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Multi-Objective Optimization Methods for Transportation Network Problems:
Definition, Taxonomy, and Annotation

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ABSTRACT

This article recapitulates literature research solving transportation problems and these variants, notably the multimodal transportation problems variants. Moreover, the existing optimization methods critiqued and synthesized their efficiency to solve the transportation problem. This problem can be identified by various criteria and objectives functions that distinguished according to the case study. Based on the existing literature research, a taxonomy is proposed to distinguish different factors and criteria that perform and influence the multi-objective optimization on the transportation network planning problems. The transportation problems are cited according to these objective functions, and the variant of the problem by referring to the previous studies. In this article, the authors have focused their attention on a recent multi-objective mathematical model to solve the planning network of the multimodal transportation problem.

KEYWORDS

Approach Methods, Exact Methods, Mathematical Programming, Multi-Modal Transport, Multi-Objective Optimization, Optimization Methods, Planning Network, Transportation Problems

INTRODUCTION

The transportation system defined as the displacement of the goods or passengers between two terminals or cities in the international or national network. The national and international networks include the conveyances, corresponding network, transportation mode, networks paths, itineraries, cities, depots, customers, stations, and terminals. The network defined by a set of nodes connected by one or more itineraries in the transportation system, each itinerary represents a transportation mode. The itinerary is represented by only one connection and one transportation mode between two nodes. The nodes are described as exchange stations that can include the transshipment, the delivery or the load and unload of the merchandise.

This article provides an overview of the literature researches based on the optimization of transport problem as well as the optimization methods applied to solve these problems in multi-objective and single objective case. The goal is to distinguish the objectives functions of the optimization transport

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problem to better satisfy the customer's demands. This satisfaction incorporates a set of objectives, such as minimizing the total cost of transport, the total time of transport or maximizing the quality of service, etc., in order to transfer the merchandise from a departure node to a destination node. These objectives are measured and evaluated differently according to the criteria and the parameters defined by the decision-maker depending on the case study.

The optimization methods and operations research play an important role in solving these problems. The role of the decision-maker is to adopt the optimization methodology or techniques to better optimize and solve the problem after having defined and modeled it. The modeling step consists to define the assumptions, the sets, and settings of the problem, the decision variables and the objectives functions that defined by the set of criteria and the set of constraints to be respected.

The aim of this paper is to recapitulate the existent optimization and resolution methods applied to solve the planning transportation networks problem, in order to help the decision-maker to identify the type of problem to be solved and to select the criteria to be optimized.

The structure of this paper is organized as follows: Section 2 outlines a classification relying on the existent characteristics of transportation problems and presents a taxonomy of objectives functions based on optimization and transportation problems. Section 3 discusses an overview of the modeling and resolution method that solves the most common transportation problems by means of a single objective. Section 4 discusses an overview of the modeling and resolution methods that solve the principal transportation problems using multiple objectives. This section ends with a synthesis and criticizes main literature researches. Section 5 focuses on a survey of the existent researches dealing with multimodal transportation problems and defining their main extensions. This section is split into three sub-sections, i.e., the single objective optimization problems, the multi-objective optimization and ultimately, a critical comment, which is discussed. Besides, a multi-objective mathematical formulation is cited. Correspondingly, the readers are referred to (Mnif & Bouamama, 2017b, 2017a). Finally, section 6 concludes with a summary and suggests some future research directions.

TAXONOMY

Extensions of Transportation Problems

Taxonomy is based on some existing researches to transportation issues and their extensions. In fact, the literature works refer to this taxonomy. It distinguishes the various characteristics of the transportation problems (see Table 1) and the various criteria that define the objectives functions considered, in the literature, to solve the transportation problems (see Table 2). These objectives functions are defined and expressed in different ways according to the criteria fixed based on the types of treated problem. However, these objectives are generally contradictory. The main objectives of transportation problems distinguished in this study, are summarized in Table 2, including the minimization of the cost, the minimization of the duration of the transport, the maximization of profit, the maximization of service quality, and the satisfaction of customers in terms of the time windows when visited by the customers.

This paper presents a taxonomy based on a sample of 50 articles of researches works. This taxonomy distinguishes the various objectives functions and defines their possible criteria and parameters. The objectives can be measured in different ways. In fact, the objective to minimize the total transport time can be determined in terms of the delay time, the service time, the transshipment time, the waiting time, etc. This taxonomy discerned various objectives treated for transportation network problems. The main objectives of transportation problems are summarized in terms transportation costs (27 articles), travel time (18 articles), risk (3 articles), distance (4 articles) and capacity (2 articles). Other articles were addressed to satisfy the demand, to maximize the service quality and to guarantee the accessibility of demand (5 articles). The majority of researches dealing with the optimization of transportation problems are interested in minimizing the total transport cost as the main objective.

The multi-objective model can be applied to various complex transport optimization issues. In many real-world problems, different goals, which depend on under estimator's consideration, may conflict with other goals. Some practical solutions for each model can be regarded as a single goal. Therefore, a set of solutions related multi-objective model need to fulfill all the objectives at an adequate level without being influenced by some other solution. In this section, we distinguish a number of objectives functions and their criteria to be satisfied for the sake of the optimization of the transportation problems.

The variety of objectives show the multi-objective nature of this problem. The multi-objective problem is characterized by the complexity and the difficulty of satisfying all the objectives at once. This complexity reflects the importance of making an analysis of the formulations dealing with transport problems in the literature, in order to get the optimal solution according to the objectives, constraints, and parameters characterizing the problem and the case treated. A substantial number of objectives functions, treated for the transportation problem, were defined according to the problem addressed (See Table 1 and Table 2). The satisfaction of all the objectives in the multi-objective problem is very difficult due to their contradictions.

Transportation problems can be classified into two main characteristics, such as the scenario problem and the physical problem. Under each of these two classes, the most discriminating criterion was listed. Each of them is divided into sub-levels. The decisions are distinct from one case to another as a large number of extensions in the transport problem of most cases; each possessing its own characteristic required of different decision depending on the context taken into account. These decisions are based on the characteristics of the transportation mode, and on specific constraints. These constraints are specified for each customer, vehicle, mode, road or means of transport, as well as the type of problem.

Table 1 illustrates the various characteristics and extensions of problems that can be considered as an optimization for transportation problems. The problems of physical characteristics were briefly summarized:

- **Vehicles:** Have different characteristics, which are related to physical restrictions, environmental concerns, and specific logistic equipment related to customers need. The characteristics of the vehicles are linked to the types of vehicle available during the planning period. The most common capacity constraints in freight transportation are expressed in terms of weight, volume, or number of containers. The vehicles have several compartments with respect to their different capacities. The use of multiple criteria is relevant based on products types loaded on the vehicles, which must remain separated during the transportation process;
- **Time-related constraints:** The time constraint is one of the most significant constraints in distribution and transportation problems. This constraint depends on one or more criteria;
- **Service time:** Defined by the time spent to perform a service. The service includes the delivery time, the loading or unloading of a commodity, the transshipment or the change of transportation mode, etc.;
- **Waiting time:** When a vehicle reaches the customer too early or when the vehicle stands by to be loaded or unloaded;
- **Delay time:** When the transportation system includes the loading or unloading of a commodity, the transshipment or a large number of visited nodes (customers, cities or depot, etc.);
- **Time Window:** Time window constraint requires that each customer must be serviced during a given time interval. In the case of the hard time window constraint, when the vehicle arrives before the specific time window beginning, this vehicle must wait until the customer becomes available; however, it is not allowed to arrive late. In the case of the soft time window, penalties are imposed for service delays that start after the time windows planned. This depends on the routing times between customers and nodes, the service times of customers and the loading-unloading times of freight. Another variant is noted, which is the multiple time windows who

each time window is associated with a customer. Frequently, the itinerary duration is limited to a predefined parameter which can be equal to the total working duration of a driver or to the routing access time. Indeed, a road segment may have a limited access given by a specific time interval when the vehicle (conveyance) can arrive.

The time window is the added constraint of time constraints, related to allowable delivery times of customers or services time. In general, the time window is defined by the earliest and the latest time when the customer will allow the start of the service:

- **Single Time window:** Defined as the limit or interval time to serve a customer;
- **Multiple time windows:** Described as the multiple customers' case, under two assumptions: (a) the allowable delivery time for each customer after an itinerary is generated. (b) Each time window for customers is not allowed to overlap.

Specific constraints:

- **Real Case:** In the real cases applications, administrators must consider various and non-standard challenging constraints stemming from the problem situations. Moreover, decisions may be constrained by the outsourcing of resources, environmental issues, and the priority given by clients or by transshipment related restrictions;
- **Incompatibility constraints:** In the real cases applications, many incompatibility constraints may occur between the actors of the problem, more precisely transport mode, customer, depot, vehicle behavior, product types, and drivers. These incompatibilities can be classified into two types according to the causing factor, i.e. physical incompatibilities and temporal incompatibilities. In the distribution of multi-commodity loads, each means of transport can be used to handle specific types of cargoes. For example, the distribution of groceries, delivering different types of products, require vehicles at different temperature levels;
- **Correspondence constraints:** There are several correspondence constraints between two terminals, by imposing the use of different transportation means to allow access to the second transport mode. This corresponds to different real cases based on multi-modal transportation systems. In the transshipment case, it must satisfy the correspondence on the capacity of conveyances, the means of transport, the itineraries, and the nodes;
- **Objectives function:** The objectives can be multiple or single to satisfy the problem. The possible applied objectives incorporate the minimization of the total transportation distance, the total duration of transport, the total transportation cost, the maximization of the service quality and the collected profit, etc. In terms of a multi-objective optimization to satisfy the different objectives that are often in conflict, the best approaches have to ensure some trade-offs between them. These approaches can include artificial intelligence or operational research techniques.

This work was based on the literature study pertaining to different transportation problems. These problems are represented in the function of the various objectives expressed by various criteria in the transportation network. The aims of this literature study can be summarized as follows:

- An outline of the mains transportation problems variants based on planning problems (see Table 1);
- An outline of the multi-objective optimization criteria, which determined and distinguished in Table 2;
- The multi-objective mathematical programming was cited to model for planning networks on multimodal transportation problem.

Table 1. Classification according to the characteristics of the transportation problem

Scenario Characteristics		Problem Physical Characteristics	
Input Data	Static	Vehicles	Capacity constraints
	Dynamic		Drivers regulations
Decision management components	Routing and location		Loading constraints
	Network planning		Autonomous Vehicles
	Shortest Path	Time-related constraints	Service time
	Routing and driver scheduling		Waiting time
	Production and distribution planning		Delay time
Operation type	Pickup and delivery	Time window	Single time window
	Loading and unloading		Multiple time windows
	Dial a ride	Specific constraints	Incompatibility constraints
Mode of transport	Single mode		Real case
	Multiple modes		Correspondence constraints
	Inter-modal	Objective function	Single objective
Maritime mode	Transship		Multiple objectives
	Quays management		
	Containers Optimization		
Type of transport	Single commodity		
	Multiple commodities		
	Passenger		
	Hazardous material		
Multi-modal network	Mode selection		
	Route selection		
	Regulation		

Multi-objective optimization methods present the keys to solve multi-objective problems. These methods are discussed in the next section.

