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UNIVERSIDADE D
COIMBRA

Erwin Joffre Delgado Bravo

STRATEGIC PLANNING OF INTERMODAL PLATFORM NETWORKS

Tese no âmbito do Programa Doutoral em Sistemas de Transportes orientada pelo Doutor António Pais Antunes e pela Doutora Ana Paula Barbosa Póvoa e apresentada ao Departamento de Engenharia Civil da Faculdade de Ciências e Tecnologia da Universidade de Coimbra.

Setembro de 2019

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To my children Carlitos and Toñito, my wife Malena, and my parents.

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Abstract

In recent years, various policies to encourage the use of the intermodal transport system, especially the rail/road combination, have been promoted by government entities as an alternative to reduce the negative externalities that unimodal transport by road entails. Despite the economic advantages of using the rail/road transport its market share is significantly lower compared to unimodal transport by road. Multiple factors affect the performance of an intermodal system, especially the location of facilities (intermodal terminals) where the mode change takes place; the terminal type selection, which depends on the different services that terminals could offer (e.g. storage, (un)loading); and its installed equipment (e.g. cranes, reach stackers) and/or infrastructure (e.g. tracks).

Usually, location and terminals type selection is carried out by a government entity. This planning is linked to the decisions of distribution done by the users of the terminals who choose the route that minimizes their own costs when transporting freight flow between two regions of a country. In this context, the present work aims to provide optimization-based tools for the strategic planning of an intermodal terminals network in a country taking into account the decisions of the terminal users.

A first approach addressed in this work consists in the formulation of mathematical models for the optimal location of intermodal terminals under a decentralized management context, subject to capacity constraints in order to minimize the total costs of distribution that include the transportation costs and the costs for installing terminals. A first proposed mathematical model is based on the assumption that the analyst, who carries out the strategic planning, knows with complete certainty the decisions made by the users. The decisions of the users are generally focused on choosing the route with the greatest utility for them. Based on the above, the demand between each pair of regions is fully allocated to the route with the greatest utility (lowest cost). The behavior of this model was analyzed with reference to a case study inspired by the Portuguese reality, contrasting its results with those obtained in a centralized management context highlighting notable differences both in number and in the location of intermodal terminals.

On the other hand, generally the behavior of the users in the modal (or routes) choice process is not completely known by the analyst. Users do not constitute a homogenous group of individuals and so they could evaluate each route option differently. Therefore, the analyst can only make inferences regarding the behavior of the users. One way to characterize the variability of user decisions is through a discrete choice model. Thus, unlike the previous model, a second mathematical model is proposed, which is based on that the demand between a pair of regions is divided proportionally in each feasible route between the two regions. The freight proportion allocated to each feasible route is given by a Multinomial Logit Model.

Due to the solution complexity observed through the computational experiences carried out on the proposed mathematical models efficient solution algorithms were proposed. These explore the concept of hybrid algorithm that combines a Genetic Algorithm and a Local Search Procedure, for getting near-optimal solutions to the problem under study in this thesis. As a critical aspect of this approach relates to the parameter tuning this was analyzed and an a heuristic based on the Iterated Local Search Algorithm was proposed in order to find a near-optimal configuration for the Hybrid Algorithm.

The validation of these algorithms was performed through a comparative analysis between the optimal results of a set of randomly generated instances and those obtained in the execution of the algorithms.

The heuristic for getting near-optimal solution to intermodal location problem under a decentralized management context based on a discrete choice model was implemented to two case studies. The first one is essentially focused on the Portuguese reality, contrasting two decentralized management approaches in decentralized management (all-or-nothing allocation vs Multinomial Logit Model), highlighting the impact of the approach on the design of the freight transport network. The second one is based on the Iberian Peninsula, evidencing significant improvements in implementing the near-optimal solution compared to the current freight transport network.

Resumo

Nos últimos anos, várias políticas de encorajamento do uso de sistemas de transportes intermodais, especialmente as ligações ferro-rodoviário, têm sido incentivadas pelas entidades governamentais como uma alternativa que visa reduzir as externalidades negativas inerentemente associadas ao transporte uni-modal rodoviário. Apesar das vantagens económicas do uso de transporte ferro-rodoviário, a sua quota de mercado é significativamente reduzida comparado com o transporte uni-modal rodoviário. A performance de um sistema multimodal é afetada por múltiplos fatores, especialmente a localização das instalações (terminais intermodais) onde a troca de modo ocorre; a seleção do tipo de terminal, que depende dos diferentes serviços que cada terminais oferece (p ex., armazenamento, (des)carregamento); e o tipo de equipamento instalado (p ex., gruas, empilhadoras) e/ou infraestrutura (p ex., trilhos).

Usualmente, a localização e a seleção do tipo de terminal são realizadas por uma entidade governamental. Este planeamento está associado às decisões de distribuição tomadas pelos utilizadores dos terminais que escolhem as rotas que minimizam os seus próprios custos aquando do transporte de carga entre duas regiões de um país. Neste contexto, o presente trabalho tem como objetivo providenciar ferramentas de otimização que sirvam de base para o planeamento estratégico de uma rede de terminais intermodais de um país tendo em conta as decisões tomadas pelos utilizadores desses mesmos terminais.

A primeira abordagem tratada neste trabalho consiste na formulação dos modelos matemáticos para a localização ótima dos terminais intermodais no contexto de uma gestão descentralizada, sujeita às restrições de capacidade no sentido de minimizar o custo total da distribuição, nomeadamente, o custo de transporte e o custo de instalação dos terminais. O primeiro modelo matemático proposto é baseado na hipótese de que o analista, o qual que realiza o planeamento estratégico, tenho conhecimento, com total certeza, das decisões tomadas pelos utilizadores. As decisões destes utilizadores são geralmente focadas na escolha da rota de distribuição que maximiza as suas respetivas utilidades. Posto isto, a procura entre quaisquer dois pares de regiões é inteiramente alocada à rota com maior utilidade (custo mais baixo). O comportamento deste modelo foi analisado usando um estudo de caso inspirado na realidade Portuguesa e

contrastado com os resultados obtidos num contexto de gestão centralizada, destacando claras diferenças em termos de número e da localização dos terminais intermodais.

Por outro lado, e de uma forma geral, o comportamento dos utilizadores no processo de escolha de modo (ou de rotas) não é completamente conhecido pelo analista. Os utilizadores não constituem um grupo homogéneo de indivíduos, podendo avaliar cada opção de rota de forma distinta. Portanto, o analista pode apenas inferir o comportamento destes utilizadores. Uma forma de caracterizar esta variabilidade é através de modelos de escolha discreta. Deste modo, ao contrário do modelo anterior, um segundo modelo matemático é proposto, o qual é baseado no facto de que a diferença de procura entre quaisquer dois pares de regiões é proporcionalmente dividida em cada rota factível entre as duas regiões consideradas. A carga alocada a cada possível rota é obtida através de um modelo de Logístico Multinomial.

Dada a complexidade da solução observada via experiências computacionais, foram propostos alguns algoritmos de soluções eficientes. Estes últimos exploram o conceito de algoritmo híbrido, que combina elementos de Algoritmos Genéticos e de Procedimentos de Procura Local, para a obtenção de soluções próximas da ótima do problema a ser estudado nesta tese. Um aspecto crítico desta abordagem refere-se à afinação dos parâmetros. Neste sentido, foi proposta uma heurística baseada no Algoritmo de Procura Local Iterada no sentido de encontrar a configuração quase ótima do Algoritmo Híbrido.

A validação destes algoritmos foi conduzida através de análise comparativa entre os resultados ótimos de um conjunto de instâncias geradas aleatoriamente e os resultados obtidos pela execução dos algoritmos.

A heurística para obter soluções quase ótimas do problema de localização intermodal sob o contexto de gestão descentralizada baseado num modelo de escolha discreta foi implementado com recurso a dois estudos de caso. O primeiro, é essencialmente focado na realidade Portuguesa, contrastando duas abordagens de gestão descentralizada (tudo-ou-nada versus Modelo Logístico Multinomial), destacando o impacto das mesmas no design da rede de transporte de carga. O segundo é baseado na Península Ibérica, evidenciando melhorias significativas na implementação da solução quase ideal em comparação com a atual rede de transporte de mercadorias.

1 Introduction

1.1 Context

Freight transport is playing an increasingly important role in the global economy in that it adds value to what is carried. Freight transport predominantly uses three transport modes: sea, rail and road. However, freight transportation operations generate a lot of negative externalities for society, especially road transport. For instance, by 2006 energy consumption for the transport sector[1] in the European Union represented 31.5% of the total final energy consumption, which also includes the services, agriculture and industry sectors, and households (European Commission (2009)), and a high contribution to the energy consumption by road transport should be noted (81.9% of the transport sector). Furthermore, the emission by the transport sector of greenhouse gases, which contribute to global warming, amounts to 19% of total emissions in the European Union, with road transport again responsible for a considerable proportion (European Commission (2009)). In recent years, road freight transportation has experienced remarkable growth thanks to various competitive strategies such as door-to-door and just-in time services (Rodrigue et al. (2013)).

These factors have attracted a great deal of attention from transport policy institutions virtually everywhere around the world. A few transport policy institutions have issued various resolutions to promote the use of sustainable transportation systems, mainly focused on multimodal transport systems. The Council Directive 92/106/EEC issued by the European Union is one example.

One multimodal transport system is the intermodal transport system. Intermodal transport is "the movement of goods in one and the same loading unit or vehicle which uses successively several modes of transport without handling of the goods themselves in changing modes" (ECMT, 1997).

Key components of the intermodal system are the facilities (intermodal terminals) where the change of transport mode takes place. The location of each facility directly affects the performance of the intermodal transport system, so this is a concern that arises in the strategic planning of the intermodal terminal network.

[1] This category does not include maritime or pipeline transport.

These decisions are usually made by a government entity that wants to determine the regions where new terminals should be located and the type/capacity of such terminals (and also, possibly, the regions where existing terminals should be closed or modified), with a view to minimizing the social costs involved in satisfying all the demands for freight transport in the country. Since all the demands are to be satisfied, it is reasonable to assume that the social benefits of freight transport are fixed (constant), and the minimization of social costs should signify the maximization of social welfare.

The social costs to be minimized comprise both internal and external costs. The former are the private costs involved in the transport of freight and in the construction, operation and maintenance of the terminals. The latter are the side effects of transport, i.e. global warming, air pollution, noise, accidents and congestion. The external costs of any activities should be internalized to achieve an efficient allocation of resources, i.e. they should be incurred by the economic agents that perform the activities (freight transport, in this case), and not by the economic agents that suffer their consequences. For this to happen, governments can levy taxes on freight transport. The internalization of the external costs of transport is a major policy concern in the European Union (European Commission, 2008). However, it should be noted that full internalization of external costs would normally require taxes to differ for the various freight transport firms, which would violate the equality principle adopted in the constitutional law of each country. This means that it would only be possible in a context where a government entity could control terminal users up to the point of imposing the transport schemes they should use (i.e. in a context of centralized management). The state-of-the-art regarding the external costs of freight transport and their internalization is described in Mostert and Limbourg (2016).

The context for the problem we are dealing with is, therefore, that of decentralized management. The government entity defines the location and type/capacity of the new terminals (and also, possibly, the changes to make in the existing terminal network) to minimize social costs while taking into account that the potential terminal users in the various regions will decide whether to resort to the terminals or not to reduce their own costs. Since it is practically impossible to account for each terminal user separately, transport costs need to be estimated based on average transport costs per unit of cargo for each transport mode. The other costs terminal users incur are the fees they pay for utilizing the terminals, and these are set by the government entity.

The first hypothesis that arises in this research work is that the approach used in the management of freight distribution between two regions directly affects both the total transportation costs as well as the optimal design of the intermodal terminal network, i.e., the number of terminals, their capacity and their location. On the other hand, given the computational complexity of the problem under study, the second hypothesis states that the use a heuristic algorithm for getting near-solutions is suitable for medium and large-scale instances.

1.2 Research objectives

The general objective of this thesis is to provide a government entity with optimization-based decision support tools for the strategic planning of a rail/road intermodal terminal network in a context where freight transport is under decentralized management. This objective is established from the literature review in which, to the best of our knowledge, the location of intermodal terminals is very often addressed in a centralized context, i.e. the decisions of the users of the terminals are not considered.

In the context of decentralized management of freight transport by users, the first scenario to be analysed is that the decision maker (analyst) in the strategic planning of the intermodal terminal network knows that terminal users will choose the transport option that minimizes their own costs. That scenario is based on the assumption that the decision maker and the users are rational individuals with full knowledge of the costs associated with each transport option.

Under the above assumptions, a first specific objective of this thesis emerges: to formulate an optimization model to locate a set of intermodal terminals in a decentralized management context, based on an all-or-nothing allocation approach in order to reduce the total transportation costs involved in the transport of freight and in the construction, operation and maintenance of the terminals.

One of the weaknesses in applying mathematical models for the intermodal terminal location problem is that it is limited to small-scale instances. Therefore, a second specific objective is raised: to design and implement an efficient solution algorithm to solve real cases. This is explored through a heuristic algorithm for getting a near-optimal solution to the intermodal terminal location problem in a decentralized management context, based on an all-or-nothing allocation approach.

Generally, the design of heuristic algorithms includes a set of parameters, which mostly serve as a threshold for the execution of a few procedures in the heuristic algorithm. The performance of the heuristic algorithm in a reference instance depends on the parameter tuning. The process of tuning parameters is usually carried out by trial and error until an adequate configuration of the algorithm is found. However, due to the excessive time-effort involved, we developed a strategy to perform it automatically by means of a non-parameterized algorithm, which leads us to our third specific objective: to design and implement a non-parametric algorithm for getting a near-optimal configuration of the heuristic algorithm over a benchmark set of instances.

