SAPIENZA
Università di Roma

# Service Network Design Problem with Quality Targets and Stochastic Travel Time: new Model and Algorithm 

Scuola di Dottorato in Automatica e Ricerca Operativa - AURO<br>Dottorato di Ricerca in Ricerca Operativa - XXIX Ciclo

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A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Operation Research

Thesis defended on 13 February 2017
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Service Network Design Problem with Quality Targets and Stochastic Travel Time: new Model and Algorithm
Ph.D. thesis. Sapienza - University of Rome
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This thesis has been typeset by $\mathrm{AF}_{\mathrm{E}} \mathrm{X}$ and the Sapthesis class.
Version: February 20, 2017
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Life Is Uncertain, Eat Dessert First

- Ernestine Ulmer


#### Abstract

Network design formulations in which time is explicitly taken as a stochastic parameter have been neglected in the service network design literature in favor of settings in which other stochastic parameters were taken into account (primarily demand).

Nowadays, however, reliability is one of the major competitive dimensions of many firms. From a customer point of view, reliability - the on-time delivery of products - is a criterion that a firm must meet a priori, just to be considered as a possible supplier. From the point of view of carriers, reliability - the on-time occurrence of operations - is strictly related to the respect of an "ideal" or "imposed" schedule. This is particularly important, for consolidation-based transportation systems, where total system costs may also involve the costs raising from missing a proper sequencing of services for some commodities.

In this work, we propose to study a service network design problem from a carrier point of view in which travel time is explicitly considered as a stochastic parameter in the decision process and in which the goal is to define a cost-efficient service network that satisfies given service quality targets consistently as close as possible in time. To the best of our knowledge, this is the first time such a problem has been investigated.

The problem is modeled as a two-stage scenario-based stochastic programming model. In the first stage, planning decisions are made considering their future effects: the selection of the services and the routing of freight are determined with the objective of minimizing the fixed service-selection and variable demand-routing costs, plus the expected penalty costs following the application of the chosen plan to the observed realizations of travel times. The second stage addresses how to deal with delays for a given travel time realization and a chosen design.

Network design problems are notoriously NP-Hard. A progressive hedging-based meta-heuristic algorithm able to provide good quality solutions to the problem is, also, proposed. The idea is to decompose the original scenario-based stochastic problem into single-scenario-sub-problems by relaxing first stage variables' non-anticipativity constraints. At each iteration, sub-problems are solved and non-anticipativity is gradually enforced trying to consolidate sub-problem solutions into a unique one, for the original problem. This is the first attempts to solve such a problem heuristically and, hence, to apply such a methodology to a SND problem with uncertainty in travel time.

An extensive experimentation is reported to show the benefits in considering explicitly travel time stochasticity into the model rather having a deterministic time assumption, structural differences between stochastic and deterministic solutions and the performance of the proposed meta-heuristic algorithm.


## Acknowledgments

This thesis would not have come to completion, without the advice and support I received from my supervisors. I would like to express my sincere gratitude to all of them. I am extremely grateful to my supervisor Professor Nicoletta Ricciardi. She was a constant presence in my faculty department always available whenever I ran into a trouble spot or had a question about my research. She continuously motivated me and encouraged me, even during tough times of the PhD. My sincere thanks also go to my supervisors Prof. Teodor Gabriel Crainic and Prof. Walter Rei for providing me the great opportunity to accomplish part of my doctoral program at CIRRELT and to learn from their research expertise. Prof. Teodor Gabriel Crainic and Prof. Walter Rei have always made their-self available to clarify my numerous doubts, despite their busy schedules, with always useful discussions giving me deep insights and suggestions at various stages of my research, spurring and steering me in the right direction whenever they thought I needed it. I have been very privileged to have worked under their careful and constant guidance.

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## Introduction

Throughout history, transportation has played a vital role in the social, political and economical development of nations, resulting as indispensable for the progress of any country by both supporting production, trade and consumption activities and ensuring the movement of people, raw material, commercial goods and cargo timely and efficiently from place to place. The transportation industry displays intricate relationships and high degree of dependency among their various components, level of decision making and types of players (each one having their means and objectives), operating in a highly competitive environment in which business operations and plans have to continuously be adjusted or adapted to face the always more rapidly changing political, social and economic conditions and trends. It is, thus, a complex domain where accurate and efficient methods and tools are required to assist planning and control the whole process. In such a competitive and mainly cost-driven environment, shippers, carriers and logistics service providers seek for ways to minimize the costs of the offered services (and making a profit) satisfying primary service-quality targets in order to achieve the critical purpose of any transportation company, regardless of the commodities flowing through them: serve and satisfy their customers.

In order to respond to demand in the most efficient and rational way, a set of operating policies governing the routing and management of resources and commodity flows have to be established. Tactical planning aims at defining those policies by guaranteeing high performance levels in terms of both economic efficiency (costs or profit) and service quality. Tactical planning is normally supported by specific mathematical models and programming tools. When considering mathematical models, network design formulations are extensively used to represent a wide range of planning problems in transportation (as well as in other fields like telecommunications, logistics or production).

In a transportation context, the objective of network design formulations is to define the most-efficient transportation plan in order to satisfy the requested demand without violating any of the imposed constraints (e.g. capacity, budget or resource constraints). Several efforts have been directed towards the formulation of network design models. Most of the proposed formulations, however, assume that all the necessary information to build a service network is available and completely known at the moment of planning. As opposed, planning usually means facing with the challenge of making decisions when only limited information is available. On one side some decisions must be made today (e.g. selection of a new service or service route to operate) on the other side important information which may help in making decisions will not be available until after such decisions are made. In other words, decisions must be made "here-and-now", but they must be designed to cope with a
future and not yet known environment.
Thanks to the tremendous progress in both fields of operation research and computer science, optimization models have been adapted to consider uncertainties. The main purpose is to account for variability beforehand in order to develop solutions which are more accurate and robust in response to external influences. Stochastic programming has, thus, become the methodology to properly account for uncertainty. Each uncertain parameter sets unique challenges. Demand, cost, profit, lead time, reliability of vehicles, customers' locations are just few examples of information seldom known with absolutely certainty in advance when planning a service network, which can be just estimated and which actual values can be only observed when operating or even after specific operations are concluded. The most studied stochastic phenomenon in the transportation planning literature is certainly customers' demand. One aspect which received little attention is, instead, time. The vast majority of proposed model formulations, in fact, assumes travel time (time needed to travel between two stops) as a deterministic parameter, commonly built as point forecast based on available historical data. However, it may differ from estimation due to a variety of influences such traffic congestion or heavy weather conditions, resulting in potential additional economical costs related to crews and resource utilization and, in addition to them, fines and loss of reputation for not respecting planned arrival times. A deterministic time assumption is, therefore, a strong assumption which not only do not represent a realistic approximation of this phenomenon but also may lead to poor routing decisions. Despite its importance, only few contributions dealing with design of transportation services and stochastic time have appeared in the literature.

In this thesis we propose to study a service network design problem from a carrier point of view in which travel time is explicitly considered as a stochastic parameter in the decision process and in which the goal is to define a service network that satisfies given service quality targets consistently as close as possible in time. Two service quality targets are considered in our setting in order to take into account both the carrier and the customers needs in having a reliable service network. From a customer point of view, reliability - the on-time delivery of products - is a criterion that a firm must meet a priori, just to be considered as a possible supplier. From the point of view of carriers, reliability - the on-time occurrence of operations - is strictly related to the respect of an "ideal" or "imposed" schedule. This is particularly important, for consolidation-based transportation systems, where total system costs may also involve the costs raising from missing a proper sequencing of services for some commodities. To the best of our knowledge, this problem has never been considered in the literature before. We define our problem as the Stochastic Service Network Design problem with Service and Demand Targets (SSND-SDT). An extensive literature review and classification of published contributions about freight transportation network design with stochastic time considering a carrier point of view is reported in this thesis pointing out the lack of research on this topic. A new model is proposed in the thesis. The SSND-SDT problem is formulated as a two-stage stochastic programming problem. In the first stage, the selection of the services and the routing of freight are determined with the objective of minimizing the fixed service-selection and variable demand-routing costs, plus the expected costs following the application of the chosen plan. The second stage addresses how to deal
with delays for a given travel time realization and a chosen design. An extensive experimental analysis is reported consisting of three parts. In the first, the purpose is to quantify the benefits obtained by considering explicitly travel time stochasticity into the model rather having a deterministic time assumption. In the second, the scope is to investigate how and why the structures of stochastic and deterministic solutions differ from each other. Three criteria are considered: reliability, costs and structural complexity. Lastly, in the third part, we investigate how the value of some parameters may change the structure of stochastic solutions.

Network design problems are notoriously NP-Hard. Stochastic network design problems of realistic size, where uncertainty is modeled through a finite set of scenarios, cannot be solved using exact methods and heuristic methodologies are needed in order to find high-quality solutions in acceptable time. In this thesis, thus, we also propose a new hierarchic progressive hedging-based meta-heuristic algorithm to tackle the problem. This is the first attempts to apply such a methodology to a SND problem with uncertainty in travel time. The proposed meta-heuristic modifies the traditional application scheme of the method in order to overcome the problems related to a quadratic reformulation and flow-degeneracy which raise, when it is classically applied to our problem. Two versions of the algorithm are proposed, differing in the kind of information exploited during the resolution process. The first version is similar to the traditional case, the second is an original feature of the thesis.

The scientific contribution of this thesis is four-fold:

- to propose a new branch of research in the field of service network design problems by introducing uncertainty in time and the need of satisfying given service quality targets;
- to provide an original two-stage stochastic linear mixed-integer programming formulation for the proposed SSND-SDT problem;
- to show the attractiveness of the formulation and explore the role and importance of the various random parameters through an extensive numerical analysis;
- to develop a progressive hedging-based meta-heuristic algorithm with a variable hierarchic approach able to efficiently find good quality solutions to the SSNDSDT.

The thesis is organized as follows. In Chapter 1 the extensive literature review and classification of existing contributions is reported, in Chapter 2 the new model and the experimental analysis are described and, lastly, in Chapter 3 both versions of the proposed progressive hedging-based meta-heuristic algorithm are illustrated alongside with experimental results.

## Chapter 1

## Freight Transportation Carriers Network Design with Stochastic Time: a Review


#### Abstract

The scope of this chapter is twofold. First, it provides terminology and main concepts used in a transportation context and in stochastic programming. Second it provides a clear summary and a structural classification of the various published contributions addressing a subset of problems that may raise in a transportation context. Our interest, in fact, lies only on tactical planning problems from a carrier point of view related to the set up of a priori freight transportation networks where time is explicitly assumed as a stochastic phenomenon to control. The objective of uncertainty are both travel time (time needed to travel between two stops) and operation time (time needed to perform operations at a stop). This defines a set of tactical planning problems focusing in particular on reliability and total lead time.

The chapter is organized as follows. Section 1.1 presents a general overview of main players involved in transportation, freight transportation systems, decision levels and some fundamental concepts needed to our scope. Frames of the research are further discussed. In section 1.2 issues related to design under stochastic time are discussed: uncertainty sources, problem definitions and mathematical stochastic formulations. Section 1.3 is dedicated to our proposed classification of the published contributions. This includes browsing, screening, collecting methodology, identification and characterization of attributes descriptions. The comprehensive classification here provided should help to highlight what kind of problems have been considered, how they are addressed and, even, what kind of problems have not been covered yet (Section 1.4).


### 1.1 Freight Transportation Systems

Several players are involved in the freight transportation industry, each differing in tasks and economic goals. Making a complete description of them is beyond the scope of this chapter. Considering our scopes and referring to [40, 31] and [32] for a more complete presentation, we only identify some of the most important decision

## 1. Freight Transportation Carriers Network Design with Stochastic Time: a

 2makers (or points of views) on freight transportation:

- government;
- shippers;
- carriers.

Demand for freight transportation derives from the interplay between producers and consumers and the significant distances that usually separate them. Producers of goods require transportation services to move raw materials and intermediate products and to distribute final goods in order to meet demand. Producers may be distinguished between those who own and operate their transportation fleet to perform transport and those who outsource part or fully this activity. Hence, they determine the demand for transportation and are often called shippers. Carriers, on the contrary, supply transportation services. They may be private or public companies. Railways, shipping lines, trucking, airlines companies are examples of carriers. Large part of the infrastructures on which transportation activities are performed (like roads, highways, railways) are constructed and sometimes operated by governments as well as the facilities surrounding those activities (significant portion of ports and airports, railways and railway facilities). Governments also regulate economic and legal aspects of the transportation industry (for instance the transport of dangerous and toxic goods) and tax it.

We are here interested in a carrier point of view, who has to define transportation services to fulfill the requests of a set of customers. We do not distinguish between carriers (public or private) and shippers that operate their own fleet as long as the faced problem is aligned to tactically plan transportation activities.

In [40, a classification of transportation activities from a planning point of view differentiates between:

- Consolidation or customized transportation;
- Long-haul transportation and vehicle routing and distribution problems;
- the multimodal (or intermodal) transportation system of a region and the transportation services of a single carrier;

For our scope, we are here only interested in the first two classes, referring the interested reader for details about the third class to the above cited publication. Nevertheless, the concepts of unimodal and multimodal (or intermodal) transportation are briefly introduced in the following.

### 1.1.1 Customized and Consolidation Transportation

In order to respond to demand, a carrier must establish a set of operating policies at a tactical level that will govern the routing of vehicles and freight. Freight may be shipped from its origin to its destination either directly or indirectly. In the first case, a carrier dedicates an entire vehicle to just single customers and consignments are tailored exactly to their needs. Such a service is known as a customized service. As opposed, in the second case, a carrier combines freight of several different customers
with possibly different origins and destinations dispatching it together into a common vehicle, sending it normally through a sequence of terminals. This is known as consolidation transportation and usually includes several surrounding activities such as warehousing, sorting, loading into or unloading from vehicles. Building a consolidation transportation network is normally a rather complex problem for carriers, who have to face with the challenge of satisfying the expectations of several different customers. Typical examples of consolidation-based transportation systems are railways, less-than-truckload motor carriers, container shipping lines. The underlying structure of a consolidation-based transportation system consists of a large and quite complex network of terminals connected by physical (or conceptual) links. Such a network is known as a hub-and-spoke network: low-volume demand is first moved to intermediate terminals, or hubs, where is consolidated with loads of other customers and moved together to other hubs. It may happen that low-volume shipments pass through several hubs before reaching their destination terminals.

Whereas customized services are organized as soon as a request from a customer pops up, for consolidation transportation carriers must establish regular services and adjust their characteristics to satisfy the expectations of the largest number of customers possible. Externally, then, they propose a series of services, each with its operational characteristics (origin, destination, intermediate stops, route, type of vehicle, capacity), operating them according to a schedule which specifies departure time at origin, arrival time at destination and arrival times at/departure times from each intermediate stop (if any). Internally, instead, carriers define an operational (or transportation) plan which contains a series of rules and policies that affect the whole system to ensure that the proposed services are performed as stated or, at least, as close as possible to the resulting (and published) schedule. It is normally difficult to build a schedule. In fact, on one side it includes the use of stochastic parameters (e.g. demand, travel time, operation time), on the other side it should, however, result in a deterministic plan to respect and on which customers rely and synchronize their own activities. Therefore, consolidation based transportation systems require extensive tactical planning to define regular services.

### 1.1.2 Long-haul Transportation and Vehicle Routing

Transportation operations may be differentiated between those that are mainly concerned with long distance movements of goods and those that perform several pick up and delivery operations over relatively short distances on a restricted area [38.

The first case is often referred to as long-haul freight transportation. It is defined as the delivery of goods over very long distances between terminals, ports and other facilities like warehouses. Long-haul transportation operations are generally divided in three sections: pre-haul also known as the first mile (the process of gathering goods from their real origin), the proper long-haul transportation (conducted via road, rail, air or water) and the end-haul transportation also known as the last mile (the process of distributing goods to their destination).

The second type of operations is usually identified as vehicle routing problem (VRP). It often relates to the pre-haul or end-haul transportation. The objective of VRP is to determine an efficient scheduling strategy for vehicles, mostly trucks,

## 1. Freight Transportation Carriers Network Design with Stochastic Time: a

 4engaged in the delivery and, sometimes, collection of goods from/to specific locations or customers, which satisfies specific business constraints. In particular, its aim is to decide which vehicle visits which customer from a given set and in which sequence (when only one vehicle is involved, the problem is refereed to as traveling salesman problem, TSP). Sometimes VRP is considered as an operational problem, where routes are built daily, depending on the customers' needs. On a classical view, it is still considered as a tactical planning problem where master routes are decided for a medium term time period and used as a basis to construct daily schedules skipping or adding stops (still maintaining the route structure) if needed. For a more complete description and presentation of the two problems we refer to [40, 32] and [31] for long-haul transportation and to [117, 28] and [76] for VRP.

Service characteristics are defined for a medium-term time period at a tactical level and are updated every few months. When formal models are proposed, such planning problems generally appear as network design formulations. Problems are, thus, formulated over a graph whose nodes represent origins, destinations, intermediate transfer points for the traffic to be routed (SND) or customers (VRP) and arcs represent potential services (SND) or link connections between those points (VRP). Depending on the specific system or transport that has to be planned, network design formulations assume specific features, constraints and network topologies (consider, for instance, the well known one-one assignment customer-vehicle in VRP). The objective of network design formulations is to choose arcs to enable the demand for transportation to be satisfied at the lowest possible system cost without violating any of the imposed constraints (e.g. capacity or resource constraints). System cost is often computed as the total fixed cost of selecting arcs plus the total variable cost of using the entire network. The costs involved in time-constrained routing and scheduling may also include travel time costs, waiting time costs at visited locations, loading/unloading time costs and, often, inconvenience costs for not respecting time-constrains (delay penalties).

### 1.1.3 Unimodal and Multimodal Transportation

The term mode of transport is applied to distinguish substantially different ways to perform the movement of goods such as road, sea, air or rail. Mode of transport can be referred as unimodal or multimodal (sometimes also intermodal or combine) transport.

Unimodal transportation involves the use of one single mode of transport to move freight. In most of the cases, this regards road transportation but can also include sea, rail, air and pipeline. Transfers are allowed and as long as the mode remains the same (as for instance, from truck to truck), it is still considered unimodal transportation. Multimodal transportation (also sometimes referred to as combined transportation) is the transportation of loads from its origin to its destination by a sequence of at least two transportation modes (by rail and road, for example), the transfer from one mode to the next being performed at an assigned terminal. Multimodal transportation takes advantage of the strengths of the different modes in order to build efficient, reliable, flexible and sustainable shipments. However, at the expenses of longer transshipment activities in terminals.

Multimodal transport requires having cargoes handling during the transportation.

The latter handling activities can be facilitated by using a standardized loading unit (a container) which is normally required in intermodal transportation, where the goods themselves do not have to be handled, but only loading units are moved when changing modes. In general terms, the objective of intermodal transport is to reduce cost and time of cargo handling during transportation, improve security and reduce damage and loss to the commodities.

### 1.1.4 Fixed Schedules and Time Windows

A schedule specifies timing information for each possible occurrence of a service during a given time period: departure time at the origin, arrival/departure time at each intermediary stop and arrival time at the final destination. The schedule, sometimes, also include indications on the, so called, cut-off time: the latest moment freight may be given to the carrier and still meet the scheduled departure of the service. If on one side the use of schedules in passenger transportation services is widespread, on the other side schedules are not always required in freight transportation. Regular navigation shipping-lines usually operate according to strict schedules as well as the majority of cargo air-services.

As an alternative to a fixed (and strict) schedule, sometimes earliest and latest times may be specified, defining a time window in which service occurrences should take place. Less-than-truckload trucking very often follows such less stringent rules.

Schedules, however, are not always followed in freight transportation. Some carriers, in fact, operate even without it, on a "go when full" policy.

### 1.1.5 Planning levels

Each of the above mentioned players involved in freight transportation has its own set of economic objectives and means to use in order to achieve them by making specific decisions. It is common practice to decompose the type of decisions each player has to make based on the time period those decisions will hold [38; 31]:

- strategic;
- tactical;
- operational.

Strategic planning involves the highest level of management and concerns longterm decisions for which large capital investments are needed. Examples of decisions at this planning level are the design of the physical network, namely the construction or upgrading of infrastructures (highways, bridges), the location of main facilities (terminals, yards, transfer zones), or the acquisition of new resources (power units, rolling-stocks). Tactical planning relates to the design of the service network or service routes. Its aim is to determine the most efficient and rational allocation and utilization of existing resources in order to guarantee high performance levels in terms of both economic efficiency (costs or profit) and service quality. Decisions at this level are sensitive only to broad variations (such as the seasonal forecast changes in traffic demand, for instance) having the goal of aligning the structure of the transportation

## 1. Freight Transportation Carriers Network Design with Stochastic Time: a

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network to the needs of future business. Examples of tactical decisions concern service characteristics (type and frequency of services and very often their schedules), general operating rules for terminals, demand routing using the available resources and terminals, repositioning of empty resources. Operational (short term) planning, instead, is performed in a highly dynamic environment where time factor plays an important role and operations from tactical planning have to be adapted to current daily conditions: vehicles and crews scheduling, maintenance activities are examples of operational decisions as well as dynamic and real-time adjustment of activities and last-minute rescheduling. Not every of the latter described players make decisions at each of those decision levels: governments, shippers as well as carrier plan strategically, but governments does not plan at a tactical or operational level, for instance.

### 1.2 Modeling Uncertainty

In [73] and [72], decision-making situations are characterized based on the quality of the available information under which decisions are made. It could be:

- under certainty, when perfect information is available and no element of chance between decisions and outcomes occurs;
- under uncertainty, when instead only imperfect information is available and element of chance between decisions and outcomes occurs.

Uncertainty is, thus, defined as the inability to determine the true state of the future business environment.

### 1.2.1 Source of Uncertainty

As said, we are here interested in the second category of situations. Under uncertainty, different quality of information may be available. The worst case is total uncertainty or complete ignorance about a phenomenon. When partial information on the stochastic phenomenon is available, three types of uncertainties may be distinguished [73, 72]:

- randomness;
- hazard;
- deep uncertainty.

