs (paths). The model has a capacity constraint for each arc (path) which is associated with train capacities. They also propose exact and heuristic algorithms based on the path-based formulation. Their heuristic algorithms include a Lagrangian relaxation-based method as well as a greedy construction method. They present computational results of their algorithms using the data provided by a major US railroad.

In the real world, sometimes, the amount of commodities, costs of transportation and etc. are not fixed and might be random or fuzzy. Yang et al. (2010) proposed a railway freight transportation model with mixed uncertainty of randomness and fuzziness. Two constraints in the proposed model are: 1) the chance that the total amount of commodities passing through each arc does not exceed its capacity should not be less than some given confidence level; 2) the chance that the total amount of commodities passing through each station does not exceed its turnover capacity should not be less than a given confidence level. A hybrid genetic algorithm was proposed to solve the model.

In 2010, for the first time, Verma et al. (2010) proposed a tactical planning model based on service network design for dangerous goods in rail transportation. The model determines train services for each demand and their frequencies, and number of dangerous goods using each yard and tracks. In the model, the demands cannot be split in different paths (unsplittable MCND variant). The objective function of the model is bi-criteria. The first objective is to minimize population exposure (the total number of people exposed to the probability of suffering the undesirable consequence of an incident), and the second objective is to minimize car routing costs and the fixed cost for a given type of train service. They proposed a Memetic metaheuristic (Moscato 1989) algorithm that combines global and local search. Table summarized research works on makeup and routing planning which have been used MCND models.

4.3. Empty car distribution

Haghani (1989) proposed a dynamic network design model which combines the empty car distribution
with the train make-up and routing problems. They converted physical network into time-space network in which nodes represent yards at different times, and links represent physical links and yard activities. Objective function and constraints of the model are non-linear and linear, respectively. Non-linear objective function is to minimize routing cost, classification cost, penalty cost of empty car demand which is not satisfied in one period, and penalty cost of loaded cars which may not receive to their destination of planning horizon. A heuristic decomposition approach is proposed to solve the model and it is successful for small problems.

Jobron et al. (2004) proposed a time dependent multicommodity capacitated network design model for empty car distribution that take into account economies of scale and a solution method based on tabu search metaheuristic for solving it. They used a network called train network to model empty car distribution problem. The network is divided into T time period. In the network, each yard is represented by at least one node at each time period, with additional node being inserted, if needed, to represent train movements. Objective function of the model is to minimize fixed cost of trains, variable cost of flow cars on the trains, and cost of salvage values of having cars at different terminals at the end of time horizon. By these fixed and variable costs, the model takes into account economies of scale. The main constraint of the model is the capacity flow of arcs (train capacity).

Zhu et al. (2009) attempted to combine blocking, makeup and empty car distribution in an integrated dynamic model. To do this, they build a 2-layer service network, one for block flows and another for car flows. In each layer, they considered T time point, and in each time point, each yard is divided into 2 nodes (IN indicates cars and block receive and OUT indicates cars and block is ready to ship out). The objective function includes 2 fixed costs on open service and block, and a variable cost on all blocks. The model have three capacity constraints on maximum cars in each train, maximum car on each block, and maximum block being built in each yard at each time. They used a tabu search metaheuristic to solve the proposed model. Their solution method obtained good solutions for rather large instances. Table summarized research works on empty car distribution which have been used MCND models.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Planning horizon</th>
<th>Model structure</th>
<th>Capacitated/ Uncapacitated</th>
<th>Path/arc-based</th>
<th>Splittable/ Unsplittable</th>
<th>Fixed cost</th>
<th>Solution method</th>
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<tbody>
<tr>
<td>Crainic et al. (1986)</td>
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<td>splittable</td>
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<td>Marin et al. (1996)</td>
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<td>path-based</td>
<td>splittable</td>
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<td>Lagrangian relaxation</td>
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<td>Marin et al. (1996)</td>
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<td>path-based</td>
<td>splittable</td>
<td>yes</td>
<td></td>
<td>descend method simulated annealing</td>
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<td>Gorman (1998)</td>
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<td>arc-based</td>
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<td>path-based &amp; arc-based</td>
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<td>Memetic algorithm</td>
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Table 4. Characteristics of MCND which is applied in different papers for empty car distribution problem

<table>
<thead>
<tr>
<th>Authors</th>
<th>Planning horizon</th>
<th>Model structure</th>
<th>Fixed cost</th>
<th>Solution method</th>
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<td>Haghani (1989)</td>
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<td>capacitated/capacitated</td>
<td>no</td>
<td>heuristic decomposition</td>
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<tr>
<td>Jobron et al. (2004)</td>
<td>operational</td>
<td>capacitated/arc-based</td>
<td>yes</td>
<td>tabu search</td>
</tr>
<tr>
<td>Zhu et al. (2009)</td>
<td>tactical</td>
<td>capacitated/path-based</td>
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<td>tabu search</td>
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5. Conclusions

This paper has proposed a review of MCND problems modeling, their applications in rail freight transportation planning, and solution methods which have been developed to solve them. This work permits to better analyze the scope of the various MCND models, to emphasize modeling challenges, to identify a number of important research avenues. We hope that this review will draw more researchers to applications of MCND to rail freight transportation planning.

References