Multi-Objectives Optimization Methods

The previous section summarizes the different objectives considered in the previous researches in order to solve the transportation problem. In this section, the principal resolution and optimization methods and techniques are introduced. The resolution techniques are divided into three major classes, i.e. exact, heuristic and metaheuristic approaches or hybrid algorithms to solve the optimization problem:

1. **Exact algorithms:** Provide an optimal solution. According to the literature, different exact solution techniques are used to solve the transportation problem. As an example, branch and bound are used as well as column generation and other methods, and in some researches, the authors use some optimization programming languages like CPLEX and AMPL. The exact algorithm is used when talking about an algorithm that always finds the optimal solution for an optimization problem. For hard optimization problems, it is often the case that there are some

Table 2. A taxonomy of objectives function in literature-based optimization and transportation problem

Objectives	Minimize		Maximize to the Minimum	Minimize		
	1. Cost	2. Time and duration	3. Quality of services	4. Capacity	5. Risk or reliability	6. Distance travel
Criteria	1.1. Transportation 1.2. Transshipment 1.3. Delay overhead 1.4. Moving empty containers 1.5. Holding empty containers 1.6. Penalty 1.7. Allocation (Storage, reloading and Transfer) 1.8. Operational 1.9. Construction 1.10. Establishment 1.11. Fee according to the demand quantity of goods 1.12. Using wagons 1.13. Opportunity	2.1. Transportation 2.2. Transshipment 2.3. Delay 2.4. Storage 2.5. Transfer 2.6. Time windows 2.7. Waiting 2.8. Handling 2.9. Service/ operating	3.1. Number of exchange of vehicles 3.2. Number of exchange of drivers 3.3. Number of unserved visits 3.4. Number of unserved transshipment 3.5. Number of vehicles used 3.6. Number of quays visits 3.7. Ride time on demand of transport 3.8. Number of stations visited 3.9. The weighted sum of passenger cost 3.10. Weight transportation volume 3.11. Number of cranes to be used 3.12. Maximize the total length of covered activities	4.1. Barge used 4.2. Volume 4.3. Localization	5.1. Bound 5.2. Transfer process	

polynomial-time approximation algorithms. However, the best-known exact algorithms require exponential execution time;

2. **Heuristic algorithms:** Theoretically they have a chance to find an optimal solution. That chance can be remote because heuristics often reach a local optimal solution and get stuck at that point. Thus, it is necessary to have modern heuristics called metaheuristics;
3. **Metaheuristic algorithms:** The systematic rules avoid local optimum or give the ability to move around the local optimum. The common characteristic of different metaheuristics is the use of some mechanisms or operation to avoid the local optimum. Metaheuristics succeed in leaving the local optimum by temporarily accepting moves that cause a worsening of the objective function value.

Multi-objective optimization problem (MOP) is called multi-criteria optimization. The problem is defined by the vector of decision variables which satisfy constraints and optimize a set of objective functions in order to get a number of feasible solutions. Mathematically, MOP is modeled and represented by a set of parameters and decision variables, a set of objectives functions, and a set of inequality and equality constraints. Some criteria or objectives decrease without causing a simultaneous increase at other criteria or objectives. The role of the decision maker is to find the best compromise solutions. Such solutions are denoted as Pareto-Optimal.

This paper investigates the researches works based on the transportation systems problems. The Particle Swarm Optimization (Bouamama, 2010) is among the resolution methods that can be cited. It is a well-known solver for the combinatorial optimization problem. In (Friesz et al., 1993), authors have developed a PSO-based approach. This approach is a dynamic distributed double guided PSO. There are various approaches to solve multi-objective problems. Among these approaches, some of which use knowledge of the problem to set preferences based on the criteria and others take into account the multi-criteria. There are other existing approaches that set all the criteria at the same level of importance.

Indeed, there are three classes of methods for solving the MOP: the transformation-based approaches to a problem with only one objective, non-Pareto approaches, and Pareto approaches. The Pareto approaches are characterized by their effectiveness in solving MOP. The solution approach is based on meta-heuristics for multi-objective optimization. These methods have proven effective to find satisfactory approximate solutions for numerous problems. However, these methods have their flaws, consisting of the impossibility of judging the quality of the approximation compared to the optimal Pareto front. The non-Pareto approaches are not directed to solve the multi-objective problem of real cases. This technique seeks to restore the original problem as a single-objective problem. However, Pareto approaches do not change the objectives of the problem and treat them without any distinction during resolution. Among these methods, the aggregation method, the ε-constraint method, and goal programming method are noted.

The aggregation method consists in transforming the MOP by a problem which combines the various objectives functions into a single objective function as a cost. The method of aggregation is one of the first methods used for the reconstruction of optimal Pareto solutions. The chosen parameters for the weight vector α influence in a direct way the achievement of the results in terms of resolving the problem (MOPα). Indeed, $\propto_i$ weight should also be selected according to the user's objectives preferences. The aggregation method has the merit of producing a single solution, which does not require an interaction with the decision maker. However, the solution provided by this method may not be acceptable, for two reasons: (a) the search space is greatly reduced prematurely by the non-availability of sufficient information, (b) the difficulty of choosing the weight values for each function without sufficient knowledge or parameters of the problem to be solved.

The ε-constraint method is to optimize a single objective function of MOP having constraints, based on other objective functions. In the ε-constraint method, the problem is formulated as a single-objective problem subject to constraints, relying on the other goals. In order to provide various optimal Pareto solutions, different values of i must be generated. A priori knowledge appropriate to intervals is given for all the objectives of MOP by the values i. In the goal programming method, the decision maker must define the goals values to set each objective. This method transforms the multi-objective problem into a single-objective problem. For example, the cost function can include a weighted norm, minimizing deviation reports to the goals. In the Pareto approaches, the notion of dominance is used in the selection of solutions generated, unlike other approaches that use a utility function or treat separately the different objectives. This approach has a major advantage over other approaches, which is the possibility of generating optimal Pareto solutions in the concave portions of the Pareto front. The Pareto approaches are essentially based on the concept of population. For this reason, the AGs have often been used to solve Pareto MOP, since the solution is based on a population. Indeed, this approach to be applied to solve the multi-objective problem, two aims must be considered in the resolution of a MOP, i.e. the convergence to the Pareto front and the diversification of solutions in this border.

Each objective function has a single solution relative to each minimized or maximized objective. MOP has multiple conflict solutions. These solutions are considered equivalent in the absence of information about a weight or importance of each objective to the others. The set of all Pareto solutions is called the non-dominated set or Pareto-front. These solutions are located on the boundary of the feasible solution space, showing the trade-off information between the conflicting objectives.

The main goal of the MO decision is to find such Pareto optimal solutions, as much as possible, in order to represent trade-off information among different objectives. The global Pareto Front can be obtained by using the exact methods after a high computational time. Concerning this disadvantage, the decision maker opts for applying the approaches methods (heuristics or metaheuristics) to avoid a premature convergence to a local Pareto set and, sometimes, to a global Pareto set.

In this study, the modeling step and the definition of the transport problem, especially the multimodal transportation problem, are highlighted. Additionally, various case studies and variants on this problem are distinguished. Then, the MOP case study on the multimodal transportation problem underlined.

Multi-Objective Transportation Problems

Transportation problem stands for the displacement of the total commodities that are initially stored at origins to destinations in such a way that minimizes the total transport cost or maximizes the total transport profit. (Kumar, 2018) Mathematically, the transport problem consists in transporting a certain commodity from each of m origins $I = 1, 2, 3, \ldots, m$ to any of n destinations $j = 1, 2, 3, \ldots, n$. The origins are factories pertaining to capacities $a_1, a_2, a_3, \ldots, a_m$ and the destinations are warehouses with required levels of demands $b_1, b_2, \ldots, b_n$. Each commodity is displaced by a transport unity from the i^{th} origin node to the j^{th} destination node. This displacement is measured by a cost c_{ij}. However, each itinerary is represented by x_{ij}, i.e. to be transported from all the origins $a_1, a_2, a_3, \ldots, a_m$ and all the destinations $b_1, b_2, \ldots, b_n$ in such a way that the total cost is minimized. The mathematical programming model for the classical transportation problem is stated as follows:

Minimize $Z = \sum_{i \in m} \sum_{j \in n} c_{ij} x_{ij}$

subject to:

$\sum_{j \in n} x_{ij} \le a_i \forall i \in m$ (Row restriction)

$\sum_{i \in m} x_{ij} \ge b_j \forall j \in n$ (Column restriction)

$x_{ij} \ge 0 \quad \forall i \in m, \quad j \in n$

The multi-objective optimization problem expresses according to the h conflicting objectives (Z_h), the resolution can obtain various optimal solutions. The h presents the set of objectives functions such as; the total cost, the total time, the capacity, the risk, and the total distance, etc. Each objectives function expressed by one or more criteria (see Table 2) as linear or non-linear functions. An objective vector constructed with the set of optimal objective solutions constitutes the best compromise of the optimal objectives vector. The multi-objective optimization problem is defined as follows:

Minimize $Z_h = f_h(x)$

subject to:

$\sum_{j \in n} x_{ij} \le a_i \forall i \in m$ (Row restriction)

$\sum_{i \in m} x_{ij} \ge b_j \forall j \in n$ (Column restriction)

$x_{ij} \ge 0 \quad \forall i \in m, \quad j \in n$

The compromise solution is the optimal objectives vector Z^*. Thus, if the optimal solution for the h^{th} objective function is the decision vector $x^{*(h)}$ with objective function solution f^*_m, the optimal vector is defined by $z^{*} = f^{*} = \left(f_1^{*}, f_2^{*}, \ldots, f_h^{*}\right)^T$. An objective function can be expressed by one or more decision variables, each variable defines a criterion. Thus, *x* is the decision variable, according to the corresponding problem can be defined by binary values, dynamics values, Integers values, etc. A transportation problem model also defined and included a set of constraints to be satisfied, which represented by equality or inequality equations. The transportation systems include the constraints of capacity, the flow conservation, the time windows, the corresponding, the transshipment, the select of the node, the select of an itinerary, etc.

Network Planning Problem

The planning transportation network is defined as a selection arc in the network *G* (*N*, *A*). $N = \left\{n_1, n_2, \ldots, n_i\right\}$ represents the set of nodes, and $A \in$ arcs (n_i, n_j) represent the transportation itinerary between two nodes n_i and n_j, and n_i is a vertex at the point of intersection of two arcs. Thus, a network *G* is the set of connected arcs, with a set of nodes *N* and the corresponding arcs *A*, when each arc measured by one or more values. It can be measured according to the cost, distance, time, etc. of the itinerary.

In the real case, each problem is defined by a specific objective in order to optimize its appropriate criteria. A model presented at (Friesz et al., 1993) solves the transportation network problem to reach a continuous multi-objective optimal design. The model explicitly incorporates user equilibrium constraints and takes the form of a difficult non-linear and non-convex mathematical program. The authors have proposed a single-level mathematical program as different from the existent standard mathematical formulation. Initially, the authors in (Friesz et al., 1993) have defined four objectives according to the table of taxonomy, taking into account, respectively, the (1.1, 1.9, 6, and 4.3) criteria. These criteria are summarized by:

Z1 = the total transportation cost that measures the network-wide congestion

Z2 = the total construction cost, which includes the cost of displacement and relocation of individuals residing near the links of the network that are to be improved

Z3 = the minimization of distance in function of the total number of miles traveled by a vehicle

Z4 = the total dwelling units taken in terms of the best way that adds a concern for the physical movement of a passenger residing near an improved link

The *Z2* and *Z4* objectives functions are merged on the sum objective. This objective is defined by adding a new parameter that represents the amplitude of the user. The vector mathematical program (VMP) is a non-convex representation that includes an improvement cost function. Besides, this non-convexity of VMP is derived from the constraint set, which is independent of the number and the type of scalar objectives Z_i. The scalar multi-class equilibrium design problems are obtained by the VMP, which considers only the scalar objective function *Z1* and expressing *Z2* as a budget constraint. Relying on the non-linear and non-convex mathematical formulation, it is difficult to solve the problem optimally. Therefore, a simulated annealing metaheuristic is proposed in (Friesz et al., 1993) in order to resolve this problem.

In (Spichkova, Simic, & Schmidt, 2015), the authors have suggested a new model of an intelligent smart route planner for autonomous vehicles. The proposed approach consists of an intelligent route planning for public transport systems in the sustainable Smart City. The proposed system allows advising the passenger to be at the stop by minimizing the corresponding time and the vehicle should arrive no later than the corresponding time at maximum. The passenger's request should include the route, the pick-up stop, day and time and the desired drop-off stop information.

The problem of motion planning of autonomous vehicles consists of selecting the geometric path and vehicle speeds to avoid obstacles and to minimize some cost functions, such as time or energy. While extensive work has focused on computing the geometric path, little attention has been given to selecting the optimal vehicle speeds. Selecting the wrong speeds can cause the vehicle to lose its path, or to waste energy time.

In (Shiller & Gwo, 1991), authors have developed a new method to plan the motions of autonomous vehicles moving on general terrains. The method allows getting the geometric path and vehicle speeds that minimize motion time, considering vehicle dynamics, terrain topography, obstacles, and surface mobility. The time optimal motions are computed by chiefly obtaining the best obstacle-free path from all paths represented by a uniform grid. This path is further optimized with a local optimization, using the optimal motion time along the path as the cost function and the control points of a spline as the optimizing parameters.

Authors in (Frazzoli, 2002) have been concerned with the problem of generating and executing a motion plan for an autonomous vehicle. In other terms, they have considered developing an algorithm that enables the robot to move from its original location to a new location (presumably to carry out an assigned task such as performing an observation or delivering a payload), while avoiding collisions with fixed or moving obstacles.