Randomness describes events which probability of occurrence can be estimated exploiting historical and accessible data trough classical forecasting and statistical analysis methods. This information, then, can be used to estimate the probability distribution of the random events disrupting business-as-usual operations. Randomness has moderate impacts and is expectable. As opposed, the information available on hazard and deeply uncertain events is scarce and their impact could be catastrophic. Hazard events describe factors or incidents affecting a longer period
and resulting often in some kind of disruptions of usual and daily business. Although hazards are rare, they show some kind of repetitiveness which may be characterized by location or severity. Models to provide likelihood of occurrence or likelihood of associated monetary losses are, normally, available. Hazard events involve natural (earthquakes, floods, volcanic eruptions, droughts, forest fires) or accidental (strikes, resource unavailability) incidents. Deep uncertain events affect a much longer future period. They are isolated, non-repetitive, extreme events characterized by the lack of any relevant statistical information to evaluate the severity of their consequence or to predict their occurrence or even their location. Events related to terrorism (sabotage, bombing) and political instability (currency devaluation, coup) are deep uncertain events.

In this chapter, we try to revise problems facing all three kinds of uncertainties disrupting travel or operation time. Regarding randomness, typical examples in our context are fluctuations caused by traffic congestion (in particular for road or rail transportation) or heavy weather conditions (in particular for ship and aircraft transportation). Operation time, instead, may be affected by parking areas or loading areas conditions, availability of personnel dedicated to loading or unloading activities, complexity of the operations to carry out. Although almost all the literature about non-deterministic network design models only consider randomness with known probability distributions (or at least some ranges in which realizations of travel or operation times occur), some recent contributions consider hazard or even deep uncertain events which cause time fluctuations.

Hazard events are considered in 84 where the routing of vehicles shipping medicines to regions hit by an earthquake is considered. To the best of our knowledge, this is the only contribution that utilizes a set of predetermined routes for the daily transportation plan (in this case from warehouses to hospitals) modifying them, when the hazard event takes place, in order to avoid, if necessary, bridges and highways, which are vulnerable infrastructures to earthquakes. This feature is not applied in [118] where, instead, schedules are determined only when the hazard event occurs, even though approximated routing aspects are fixed in advance. In [98] and [104], instead, routing problems are addressed after the hazard event took place. Similarly, in [47], a delivery problem of valuable emergency supplies from relief warehouses to distressed population centers is addressed. Here, routing is performed considering the possible occurrence of secondary disasters, which may jeopardize the fluidity of disaster relief operations. Secondary disasters include after-shocks triggered by earthquakes, landslides triggered by floods, avalanches induced by winds.

To the best of our knowledge, [105] is the only contribution in transportation network design planning in which a deep uncertain event is considered. Here, the focus is to route vehicles in order to efficiently distribute medical supplies to the population in response to large-scale emergencies (they considered a bio-terrorism attack) in the presence of uncertain travel time (and demand as well).

Transportation problems under uncertain travel or operation time caused by hazard or deep uncertain events is an extremely important branch of study since unmet time-targets in such emergency situations can often result in loss of lives.

## 1. Freight Transportation Carriers Network Design with Stochastic Time: a

 8
### 1.2.2 Problem Definitions

The goal of network design problems is to define a transportation network in order to fulfill the requested demand of customers alongside with additional constraint in a rational and efficient manner.

Traditionally, from the perspective of carrier companies, it has always meant minimizing total costs, normally related to the number of activated vehicles or services and routing costs related to freight transportation. Uncertainty of travel and operation time may influence this total cost as well. Which influences the most, depends on the specific problem under study. If routes are longer than as planned, costs of crews or resources may increase: in real-world situations, for instance, drivers have fixed working hours and are usually more paid for work done overtime. Total completion time of the activities of all vehicles involved in the transportation network, that is the time at which the last vehicle ends all its activities, plays an important role in such problems.

Nowadays, however, reliability is one of the major competitive dimensions of many firms. From a customer point of view, reliability - the on-time delivery of products - is a criterion that a firm must meet a priori, just to be considered as a possible supplier, rather than a characteristic to verify a posteriori 61. It is related to the respect of the requested time windows or promised upon time of delivery. From the point of view of carriers, reliability - the on-time occurrence of operations - is strictly related to the respect of an "ideal" or "imposed" schedule. This is particularly important, for consolidation-based transportation systems, where total costs may also involve the costs raising from missing a proper sequencing of services for some commodities. Obviously, uncertainty of time may jeopardize those connections [94].

## Optimizing considering Total Completion Time

The purpose here is to define efficiently a set of a priori routes or services by controlling the total completion time, alongside with other constraints.

Laporte [76] was the first to incorporate stochastic travel and operation times as part of a VRP model. The scope was to determine routes by limiting the expected total completion time of the activities of all vehicles involved in the transportation network. In [69], the target is still minimizing the expected completion time of the vehicles involved in a VRP problem, but here the focus lies on the length of the longest route. Different authors have, then, considered completion time as target in their works, relating uncertainty to operation time only [79; 64] or to travel time only [9, 120, 83] or by enriching the problem with route structural constraints [75], time-dependent travel time variations [120, 86, 22; 90] or simultaneous pick-up and deliver [137]. Furthermore, in [134] a dispatching problem is considering alongside with production elements; in [122], a shortest path problem (SPP) is considered where whole connections may fail in time.

## Optimizing considering an Existing Schedule

The purpose, here, is to ensure efficient, reliable and accurate transportation systems, by defining transportation operations that consistently adhere as much as possible to
a given schedule after the uncertainty of the duration of single operations is realized. The scope is, alongside with classical economic objectives, limiting the total earliness and lateness with respect to given time instants.

From the point of view of carriers, an "ideal" or "imposed" schedule is considered. In 41 for instance, road transportation services have to be planned in order to catch available (rail and maritime) transportation services operating according to fixed schedules to perform part of the whole shipment. Services are built in order to ensure safe connections with a given probability. A similar problem is addressed by [119]. Here, when connections are missed additional costs have to be paid in order to still fulfill demand by alternative services. In [124, the optimization of sailing speed of a fleet of container shipping lines is taken into account by also analyzing the characteristics of bunker consumption in order to achieve target arrival times at a sequence of ports. There is a fixed schedule to respect, but late departure times are possible related to longer than as planned port operations.

When the customers' point of view is considered, the time dimension is incorporated in problems in the form of customer-imposed time window constraints and carriers should define services scheduled in such a way to perform deliveries before a given due date or within specified time windows as reliable as possible. Time windows may be hard, that is, visits have to be performed only inside such time slots, as in [43; 44; 59; 3]. Sometimes, instead, requested time windows may be violated if a penalty is paid. Such time windows are called soft time windows and the target in such cases is a combination of expected travel costs and penalties for the violations [113; 101]. In some other cases, the focus lies only on lateness [1], allowing early arrivals without any consequence (right time windows).

Different variants of the VRP with time windows have been considered, enriching even more this topic: in [110] a VRP with stochastic operation time is considered, where customers appear probabilistically with their time windows; different levels of congestion depending on the time of the day are considered, for instance, in [114; in [23] a TSP problem with time-varying stochastic travel time and pick-up and deliver operations is considered; in [20] a variant of the VRP with time windows, where vehicles do not need to return to the initial depot is proposed (this variant of the VRP is also known as orienteering problem).

In the vast majority of the published works, the latter criteria are applied globally, that is applied universally to the whole transportation network without any distinction. All services, commodities, customers are considered equally important. In practical applications, however, as suggested in [81], the above described criteria may be differentiated and dissimilar with respect to type of service, importance of customer, geographical region, priority of commodity. In [1], for instance, a VRP is considered where the set of available customers is divided in groups: customers which are mandatory to visit, customers which may be visited and customers which have time restrictions. These groups do not define a partition of the entire customers' set, so that the visit to a specific customer may be optional but still in a given time window. In 65], an extension is proposed with correlated travel times. In [112] and [19], customers have a priority-level defined as a reward the carrier gets by visit them on time.

## Optimizing considering additional Criteria

Classically, the objectives of network design problems are strictly related to economic factors (minimizing travel costs, minimizing total penalties). As never before, however, options that allow to minimize the negative impacts of transportation, like pollution ( $\mathrm{CO}_{2}$ emissions), are always more requested by customers and, consequently, sought by carriers to establish not only efficient but also environmental friendly systems. To the best of our knowledge, few works also consider this criterion in planning transportation activities: [41] and [108] for SND and [4] for VRP (in an urban area). In [111, instead, a TSP problem where freight deliveries are performed by means of environmental friendly hybrid vehicles in urban areas is described. Here, an intelligent planning of powertrain selection is also considered to efficiently use the hybrid vehicles.

## Extensions to additional Stochastic Elements

The literature about transportation planning and stochastic time is far from being complete. This is even more true when planning problems with stochastic time and other stochastic elements are considered. Nevertheless, some first contribution is available. An extension of their green intermodal SND problem with stochastic time, including uncertainty in demand, is proposed in [41]. This extension especially affects the capacity of the selected transportation network. The authors conclude stating that demand uncertainty has impact on the planning problem they faced, but it is less affective than travel time uncertainty. In [78; [17] and [59] stochastic time and stochastic demand are considered as well, but in a VRP context. A variant of the VRP in which customers appear probabilistically and their service times are uncertain as well is proposed in [110.

### 1.2.3 Mathematical Formulations

Stochastic programming has become the methodology of choice to properly account for uncertainty. In network design, the purpose of stochastic programming is to account for variability beforehand in order to build a single design that remains cost-effective and robust in response to different realization of stochastic parameters.

The most commonly used approaches to incorporate uncertainty into a decision model - quickly described in the following - are:

- Recourse Programming (RP);
- Probabilistic Programming (PP);
- Robust Optimization (RO).

When information about the stochastic event is enough to estimate an approximated probability distribution, RP or PP may be used. As opposed, when historical data are not available in sufficient amount and only a bounded uncertainty set of possible outcomes may be estimated, robust optimization methodologies may be exploited.

## Recourse Programming

In RP some decisions or recourse actions can be taken based on the revelation of new and certain information, after a first decision is made. The information revelation process defines how and when the values of stochastic parameters are observed. The decision variables of such approaches are, then, defined according to when the stochastic parameters become known: decisions that have to be taken before any stochastic parameter is observed are called first-stage or a priori decisions; decisions that can be taken after the value of the stochastic parameters is observed are called second-stage or recourse decisions, and define how solutions can be modified or adjusted as more information becomes available. In RP some decisions or recourse actions can be taken after first stage decisions are made. Recourse decisions, and their associated costs, are directly related to the outcomes of the stochastic parameters. The recourse function is normally introduced in the objective of the model, which aims at minimizing, thus, the costs of making a first-stage decision and the expected costs of applying it in the future (second stage). The easiest recourse is the so-called simple recourse, which does not consider extra actions in the second stage, rather just to pay for consequences.

In our context, this may be translated as paying a penalty proportional to the duration in excess of a pre-set time limit. A variety of penalty structures (fixed penalty, linear penalty function depending on per unit time violation, quadratic penalty function, symmetric, asymmetric) are described in [101, alongside with examples of their practical applications. In the vast majority of publications, however, a linear loss function is considered. Other than real monetary fines, sometimes intangible costs are also included to represent the costs in terms of loss of reputation by not respecting those constrains [113].

Recourse actions (or recourse policies) may take several different forms, being linked to both the specific problem under study and the moment at which new information is made available. In [119], for instance, a "common industrial practice" in dealing with consolidation is applied, upon observing a delay to an upcoming shipment: breaking the consolidation that involves the tardy shipment, release the on-time shipments following the start-up plan and ship the tardy shipment trough the faster and available route. The start-up plan is, then, built minimizing the expected costs of such adjustments.

Regarding the VRP context, in 44 two alternative recourse policies are considered when an observed time realization jeopardizes the respect of next-customers requirements: a skip-current-customer recourse or a skip-next-customer recourse. In both cases a no-service penalty is charged. A recourse similar to the first one is considered in [127], while, the second recourse is applied in [20] as well. In [105], three specific recourse actions are proposed to deal with deep uncertain travel time caused by a bio-terrorist attack, where the fast response to new information can make an appreciable health difference and even lead to saving of lives.

When information revelation process consists of multiple levels, more than two stages may be considered. This leads to a multi-stage structure of the problem where at each level recourse actions may be performed. Unfortunately, to the best of our knowledge, this approach has not been used yet in a time stochastic approach.

For a more complete and exhaustive presentation of recourse programming we
refer to [16, 95] and [102].

## Probabilistic Programming

PP imposes that some of the constraints, called probabilistic or chance constraints, are satisfied with a certain probability. In PP the description of second-stage or recourse actions is avoided. Such models, in fact, are used when the cost (or benefits) of second-stage decisions are difficult to assess, guaranteeing however that the risks (defined here as the probabilities of observing specific random events) of applying a first-stage decision are limited and below a certain threshold. The solution of chance constrained models, therefore, does not take into account the cost of corrective actions and may have bad performances unless measures to estimate failure costs (arising from the not satisfaction of the probabilistic constraints) are taken. For a more detailed presentation of probabilistic programming we refer again to [16; 95] and [102].

Specifically in our context, probabilistic constraints may ensure that the probability that the planned routes do not meet time windows or deadlines when the uncertainty about times is revealed, does not exceed a prefixed threshold.

Sometimes it may be particularly challenging to evaluate the probability of the occurrence of an event explicitly trough its distribution, which may involve very often the computation of the convolution of many random variables. The convolution procedure can be straightforward when special properties (like additivity) of the chosen probability distributions can be exploited, or very complex otherwise. For this reason, most of the existing approaches are conceived to exploit the properties of distributions, like Normal or Gamma (which are additive family of distributions). This may be mathematically convenient, allowing to easily compute the needed convolutions, but may not truly represent travel or operation times properly lacking of accuracy and precision. Recently, [52] proposed the use of Phase-type distributions to overcome the above mentioned problems. Thanks to its flexibility and tractability, Phase-type distributions can as accurately as needed approximate any positive continuous distribution enabling to compute convolutions in an exact and algorithmically tractable manner.

A second way may be to resort to the approximation of the true probability of the occurrence of events. The approximation consists in replacing the actual distribution with an empirical one obtained by sampling values from it. This method can be used to approximate the expectation of an objective function trough its sample average estimation (hence the name, sample average approximation, SAA) or to approximate chance-constraint, where the true probability of the constrained event is approximated by its frequency of occurrence within the defined sample of values. For more details we refer to [71] and [92]. In our context, different authors resorted to the latter approximation to solve their network design problems under travel time or operation time stochasticity, see for instance 41 for a SND context or [69] for VRP. [122] provide an introduction to the application of SAA to stochastic routing problems with expected value objectives.

## Robust Programming

RP and PP start by assuming that the probability distributions governing the random phenomenon can be estimated precisely. The latter can be an extremely hard task, if not impossible, when historical data are not available in sufficient amount (for instance, the travel time on a new road never been covered yet). To overcome this difficulty, robust optimization methodologies may be exploited, which assume that the outcomes of an uncertain phenomenon belong to a bounded uncertainty set, which may be easier to identify, not requiring any assumption on probability distributions. Thus, instead of seeking to immunize the solution in some probabilistic sense against stochasticity, a solution that is feasible for any realization of the uncertainty in the given estimated set is constructed. The goal of this approach, therefore, is to optimize against the worst realization of a situation that might arise, constructing solutions which exhibit little sensitivity to data variations. For a detailed presentation of this field we refer to [7: 12) [14] and [74].

In our context, the above mentioned set may be bounded by the best-case and worst-case travel or operation times. In [57], instead of considering one bounded uncertainty set for each link, two uncertainty sets are available considering the bestcase and worst-case travel times in peak and non-peak hours. Traditionally, most of the applied robust optimization methodologies relate to worst-case approaches [110) 1. Nevertheless various other concepts of robustness have also been proposed: the robust deviation criterion is applied in [88, 87] and [138]; a modification is proposed in [25], which ensures that the optimization is performed on a modified range instead of considering extreme realizations of the uncertain data; in [107] a lexicographic min-max criterion is considered.

## Alternative Formulations

Sometimes instead, none of the above mentioned approaches is considered, rather an objective function is built to control specific characteristics or performance metrics of the service network (OC). In such case, the uncertainty is controlled considering an expectation of the cost raised as consequence of travel or operation time uncertainties [69]. These formulations can also be extended to consider risk aversion of carriers through the use of risk measures. In [77] for instance, alongside with the expectation, the variance of time distributions is also incorporated in the objective function (this approach is similar to the mean-variance approach used in financial planning of portfolios). The risk-aversion of carrier may also be decided.

### 1.3 Classification of the Existing Literature

Thanks to the systematic literature review of the published contributions, we were able to identify recurrent attributes and characteristics of the treated problems and, based on the features of each work, to categorize them so as to identify similarities.

### 1.3.1 Research Methodology and Criteria

In order to have a broad access to works from different origins, international databases search and free web search were used to collect reference papers. To cover alternative

## 1. Freight Transportation Carriers Network Design with Stochastic Time: a

denominations of similar words, the search key-terms we selected include: stochastic, random, uncertain, interval, travel, operation, service, time, routing, vehicle routing, shortest path, scheduling, network design, service network, freight transportation. In addition, we also collect references from already found papers. Although the free web search provides an interestingly wide coverage, often studies carried out before 1995 will not be found on the web. The classification we propose, even though could not be exhaustive, considers all the most meaningful contributions found following the above described criteria. This includes journal articles, technical reports and articles from conference proceedings. As said, we excluded from the set of results the studies dealing with people transportation, strategic and operational problems as well as dynamic or real-time programming. After an initial screening, 67 articles published since 1962 (when the VRP with stochastic time was published first, [76]) were identified. The number of contributions and year of publication for all the articles are summarized in Figure 1.1.


Figure 1.1. Number of Contributions and Year of Publication

### 1.3.2 Identifying Domains and Attributes

In order to provide a clear overview of the contributions appeared in the literature and summary their main features, we propose a classification according to four axes.

The first axis relates to the domain of the freight transportation problem. We considered customized transportation services and SND, VRP and TSP, for consolidation-based transportation systems. All other axes are strictly related to the time uncertainty dimension. The second axis frames the source of uncertainty. We considered all the three types of uncertainty described in [73], namely randomness, hazard and deep uncertainty. The third axis relates to the objective of uncertainty which may be travel time or operation time. The fourth axis relates to the objective of the optimization. We distinguish here among three categories: when the scope is merely to control the total length of routes or when some kinds of reliability is also looked for (we did not distinguish between the existence of an "ideal" schedule or
"imposed" time windows as, as said, they both involve the seeking of reliability, even though from different point of views). In addition, sometimes the plan is sought by considering other objectives, we grouped them in a generic class "other". The last axis categorizes problems with respect to the formulation used to cope with uncertainty. Summarizing, the following axes are proposed in our taxonomy:

1. Transportation System
1.1. SND;
1.2. VRP;
1.3. TSP;

### 1.4. Customized Transportation;

2. Source of Uncertainty
2.1. Randomness;
2.2. Hazard;
2.3. Deep uncertain;
3. Objects of Uncertainty
3.1. Travel Time;

### 3.2. Operation Time;

4. Objective of Optimization

### 4.1. Existing Schedule;

### 4.2. Total Completion Time;

4.3. Other;
5. Formulation
5.1. PP;
5.2. RP;
5.3. RO;
5.4. OC;

### 1.4 Results and Discussion

The proposed classification is shown in Tables 1.1 and 1.2 . The authors of the 67 published articles are listed in the first column of each table. The remaining columns represent the domains and the attributes discussed above. For each article, if it matches the attribute of the column the corresponding cell is marked with $\checkmark$.

Based on the reviewed research, some preliminary observations may be done. First, as shown in Figure 1.1, scientific interest in the field of network design planning with stochastic travel or operation time does not seem to have been uniform in time. As opposed, after an initial interest, this topic seems to be neglected for a while, clearly showing new increasing attention by researchers as measured by the number of contributions in the last few years. Recent technological developments and systems allowing the collection of large amount of accurate data may have facilitated this study, which is already computationally expensive in a deterministic environment.

Second, as shown in Figure 1.2, the vast majority of the authors, even though considering consolidation-based transportation systems, examine VRP problems, making network design planning with stochastic travel or operation time a domain certainly studied, but far from being studied in all its facets. VRP, thus, seem to be the field of preferred application not only gaining in completeness but also in constant refinement and diversification. As opposed very few contributions belongs to the SND category or customized transportation.

Third, the vast majority of random events that influence travel or operation times belong to randomness [73; 72]. Hazard events or deep uncertain event are still ignored by the most. In particular, to the best of our knowledge, there is only one contribution which considers deep uncertain catastrophic events. Although a



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Freight Transportation Domain


Figure 1.2. Number of Contributions and Freight Transportation Domain
growing interest has been observed recently on such phenomenons, the interest still lies on problems in which stochastic demand is accounted or to strategic planning.

Objective of Uncertainty


- Travel and Operation - Travel - Operation

Figure 1.3. Number of Contributions and Objective of Uncertainty
The most studied uncertain phenomenon is certainly travel time (see Table 1.3). Operation time is, instead, the less considered stochastic phenomenon. In some situation, though, travel time between locations are relatively short and therefore can be assumed constant when compared to the variation in operation times at each location. In a urban area, for example, a driver might have several close locations to visit without knowing exactly how much time should spend at each of them. In such situations, operation time assumes more importance. This phenomenon is, thus, as important as travel time uncertainty when planning a transportation network and, even, influence it.

The objective of the optimization seem to cover both criteria, uniformly. Nevertheless, the interest in completion time seem to have decreased over time in favor of optimizing with respect to an existing schedule. Building reliable systems from both customers and operations points of views seem to be the major interest now (see Figure (1.4).