As explained above, it is assumed that the analyst has complete knowledge regarding of the decisions taken by the terminal users. However, this assumption is not sound when it comes to real practice. Firstly, from the perspective of the users of the terminals, there are other factors that could affect the attractiveness of a rail-road intermodal transport system; for instance, rail haul distance, delivery time, reliability, frequency, accessibility and so on (Ben-Akiva M. et al. (2013)), which enable users to evaluate and select a transport mode and/or route according to their own best interest. Also, two users do not always make the same choice in the same scenario because they could assess each of the distribution options differently. On the other hand, from the perspective of the analyst, their decisions are based on information obtained through surveys or from econometric models that predict the behavior of terminal users. However, these sources of information can provide inaccurate data due to errors in their experimental design, e.g. specification errors in the construction of an econometric model that quantifies the demand as a function of a set of variables.

The above explanation enables us to define the fourth specific objective: to formulate an optimization model to locate a set of intermodal terminals in a decentralized management context, based on a discrete path choice model in order to minimize the total transportation costs involved in the transport of freight and in the construction, operation and maintenance of the terminals.

Finally, our fifth specific objective concerns the design and implementation of a heuristic algorithm for getting a near-optimal solution to the intermodal terminal location problem in a decentralized management context, based on a discrete path choice model.

1.3 Outline

To achieve the objectives outlined in the previous section, a series of activities were carried out, which are detailed in the next three chapters.

In Chapter 2, we present a tool based on an optimization model for the strategic planning of the intermodal terminal network in a decentralized management context based on an all-or-nothing allocation approach, i.e. the strategy adopted incorporates the interests of both the government entity that designs the intermodal terminal network and the terminal users who decide to resort to them only if it is convenient in terms of cost. During the development of this work, the contrast between the solutions in a decentralized and centralized management context is clarified in a case study inspired by the Portuguese reality.

When solving the model proposed in Chapter 2 is was verified by several computational experiences the complexity of the problem under study in medium and large-scale instances; this leads us to the development of heuristic algorithms to solve it. A heuristic algorithm for getting near-optimal solutions to the problem under study was then developed. This approach is presented in Chapter 3 and includes an algorithmic approach for its automatic configuration which is explained in detail on that section.

The fourth and fifth specific objectives stated in the previous subsection are addressed in Chapter 4. In this chapter a mathematical model is formulated for the intermodal terminal location problem in a decentralized management context in which, unlike the model proposed in Chapter 2 where freight demand of each pair of region is allocated on the lowest cost route between them, the allocation of freight demand of each pair of region is proportionally split among all the feasible routes from origin region to destination region. The proportion of freight demand on each feasible route is characterized by a discrete path choice model. Additionally, due to the computational complexity of the proposed model, a heuristic algorithm for getting a near-optimal solution to the problem under study is developed. The performance of the heuristic algorithm is evaluated in a set of benchmark instances. In addition, the results of its application to two case studies inspired by the Iberian Peninsula and Portugal are shown.

Finally, Chapter 5 presents a summary of the conclusions obtained throughout this work as well as some directions for future research.

2 An Optimization Model for the Intermodal Terminal Location Problem under a Decentralized Management based on an All-or-nothing Allocation Approach.

2.1 Introduction

Freight transport plays an increasingly important role in the global economy, therefore attracting a great deal of attention from transport policy institutions. Amongst the main policy directions explored by these institutions to make freight transport more sustainable is intermodality (or intermodalism). According to Rodrigue (2017, Chap. 5), this is “the movements of passengers or freight from an origin to a destination relying on several modes of transportation”, when “each carrier is issuing its own ticket (passengers) or contract (freight)”. The history of intermodality started to develop fast in the 1960s, coinciding with the rise of containerization in maritime transportation (Donovan 2000). Since then, intermodality policies have been pursued virtually everywhere in the world. This is in particular the cases of the United States after the publication of the Intermodal Surface Transportation Efficiency Act in 1991 (updated in 1998), and of the European Union after the adoption of Council Directive 92/106/EEC in 1992 (whose effects were assessed in the report “Analysis of the EU Combined Transport” prepared in 2015 for the European Commission (see https://ec.europa.eu/transport/themes/logistics/studies_en).

The key facilities of an intermodal freight transport system are the intermodal terminals. These are the facilities where freight is transferred between transport modes. In addition to loading and unloading operations, intermodal terminals may offer services such as temporary storage or intermediate buffer, and even pre-delivery inspection or enhancement work on the goods being transported (Bektas 2016, Chap. 1).

The performance of an intermodal transport system depends heavily on the location and type/capacity of its intermodal terminals. In general, decisions on these issues are taken or at least controlled (through economic activity and/or land use licensing mechanisms) by a governmental entity at the national and/or local level, even if their operation may be later awarded to private concessionaires. The governmental entity is naturally expected to make these decisions in the best public interest, but needs to take into account the fact that, except perhaps in highly centralized economies, terminal users will subsequently take advantage of them or not in their operations according to their own best interest (i.e., o minimize their own terminal and transport costs). There are therefore two levels of decision (governmental entity and terminal users) impacting on the performance of the system, and we are in a decision context that, in line with Vasconcelos et al. (2011), we designate as decentralized management.

In this chapter, we propose an optimization model aimed to assist a governmental entity in the planning (or re-planning) of intermodal terminals at the network level. It is specifically developed for application to rail-road terminals, but could easily be adapted to any other types of terminals. The model allows to determine the optimal locations and types/capacities of the terminals to operate in a territory (e.g., a country or a set of countries willing to share their intermodal transport policy) in a decentralized management context, given the freight flows expected to take place between the regions of that territory in some reference planning year. The objective of the governmental entity is to minimize the (socioeconomic) costs of moving freight and installing, operating and maintaining the terminals.

The model we have developed fits into a growing body of research that has been reviewed in Caris et al. (2008) and, more recently and thoroughly, in SteadieSeifi et al. (2014), where a long section is devoted to strategic (network-level) planning problems and, more specifically, to the intermodal terminal location problem. It also fits into the research agenda suggested a few years ago by Caris et al. (2013) regarding the main decision-support problems raised by intermodal terminals. In this agenda, two specific challenges involving intermodal terminal location problems are highlighted: first, the inclusion of economies of scale in terminal handling costs; second, the connection between terminal location and service design. Both these challenges are, at least to some extent, addressed by our model.

It is important to clarify at the outset that the model we propose is not intended to return the exact location for each intermodal terminal – just the region where, in a subsequent stage, the ideal site for its placement should be looked for, considering all relevant criteria. There is also a significant body of research on the site-level evaluation of the location of intermodal terminals and related facilities (freight villages, logistic centers, etc.), predominantly based on multicriteria decision-aid methods, in some cases combined with fuzzy-set theory approaches. Examples of criteria considered at this level include the contribution to the local economy (particularly to employment), the easiness of access, the impact on the environment, the compatibility with land-use plans, and the complementarity with other policy initiatives. Some of the main references for this research are Kapros et al. (2005), Ballis and Mavrota (2006), Kayikci (2010) and Tadić et al. (2014).

The remainder of the chapter is organized as follows. In the next section, additional information is provided about rail-road terminals, their types and respective costs. Then, we describe in detail the problem at stake and provide an overview of the related modeling literature. This is followed by the presentation of the optimization model we have developed to address the problem, where we highlight the constraints required to cope with a decentralized management context. The behavior of the model is illustrated and discussed afterward, with reference to a case study inspired by the Portuguese reality. Model solving issues are examined next. In the final section of the chapter, we summarize the research done so far and indicate directions for our future work on the intermodal terminal location problem in a decentralized management context.

2.2 Rail-road Terminals

The basic service performed by rail-road terminals is the transfer of freight (bulk or loading units such as containers) between the rail and the road transport modes, but they can offer various other services. In Figure 2.1 we display the typical layout of a rail-road terminal showing the various components they may include between the road access area and the rail access area, and in Figure 2.2 we specify the services provided by intermodal rail terminals (i.e., rail-road terminals but also rail-barge-road, rail-road-sea and rail-road-barge-sea terminals). The types of service offered by these terminals are naturally related to the volumes of freight they handle and to their capacity, and these are in turn related to the costs of building, equipping, operating and maintaining the terminals.

The costs of intermodal rail terminals have been recently analyzed in detail by Wiegmans and Behdani (2017) based on the rather scarce literature available on the subject (a significant part of which is grey literature issued from European Commission projects). The analysis was conducted considering five types of terminals classified according to capacity level: XXL, XL, L, M, and S (Table 2.1). The capacity of the larger terminals (XXL) attains 500,000 TEU/year, whereas the capacity of the smaller terminals (S) is below 10,000 TEU/year (TEU, i.e., twenty-foot equivalent units, is a measure of capacity often used for container terminals). According to Christiansen et al. (2007), a 1-TEU container carries up to approximately 28 tons of cargo with a volume of up to 1,000 cubic feet. In Table 2.2, we provide information on the physical characteristics and investment costs for terminals of different capacities.

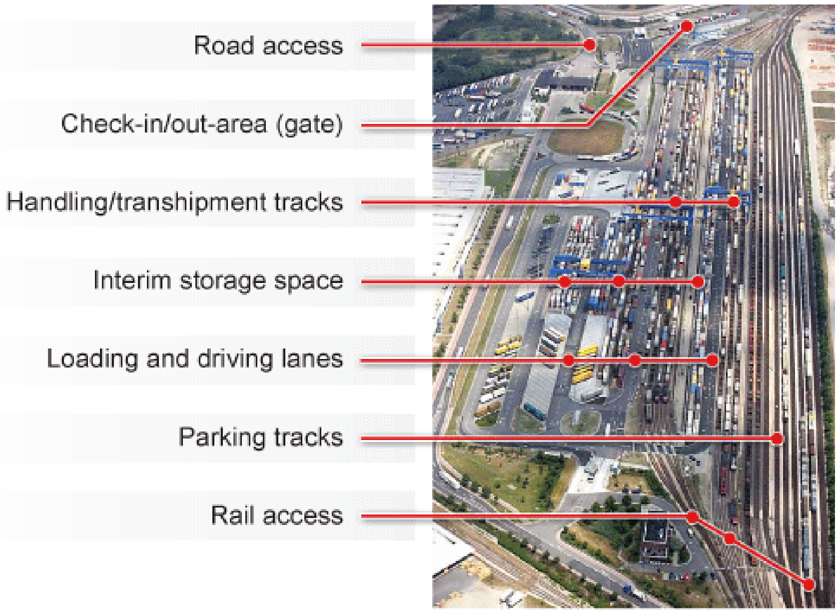


Figure 2.1 Typical layout of a rail-road terminal.

(Source: http://www.intermodal-terminals.eu/content/e15/index_eng.html)

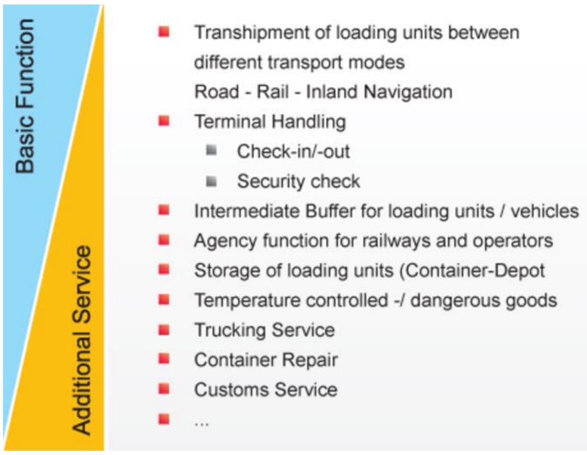


Figure 2.2 Services provided by an intermodal rail terminal.

(Source: http://www.intermodal-terminals.eu/content/e15/index_eng.html)

Table 2.1 Types of Intermodal rail terminals.

Terminal type	Capacity (10^3 TEU/year)
XXL	>500
XL	100-500
L	30-100
M	10-30
S	<10

Table 2.2 Costs of intermodal rail terminals.

Terminal type	Capacity (10^3 TEU/year)	Infrastructure (Rail tracks)	Area (ha)	Equipment costs (10^6 €)	Realization costs (10^6 €)
XXL	500	12	40	23.0	138.0
XL	100	6	10	13.0	47.0
L	30	3	6	3.0	9.5
M	20	2	4	1.5	5.5
S	10	1	4	1.0	3.5

2.3 Problem Description

The specific problem we are dealing with in this chapter considers a territory (country) divided into regions linked by a road network and a rail network, as exemplified in Figure 2.3. In this example, there are eight regions represented by the respective centroids (A, B, …, H). The road network connects all the regions, but this is not necessarily the case of the rail network. In some of the regions served by the rail network, there may be already an intermodal terminal, as it occurs with regions E and G. The other regions where the road network and the rail network intersect (B and H), or at least some of them, are possible locations for new intermodal terminals. The freight tonnages to be moved between every pair of regions, or origin-destination (OD) freight demands, are known in some reference planning year (in the sense that they were estimated with enough accuracy). A part of this freight, because of their nature, will be moved by road only, but the other part may be moved by a combination of road and rail through two intermodal terminals if this is beneficial for the companies operating in the regions. For instance, the freight to be delivered from region A to region H can be moved by road through regions B, D, and F, or it can be moved first by road to the terminal located in region E, then by rail to the terminal located in region G, and finally by road again to region H.

The problem we want to address is that of a governmental entity willing to determine the regions where new rail-road terminals should be located and which should be their type/capacity (and also, possibly, the regions where existing terminals should be closed or their type should be modified), so that the (socioeconomic) costs involved in satisfying all the demands for freight transport in the territory are minimized. Since all the demands are to be satisfied, it is reasonable to assume that the (socioeconomic) benefits from freight transport are fixed (constant), and the minimization of costs will signify the maximization of net benefits.

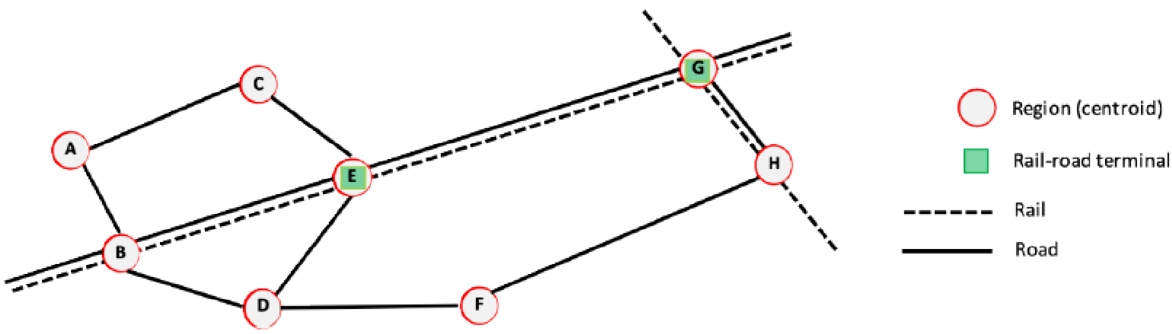


Figure 2.3 Rail-road network scheme.