Planning the path of an autonomous, agile vehicle in a dynamic environment is a very complex problem, especially when the vehicle is required to use its full maneuvering capabilities. Recent efforts have aimed at using randomized algorithms for planning the path of kinematic and dynamic vehicles have demonstrated considerable potential for implementation on future autonomous platforms. In (Frazzoli, 2002), the authors have proposed a randomized path planning architecture for dynamical systems in the presence of fixed and moving obstacles. This architecture addresses the dynamic constraints on the vehicle's motion, and it provides at the same time a consistent decoupling between low-level control and motion planning. The proposed algorithm can be applied to vehicles whose dynamics are described either by ordinary differential equations or by higher-level, hybrid representations. Simulation examples involving a ground robot and a small autonomous helicopter are presented and discussed.

Optimization Problem of Rotation Barges and the Containers Assignments

Assuming that there is a set of containers, the main goal is to solve an optimization problem by planning the barriers during a rotation of the barges and containers. The planning solution must satisfy a set of constraints and objectives when loading containers and routing. The method of decision proposed in (Yim, Hanafi, Semet, & Korbaa, 2005) solves the problem of a quays management and rotation barges as well as the containers assignment. This method relies on data provided by space-based and optimized-based techniques such as dynamic programming and linear integer programming. The work in (Yim et al., 2005) was validated by a real case in the port of Lille.

The authors in (Yim et al., 2005) considered three objectives: the total volumes of capacity barges used; the number of visited quays; and the total distance. These three objectives are hierarchically aggregated, respectively, into a single function. The weights of each objective are represented by order of priority $\alpha 1 > \alpha 2 > \alpha 3$, having an exponential priority.

The objective function is presented as a linear function of three parameters which grants a weight to each: the total volume capacity of the barges used, the number of quays visited and the total distance. According to the presented taxonomy of objective functions, the criteria correspond to 4.1, 3.6 and 6 criteria.

In the (Yim et al., 2005) research, there has been a lack of optimization at the storage level of empty containers in the queue and determining the barge loading platforms as well as a lack of optimization in the total transportation time such as the waiting time, the travel time, etc., parameters.

The proposed model in (Yim et al., 2005) can be strengthened by the addition of valid constraints, particularly, on barges for container allocation and the minimal number of barges serving at the quay. The complexity of the barges rotation problem and container allocation allows a long calculation by a conventional method.

To address this drawback in the case of a planning at real-time, in (Ghoseiri & Ghannadpour, 2010) the authors have suggested a two-phase heuristic, wherein the first phase determines the composition of the fleet, i.e. in choosing the barges that will be effectively involved in the rotation and the second phase solves the model, however, they have considered only the selected fleet in the first phase. The problem of the first phase is modeled as a mathematical integer program, namely a big packing problem.

The resolution method of separation and evaluation techniques solves, in a short time, the barges rotation problem with 60 containers, however, it is not capable of getting the optimal solution in a reasonable calculation time when the number of containers' exceeds 100. In this case, the solution is given by a high execution time. Moreover, there are other approaches that are more promising in terms of allowing live scheduling rotation barges and allocation of containers.

In (Zaghdoud, 2015), authors have developed a container assignment system for intelligent autonomous vehicles in a container terminal. In the first contribution, they have proposed a static system for the multi-objective problem to optimize the total duration of the containers transportation, the waiting time of vehicles at loading points and the equilibrium of working time between vehicles. The approach used is the genetic algorithm (GA). In the second contribution, they have proposed the robustness system in a dynamic environment which has been integrated. A delay of the arrival of a ship at the port or a malfunction of one of any equipment of the port can cause a delay of one of the operations of the loading or unloading process. This will affect the container assignment operation. The idea is to add new containers to vehicles that are already unavailable.

The authors in (Yim et al., 2005) have treated rotation barges and the containers' assignments problem by satisfying three objectives. These three goals are summed up in the minimization of the total volumes of capacity barges used, the number of quays visited and the total distance. They use a CPLEX 6 solver for implementation. Then, they apply the heuristic algorithms to resolve this problem. The resolution method is based on the two-phase approach as well as the separation and evaluation method.

In (Coslovich, Pesenti, & Ukovich, 2006), the authors deal with a container transportation problem that is divided into three separate simpler sub-problems. These latter are defined by the pairings that include every order, the resources to assign to each pairing, and the containers possible reposition. The operating costs are given as time horizon when carrying on shippers. Then, they use the heuristic algorithms based on the decomposition of the problem on three sub-problems related to a cost. The integer programming model is characterized by the Linear programming relaxation based on Lagrangian relaxation.

The Vehicle Routing Problem (VRP)

The VRP plays a central role in the areas of physical distribution and logistics. The VRP can be described as the problem of finding an optimal routing network between one or more nodes, represented by geographical position as city, depot or client, in order to satisfy a number of constraints and objectives. These latter are different from one variant to another and they are specific to the case being treated. There are a variety of extensions of this problem class.

In the multi-objective framework, (Ghoseiri & Ghannadpour, 2010) treat the routing problem by means of time windows. They respect a node capacity constraint and a limited terminal, which satisfy the customer's needs on the arrival of a merchandise by the predefined time windows. In (Ghoseiri & Ghannadpour, 2010), the VRP with time windows (VRPTW) problem is defined as a multi-objective problem, while minimizing the distance traveled by vehicles and minimizing the total number of vehicles used and respecting vehicle capacity and time windows in order to meet all requirements of a customer.

Indeed, the decision maker must specify optimistic aspiration levels for each objective of the problem to be achieved, while minimizing the deviations between the achievement of goals and their aspiration levels. In (Yuqiang, Xuanzi, & Guangzai, 2013), the authors formulated this problem using the MOV-GP (II) approach and the formulation was based on goal programming. The advantage of the proposed MOV-GP (II) formulation is that it does not need additional constraints for each objective. They defined two parameters to indicate the aspiration levels of the objectives that control the distance traveled by vehicles and the total number of vehicles used to serve the customers. According to the taxonomy of objective function, they considered the (6) and (3.5) criteria. MOV-GP (II) formulation takes into account the defined goals, aspiration levels, and the deviations variables by the MOV-GP (I). The formulation of the MOV-GP (I) allows minimization of suction level deviations; this function will be changed by modeling it with the GP. The vehicle routing problem for a single distribution center with dynamic road capacity constraint is solved in (Yuqiang et al., 2013). The model proposed to solve a single distribution center and a single vehicle is defined as the RVRP type problem with soft time windows and dynamic constraint. The transportation fee is calculated according to the demanded quantity of goods, and the penal cost, associated with the time window. The objective function proposed in (Pradhananga, Taniguchi, Yamada, & Qureshi, 2014) is to minimize the total cost of transport according to the demand quantity of goods. The first item of the polynomial objective function is the transportation fee regarding the demanded quantity of the goods. The second item of the objective function is the penal cost when it does not respect the time window. According to the taxonomy, authors have considered the (1.11) and (2.6) criteria while adding a penalty cost.

A bi-objective Vehicle Routing and Scheduling Problem of Hazardous material with Time Windows (HVRPTW) is presented in (Pradhananga et al., 2014). It deals with the case of a road network of Osaka city, Japan. This problem aims to minimize the risk associated with each itinerary. In the proposed model by (Pradhananga et al., 2014), the risks are related to an itinerary based on an undesirable HazMat incident. These risks are measured by the sum of the probability of occurrence of the event times and its consequences associated with all links. Although a number of consequences depend on the HazMat incident are possible, they satisfy the human needs taking into account a top priority. The considered bi-objective problem is to minimize the total transport duration with the total risk at the transportation network. The routing solutions in the Pareto front are a compromise solution about the cost and risk objectives. A comparison of environmental impacts can provide additional information to the decision maker in order to select the optimal solution according to a process of decision-making. In (Pradhananga et al., 2014), VRP is defined by considering an urban road network of nodes and links (N, L) where the set N includes the depot nodes, the customer nodes or non-customer nodes and the set L includes all possible connections between N nodes. For each link connecting a pair of nodes, two attributes, representing the average travel time and risk, respectively, are defined. The risk attribute is the product of the probability of the HazMat incident on a link and the exposure population along the link. The HVRPTW is defined in a directed graph G(V, A) by vertices and arcs. The vertices set V includes the depot (vertex 0) and a set of customer vertices C. The arcs set A includes all non-dominated paths between the vertices in V obtained based on travel time and risk objectives. The non-dominated paths are assumed to be determined beforehand using a labeling algorithm. The mathematical formulation, proposed in (Lim, Lim, & Rodrigues, 2002), is defined as a bi-objective HVRPTW which seeks to minimize the total cost and the total risk.

The HVRPTW model imposes hard time windows constraints of arriving at each customer. During the service, vehicles that arrive after the end of the time window are not allowed to wait, however, vehicles that arrive earlier are allowed to wait for the start of the time windows. The arrival time for the customer to serve must be a positive value. Solutions reached by a minimum number of vehicles are considered better than the solutions given by larger numbers of vehicles in measuring the total emissions criterion. The emission intensities are mainly dependent on the number of the use of links in a transportation network and their affectation according to the repetitive use of links. The terms of cost and risk in the proposed objective function are based on the travel time and the size of the population. The model can be classified in the most realistic and dynamic stochastic models for the rotation issue and multi-objective scheduling in the transportation of hazardous materials that take into account the stochastic and dynamic characteristics of travel time and modalities population. All the routing solutions given in the Pareto front are trade-off solutions in terms of objectives values of cost and risk. The comparison of environmental impacts can provide the decision-maker with additional information to help in the decision-making process. Emissions of CO2, NOx and SPM criteria are compared for four Pareto optimal solutions selected by a real instance HVRPTW.

(Asadi-Gangraj & Nayeri, 2018) propose a Multi-objective Mixed Integer Programming model. The authors point out the vehicles routing problem with time windows, driver-specific times and vehicle-specific capacities. The first objective aims to minimize traveling distance and the second objective aims to minimize working duration. Constraints of the model include assignment, flow conservation, time windows, and scheduling constraints. This problem is considered NP-hard. Hence, they propose a hybrid approach based on the LP-metric method and genetic algorithm to solve the VRP.

The Pickup and Delivery Problem With Time Windows (PDPTW)

The PDPTW problem is a variant of the VRPTW problem. In (Kammarti, Hammadi, Borne, & Ksouri, 2005), the authors seek to minimize the total number of vehicles, the total distance of the itinerary, the total transportation time and the total waiting time. They have defined this multi-criteria problem as a problem of vector optimization, which seeks to optimize several components of a vector function cost. They have added the objective function to minimize the number of vehicles used and the parameters that characterize each individual. They have proposed a multi-criteria approach based on genetic algorithms to minimize the weighted sum of the number of vehicles used, the sum of the delays and the total cost of transportation. This method can obtain the Pareto optimality. The selected solution is provided by the Pareto optimality, defined by the point where the hyperplane has a common tangent with the feasible space. The PDPTW considers and respects the time windows constraints. This parameter is defined by customers or suppliers that are geographically in the space. Each itinerary selected must satisfy the precedence constraints, i.e. customers should not be visited before their suppliers.

In (Kammarti et al., 2005), the authors solve this problem using this variant by means of a single vehicle (1-PDPTW). The main aims are to minimize the compromise between the total travel distance, the total waiting time and the total delay time. The proposed solution is given by using the evolutionary algorithm with a genetic operator, and the Tabu search. The proposed method denotes a new approach based on the lower bounds and the Pareto dominance method. In the proposed formulation (Kammarti et al., 2005), each objective has weights. The main limit of this formulation is the lack of sub-towers disposal constraints to reduce complexity. The objectives functions represent a compromise between the total distances traveled (6) criterion, the total waiting time (2.7) criterion, and the total delay time (2.3) criterion while respecting the time windows for arriving at the node. Each criterion of the objective function has a weighting (Dridi, Kammarti, Ksouri, & Borne, 2009).

In (Dridi, Kammarti, Ksouri, & Borne, 2010), the authors solve the PDPTW problem with several vehicles (m-PDPTW). This problem is defined by a single objective that aims to minimize the total cost of transport (1.1) criterion from the taxonomy table, to serve all customer requests. This cost depends on each vehicle used and the distance traveled by each vehicle. It should be using a metaheuristic as the genetic algorithm to avoid the infeasible solutions. The mathematical formulation presented in (Kammarti et al., 2005) is characterized by the same parameters used in (Zidi, Mesghouni, Zidi, & Ghedira, 2012, 2011; Zidi, Zidi, Mesghouni, & Ghedira, 2011) to solve the problem of PDPTW. The aims of objectives functions are to minimize the compromise between the number of vehicles (3.5) criterion, the respect of arriving at the time windows (2.6) criterion, and the total cost of transport (1.1) criterion.