Figure 1.4. Number of Contributions over Years and Objective of Optimization

Lastly, considering mathematical formulations, the use of expectation seem to be the favorite way to control uncertainty. Although the latter approach still requires its calculation often through convolution, it may be consider less complicated as a robust, probabilistic or recourse programming approach (see Figure 1.5).

## Stochastic Formulation



Figure 1.5. Number of Contributions and Stochastic Formulations

Research gaps in the field are evident. Clearly, technological progress (power of computers and information systems) will increase the amount of research on this particular field. As already mentioned, VRP seem to be much more taken into account. New trends, such multi- or intermodal transportation, are extending existing transportation systems and integrating available transportation options in a sustainable way. Very less is done in this perspective related to time uncertainty. Very few contributions are also available for hazard or deep uncertain source of uncertainties. There is still a need to understand the real problems that may raise when such highly chaotic and unpredictable events occur. One additional future research direction may also allow for the combination of multiple stochastic aspects. A challenge will be to understand how much influence each individual parameter
can have and what could be the consequence of the interaction between these phenomenons. Another direction of future research will emerge from the increasing demand for solving rich or multi-attribute problems or integration of various policies. Very less, in fact, has been done by considering different vehicles, class of services, class of customers, region and so on, which may bring near theory to practice. Lastly, as often observed by researchers, the traditional approach in the industry has been to separate planning activities into several components and focusing separately on a specific part of the whole tactical planning problem. This natural tendency yields more manageable subsystems but also presents several limitations. In particular, important interactions link routing and scheduling problems. Integrating these two categories of decisions seem to be an announced, but still not yet covered field of research.

The aspect we decided to study in this thesis has never been considered in the literature before. Relating to the classification attributes we have, our research is positioned as follows: we consider a consolidation-based service network design (SND) problem where the business-as-usual (Randomness) fluctuations of stochastic travel time (Travel) are explicitly taken into account in the decision process in order to define a plan that mitigate the impact of delays (and additional costs) with respect to both an "ideal" schedule and customers' imposed due dates (Existing Schedule). The latter, model service quality targets that consider both carrier and customers point of views. Although SND problems with stochastic travel time have already been considered (with very few contribution, though) in the literature, its characteristics (particularly, the double targets combined with stochastic travel time), make our problem an original and not yet studied problem. Regarding formulation, a two-stage stochastic network design formulation is proposed (RP).

## Chapter 2

## Scheduled Service Network Design with Quality Targets and Stochastic Travel Time

The design of a service network for consolidation-based carriers is a complex planning process involving interrelated and interdependent decisions with the scope of building plans with high performance level in economic efficiency respecting service quality targets as close as possible consistently in time. The uncertainty in travel or operation time may jeopardize this goal.

In this chapter, we propose to study a scheduled SND problem focusing on the uncertainty related to the variability of travel time in order to build a reliable plan for a given time horizon with the respect to given service quality targets. Two service quality targets are taken into account, in order to consider reliability from a carrier and from a customer point of view.

The chapter is organized as follows. In Section 2.1, the problem we faced is described. Although this section may repeat some concepts already discussed in the previous chapter, we extend some definitions in order to have a complete terminology for our problem. In Section [2.2, assumptions, notation as well as the stochastic programming model are described. In Sections 2.3 and 2.4 the extensive experimentation and related results are reported.

### 2.1 Problem Description

Freight transportation is a highly competitive and complex market, where transportation firms have to satisfy their customers offering low price services with high performance levels both in terms of reliability and service quality. An efficient allocation and utilization of available resources (both human and material) have to be carefully sought in order to fulfill this goal and still making a profit.

Freight consolidation is one of the many ways to lower transportation costs, taking advantage of economies of scale. Consolidation-based transportation systems are systems where freight of several different customers with possibly different origins and destinations is assembled and dispatch together into a common vehicle for part of the whole journey. These systems are in contrast to customized transportation
systems in which consignments are tailored exactly for each single customer. Typical examples of consolidation-based transportation systems are railways, less-thantruckload motor carriers, container shipping lines. The structure of a consolidationbased transportation system consists of a large and quite complex network of terminals connected by physical (or conceptual) links. Such a network is known as a hub-and-spoke network: low-volume demand is first moved to intermediate terminals, or hubs, where is consolidated with loads of other customers and moved together to other hubs. Other than by its origin, destination, entry and due dates, each shipment has, normally, several physical characteristics (e.g weight, volume) and may have specific shipment-requirements (e.g. delivery condition, type of vehicle).

In order to move freight and satisfy customers' requests, carriers establish regular transportation services selecting them appropriately from a set of possible services that may be operated. Carriers, then, externally propose a series of services, each with its operational characteristics (origin, destination, intermediate stops, route, type of vehicle, capacity, etc.), operating them repeatedly and regularly over a chosen time period, according to a schedule. The schedule specifies for each single offered service: departure time at origin, arrival time at destination and arrival times at/departure times from each intermediate stop (if any). Internally, instead, carriers define an operational (or transportation) plan which contains a series of rules and policies that affect the whole system to ensure that the proposed services are performed as stated or, at least, as close as possible to the resulting (and published) schedule. Among them, service quality targets (quality targets or, simply, target in the following) indicate the minimum level of service quality that has to be reached by the selected transportation services. Service quality is quantified by service quality measures, which generally relate to the respect of the promised or agreed upon time of delivery of freight at destination (to measure the reliability of deliveries from the customers point of view) and to the respect of the schedule (to measure the reliability of operations and reputation of the firm). Quality targets, then, define the degree of conformity to the schedule and demand promised due dates the carrier desires to achieve with the selected services. For instance, externally a carrier may propose for a given traffic-class deliveries in 24 hours. Considering the uncertainty in duration of the various activities of a carrier (e.g. travel time, operation time for consolidation activities), it is almost impossible to guarantee $100 \%$ on-time operations (as externally promised), competitiveness and profitability at the same time. Consequently, internally, a certain level of service quality is chosen considering a trade-off between operating costs and service performances (e.g. the selected services activated to carry freight belonging to that particular traffic-class must ensure on time deliveries at least $90 \%$ of the time). Policies related to the penalty when not respecting the promised due date have to also be defined and, normally, customers are significantly involved through their contracts.

The transportation plan is defined at a tactical level. Main tactical decisions are: the type of services to operate, their routes, frequency and schedules; the routing of freight, that is, services used and terminals passed through; general operating rules and policies for terminals; general empty balancing strategies. How to achieve the most advantageous trade-off between operating costs (and consequent firm profitability) and service performance (by still respecting the predefined targets) constitutes one of the major objectives of tactical planning, which appears particularly
difficult in consolidation-based systems due to the network-wide scale of decisions involved and the complexity of each type of operation [31; 32; 37].

Service Network Design (SND) is typically developed to assist tactical planning of operations. The objective is to define a cost-efficient transportation plan - selection of services, their schedule and the routing of the demand - that achieves the chosen level of service quality and satisfies demand. The corresponding mathematical model takes the form of a network design formulation. The vast majority of proposed model formulations assume travel time as deterministic parameter, commonly built on point forecasts based on available inter-terminal travel time duration historical data: the usual or most observed time realization, a sophisticated statistical estimation, a scalar transformation of the distance. It is, however, not absolutely guaranteed that the travel time observed in actual operations always respects that forecast. In many real-life applications, in fact, a considerable degree of variability in travel time could be observed and a deterministic time assumption (in this case, the perfect knowledge of future time realizations) does not represent an accurate and realistic approximation of actual travel times. Unexpected time fluctuations eventually cause delays, which, for carriers, result in potential additional economical costs related to crews and resource utilization and, in addition to them, fines and loss of reputation and reliability for not respecting planned arrival times and customers' due dates.

Therefore, in this work, we propose a model that accounts for time variability and for the costs derived from delays as its consequence in order to define a plan that mitigate the impact of those additional costs. Travel time, thus, is explicitly considered as a stochastic parameter in the design of the plan.

Stocasticity has been classified in different ways. [72] distinguish three types of uncertainties: randomness, hazard and deep uncertainty. Randomness is characterized by random variations related to regular-usual operations; hazard by low probability unusual event with a high impact; deep uncertainty by the lack of any information to assess the probability of plausible future very disruptive and catastrophic events. Our main research interest lies on the first class, that is the travel time variation that may be observed in "normal" and "smooth" conditions.

We define the medium-term future time period for which a consolidation-based carrier needs to define a plan now as the planning horizon (e.g., six months). The plan has to be decided for a chosen planning period, defined as the schedule length (e.g. a week) and has to be repeated periodically for the whole duration of the planning horizon. In addition, the schedule length it-self is divided into a number of time instants (e.g. day) among which small time periods lie. The plan has to be defined considering a given transportation network composed by a number of terminals and links connecting each terminal to the another ones. For each link connecting two stops, a travel time probability distribution is assumed to be known, estimated from historical data. Demand is assumed to be given over the schedule length. For each demand, its origin, destination, volume, entry and due dates are given as well. A set of viable and capacitated transportation services that potentially could be activated by the carrier to answer to demand is given over the schedule length. We define those services as the potential services. Each potential service is defined by its origin and destination terminals, route, departure time at origin, departure and arrival times at intermediate stops (if any), and arrival time at destination. We qualify these times, and the associated inter-terminal travel times,
as "usual" as they correspond to operations in normal conditions.
Internally, a number of quality targets are defined which the selected services have to satisfy: the first one is service related, the second one is demand related. The first target is defined as the target of services. It is expressed by the following condition: each service has to respect its usual arrival time (or planned arrival time) at least with probability $\alpha$, considering all its repetitions during the planning horizon, and delays should be not greater then a pre-specified time amount, with probability 1 (note that both expressions should hold in "normal" conditions). If the service is a direct service, this condition is applied only considering its final destination, while if the service has intermediate stops, the condition have to hold for each intermediate stop separately. A similar expression may also be used to represent the second target, defined as the target of demand. It specifies the minimum probability with which due dates of demand have to be respected over the whole planning horizon and the maximum allowed delay.

Hence, we define our problem as the Stochastic Service Network Design problem with Service and Demand Targets (SSND-SDT). Three types of costs are taken into account. The first is the fixed costs associated with the inclusion of a service in the final plan; the second one is a cost that varies proportionally with the volume of demand moved in the network; the third one is the cost in which the carrier incurs if a delay in operations or consignment is observed. A different cost is considered if the delay regards a service or the transported demand. Note that, the lateness of a service at a particular stop does not always imply that the transported demand is also late (in fact, demand could be shipped in advance with respect to its due date to its final destination ), but implies a loss of reputation and reliability for the carrier, as well as potentially, additional costs for crews and resource utilization. At the same time, it could happen that some demand is late at its particular destination also when the service on which it is transported is not. In this case, the carrier has to pay to the customer a fine for the late arrival of the requested demand only.

The goal of the problem is selecting the services and routing the freight now for the next future in order to satisfying the customers' demand and the predefined quality targets in the most efficient way, in terms of total system costs, involving fixed service selecting costs, variable moving costs and the expected extra costs of applying the chosen plan in the future.

### 2.2 Modeling Framework

In this section, the above described tactical problem is formulated following a stochastic mathematical programming approach. In particular, we formulate the problem as a two-stage stochastic programming model (for a complete presentation of this field [16; 95] or [67).

Some assumptions are made:

- service time at terminals (for loading/unloading sorting and consolidation operations) is assumed deterministic and constant;
- travel time random variables are assumed to be independent with known probability distributions;
- early arrivals of services at terminals are allowed and do not imply extra costs;
- although a service arrives at a stop earlier than as planned, terminal operations cannot start earlier than as scheduled;
- if a service arrives later than as planned, terminal operations begin as soon as the service arrives.

Considering the complexity of the problem, as a first and novel step in the field we decided to define an additional assumption. In real operation, a demand itinerary may include a missed connection between two consecutive services (the arrival time of a commodity to a terminal may be later than the departure of the needed consecutive service). If a scheduled service cannot be reached because of delays in the previous services, then replanning is required to find a new itinerary for the late commodity till destination. In our setting, we assume that a delay can never be so long to define such a situation. That is, connections are always caught, even though delays are observed.

### 2.2.1 General Notation and Mathematical Model

The physical network on which the carrier operates is represented by a graph $G_{\text {phys }}=\left(N_{\text {phys }}, A_{\text {phys }}\right)$, which nodes in set $N_{\text {phys }}$ represent the physical terminals composing the physical network and arcs in $A_{\text {phys }}$ represent the physical connections between terminals on which the services move. To each arc is associated a point forecast of the usual travel time and a travel time random variable. In this network, demand appears at certain points in time. Assumed that the schedule length is divided in $T+1$ time instants, the set of nodes of $G_{p h y s}$ is replicated $T+1$ times. We define the resulting set of replicated nodes as $N$. Each node of $N$ represents one of the physical freight terminals that composes the physical transportation network at different time instants $(0, \ldots, T)$.

Demand is represented in terms of commodities, that is collection of similar products requiring transport between an origin-destination pair trough the physical network at certain points in time. Let $K$ be the set of commodities that have to be transported. Each commodity $k \in K$, requires the transport of a certain volume $w(k)$, from an origin $o(k)$, to a destination $d(k)$, respecting its entry and due dates, respectively $a(k)$ and $b(k)$. Supply, $w(k)$, and demand, $-w(k)$, are then associated appropriately to the nodes of $N$ according to $a(k)$ and $b(k)$.

Let $R$ be the set of potential services that the carrier may use to answer to demand. Each services $r \in R$ has a route in the physical network. By resorting to the notation introduced in [30], we define each route with the following ordered set of visited terminals $\sigma(r)=\left\{z_{n} \in N_{\text {phys }}, n=1, \ldots,|\sigma(r)|\right\}$, where if $r$ visits terminal $n$ before terminal $m$ then $n<m$. If service $r$ is a direct service, $\sigma(r)$ contains only two elements: $z_{1}=o(r)$ and $z_{|\sigma(r)|}=d(r)$, where $o(r)$ is the origin and $d(r)$ is the destination terminal of service $r$. On the same physical route may move different services, having the same set of stops but different leaving time at origin, denoted by $f_{o(r)}$ (and, consequently, different arrival time at destination) or services having the same origin and destination terminals but not the same set of intermediary stops. The path segment between two consecutive stops $z_{l}$ and $z_{l+1}$ of service $r$ is called
service leg and is denoted by $l(r)$. Each service leg is composed by one or more arcs of $A_{\text {phys }}$ and its usual travel time and associated travel time random variable is respectively the sum of the usual travel times and the convolution of travel time random variables (note the independence assumption) of the arcs in $A_{\text {phys }}$ making up that service leg. The capacity of each service is denoted by $u_{r}$. Furthermore, we assume that handling of freight at terminals require a fixed and deterministic time amount, denoted by $t$.

As for many scheduled SND problems, our problem is addressed trough a timeexpanded network $G=(N, A)$ which represents all the potential transportation services that could be offered by the carrier in time and space, over the given schedule length. The set $A$ is composed by two sets: $A^{H}$ and $A^{M}$. Each of those two sets is composed by arcs defining a specific activity. An arc $(i, j) \in A^{H}$ links two nodes representing the same physical terminal in two consecutive time instants and is used to model idle time at terminal for freight or operation time at terminal for services. These arcs are also often referred to as holding arcs. An $\operatorname{arc}(i, j) \in A^{M}$ links nodes representing different physical terminals in different time instants and is used to model the movement of a service between two different physical terminals at certain point in time. Each movement arc between two nodes $i \in N$ and $j \in N$ represents a specific service leg of a potential service in time. We sometimes refer to such arcs as $i(r) \in L(r)$, instead of $(i, j) \in A^{M}$, where $L(r)$ is the set composed by the service legs of service $r \in R$ in the time-expanded network. The travel time point forecast, denoted by $\hat{\tau}_{i(r)}$, and the travel time random variable, denoted by $\tau_{i(r)}$, are associated to each service leg $i(r)$, according to the leg of the physical network it represents in the time-expanded network.

We model three types of costs. The first is a variable cost associated to each arc $(i, j) \in \mathcal{A}$ and each commodity $k \in K$, denoted $c_{i, j}^{k}$. These costs represent:

- the cost associated with the transport of commodity $k$, if $(i, j) \in \mathcal{A}^{\mathcal{M}}$;
- the cost associated with the handling of commodity $k$ at terminals, if $(i, j) \in$ $\mathcal{A}^{\mathcal{H}}$.

The second type of cost is the fixed cost $c_{r}$ required to activate a service, which captures all the expenses of including it in the final plan. The third is the cost that has to be paid for delays (either of services or demand) and will be described in detail later on.

The information revelation process defines how and when the values of stochastic parameters are observed. In real-life operations, delays are known the moment they happen (or at latest when arriving at a stop). Contractual economical obligations are then paid, almost immediately, if needed. For our tactical planning purposes we need to model the information revelation process. We approximate it as follows: for a given plan, transportation services are performed according to it for the entire schedule length. At its end, that is at time instant $T$, it becomes known which services and which demand arrived late, depending on the actual travel time observed. That is, a the end of each repetition of the schedule, uncertainty on travel time is completely resolved, in our formulation, for the entire network. Consequent costs, thus, are calculated and paid at the end of each repetition of the schedule. Additionally, once the service network is established, it cannot be modified, regardless the values of
observed travel times (only penalties are paid). This approximation allows us to represent the problem as a two-stage stochastic optimization model with simple recourse.

In the first stage, planning decisions are made considering their future effects: the selection of the services and the routing of freight are determined with the objective of minimizing the fixed service-selection and variable demand-routing costs, plus the expected costs following the application of the chosen plan to the observed realizations of travel times. Two sets of first stage decision variables are defined, which model selection of services and routing of demand:

- binary variables $y_{r} \in\{0,1\}, \forall r \in R$ represent whether a service $r$ is selected $\left(y_{r}=1\right)$ in the final plan or not $\left(y_{r}=0\right)$;
- non-negative and continuous variables $x_{i j}^{k}, \forall k \in \mathcal{K}, \forall(i, j) \in \mathcal{A}$ represent the flowing of commodity $k$ in the network. In particular, the amount of commodity $k$ transported on $\operatorname{arc}(i, j) \in \mathcal{A}^{M}$ or waiting at a terminal, if $(i, j) \in \mathcal{A}^{H}$.

The second stage addresses how to deal with delays for a given travel time realization and a chosen design. Let $\Omega$ define the set of possible outcomes of the random variable travel time and let $\omega$ be a random element in that set. Since randomness only occurs on moving arcs, we use here a leg-notation. A travel time realization of service leg $i(r) \in L(r)$ is denoted $\tau_{i(r)}(\omega), \forall i(r) \in L(r), \forall r \in R$. Three sets of second stage variables are defined, which model for a travel time realization $\omega$ leaving times and arrival times of each service from/to each terminal of its route and arrival time of each commodity at destination:

- non-negative and continuous variables $\delta_{i(r)}(\omega), \forall i(r) \in L(r), \forall r \in R$ represent the time instant in which service $r \in R$ begins its movement on service leg $i(r) \in L(r)$;
- non-negative and continuous (dummy) variables $\eta_{i(r)}(\omega), \forall i(r) \in L(r), \forall r \in R$ represent the time instant in which service $r \in R$ ends its movement on service $\operatorname{leg} i(r) \in L(r)$;
- non-negative and continuous variables $\varepsilon_{k}(\omega), \forall k \in K$ represent the time instant in which commodity $k \in K$ arrives at its destination.

The chosen quality targets may be easily expressed through probabilities. From the available travel time random variables $\tau_{i(r)}$, two other sets of random variables may be deduced: the arrival time random variables of service $r$ at a general stop $i+1$, denoted $\eta_{i(r)}, \forall i(r) \in L(r), \forall r \in R$, and the arrival time random variables of commodity $k$ at destination $d(k)$, denoted by $\varepsilon_{k} \forall k \in K$. Regarding the target related to arrival time, for a direct service $r \in R$ that should achieve at least an $\alpha \cdot 100 \%$ on-time arrivals at destination, the target can be expressed as the probability of arriving at destination before the usual arrival time instant, defined $e_{i(r)}$, that is, $P\left(\eta_{i(r)} \leq e_{i(r)}\right) \geq \alpha$. Similar expressions may also be used to represent the targets of services with intermediary stops (the expression has to hold independently for each intermediary stop) and for on-time delivery of demand. In the latter cases, since we assumed independence between travel time random variables but delay
propagation, $\eta_{i(r)}$ and $\varepsilon_{k}$ have to be computed as the convolution of the travel time random variables involved, respectively in the route of $r$ and in the path of $k$. In our formulation, we do not consider probabilistic constraints to control the satisfaction of targets, rather we model the same underlying significance of them by penalizing appropriately observed lateness. Lateness of a service is considered as soon as the observed arrival time at a stop exceeds the usual arrival time at that stop. A penalty proportional to the difference between $\eta_{i(r)}(\omega)$ and $e_{i(r)}$ is then applied. The penalty to pay if service $r$ is late on service leg $i(r)$ is denoted by $\lambda_{i(r)}^{r}$. The same idea is followed to model target of services with intermediary stops and the target of demand. The latter is modeled by penalizing the excess of time between the actual arrival time of commodity $k, \varepsilon_{k}(\omega)$, and its due date $b(k)$. This fixed penalty cost, instead, is denoted by $\lambda^{k}$.

Regarding the target related to the maximum delay, the target of a direct service can be expressed through probabilities as well: $P\left(\eta_{i(r)} \leq B\right)=1$, where $B$ represents the maximum acceptable (or long) delay. The parameter $B$ may be a percentile of the travel time probability distribution $\tau_{i(r)}$ (e.g., $90^{t h}$ or $95^{t h}$ ) or may be an estimation based on statistical measurement (e.g. the expected value plus the standard deviation). Similar expressions may be deduced to represent the target of services with intermediary stops and of demand. These targets are modeled through penalties as well in the model. A very high penalty proportional to the difference between $\eta_{i(r)}(\omega)$ and $B$ is applied. The penalty cost is denoted $\Lambda_{i(r)}^{r}$. The same idea is followed to model the target of maximum delay of demand: a penalty proportional to the difference between the actual arrival time of commodity $k, \varepsilon_{k}(\omega)$, and its maximum allowed delay $B^{k}$ is applied. This fixed penalty cost is denoted by $\Lambda^{k}$.