The previous explanations clearly suggest that we are dealing with a hub location problem, where, obviously, the hubs are the rail-road terminals. Hub location problems can be classified according to three important criteria. One of them separates single allocation problems, i.e., each spoke (region) is allocated to one and only one hub, from multiple-allocation problems, i.e., some spokes may be allocated to more than one hub A second one distinguishes between strict hubbing, i.e., all spokes are allocated to a hub, from non-strict hubbing, i.e., some spokes are not allocated to a hub, being served directly from other regions. The third criterion refers to whether the number of hubs is predetermined (p-hub problem, where p is the number of hubs), or, alternatively, it is determined endogenously as a function of the costs of installing, operating and maintaining a hub, including the fixed costs (fixed-charge hub problem).

The problem at stake can be classified as a multiple-allocation non-strict hubbing fixed-charge hub location problem. The costs to minimize comprise both internal costs and external costs. The former are the private costs involved in the transport of freight and in the construction, operation and maintenance of the rail-road terminals. The latter correspond to the side effects of transport, i.e., global warming, air pollution, noise, accidents and congestion. In order to achieve an efficient allocation of resources, the external costs of any activities should be internalized, i.e., should be incurred by the economic agents that perform the activities (freight transport in this case), and not by the economic agents that suffer their consequences. For this to happen, governments can levy taxes on freight transport. The internalization of the external costs of transport is often a major policy concern. However, it should be noted that full internalization of external costs would normally require taxes to be different across freight transport firms, which would violate the equality principle adopted in the constitutional law(s) of virtually every country. This means that it would only be possible in a context where a governmental entity could control terminal users up to the point of imposing the transport schemes they should use (i.e., in a context of centralized management). The state-of-the-art on the external costs of freight transport and their internalization is provided in Mostert and Limbourg (2016).

The context for the problem we are dealing with is, therefore, that of decentralized management. The governmental entity defines the location and type/capacity of the new rail-road terminals (and also, possibly, the changes to make in the current terminal network) to minimize costs, but taking into account that the potential terminal users in the various regions will decide whether to resort to the terminals or not for minimizing their own costs. Since it is practically impossible to account separately for each terminal user, transport costs need to be estimated based on average transport costs per unit of freight by rail and road. The other costs that terminal users need to cope with are the fees they pay for utilizing the terminals. These fees are set by the governmental entity, and their value could also be determined endogenously to minimize costs (taking into account that these fees are paying a service, and that the service is basically the same in every terminal or, at most, may vary with the type of terminal). Alternatively, it is possible to test several different possible values for the fees, and then choose among them the ones that lead to the lowest costs.

2.4 Related Work

As stated in the previous section, intermodal terminal location problems are a special type of hub location problems. This means that the vast literature on this problem, reviewed, for instance, by Alumur and Kara (2008), Campbell and O'Kelly (2012), Farahani et al. (2013) and Contreras (2015), is, to some extent, related to our work. However, in the following, we will focus solely on the research that specifically addresses intermodal terminal location problems (Table 2.3).

This stream of research has been initiated in the turn of the XXth century with a series of three papers by Arnold and Thomas (1999) and Arnold et al. (2001, 2004). These authors dealt with the intermodal terminal location problem using two fixed-charge models: a hub location model with four-index flow decision variables (x_{jk}^{gh} is equal to 1 if flow from origin j to destination k is sent through hubs g and h in this order, and is equal to zero otherwise); and, to circumvent the difficulties they were facing to handle the huge number of decision variables of the former model, an uncapacitated multi-commodity minimum cost network flow model with three-index decision variables (x_{jk}^{e} is equal to 1 if the itinerary for hauling the commodity from origin j to destination k contains arc e, and is equal to zero otherwise). However, even when the latter model was used, these authors could only tackle an application to the Iberian Peninsula, involving the location of 13 new intermodal terminals (to complement the current network of 15) through a greedy algorithm.

Table 2.3 Related work on intermodal terminal location problems.

Paper	Formal optimization model	Model formulation: Includes fixed costs	Includes capacity constraints	Applies to decentralized management context	Solution method	Model application(s) (number of possible new terminals)
Arnold et al. (1999)	Yes	Yes	Yes	No	No	No
Arnold et al. (2001)	Yes	Yes	Yes	No	Exact	Belgium (12)
Arnold et al. (2004)	Yes	No	No	No	Heuristic	Iberian Peninsula (13)
Limbourg et al. (2009)	Yes	No	No	No	Heuristic	Europe (84)
Ishfaq et al. (2011)	Yes	Yes	No	No	Tabu Search	Randomly-generated
Vasconcelos et al. (2011)	Yes	Yes	No	Yes	Exact	Brazil (3)
Sörensen et al. (2012)	Yes	Yes	Yes	No	GRASP	Randomly-generated
Sörensen et al. (2013)	Yes	Yes	Yes	No	GRASP	Randomly-generated
Lin et al. (2014)	Yes	Yes	Yes	No	Heuristic	Randomly-generated
Santos et al. (2015)	Yes	No	No	No	Exact	Belgium (35)
Zhang et al. (2015)	No	Yes	No	Yes	Genetic Algorithm	The Netherlands (42)
Lin et al. (2016)	Yes	Yes	Yes	No	Heuristic	Randomly-generated

Several authors who have dealt recently with the intermodal terminal location problem based their work on the hub location model proposed by Arnold et al. (2001). Sörensen et al. (2012) focused on the exact same model and presented two metaheuristics to solve it: a GRASP algorithm and an attribute-based hill climbing algorithm, in both cases complemented with a greedy (add-and-remove) algorithm. These algorithms were tested on a computational study involving 100 randomly-generated instances of $10 \times n$ ($n = 1, \dots, 10$) demand centers and possible intermodal terminal locations. The conclusion was that both metaheuristics performed at the same level and, in small instances for which it was possible to find the optimal solutions, generally quite well. However, in the worst cases, the metaheuristics missed the optimal solution value by over 20%, which is far from being reasonable. The GRASP algorithm was later adapted by Sorensen and Vanovermeire (2013) to handle a bi-objective hub location model where the objective of terminal operators (minimize terminal costs) was separated from the objective of terminal users (minimize transport costs). Lin et al. (2014) proposed an enhanced formulation of the Sorensen et al. (2012) model and two simple matheuristics to solve it. The results they have obtained for the same instances clearly outperformed their previous results with respect to solution quality and computational effort. More recently, Lin and Lin (2016), addressed the same problem through a new matheuristic within which the selection of terminals and the routing of transport flows are carried out in separate stages. This approach enabled a substantial decrease in the number of decision variables considered in Lin et al. (2014) and a reduction of computation time by approximately 50% while keeping solution quality at the same level.

Along the same line of research, it is also worth mentioning the works of Ishfaq and Cox (2010) and Santos et al. (2015), both dealing with problems somewhat more involved than those tackled by Arnold et al. (2001). The former authors represented their problem with a model based on four-index flow decision variables, and focused, above all, in solution methods. In particular, they proposed a tabu search metaheuristic that performed well in randomly-generated instances of up to 30 possible terminal locations (coincident with demand centers). Santos et al. (2015) is, to the best of our knowledge, the first paper where an intermodal terminal location problem is formulated with three-index flow decision variables similar to the ones first proposed by Ernst and Krishnamoorthy (1998) and to the ones we use in our model (see Section 2.5). Hub location models with these types of variables are typically solved much faster than with four-index variables. In Santos et al. (2015), the application of the model is exemplified for a real-world setting, Belgium, considering two transport modes (road and rail) and 35 possible terminal locations. Finally, we should mention here a recent article by Ghane-Ezabadi and Vergara (2016), where a new formulation for the intermodal terminal location problem is proposed. Using a decomposition-based search algorithm, these authors were able to solve randomly-generated instances of the problem involving the location of 4 terminals in 30 possible locations (in around 20 minutes).

A feature common to the models dealt with in the papers mentioned above (and several others) is that they apply to a centralized management context. The only authors who have developed an optimization model for an intermodal terminal location problem in a decentralized management context are Vasconcelos et al. (2011). The problem they have tackled is uncapacitated (i.e., it does not take into consideration terminal types/capacities), and the model they formulated relies on a questionable assumption (i.e., firms send their freight either by road only or through pre-defined intermodal road-barge terminals). The application of this model is illustrated with an application to Brazil (12 terminals, 9 of which already in place). Other authors that proposed approaches applicable to a decentralized management context are Limbourg and Jourquin (2009) and Zhang et al. (2013, 2015). However, in both cases, the problems they have addressed were not formulated as optimization models, and were tackled through heuristics (hill-climbing and genetic algorithms, respectively). Hence, the quality of the solutions found could not be properly assessed (against the global optimum solutions).

2.5 Optimization Model

The optimization model we have developed for the problem described in Section 2.3 combines a model applicable to a centralized management context with additional constraints accounting for the decentralized management context. The model and the additional constraints are presented below in separate subsections.

2.5.1 Centralized Management

In the formulation of the optimization model for the intermodal terminal location problem under centralized management, we will use the following notation:

Indices

i- intermodal terminal type

j, k, g, h -region

Sets

$\boldsymbol{N} = \{1, 2, 3, \dots, |N|\}$ - set of regions;

$\boldsymbol{I} = \{1, 2, 3, \dots, |I|\}$ - set of intermodal terminal types.

Parameters

$q_{jk} \geq 0$ - freight tonnage originated in region j to move to region k (TEU/year);

$q_j^{tot} \geq 0$ - total freight tonnage to be moved from region j (TEU/year);

c_{jk}^{ro}/c_{jk}^{ra}[2] ≥ 0 - generalized transport cost by road/rail between regions j and k, considering the time involved in loading and unloading operations. (€/TEU/km);

$d_{jk}^{ro}/d_{jk}^{ra} \geq 0$ - travel distance by road/rail between regions j and k (km);

$z_{min}^{i}/z_{\max}^{i} \geq 0$ - minimum/maximum capacity (or utilization of capacity) for a terminal of type i (TEU/year);

$cf_i \geq 0$ - discounted installation and operation costs for a terminal of type i (€/year);

$a_g^i = 1$ if a terminal of type i can be installed in region g (the road and rail networks need to intersect in this region), otherwise $a_g^i = 0$.

Decision variables

$y_g^i = 1$ if a terminal of type i is located at region g, otherwise $y_g^i = 0$;

$u_{jg}^i \geq 0$ - proportion of the freight tonnage originated in region j moved to a terminal of type i located in region g (see Figure 2.4);

$w_{jgh}^i \geq 0$ - proportion of the freight tonnage originated in region j moved to a terminal of type i located in region h through a terminal located in region g;

$v_{jhk} \geq 0$ - proportion of the freight tonnage originated in region j moved to region k through a terminal located in region h;

$x_{jk} \geq 0$ - proportion of the freight tonnage originated in region j moved directly (by road) to region k;

$z_g^i \geq 0$ - flow handled in a terminal of type i located in region g.

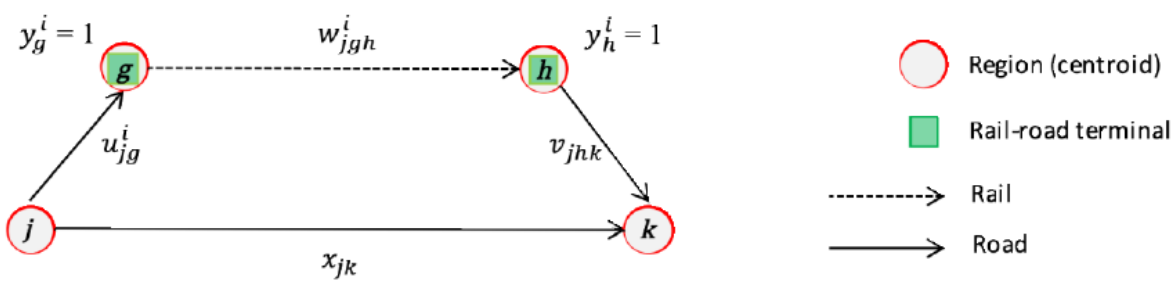


Figure 2.4 Location and flow decision variables

[2] The ratio of unitary cost by rail to unitary cost by road reflects economies of scale in the intermodal transport.

Using the notation, the optimization model consists of the following objective function and constraints.

Objective function

The objective function (1) of the model represents the total annual costs to be minimized. It comprises five terms. The first one expresses the costs of moving freight by road directly to their destination. The second, third and fourth term describe the transport costs of sending the freight through the intermodal terminals in the three stages of the trip: from the origin to the first terminal, by road; between terminals, by rail; and from the second terminal to the destination, again by road. Finally, the fifth term expresses the intermodal terminal costs. These costs comprise the annual-equivalent installation costs (applicable only in the case of new terminals) and the annual operation and maintenance costs, which are assumed to be fixed for each type of terminal.

$$\begin{aligned}\min C = & \sum_{j \in N} \sum_{k \in N} c_{jk}^{ro} d_{jk}^{ro} q_j^{tot} x_{jk} + \sum_{j \in N} \sum_{i \in I} \sum_{g \in N} c_{jg}^{ro} d_{jg}^{ro} q_j^{tot} u_{jg}^i + \\ & + \sum_{j \in N} \sum_{i \in I} \sum_{g \in N} \sum_{h \in N} c_{gh}^{ra} d_{gh}^{ra} q_j^{tot} w_{jgh}^i + \sum_{j \in N} \sum_{h \in N} \sum_{k \in N} c_{hk}^{ro} q_j^{tot} d_{hk}^{ro} v_{jhk} \\ & + \sum_{g \in N} \sum_{i \in I} cf_i y_g^i \end{aligned} \tag{1}$$

Constraints

We will start by the constraints aimed to ensure that freight demands are satisfied, and then move to the constraints that guarantee the continuity of freight flows. Next, we focus on the constraints representing the location of intermodal terminals and, finally, on the capacity constraints.