Dial a Ride Problem (DRP)

The DRP defined when a shipment must be transported between the specified pickup and delivery locations. This problem is defined by a set of transport demands and the goal is to serve them according to the number of vehicles used. Each transport demand is modeled by a request containing information on demand. The aim is to serve it, and it must recover a passenger or goods from an origin at a destination point. The DRP is considered as a collective individualized transport starting on demand. The main objective is to minimize the total distance traveled. Indeed, the vehicle routing and scheduling problems are the generic class of problem to which the dynamic DRP belongs. The difference between static and dynamic DRP is that the transport requirements are not known in advance, they will be processed in real-time over time. A multi-objective mathematical model for the DRP problem is described in (Zidi et al., 2012; Zidi, Mesghouni, et al., 2011; Zidi, Zidi, et al., 2011). This formulation presents the DRP by a multi-objective function as follows:

- **Economic criterion (ECO):** Minimize transport costs (1.1) criterion: the cost per kilometer of vehicle use;
- **Service quality (SQ) criterion, which is composed of two major criteria:** The Ride Time (RT) (3.7) criterion and the Number of Stations Visited (NSV) (3.8) criterion, (see Table 1).

The objectives functions of the transport problem take into account the service quality provided to travelers.

The proposed formulation of the DRP by Zidi et al. does not attribute a weight at each objective function or applied for the aggregate method to solve the multi-objective problem; although they use a domination concept in the resolution of the multi-objective DRP. Moreover, they apply the concepts of Pareto optimality and a-efficiency in order to find the best compromise solution to this problem. Thus, this reduces the set of feasible solutions for the considered problem. In fact, this method has advantages compared to the aggregation method. However, all the objectives functions in this formulation have the same importance in the optimization process.

There are no polynomial algorithms to resolve optimally within reasonable time NP-complete optimization problems. To resolve these problems an approximate method must be applied. In (Zidi et al., 2012; Zidi, Mesghouni, et al., 2011), the authors propose a Multi-Objective Simulated Annealing algorithm that is applied to solve this multi-criteria problem. The contribution in (Zidi et al., 2012) is the resolution of the DRP in the static and dynamic context to give an optimal solution. To the complexity of the DRP reason, authors propose a non-aggregative approach based on Multi-Objective Simulated Annealing (MOSA) algorithm. This algorithm is applied to simulate annealing metaheuristic with the addition of Multi-Agent systems in order to solve this problem in dynamic cases. The proposed model is able to represent the problem in a generalized model, and it is easily adapted to other already known models.

Classification and routing are performed by the principal of the distribution heuristic and the neighborhood structure. The proposed programming heuristic in (Zidi et al., 2012) consists in calculating the appropriate departure times of the vehicles from the depot. In addition, the proposed heuristic is used to reduce the violation of time window constraint. In (Zidi et al., 2012), the main idea of this approach is to apply the concept of domination and the annealing scheme algorithm. Besides, MOSA can find a subset group of Pareto solutions in a short period of time. Afterward, it generates more solutions by repeating the tests for detailed information on the Front Pareto. Some improvements can be made to the proposed approach in (Friesz et al., 1993) such as the resolution of the problem with heterogeneous vehicles to assign each customer to the appropriate vehicle, the hybridization of the MOSA approach and, applying this approach on a real case.

Berth Allocation Problem

In (Imai, Nishimura, & Papadimitriou, 2001), the authors have treated a dynamic berth allocation problem of the containers in the port. The objective is to minimize the total of waiting and handling times for every ship to yield an optimal ship-berth-order assignment to the dynamic berthing plan. They have proposed a heuristic algorithm to resolve this problem. This heuristic is applied to the sub-gradient optimization procedure based on the Lagrangian relaxation of the original problem.

In (Imai, Sun, Nishimura, & Papadimitriou, 2005), the authors have treated the Berth allocation problem of the container in the port. The main aim is to give the berth allocation in the discrete quay location (BAPD) in order to satisfy the total service time. They propose heuristic algorithms to solve this problem. The proposed algorithm divides the problem into two steps to solve it: (a) the BAPD algorithm identifies a solution given in several parts berths, (b) the procedure relocates the ships that may overlap or be located sparsely in the schedule space that is defined by the first BAPD algorithm.

In (Imai, Nishimura, & Papadimitriou, 2003), the authors have treated the Dynamic Berth Allocation problem. This problem is defined by two-objective berth allocation problem when shipping service quality expressed by the minimization of total delay time in ship departure (the weight, however, is not taken into account) and the berth use expressed by minimizing the total service time. The authors have developed two heuristics for the single-objective BAP based on the sub-gradient optimization. This heuristic is defined by the Lagrangian relaxation and the genetic algorithm (GA).

In (Imai, Zhang, Shimura, & Papadimitriou, 2007), the authors have defined the berth allocation problem for container transportation by considering the service time and the delay times criteria. The goal is to satisfy two-objective in berth allocation problems such as the minimization of the total service time and the total delay time. The optimization of the total service time of ships is estimated from the departure time. The authors have developed two heuristics algorithms based on existing procedures of the sub-problem optimization and the genetic algorithm. These algorithms are implemented in the C language.

Traveling Salesman Problem

The traveling salesman problem (TSP) is defined by the given set of locations and the distances between two cities. The optimizer attempts to find the shortest possible route that visits each city, exactly once and returns to the origin city. Mathematically, the TSP formulated as a graph is represented by a weighted graph, where edges are the cities and the arcs are holding the distance between them.

(Sabry, Benhra, & Bacha, 2018) have solved the TSP with green constraints, defined as multi-objectives in terms of emissions, time and distance in the metropolitan environment of the city of Casablanca. They have included the emissions criteria (the total emitted CO_2. The model takes into consideration the distance, total activity, modal configuration, and other technical and fuel-related factors. (Sabry et al., 2018) have proposed an approach based on the ant colony of optimization metaheuristic to green optimization that takes into consideration the distance, total activity, modal configuration, and other technical and fuel-related factors. The metaheuristic converges and manages to return good solutions.

Solid Transportation Problem

The solid transportation problem (STP) is defined as a special case of the transportation problem. In real-world cases, multiples transportation modes are used to ship the goods from departure to destination nodes. Each transportation modes and means called conveyance. The STP considers three constraints namely departure, destination, and conveyance capacity. In (Jalil, Javaid, & Muneeb, 2018), the authors modeled the decision-making system based on multiple objectives that are minimized in a hierarchical order. The objective function at each level is solved separately to obtain the satisfactory solutions.

(Javaid, Jalil, & Asim, 2017) contribute by developing a multi-objective fractional transportation planning decision model via uncertainty theory. The models with uncertain variables are often complex to deal with, hence the concept of expected constraint programming is applied to develop the model. Fuzzy goal programming technique (max-min approach) is proposed to solve the multi-objective fractional transportation model. Fractional programming problems take into account the situations where the decision maker is interested to maximize or minimize the ratios of some functions rather than a simple function.

The STP considers two main assumptions. Due to a damageability of the units, the transported damaged amount is constant, and a single item of a homogeneous product should be transported from sources to destinations. Mathematically, this problem is defined by m origins nodes, n destinations and k conveyances, including different modes of transport. (Pramanik, Jana, & Maiti, 2013) The multi-objective solid transportation problem (MSTP) for a damageable item is formulated and solved. The formulation incorporates multiple criteria such as transportation costs, resources, demands and capacities of conveyances, which are random fuzzy in nature. The STP is formulated as a decision-making model optimizing possible value at risk by incorporating the concept of value at risk into a possible and necessary measure theory. The transported item is likely to be damaged during transportation and damageability is different for different conveyances along different roots. The reduced deterministic constrained problem is solved using a generalized reduced gradient (GRG) method. The model is illustrated with numerical examples and some sensitivity analyses are made on damageability.

(Yang & Liu, 2007) have investigated a fixed charge solid transportation problem in the fuzzy environment, by considering that the direct costs, the fixed charges, the supplies, the demands, and the conveyance capacities are supposed to be fuzzy variables. In order to solve the proposed model, a hybrid intelligent algorithm is designed based on the fuzzy simulation technique and Tabu search algorithm. The objective function implies optimizing the expected value of the total transportation cost, i.e. seeking the expected transportation plan; the first constraint implies that the total amount transported from source i is no more than the expected value of its supply capacity; the second constraint implies that the total amount transported from i sources should satisfy the expected value of the demand of destination j; the third constraint states that the total amount transported by conveyance k is no more than the expected value of its transportation capacity.

According to the idea of optimizing the expected value of the objective under expected constraints, the expected value model is constructed. The construction of chance-constrained programming model is in accordance with the idea of optimizing the critical value of the objective under the chance constraints.

As known, the tabu search algorithm is a suitable method to solve the complex combinational optimization problem. (Yang & Liu, 2007) have designed a Tabu search algorithm based on fuzzy simulation to seek the approximate best transportation plan. The introduced models and algorithm present a coal transportation problem, and accordingly, a chance-constrained programming model and a dependent-chance programming model are employed as the experimental models. The results prove that the designed algorithm is robust.

Synthesis

Interesting numbers of studies are addressed to solve the network planning problem of the transportation and the multi-objective problem that is defined on various means as (Ghoseiri & Ghannadpour, 2010). This multi-objective problem is solved by minimizing the total cost (criterion given by the user) to satisfy the requirements of the user.

The VRPTW problem is solved in (Ghoseiri & Ghannadpour, 2010) according to a multi-objective model. The objectives are considered to minimize the distance traveled and the total number of vehicles used. The time window is defined as a constraint of the model. The RVRP is a VRP with road capacity constraint and dynamic constraint, developed in (Pradhananga et al., 2014). The first objective is to minimize the transportation cost according to the demand quantity of goods and the second objective is the penal cost of time windows. Another variant of VRP, defined as HVRPTW for the hazardous material, is solved in (Kammarti et al., 2005). The objective function is to minimize the total cost and risk, however, the time window is defined as a constraint of the model.

The variant of VRPTW is solved in (Dridi et al., 2010) as the PDPTW with a single vehicle. The main goals are to minimize the compromise between the total travel distances and to respect the time windows for the total waiting time and the total tardiness time to be minimized. The same problem is solved in (Dridi et al., 2009). The proposed formulation minimizes the number of vehicles, the cost of transport and the delays time by respecting time windows. In addition, the PDPTW problem with several vehicles (m-PDPTW) is treated in (Zidi et al., 2012; Zidi, Mesghouni, et al., 2011; Zidi, Zidi, et al., 2011). The proposed formulation of this problem satisfies only a single objective that seeks to minimize the total cost of transport. This cost depends on the distance traveled parameter of each vehicle.

The DRP is defined in (YIM et al., 2005) by the multi-objective formulation. The multi-objective functions are concerned with minimizing the transport cost and maximizing the service quality depending on the two criteria, i.e. the ride time and the number of stations visited. Besides, another related problem of the transportation problem is the quays' optimization problem of rotation barges and the containers assignments presented in (Ghoseiri & Ghannadpour, 2010). The mathematical formulation is defined by three objectives. These objectives are hierarchically aggregated into a single function with the weight associated with each objective. Respectively, the total volume of barges capacity used, the number of visits quays and the total distance traveled, etc.

MULTIMODAL TRANSPORTATION PROBLEM

Multimodal transport offers an advanced platform for more efficient, reliable and flexible freight transport. This problem defined as the fusion of a set of networks G^k (N^k, A^k), each network associated with k^{th} transportation mode. $N^k = \left\{n_1^k, n_2^k, \dots, n_i^k\right\}$ represents the set of nodes, and $A^k \in \text{ arcs } \left(\mathrm{n}_{\mathrm{i}}^{\mathrm{k}}, n_j^k\right)$ represent the transportation itineraries between two nodes, and it exists one or more itineraries (arcs) between two nodes. Thus, a network G^k is the set of connected arcs, with a set of nodes N^k and the corresponding arcs A^k, when each arc measured by one or more values.