### 2.2.2 Formulation of the Scheduled Service Network Design Model with Quality Target and Stochastic Travel Time

The goal of the SSND-SDT model is to select the services and route the freight in order to satisfying the customers' demand and the quality targets in the most efficient way, that is, minimizing fixed service selecting costs, variable moving costs and the expected extra costs if delays are observed when applying the chosen plan.

In order to introduce the model, we need to define for each node $i \in N$ its set of successor nodes, formally, $\mathcal{N}^{+}(i)=\{j \in \mathcal{N}:(i, j) \in \mathcal{A}\}$ and its set of predecessor nodes, $\mathcal{N}^{-}(i)=\{j \in \mathcal{N}:(j, i) \in \mathcal{A}\}$.

The two-stage formulation may be written as follows.

$$
\begin{gather*}
\min \sum_{r \in R} c_{r} y_{r}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j}^{k}+\mathbb{E}_{\tau_{i(r), i(r) \in L(r), r \in R}}\left[Q\left(y, x ; \tau_{i(r)}(\omega)\right)\right]  \tag{2.1}\\
\sum_{j \in N^{+}(i)} x_{i j}^{k}-\sum_{j \in N^{-(i)}} x_{j i}^{k}= \begin{cases}w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \quad \forall i \in N, \forall k \in K \\
-w(k) & \text { if } i=d(k)\end{cases}  \tag{2.2}\\
\sum_{k \in K} x_{i(r)}^{k} \leq u_{r} y_{r} \quad \forall i(r) \in L(r), \forall r \in R  \tag{2.3}\\
x_{i j}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A  \tag{2.4}\\
y_{r} \in\{0,1\} \quad \forall r \in R \tag{2.5}
\end{gather*}
$$

where

$$
\begin{array}{r}
Q\left(y, x ; \tau_{i(r)}(\omega)\right)=\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r)}(\omega)-e_{i(r)}\right)_{+}+ \\
\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r)}(\omega)-B\right)_{+}+  \tag{2.6}\\
\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k}(\omega)-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k}(\omega)-B^{k}\right)_{+}
\end{array}
$$

The objective 2.1 is to minimize the total cost of the system, which consists of three elements: the fixed cost of operating services, the transportation costs for routing commodities and the expected cost of recourse for applying the chosen plan. The function $Q\left(y, x ; \tau_{i, j}(\omega)\right)$ is dependent on both design decisions and routing decisions and, in addition, on the realizations of the random variable $\tau_{i(r)}$. Equations (2.2) are the commodity flow conservation constraints. Equations (2.3) are linkingcapacity constraints, which state that a commodity flow may be positive on movement arc $i(r) \in L(r)$ but not exceed the capacity of the service $r$ travelling on it, only if $r$ is selected, that is $y_{r}=1$, and have to be 0 otherwise. We assume not capacity restriction at terminals. Relations (2.4) and (2.5) are non negativity and binary constraints which define the domains of the decision variables.

The second stage, composed by (2.6), computes the total penalty costs of service and demand late arrivals, where the first two terms relate to targets of services, the last two to targets of demand and where the operator $(x-y)_{+}$returns the difference between $x$ and $y$ if positive and 0 otherwise.

The following equation (2.7) defines how to compute $\eta_{i(r)}(\omega)$ for each service.

$$
\begin{equation*}
\eta_{i(r)}(\omega)=\delta_{i(r)}(\omega)+\max \left(\hat{\tau}_{i(r)}, \tau_{i(r)}(\omega)\right) \quad \forall i(r) \in L(r) \tag{2.7}
\end{equation*}
$$

where

$$
\delta_{i(r)}(\omega)=\left\{\begin{array}{ll}
f_{i(r)} & \text { if } i=o(r)  \tag{2.8}\\
\eta_{i^{-}(r)}(\omega)+t & \text { if } i \neq o(r)
\end{array} \quad \forall i(r) \in L(r), \forall r \in R\right.
$$

If the observed travel duration $\tau_{i(r)}(\omega)$ is lower than the "usual" one, the service arrives early but have to wait to begin terminal operations, the actual travel time is then considered as that one of the point forecast $\left(\hat{\tau}_{i(r)}\right)$. If travel duration is higher than the "usual" one, terminal operations begin as soon as the service $r$ finishes its movement on that leg $\left(\delta_{i(r)}(\omega)+\tau_{i(r)}(\omega)\right)$. This time instant is directly related to the moment in which the movement on that leg may start. Equations (2.8) define those instants. It is easy to compute for direct services or, at least, for each initial leg, since it is equal to the planned leaving time from service origin (first part of (2.8)). If a service has an intermediate stop, instead, its leaving time from it is dependent on what happened on the previous service leg, denoted $i^{-}(r)$, and it is computed as the summation of the arrival time at that stop (that is, the ending time instant of the previous leg $\left.i^{-}(r)\right)$ plus the deterministic service time $t$. Variables $\varepsilon_{k}(\omega)$ are computed by the summation of the time required to the commodity $k$ to reach its destination, this involves all the service legs on which it is transported and handling or idle time at terminals (if any).

It is worth to notice that the model may be easily modified if the interest is only focused on one of the considered targets, by considering only the penalties related to the target of interest. That is, if the focus is only the target of demand, then the penalties related to the target of services have to be fixed to 0 still maintaining the penalties for the target of demand.

As often done in stochastic programming, the random probability distribution of the stochastic phenomenon is approximated by a set of scenarios, a set of possible realizations, in our case, of travel times, that reasonably are representative of the future. By modeling uncertainty through scenarios the stochastic problem becomes a deterministic mixed integer linear program, which may be solved exploiting technique used in deterministic optimization, even though it may becomes generally of very large dimensions.

Let $S$ represent the set of scenarios and let $s$ be an element of $S$. Each scenario $s$ has dimension $\left|A_{p h y s}\right|$. A probability $p_{s}$ is assigned to each scenario, such that $p_{s} \leq 1, \forall s \in S$ and $\sum_{s \in S} p_{s}=1$. The above mentioned expected costs of applying a chosen plan in the objective function is, then, approximated by the expected penalties that could be paid for it. The expectation is computed considering the latter probabilities and the delays calculated in the second stage, considering the time realizations of set $S$, denoted $\tau_{i(r)}(s)$. The sets of second stage variables are, thus, defined, as follows:

- non-negative and continuous variables $\delta_{i(r) s}, \forall i(r) \in L(r), \forall r \in R$ represent the time instant in which service $r \in R$ begins its movement on service leg $i(r) \in L(r)$ in scenario $s \in S$;
- non-negative and continuous (dummy) variables $\eta_{i(r) s}, \forall i(r) \in L(r), \forall r \in R$ represent the time instant in which service $r \in R$ ends its movement on service leg $i(r) \in L(r)$ in scenario $s \in S$;
- non-negative and continuous variables $\varepsilon_{k s}, \forall k \in K, \forall s \in S$ represent the time instant in which commodity $k \in K$ arrives at its destination in scenario $s \in S$.

The two-stage formulation may be written as follows.

$$
\begin{gather*}
\min \sum_{r \in R} c_{r} y_{r}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j}^{k}+\sum_{s \in S} p_{s}\left[Q\left(y, x ; \tau_{i(r)}(s)\right)\right]  \tag{2.9}\\
\sum_{j \in N^{+}(i)} x_{i j}^{k}-\sum_{j \in N^{-}(i)} x_{j i}^{k}=\left\{\begin{array}{ll}
w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \\
-w(k) & \text { if } i=d(k)
\end{array} \forall i \in N, \forall k \in K\right.  \tag{2.10}\\
\sum_{k \in K} x_{i(r)}^{k} \leq u_{r} y_{r}  \tag{2.11}\\
x_{i j}^{k} \geq 0 \quad \forall i(r) \in L(r), \forall r \in R  \tag{2.12}\\
y_{r} \in\{0,1\} \quad \forall k \in K, \forall(i, j) \in A \tag{2.13}
\end{gather*}
$$

where

$$
\begin{array}{r}
Q\left(y, x ; \tau_{i(r)}(s)\right)=\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+ \\
\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+  \tag{2.14}\\
\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+}
\end{array}
$$

### 2.3 Experimental Setting

In this section, we try to understand the role of stochastic travel time in defining a consolidation-based transportation plan at a tactical level, when internal targets are considered. A number of experiments are set up to investigate the problem. In particular, the experimentation focuses on the comparison between the deterministic and stochastic formulations and their solutions under different parameter settings. A stochastic formulation may easily be transformed into its respective deterministic counterpart by replacing stochastic parameters by their expectations or other approximations. In our case, the stochastic parameters are replaced by $\hat{\tau}_{i(r)}$, that is the point forecast of each leg $i(r) \in L(r), \forall r \in R$.

The experiments consist of two parts. In the first part, a number of instances with different characteristics - in terms of level of variability, number of commodities, wideness of delivery time windows and penalty costs - are solved considering the
stochastic and the deterministic formulations. The results are, then, compared in a stochastic environment through a Monte Carlo simulation. The purpose of this analysis is to quantify the potential benefits that may be obtained by considering explicitly stochasticity into the model rather having a deterministic time assumption. We refer to this set of experiments as Evaluation Analysis. In order to further investigate and detail the differences between transportation plan solutions obtained from the stochastic formulation and its respective deterministic counterpart, service designs and commodity routes are compared considering three criteria: reliability, costs and structural complexity. We refer to this set of experiments as Structural Comparison. The second part of the experimentation consists of a comparison between stochastic solutions. The purpose is to investigate how the value of some parameters may change their structures. We refer to this set of experiments as Comparative Analysis.

SND problems are generally difficult to solve and this is even more true when the size of a problem is increased by a set of scenarios. In order to have a complete understanding of the problem, we only study small to medium-sized problem instances, which, can be solved optimally.

In the following sections, the generation of test instances, scenario generation procedure, results and analysis are presented. Both mixed-integer linear programming models (deterministic and stochastic) were implemented in OPL language and instances were solved by a standard linear programming solver, namely Cplex 12.6 (IBM ILOG, 2016) with a branch and bound method. All experiments were conducted on an Intel Xeon X5675 with 3.07 GHz and 96 GB of RAM.

### 2.3.1 Instances and Scenario Generation

The physical service network we consider in all our experimentations is inspired by that one used in [36], which consists of 5 physical nodes and 10 physical arcs (and shown in Figure 2.1.


Figure 2.1. Physical Service Network
The service network is repeated for 15 periods and, as in [36], has a cyclic nature (see Figure 2.2).

We consider 6 problem classes defining demand, differing in number of commodities and wideness of delivery time windows. Three level of demand are taken into account. Level 1 considers a low number of commodities ( 15 commodities), level 2 a medium number ( 20 commodities) and the last level, namely level 3 , a relatively high number of commodities, given the need of finding optimal solutions ( 25 commodities). Origin, destination and volume of commodities are randomly generated. Two different wideness of delivery time windows are examined. The first


Figure 2.2. Time-Expanded Service Network
is loose $(l)$ and considers due dates after $11-14$ periods after the availability dates of each commodity over the total schedule length of 15 periods, the second is tight $(t)$ and considers due dates after $9-12$ periods after the availability dates (note that 8 is the minimum time period to use two consecutive services). Destinations are randomly generated according to delivery time windows ranges. Each problem class (Pclass-) is identified by a couple defining the level of demand ( 1,2 or 3 ) and the wideness of delivery time windows ( $l$ or $t$ ) and contains 10 randomly generated instances.

To answer demand a certain number of direct potential services are available and, in addition to them, a few number of potential services with one intermediate stop. The activation cost of a direct service is proportional to the distance that service covers (services need 3,4 or 5 time periods to reach their destination). The activation cost of a service with an intermediate stop is $35 \%$ less than if for the same path two direct services would be activated. The set of services and their activation costs do not vary across instances.

The random event under study, namely the travel time between terminals in normal conditions, is represented by a random variable which must have specific characteristics. It should have a lower bound, since there is always a minimum time to cover the distance between two points defined by physical constraint (e.g., speed limits). After this minimum time, the probability should rapidly increase to a maximum representing the most usual or observed travel time realization (the mode) after which the probability should slowly decrease with a tail skewed to the right. In our case, the distribution also has an upper bound, since in normal condition infinite travel times are not ascertained (we do not consider a distribution with infinite tails). In our experimentation, thus, the random event is described by a Truncated Gamma (TG) probability distribution, which matches all the needed requirements (see Figure 2.3(a)).

The scenario generation process is, thus, performed by generating random values from a set of TG distributions (which differ by several characteristics, described in the following). A TG depends on two parameters alike a classical gamma distribution: a shape parameter and a scale parameter (for more details we refer to [91; 27; 24]). In our case, those parameters are estimated once the mode, the variance and the


Figure 2.3. Travel Time Random Distributions
range (difference between lower and upper bounds of the truncation) are fixed. The mode is also used as the travel time point estimations in the deterministic settings of the problem.

To better demonstrate how uncertainty affects solutions, we assess 12 scenario classes. We considered 4 variability levels (measured in terms of standard deviation): low, medium and high. In addition to them, a forth mixed-level is considered, where to a subset of physical arcs a low variable travel time is assigned and to the remaining arcs a high one. Besides the above mentioned levels of variability, also three ranges are considered. Ranges are related to what is considered "normal" with respect to travel time and are fixed, that is they are not dependent on the time a service needs to cover the distance from a stop to the following one. If on one side we always consider a same lower bound for the above mentioned distributions, on the other side three different upper bounds are chosen: the first is tight ( $t$, mode $-30 \%$ of a time period), the second is medium ( $m$, mode +1 time period) and the third is loose ( $l$, mode $+130 \%$ of a time period). The combination lower bound - upper bound define the range of the distribution. The looser is the range the wider is the concept of "normal" travel time. Scenario classes (Sclass-) are thus identified by the couple level of variability (1 low variability, 2 medium variability, 3 high variability and
$M$ mixed variability) and range ( $t, m$ and $l$ ). In Figure 2.3(b) distributions for a same range and different standard deviations are plotted, while in Figure 2.3(c) distributions for the same level of variability and different ranges are shown.

Experimentation is performed considering the SSND-SDT model under 3 different levels of increasing penalty costs. Furthermore, one target at a time is also taken into account, that is only considering the target of service (SSND-ST) or only considering the target of demand (SSND-DT). The latter models are built by simply fixing at 0 the penalties of the not-considered target.

Summarizing, we have 6 types of deterministic problem classes derived by the combined use of the 3 levels of commodity demand and the 2 different delivery time windows. For each class, we generated 10 instances for a total of 60 deterministic instances. For each deterministic instance, 36 stochastic instances are constructed, combining all the above described parameters between each others (4 levels of variability, 3 ranges and 3 penalty rates).

### 2.4 Results and Analysis

In this section, we report the results of the above mentioned and described evaluation, structural and comparative analyses. Before starting with the analyses however, in-sample and out-of-sample stabilities are discussed.

### 2.4.1 In-Sample and Out-of-Sample Stability

When random scenario generation procedures (such as sampling from a distribution) are involved, stability requirements assume great importance in order to verify the correctness of the scenario generation procedure and the representativeness of the generated values in order to avoid some kind of bias on the results of the optimization model.

Two stability conditions must normally be satisfied by a scenario-generation procedure: in-sample and out-of-sample stability. The first represents a test of the internal consistency of the model: the value of the objective function obtained by solving the model considering different scenario sets of the same size generated by the same procedure should be (about) the same in all cases. In-sample stability assures that the objective function value of the problem would (approximately) not change if the scenario set, instead, is changed, ensuring that the solution does not directly depend on the specific scenario set used, rather is a unique result of the mathematical model. While for in-sample stability only solving the scenario-based optimization problem is needed, for out-of-sample stability solutions should be evaluated on the "true" objective function of the problem, that is considering the real stochastic phenomenon. Out-of-sample stability is then attained if, when evaluating solutions coming from different scenario sets on the (same) true objective function, always (about) the same values are observed. Normally, this analysis is performed resorting to some simulation techniques on a benchmark distribution, which is assumed to correctly and completely represent the stochastic phenomenon. When out-of-sample stability is verified, we may conclude that the scenario sets generated by the scenario generation procedure are representative of the real phenomenon (e.g. it does not consistently avoid a difficult tail of the underlying "true" distribution).

When both stabilities are verified, the scenario generation method may be considered effective, in the sense that it does not cause instability in the solutions of the model. For a more complete explanation and deeper details about in- and out-of sample stability, we refer to [67] and [68].

In order to verify stability requirements, tests were conducted only considering the highest variability level (level 3 ), but varying their ranges ( $t, m$ and $l$ ). A subset of instances were selected from the 10 belonging to each problem class. Each instance was solved 10 times by generating new scenario sets, once fixed $t, m$ or $l$.

In-sample stability achieving a difference between the highest and the lowest optimal values across scenario sets always less than $1 \%$ for each problem class is obtained by using sets of 30 scenarios. In Table 2.1 average results are shown for the third problem class and the third penalty level (we refer to the Appendix B for more results).

|  | PClass-31 | PClass-31 |
| :--- | :---: | :---: |
| SClass-3t | 0.72 | 0.65 |
| SClass-3m | 0.77 | 0.75 |
| SClass-31 | 0.56 | 0.51 |

Table 2.1. In-Sample Stability Test

Out-of-sample stability was tested considering 30 -scenario-sized sets to find solutions and 100 -scenario-sized sets (generated from the same truncated distributions used to construct the scenario sets for the optimization process) as the "true" stochastic phenomenon. A procedure similar to Monte-Carlo simulation is used to evaluate the solutions. The evaluation was performed by fixing the first-stage variables obtained as results of the stochastic programs on the 30 -scenario-sized sets, and optimizing the temporal flow by solving again the the second stage on the 100 -scenario-sized sets. In all cases, the difference between the highest and the lowest optimal values across scenario sets is $3 \%$. To illustrate, we report in Table 2.2 average results for the same problem classes, scenario classes and penalty mentioned above (again, we refer to the Appendix B for more results).

|  | PClass-31 | PClass-31 |
| :--- | :---: | :---: |
| SClass-3t | 2.24 | 0.61 |
| SClass-3m | 1.08 | 1.44 |
| SClass-3l | 2.33 | 0.79 |

Table 2.2. Out-of-Sample Stability Test

Although increasing the number of scenarios could lower even more the in-sample and out-of-sample values (increasing so also stability), considering the purpose of solving exactly problem instances, we consider 30 scenarios enough. The set size of 30 scenarios is, thus, sufficiently large for us to ensure a good level of in-sample and out-of-sample stability, while being still easily solvable relatively fast to find optimal solutions. All the instance problems are, thus, solved considering the before mentioned size of 30 -scenario sets.

### 2.4.2 Evaluation Analysis

The purpose of this analysis is to quantify the potential benefits that may be obtained by considering explicitly stochasticity into the model. The analysis concerns a comparison between solutions obtained from the two formulations.

A solution, whether deterministic (SDM) or stochastic, consists of a set of activated services and the paths used by freight-flows to reach their destinations. Stochastic solutions are found considering the three formulations and are defined as (SSM-ST) when only service target, (SSM-DT) when only the target of demand and (SSM-SDT) when both are considered. A general comparison between deterministic and stochastic solutions is given related to the set up cost of the network: service activation costs plus routing costs. After that, a comparison is given considering the behavior of the solutions when actually applied. Each solution is "plunged" in a stochastic environment, defined by a scenario set of a bigger size (100 scenarios) with respect to that one used to find the solutions in the stochastic formulations (30 scenarios). In order to quantify and evaluate SDM, SSM-ST, SSM-DT and SSM-SDT behaviors, a procedure similar to Monte-Carlo simulation is applied. The focus of this comparison are the costs raised as penalties.

In general, the collected data from solving the problems, may suggest a well defined behavior of SSM-ST, SSM-DT and SSM-SDT compared to SDM. Let us first consider SSM-ST and SDM. SSM-ST set up costs are, in general, not very dissimilar from the corresponding SDM (note that we are comparing set up costs and not objective values). However, the set up costs of the SSM-ST show an interesting characteristic. In fact, comparing the number of activated services, in almost all cases less services operate in SSM-ST than in SDM, even though the solutions share part of them. This may be explained considering that each service involves penalties at some point and the trend in SSM-ST is to activate only the strictly necessary services to fulfill demand. A higher routing cost seems to be a feature of SSM-ST compared to the SDM. Routing in the stochastic case appears, thus, more tricky since demand, in the majority of the cases, is delivered from their origin to their destination using less services with respect to SDM, leading to freight-paths which are more tangled and with longer idle time at intermediary stops. The set up cost of the network in SSM-ST, therefore, is the result of two opposite effects: on one side fixed costs are lowered as well as the number of activated services, on the other side routing costs are gradually increased. This characteristic of SSM-ST appears as in contrast with the effect that stochastic demand may have on the design of a service network. In this case, in fact, the number of services is, normally, increased [126] in order to hedge the effects of the uncertain phenomenon, here instead is decreased.

The major effect appears when the highest penalty level is coupled with the highest level of variability, causing the highest decrease of activated services and consequently the highest increase of routing costs. To illustrate, average results for instances belonging to the third problem class (SClass $-3 t$ and SClass $-3 l$ ) solved considering increasing level of variability (scenario classes SClass-1m,SClass-2m and SClass $-3 m$ ) under the highest penalty level (level 3) are shown in Table 2.3 . where set up costs, fixed activation service costs, number of activated services and routing costs are reported (we refer to the Appendix B to comprehensive results).