The demand satisfaction constraints included in the model are of two kinds. Constraints (2) ensure that all the freight originated in a given region , *j*, will be sent to the destination regions either directly by road (sum of x_{jk} for every region *k*) or through a first intermodal terminal (sum of $u_{jg}^i$for every terminal g of type *i*), whereas constraints (3) guarantee that they will arrive to the right region, *k*, through a second terminal, h (v_{jhk}) , by road (x_{jk}).

$$\sum_{g\in N}\sum_{i\in I} u_{jg}^{i} + \sum_{k\in N} x_{jk} = 1, \forall j \in \boldsymbol{N} \tag{2}$$

$$\sum_{h\in N} v_{jhk} + x_{jk} = \frac{q_{jk}}{q_j^{tot}}, \forall j,k \in \boldsymbol{N} \tag{3}$$

The continuity constraints included in the model are also of two kinds: constraints (4) guarantee that the freight arriving to an intermodal terminal located in g either coming from a region j (u_{jg}^{i}) or from another terminal h (w_{jhg}^{i}) is the same that leaves that terminal either to another terminal (w_{jgh}^{i}) or to its destination region k (v_{jgk}); constraints (5) guarantee that the freight arriving to an intermodal terminal located in g from a region j must be sent to another terminal h.

$$\sum_{i\in I} u_{jg}^{i} + \sum_{h\in N}\sum_{i\in I} w_{jhg}^{i} = \sum_{h\in N}\sum_{i\in I} w_{jgh}^{i} + \sum_{k\in N} v_{jgk}, \forall j,g \in \boldsymbol{N} \tag{4}$$

$$\sum_{i\in I} u_{jg}^{i} = \sum_{h\in N: h\neq g,}\sum_{i\in I} w_{jgh}^{i} \quad \forall j,g \in \boldsymbol{N} \tag{5}$$

The following constraints (6 to 10) define the terminal locations. Constraints (6) specify that there can be at most one intermodal terminal in each region, of one of the possible terminal types. Constraints (7) specify the regions where terminals may be installed (e.g., regions where the road and rail network intersect). If this is the case, then $a_g^i = 1$ and only one of the binary variables representing the location of a terminal, y_g^i, can be equal to 1. Otherwise, $a_g^i = 0$ and $y_g^i = 0$ for every terminal type i. The remaining constraints of this kind relate intermodal terminal locations with freight flows. Constraints (8) guarantee that freight will not be sent from a region j to an intermodal terminal g that does not exist (i.e., the sum of y_g^i is equal to zero), forcing every u_{jg}^i to be zero. If, instead, a terminal exists, then, at most, all the freight originating in that region will be sent through that terminal. Constraints (9) play a similar role with respect to the freight sent to region k from a terminal located at h. Likewise, constraints (10) ensure that freight can only be moved to a terminal in a given region, h, if a terminal operates in that region.

$$\sum_{i \in I} y_g^i \leq 1, \forall g \in \boldsymbol{N}, \tag{6}$$

$$y_g^i \leq a_g^i, \forall g \in \boldsymbol{N}, i \in \boldsymbol{I} \tag{7}$$

$$\sum_{i \in \boldsymbol{I}} u_{jg}^i \leq \sum_{i \in \boldsymbol{I}} y_g^i \,, \forall j, g \in \boldsymbol{N}, \tag{8}$$

$$\sum_{j \in \boldsymbol{N}} v_{jhk} \leq \sum_{i \in \boldsymbol{I}} y_h^i \,, \forall\, h, k \in \boldsymbol{N} \tag{9}$$

$$w_{jgh}^i \leq y_h^i, \quad \forall\, j, g, h \in N \quad i \in I \tag{10}$$

The capacity constraints specify the maximum and minimum freight tonnage that can be handled by an intermodal terminal. The freight tonnage handled by an intermodal terminal g is given by constraints (11), where the freight coming directly to g from the different regions (sum of $q_j^{tot} u_{jg}^i$) is added to the freight coming to g through other terminals (sum of $q_j^{tot} w_{jhg}^i$). Constraints (12) and (13) ensure that this quantity is within pre-defined limits (z_{max}^i and z_{min}^i) that depend on the terminal type i.

$$z_g^i = \sum_{j \in N} q_j^{tot} u_{jg}^i + \sum_{h \in N} \sum_{j \in N} q_j^{tot} w_{jhg}^i \,, \forall g \in \boldsymbol{N}, \forall i \in \boldsymbol{I} \tag{11}$$

$$z_g^i \leq z_{max}^i y_g^i, \forall g \in \boldsymbol{N}, \forall i \in \boldsymbol{I} \tag{12}$$

$$z_g^i \geq z_{min}^i y_g^i, \forall g \in \boldsymbol{N}, \forall i \in \boldsymbol{I} \tag{13}$$

Finally, constraints (14) and (15) represent the domain of the variables.

$$z_g^i, x_{jk}, w_{jgh}^i, v_{jhk}, u_{jg}^i \geq 0, \forall j, g, h, k \in N, \forall i \in I \tag{14}$$

$$y_g^i \in \{0, 1\}, \forall\, g \in N, \forall i \in I \tag{15}$$

2.5.2 Decentralized Management

The model presented in the previous subsection is valid in a centralized management context, and, in particular, when a governmental entity decides not only on the location and capacity of intermodal terminals, but also on how these facilities should be used to minimize total (socioeconomic) terminal and transport costs. In a context of decentralized management, it is necessary to augment the previous model with constraints guaranteeing that the decisions on the use of terminals are made by the companies that move freight to minimize their own transport costs. The new parameters, decision variables and constraints to include in the model are as follows.

Parameters

$p \geq 0$ -terminal usage flat rate (€/TEU);

Decision variables

$r_{jkgh} = 1$ if the freight tonnage originated in region *j* is moved to region *k* through terminals located in regions g and h, otherwise $r_{jkgh} = 0$

$s_{jk} \geq 0$ -minimum transport cost for moving freight between regions *j* and *k* (€/TEU).

Constraints:

$$r_{jkjj} + \sum_{g \in N} \sum_{h \in N: h \neq g} r_{jkgh} = 1 \ , \forall j, k \in \boldsymbol{N} \tag{16}$$

$$s_{jk} = \min c_{jk}^{ro} d_{jk}^{ro} r_{jkjj} + \sum_{g \in N} \sum_{h \in N: h \neq g} \left(c_{jg}^{ro} d_{jg}^{ro} + c_{gh}^{ra} d_{gh}^{ra} + c_{hk}^{ro} d_{hk}^{ro} + 2p \right) r_{jkgh} \quad \forall j, k \in \boldsymbol{N} \tag{17}$$

Constraints (16) specify that only one route will be used to move freight between regions, either by road only ($r_{jkjj} = 1$) or through intermodal terminals (one of the binary variables $r_{jkgh} = 1, h \neq g$) and constraints (17) ensure that this route is the least-cost route. Note that, if intermodal terminals are included in the route, then companies will have to pay their use. We assume this payment is made twice (first, when the freight enters the rail network and, second, when it leaves it), and consists in a flat rate, p, per unit of freight tonnage.

The latter constraints (17) are nonlinear, but can be replaced by linear constraints (thus making the model in principle easier to solve). These constraints and the additional decision variables that need to be considered in their formulation are presented below.

Decision variables

$u'_{jg} = 1$ if the freight tonnage originated in region *j* is sent to a terminal located in region *g*, otherwise $u'_{jg} = 0$

$w'_{jgh} = 1$ if the freight tonnage originated in region *j* is sent from a terminal located in region *g* to a terminal located in region *h*, otherwise $w'_{jgh} = 0$

$v'_{jhk} = 1$ if the freight tonnage originated in region *j* is sent from a terminal located in region *h* to region *k*, otherwise $v'_{jhk} = 0$

s'_{jkgh} cost of a route between regions *j* and *k* passing through terminals located in regions *g* and *h*

Constraints:

Two new sets of constraints have to be included in the model to replace constraints (17): the first set identifies the segments included in the least-cost routes between any pair of regions, and the second set computes the costs for making such routes.

We start by the first set:

$$x_{jk} \leq r_{jkjj} \leq \frac{q_j^{tot}}{q_{jk}} x_{jk} \quad \forall j, k \in N \tag{18}$$

$$\sum_{i \in I} u_{jg}^i \leq u'_{jg} \leq q_j^{tot} \sum_{i \in I} u_{jg}^i, \forall j, g \in N \tag{19}$$

$$\sum_{i \in I} w_{jgh}^i \leq w'_{jgh} \leq q_j^{tot} \sum_{i \in I} w_{jgh}^i, \qquad \forall j, g, h \in N \tag{20}$$

$$v_{jgk} \leq v'_{jgk} \leq \frac{q_j^{tot}}{q_{jk}} v_{jgk}, \quad \forall j, g, k \in N \tag{21}$$

$$r_{jkgh} \geq -2 + u'_{jg} + w'_{jgh} + v'_{jhk}, \quad \forall j, k, h, g \in N: g \neq h \tag{22}$$

$$3r_{jkgh} \leq u'_{jg} + w'_{jgh} + v'_{jhk}, \quad \forall j, k, h, g \in N: g \neq h \tag{23}$$

Constraints (18) indicate whether the freight originated in a given region j is moved by road directly to some other region k. Indeed, if $x_{jk} > 0$ then $r_{jkjj} = 1$ (else, if $x_{jk} = 0$ then $r_{jkjj} = 0$). The other constraints in this set apply when freight is moved by road and rail, that is, when intermodal terminals (g and h) are used. Constraints (19) define the first segment of the least-cost route, as $u'_{jg} = 1$ if and only if $\sum_{i \in I} u^i_{jg} > 0$. Constraints (20) and (21) play the same role with respect to the second and third segments, setting the value of variables w'_{jgh} and v'_{jhk}. Finally, constraints (22) and (23) link route information with segment information, since, considered together, they ensure that $r_{jkgh} = 1$ only if $u'_{jg} = w'_{jgh} = v'_{jhk} = 1$

The set of constraints that computes transport costs is as follows:

$$s'_{jkjj} = c^{ro}_{jk} d^{ro}_{jk}, \qquad \forall j,k \in N \tag{24}$$

$$s'_{jkgh} = \left(c^{ro}_{jg} d^{ro}_{jg} + c^{ra}_{gh} d^{ra}_{gh} + c^{ro}_{hk} d^{ro}_{hk} + 2p\right) + \left(2 - \sum_{i \in I} y^i_g - \sum_{i \in I} y^i_h\right) M, \quad \forall j,k,g,h \in N \tag{25}$$

$$s_{jk} \leq s'_{jkjj}, \forall j,k \in N \tag{26}$$

$$s_{jk} \leq s'_{jkgh}, \forall j,k,g,h \in N: g \neq h \tag{27}$$

$$s_{jk} = c^{ro}_{jk} d^{ro}_{jk} r_{jkjj} + \sum_{g \in N} \sum_{h \in N: h \neq g} \left(c^{ro}_{jg} d^{ro}_{jg} + c^{ra}_{gh} d^{ra}_{gh} + c^{ro}_{hk} d^{ro}_{hk} + 2p\right) r_{jkgh} \tag{28}$$

Constraints (24) compute transport costs when freight is moved by road only between any pair of regions, j and k, and constraints (25) do the same when it is moved by road and rail. The costs for routes passing through regions where intermodal terminals are not located must be such that they are never chosen (this can be achieved by setting$M > c^{ro}_{jk} d^{ro}_{jk}$, even if only slightly). Constraints (26) and (27) guarantee that the least-cost routes will be selected for any pair of regions, and constraints (28) compute the value of the transport costs (including the usage flat rate paid in the intermodal terminals if road and rail are used).

Finally, the following constraints represent the domain of the variables

$$s'_{jkgh}, s_{jk} \geq 0, \quad \forall j,k,h,g \in N \tag{29}$$

$$r_{jkgh}, u'_{jg}, w'_{jgh}, v'_{jhk} \in \{0,1\}, \forall j,k,h,g \in N \tag{30}$$

2.6 Case Study

The results obtained through the application of the optimization model presented in the previous section are explained and discussed below for a case study inspired by the Portuguese reality. The study was carried out based on the 23 NUTS 3 regions of (mainland) Portugal (Figure 2.5). NUTS are territorial units of three hierarchical levels set up in the European Union in 2003 for statistical and policy purposes; see https://ec.europa.eu/eurostat/web/nuts/background. NUTS 3 correspond to a level of geographic detail that may be deemed too low for studying intermodal terminal location in a true real-world study. However, this level of detail is very convenient for illustrating the behavior of the proposed model – and the main focus of this chapter is the model, not the case study. The NUTS 3 regions of Portugal are represented in Figure 2.5. In the following subsections, we describe the case study data, and explain and discuss the results obtained through the optimization model. Information on model solving issues is provided in the next section.

2.6.1 Study Data

The application of the optimization model requires the following types of data: (1) locations and types of existing rail-road terminals, as well as of possible new terminals; (2) configuration of the rail and road networks; (3) freight tonnage for each pair of regions; (4) generalized transport costs by rail and road for each pair of regions; (5) intermodal terminal costs, usage fees and freight operation ranges for the different types of terminals.

Figure 2.5 NUTS 3 of mainland Portugal

In contrast to some parts of Central Europe where rail-road terminals are numerous, in Portugal there are only five such facilities. Four of these terminals are located next to the country's largest ports, also handling maritime freight (Figure 2.6, middle): Lisbon, of type XL; Leixões (Oporto), of type L; and Aveiro and Sines (Alentejo Litoral), both of type M. The only existing inland terminal is located at Guarda (Beira e Serra da Estrela), next to the main motorway (A25) and the main rail line (Linha da Beira Alta) connecting Portugal to Spain and the rest of Europe, being also of type M.