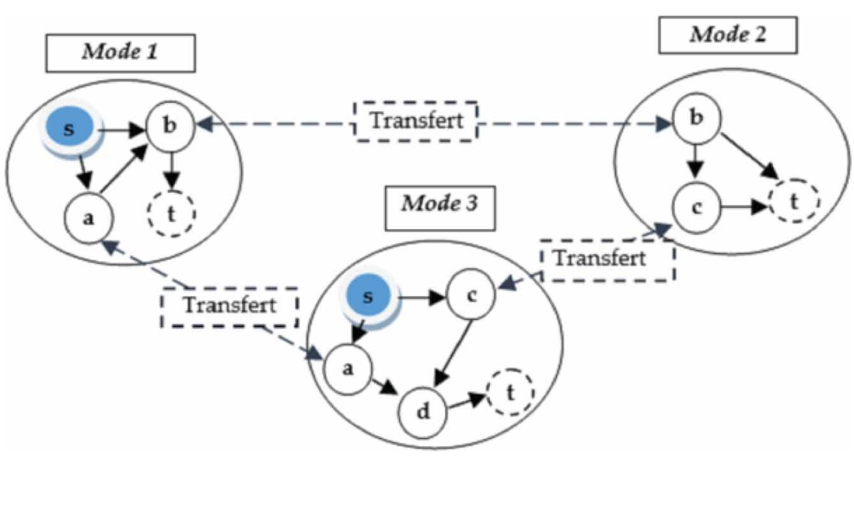
In order to make sustainable planning in a multimodal transport system, it is very interesting to use methods included in the fields of operational research. The optimization of planning in a multi-modal transportation network is formulated by several manners in literature. This paper reviews various works that solve the network planning problem, by analyzing the different mathematical optimizations on multi-modal transport network problem and their variants. Previous research identified a large number of factors that prove to influence the extent of the optimization problem in the field of transport. Therefore, this study offers two main contributions. In fact, the existing works in the literature on the optimization problem were summarized and a literature review of the multi-modal transportation network planning problem was presented along with the taxonomy about the principal objectives treated and synthesized, a critical discussion and the comparison of various existing resolution methods.

The multimodal transportation offers a full range of transportation modes and itinerary options, allowing them to coordinate supply, production, storage, finance, and distribution functions to achieve the most effective relationships using multiple means of transport. The goal is to move from the starting city to the destination city through other intermediate cities, knowing that there are several itineraries between them. The transport network is multi-modal with various means of transport such as train, boat, airplane, truck, bus, metro, or others, used to reach a destination in accordance with customer's requirements and the constraints of the problem. In general, the objective of a multimodal network planning problem is to optimize reliable transport chains for a passenger or freight. There are various measures to check a multi-modal path, such as the travel cost, in-vehicle time, waiting time, length, travel time, transfer time, the number of transfers, etc. The main objective of this problem is to find the shortest and the most efficient way of satisfying a set of objectives, and a set of operational constraints according to customer demands. Each case treated is defined by the specific parameters specific to the treated problem. Since each variant possesses its own characteristics, several forms of the formulation or definitions of problems are distinguished to reflect the presence of several decisions variables. These decisions variables are based on the special characteristics of the goals and constraints of the treated problem. These constraints are specified for each customer, vehicle, mode, road or means of transport, as well as the type of treated problem. Based on the existing literature works, it can be found that the majority of works have solved this problem by using linear programming inspired methods since it is a method that solves the problem of the exact manners in order to mostly optimize a set of objectives and satisfy a set of constraints.

This paper is interested chiefly in the literature reviews that solve the multimodal transportation problems. The principle is to find the shortest path and the most efficient way by using several transportation modes in order to provide customers' demands while satisfying several objectives to a large set of operational constraints. Among the requirements of the clients aimed to be satisfied with the minimization of the total transportation cost, the total transportation duration, the total transportation risk or the maximization of the quality of service have been quoted. The optimization by operation's research proves their efficiency in the resolution step of these problems. The components of the multi-modal transportation system are the mode of transport, the itinerary, and the infrastructure condition. The intersections of these components bring about the concepts of assignment and transportation. The multi-modal transport problem is defined by the use of several modes of transport wherein each mode is identified by these appropriate nodes and paths and their connection nodes to change the mode. Figure 1 shows a graphical representation of a multi-modal transport network. The problem is delineated by choosing the best path and the optimal mode according to the case-study taken into account. This problem contains several system constraints that involve using the optimization methods to satisfy all the constraints and objectives of the problem fixed by the decision-maker to request the customer's requirements.

In order to solve the multi-objective problem, the decision-maker is charged with the selection of the best itinerary, while satisfying a set of objectives that present the best compromise between these objectives, such as transportation cost and transport duration, etc. The selection of the transportation mode to optimize the transport itinerary in the multimodal network is a major concern for the shippers, carriers, and customers. The literature on multi-objective optimization of multimodal transportation networks shows a variety of resolving models by using the mathematical formulation. Each model is

Figure 1. Multi-modal transportation network



characterized by the specific parameters that define the treated problem. In real cases, each problem will be defined by one or more objectives in order to optimize their appropriate criteria.

In the multi-objective framework (Yuqiang et al., 2013) have solved the vehicle routing problem with the time window. The objectives are to minimize both the traveled distance and the total number of vehicles used, and the time window that is defined as a constraint of the model. In (Wan & Lo, 2003), the authors have solved RVRP with road capacity and a dynamic constraint. The objective is to minimize the cost of transport. The transportation fee is measured according to the demanded quantity of the goods, and the penalty cost according to the time window.

The mathematical formulation of the transportation network design is usually intractable by exact approaches. In (Verga, Silva, Yamakami, & Shirabayashi, 2013), the authors have developed a MILP formulation in order to minimize the operating cost, respecting a bus capacity constraint in the public context. The objective is to minimize the operating costs while responding to the considered capacity system constraints and bounding the exchange action frequency. The characteristic of their formulation allows generating implicitly the structure of the routes.

In (Gédéon, Florian, & Crainic, 1993), the authors have treated another variant of the multimodal transport network problem characterized by the uncertain costs of the edges. This problem has been modeled based on graph theory, where each transport mode is represented by a sub-graph, and the whole graph is the sum of all sub-graphs. The proposed mathematical formulation describes non-linear constraints, in order to develop an algorithm that reaches a set of Pareto solutions and to find the best routes between the origin and the destination. Each sub-graph represents one transport mode. In addition, this sub-graph will be connected in order to represent the transfer edges. The parameters of cost and time are uncertain since they are represented by fuzzy numbers. Each node represents a place where the user chooses the preferred mode. The selected options are to be continued in the selected mode. Only the uncertainties of travel time are considered during the formulation to be optimized, nevertheless, they neglected other goals, like total transportation cost, the quality of service, etc. In (Liu, Mu, & Yang, 2014; Liu, Yang, Mu, Li, & Wu, 2013), the authors have solved a transshipment problem of freight flows over a multimodal network. They have optimized the flow costs by minimizing the convex cost in order to determine the origin-destination matrix which corresponds to the minimal cost flows. They assume that the cost is the same for all products regardless of their origin.

The multimodal shortest path problem (M-SPP) is defined by the research of a path from a specific origin to a particular destination in a given multimodal network while minimizing the total transportation costs, the total transportation time, or the distance of itinerary. In (Liu et al., 2014, 2013), the authors have treated the multi-criteria multi-modal shortest path problem (MM-SPP). The aims are to optimize the transfer delays and to respect time-window at the arrival node. This problem is included in the class of an NP-hard problem. (Cai, Zhang, & Shao, 2010) have developed an exact algorithm to solve the MM-SPP by minimizing the total itinerary duration, minimizing the total transportation cost and minimizing the delays time in the transfer parking while respecting the time window in the arrival at the destination. They have solved the MM-SPPs with transfer delay by an improvement of the exact label-correcting algorithm (LCA). Then, they added the time-window constraint to respect the arrival time of the client.

In (Cai et al., 2010), the authors have developed a mathematical model to solve the multi-modal transport problem with the full loads and time windows. This is considered as a complex problem. The (L. Zhang & Peng, 2009) and (Wan & Lo, 2003) present the same model. They have considered this problem with two objectives: (a) minimizing the total cost of transport, which includes transport costs, change cost and time overhead, (b) minimizing the total time of transport, including the total duration of transport, the time of transshipment and the delay time. The proposed model does not provide a feasible solution to the problem. In order to resolve this problem, the authors have implemented a multi-objective genetic algorithm with random weighting. This algorithm is adopted as an optimization procedure, combined with MATLAB.

There are several optimization measures to evaluate a multi-modal path, such as the transportation cost, duration of transport, waiting time, the length of itinerary, travel time, transfer time, the number of transfers, etc. The multimodal context of the majority of the previous works is divided into two major objectives, namely the minimization of transportation cost or of the duration of transport. Each objective is measured according to one or several parameters that are specific to the case of the problem treated. It should, also, be cited as an example that transport costs can be measured by the cost of transportation, operating costs, transfer costs, cost depending on duration, the cost of loading the goods, or the cost of the assignment Resources, etc.

Multimodal Transport Optimization Problem With Single Objective

Multimodal Network Planning

The concept of Integrated Multi-modal Network Planning means that:

- The public transport networks should provide a good service to access an entire region;
- The key to a good system is well-organized, legible routes with fast, effective and easy interchanges between services;
- Different itineraries must be planned to complement each other (must be continuous) and do not compete (which usually means having a regulatory authority over strategic planning responsibility and authority over the network);
- The mechanism allowing quick transfers between lines;
- Ticketing systems for the network should support easy transfers between lines, and treat all modes in the same way as much as possible.

In general, the objective of a multi-modal network planning problem is to optimize the contribution of reliable transport chains with public or freight transportation. In (Wan & Lo, 2009), the authors have developed a mathematical formulation MILP to minimize the operator's cost subject to the capacity of transport means constraint. The main characteristic of this formulation is to generate implicitly the structure of the itineraries. However, this requires specifying a maximum number of routes in the solution. The proposed objective function minimizes the operating costs and the constraints of the system considered the capacity and bounded frequency. The routes are generated implicitly by specially introduced variables. In particular, a non-trivial problem is to exclude cyclic lines from the solution. The implementation of this model is realized by CPLEX.

In (Wan & Lo, 2009), the authors have treated the congestion in the multi-modal transit network design planning problem of transit services. This problem is formulated as a multi-route transit network design problem. The objective of this formulation is to minimize the sum of the operating costs of all transit lines. The formulation is presented as a mixed integer program. Through the integer variables, they follow the path of each line and the traffic volume along its alignment. Thus, this allows obtaining a better efficiency by specifying the required line frequencies and the capacities which are not taken into account in the previous approaches.

Wan et al. describe a formulation to determine multiple transit lines on a network, providing direction in the vehicle services for all travel demands (Verga et al., 2013). Through the representation of node labels, the route structure and the flow on every segment of a route are represented explicitly. Some information is used to specify the appropriate line frequencies in order to meet all the demands in accordance with minimum cost. The authors have extended the formulation as the multi-objective model to capture the complicated interactions between service provisions and passenger choices.

In (Verga et al., 2013), the authors have treated another multi-modal transport network problem with uncertain costs on the edges. They have applied the proposed approach in the real case of Sioux Fall network. The authors have developed a new approach to solve a multi-modal transport problem. The proposed algorithm is an adaptation of a classic Ford-Moore-Bellman algorithm and does transform the uncertainty into a classical number. The uncertain cost values of each edge are dealt with using the fuzzy set theory. The uncertain information is preferred, i.e. the missing information to obtain a satisfactory solution, which can be closer to the optimal solution (Liu et al., 2014).

In (Castelli, Pesenti, & Ukovich, 2004), the authors have solved the scheduling problem in the multimodal transportation network systems by mainly being devoted to commuters. The objective of the proposed model is to minimize the operating costs. The mathematical model is integrated into a heuristic procedure based on Lagrangian relaxation, decomposed into a set of single line problems. The proposed algorithm defines the best schedules and solves the transfer coordination problem.

Multi-Modal Shortest Path Problem (M-SPP)

In the case of multi-modal transport, changing from one mode of transport, it has to go from one correspondence node to another. The passage time between these nodes will be penalized by a cost. The aim is to solve the multi-modal transportation networks problem by getting the Origin-Destination of the shortest path. The goals are to minimize the overall cost, time and users' flow commodity associated with the required paths. In the multi-modal network, the transfer time includes the total waiting time at transfer stops, the total walking time between transfer stops and the stopping time at the transferred stop, and the travel time includes the overall in-vehicle time and the total transfer time in the network.

The M-SPP aims to find the short path from an origin to a destination node in a multi-modal network while minimizing the total transportation costs. The complexity of finding the multi-modal route is obviously higher than a single modal one. On the multi-modal network's level, several modes of transportation operate concurrently under the changing conditions. The multi-criteria multi-modal shortest path problem belongs to the set of NP-hard problems. The related M-SPP is one of the most important and practical problems in several fields such as urban transportation system and freight transportation. In order to reach the destination, the passengers or the goods will alternate between different modes. The time-window is usually associated with the M-SPP as a special demand.