The opposite behavior, is observed for SSM-DT. SSM-DT set up costs are, in

|  | PClass-3t |  |  |  |  | PClass-3l |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Set up | Fixed | Tot.Serv | Routing | Set up | Fixed | Tot.Serv | Routing |  |
| SClass-1m | 6326,5 | 136,2 | 31,3 | 6190,3 | 6684,8 | 167,2 | 37,4 | 6517,6 |  |
| SClass-2m | 6330,7 | 135,9 | 31,1 | 6194,8 | 6705,2 | 163,1 | 37 | 6542,1 |  |
| SClass-3m | 6333,6 | 131 | 30,5 | 6202,6 | 6713,7 | 158,4 | 36,6 | 6555,3 |  |
| SDM | 6340,8 | 139,8 | 31,4 | 6201 | 6694,8 | 177,1 | 39,5 | 6517,7 |  |

Table 2.3. SSM-ST: average costs and number of services for penalty level 3 and varying variability
general, more expensive than the corresponding SDM. But differently from SSM-ST and similarly to the mentioned results related to stochastic demand, the increase of set up costs is directly related to the increase of the number of activated services. The reason is to limit as much as possible the cases of just-in-time arrivals, which are more susceptible to penalties, in order to respect agreed upon time delivery due dates. Routing costs change as consequent depending on the activated services. If on one side tangle paths are a feature of SSM-ST, on the other side freight arrivals at least one period before due dates seem to be a feature of SSM-SD. Table 2.4 shows the same average results for the same problem classes, scenario classes and penalty level considered above.

|  | PClass-3t |  |  |  | PClass-3l |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Set up | Fixed | Tot.Serv | Routing | Set up | Fixed | Tot.Serv | Routing |
| SClass-1m | 6344,8 | 144,2 | 32,4 | 6200,6 | 6697 | 178,4 | 39,8 | 6518,6 |
| SClass-2m | 6350,6 | 144,4 | 32,9 | 6206,2 | 6715,2 | 176,9 | 40 | 6538,3 |
| SClass-3m | 6351,9 | 144,1 | 32,9 | 6207,8 | 6717,1 | 175,9 | 39.7 | 6541,2 |
| SDM | 6340,8 | 139,8 | 31,4 | 6201 | 6694,8 | 177,1 | 39,5 | 6517,7 |

Table 2.4. SSM-DT: average costs and number of services for penalty level 3 and varying variability

The performance of SSM-ST and SSM-DT when actually applied are always better than the performance of SDM. The evaluation is made with our Monte-Carlo simulation procedure and performances are quantified by the penalties that have to be paid when solutions are plunged in a same stochastic environment. We define the full cost of the network as the set up cost plus the penalties applied when performing the plan. SSM-ST and SSM-DT show a full cost always lower than the corresponding SDM, showing that considering the stochastic nature of travel time explicitly in the decision process may hedge or, at least, reduce the effects and consequence of its uncertainty, despite an initial higher set up cost. To illustrate, we show in tables 2.5. 2.6, 2.7 and 2.8 average results of our Monte-Carlo simulation procedure for the same problem classes, scenario classes and penalty level considered above in order to compare SDM and, respectively, SSM-ST and SSM-DT. In the tables, average full costs and penalties are shown. It is also specified if the average amount of penalty belongs to short or long delay.

SSM-SDT appears as the compromise between SSM-ST and SSM-DT, showing characteristic coming from both of them. The SSM-ST component, however, influ-

|  | PClass-3t |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short | Pen. long |
| SClass-1m | 17871,2 | 11544,7 | 11118,2 | 426,4 |
| SDM | 18221,3 | 11880,5 | 11437,4 | 443,0 |
| SClass-2m | 36835,2 | 30504,48 | 13162,2 | 17342,2 |
| SDM | 39439,9 | 33099,1 | 13214,0 | 19885,1 |
| SClass-3m | 46531,2 | 40197,5 | 15873,4 | 24324,1 |
| SDM | 50362,1 | 44021,3 | 16532,2 | 27489,0 |

Table 2.5. SSM-ST: average performance costs for penalty level 3 and varying variability

|  | PClass-3l |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short | Pen. long |
| SClass-1m | 20636,1 | 13951,2 | 13474,9 | 476,3 |
| SDM | 21550,5 | 14855,7 | 14336,4 | 519,3 |
| SClass-2m | 42864 | 36158,8 | 16443,6 | 19715,2 |
| SDM | 51719,8 | 45025 | 16959,2 | 28065,8 |
| SClass-3m | 54481 | 47767,7 | 19589 | 28178,7 |
| SDM | 65478,2 | 58783,4 | 20940,6 | 37842,7 |

Table 2.6. SSM-ST: average performance costs for penalty level 3 and varying variability
ences SSM-SDT the most. The set up cost, in fact, has exactly the same behavior as in SSM-ST when penalties or variability levels increase: a decrease of the activated services and fixed costs and a consequent increase of routing costs. Nevertheless, its SSM-DT component tries to limit the just-in-time delivery cases as well as favoring deliveries one period before their due dates, if not earlier. Routing appears, thus, very tricky since demand, in the majority of the cases, is not only delivered in advance in order to lower the expenses related to the late arrivals of freight but also moved through the network with less services than in SDM. Freight-paths seem to be even more tangled than in SSM-ST and including longer idle time at some intermediary stops. Average set up costs and performance results are shown in Tables $2.9,2.10$ and 2.11 .

### 2.4.3 Structural Analysis

SSM-SDT, SSM-ST and SSM-DT show, thus, different features, but how are they structurally different from SDM? In general, SDM have the typical characteristics of consolidation-based transportation networks: different commodities share the capacity of single services for the vast majority of their journey, passing through several intermediary stops and often idle there before arriving at destination. In addition, just-in-time arrivals of freight at destination (with respect to due dates) seem to be a widespread feature of SDM: almost half of the commodities (still referring to the same problem classes PClass $-3 t$ and PClass $-3 l$ ) arrives just-in-time. Furthermore, in order to lower fixed costs and recalling that services with stops are less expensive than direct services in our experimentation, the firsts are always privileged when possible with respect to the others.

The most substantial difference between SSM-ST and SDM solutions is the

|  | PClass-3t |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short | Pen. long |
| SClass-1m | 8647 | 2302,2 | 2222,9 | 79,3 |
| SDM | 11068,5 | 4727,7 | 3069,3 | 1658,4 |
| SClass-2m | 13388,8 | 7038,1 | 2485,5 | 4552,6 |
| SDM | 21332 | 14991,2 | 3421,5 | 11569,6 |
| SClass-3m | 15615,6 | 9263,7 | 2877,3 | 6386,4 |
| SDM | 25199,9 | 18859,1 | 4327,9 | 14531,1 |

Table 2.7. SSM-DT: average performance costs for penalty level 3 and varying variability

|  | PClass-3l |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short | Pen. long |
| SClass-1m | 10186,5 | 3489,5 | 3314,7 | 174,7 |
| SDM | 14803,6 | 8108,8 | 3826,6 | 4282,2 |
| SClass-2m | 17215,1 | 10499,9 | 3773,5 | 6726,3 |
| SDM | 28410,2 | 21715,4 | 4275,3 | 17440 |
| SClass-3m | 20735,9 | 14018,8 | 4537,2 | 9481,5 |
| SDM | 33396,2 | 26701,4 | 5335,5 | 21365,8 |

Table 2.8. SSM-DT: average performance costs for penalty level 3 and varying variability
number of activated services having more than one stop. In the experimentation, we assumed that travel time perturbations are independent among service legs. However, delays propagate in the network. If a service has one intermediate stop before reaching its destination and experiences a delay in its first leg, most probably it will arrive at destination (its second stop) later than as scheduled, unless in the second leg the observed travel time is much lower than the forecast and absorbs the delay. In general, however, having not direct services means having a higher risk of paying penalties. When uncertainty becomes an issue, therefore, solutions habitually move from less expensive indirect services to set up the network to more expensive direct connections which, however, lower the risk of extra costs when actually the services really operate. This result is in line with what observed in all of the test cases. We show in Table 2.12 results for the usual problem classes: as soon as variability is introduced, not-direct services are substituted with direct services (even, in the less variable cases, this causes an initial slight fixed cost increase).

In Figure 2.4, a subset of activated services and the consequent changing in routes of some commodities are shown. Dashed edges represent not-direct services while solid edges direct services. To each service arc the amount of commodity shipped is depicted (three commodities are considered, differentiated by underlines). In the SDM two not-direct services are activated and all the three commodities are shipped with them. In SSM-ST the not-direct services are avoided. The services are replaced by their parallel direct services. Commodities are either shipped with them, or, even, shipped through a completely different route.

It turned out that when the uncertainty on travel time and demand target are considered, the first characteristic that a SDM looses is just-in-time arrivals. The network is built in such a way to allow freight arrivals at least one period in advance

|  | PClass-3t |  |  |  |  | PClass-3l |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Set up | Fixed | Tot.Serv | Routing | Set up | Fixed | Tot.Serv | Routing |  |
| SClass-1m | 6347,2 | 136,9 | 31,6 | 6210,3 | 6703,5 | 170,2 | 38,6 | 6533,3 |  |
| SClass-2m | 6333,6 | 136,6 | 31,4 | 6219,4 | 6742,2 | 161,9 | 37,3 | 6580,3 |  |
| SClass-3m | 6365,9 | 135,1 | 31,2 | 6230,8 | 6765,5 | 156,4 | 36,3 | 6609,1 |  |
| SDM | 6340,8 | 139,8 | 31,4 | 6201 | 6694,8 | 177,1 | 39,5 | 6517,7 |  |

Table 2.9. SSM-SDT: average costs and number of services for penalty level 3 and varying variability

|  | PClass-3t |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short ST | Pen. long ST | Pen. short DT | Pen. long DT |
| SClass-1m | 20245,6 | 13898,4 | 11227,4 | 419,8 | 2190,4 | 60,7 |
| SDM | 22949,04 | 16608,2 | 11437,4 | 443 | 3069,3 | 1658,3 |
| SClass-2m | 44871,2 | 38515,3 | 13173,7 | 18233,4 | 2541,6 | 4566,5 |
| SDM | 54431,2 | 48090,4 | 13214 | 19885,1 | 3421,5 | 11569,6 |
| SClass-3m | 57512 | 51146,1 | 16247,7 | 25483,8 | 2986,8 | 6427,7 |
| SDM | 69221,2 | 62880,4 | 16532,2 | 27489 | 4327,9 | 14531,1 |

Table 2.10. SSM-SDT: average performance costs for penalty level 3 and varying variability

|  | PClass-3l |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Full Cost | Tot Penalty | Pen. short ST | Pen. long ST | Pen. short DT | Pen. long DT |
| SClass-1m | 24389,8 | 17686,3 | 13792,7 | 469,6 | 3270,4 | 153,5 |
| SDM | 29659,4 | 22964,6 | 14336,4 | 519,3 | 3826,6 | 4282,2 |
| SClass-2m | 54048,8 | 47306,6 | 16332,5 | 19924,8 | 4032,1 | 7017,1 |
| SDM | 73435,3 | 66740,5 | 16959,2 | 28065,8 | 4275,3 | 17440,1 |
| SClass-3m | 67839,4 | 47306,6 | 16332,5 | 19924,8 | 4032,1 | 7017,1 |
| SDM | 92179,6 | 85484,8 | 20940,6 | 37842,8 | 5335,5 | 21365,8 |

Table 2.11. SSM-SDT: average performance costs for penalty level 3 and varying variability
with respect to due dates, if not even earlier. Sometimes, when an early arrival is not possible for a commodity entirely, it is split and part of it (the majority, normally) is shipped in advance. To allow freight early arrivals, as mentioned, the number of services is increased by activating an additional set of services needed to deal with this purpose. In Table 2.13 the percentage amount of freight delivered in advance is given and compared to the amount of just-in-time delivered freight in the deterministic and stochastic environments. The just-in-time percentage of freight decreases from almost the $50 \%$ of the deterministic case to the $28 \%$ when the highest level of variability and tight delivery time windows are taken into account (a similar result is observed in the loose time windows case).

In Figure 2.5 the routes of two commodities are shown. Solid arcs represent the path of commodity 24 . On each arc the amount of freight shipped on that connection is reported. The same for the second considered commodity, number 11, which path is represented by dashed arcs. In the SDM, commodity 11 arrives at its destination just-in-time as well as the majority of commodity 24. In SSM-DT both commodities are shipped well in advanced. Both commodities follow (more or less) the same physical paths, but shifted one period before.

Our experiments show that solutions based on a stochastic approach can be structurally different from their deterministic counterparts showing characteristics


Figure 2.4. SDM vs. SSM-ST


Figure 2.5. SDM vs. SSM-DT

|  | PClass-3t |  |  | PClass-3l |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Tot.Serv | Direct | Not Direct | Tot.Serv | Direct | Not Direct |
| SClass-1m | 31,3 | 28,7 | 2,6 | 37,4 | 33,8 | 3,6 |
| SClass-2m | 31,1 | 28,4 | 2,5 | 37 | 33,7 | 3,3 |
| SClass-3m | 30,5 | 28,1 | 2,4 | 36,6 | 33,7 | 2,9 |
| SDM | 31,4 | 28,4 | 3 | 39,5 | 35,5 | 4 |

Table 2.12. SSM-ST: average number of direct and not-direct services for penalty level 3 and varying variability

|  | PClass-3t |  | PClass-3l |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Early (\%) | Just-in-Time (\%) | Early (\%) | Just-in-Time (\%) |
| SClass-1m | 67,3 | 32,7 | 51,6 | 48,4 |
| SClass-2m | 70,5 | 29,5 | 55,3 | 44,7 |
| SClass-3m | 71,3 | 28,7 | 58 | 42 |
| SDM | 53,6 | 46,4 | 44 | 56 |

Table 2.13. SSM-DT: percentage amounts of early and just-in-time freight arrivals for fixed level of penalty and varying variability
that a deterministic model would never produce. Such structural differences might vary from case to case, but there are two characteristics that seem to show up in most of the cases when dealing with uncertainty of travel time and service or demand target, that is respectively, the number of activated services with more than one stop, which decreases, and the arrival times of commodities at destination, which is performed in advance.

When both targets are simultaneously considered, the same not-direct-services and early-freight-arrivals oriented trends are observed. Nevertheless, the coexistence of those two components cause changing in the network at a slower rate when compared to the single target problems SSM-ST or SSM-DT (see Table 2.14).

|  | PClass-3t |  |  |  |  | PClass-3l |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Tot.Serv | Direct | Not Direct | Early (\%) | Just-in-Time (\%) | Tot.Serv | Direct | Not Direct | Early (\%) | Just-in-Time (\%) |
| SClass-1m | 31,2 | 28,6 | 2,6 | 66,7 | 3,3 | 38,6 | 35,2 | 3,4 | 53,3 |  |
| SClass-2m | 31,4 | 28,8 | 2,6 | 68,2 | 31,8 | 37,6 | 34,6 | 3 | 46,7 |  |
| SClass-3m | 31,2 | 28,7 | 2,5 | 70 | 30 | 36,3 | 46,7 |  |  |  |
| SDM | 31,4 | 28,4 | 3 | 53,6 | 46,4 | 39,5 | 35,5 | 4 | 44 | 4 |

Table 2.14. SSM-SDT: average number of direct and not-direct services and percentage amounts of early and just-in-time freight arrivals for fixed level of penalty and varying variability

### 2.4.4 Comparative Analysis

The goal of this analysis is to investigate how the values of the parameters may change the structure of stochastic solutions. In order to achieve this purpose, solutions are derived by varying the parameters described at the beginning of this section one at a time, keeping all the other parameters fixed. In the following, comparisons are made still referring to the same problem and scenario classes, but only comparing

SSM-ST or SSM-DT (since SSM-SDT represent a solution in between them).

## Impact of Delivery Due Dates Width

The analysis of shipment plan reliability with respect to delivery time windows involves only SSM-DT. When target delivery times are tight, it is not always possible to define a plan in which deliveries are performed in advanced with respect to the agreed upon time of deliveries. Suppose the delivery time window of a commodity is too tight - the commodity leaves immediately its origin and is shipped to its destination without any waiting time at intermediary stops - it is impossible to increase the reliability of its arrival time at destination: there is simply no possibility to change path and the stochastic program has no impact (at least, with our setting).

When time windows slightly stretch from the latter situation, enough flexibility is given to the network and the selection of services allows commodities' arrivals at destination at least one period before the due dates (maybe even the same physical path may be chosen). More idle time is allowed and the difference in reliability can be significant. However, when the time between entry and due dates is too loose and the costs of operating the network become high - as we said, the fixed activation costs as well as routing costs heavily increase (consider for instance just the idle time cost) - reliability of demand is slightly disregard in favor of more carrier-economic-oriented goals.


Figure 2.6. Impact of Delivery Time Windows Width

Consider the situation depicted in Figure 2.6. Here the origin of a shipment is 1 and the destination is represented by the vertices labelled with 3 , each one defining a due date delayed by one period. A set of parallel potential services are available connecting directly the origin to the destination plus two less expensive not direct connections (costs are depicted in the figure). If the due date is just after the entry date no other possibilities than the service 1 may be considered (SSM-DT is equal to SDM ) and penalties are paid. If the due date is shifted of one period the SSM-DT will always choose again service 1 in order to not pay additional penalty costs (in a deterministic setting service 1 and 2 are equivalent). As soon as the due date is shifted again and the two less expensive connections (service 4 and 5) are available, the solution avoid the more expensive service 1 despite of the potential loss of reliability in order to decrease operating costs. A carefully adjustment of penalties is, thus, needed in order to enforce reliability considering both activation costs and, in particular, idle costs.

## Impact of Penalty Costs

With the increase of the penalty costs, the optimization attempts to enhance reliability in order to avoid large penalty costs when the plan actually runs. The higher the penalty the more robust is the shipment plan reliability. We compare results considering the lowest and highest level of penalty (level 1 and 3 ).

We first consider the case of increasing the penalty on services' performances. As expectable, by increasing the penalty the amount of total delay in the transportation network decreases (as said, a way is to avoid not direct services). The major decrease concerns the most expensive delays, that is delay over the threshold $B$. The higher the penalty, the lower are such delays. By an increase of three times the penalty (that is by tripling our need of reliability), the fixed cost of the network increases of about the $0.03 \%$ with a decrease of the amount of total delay of about the $3 \%$ of short delays and $10 \%$ of long delays.

Considering only the target of demand, instead, the number of commodities delivered in time (of the plan obtained by considering the highest level of penalty with respect to the plan obtained with its lowest level) increases of about the $8 \%$ (consider that the number of commodities is 25 in total). In addition, the total amount of delay decreases of the $12 \%$, which the vast majority relates to large delays (over the threshold $B^{k}$ ). This, at the expense of an initial additional set up cost of $0.05 \%$. In Table 2.15 the effects of increasing penalty values on the amount of delay (expressed in percentage) may be compared.

|  | Demand Target |  |  | Service Target |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Fixed Cost (\%) | Short delay (\%) | Long delay (\%) | Fixed Cost (\%) | Short delay (\%) | Long delay (\%) |
| penalty 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| penalty 2 | +0.01 | $-3,26$ | $-9,99$ | +0.01 | $-1,06$ | $-5,66$ |
| penalty 3 | +0.05 | $-7,48$ | $-18,36$ | +0.03 | $-3,38$ | $-9,95$ |

Table 2.15. Effects of the increase of penalties on the amount of delay

## Impact of Travel Time Variability

The effects of the variability has already been discussed in the previous sections for both targets in comparison with the deterministic case. Here, however, we give some more little details. Starting with the target of services, as the variability increases the number of direct services increases as well, even though it is beneficial from an economic point of view to use the less expensive services with stops. As mentioned before, the drawback of using such services is that they accumulate delay during their trips. The more legs they have to travel along before reaching their destinations, the more disadvantageous they are from a reliability point of view. From the demand target side, as the variability increases, the amount of commodity delivered at least one period before increases as well in order to limiting the probability of paying some penalty for the late arrivals of freight. In Figures 2.7(a) and 2.7(b) the last described behavior may be observed: the percentage of direct and not-direct services and the percentage amount of demand delivered just-in-time and in advance are depicted (commodities delivered at destination through a service arc are just-in-time deliveries).


Figure 2.7. Variability Effects

## Impact of Travel Time Variability - the Mixed-Level Case

The mixed-level case considers that the travel time probability distributions of a subset of physical arcs have a low variability (level 1), while the remaining physical arcs have a high one (level 3 ). In our experimentation, we consider that the physical links having the latter characteristic are the physical links connecting vertex 1 to vertex 2 and vice-versa (as shown in Figure 2.8). We compare SDM and SSM-SDT considering the third level of penalty.


Figure 2.8. Physical Service Network MIX case
In addition to the above mentioned characteristics, the structure of the SSM-SDT shipment plan is also changed in such a way to avoid selecting services travelling along those more variable and risky (in terms of future penalties) links, favoring the activation of services travelling along less variable and, thus, safer links. In Figure 2.9, the routes of two commodities are shown. In the SDM case, the services travelling along the more risky link $1-2$ are used, since they establish a faster connection between those vertices. As opposed, in the MIX case, they are totally avoided and commodities are shipped through more tangled paths. It is worth to notice that, again, a careful assignment of penalty values is required. In fact, if the risky connection is very important, it will be chosen despite the consequences.

## Impact of Distribution Ranges

Ranges of probability distributions are related to what is considered "normal" with respect to travel time. On one side, by increasing ranges we "expand" this concept


Figure 2.9. SDM vs. MIX case
and admit even more "extreme" cases in the "normal" travel time set which, at the same time, are seldom observed. On the other side, the risk in using a tight range, is giving an over-weight to some observations. Comparing the right tails of the three ranges, the most weighted belongs to the tight range (we refer to Figures 2.3(c) and $2.3(\mathrm{~d})$. The exact range should be carefully sought. In our experimentations, for instance, the most appropriate range seem to be the medium range, which on one side considers enough observations and on the other side do not extend the concept in a too long way.

## Chapter 3

## A Progressive Hedging-Based Meta-heuristic Algorithm

Network design problems are notoriously NP-Hard. Even in deterministic formulations, they are difficult to solve except for trivial small-sized cases. Consequently, this applies also to stochastic problems when uncertainty is modeled through a finite set of scenarios, that in fact, translates a stochastic formulation into a large-scale deterministic model. In general, thus, such problems cannot be solved exactly and heuristic methodologies are needed in order to find high-quality solutions in acceptable time. In this context, decomposition strategies can be exploited to manage such problems, despite their size.