The possible locations for new terminals we have considered in our study, of the same three types (XL, L and M), were the other 16 NUTS 3 regions served simultaneously by the road and rail networks (i.e., all regions except the two that are not connected to the rail network – Alto Tâmega and Trás-os-Montes). Following a massive investment program in road infrastructure undertaken between 1985 and 2016 with a strong support from the European Union, Portugal is now provided with a dense network of good-quality motorways and fast two-way highways that provide easy access even to the remotest parts of the country. In contrast, the rail infrastructure received little attention in the same period, and several lines have been closed. Line closures affected essentially the inland regions, which are now served poorly by the rail network or are not served at all. The coastal regions are better served, but the lines that connect them are rather congested, and priority is given to passenger traffic to the detriment of freight transport. Schemes of the rail and road networks are also provided in Figure 2.6 (left and right).

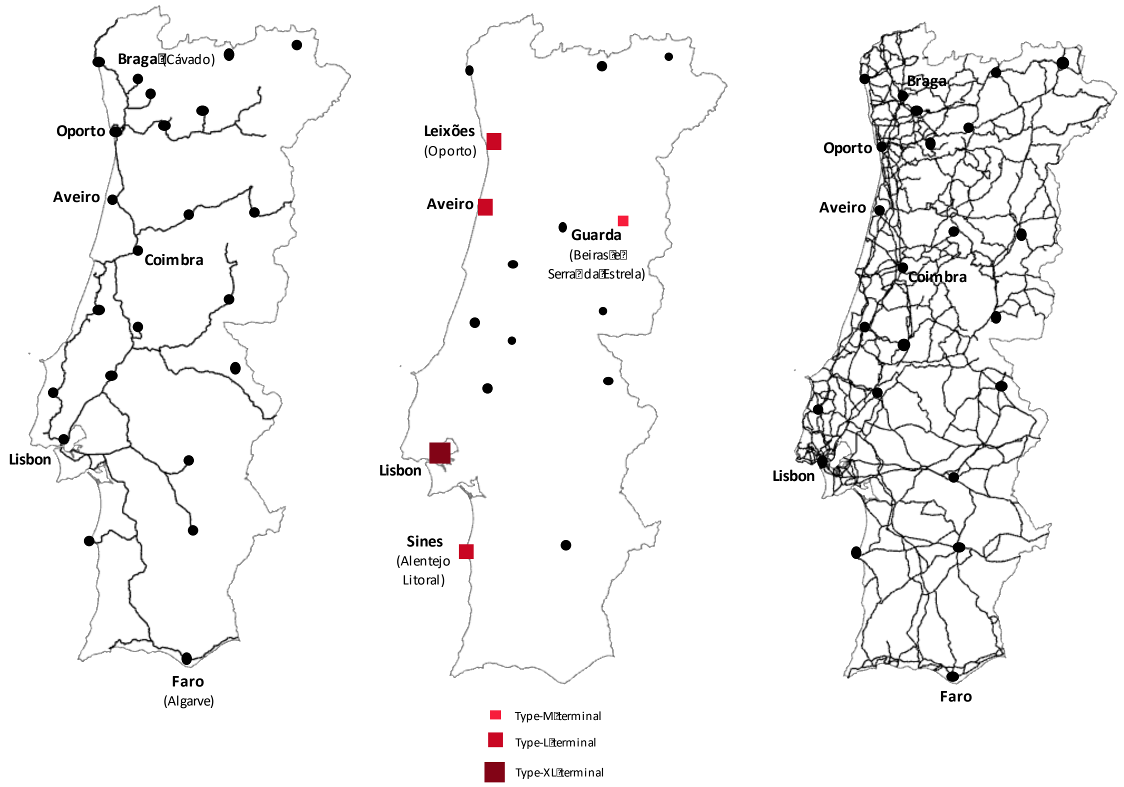


Figure 2.6 **Rail network (left), existing rail-road intermodal terminals (middle), and road network (right) of Portugal.**

The freight tonnages were estimated based on information published by INE, the Portuguese statistics bureau, for the year 2014. According to this information, in that year a total of approximately 130 million tons of freight were moved by rail and road in (mainland) Portugal. Since INE only provides information for the freight tonnages moved between the five NUTS 2 regions (Norte, Centro, Lisboa, Alentejo and Algarve), we had to extrapolate their values for the NUTS 3 regions. This was done assuming that the freight tonnages moved between the NUTS 2 regions were distributed across NUTS 3 regions proportionally to the products of the populations of these regions. We also assumed that 80% of the total freight was captive of the road mode, and only the remaining 20% could be distributed across the two modes (this is, approximately, the share of the rail mode in France, where a dense network of rail-road terminals is available). It should be noted that, according to our calculations, only around 3% of the total freight tonnages generated by the NUTS 3 regions was moved through the rail network, which may be partly explained by the lack of rail-road terminals affecting the country. We would have liked to make these extrapolations in a more sophisticated manner (see, e.g., Chow et al. 2010 and Tavasszy et al. 2012), but this would have been worthless because our results could not be validated (or invalidated) with the data we had available. In favor of our results, it should be said that the freight tonnages we have obtained are certainly not implausible for people acquainted with freight transport in Portugal.

The generalized transport costs were calculated by multiplying an average cost per unit of distance (km) dependent on the transport mode by the distances measured for that mode on the transport network. The computation of accurate generalized transport costs can be a difficult task, as shown, e.g., in Janic (2007), Hanssen et al. (2012) and Mostert and Limbourg (2017). For our case study, we have used values for the average unit transport costs based on the work of Bína et al. (2014): 3.6 €/TEU/km for road transport, and 2.0 €/TEU/km (57% lower) for rail transport. These values were assumed to capture both internal and external costs.

The intermodal terminal costs were obtained based on Wiegmans and Behdani (2017). For type-M terminals, the annual fixed costs (annual-equivalent installation costs plus operation and maintenance costs) were taken to be 0.62×10^6 €/year. These terminals were assumed to operate an annual freight tonnage in the range [12.36, 30] TEU/year. The minimum of these two values was obtained so that the profits generated by any terminal would be non-negative assuming a usage flat rate of 50 €/TEU. For type L terminals, the same costs were 3.06×10^6 €/year, and the freight operation range was [61.15, 100] TEU/year, and for type XL terminals they were 8.98×10^6 €/year and [179.54, 500] TEU/year. The annual-equivalent installation costs were determined assuming a discount rate of 5%/year and a useful lifetime of the terminals of 30 years.

2.6.2 Study Results

The results for our case study were obtained in two stages. In the first, we applied the optimization model to what we called the reference scenario – i.e., the scenario defined by the data described in the previous subsection. In particular, we examined the impact of the management context (centralized vs. decentralized) on the model (optimal) solutions. The second stage consisted in a sensitivity analysis of the solutions to changes in the most uncertain parameters, i.e., freight demand and transport costs. Obviously, the applicability of the results presented below needs to be taken with caution due to the data limitations we have recognized above. A true real-world study would undoubtedly require more accurate data.

2.6.2.1 **Reference Scenario**

We will start by presenting and analyzing the global results of the application of the model (e.g., number and location of new intermodal terminals), and then move to more detailed results (e.g., transport cost changes across NUTS 3 regions if model solutions were implemented).

Our results are summarized in Figure 2.7 and Table 2.4. There we provide information on the number and types of intermodal terminals to operate, on the freight tonnage to move by rail and road (TEU and TEU×km) and on the respective transport costs, both for the current terminal network (if operated according to our optimization model) and for the optimal terminal network in a centralized and a decentralized management context.

Overall, the most striking result is that the changes to the current network would be much larger in a centralized management context than in a decentralized one; that is, the management context has a prominent influence on the solution to implement. Indeed, in a centralized context, new terminals should be installed in every region served by the rail network where a terminal does not exist at present. This means that 16 new terminals should be built, being 7 of type L and 9 of type M. In contrast, in a decentralized context, the number of terminals to build would sharply decrease to just 6, being 2 of type L (located in Alentejo Central and Douro) and 4 of type M (in Algarve, Ave, Cávado and Oeste).

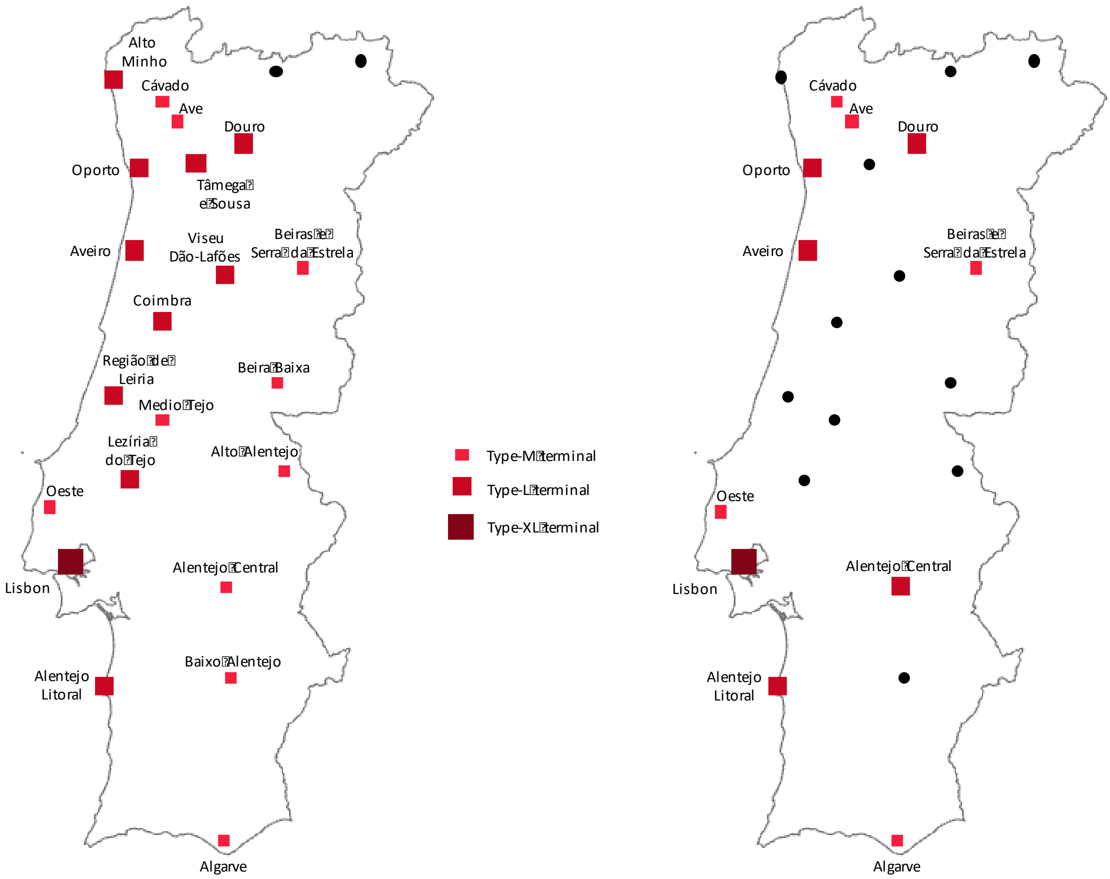


Figure 2.7 Optimal location and type of intermodal terminals under centralized management (left) and under decentralized management (right).

Table 2.4 Main features of the current and optimal intermodal terminal networks.

Solution features		Intermodal terminal network		
		Decentralized management		Centralized management
		Current	Optimal	Optimal
Number of new terminals	XL	-	0	0
	L	-	2	7
	M	-	4	9
Freight tonnage (10^6TEU/year)	Intermodal	0.137 (3.2%)	0.281 (6.6%)	0.67 (15.8%)
	Road-only	4.103	3.959	3.570
Freight tonnage × km (10^6TEU×km/year)	Rail	38.4 (5.0%)	68.24 (8.8%)	115.10 (14.8%)
	Road	734.67	709.27	661.85
Annual-equivalent terminal investment costs (10^6 €/year)		-	8.58	26.96
Total terminal revenues (10^6 €/year)		13.66	28.12	66.97
Total terminal and transport costs (10^9 €/year)		2.722	2.698	2.632

Other important results concern the mode shares and the costs. At present, and as shown in Table 2.4, if the current terminals were operated optimally in a decentralized management context, only 3.2% of the freight tonnage would be moved by rail (note that this percentage is calculated considering also the freight taken as captive of the road mode). This would signify a mode share of 5.0% for rail in terms of TEU× km. Through the construction and operation of new terminals, these percentages could increase to 6.6% and 8.8% respectively. In a centralized management context, they would be much higher, i.e., 15.8% and 14.8%. With respect to total costs (terminal and transport), the impact of the changes would not be impressive in terms of percentages, because the main origins and destinations of freight are already served by terminals. However, in absolute terms, the savings would be very significant: 24 or 90 million € annually, depending on the management context being decentralized or centralized.

Moving now to a more detailed analysis of results and focusing on the decentralized management context, we next discuss how freight transport costs would change across NUT 3 regions if the current intermodal terminal network were replaced by the optimal network. This is shown in Table 2.5. The regions that would benefit the most from the changes are Algarve (with cost savings of 5.02%), Alentejo Central (3.66%) and Douro (3.06%), i.e., as could be expected, regions where new terminals would be located. However, it should be noted that transport costs would decrease less in some of these regions than in regions that would not receive new terminals; for instance, the savings for Oeste (0.96%) would be clearly lower than those for Alto Alentejo (2.04%). This shows that benefits are not necessarily concentrated in the regions of the new terminals, being instead distributed across regions according to an irregular geographical pattern. In this case, the configuration of the rail and road networks dictates that the lowest cost savings (of only 0.25%) are made by the regions of Beiras e Serra da Estrela and Viseu Dão-Lafões, both situated in the deprived off-coast areas of central Portugal.

To finalize this subsection, we will now look into the freight tonnage that the different intermodal terminals would handle in a decentralized management context, and into the freight transport operations to perform based on these terminals.

Information on freight handling is provided in Table 2.6. It can be seen there that, if the optimal network were implemented, then the existing terminals would generally operate at least the same freight tonnage as they do in the current network. The exception is the terminal of Oporto, where the tonnage would decrease slightly, from 67.4×10^3 to 65.3×10^3 TEU/year (-3.1%). In contrast, in Alentejo Litoral, it would increase sharply, from 34.6×10^3 to 53.0×10^3 TEU/year (+53.2%). It can also be seen in the same table that all terminals would be operated at a level compatible with their types/capacities. In particular, this signifies that they would all be profitable (i.e., revenues would exceed costs in every terminal).