In (Jing, Liu, & Cao, 2012), the authors have developed a new medialization when the M-SPP satisfies the delay and the arriving of time windows, presented by a simple form. Existing methods do not supply an exact solution of the M-SPP with delays, by designing a triplet label at each node. The proposed formulation satisfies the main objective. This objective is to minimize the total travel duration, including the transfer delays that happen which must comply with a time window. The running time will be increased by the number of modes of transport used. They are considered the way service time, and they also improve the convergence by an exact algorithm; however, they do not include a similar path.

Route Selection Problem

In order to solve the selection problem of modes and roads in multi-modal transportation, the decision maker is charged with selecting the best itinerary, knowing that there are several routes between two cities. This itinerary presents a compromise between objectives as the total transportation cost and the total cost. In (Jing et al., 2012), the authors have proposed a mathematical formulation to solve and optimize the virtual transport network problem in multi-modal transport. The objective function of the formulation aims to minimize the total cost of transport (1.1) criterion and the transfer cost (1.2) criterion. Each route has a cost, a transit time and a single mode. The goal is to select a path between two neighboring sites to minimize the cost of moving a site to a writer and the total duration may not exceed a time. (Jing et al., 2012) suggest a hybrid genetic algorithm based on chromosome coding, genetic operators, and restriction controlling method as well as population diversity controlling method. This approach is inspired by a combination of technical knowledge. However, the total time of transport obtained in (Lee, Chew, & Lee, 2006) is larger than the solution found in the literature.

Multi-Commodity Flow

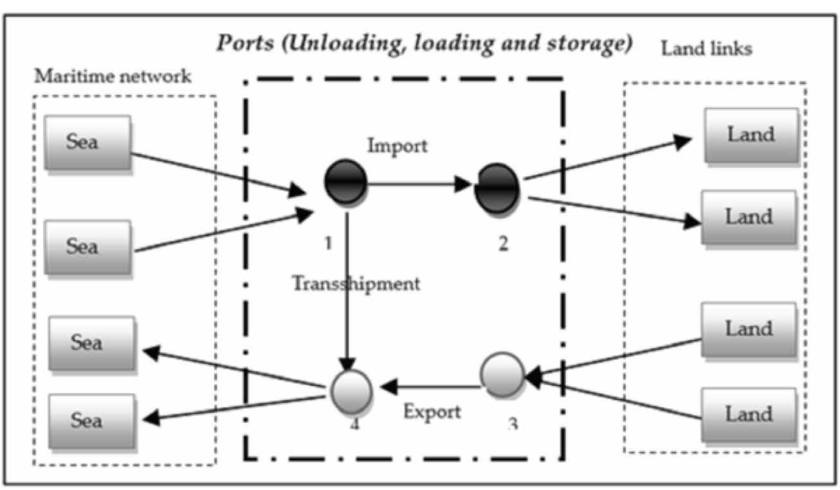
The network design problems arise in different application areas, mainly using the multi-commodity flow structure. Fixed charge capacitated multi-commodity network design (CMND) problem presents the major problem class of multi-commodity networks design problems. The CMND formulation represents a generic model for the planning problems in the construction, improvement, and operations of transportation, logistics, production, and telecommunication systems. In (Lee et al., 2006), the authors have developed a scientific and systematic approach to the flow of containers for the Asia-Pacific region. In this case, strategic planning proposes a decision support that satisfies various objectives such as terminal handling costs and turnaround times.

A multi-commodity flow model is proposed in (Lee et al., 2006) to treat the sensitivity of the cargo flow between ports in terms of efficiency, port charges, and freight costs. The problem is formulated as a multi-commodity network model. The objective function is defined by the transport cost and the opportunity cost that is attributed to the time spent by the cargo on the links. The first term in the objective function represents the transport cost corresponding to (1.1) criterion and the second term represents the opportunity cost that corresponds to (1.13) criterion, which is attributed to the time spent by the cargo on the links. The constraints respect the conservation of flow and the annual capacity for each link, also the annual capacity of the port (Lee et al., 2006). The model satisfies an optimization at the level of transport cost and opportunity cost. Nevertheless, this model needs to be improved in order to evaluate the attractiveness of a port using other quality factors. There is still a need to improve or revise economic parameters such as transport costs, delays, and capacity constraint.

In (Luo & Grigalunas, 2003), authors have formulated a new model to solve the multi-modal network transport problem with flexible time and scheduled services arising from the operations of a logistics company in Italy. They have combined several features, such as scheduling, flexible time transport, and consolidation options. Besides, they have proposed a network representation of this problem. Then, they have developed an approach that exploits specific problematic features such as cost function properties and realistic upper limits on feasible paths. They have performed computational experiments based on decomposition, and the representation of the virtual network can sometimes give rise to very large digraphs.

A multi-modal container transportation model is developed in (Le Thi, Ndiaye, & Pham Dinh, 2008) for optimization economic. This model is proposed to estimate the annual container transportation demand for major container ports and to evaluate the impact on port demands by

Figure 2. Network representation for the port (Lee et al., 2006)



changing port fees. The model is designed to estimate port demand by optimizing the total cost of the container transportation process through a multi-modal network, including ports, rails, highways and shipping lines.

Synthesis

The multi-modal transportation problems in the majority of the literature works are solved by satisfying two major objectives, namely the minimization of total cost and the minimization of the total time. This section presents a recap of the various problems met in multi-modal transport context that addresses the optimization problem with a single objective. Most of the research work is met to consist in minimizing the cost, like the cost of transport, operating cost, transfer cost, the cost and the duration of goods loading, or resource assignment cost, etc. The objectives are defined according to the specific parameters of the type of problem treated.

MULTI-OBJECTIVE OPTIMIZATION

The problem of rotation transport of containers has a market potential, conditioned by the refinement of its quality of service (improvement of the system and services). Multimodal transport of containers has an iterative of rotation transport that requires competitiveness in terms of service quality, cost and other criteria.

The multi-modal transportation has become a key platform for containerized transportation solutions. Moreover, the multi-modal transportation process considers various criteria and objectives according to the variant treated. These objectives might be conflicting with each other, requiring multi-objective methodologies to solve this problem. The criteria such as the limited number and capacity, additional regulations (e.g. regulations of working hours of drivers), and simultaneous planning of multiple resources (e.g. vehicles and drivers) should be incorporated. In this respect, the dynamic data or the stochastic data also remain a major research challenge. This section quotes the major works of literature that furnish a multi-objective optimization solution to the multi-modal transportation problem.

Multi-Modal Transport of the Container

In (Le Thi et al., 2008), the proposed optimization aims to minimize the frequency of transfers to the yards for the loading of containers problem on trains in the rail-rail transshipment site. Depending on their final destination, the containers are unloaded from their first original train by automated handling systems, to be recharged on a train leaving at a defined location.

The effective operational management can be described by two main problems of optimization:

1. The determination of the loading-reloading points of containers on different trains;
2. Planning of handling equipment that transfers containers from a train of arrival to a train of departure.

The main goal is to optimize the site management from the total processing time of trains. The main problem is to initially load and allocate the available site containers while minimizing their movement during transfer and minimizing the number of cranes used. Therefore, the transfer tasks are taken when the train arrives at a station. The operations are planned to minimize the total duration and to limit the immobilization of trains. The authors in (Le Thi et al., 2008) are only concerned with determining container sites on trains under various constraints. The objective is to minimize the total allocation cost of containers about a set of transferring trains to a set of corresponding trains, which refers to the (1.7) criterion (see Taxonomy Table 1). The problem is defined as a 0-1 linear program. Thanks to exact penalty techniques in DC programming, the problem is transformed into a polyhedral

DC program. Authors have proposed in (Le Thi et al., 2008) an optimization solution for the load and transfer of container with explicit storage constraint. The proposed model improves the upper bound and the total time of travel. The principle of optimization is to join the initial loading and the transfer. They have compared the optimization of the load along transfer, as well as the choice of the corresponding train for the transfer of containers. However, the data sets are close to real-data. The aim consists of improving the optimal value of the objective function and the number of movements of cranes generated. The results presented in (Choong, Cole, & Kutanoglu, 2002) show that it is possible to remove all the changes in the zones and to improve globally the performance of the yard.

The results exhibit the effectiveness of DCA in the method that improves the upper bound and the total travel time. The method of DCA defined by combination with BB gives a workable local solution. This combination is more interesting than the BB. The obtained results found appreciably the same upper bound, but the running time and the number of iterations of CPLEX 9.1 remain very large.

An integer programming model is proposed in planning horizon effects on empty container management for multi-modal transportation network problems (Choong et al., 2002). Although the appropriate length of the planning horizon depends on the network under consideration, a longer planning horizon can give better empty container distribution plans for the earlier periods. The longer horizon allows better management of containers outsourcing and encourages using the slower and cheaper transportation modes (as the barge). However, the advantages of using a long rotation horizon might be small for a system that has a sufficient number of containers, since such a system has small end-of-horizon effects. For a network with a barge transportation mode, the planning horizon should have enough length for the model to have a chance to consider using the slower cheaper barge mode.

The proposed model in (Aifadopoulou, Ziliaskopoulos, & Chrisohoou, 2008) is based on an integer programming method that minimizes the total costs depending on the empty containers moved, in order to meet the requirements for moving loaded containers. The proposed model aims to minimize the total cost of the empty container and to plan it over a given horizon. The total cost includes the cost of transporting empty containers between locations (1.4) criterion, the cost of holding empty containers at container pools (1.5) criterion, and the cost of bringing in containers from outside the system (leasing, buying, or borrowing containers). At container pools, holding cost is incurred only on non-moving empty containers that stay at the end of a period. To prevent containers from being moved as well as to avoid staying at the container pool over the period and being charged for holding cost, the model must be modified. This modification is concerned by the adding of holding cost about the moving cost of the moving containers.

The barge is a means that can be used to carry loaded containers. It is more profitable to carry as many loaded containers as possible. If there are free spaces on the barge, they may be used for moving empty containers at very low marginal cost. In (Choong et al., 2002), the authors have proposed a mathematical model to solve a network flow problem. This problem is defined as the planning and management of empty containers for a multi-modal transportation network. The impact of choosing a planning horizon that is too short depends on three conditions:

1. **The concentration of the activities in the network:** If the periods immediately after the short planning horizon are very active, a longer planning horizon might give a better solution;
2. **The transit time of the container movements:** A system that has long transit times may need a longer planning horizon to allow the model to select slow, cheap modes that work well in the real-world's infinite horizon;
3. **End-of-horizon effects:** A small end-of-horizon effect may reduce the significance of lengthening the planning horizon.

The test cases reveal that the end-of-horizon effect is smaller when the average travel distance in the system is short or the initial inventory at each container pool is high. They can integrate the loaded and empty container flow decisions in a single model. Since the location and number of container pools can have a large impact on the solution, it might be worthwhile to look at location-allocation models along with the planning horizon considerations. The uncertain nature of demand and supply in the container management problem can also be considered.

Network Planning

The multi-modal of the transportation system must consider the representation of Multi-modal Networks Planning as follows:

- Multi-modal network planning should be integrated into long-range comprehensive plans that address land use, transportation, and urban form;
- Network planning should address mobility and access needs to be associated with passenger travel, goods movement, utility placement or emergency services;
- Reserving right-of-way for the ultimate width of thoroughfares should be based on long-term needs defined by objectives for both community character and mobility.

A mixed assignment problem of a transshipment problem is considered in (Aifadopoulou et al., 2008). Authors have proposed an algorithm that identifies feasibly connected routes for passenger trip planning in a national network with competitive modes based on each user's request, which extracts the optimal path based on the priorities and target values of the duration and the cost of the trip. This algorithm inspired by the mathematical formulation uses the "Goal Programming". The principle of Goal Programming is to minimize deviations from a fixed goal introduced by the decision maker for each objective.