In this chapter, we propose a new hierarchic progressive hedging-based metaheuristic algorithm to tackle the problem described previously. It modifies the traditional application scheme of the method in order to overcome the problems related to a quadratic reformulation and flow-degeneracy which raise when it is classically applied to our problem. Two versions of the algorithm are proposed, differing in the kind of information exploited during the resolution process. The first version is similar to the traditional case, the second is an original feature of the thesis.

The chapter is organized as follows. In Section 3.1 a brief introduction of decomposition strategies is given, focusing particularly on scenario-based decomposition strategies. In section 3.2, a traditional progressive hedging-based strategy is directly applied to our problem formulation. Problems and issues of the latter application are discussed in Section 3.3 and a new variable hierarchic-based methodological approach is proposed. In Sections 3.4 and 3.5 the experimental setting and related results are described.

### 3.1 Decomposition Strategies for Two-Stage Stochastic Programs

Two decomposition strategies have been successfully applied to stochastic problems. The first is a variable-based decomposition strategy and is known as Bender decomposition [8. Following this strategy, the variables of a stochastic problem are partitioned into two subsets so that a master problem is solved over the first set of
variables and the second set of variables is determined in the sub-problem, given a master problem solution. If the sub-problem determines that the master problem decision does not define any feasible solution at a sub-problem level, so-called Benders feasibility cuts are generated and added to the master problem. Feasibility cuts might be not enough though to find optimal solutions and so-called optimality cuts are, thus, also generated and added to the master problem. Master problem and sub-problem are then iteratively solved respectively to guide the search process and to generate Benders cuts. Applied to two-stage stochastic formulations, this strategy enables to partition variables according to the realizations of the stochastic event [50]: first stage variables may be involved in the master problem and second stage variables in the sub-problem (sometimes, in fact, such a decomposition is also known as stage-based decomposition). We refer to [97] for a complete presentation of this approach.

The second decomposition strategy is, instead, scenario-based. The idea is to decompose the original scenario-based stochastic problem into sub-problems, according to its set of scenarios and, then, iteratively solve them. From their solutions one may be able to discover similarities and trends and eventually come up with a "well hedged" solution for the original problem, which can be expected to perform rather well under all scenarios. Sub-problems can be solved directly by commercial solvers, mitigating the computational difficulty associated with the size of the original problem instance. The general principle that allows to proceed in this manner, that is generating improved sequences of solutions, is what Rockafellar and Wets called the principle of progressive hedging [100]. In the progressive hedging (PH) algorithm they proposed [100], scenario decomposition is reached by relaxing first stage variables' non-anticipativity constraints (the constraints ensuring that a single solution is used under all considered scenarios) trough the augmented Lagrangean method (we refer to [11; 99] for more details on this method). At each iteration, scenario sub-problems are solved and their solutions (which are possibly different from each others) are exploited to have an estimation of the solution of the original problem, through an aggregation operator. Non-anticipativity is, then, gradually enforced by the appropriate modification of the augmented Lagrangean multipliers and fixed costs based on the deviations of sub-problem solutions from the estimated solution. The modification rewards the proximity to or penalizes the distance from this estimation, trying to consolidate them into a unique solution, iteration after iteration, for the original problem.

One advantage of scenario-based decomposition techniques over stage-based decomposition is a more uniform distribution of sub-problems' difficulty. In particular, the computational difficulty of the master problem in Bender decomposition methods can grow significantly as the number of iterations grows [58]. The simplicity and flexibility of PH algorithm make it attractive for solving stochastic network design problems.

While the convergence of the PH algorithm to a global optimum has been proved for continuous stochastic programs [99], it may not converge in the integer case: every attempt to apply this approach to integer programming formulations, thus, results as a heuristic. Nevertheless, it has been proven to be computationally efficient in various type of problems as operation planning [53, lot-sizing [58] and portfolio management [89] problems as well as in several mixed-integer programs 82] as, for
instance, unit commitment and server location [56; 48], scheduling [21], resource allocation [130] and network design problems [89, 63, 46, 34.

When considering a PH approach, three aspects have to be carefully defined:

- the decomposition strategy (which may involve building sub-problems for each scenario or for a cluster of scenarios);
- the aggregation process to synthesize local solutions in an overall solution (traditionally, the average over the current local solutions);
- the search of consensus strategy, which taking advantage of local information yielded by sub-problem solutions, drives the search mechanism toward a unique solution for the original problem (it normally involves adjusting multipliers or costs appropriately).

Studying problem structure may help to assess the best way to decompose the original problem in order to provide the most efficient alternative (regarding time performances) among different suitable decomposition strategies, as illustrated in [53]. The authors compared the classical decomposition strategy based on the relaxation of the non-anticipativity constraints involving all first stage variables of the problem with their proposal, which take advantage of the special structure of their operation planning problem. In particular, their problem have a subset of variables, which once defined allow for the direct determination of all other variables of the problem uniquely. Their non-anticipativity relaxation proposal, thus, involves only the variables of that subset by gaining in computational efficiency. The PH , in its original form, is not necessarily very efficient when applied in the presence of integrality constraints, in [63] some suggestions to improve the efficiency of the method in the strict context of integrality constraints are examined. A proven way to accelerate PH convergence is to decompose by bundles of scenarios, rather than by individual scenarios. This strategy is discussed in [48] - which describe also the application of the algorithm for a multi-stage problem - and extended in the context of stochastic network design in [35]. In the latter contribution questions like "how many groups should be created?", "should scenario-groups be similar or not?", "should groups induce a partition of the scenario set or not?" are discussed. The authors concluded that by solving multi-scenario sub-problems, the meta-heuristic produces better results in terms of solution quality and computing efficiency. In particular a covering strategy leads the highest quality solutions. In [89] an extensive study on a PH algorithm applied to a financial problem is made. The authors proposed search of consensus strategies to speed up its convergence. In [130] such techniques are further explored, considering also variable-dependent strategies and acceleration techniques for one-side constraints. Some of these strategies are also considered in the development of a progressive hedging-based meta-heuristic algorithm for the SSND-SDT.

### 3.2 The Traditional Progressive Hedging-Based Metaheuristic

A PH-based meta-heuristic algorithm to find solution to a mixed integer stochastic problem is proposed in [34]. They consider a multicommodity service network design problem in which demand is stochastic. A two-stage stochastic programming formulation is proposed where design decisions make up the first stage and routing of commodities, according to observed demand, make up the second stage. They proposed a two phases algorithm, the first phase being inspired by the PH of Rockafellar and Wets [100].

Following their strategy, first a scenario decomposition is applied to separate the original stochastic problem in according to the set of scenarios approximating the random event. Scenario decomposition, as traditionally done, is performed by relaxing non-anticipativity constraints of the first stage variables of the problem. This yields to a set of deterministic sub-problems, one for each scenario, where design decisions depend upon them (for more detail, we refer to [34]). By solving sub-problems, local solutions are obtained, most likely defining different designs. An aggregation process builds, then, an overall solution design (generally continuous and, thus, not feasible and used as an indicator of existing trends among scenarios) as the expectation over the current local solutions. The differences that may exist between local designs and the overall design, is then reflected as "penalties" in the objective function of the sub-problems. Sub-problems are, then, solved again. The goal of this first phase is to recognize trends among scenario solutions identifying a subset of arcs for which "consensus" appears possible. Cost adjustment, therefore, is used to guide local scenario designs toward consensus, without forcing it.

The second phase of the meta-heuristic is performed after a certain amount of iterations of the first phase, if consensus has only been reached for a subset of first stage variables. It solves a reduced multi-scenario formulation on the design arcs for which consensus has not been found through the iterative search phase, fixing those design arcs for which instead consensus has been reached.

From the original PH and the latter approach, we exploit not only the means to decompose a stochastic problem by scenario sub-problems, but also the idea of using globally local information yielded by the resolution of scenario sub-problems. Nevertheless, we introduce some modifications which first allow us to work on a linear reformulation, instead of a quadratic reformulation which we will have by traditionally applying the original method, and second to avoid degeneration problems during the search of consensus strategy, which the traditional method may be subject to, when applied directly to our problem.

In the following, first the traditional scenario decomposition strategy is applied to our model formulation in order to highlight the problems and issues related to the classical application of the PH approach and, then, the new methodological approach is described.

In order to have scenario separability, a reformulation of the original model is needed. Firstly, a copy of each first stage decision variable has to be defined for each scenario. In our case, it involves creating copies of design and routing variables: $y_{r s}, \forall r \in R, \forall s \in S$ and $x_{i j s}^{k}, \forall k \in \mathcal{K}, \forall(i, j) \in \mathcal{A}, \forall s \in S$. This yields to the
following reformulation of the problem:

$$
\begin{align*}
& \min \sum_{s \in S} p_{s}\left(\sum_{r \in R} c_{r} y_{r s}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j s}^{k}+\right. \\
& \sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+  \tag{3.1}\\
& \left.\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+}\right) \\
& \sum_{j \in N^{+}(i)} x_{i j s}^{k}-\sum_{j \in N^{-}(i)} x_{j i s}^{k}= \begin{cases}w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \quad \forall i \in N, \forall k \in K, \forall s \in S \\
-w(k) & \text { if } i=d(k)\end{cases}  \tag{3.2}\\
& \sum_{k \in K} x_{i(r) s}^{k} \leq u_{r} y_{r s} \quad \forall i(r) \in L(r), \forall r \in R, \forall s \in S  \tag{3.3}\\
& x_{i j s}^{k}=x_{i j s^{\prime}}^{k} \quad \forall k \in K, \forall(i, j) \in A, \forall s, s^{\prime} \in S, s \neq s^{\prime}  \tag{3.4}\\
& y_{r s}=y_{r s^{\prime}} \quad \forall r \in R, \forall s, s^{\prime} \in S, s \neq s^{\prime}  \tag{3.5}\\
& x_{i j s}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A, \forall s \in S  \tag{3.6}\\
& y_{r s} \in\{0,1\} \quad \forall r \in R, \forall s \in S \tag{3.7}
\end{align*}
$$

Constraints (3.4) and (3.5) are the non-anticipativity (or implementability) constraints. They make sure that design and routing variables are not tailored for each single scenario, rather define a unique and implementable solution. Whereas such condition is implicit in the formulation (2.9) - (2.13), in the reformulation (3.1) - (3.7) is explicitly stated as constraints trough (3.4) and (3.5). That is, the two formulations are equivalent. Scenario separability is, then, achieved through the relaxation of these constraints.

The number of non-anticipativity constraints, however, may become quite large given the size of the set $S$. Therefore, another way to express the non-anticipativity constraints can be considered. Let $\bar{y}_{r}$ and $\bar{x}_{i j}^{k}$ define respectively a feasible design and routing solutions. An equivalent way to impose that all designs and routings must be equal to each other ( $(\sqrt[3.4]{ })$ and (3.5) is to require that each scenario design and routing must be equal to the latter mentioned feasible and fixed design and routing solutions. Therefore, (3.4) and (3.5) may be replaced by

$$
\begin{gather*}
y_{r s}=\bar{y}_{r} \quad \forall r \in R, \forall s \in S  \tag{3.8}\\
\bar{y}_{r} \in\{0,1\} \quad \forall r \in R \tag{3.9}
\end{gather*}
$$

$$
\begin{equation*}
x_{i j s}^{k}=\bar{x}_{i j}^{k} \quad \forall k \in K, \forall(i, j) \in A, \forall s \in S \tag{3.10}
\end{equation*}
$$

$$
\begin{equation*}
\bar{x}_{i j}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A \tag{3.11}
\end{equation*}
$$

Constraints (3.8) and 3.10 require each scenario design and each scenario routing to be equal, respectively, to a fixed design and to a fixed routing solution, which as imposed by constraints (3.9) and (3.11), satisfy the traditional binary and non-negativity conditions. We define in the following the $\bar{y}_{r}$ and $\bar{x}_{i j}^{k}$ respectively as overall design and overall routing solutions.

By considering the latter constraints for the non-anticipative requirements and performing relaxation through the augmented Lagrangean method, the following objective function is, then, obtained:

$$
\begin{array}{r}
\min \sum_{s \in S} p_{s}\left(\sum_{r \in R} c_{r} y_{r s}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j s}^{k}+\right. \\
\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+ \\
\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+}+  \tag{3.12}\\
\sum_{r \in R} \phi_{r s}\left(y_{r s}-\bar{y}_{r}\right)+\frac{1}{2} \sum_{r \in R} \rho\left(y_{r s}-\bar{y}_{r}\right)^{2}+ \\
\left.\sum_{(i, j) \in A} \phi_{i j s}^{k}\left(x_{i j s}^{k}-\bar{x}_{i j}^{k}\right)+\frac{1}{2} \sum_{(i, j) \in A} \psi\left(x_{i j s}^{k}-\bar{x}_{i j}^{k}\right)^{2}\right)
\end{array}
$$

where $\phi_{r s}$ and $\phi_{i j s}^{k}$ are respectively the Lagrangean multipliers used to relax constraints (3.8) and (3.10), and $\rho$ and $\psi$ are penalty ratios. Note that the differences between each scenario solution and overall solutions can be penalized individually. The latter objective function may be reduced by taking advantage of the binary requirements of the service design variables, finally defining the formulation:

$$
\begin{array}{r}
\min \sum_{s \in S} p_{s}\left(\sum_{r \in R}\left(c_{r}+\phi_{r s}+\frac{1}{2} \rho-\rho \bar{y}_{r}\right) y_{r s}+\right. \\
\sum_{(i, j) \in A} \sum_{k \in K}\left(c_{i j}^{k}+\phi_{i j s}^{k}+\frac{1}{2} \psi x_{i j s}^{k}-\psi \bar{x}_{i j}^{k}\right) x_{i j s}^{k}+  \tag{3.13}\\
\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+ \\
\left.\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+}\right)
\end{array}
$$

$$
\begin{gather*}
\sum_{k \in K} x_{i(r) s}^{k} \leq u_{r} y_{r s} \quad \forall i(r) \in L(r), \forall r \in R, \forall s \in S  \tag{3.15}\\
x_{i j s}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A, \forall s \in S  \tag{3.16}\\
y_{r s} \in\{0,1\} \quad \forall r \in R, \forall s \in S
\end{gather*}
$$

Formulation (3.13) - 3.17) is scenario separable, once an overall design $\bar{y}_{r}$ and an overall routing $\bar{x}_{i j}^{k}$ are fixed to given values. The model, then, decomposes according to the scenarios of set $S$. Each scenario sub-problem can then be expressed as follows:

$$
\begin{gather*}
\min \sum_{r \in R}\left(c_{r}+\phi_{r s}+\frac{1}{2} \rho-\rho \bar{y}_{r}\right) y_{r s}+ \\
\sum_{(i, j) \in A} \sum_{k \in K}\left(c_{i j}^{k}+\phi_{i j s}^{k}+\frac{1}{2} \psi x_{i j s}^{k}-\psi \bar{x}_{i j}^{k}\right) x_{i j s}^{k}+  \tag{3.18}\\
\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+ \\
\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+} \\
\sum_{j \in N^{+}(i)} x_{i j s}^{k}-\sum_{j \in N^{-}(i)} x_{j i s}^{k}= \begin{cases}w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \quad \forall i \in N, \forall k \in K, \forall s \in S \\
-w(k) & \text { if } i=d(k)\end{cases}  \tag{3.19}\\
\sum_{k \in K} x_{i(r) s}^{k} \leq u_{r} y_{r s} \quad \forall i(r) \in L(r), \forall r \in R, \forall s \in S  \tag{3.20}\\
x_{i j s}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A, \forall s \in S  \tag{3.21}\\
y_{r s} \in\{0,1\} \quad \forall r \in R, \forall s \in S \tag{3.22}
\end{gather*}
$$

The traditional application of the PH approach to our problem highlights two disadvantages. First, even though the difficulty related to the size of the original problem is split and distributed among sub-problems, each sub-problem assumes now a non-linear reformulation. In fact, if on one side the binary requirements of the service design variables allow a reduction of part of the objective function 3.12,
the continuous nature of routing variables does not allow it and the reformulation end up having quadratic routing variables, needing appropriate resolution methodes.

In addtion, such an approach involves the search of consensus of both service and routing decisions. In general, SND problems are degenerative in the sense that for a given network design several equivalent - in terms of costs - but different - in terms of paths - routings may be defined. Similarly, the same degeneracy may be observed during the first phase of the algorithm: if consensus is reached for design variables, several equivalent flow path solutions could be found for it, lengthening the convergence of phase one. The search of consensus seems, thus, to be inconvenient for such variables.

In next the section (Section 3.3), we propose a novel strategy to overcome both the above mentioned problems by introducing a hierarcy of importance on variables.

### 3.3 The Hierarchic Progressive Hedging-Based Metaheuristic

When the classical decomposition strategy of Rockafellar and Wets (that is, relaxing non-anticipativity constraints of all first stage decision variables) is applied to our problem, two major inconveniences, as shown, occur:

- we end up with a quadratic reformulation in the routing variables;
- the research of consensus not only involves binary design variables, but also non negative continuous routing variables, introducing degeneracy and "noise" in the resolution method.

In order to have a linear reformulation and overcome degeneracy problems, we do not consider all the first stage variables for consensus. Rather, we introduce a hierarchy of "importance" on first stage variables, looking for consensus only on a subset of them. In particular, consensus is still sought for design variables, relaxing non-anticipativity constraints at the beginning and enforcing them during the execution of the algorithm, but it is not for routing variables. This leads to a linear reformulation of the problem, but stress even more the heuristic behavior of the approach.

The methodological approach proposed here, then, will be applied using the following reformulation of the problem:

$$
\begin{array}{r}
\min \sum_{s \in S} p_{s}\left(\sum_{r \in R}\left(c_{r}+\phi_{r s}+\frac{1}{2} \rho-\rho \bar{y}_{r}\right) y_{r s}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j s}^{k}+\right. \\
\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+  \tag{3.23}\\
\left.\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+}\right)
\end{array}
$$

$$
\begin{align*}
& \sum_{j \in N^{+}(i)} x_{i j s}^{k}-\sum_{j \in N^{-}(i)} x_{j i s}^{k}=\left\{\begin{array}{ll}
w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \\
-w(k) & \text { if } i=d(k)
\end{array} \quad \forall i \in N, \forall k \in K, \forall s \in S\right.  \tag{3.24}\\
& \sum_{k \in K} x_{i(r) s}^{k} \leq u_{r} y_{r s} \quad \forall i(r) \in L(r), \forall r \in R, \forall s \in S  \tag{3.25}\\
& x_{i j s}^{k} \geq 0 \quad \forall k \in K, \forall(i, j) \in A, \forall s \in S  \tag{3.26}\\
& \quad y_{r s} \in\{0,1\} \quad \forall r \in R, \forall s \in S \tag{3.27}
\end{align*}
$$

$$
\begin{gather*}
\min \sum_{r \in R}\left(c_{r}+\phi_{r s}+\frac{1}{2} \rho-\rho \bar{y}_{r}\right) y_{r s}+\sum_{(i, j) \in A} \sum_{k \in K} c_{i j}^{k} x_{i j s}^{k}+ \\
\sum_{r \in R} \sum_{i(r) \in L(r)} \lambda_{i(r)}^{r}\left(\eta_{i(r) s}-e_{i(r)}\right)_{+}+\sum_{r \in R} \sum_{i(r) \in L(r)} \Lambda_{i(r)}^{r}\left(\eta_{i(r) s}-B\right)_{+}+  \tag{3.28}\\
\sum_{k \in K} \lambda^{k}\left(\varepsilon_{k s}-b(k)\right)_{+}+\sum_{k \in K} \Lambda^{k}\left(\varepsilon_{k s}-B^{k}\right)_{+} \\
\sum_{j \in N^{+}(i)} x_{i j s}^{k}-\sum_{j \in N^{-}(i)} x_{j i s}^{k}=\left\{\begin{array}{ll}
w(k) & \text { if } i=o(k) \\
0 & \text { if } i \neq o(k), i \neq d(k) \\
-w(k) & \text { if } i=d(k)
\end{array} \quad \forall i \in N, \forall k \in K, \forall s \in S\right.  \tag{3.29}\\
\sum_{k \in K} x_{i(r) s}^{k} \leq u_{r} y_{r s} \quad \forall i(r) \in L(r), \forall r \in R, \forall s \in S  \tag{3.30}\\
x_{i j s}^{k} \geq 0  \tag{3.31}\\
\forall k \in K, \forall(i, j) \in A, \forall s \in S  \tag{3.32}\\
y_{r s} \in\{0,1\}
\end{gather*} \quad \forall r \in R, \forall s \in S
$$

Note that now, activation cost of service $r$ is composed by the expression $\left(c_{r}+\phi_{r s}+\frac{1}{2} \rho-\rho \bar{y}_{r}\right)$. Each sub-problem may be solved separately by applying efficient meta-heuristics approaches or even, when the size of sub-problems allows it (like in our case), by an exact method. When sub-problems are solved, from their solutions two kinds of information are simultaneously obtained: a vector which defines the activated service design $\mathbf{y}^{s}$ on scenario $s$ and a vector defining the related routing of flows $\mathbf{x}^{s}$. As classically done then, an aggregation operator brings together information about the variables for which consensus is looked for, from a sub-problem level to define what we called the overall design. As said, based on the "distance" of
local solutions from it, costs are adjusted to guide toward consensus. We propose a first version of the algorithm only considering such scheme.

Nevertheless, in our case, we still do have additional available information, albeit scenario dependent: the routing of flows. Not considering such flow-information may disregard important insights regarding the actual differences there may be in the utilization of the services selected in the different scenario sub-problem solutions. This amount of flow-information, which is given and do not require any additional effort when solving sub-problems, could be exploited as well in a search-of-consensus strategy. We propose, therefore, a second version of the algorithm in which such knowledge is considered in the seeking of consensus strategy.