Table 2.5 Freight transport costs of NUTS 3 before and after the implementation of the optimal intermodal terminal network under decentralized management.

Region	Transport costs (10^6 €/year)		Transport cost savings (%)
	Current network	Optimal network under decentralized management	
Alentejo Central	103.7	99.9	3.66
Alentejo Litoral	171.7	169.3	1.40
Algarve	27.9	26.5	5.02
Alto Alentejo	112.7	110.4	2.04
Alto Minho	104.7	103.8	0.86
Alto Tâmega	92.5	91.5	1.08
Ave	83.0	82.0	1.20
Aveiro	130.2	129.2	0.77
Baixo Alentejo	136.0	135.5	0.37
Beira Baixa	153.2	152.7	0.33
Beira e Serra da Estrela	121.9	121.6	0.25
Cávado	85.4	83.9	1.76
Coimbra	109.0	108.6	0.37
Douro	84.9	82.3	3.06
Leiria	133.0	131.9	0.83
Lezíria do Tejo	85.5	85.0	0.58
Lisbon	315.8	311.3	1.42
Médio Tejo	110.8	110.3	0.45
Oeste	135.9	134.6	0.96
Oporto	95.6	93.7	1.99
Tâmega e Sousa	64.3	64.1	0.31
Tras-os-Montes	146.1	144.3	1.23
Viseu Dão-Lafões	117.8	117.5	0.25
Portugal	2721.6	2689.9	1.16

Table 2.6 Freight handled by the intermodal terminals.

Region	Current network		Optimal network under decentralized management	
	Terminal type	Freight handled (10^3TEU/year)	Terminal type	Freight handled (10^3TEU/year)
Alentejo Central	-	-	L	65.3
Alentejo Litoral	L	34.6	L	53.0
Algarve	-	-	M	14.5
Ave	-	-	M	24.8
Aveiro	L	45.8	L	76.0
Beira e Serra da Estrela	M	25.5	M	25.5
Cávado	-	-	M	23.9
Douro	-	-	L	79.3
Lisbon	XL	99.9	XL	110.8
Oeste	-	-	M	23.9
Oporto	L	67.4	L	65.3

The freight transport operations to perform are exemplified for the Douro region, where a new type-L terminal would be installed. As shown in Figure 2.8, the freight generated in this region would be delivered to the other regions either by road only or through a combination of road and rail (thus through the new Douro terminal). As could be expected, road (only) would be used for moving freight to close regions without terminal such as Tâmega e Sousa, Alto Tâmega and (the not so close) Beira Baixa. Freight would also be moved by road to the Beiras e Serra da Estrela region, despite there is a terminal, because the rail connection is poor. Freight transport to the majority of regions would be made through the Douro terminal. This is particularly the case of the more distant regions regardless of whether there is or would be a terminal (as in Lisbon, Alentejo Central, Alentejo Litoral and Algarve) or not (as in Baixo Alentejo). The optimal routes for the freight generated in the Douro region that is moved by a combination of rail and road to regions without terminal are displayed in Figure 2.9. Most of this freight would first be hauled by rail to the terminal of Aveiro and then by road to the destinations (Coimbra, Leiria, Médio Tejo, Lezíria do Tejo and Alto Alentejo). The only regions that would be served through other terminals are Alto Minho and Baixo Alentejo, for which the intermediate terminals would be Oporto and Alentejo Central, respectively. It should be noted that, given the location and capacity of the terminals in the optimal network, these routes would be, in every case, the least cost ones connecting the Douro region to the other regions (as we are considering the management context to be decentralized).

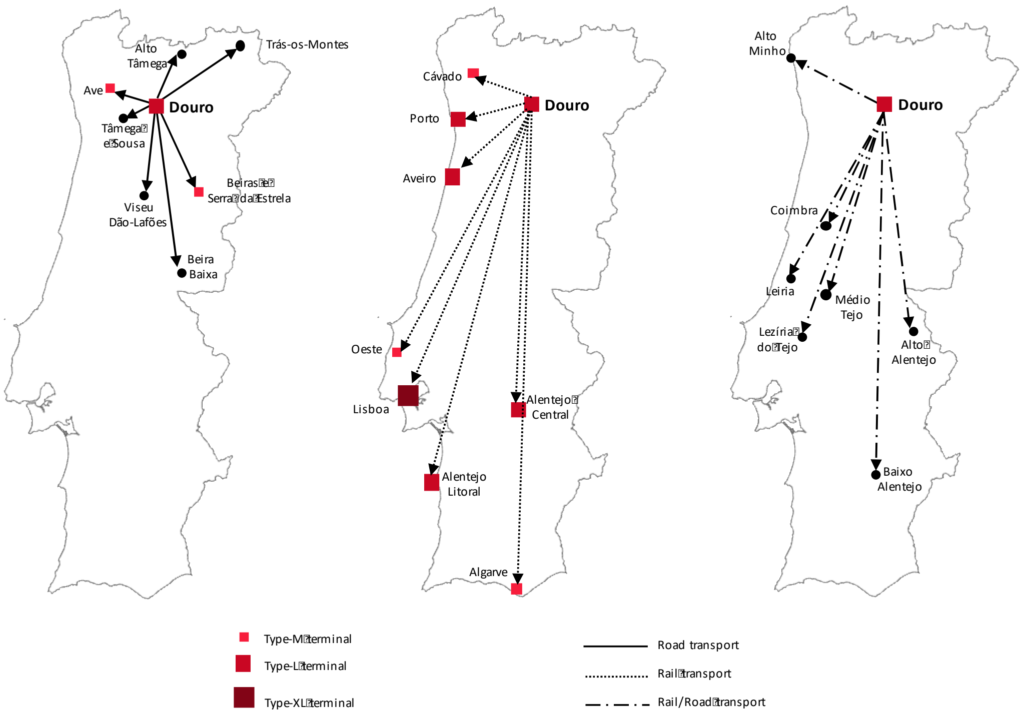


Figure 2.8 Optimal transport modes to use in the delivery of freight generated in the Douro region: road (left), rail (middle) and combination of both modes (right).

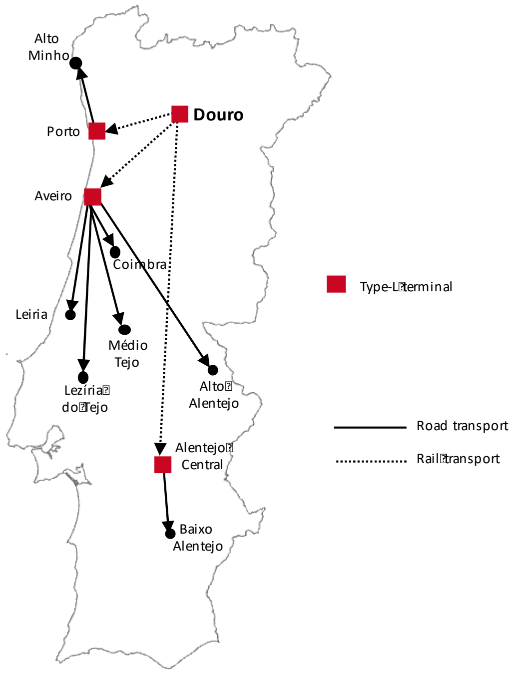


Figure 2.9 Optimal routes to deliver freight generated in the Douro region when both rail and road are used as transport modes.

2.6.2.2 **Sensitivity Analysis**

In the analysis performed to understand the sensitivity of the solutions provided by the model to changes in freight demand and transport costs in a decentralized management context, we considered the following six scenarios (as alternatives to the reference scenario):

- S1 - Increase of freight demand by 20% (in every region)
- S2 - Decrease of freight demand by 20% (in every region)
- S3 - Increase of rail unit costs by 20%
- S4 - Decrease of rail unit costs by 20%
- S5 - Increase of road unit costs by 20%
- S6 - Decrease of road unit costs by 20%

The results obtained for these scenarios are summarized in Table 2.7. It can be seen there that, as could be expected, the increase of freight demand (Scenario S1) would lead to an optimal solution characterized by an increase in the number and capacity of terminals. This increase would be very significant: 10 new terminals against only 6 in the reference scenario (9 of which of type L instead of just 2). Accordingly, the share of freight tonnage to be moved through the intermodal terminals would more than double (from 6.6% to 13.6%). What we did not expected was that the optimal solution for the decrease of freight demand (S2) would also involve the increase in the number and capacity of terminals (7 new terminals, 4 of which of type L) and the increase of the intermodal mode share. But this was not the only surprising result. Indeed, we have found out that the optimal solution if rail unit costs were higher (S3) would also be characterized by a larger share of intermodal transport (thus, of rail) than in the reference scenario (7.2% against 6.6%), though naturally not as large as when rail unit costs decrease (S4). The more normal results we got were observed when the road transport unit costs increased (S5) and decreased (S6), as, in these scenarios, the share of freight tonnage handled through the intermodal terminals would, respectively, increase (to 14.6%) and decrease (to 5.9%, i.e., slightly). It should be noted that, also in these scenarios, the number and capacity of terminals should be larger than in the optimal solution for the reference scenario. This is explained by the fact that a decentralized management is considered, and we have included in the model constraints guaranteeing that the decisions on the use of terminals are made by the companies that move freight to minimize their own transport costs.

Table 2.7 Sensitivity of optimal solutions to variations in freight demand and transport costs in a decentralized management context.

Solution features		Reference	Freight demand		Rail transport unit costs		Road transport unit costs	
			S1	S2	S3	S4	S5	S6
			+20%	-20%	+20%	-20%	+20%	-20%
Number of new terminals	XL	0	0	0	0	0	0	0
	L	2	9	4	3	11	10	2
	M	4	1	3	8	0	1	8
Freight tonnage (10^6TEU/year)	Intermodal	0.281 (6.6%)	0.608 (12.0%)	0.345 (10.2%)	0.307 (7.2%)	0.614 (14.5%)	0.619 (14.6%)	0.250 (5.9%)
	Road only	3.959	4.479	3.047	3.933	3.626	3.621	3.990
Total terminal and transport costs (10^9€/year)		2.698	3.190	2.141	2.703	2.605	3.122	2.175

The complex pattern of the variations in optimal solutions can be perceived well in Table 2.8. It shows the impact of changes in rail transport unit costs between -20% and +20% of the reference value (2.0 €/TEU/km) with steps of 5%. When these costs decrease, nothing strange happens. The rail modal share increases steadily, from 6.6% to 9.9% when the unit costs decrease by 5% and to 10.2% when they decrease by 10%, reaching 14.5% when the decrease is 20%. At the same time, the total costs (terminal and transport) decrease, also steadily, from 2.698 to 2.605×10^9 €/year (i.e., around 3.4%). However, when the rail transport unit costs increase, the change of the rail modal share is very irregular: it decreases to 6.4% when the increase of unit costs is 5%, but when this increase is 10%, counterintuitively, it increases to 8.9%; then, it increases even more, to 10.0%, when the unit costs are 15% higher than the reference value, before decreasing to 7.2% when they are 20% higher. This irregularity is also observed with respect to the total costs, which are higher for the reference value of the rail unit costs than when these costs are 10% and 15% higher (reaching 2.684 and 2.687×10^9 €/year, respectively)..

Table 2.8 Sensitivity of optimal solutions to changes in rail transport unit costs in a decentralized management context.

Solution features		Variation in rail transport unit costs								
		-20%	-15%	-10%	-5%	0%	5%	10%	15%	20%
Number of new terminals	XL	0	0	0	0	0	0	0	0	0
	L	11	8	5	5	2	2	4	5	3
	M	0	2	2	2	4	3	6	7	8
Freight tonnage (10^6TEU/year)	Intermodal	0.614 (14.5%)	0.534 (12.6%)	0.431 (10.2%)	0.418 (9.9%)	0.281 (6.6%)	0.269 (6.4%)	0.376 (8.9%)	0.422 (10.0%)	0.307 (7.2%)
	Road only	3.626	3.706	3.809	3.822	3.959	3.97	3.864	3.817	3.933
Total terminal and transport costs (10^9€/year)		2.605	2.627	2.655	2.666	2.698	2.704	2.684	2.687	2.703

Overall, these results clearly indicate that the interplay between the constraints included in the model – in particular, the capacity constraints and the decentralized management constraints – leads to changes in the optimal solutions that are extremely difficult to anticipate.

In order to understand the reasons why optimal solutions vary sometimes in a surprising manner, we have performed a detailed analysis of such solutions when the rail transport unit costs increase by 5% and 10% with respect to their reference value of 2.0 €/TEU/km (all else being as in the reference scenario).

First, we will consider the case of a 5% increase in rail transport unit costs (Δc^{ra} = 5%). As shown in Table 2.9, the optimal solution obtained for the reference scenario (e.g., considering the existing terminal network) would be feasible in this scenario. Naturally, its total costs would be higher than in the reference scenario (2.707 vs. 2.698×10^9 €/year). However, it has been possible to find a better solution by replacing the terminals of Alentejo Central, Algarve and Oeste by terminals in Alto Alentejo and Lezíria do Tejo. In these conditions, the freight processed in the Douro terminal and sent to the terminals replaced would be sent instead to the terminal of Lezíria do Tejo and then distributed from there by road to its destinations. Additionally, the freight to the Alto Alentejo region would be sent directly there by rail, and not by a combination of rail and road (through the terminal of Aveiro). Together, these changes would make the total costs to increase to 2.704×10^9 €/year, that is, a little less than if the terminals were kept in the same locations.

We now move to the more interesting case of a 10% increase in rail transport unit costs (Δc^{ra} = 10%). In this case, the optimal solution obtained for the reference scenario would not be feasible, since the terminals in Alentejo Central, Douro and Oeste would operate below the minimum capacity (see Table 2.9). This is normal because of the increase in transport costs. However, at the same time, and more importantly, this increase would make it possible to open some terminals that otherwise would operate above the maximum capacity for the respective type. The significant increase in the number of terminals, both of type L (from 5 to 7) and of type M (also from 5 to 7), is due to this reason, as we confirmed by verifying that this solution would not be feasible in the conditions of the reference scenario – the maximum capacity of the terminals in Alto

Alentejo and Tâmega e Sousa would be exceeded. The end result of these contradictory effects – increase in rail transport unit costs leading to a decrease in the use of rail transport and increase in the number and capacity of terminals leading to an increase in the use of rail transport – is that, altogether, they favor rail transport (whose modal share would increase from 6.6% to 8.2%) and make total costs lower (2.684×10^9 €/year instead of 2.698×10^9 €/year).