The mathematical programming model is defined as a mixed-use and transshipment problem. The mathematical model is a multi-objective linear integer program (LIP) that aims to take into consideration the totality of the objective functions. In the linear, as well as in the multi-objective LIP, if the set constraints are not compatible, there will be no feasible solutions for the problem. Nevertheless, in the multi-objective linear programming, a certainly feasible solution that simultaneously accounts for all competing objectives is not always expected. The aim is to find a solution that satisfies the system's constraints, being as close as possible to the optimum. Thus, the effort focuses on a particular goal's programming methodology. All objective functions are turned to system constraints introducing the deviation variables from the goals set by the user, and the problem objective is to minimize the deviations. The goal Programming method is to transform all the function's objectives to the constraints of the system by introducing the declination variable targets set by the user, in order to minimize the variations of the objective function. The proposed model in (Aifadopoulou et al., 2008) is defined by three types of constraints:

1. **Time Compatibility of Links Constraints:** In case of an origin node, the arrival time of the selected route should lie between the desired time windows set by the user. In case of a hub node constraint that would allow transit;
2. **Either at the same terminal or selecting terminal, the change should be considered:** Waiting time caused by transit should not exceed the acceptable maximum waiting time given by the user;
3. **Network Constraints:** Between two distinct cities (origin and destination city), only one itinerary should be selected. Therefore, the sum of the inputs to the city should be equal to the sum of its outputs;
4. **Transforming the Objectives to Constraints:** These constraints involve introducing the deviation variables that have the positive and negative deviation to each objective (total cost and total duration of transport) set by the user. The objectives functions of the model tackled take into account the total cost of the route (1.1) criterion and the total duration (2.1) criterion, defined as a linear goal programming problem.

They solve this problem by using a new algorithm since the proposed GP model is very complicated. The proposed algorithm provides a Web link component, which aims at displaying information for the user through the Internet for traveling in public transport applied in Greece case. The presentation of an identification process path takes into account delays of different modes. The idea is to supply a systematic process that identifies possible paths based on the compatibility of the different modes, links and user preferences.

The authors have used the Lexicographic Goal Programming which is based on conventional preemptive priority structure in which the decision-maker is required to classify the objectives so that the most important objectives are the first priority level until the objectives are classified from the most to the least important. This hierarchical structure is intended to ensure that the objectives of lower levels are considered only if the objectives of the higher levels are already optimized. However, the weighted lexicographical GP has multiplied the number of parameters to be set and the number of variables to be determined (Tuzkaya, Onut, & Tuzkaya, 2014).

In (Tuzkaya et al., 2014), the authors have defined multilevel optimization models as a hierarchical structure to reach the solution of the problem. They have proved that multilevel programming (MLP) can be applied to different areas or fields successfully. The proposed is a model defined by the objective function that maximizes the satisfaction degree of the worst objective and the decision variable values with respect to their tolerance gaps. The principle of the procedure is to solve the problem by satisfying each objective at a level separately. The proposed model in (Liu et al., 2014, 2013) uses new parameters like the weight of the transportation mode and demand volume of product from demand point, etc. the authors have used the Max-Min of the fuzzy operators to transform the proposed model into a multi-objective model at one-level. By this model, the obtained solution satisfies all levels, however, the model remains very complicated.

In order to solve this problem, many researchers have proposed a various formulation of the multimodal problem according to distinct objectives as (Mnif & Bouamama, 2017a, 2017b). In a recent paper by (Mnif & Bouamama, 2017a, 2017b), the authors have suggested a multi-objective mathematical model in order to optimize the multimodal and multi-objective transport network planning problem. They have proposed a multi-objective formulation. In fact, the first objective is to minimize the total cost of transport in a multimodal network, including the cost of transport, transshipment cost, the cost imposed on changing the transport mode and the overhead costs that are imposed on delays. The second objective is to minimize the total duration of the multimodal transport network, including the itinerary time, the duration of a change in the transport mode, the transshipment duration, and the delays duration. The third goal is to ensure the respect of arrival at the destination node in the planned time which is included in the pre-established time window. Nevertheless, the exact method may have not found any solutions in some situations. Moreover, it takes a lot of execution time in a real-time computing system. However, the approaches methods can achieve very fast execution time and can even achieve acceptable rune times to solve an NP-hard. Besides, they can get an efficient solution for multi-objective problems. In the resolution step of the NP-hard problem through the complete method, the failure increases and a solution to this problem cannot be found because of the conflicting objectives. A wide range of mathematical programming techniques to solve multi-objective problems are available in the literature work. However, mathematical programming techniques have certain limitations when tackling multi-objectives problems. The main disadvantage of the mathematical programming methods is that they are susceptible to the shape of the Pareto front and they may not be executed when the Pareto front is concave or disconnected. Besides, most of them only generate a single solution for each run.

However, in (Mnif & Bouamama, 2017c) the authors have introduced a new approach called multi-objective firework algorithm (MFWA). The proposed approach allows solving the multimodal transportation network problem. The main goal is to develop a decision-system that determines the multimodal shortest path. The optimization involves reaching the efficient transport mode and multimodal path, in order to move from one country to another while satisfying the set of objectives.

Moreover, the firework algorithm has distinct advantages in solving complex optimization problems and in obtaining a solution by distributed and oriented research system. This approach presents a search way that is different from the swarm intelligence based stochastic search technique. For each firework, the process starts by exploding a firework in the sky. The search space is filled with a shower of sparks to get diverse solutions. This new approach proves its efficacy in solving the multi-objective problem, shown by the experimental results.

The fixed-charge network design problem is a variant of the network planning problem defined on an undirected network. This problem is also defined by distribution problems or shipment of commodities. Moreover, each shipment between a given origin and a given destination has a fixed cost (Sun, Aronson, Mckeown, & Drinka, 1998). The fixed charge criterion takes two types of costs into consideration, i.e. the direction cost (per unit transportation amount) and the fixed charge (fixed cost when the transport activity occurs from an origin to a destination) by conveyance. (Sun et al., 1998) have proposed a Tabu search approach for the fixed charge transportation problem using two strategies for each of the intermediate and long-term memory processes. Tabu search procedure obtains optimal or near-optimal solutions in a reasonably short time.

The fixed-charge network planning problem may include multi-commodity capacities version.

Multi-Objective Multi-Modal Shortest Path Problem (MM-SPP)

(Liu et al., 2014, 2013) have proposed an exact algorithm to solve the MM-SPP that assures the minimization of the total transportation time. This criterion includes the delaying time of stopping and respecting of the arrival at a time window of destination, as well as the total transportation cost of UTN. The UTN is composed of multiple modes e.g., automobile, bus, subway, light rail, pedestrian, etc. The authors (Liu et al., 2014, 2013) have chiefly solved the MM-SPPs with transfer delay by improving the exact label-correcting algorithm (LCA). Then, they have proposed the MM-SPPs with respect to both of the transfer delay criteria and the time-window criteria on the arrival time. There are various criteria to evaluate a multi-modal path, such as the transport cost, the waiting time, length of itinerary, travel time, transfer time, the number of transfers, etc. Sometimes, to switch between different modes, the passengers or goods must pass through other intermediate nodes. More specifically, when it comes to passenger transportation, changing the mode of transportation needs an extra time such as walking time, for moving from one station to another in the multi-modal path.

In (Liu et al., 2013) the authors have proposed a multi-criteria optimization based on minimizing the transfer delay and must comply with a time window. The execution time will be increased according to the increase in the number of transport modes. The main objective is to minimize, initially, the total travel time that includes the time of delays, the duration of stopping, the respect of the arriving at the destination belongs at the time window defined, and then the total cost of the transport. They referred to the time window as a model constraint to respect the arrival time and the service time at the stop.

(Liu et al., 2013) have proposed an exact algorithm to minimize transfer delays, the total transport time and total transport cost. This algorithm is improved by the convergence that considers the service time associated with each transport mode and not taking into account the similar paths. The objective of the MM-SPP problem is the minimization of the delay of transfer, the transportation time and the transportation cost. The authors have suggested a label correcting approach. This approach is denoted via two algorithms to solve the MM-SPP by satisfying all the objectives. Furthermore, both of these two algorithms are proved to be exact. In the proposed algorithms, they consider not only the multi-modal transportation in UTN but also the further application of the proposed algorithms in other analogous problems.

In (Y. Zhang & Wang, 2015), (Y. Zhang, Liu, Yang, & Gao, 2015), authors have presented the Multi-Modal Shortest Path Problem with Fuzzy Arc Travel Times in the multi-modal network that minimizes the total travel time. The total travel time is composed of two parts, i.e. the travel time of travel arcs and transfer time of transfer arcs, for the multi-modal shortest path problem, where travel time on each arc is treated as a fuzzy variable. The changes between different transports modes are expressed as a kind of arcs, referred to as transfer arcs. In order to find a path for the minimum total travel time for the traveling process, they have intended to formulate a chance-constrained programming model. In (Y. Zhang & Wang, 2015), (Xie, Lu, Wang, & Quadrifoglio, 2012), the authors, motivated by the fuzzy programming, have proposed the chance-constrained programming method to formulate the fuzzy model according to different decision criteria to define the shortest path in fuzzy set theory. The idea of the chance-constrained programming aims to optimize the critical value of the objective function under the chance constraints with a given confidence level Null. The shortest path in the multi-modal network, whose total travel time is to minimize, the total transportation time, is composed of two parts, i.e. travel time on travel arcs and transfer time on transfer arcs.

Route Selection Problem

There are four classes of routing problems which can be distinguished: problems where goods are either delivered or picked-up, problems where goods are loaded and unloaded, problems where goods are loaded at the board when the delivery part of the route is completed, and problems of dial-a-ride. The goods are loaded at the depot and then unloaded at customer locations, or pickup tasks are performed at the customer sites and the unloading at the depot.

There are four major components in the objective function, which account for the total itinerary risk, total itinerary cost, transfer yard capital and operating costs (1.8) criterion, and total risk during the transfer process (5.2) criterion.

(Xie et al., 2012) have proposed a model that guarantees a set of constraints such as:

- Flow conservation of highway nodes;
- Flow conservation of railway nodes;
- Flow conservation for candidate transfer yards;
- The total risk on each itinerary must be less than a given value;
- Reflected each candidate transfer yard can only handle a limited number of HAZMAT shipments and their capacity.

(Xie et al., 2012) have suggested a multi-objective model for a multi-modal problem that can simultaneously optimize transfer yard locations and HAZMAT transportation routes. This optimization satisfies the two objectives by minimizing the total risk and total cost of transport. The proposed model is formulated as a mixed integer linear program and coded by CPLEX studio using OPL. It has been implemented by means of extensive tests on two sample multi-modal networks consisting of highways and railways. From the results based on a first sample network, it is found that the risk and cost weights in the objective function can have a significant impact on the number of candidate transfer yards to be selected. Railways typically have much lower accident rates than highways and many HAZMAT transportation demand nodes are connected to the highway network directly. In fact, at long distance, the shipments have the highest risk probability, and thus a large number of candidate transfer yards will be selected in order to take advantage of the lower risk through railways.

Loading and Allocation Problem

In (Le Thi et al., 2008), the authors have treated the multimodal transport problem at the loading and allocation problem of containers. The proposed resolution is based on the exact penalty techniques in DC Programming that transformed into a polyhedral DC Program. DCA_BB algorithms provide a significant solution compared to standard BB approaches and CPLEX code. The aim is to optimize the yard management from the viewpoint of total train processing time. The objectives functions are summarized as follows:

- The minimization of the displacement during the transfer in order to limit the number of cranes to be used;
- The minimization of the total duration and limitation of the immobilization of trains in the yard;
- The minimization of the total allocation cost of containers. The resolution is based on the heuristic algorithms.

The combinatorial optimization problem reformulated as a DC program with a natural choice of DC decomposition and the DCA consists in solving a finite sequence of linear programs. In (Cappanera & Gallo, 2004), the authors have solved the airline crew rostering (ACR) problem with 0-1 multi-commodity flows in an airline. The main goal is to maximize the total length of covered activities achieved by minimizing the duration of uncovered activities that will be assigned to the extra staff to guarantee the service need. The model also satisfies the set of constraints, such as the flow conservation, the mutual capacity, the working days, the resources, the preassigned activities and the forbidden assignments. The exact penalty technique in DC Programming is transformed into a polyhedral DC Program. The obtained result by the DCA_BB algorithms is hopeful that the standard BB approaches and CPLEX code. Their main contribution is the definition of a linear programming formulation, a cutting plane approach, and the Flow approach.

In (Choong et al., 2002), the authors have solved the planning of the empty container management problem and the selection problem in the inter-modal transportation networks. The aims are to satisfy the total cost of empty container management over a given planning horizon, in order to meet the requirements of moving loaded containers. A case study is defined as potential container-on-barge operations within the Mississippi River basin, wherein an optimization programming language (OPL), based on the AMPL modeling language and the CPLEX solvers for modeling step, is used.