The search of consensus is the objective of the first phase of the algorithm, at the end of which the second phase is performed. In this phase, a variables-reduced multi-scenario formulation is solved fixing those design arcs for which consensus has been reached, with the aim of finding the final solution of the original problem in terms of routing of freight and remaining design variables. Although some of the design variables are fixed, the remaining design and routing decisions are still taken before any stochastic information is revealed, still maintaining the structure of a two-stage formulation on those variables.

Referring to the three aspects needed to be defined in a PH approach and highlighted in Section 3.1, the decomposition strategy applied here considers singlescenario based sub-problems. The aggregation operator used to synthesize local information is described in the next session (Section 3.3.1), while the proposed global and local cost adjustment strategies used to guide local solutions toward consensus are described after it (Section 3.3.2).

### 3.3.1 Extracting the Overall Design

The overall design summarizes into a single design the local information obtained by solving sub-problems and provided by the different scenario designs. It represents both an estimation of global trends and a referent point to "guide" iteration after iteration the sub-problems' solutions toward consensus. In addition, its scope is also to define the constant values needed to allow separability during the running of the PH algorithm. We decided to make use of an average function as aggregation operator (likewise as [34] and [100).

Let $\nu$ define the iteration index of the meta-heuristic. Given the scenario probabilities $p_{s}$, a weighted average is used to combine local information into the overall design as shown below:

$$
\begin{equation*}
\bar{y}_{r}^{\nu}=\sum_{s \in S} p_{s} y_{r s}^{\nu} \quad \forall r \in R \tag{3.33}
\end{equation*}
$$

The values of $\bar{y}_{r}^{\nu}$ are between 0 and 1 , namely $\bar{y}_{r}^{\nu} \in[0,1]$. When all scenarios agree on the selection status of a service $r$, consensus is observed and $\bar{y}_{r}^{\nu}$ assumes an integer value. In particular, if $\bar{y}_{r}^{\nu}=1$, all scenarios agree on activate service $r$. As opposed, if $\bar{y}_{r}^{\nu}=0$, all scenarios agree on not activate service $r$. Then, if an integer value is observed for all overall design arcs, an overall consensus has been obtained (and the first phase ends). Nevertheless, operator (3.33) does not necessarily produce a feasible design. Most of the time, in fact, this is the case and one observes that
$0<\bar{y}_{r}^{\nu}<1$, for a number of design arcs, which, given the integrality requirements of design variables, defines an infeasible solution for the original problem. Although infeasible, these values may still be used to recognize trends among scenario solutions. Therefore, for a service for which non-consensus is observed, a low - close to zero value for $\bar{y}_{r}^{\nu}$ indicates a trend toward not activate service $r$. Symmetrically, a high close to one - value indicates a trend to activate that service.

### 3.3.2 Meta-heuristic Search for a Global Design

We consider different strategies to gradually "guide" local solutions towards consensus on the services to include or not in the final design. The first and second strategy operate at a global level, respectively by modifying the augmented Lagrangean parameters [82, 100] and by adjusting fixed costs directly [34]. In addition, a third strategy is proposed to exploit local information related to the routing of flows, which further modify fixed costs at a local level.

## Modifying the Augmented Lagrangean Parameters

The first strategy operates globally and considers only information related to design variables provided by the sub-problems resolution. It is inspired by the augmented Lagrangean method and modifies Lagrangean multipliers and parameter $\rho$ associated to the non-anticipativity constraints.

Let $\phi_{r}^{s \nu}$ be the value of the Lagrangean multiplier associated with the nonanticipativity constraint of design variable $r$ of scenario sub-problem $s$ at iteration $\nu$, and let $\rho^{\nu}$ be the value of the penalty ratio at the same iteration. The parameters are then updated as follows:

$$
\begin{gather*}
\phi_{r s}^{\nu} \leftarrow \phi_{r s}^{\nu-1}+\rho^{\nu-1}\left(y_{r s}^{\nu}-\bar{y}_{r}^{\nu-1}\right) \quad \forall r \in R  \tag{3.34}\\
\rho^{\nu} \leftarrow \gamma \rho^{\nu-1} \tag{3.35}
\end{gather*}
$$

Update rule 3.34 represents the steepest ascent step in the space of the dual problem [89] and depends on parameter $\rho^{\nu}$. Initially, $\rho^{0}$ is set to an arbitrarily positive small value and is dynamically adjusted at each iteration through parameter $\gamma$, which is a constant $\gamma>1$. Although dynamic adjustments of the penalty parameter are not covered by the convergence theory for the PH algorithm, in [89] is found that this strategy can improve the overall convergence behavior.

The objective of this adjustment is to give an incentive to the activation or not activation of a service when its status is different from that one in the current reference overall design. It is motivated by considering that for any design variable $y_{r s}^{\nu}$ in a scenario sub-problem $s$, at iteration $\nu$ three different occurrences may be observed (note that the scenario sub-problem design variable $y_{r s}^{\nu}$ assumes only integer values, namely either 0 or 1 ):

- $y_{r s}^{\nu}<\bar{y}_{r}^{\nu}$. In this case, service $r$ is not activated in scenario-design $s$, but the trend (the reference point $\bar{y}_{r}^{\nu}$ ) suggests that not all the other scenarios agree on this decision. The idea is, then, to promote the activation of that service by reducing its cost in the scenario sub-problem $s$;
- $y_{r s}^{\nu}>\bar{y}_{r}^{\nu}$. This is the opposite situation, in which service $r$ is activated in scenario-design $s$, but not all other scenarios agree on this decision. The cost is adjusted so as to give a disincentive to activate that service within the scenario sub-problem $s$. The more sub-problems do not activate that service the stronger is the disincentive;
- $y_{r s}^{\nu}=\bar{y}_{r}^{\nu}$. Here universal consensus is observed among the scenario subproblems. This may concern both the activation or not activation of a service. The fixed cost, in this case, remains unchanged.


## Fixed Costs Adjustments

In addition to the latter, we also consider a heuristic fixed cost adjustment strategy inspired by [34. It modifies, globally at each iteration, the fixed costs of the design arcs with a status different from what a majority of the other arcs agree upon at the current iteration.

Starting from the reference point $\bar{y}_{r}^{\nu}$ at iteration $\nu$, the global adjustment attempts to favor what appears as the current trend among scenarios to include or exclude service $r$ in the final network design. As explained before, a low value of $\bar{y}_{r}^{\nu}$ indicates that the trend is to not activate service $r$, as it is activated only in a small number of sub-problems. As opposed, a high value of $\bar{y}_{r}^{\nu}$ indicates that the trend is to activate that service, meaning that it is activated within the majority of scenario designs.

As discussed in [34], one can conclude that when $\bar{y}_{r}^{\nu}$ is less than a given threshold thres $_{\text {low }}$, increasing the cost $c_{r}$ of service $r$ may drive the sub-problems to avoid activating it. On the other hand, when $\bar{y}_{r}^{\nu}$ is higher than a given threshold threshigh, lowering the cost $c_{r}$ of service $r$ should attract the scenario sub-problems to activate it. The thresholds may be fixed as less and more than half the scenarios.

When only design information are considered in costs adjustments, three occurrences may be observed and, following [34], cost modification operates in the following way:

$$
c_{r}^{\nu}= \begin{cases}\beta c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu-1}<\text { thres }_{\text {low }}  \tag{3.36}\\ \frac{1}{\beta} c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu-1}>\text { thres }_{\text {high }} \\ c_{r}^{\nu} & \text { otherwise }\end{cases}
$$

with parameters $\beta>1,0<$ thres $_{\text {low }}<0.5,0.5<$ thres $_{\text {high }}<1$ and $c_{r}^{\nu}$ representing the modified activation cost of service $r$ at iteration $\nu$.

## Exploiting Local Flow Information

We also propose a further cost adjustment at a local level, which exploits the information related to the level of utilization of each activated service at a local level. This information is given when sub-problems are solved and does not imply extra efforts to have it.

At iteration $\nu$ for a given service $r$ and sub-problem $s$, two information, as said, are available: the trend among scenarios related to the status of that service reflected by the reference point $\bar{y}_{r}^{\nu}$ and its utilization rate in sub-problem $s$ reflected by the sum of flows of the different commodities passing through the service leg $i(r)$ on
which service $r$ travels along, defined as $\sum_{k \in K} x_{i(r) s}^{k \nu}$. In this case, four occurrences may be observed:

$$
\begin{array}{ccc}
\bar{y}_{r}^{\nu}>\text { thres }_{\text {high }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}>\text { thres }_{\text {high }}^{k} \\
\bar{y}_{r}^{\nu}<\text { thres }_{\text {low }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}<\text { thres }_{\text {low }}^{k} \\
\bar{y}_{r}^{\nu}>\text { thres }_{\text {high }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}<\text { thres }_{\text {low }}^{k} \\
\bar{y}_{r}^{\nu}<\text { thres }_{\text {low }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}>\text { thres }_{\text {high }}^{k} \tag{3.40}
\end{array}
$$

with parameters $0<$ thres $_{\text {low }}<u_{r} / 2, u_{r} / 2<$ thres $_{\text {high }}<u_{r}$.
The significance of the latter occurrences is explained in the following. Case (3.37) and (3.38) are easily interpretable, (3.39) and (3.40) need some more explanation instead.

Case (3.37) defines a situation in which the trend among scenarios is to activate service $r$ operating on service leg $i(r)\left(\bar{y}_{r}^{\nu}>\right.$ thres $\left._{\text {high }}\right)$, which is also highly utilized at a flow level in sub-problem $s\left(\sum_{k \in K} x_{i(r) s}^{k \nu}>\right.$ thres $\left._{\text {high }}^{k}\right)$. The local adjustment we propose attempts, then, to favor the utilization of this service, lowering its activation cost and trying to "push" consensus toward the activation of service $r$.

Case (3.38) defines a situation in which the trend among scenarios is to not activate service $r$ operating on service leg $i(r)\left(\bar{y}_{r}^{\nu}<\right.$ thres $\left._{\text {high }}\right)$, which is also slightly utilized at a flow level in sub-problem $s$, if the service $r$ is active $\left(\sum_{k \in K} x_{i(r) s}^{k \nu}<\right.$ thres ${ }_{\text {high }}^{k}$ ). The local adjustment attempts, then, to discourage the utilization of this service, increasing its activation cost and trying to "push" consensus towards the not activation of service $r$.

Case (3.39) defines the occurrence in which the trend among scenarios is to activate service $r\left(\bar{y}_{r}^{\nu}>\right.$ thres $\left._{\text {high }}\right)$, which is however slightly utilized at a flow level in sub-problem $s\left(\sum_{k \in K} x_{i(r) s}^{k \nu}<t h r e s_{h i g h}^{k}\right)$. The service leg $i(r)$ operated by service $r$ may be, thus, interpreted as a "safe" leg, which is activated in order to hedge against uncertainty, although it is not used at its maximum capacity. The local adjustment attempts, then, to favor the utilization of this service, lowering the activation cost of the service traveling trough it. The cost, though, is not decreased with the same degree as in case (3.37). Incentive and disincentive for the latter occurrences are shown below.

$$
c_{r s}^{\nu}=\left\{\begin{array}{llll}
\frac{1}{\beta^{2}} c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu}>\text { thres }_{\text {high }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}>\text { thres }_{h i g h}^{k}  \tag{3.41}\\
\frac{1}{\beta} c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu}>\text { thres }_{\text {high }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k \nu}<\text { thres }_{\text {low }}^{k} \\
\beta c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu}<\text { thres }_{\text {low }} & \text { and } & \sum_{k \in K} x_{i(r) s}^{k(r)}<\text { thres }_{\text {high }}^{k} \\
c_{r}^{\nu} & \text { if } \bar{y}_{r}^{\nu-1}=0.5 & &
\end{array}\right.
$$

Condition (3.40) appears as the most interesting. Here, the majority of the scenario sub-problems deactivate certain services, which are not only activated but
also heavily used in a small subset of scenario sub-problems. In this occurrence, thus, service $r$ operating on service leg $i(r)$ is activated and highly used in scenario sub-problem $s\left(\sum_{k \in K} x_{i(r) s}^{k \nu}>\right.$ thres $\left.h_{h i g h}^{k}\right)$. Service $r$, however, in the majority of the other scenario sub-problems is not activated ( $\bar{y}_{r}^{\nu}<$ thres $_{\text {high }}$ ).

The question raised here is how important these services could be with respect to the final design. That is, how a small subset of highly used but not agreed upon services should weight and influence a bigger set of services on which the majority of sub-problems agree on their (not activated) status. Should this minority of services be included or excluded from the final plan? Should the methodology simply ignore this small set of services, considering also that each activated service involves costs?

The main problem is, therefore, how to consider the minority of services which satisfy condition (3.40). The strategy we propose, here, is described in the following. We try to limit at each iteration the number of services satisfying condition (3.40). When sub-problem $s$ is solved, the latter four conditions are verified. The number of services satisfying condition (3.40) are counted. In the next iteration when the same sub-problem $s$ is solved again, we try to solve it by limiting the number of those services. This goal is reached by adding to the linear reformulation of sub-problems, an additional constrain. Let $h_{s}^{\nu-1}$ be the number of services satisfying condition (3.40) at iteration $\nu-1$ for sub-problem $s$, at iteration $\nu$ sub-problem $s$ is solved (after the usual costs and multipliers modifications) by constraining the number of those service at $h_{s}^{\nu}=h_{s}^{\nu-1}-1$. If a solution is found trend and costs modifications allow to switch to other services. If a solution is not found, the latter are necessary services to find a feasible solution in sub-problem $s$ and therefore are fixed at an overall level in next iterations.

In order to limit the number of those services, a new constrain, as said, is added to sub-problem $s$. We define the set $C_{4 s}^{\nu}=\left\{r \in R: \bar{y}_{r}^{\nu}<\right.$ thres $_{\text {low }}$ and $\sum_{k \in K} x_{i(r) s}^{k \nu}>$ thres $\left.{ }_{\text {high }}^{k}\right\}$ for each sub-problem $s$ at iteration $\nu$. In addition, we define the parameter $a_{r s}^{\nu}, \forall r \in R, \forall s \in S$ which assumes value 1 if service $r \in C_{4 s}^{\nu}$ and 0 otherwise. Let $h_{s}^{\nu-1}$ define $\left|C_{4 s}^{\nu-1}\right|$, the new constrain added at iteration $\nu$ to sub-problem $s$ is then

$$
\begin{equation*}
\sum_{r \in R} a_{r s}^{\nu} y_{r s} \leq h_{s}^{\nu-1}-1 \tag{3.42}
\end{equation*}
$$

### 3.3.3 The Complete Progressive Hedging-Based Meta-heuristic Algorithms

The Algorithm below sums up the entire procedures described above. We define the version exploiting only design information as (D), while the version considering both design and flow information is identified as (DF). In the current implementation, at each iteration each sub-problem is solved optimally by using a linear solver. Each sub-problem at each iteration takes the form of a deterministic SND problem with possibly modified service costs from one iteration to the others.

As earlier mentioned, there are no theoretical criteria for the convergence of the PH algorithms in the integer case. We, therefore, stop the first phase either when consensus is obtained on the $90 \%$ of design arcs (this stop criterion is motivated by the high flow-degeneracy problem), or when a classical meta-heuristic criteria is satisfied, namely, reaching a total of 30 iterations or after 4 hours running time.

```
Algorithm 1 The Hierarchic Progressive Hedging-Based Meta-heuristic
    Initialization \(\nu=0\)
    \(\phi_{r s}^{\nu} \leftarrow 0, \forall r \in R, \forall s \in S\);
    \(\rho^{\nu} \leftarrow \rho^{0} ;\)
    \(c_{r s}^{\nu} \leftarrow c_{r}, \forall r \in R, \forall s \in S ;\)
    Solve the corresponding \(|S|\) SSND-SDT sub-problems;
    \(\bar{y}_{r}^{\nu} \leftarrow \sum_{s \in S} p_{s} y_{r s}^{\nu}, \forall r \in R ;\)
    First Phase:
    while stopping criterion is not met do
        \(\nu \leftarrow \nu+1 ;\)
        adjust globally \(c_{r}^{\nu}, \forall r \in R\) using equation (3.36);
        if \(\mathbf{D F}=\) TRUE then
            adjust locally \(c_{r s}^{\nu}, \forall r \in R, \forall s \in S\) using equation (3.41);
            \(h_{s}^{\nu} \leftarrow\left|C_{4 s}^{\nu}\right|, \forall s \in S\);
            add constrain (3.42) with \(h_{s}^{\nu-1}\) to sub-problem \(s\);
        end if
        fix some \(y_{r}^{\nu}\) appropriately;
        Solve the \(|S|\) SSND-STT modified sub-problems;
        if \(\mathrm{DF}=\) TRUE then
            while Solve \(==\) TRUE do
                \(h_{s}^{\nu-1}++;\)
            end while
            fix \(y_{r}^{\nu}\) appropriately;
        end if
        Update:
    \(\bar{y}_{r}^{\nu} \leftarrow \sum_{s \in S} p_{s} y_{r s}^{\nu}, \forall r \in R ;\)
    \(\phi_{r s}^{\nu} \leftarrow \phi_{r s}^{\nu-1}+\rho^{\nu-1}\left(y_{r s}^{\nu}-\bar{y}_{r}^{\nu-1}\right), \forall r \in R, \forall s \in S\);
    \(\rho^{\nu} \leftarrow \gamma \rho^{\nu-1} ;\)
    end while
    Second Phase:
    Fix the design variables for which consensus is obtained;
    Solve the restricted multi-scenario SSND-SDT formulation.
```

When first phase is completed, the second phase solves a restricted in terms of variables but full in terms of scenarios stochastic SSND-SDT problem obtained by fixing all design arcs for which consensus has been achieved.

### 3.4 Experimental Setting

In this section, we report the experiments, and the related results, made to evaluate the performance of the proposed algorithm. A subset of the instances considered in the previous chapter are solved with the proposed PH-based meta-heuristic considering both PH-D and PH-DF cost adjustment approaches. Meta-heuristic results are compared with exact solutions obtained by solving directly the multiscenario formulations. In addition, in order to quantify the gain of using local flow information, solutions obtained by the PH-DF and PH-D versions are compared.

The set of problem instances used in the experimentation, is a subset of instances generated before. We chose the $40 \%$ of instances belonging to Pclass - $1 t$ and Pclass - $1 l$ (in tables defined as Inst $1-4$ and Inst11-14) and to Pclass - $3 t$ and Pclass - $3 l$ (in tables defined as Inst $41-44$ and Inst51-54), the latter being the most complicated to solve with an exact method. The scenario set belongs to SClass - $3 l$ and the penalty to the third level.

All experiments were conducted on an Intel Xeon X5675 with 3.07 GHz and 96 GB of RAM. Full-scenario problems and single-scenario sub-problems were solved by a standard linear programming solver, namely Cplex 12.6 (IBM ILOG, 2016) with a branch and bound method.

### 3.4.1 Parameter Setting

The parameters that need to be fixed before running the algorithm are the following. Parameter $\rho$ and parameter $\gamma$, used in expression (3.35); thres ${ }_{\text {low }}$ and threshigh used in expression (3.36) as well as parameter $\beta$; lastly and only for version PH-DF, thres $s_{\text {low }}^{k}$ and threshigh. Same parameters' values are used in both versions of the algorithm. Fixed (and local) cost adjustments were performed with $\gamma=1.1$ and $\beta=1.1 ;$ thresholds were set to threshigh $=0.8$, thres $_{\text {low }}=0.2$ for global adjustments and thres ${ }_{\text {high }}^{k}=1+u_{r} / 2$ and thres $s_{\text {high }}^{k}=\left(u_{r} / 2\right)-1$ for local adjustments.

The performance of the method is generally sensitive to the choice of the penalty parameter $\rho$, which scales the penalty term [11]. Theory suggests that high values of the penalty parameter should induce faster, but often prematurely, convergence leading to ill-conditioned solutions. Conversely, small values of $\rho$ yield to weaker enforcement of the non-anticipativity constraints resulting in a more gradual convergence to, typically, better solutions after, however, many iterations [123; 89]. This is indeed supported by empirical evidence also in our case. We solve many times the same instance sets running the meta-heuristic considering both cost adjustment procedures with different values of $\rho$, ranging from 0.1 to 100 . Results are reported in the next section. First, performance results of the algorithm considering the general PH-D approach are given. Then, a comparison between PH-D and PH-DF approaches is reported to understand where the additional flow information may be beneficial for the resolution process.

### 3.5 Results and Analysis

Table 3.1 displays the performance results of the meta-heuristic algorithm considering the PH-D approach when applied to a subset of the selected instance set. The reported values refer, respectively, to exact solutions (Cplex) and the best solutions found using the PH-D approach with $\rho^{0}=10$. Total computation time expressed in seconds, gaps and number of iterations are also reported.

|  | Cplex |  | PH-D |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| InstID | Time | Value | Time | Value | Iterations | Difference PH-D-Cplex | Gap (\%) |
| Inst1 | 65,3165 | 4432,57 | 786,442 | 4435,49 | 3 | 2,92 | 0,065876004 |
| Inst2 | 40,5959 | 3964,38 | 358,152 | 3971,91 | 1 | 7,53 | 0,189941428 |
| Inst3 | 42,8647 | 4629,9 | 395,273 | 4629,9 | 1 | 0 | 0 |
| Inst4 | 41,6968 | 3950,76 | 357,658 | 3954,68 | 1 | 3,92 | 0,099221416 |
| Inst11 | 45,1247 | 4538,18 | 383,938 | 4538,18 | 1 | 0 | 0 |
| Inst12 | 44,7421 | 3701,94 | 366,802 | 3701,94 | 1 | 0 | 0 |
| Inst13 | 42,7629 | 3834,58 | 683,646 | 3841,76 | 3 | 7,18 | 0,187243453 |
| Inst14 | 43,4982 | 4562,23 | 723,716 | 4567,67 | 3 | 5,44 | 0,119239933 |
| Inst41 | 92,066 | 7151,51 | 739,209 | 7153,12 | 1 | 1,61 | 0,022512728 |
| Inst42 | 79,3316 | 6838,44 | 853,459 | 6838,44 | 1 | 0 | 0 |
| Inst43 | 66,1475 | 6246,38 | 605,772 | 6250,66 | 1 | 4,28 | 0,068519687 |
| Inst44 | 81,8429 | 6660,29 | 787,476 | 6660,29 | 1 | 0 | 0 |
| Inst51 | 170,349 | 7720,57 | 3235,76 | 7730,77 | 6 | 10,2 | 0,132114598 |
| Inst52 | 65,6029 | 6971,69 | 784,865 | 6971,69 | 1 | 0 | 0 |
| Inst53 | 92,4215 | 7295,06 | 1577,16 | 7300,43 | 3 | 5,37 | 0,073611458 |
| Inst54 | 67,4408 | 6638,79 | 869,575 | 6638,79 | 2 | 0 | 0 |
|  |  |  |  | mean | 1,875 | 3,028125 | 0,059892544 |

Table 3.1. Performances of Cplex and PH-D approach with $\rho^{0}=10$

Cplex solves in less than 3 minutes of computation time all instances. The PH-D approach finds in general good quality solutions. The $40 \%$ of the instances are solved achieving the optimum and the gap between the best found PH-D solution and the optimum is always less than $2 \%$. Here, in half of the instances, the algorithm stops after just 1 iteration. Normally, for real size instances this behavior may be risky and a stricter stop rule should be defined when a so fast termination is observed.