Table 2.9 Optimal terminal network in the reference scenario and if rail transport unit costs increase by 5% and 10%.

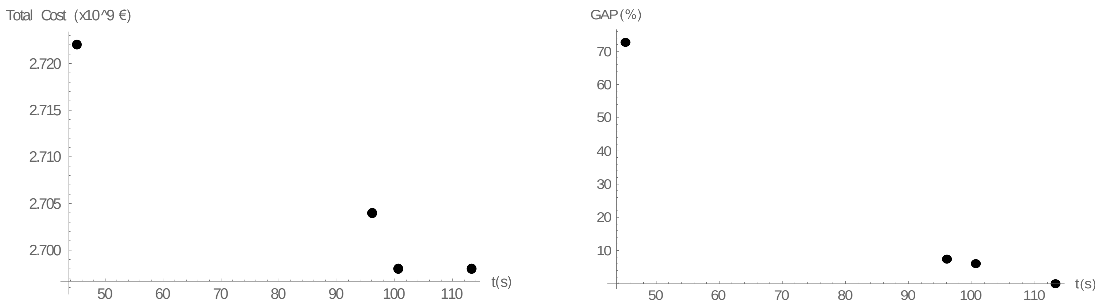
Region		Optimal terminal network						
	Reference scenario				Increase of rail transport unit costs (Δc^{ro})			
					5%		10%	
	Type	Capacity (10^3 TEU/year)	Freight handled Δc^{ro}=5%	Freight handled Δc^{ro}=10%	Type	Capacity (10^3 TEU/year)	Type	Capacity (10^3 TEU/year)
Alentejo Central	L	65.3	60.7	60.3*	-	-	-	-
Alentejo Litoral	L	53	50.8	50.8	L	56.6	L	48.1
Algarve	M	14.5	12.8	12.8	-	-	M	12.8
Alto Alentejo	-	-	-	-	M	29.7	M	24.5
Ave	M	24.8	24.8	23.7	M	25.5	-	-
Aveiro	L	76	73.1	78	L	71.6	L	48.7
Beira Baixa	-	-	-	-	-	-	M	28.9
Beira e Serra da Estrela	M	25.5	24.6	24.6	M	25.6	M	27.4
Cávado	M	23.9	23.9	16.6	M	23.9	M	17.9
Coimbra	-	-	-	-	-	-	L	80.9
Douro	L	79.3	70.1	51.3*	L	71.3	-	-
Leiria	-	-	-	-	-	-	L	99.1
Lezíria do Tejo	-	-	-	-	L	71.4	L	62.7
Lisbon	XL	110.8	110.8	111.2	XL	104.5	XL	137.9
Oeste	M	23.9	20.1	9.3*	-	-	M	23.4
Oporto	L	65.3	56.7	47.4	L	58.6	L	37
Tâmega e Sousa	-	-	-	-	-	-	M	29.6
Viseu Dão-Lafões	-	-	-	-	-	-	L	73.5
Freight tonnage (10^6TEU/year)	Intermodal	0.281 (6.6%)				0.269 (6.4%)		0.349 (8.2%)
	Road only	3.959				3.971		3.863
Total terminal and transport costs (10^9€/year)		2.698	2.707			2.704		2.684

* infeasible values

2.7 Model Solving

The various instances of the proposed optimization model dealt with in the case study presented in the previous section were implemented in the GAMS modeling language (version 24.0.2) and handled through the ILOG CPLEX optimization solver (version 12.5.0.0) on a computer equipped with an Intel Core i7-5500U 2,66 Ghz processor and 8 GB of RAM.

Owing to the extraordinary advances of (integer linear) optimization in the last decades (see, e.g., Lodi 2010), the model was solved relatively quickly even when the decision context was decentralized. In fact, the computation time required to run each instance was always inferior to 3 minutes. The evolution of the solution value and optimality gap over time in the reference scenario is depicted in Figure 2.10.



2.10 Evolution of the solution value (left) and optimality gap (right) over time in the reference scenario.

Since the problem we have tackled involved only 16 locations for installing possible new terminals, we have carried out a computational study to investigate how the computational effort would vary as a function of problem size. For this, we have used randomly-generated instances defined for rectangle-shaped territories divided into a given number the regions. The size of the territories and the location of the centroids of the regions were chosen at random (provided that the straight-line distance between them was at least 50 km), as well as the GDPs of the regions. Both the size and the GDP of the regions were chosen to follow the same probabilistic distributions as the size and GDP of the NUTS 3 regions of the European Union. Each region (centroid) was assumed to be connected to all other regions by straight-line road and rail segments. The freight tonnage to move between each pair of regions was assumed to be proportional to the product of their GDP and inversely proportional to the straight-line distance between them (i.e., freight demands were calculated according to a unconstrained gravity-type model). The terminal costs and usage rate, the rail and road transport unit costs, and the terminal types and capacity limits were the same as those considered in the reference scenario of the case study presented in the previous section.

In Table 2.10, we present the results of the application of our model to instances of 15, 20, 25, 30, 35 and 40 regions, considering 5 different (randomly-generated) territories in each case. For each instance, we have allowed a maximum computation time of three hours (180 minutes).

Table 2.10 **Results of the computational study.**

Instance size (number of regions)	Centralized management						Decentralized management					
	Computation time (minutes)			Optimality gap (%)			Computation time (minutes)			Optimality gap (%)		
	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
15	< 1	< 1	< 1	0	0	0	35	71	149	0	0	0
20	< 1	2	7	0	0	0	15	136	> 180	0	12.7	21.9
25	< 1	1	2	0	0	0	> 180	> 180	> 180	24.7	25.7	27.6
30	< 1	5	13	0	0	0	> 180	> 180	> 180	25.1	27.5	29.2
35	< 1	77	> 180	0	0.3	0.8	> 180	> 180	> 180	31.2	31.7	32.5
40	< 1	73	> 180	0	0.5	1.3	> 180	> 180	> 180	32.2	33.4	34.5

Three main conclusions may be drawn from the analysis of Table 2.10, all of them aligned with our expectations. The first is that the instances of our case study were solved much faster than randomly-generated instances of (approximately) the same size (maximum of 3 minutes against minimum of 35 minutes). We were not very surprised by this finding because, according to our experience with other models, it is frequent that, when problems have a geographic nature, real-world instances are easier to solve than randomly-generated instances. Another conclusion is that instances defined for a decentralized management context are substantially more difficult to solve than those defined for a centralized management context. For example, the computation time required to solve 15-region instances in the latter context has always been inferior to 1 minute, whereas it has always exceeded 35 minutes in the former. Moreover, in a decentralized management context, it has never been possible to solve to exact optimality any instance of 25 regions or more, and after three hours of computations the optimality gap was still considerable (34.5% in the worst case). In contrast, in a centralized management context, all instances of 30 regions or less were solved to exact optimality in 13 minutes at most, and, for larger instances, the optimality gap after three hours was 1.3% at most. Finally, the third conclusion is that the computational effort tends to increase quickly with instance size. This is clear in a centralized management context, as 15-region instances always took less than one minute to solve, whereas 40-region instances (those which could be solved in three hours) took on average 73 minutes. In a decentralized management context, the increase in computational effort can only be assessed through the optimality gap, which was 0% in the 15-region instances and 12.7% on average in the 20-region instances, and reached 33.4% on average in the 40-region instances. This certainly indicates that computation times grow fast with instance size also in this context.

In these conditions, it is quite obvious that, particularly when the management context is decentralized, instances of our model not much larger than the ones we have dealt with in the case study may be difficult (if not impossible) to handle through the ILOG CPLEX optimization solver (and probably any other). This signifies that, for larger instances, faster solution methods will have to be devised, including, e.g., metaheuristic methods.

2.8 Conclusion

In this chapter, we have proposed a new optimization model aimed to assist a governmental entity in the planning or re-planning of intermodal terminals at the network level with the objective of minimizing the total (socioeconomic) terminal and transport costs. The model allows to determine the optimal locations and types/capacities of the terminals to operate in a territory in a decentralized management context, given the freight demands expected to take place between its regions in some reference planning year. In such context, the governmental entity decides the location and type/capacity of the terminals, but does not control their utilization i.e., terminal users patronize them or not according to their own best interests. Though, our focus in the chapter was placed on rail-road terminal networks, the model can be easily adapted to accommodate any other types of terminals.

The behavior of the model was illustrated and discussed for a case study inspired by the Portuguese reality. The results we have obtained in this study clearly show the influence of the decision context: under decentralized management, the optimal terminal network would involve a much smaller number of terminals than under centralized management (i.e., if the governmental entity could fully control the utilization of the terminals to minimize terminal and transport costs). It should be emphasized here that some of the results we have obtained were rather surprising. For example, we have shown that, under a decentralized management context, an increase in rail transport unit costs may lead to an increase in the optimal number and capacity of terminals, as well as to an increase in the rail modal share, as the decisions on the use of terminals are made by the companies that move freight to minimize their own transport costs.

The case study included in the chapter, inspired by the Portuguese reality, demonstrates well the usefulness of the proposed optimization model. In this case, we could solve the model quite fast using ILOG CPLEX even when the management context was decentralized because only 16 regions were considered as possible locations of new terminals (of three types). However, a computational study clearly revealed that larger instances of our model, like the ones corresponding to mainland Spain (47 NUTS 3 regions) or France (94), would certainly be impossible to handle without resorting to faster solution methods. Consequently, one of the directions of our future work on intermodal terminal location problems will be the development of a metaheuristic method (namely, an evolutionary algorithm) for solving our model.

Another direction we intend to pursue in the future relates to what we recognize to be a limitation of our model, i.e., the assumption that, in a decentralized management context, all freight generated in a region is sent to the other regions through the least-cost route. It is obviously highly unlikely that this happens, and it would definitely be more realistic to assume that routes (and modes) are chosen according to the principle that the less costly is a route, the lower is the probability that this route is chosen. Logit functions are the ones typically used in transport studies to represent this principle. However, they are nonlinear, and therefore the inclusion of such functions in the proposed optimization model will make it more complex and more difficult to solve. The adaption of the metaheuristic we aim to develop for our model may be an idea to explore in this regard.

The third direction we expect to follow in our future research relates to the consideration of uncertainty in freight demand. Indeed, instead of planning the intermodal terminal network for the freight demands expected to take place in some reference planning year, it would certainly be more accurate to decide on the location and type/capacity of terminals taking into account possible scenarios for the evolution of these demands and their respective probabilities. Once again, this would make the proposed optimization model more complex and difficult to solve. Would the gains in optimal solutions justify the additional complexity? This is an important question that we will try to answer through our research.

3 Hybrid Genetic Algorithm for Intermodal Terminal Location Problem in a Decentralized Management Context, based on an All-or-nothing Allocation.

3.1 Introduction

Heuristic algorithms have been implemented in several decision problems, usually when the mathematical formulations cannot get the optimal solution in reasonable computation times (in a few cases it is impossible to get the optimal solution). Evolutionary algorithms or heuristics based on a local search procedure (e.g. GRASP, Iterated local search, etc.) are among the algorithmic approaches used for getting near-optimal solutions to large-scale decision problem. An example of these problems is the location of intermodal terminals in a decentralized context based on an all-or-nothing approach, which was analyzed in detail in the previous chapter.

The intermodal terminal location problem can be categorized as a variant of the classic hub location problem. The difference is that both direct freight shipment between regions and multiple allocations to a hub (intermodal terminal) from a non-hub are allowed. Also, intermodal terminals have a limited capacity operation (which depends on the installed infrastructure) and setup costs so that the number of terminals is not a constraint (Chang-Chun et al. 2016). The algorithmic complexity of the intermodal terminal location problem (Sörensen et al. 2012) leads us to design and implement of heuristic algorithms to determine near-optimal solutions for the problem in question.

Generally, in the design of heuristic algorithms a set of parameters are introduced. Some of these parameters have the function of enabling the execution of certain procedures in the algorithm. The performance of the heuristic algorithm in some instances depends largely on the parameter settings. One strategy for the parameter tuning process is to do it manually. However, this process can take a lot of time/effort.

In this chapter, we propose a hybrid algorithm for getting near-optimal solutions to the intermodal location problem in the context of a decentralized management based on an all-or-nothing allocation approach. Additionally, due to the computational complexity of the parameter tuning process, we propose a non-parametrized algorithm for the automatic configuration of the hybrid algorithm.

The remainder of this chapter is organized as follows: next, we describe the problem to be addressed and a review of related works in this research line. The literature review covers the algorithmic approach used to obtain near-optimal solutions to the hub location problem and the algorithm configuration problem. After that, we detail the proposed hybrid algorithm for getting near-optimal solutions for the problem addressed in chapter 2 and the algorithmic approach for its configuration. This is followed by a presentation of the computational results of the hybrid algorithm used in a hypothetical case study inspired by the Portuguese reality and in a set of benchmark instances in order to evaluate the efficiency and effectiveness of the proposed heuristics. In the final section of the chapter, we summarize the research done so far and indicate directions for our future work on the intermodal terminal location problem in a decentralized management context.

3.2 Problem Description

A weakness of formulating a mathematical model to determine the optimal location of the terminals under a management decentralized context based on all-or-nothing allocation approach which was analyzed on the chapter 2 is that it is possible solves only small-scale instances. In fact, the extensive computational experiences carried out in the previous chapter (see section 2.7) have evidenced the need of providing a suitable algorithmic approach to determine near-optimal solutions in reasonable computation times for large-scale instances related to the problem in question. Most of these approaches are focused on implementing algorithms based on metaheuristic or heuristics. Thus, one of the objectives of this work is to design a heuristic algorithm to obtain near-optimal solutions for large-scale instances related to the problem described on chapter 2.