Planning and Regulation Problem

The criteria of regulation and the quality of service are essential for the users of transportation systems. (Ben Rabah, Hammadi, & Tahon, 2014) select five criteria of regulation. These criteria are summed up as follows: regularity, transfer, punctuality, quality of service, and commercial kilometers. The objectives are to minimize the passengers waiting time at the different stops, the correspondences transfer time, the duration of itineraries in the network, the difference between theoretical and real crossed kilometers for any vehicle, and to minimize four terms fixed by CISIT project (number of stations not served, the number of changes of vehicles and drivers and the number of transshipment).

Five criteria of regulation:

1. **Regularity criterion (expressed by the waiting time of passenger):** The regularity criterion is represented by a time interval between the start times of two successive vehicles at the same station. This criterion aims to minimize the waiting time of all passengers at stops of a network, (2.7) criterion;
2. **The correspondence criterion (expressed by the transfer time):** The correspondence criterion is linked to the transfer time between the different network nodes. It complies with the time windows (2.6) criterion;
3. **The time criterion of the Road:** This criterion aims to minimize the total length of embedded itineraries by different vehicles depending on their charges, (2.1) criterion;
4. **Commercial kilometers:** This criterion is represented by the distance in kilometers as desired by the transportation company. Each disturbance affecting the network's traffic may decrease or increase the commercial distance crossed. Accordingly, the minimization of the difference between the theoretical value of kilometers and the value of real kilometers of a route for each vehicle, (6) criterion is added;
5. **Quality of service:** This criterion is expressed differently from one operator to another. The quality of service is measured by the reduction of the maximum of three terms: the number of

unserved, the number of changes of vehicles and drivers and the number of transshipments. (3.3), (3.1), (3.2) and (3.4) criterion, respectively, corresponding to the table of taxonomy, are taken into account. Several constraints must be considered in a real-time regulation of traffic. Constraints can be linked to time (depending on the vehicle) or related to space (depending on stops) pertaining to the network configuration.

This model is formulated by five constraints:

1. **Compliance:** Each vehicle passes through a given point, from a single point of origin, and goes to an immediate and unique destination point;
2. **The safety time:** This is the minimum time interval between vehicles at the stop;
3. **Parking time:** This is the limit of downtime vehicle at a station;
4. **Transfer:** This is the time-limit connection time between two modes or transfer time;
5. **The charge:** This is the loading time of the vehicle that must be respected, and which must not exceed the maximum time allowed.

The control problem is formulated as a multi-objective optimization problem, defined by the variation between the theoretical status and regulated network status. In (Ben Rabah et al., 2014), authors have developed the regulatory model using multi-agent systems to satisfy and optimize the five criteria.

DISCUSSION AND SYNTHESIS

The multimodal transportation network studies were carried out by means of several problems such as planning networks, shortest path, maritime or airline with urban centers, freight transport, transmission line, loading-unloading terminals, schedules, etc. The focus of a large number of researches works in the literature has been based on planning network. The goal is to move from the starting city to the destination city through other intermediate cities, wherein there are several routes between two cities. In the multi-objective optimization problem, the decision maker is charged with an efficient choice of existing routes in order to select the best itinerary according to a compromise solution between a set of objectives such as the minimization of the transport cost and the duration of transport, the maximization of service quality, etc. (Mnif & Bouamama, 2017b).

In order to evaluate a multi-modal path various factors are considered, such as the travel cost, in-vehicle time, waiting time, length, travel time, transfer time, the number of transfers etc. The optimization and operation research play an important role in solving this problem. The main objective of this problem is to determine the shortest and most efficient way of satisfying a set of objectives, and a set of operational constraints according to customer demands. For an optimal choice of a transport mode or a multimodal network, various criteria must be taken into consideration depending on the case study, although these criteria are conflicting.

A recent research (Mnif & Bouamama, 2017b) has proposed a multi-objective mathematical model in order to solve multi-modal transport problems that satisfy multiple criteria. The proposed multi-objective model is defined by three objectives, i.e. the minimization of the total cost, and the total duration of an itinerary while respecting the arrival of goods at a customer in the corresponding time window. The considered assumptions consist in initially, only one mode of transport and a path can be selected between two nodes to carry the goods; then, the transport cost is linear with the quantity of commodity to be transported and the capacity of transportation units; eventually, the transshipment of commodities can only happen once more at each city.

The mathematical formulation is a determinant step in the resolution step and the optimization step of any problem. Indeed, it allows defining and characterizing the sets, the parameters, the decision variables, the optimization criteria and constraints that will satisfy the specific decisions.

The proposed formulation by (Mnif & Bouamama, 2017b) is presented as follows:

N : The set of all nodes
K : The set of transport mode
Q : The total quantity of goods
P : The maximum transfers duration
p_i : The delay period at node *i* if a delay occurred
f_i : The overhead expenses per hour if a delay occurred at node *i*
$C_i^{k,l}$: The transport cost of a unit quantity from node *i* to node *j*, by using k^{th} transport mode
$c_i^{k,l}$ $\mathrm{c}_{\mathrm{i}}^{\mathrm{k,l}}$: The fee for transport mode changed from *k* to *l* at the node *i*
$t_{i,j}^k$: The transport time from node *i* to node *j*, with k^{th} transport mode selected
TW_{ij} : The largest time windows of cargos arriving from node *i* to node *j*
tw_{ij} $\mathrm{tw}_{\mathrm{ij}}$: The shortest time windows of cargos arriving from node *i* to node *j*
$a_i^{k,l}$: The transfer time from transport mode *k* to the transport mode *l* at the node *i*
F^k : The vehicle capacity from the k^{th} transportation mode
S^k : The number of vehicles used by the k^{th} transportation mode in order to transport the whole quantity of the freights. With, $S^k = \text{Rounds}\left(\frac{Q}{F^k}\right)$ upward, that returning the smallest integral value that is not less than $\left(\frac{Q}{F^k}\right)$.

The decision variables allow expressing the constraints and optimization criteria:

$$x_{i,j}^k = \begin{cases} 1 & \text{if the } k^{th} \text{ transport mode is selected from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_i^{k,l} = \begin{cases} 1 & \text{if the transport mode changed from } k \text{ to } l \text{ at } i\text{, when } k \neq l \\ 0 & \text{otherwise} \end{cases}$$

$$u_i = \begin{cases} 1 & \text{if there is a delay at the node } i \\ 0 & \text{otherwise} \end{cases}$$

Minimize:

$$\sum_{i\in N}\sum_{j\in N}\sum_{k\in K} C_{i,j}^k . S^k . x_{i,j}^k + \sum_{i\in N}\sum_{k\in K}\sum_{l\in K} c_i^{k,l} . y_i^{k,l} + \sum_{i\in N} u_i . f_i . p_i \tag{1}$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{k\in K} t_{i,j}^k . x_{i,j}^k + \sum_{i\in N}\sum_{k\in K}\sum_{l\in K} a_i^{k,l} . y_i^{k,l} + \sum_{i\in N} u_i . p_i \tag{2}$$

$$Max\left[\left(\left(\sum_{i\in N}\sum_{j\in N}\sum_{k\in K}t_{i,j}^{k}.x_{i,j}^{k}+\sum_{i\in N}\sum_{k\in K}\sum_{l\in K}a_{i}^{k,l}.y_{i}^{k,l}+\sum_{i\in N}u_{i}.p_{i}\right)-\sum_{i\in N}\sum_{j\in N}TW_{ij}\right),0\right]+$$
$$Max\left[\left(\sum_{i\in N}\sum_{j\in N}tw_{ij}-\left(\sum_{i\in N}\sum_{j\in N}\sum_{k\in K}t_{i,j}^{k}.x_{i,j}^{k}+\sum_{i\in N}\sum_{k\in K}\sum_{l\in K}a_{i}^{k,l}.y_{i}^{k,l}+\sum_{i\in N}u_{i}.p_{i}\right)\right),0\right] \tag{3}$$

subject to:

$$\sum_{k\in K}x_{i,j}^{k}=1\forall i,j\in N \tag{4}$$

$$\sum_{k\in K}x_{i,j}^{k}-\sum_{k\in K}x_{j,i}^{k}=0\forall i,j\in N \tag{5}$$

$$x_{j,i}^{k}+x_{i,j}^{l}\geq 2.y_{i}^{k,l}\forall i,j\in N \tag{6}$$

$$\sum_{k\in K}\sum_{l\in K}y_{i}^{k,l}=1\forall i\in N \tag{7}$$

$$\sum_{i\in N}\sum_{k\in K}\sum_{l\in K}y_{i}^{k,l}.a_{i}^{k,l}\leq P\forall i\in N \tag{8}$$

$$x_{i,j}^{k},y_{i}^{k,l}\in\left\{1,0\right\}\quad\forall i,j\in N\ \ et\ \forall\ \ k,l\in K \tag{9}$$

The equations that describe this mathematical formulation can be summarized as follows: Equation (1) represents the first objective that seeks to minimize the total cost of the multimodal network, including the cost of the itinerary, transshipment cost and overhead cost on delay. Equation (2) defines the second objective, which seeks to minimize the total duration of multimodal transportation, including the period of the itinerary, changing period and delay duration. Equation (3) expresses the third objective that guarantees the arrival at the destination in the time window. Constraint (4) is specific to the selection of transportation mode, i.e. only one mode of transport and one itinerary can be selected between two nodes. If it is zero, it means that the node *i* is not included in the transport. Equation (5) to satisfy the flow conservation constraint at each node j that normalizes the flow out and the flow in. Furthermore, the conservation of flow at origin node j that requires the flow originating at node j to equal the flow entering the links which leave node j. Constraint (6) shows that the selection of the route should be ensured by a continuous itinerary. Equations (7) and (8) are relative to the transshipment constraints. Constraint (7) indicates that one change of transport mode can happen once at each node. Constraint (8) represents the maximum time to be respected by the total transshipment time. The decision-making variables taking the integer binary value are described by Equation (9).

In summary, the MOP is NP-Hard problem, highlighting conflicts between various objectives, and the exact methods may fail when sample sizes are large. The failure is ascribed to their computational complexity that is exponential (depends on three indexes). The emergence of conflicting objectives gives rise to the increasing difficulty of achieving a feasible solution. Hence, the optimization approaches have taken advantage of the computational time. They can solve the MOP in a reasonably short time.

The role of the decision maker is to introduce the robust and distribute search on optimization approach to efficiently overcome the premature convergence of the search. Evidently, the choice of optimization approach depends on the problem type and the case study. There are two main classes of approaches, based on individual search and based on population search. The population approaches are inspired by the evolutionary system, such as genetic algorithm, particle swarm optimization, fireworks algorithm, etc. for optimization.

CONCLUSION AND FUTURE WORKS

In conclusion, this paper provides a detailed and comprehensive survey of the multi-objective optimization model on the transportation problem. This paper discusses the different related problems to the planning network transportation problem when focused on multi-objective optimization. It notices that the multimodal transportation problem includes various sub-problems. This paper presents an overview of the existing resolution methods to solve the planning problem in the transportation network. Moreover, the variants of these studied problems are classified according to their objectives and their type of extension problem. Using the survey presented in this article, it can be successfully noted that a detailed analysis of the different existing classes of problems helps to solve them in order to better understand and distinguish the transportation networks planning problem as well as its extension. Different decision methods and modeling forms in the literature researches are presented to solve the transportation problem.

The main objective of the transportation problem is to minimize the total transportation cost that can be express by various criteria according to the case study. Furthermore, we distinguish other objectives functions such as transportation time, risk, shortest paths, transportation capacity, time window, traveling distance, etc. These objectives in a few models are expressed according to costs.

It is noteworthy that the multi-objective optimization problem is NP-Hard. Therefore, an optimal solution for realistic instances cannot be obtained within a reasonable computational time using the exact methods. Hence, the decision-maker will opt for the prospect of developing incomplete methods or approaches to robust and distributed optimization. Consequently, as the development of models and techniques to discuss relevant decision problems in transport networks are fruitful, there are still numerous prospects of future works of researches, such as the following:

- There are still opportunities for integrating problems that are solved separately, endorsing a multi-criteria analysis approach;
- The development of robust and dynamic approaches to multi-objective planning problems;
- The introduction of other criteria to evaluate the total cost;
- The merger of two problems, such as the network planning problem with the assignment problem of the container in the port;
- The introduction of dynamic constraints;
- The activation or deactivation of objectives according to the customers' requirements, by affecting weight at each objective to be satisfied;
- The multi-objectives transportation problem under fuzzy environment.

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