In Table 3.2, average results for different initial settings of the parameter $\rho^{0}$, ranging from 0.1 to 100 , are reported. In line with the results known in the literature, when $\rho^{0}$ is small, convergence of the first phase (to one of the stop rules) is slow, but at the same time the mechanism has enough time to "absorb" all the information from the scenarios. For a big value, convergence is too fast and this is not always possible. The algorithm, in fact, is able to solve some of the instances achieving the optimum, but the high value of $\rho^{0}$, as opposed, induce a prematurely convergence ending just at local optimum solutions: the number of instances solved reaching the optimum decreases as the parameter $\rho^{0}$ increases. At the same time, the accuracy of solutions decreases as well, as shown by the optimality gaps. The best performances in terms of accuracy are achieved when $\rho^{0}$ takes a value equal to 5 or 10 . When also the number of iterations is considered, then, the best performance is reached by fixing $\rho^{0}=10$.

How does the flow-information intervene? Using flow-information may improve

| $\rho^{0}$ | Time | Iterations | Difference PH-D-Cplex | Gap (\%) | (\%) of Optimum |
| :--- | :---: | :---: | :---: | :---: | :---: |
| 0,1 | 2354,97 | 8,06 | 3,68 | 0,07017 | $44(\%)$ |
| 0,3 | 7226,46 | 3,88 | 4,33 | 0,08425 | $31(\%)$ |
| 0,6 | 1231,63 | 3,00 | 3,68 | 0,07017 | $44(\%)$ |
| 1 | 1055,62 | 2,50 | 3,49 | 0,06782 | $44(\%)$ |
| 1,5 | 1073,56 | 2,38 | 3,34 | 0,06582 | $44(\%)$ |
| 2,5 | 863,49 | 2,00 | 3,34 | 0,06582 | $44(\%)$ |
| 5 | 926,80 | 2,19 | 3,03 | 0,05989 | $44(\%)$ |
| 10 | 844,31 | 1,88 | 3,03 | 0,05989 | $44(\%)$ |
| 20 | 896,44 | 2,19 | 3,43 | 0,06548 | $38(\%)$ |
| 50 | 915,66 | 1,56 | 4,50 | 0,08452 | $31(\%)$ |
| 100 | 805,14 | 1,06 | 5,40 | 0,10309 | $31(\%)$ |

Table 3.2. Average performances of PH-D approach with different values of $\rho^{0}$
the quality of the solution, when $\rho^{0}$ is small. In Table 3.3 the same instances of Table 3.1 are solved with $\rho^{0}=0.3$ using both the PH-D and the PH-DF approaches.

|  | Cplex | PH-D |  |  |  | PH-DF |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| InstID | Value | Time | Value | Iterations | Gap (\%) | Time | Value | Iterations | Gap (\%) |
| Inst1 | 4432,57 | 3792,66 | 4435,49 | 6 | 0,065876004 | 4395,31 | 4435,49 | 11 | 0,065876004 |
| Inst2 | 3964,38 | 5776,88 | 3972,3 | 1 | 0,199779032 | 754,894 | 3971,91 | 1 | 0,189941428 |
| Inst3 | 4629,9 | 5732,79 | 4639,48 | 1 | 0,206915916 | 753,713 | 4629,9 | 1 | 0 |
| Inst4 | 3950,76 | 5703,64 | 3954,68 | 1 | 0,099221416 | 737,532 | 3954,68 | 1 | 0,099221416 |
| Inst11 | 4538,18 | 5697,76 | 4538,18 | 1 | 0 | 769,88 | 4538,18 | 1 | 0 |
| Inst12 | 3701,94 | 5773,85 | 3701,94 | 1 | 0 | 749,04 | 3701,94 | 1 | 0 |
| Inst13 | 3834,58 | 5700,85 | 3841,76 | 11 | 0,187243453 | 4056,07 | 3841,76 | 11 | 0,187243453 |
| Inst14 | 4562,23 | 5825,51 | 4571,05 | 6 | 0,193326509 | 2470,5 | 4571,05 | 6 | 0,193326509 |
| Inst41 | 7151,51 | 8478,38 | 7153,12 | 1 | 0,022512728 | 1892,92 | 7153,12 | 2 | 0,022512728 |
| Inst42 | 6838,44 | 8578,23 | 6838,44 | 1 | 0 | 1434,73 | 6838,44 | 1 | 0 |
| Inst43 | 6246,38 | 8623,35 | 6250,66 | 1 | 0,068519687 | 1166,56 | 6250,66 | 1 | 0,068519687 |
| Inst44 | 6660,29 | 9214,55 | 6660,29 | 1 | 0 | 1406,49 | 6660,29 | 1 | 0 |
| Inst51 | 7720,57 | 10320 | 7737,75 | 19 | 0,22252243 | 12483,9 | 7737,75 | 19 | 0,22252243 |
| Inst52 | 6971,69 | 9034,35 | 6971,69 | 1 | 0 | 1347,79 | 6971,69 | 1 | 0 |
| Inst53 | 7295,06 | 9125,4 | 7300,43 | 7 | 0,073611458 | 6088,84 | 7300,43 | 9 | 0,073611458 |
| Inst54 | 6638,79 | 8245,11 | 6639,35 | 3 | 0,008435272 | 2217,58 | 6638,79 | 3 | 0 |

Table 3.3. Performances of Cplex, PH-D and PH-DF with $\rho^{0}=0.3$

The PH-DF approach is more precise than the PH-D in some few cases. However, it seems to have little impact on the quality of the solutions compared to the higher computational effort required to find them. This additional effort is certainly due to the higher number of operations characterizing the PH-DF with respect to PH-D. On average, in fact, the computational time savings of PH-D with respect to PH-DF are of the $60 \%$ and the gain in accuracy of the PH-DF over the PH-D is only of the $0,002 \%$ on average, very negligible. In general, improvement are observable till $\rho^{0}=1$ (as shown in Table 3.4). After this value, the two approaches have exactly the same behavior. Nevertheless, the PH-DF approach continues loosing computation efficiency when instances become larger.

It could be concluded that, in general, the flow-information that may be derived by the scenarios can be "absorb" only when enough time is given to the methodology.

| $\rho^{0}$ | Iterations | Total Gain | (\%) Gain |
| :--- | :---: | :---: | :---: |
| 0,1 | $-6,61$ | 0,182 | 0,002 |
| 0,3 | 11,43 | 0,658 | 0,014 |
| 0,6 | 2,04 | 0,182 | 0,002 |
| 1 | $-2,56$ | 0 | 0 |
| 1,5 | $-2,56$ | 0 | 0 |

Table 3.4. Average gain (and losses) in number of iterations and performances of PH-DF compared to PH-D with different values of $\rho^{0}$

A fast convergence, that in our case is observable already when $\rho^{0}=1$, even if is enough to "obtain" information related to the service trends, is not enough to "obtain" and exploit flow information. Nevertheless the information of service trends is sufficient to find good quality solutions. It could be hypothesized that the PH-DF approach may be useful if no insights are given about the most appropriate value $\rho^{0}$ to utilize in the algorithm and fast solutions are not required. It should also be considered that flow information is obtained just by solving sub-problems not requiring any extra computation effort and, as seen, could be beneficial. At the same time, however, it increases the computation time considerably gaining just in small refinement making of the simple PH-D approach a more suitable way to solve problem instance efficiently when rapid solutions are sought.

The above reported results are based on relatively small size instances compared to what could be a practical problem in a real-life situation. Next step in our work is to apply the algorithm to bigger instances.

## Conclusions and Future Research

Network design formulations in which time is explicitly taken as a stochastic parameter have been neglected in favor of settings in which other stochastic parameters were taken into account (in particular with respect to demand). Nevertheless, considering such a random parameter is beneficial in particular considering the need of building reliable services.

In this thesis, a new problem which scope is to build an economically-efficient freight transportation network respecting given service quality targets consistently as close as possible hedging the uncertainty in travel time is proposed. An extensive review and classification of published contributions on network design problems in which time is explicitly accounted as a stochastic parameter is presented, pointing out the lack of contributions dealing with this specific problem and highlight, in addition, the need of further research in other directions. An original two-stage stochastic linear mixed-integer programming formulation for the new problem is proposed. Extensive experimentation shows the benefits obtained by considering explicitly travel time stochasticity into the model, how and why the structures of stochastic and deterministic solutions differ from each other and how the value of some parameters may affect the structure of stochastic solutions. Lastly, given the NP-hardness of network design problems and the inability of traditional solvers to find solutions in reasonable time, a progressive hedging-based meta-heuristic algorithm able to provide efficiently good quality solution is, also, proposed. It modifies the traditional application scheme of the method in order to overcome the problems related to a quadratic reformulation and flow-degeneracy which raise, when it is classically applied to our problem. Two versions are described, differing in the usage of information exploited in the resolution process.

This thesis opens a number of interesting research avenues related to the problem setting it-self and to the proposed meta-heuristic approach. Let us first start with the problem setting. The problem has been set up considering several simplifying assumptions about services and network:

- service time is assumed deterministic;
- the definition of services includes their routes and ideal schedules;
- the services that potentially could be offered are given;
- the selection of the services is allowed only in the given set;
- demand is assumed given over the schedule length;
- service connections are always caught.

Before all else, different assumptions about time distributions could extend the model. That is, in our first basic problem setting, each time distribution is assumed independent from all the other travel time distributions. Nevertheless, a form of propagation of the delay is taken into account in the present work, which involves though only not-direct services. In fact, if a service having two stops experiences a delay in its first leg, it is propagate in its second leg as well. The probability of experience a delay in the second leg, however, is not dependent on what happened in the first leg. One aspect that could be considered involves the relaxation of the latter assumption, considering correlations among distributions. On real application, in fact, the assumption of independence is not always true and a certain degree of correlation is always observed (even though negligible in some cases). This may, in general, involve just physical arcs, regardless of the services active on them.

In addition to the correlation assumption, extensions could be done considering both travel and operation times as stochastic parameters. The simplest way to consider stochastic operation time is to associate an operation time probability distribution to each holding arc of the time-expanded network. Operation time distributions may be independent from each other or even dependent on travel time distributions (consider that if a service is late and arrives late at a terminal, it may loose its priority in loading/unloading operations), on the specific terminal to which the distribution refers (allowing longer operation times for "difficult" or highly utilized terminals) or on the volume of freight (or number of services) passing trough it at a given time (the more freight or services passing through it, the longer operation times may require).

Regarding the last assumption we made, future research will certainly consider the possibility of recourse, if the pre-defined sequencing of services is missed for some commodities. Different adjustment plans could be considered upon observing a delay. A common way is to activate ad hoc services to deliver the tardy shipments till destination. The second stage, then, will consider not only the already defined costs, but also the additional cost required for adjust the shipment plan.

One possible further extension could concern the assumption about the given services. Here, we have a set of services - each one having its own and given route and ideal schedule - from which choose the most convenient ones with respect to given targets. A first extension may be to work with a given set of services, but having their schedules as decision as well. A second extension, then, may be to have a dynamic generation (and selection) of services (this includes their routes and schedules). An accurate study of time distribution (both of travel and operation time) for defining schedules and respecting targets should be performed.

The assumption we made about given demand over the schedule length is in line with the assumption of the given set of potential services: in fact, services are potentially offered only there where really needed. Demand stochasticity is a natural extension of the model (also in line with new research trends combining more than one uncertain parameter). If demand is assumed not given over the schedule length, however, the given set of services could be not sufficient to satisfy customers' requests or targets and the generation of additional services should again be considered.

Lastly, in this work we assumed that all resources to perform services and terminal operations (like power units, carrying units, loading/unloading units and crews) are given and we did not assume any particular restriction on them. Extensions could concern the introduction of specific constraints about the restriction of resources, resource management or heterogeneous resources or, given the importance that idle time plays, inventory restrictions. Different targets may also be considered depending on classes of services or traffic demands.

All the above mentioned extensions define new characteristics for the basic problem we considered in this work and interesting new problem settings to study and explore.

Considering the meta-heuristics here proposed, several issues need further investigation and a number of research avenues appear promising to improve their performances. In general, the exploration of alternative mechanisms to modify fixed costs to guide consensus towards a unique overall solution is an avenue to further explore. In our case, this may also concern the modification of the variable flow costs on the service legs for which consensus is still not found in order to push the flow distribution to change and agree on the activation of a service. Some kinds of hybrid approach may also be considered in which fixed cost and variable costs adjustments may alternate, for instance when given cost-thresholds are satisfied.

The decomposition of a stochastic program across scenarios divides an original large-scale problem into manageable sub-problems. The independence of the sub-problems makes the algorithm particularly suited for execution on parallel multiprocessors. As stated by many researcher, parallel computing becomes necessary at some point to solve dynamically sub-problems if the number of scenarios highly increases. Extensions to parallelism could possibly enhance problem solving capabilities.

Perhaps, the most impacting improvement can be obtained by bundling scenarios and creating multi-scenario sub-problems instead of single-scenario sub-problems, as done in here. One research issue may then concern the impact of several criteria to divide scenarios. Should scenario-groups partition or cover the original set of scenarios? Should the scenarios in each group be (dis)similar? Intuitively, aggregation of scenarios should yield more rapid agreement in solutions, involving however a higher complexity of sub-problems. Bundling methods, thus, appear as an interesting additional issue to explore in future.

## Appendix A

## Notation

The notation used throughout the thesis is presented below.
Sets:
$G_{p h y s} \quad$ physical network on which the carrier operates;
$N_{\text {phys }} \quad$ physical terminals composing the physical network;
$A_{\text {phys }} \quad$ physical connections between physical terminals;
$G \quad$ time-expanded service network;
$N$
$N^{+}(i)$
set of successor arcs of $i \in N, N^{+}(i)=\{j \in \mathcal{N}:(i, j) \in \mathcal{A}\}$;
$N^{-}(i) \quad$ set of predecessor arcs of $i \in N, N^{-}(i)=\{j \in \mathcal{N}:(j, i) \in \mathcal{A}\} ;$

A
set of arcs in the time-expanded network;
$A^{H}$
set of holding arcs in the time-expanded network;
$A^{M} \quad$ set of movement arcs in the time-expanded network;
$K \quad$ set of commodities;
$R \quad$ set of potential services;
$L(r) \quad$ set of service legs of service $r, r \in R$;
$\Omega \quad$ set of possible outcomes of random travel time;
$S$
set of scenarios;
$T$ schedule length.

## Parameters:

$o(k) \quad$ origin of commodity $k, k \in K$;
$d(k) \quad$ destination of commodity $k, k \in K$;

| $a(k)$ | entry date of commodity $k, k \in K$; |
| :---: | :---: |
| $b(k)$ | due date of commodity $k, k \in K$; |
| $w(k)$ | volume of commodity $k, k \in K$; |
| $c_{i, j}^{k}$ | cost of commodity $k$ on $\operatorname{arc}(i, j), k \in K,(i, j) \in A$; |
| $\lambda^{k}$ | penalty cost for short delay of commodity $k, k \in K$; |
| $B^{k}$ | maximum allowed delay of commodity $k, k \in K$; |
| $\Lambda^{k}$ | penalty cost for long delay (greater than $B^{k}$ ), $k \in K$; |
| $o(r)$ | origin terminal of service $r, r \in R$; |
| $d(r)$ | destination terminal of service $r, r \in R$; |
| $f_{o(r)}$ | leaving time at origin of service $r, r \in R$; |
| $u_{r}$ | capacity of service $r, r \in R$; |
| $c_{r}$ | cost of including service $r$ in the final plan, $r \in R$; |
| $\sigma(r)$ | ordered set of visited terminals of service $r, r \in R$; |
| $i(r)$ | service leg of service $r, i(r) \in L(r), r \in R$; |
| $\hat{\tau}_{i(r)}$ | travel time point forecast of leg $i(r)$ of service $r, i(r) \in L(r)$ $r \in R$; |
| $e_{i(r)}$ | usual ending travel time instant of service $r$ on leg $i(r), i(r) \in L(r)$, $r \in R$; |
| $\lambda_{i(r)}^{r}$ | penalty cost for short delay on leg $i(r)$ of service $r, i(r) \in L(r)$, $r \in R$; |
| B | maximum allowed delay for services; |
| $\Lambda_{i(r)}^{r}$ | penalty cost for long delay (greater than $B$ ) on leg $i(r)$ of service $r, i(r) \in L(r), r \in R$; |
| $t$ | deterministic operation time; |
| $p_{s}$ | probability assigned to scenario $s \in S$; |
| $\tau_{i(r)}(s)$ | travel time realization of leg $i(r)$ of service $r$ of scenario $s, i(r) \in$ $L(r), r \in R, s \in S ;$ |
| $\phi_{r s}$ | Lagrangean multiplier used to relax non-anticipativity constraint of first stage variable $y_{r}$ in scenario sub-problem $s, r \in R, s \in S$; |
| $\phi_{i j s}^{k}$ | Lagrangean multiplier used to relax non-anticipativity constraint of first stage variable $x_{i j}^{k}$ in scenario sub-problem $s,(i, j) \in A$, $s \in S ;$ |

$\rho, \psi \quad$ penalty ratios;
$\gamma, \beta \quad$ updating parameters;
$\bar{y}_{r} \quad$ overall estimation value of variable $y_{r}, r \in R$;
$\bar{x}_{i j}^{k} \quad$ overall estimation value of variable $x_{i j}^{k},(i, j) \in A$;
$\sum_{k \in K} x_{i(r) s}^{k} \quad$ sum of flows of all commodities passing through the leg $i(r)$ of service $r$.

Distributions:
$\tau_{i(r)} \quad$ travel time probability distribution of leg $i(r)$ of service $r, i(r) \in$ $L(r), r \in R$;
arrival time probability distribution of service $r$ at the end of leg $i(r), i(r) \in L(r), r \in R$;
$\varepsilon_{k} \quad$ arrival time probability distribution of commodity $k$ at destination $d(k), k \in K$.

Variables:
$y_{r} \quad y_{r} \in\{0,1\}, \forall r \in R$ represent whether a service $r$ is selected ( $y_{r}=1$ ) or not ( $y_{r}=0$ ) in the final plan;
$x_{i j}^{k} \quad x_{i j}^{k} \geq 0, \forall k \in \mathcal{K}, \forall(i, j) \in \mathcal{A}$ represent the amount of commodity $k$ flowing on $\operatorname{arc}(i, j) \in A$;
$\delta_{i(r) s} \quad \delta_{i(r) s} \geq 0, \forall i(r) \in L(r), \forall r \in R, \forall s \in S$ represent the time instant in which service $r \in R$ begins its movement on service leg $i(r) \in L(r)$ in scenario $s \in S$;
$\eta_{i(r) s} \quad \eta_{i(r) s} \geq 0, \forall i(r) \in L(r), \forall r \in R, \forall s \in S$ represent the time instant in which service $r \in R$ ends its movement on service leg $i(r) \in L(r)$ in scenario $s \in S$;
$\varepsilon_{k s} \quad \varepsilon_{k s} \geq 0, \forall k \in K, \forall s \in S$ represent the time instant in which commodity $k \in K$ arrives at its destination in scenario $s \in S$.

## Appendix B

## Additional Tables

The Tables reported below show average results related to in-sample and out-ofsample stability tests. Subsequent Tables show average results related to solution features and Monte-Carlo simulations for all the considered problem instances.

|  | PClass-1t | PClass-1l |
| :--- | :---: | :---: |
| SClass-3t | 0.59 | 0.64 |
| SClass-3m | 0.63 | 0.92 |
| SClass-3l | 0.56 | 0.73 |

Table B1. In-Sample Stability Test

|  | PClass-2t | PClass-2l |
| :--- | :---: | :---: |
| SClass-3t | 0.67 | 0.68 |
| SClass-3m | 0.67 | 1.04 |
| SClass-3l | 0.6 | 0.61 |

Table B2. In-Sample Stability Test

|  | PClass-1t | PClass-1l |
| :--- | :---: | :---: |
| SClass-3t | 2.62 | 1.9 |
| SClass-3m | 2.69 | 1.46 |
| SClass-3l | 2.96 | 1.09 |

Table B3. Out-of-Sample Stability Test

|  | PClass-2t | PClass-2l |
| :--- | :---: | :---: |
| SClass-3t | 2.14 | 1.36 |
| SClass-3m | 2 | 0.93 |
| SClass-3l | 2.9 | 1.89 |

Table B4. Out-of-Sample Stability Test




|  | $\left\|\begin{array}{ll} 0 \\ 0 \\ 0 & z \\ 0 & z \\ 0 & z \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array}\right\|$ |
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