However, certain algorithms could depend on a set of parameters which directly affect their performance in terms of the quality and robustness of the results and computational effort. For instance, the performance of genetic algorithms depends on a set of parameters such as mutation rate and crossover rate, among others. Another example is the case of tabu search, whose performance depends on the size of the tabu list, the tabu tenure, among others. The parameter tuning process aims to assign values to the parameters in order to optimize the performance of an algorithm. However, the performance of the algorithm does not depend only on the parameter values but on the analyzed instance, too.

Figure 3.1 shows the performance of a hypothetical parametrized algorithm as a function of an instance and a real parameter. The number of instances analyzed by the hypothetical parametrized algorithm is 1000 and the parameter domain are the real numbers between 0 and 100.

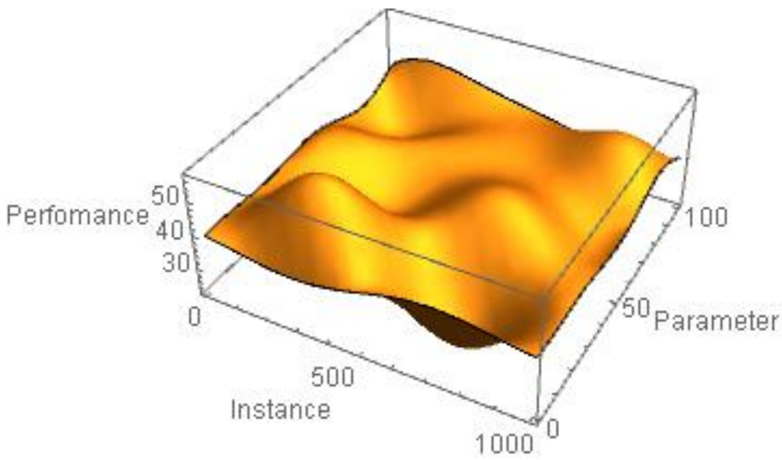


Figure 3.1 Performance of an algorithm as a function of an instance and a parameter value

As can be seen, the performance of the hypothetical algorithm has multiple local optimal, which occur only for one instance and one parameter value. For instance, Figure 3.2 shows that the red areas have the highest performance. However, this performance is only possible if it is executed in instances numbered approximately from 100 to 250, and the parameter takes values approximately between 10 and 25. On the other hand, it can be observed that if the value of the parameter is set to approximately 40, the performance of the algorithm is adequate in the most of instances analyzed (green color).

One strategy to configure an algorithm is to do it manually. However, this manual process entails an excessive amount of time, to some extent due to the number of instances analyzed and the number of parameters, and their type (real, discrete). Thus, due to the high computational complexity of this process, we aimed to automate it by a non-parameterized algorithm that provides a parameter setting which would be suitable for a large number of instances.

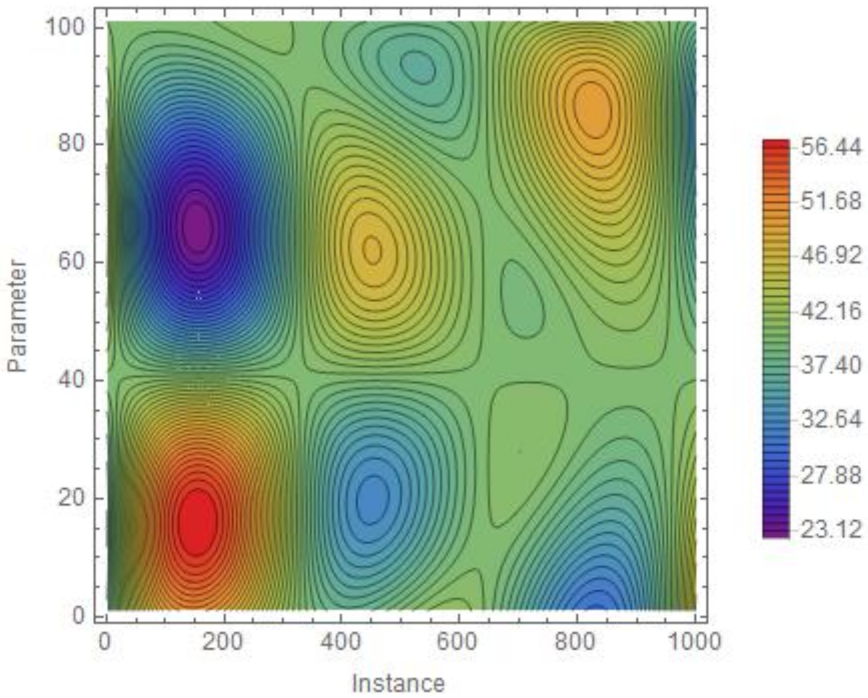


Figure 3.2 Contour plot of the performance function shown in Figure 3.1

3.3 Related Work

As said before the hub location is an NP-HARD problem (Sörensen et al. 2012) and its exact solution, as showed in the previous chapter is quite hard to reach. Consequently the solution of real-world cases by exact methods is limited to small-scale instances.

Therefore, and accounting for the aim of this chapter, in this literature review we analyze the algorithmic strategies based on heuristics or metaheuristics that have been explored to find near-optimal solutions to the hub location problem at a reasonable computational cost.

One approach in the search for feasible solutions to the hub location problem is through constructive heuristics. These heuristics begin from the trivial solution, i.e. no hub is open, and the state of a hub (chosen by some criterion) is changed iteratively. This process is performed until the exploration of all non-open hubs is completed. For instance, Sörensen et al. (2012) applied this strategy based on a GRASP algorithm. Their criterion of selection is the ratio between the fixed installation cost and the capacity of a terminal.

Another approach is based on a local search procedure, which operates from an initial solution. In this strategy, the "neighborhood" of a current feasible solution is explored in order to find a solution that improves the current solution. Various strategies have been considered to generate the neighborhood of a current solution. A strategy consists of changing the operation state of a hub (open or closed) (Sörensen et al. (2012)). Another strategy consists of exchanging the state of operation between two terminals (Hoff et al. (2017)).

The hub location problem has been also solved using tabu search. These incorporate some memory structures into the local search procedure which avoid the problem of becoming stuck in a local optimum by exploring appropriate regions in the solution space (intensification) and/or studying other unexplored regions in the solution space (diversification). Most of these works do not consider the capacity of the terminals to be a constraint. Abyazi-Sani et al. (2011), for example, proposes an algorithm based on tabu search, where the initial solution is built by a constructive heuristic. They generate the neighborhood of a solution by switching the hub status. Each movement, i.e. the last status (opened or closed) of a terminal, is stored in a fixed size list (tabu list or short-term memory) which prevents cycling. Also, they used a long-term memory to explore other regions. A similar strategy is used by Sun M. (2006). He includes a medium-term memory as a resource for the intensification process by establishing the relative frequency in which a terminal remains opened (or closed) which likely means the terminal must be opened (or closed).

Some works based on evolutionary algorithms have been exploited in facility location problems. Generally, in these algorithms a chromosome (solution) is represented by an array where each position in the array represents a gene. Also, the content of each gene (position in the array) represents the hub assigned to it (Damgacioglu et al. (2015), Topcuoglu et al. (2005), Stanojević et al. (2015)). Regarding the fitness function of a chromosome, this depends on constraints embedded in the problem. For instance, Damgacioglu et al. (2015) define the fitness function as the reciprocal of total transportation cost, i.e., lower transportation cost implies greater fitness because they are dealing with an uncapacitated hub location problem. Lin C., (2012) take a similar approach. In contrast, Stanimirović (2010) assigns a value 0 to fitness function of a chromosome if it does not meet capacity constraint. Otherwise, evolutionary algorithms integrate procedures such as mutation and crossover. The crossover operator combines the genetic information between two chromosomes (solutions). In some works, the exchange depends on constraints embedded in the model. For instance, Kratica J. et al. (2011) apply a “standard one-point crossover operator” in a location problem where the number of facilities is not a constraint. In that strategy, a reference point is randomly selected and the genetic information is exchanged from that reference point. Cunha C. et al. (2007) describe an alternative strategy by defining two reference points. Stanimirović (2010), however, defines a particular crossover operator in order to prevent offspring fail to meet a fixed number of opened terminals. Otherwise, in all the works analyzed in this research line, the usual mutation procedure consists of changing the genetic information on a randomly selected gene, i.e., if a hub is opened, then the mutation procedure would close it. An extensive review of the literature on evolutionary algorithms and tabu search for solving the hub location problem can be found in Zanjirani R. et al. (2013).

Other authors have contributed in this area by designing heuristics whose approach consists of dividing the problem into two stages. Generally, the first stage is to solve the terminal location problem by ignoring terminal capacity constraints and the second stage is to allocate the demand flows to the terminal network generated in the previous stage. For instance, Ebery et al. (2000) propose an algorithm based on the strategy described above. In the first stage they solve the uncapacitated hub location problem by means of a shortest path algorithm proposed by Ernst et al. (1998). In the second stage, an iterative procedure allocates flow to network until a feasible solution is found. In addition to that process, a local search procedure is applied to any solution by swapping the assigned hubs in each pair of nodes. Using this approach, Lin et al. (2012) apply a linear relaxation to the binary constraints corresponding to the state of the terminals (open and closed) in the first stage. In the second stage, the freight flows are assigned from the non-hub nodes to hubs, provided that the hubs are opened. Since the solutions of the first stage may not be feasible, i.e., the variable that characterizes the state of a terminal takes values between 0 and 1, the status of some of these variables is fixed randomly and it is returned to the first stage. This process is performed iteratively until some feasible solution is obtained. A similar approach is applied in Lin et al. (2014).

On the other hand, near-optimal solutions for some optimization problems are obtained from algorithms that result from blending two or more heuristic or metaheuristic. For instance, to blend a local search procedure and a genetic algorithm have a lot of advantage such as the improvement in the quality of the solutions and the speed of convergence of the algorithm (El-Mihoub et al. (2006), Grosan et al. (2007), Meenu et al. (2014)).

In this research line, Ernst et al. (1999) implement a hybrid algorithm based on simulated annealing and random descent applied to a postal delivery network. In many cases, a complementary algorithm is a local search procedure (Sörensen et al. (2012)).

A weakness of heuristics is that there is no certainty about the quality of the solutions found. Some authors (He et al. (2015), Ishfaq et al. (2011), Lin et al. (2012), Contreras et al. (2011)) have designed hybrid algorithms that combine a heuristic algorithm and relaxations. The objective of this approach is to compare the solutions obtained by heuristics with those obtained by relaxation of the original problem and to use it as a stop criterion. One of most used relaxations is Lagrangian relaxation.

The great majority of the algorithms described above depend on parameters which must be adjusted in order to optimize the algorithm performance on a specific instance. Generally, this parameter tuning process is carried out at hand, partially exploring the space of parameter configuration by trial and error (which spend excessive computational time). Several methods have been evaluated to tackle this problem automatically (Hutter et al. 2009), but it depends on type parameter to be adjusted (discrete-value and real-value,). A few methods include heuristics such as iterated local search or evolutionary algorithms (Freisleben et al. 1993, Terashima-Marín et al. 1999, Hutter et al. 2007, Hutter et al. 2009), or statistical methods (Gratch et al. 1992, Greiner 1996, Coy et al. 2001, Ramos et al. 2005, Hoos et al 2011, López-Ibañez et al. 2016) in the automatic algorithm configuration.

In this work and taking into account the strengths of implementing a hybrid algorithm. we propose a hybrid heuristic which embeds a genetic algorithm and a local search procedure to achieve a near-optimal solution for the problem described in Section 2.3. To evaluate the performance of the proposed algorithm, we generated a benchmark instance set that, to some extent, characterizes inter-regional trade in Europe. However, since the hybrid heuristic is a parameterized algorithm and the benchmark instance set is diverse, we propose an algorithm based on an iterated local search for getting a suitable parameter configuration.

3.4 Hybrid Genetic Algorithm

Genetic algorithms are metaheuristics inspired by the theory of evolution that use concepts such as natural selection, reproduction, and mutation (Holland, 1992). Genetic algorithms reproduce the evolution of a set (population) of individuals (chromosomes) that interact (crossover) to generate offspring which retain certain characteristics of their parents. During this process of reproduction some unexpected changes (mutation) may occur in the genes of individuals.

Several components have been incorporated into the genetic algorithm to improve its efficiency and effectiveness in the search for solutions to complex problems, which has given rise to several variants. In this research, a local search process is incorporated into the genetic algorithm to determine near-optimal solutions for the intermodal terminals location problem under a decentralized management described in Section 2.3. In Figure 3.3 the pseudo code of the proposed hybrid genetic algorithm (HGA) is shown.

Algorithm 1: Hybrid genetic algorithm (HGA) for the intermodal terminal location problem

---

Input: An instance $\iota \in \mathrm{I}$ (I: benchmark instance set)

Output: An Intermodal Terminals Network on ι

- Generation of Initial Population of Chromosomes

While Stop Criterion is not met **Do**

Repeat

- $A_1, A_2 \leftarrow$ Select parent chromosomes ()
- $\mathrm{A}_1{}', \mathrm{A}_2{}' \leftarrow$ Crossover Operator $(\mathrm{A}_1, \mathrm{A}_2)$ and Mutation Operator $(\mathrm{A}_1, \mathrm{A}_2)$
- If Local Search Condition is met, then:

  $\mathrm{A}_1{}'', \mathrm{A}_2{}'' \leftarrow$ Local Search$(\mathrm{A}_1{}')$ and Local Search$(\mathrm{A}_2{}')$

- $f(\mathrm{A}_1{}''), f(\mathrm{A}_2{}'') \leftarrow$ Fitness Evaluation $(\mathrm{A}_1{}'', \mathrm{A}_2{}'')$

Until enough offspring created

- Select new population

End

Figure 3.3 Pseudo-code of Hybrid Genetic Algorithm (HGA) for the intermodal terminal location problem under a decentralized management.

3.4.1 Description of the Hybrid Genetic Algorithm (HGA)

The implementation of the HGA requires the definition of its various components:

- Representation of an individual from the population (chromosome)
- Generation of the initial population
- The fitness function.
- Crossover operator.
- Mutation operator
- Local search process
- Stopping criterion

3.4.1.1 **Encoding Individual (Chromosome)**

To find a near-optimal solution to the problem described in Section 2.3 through HGA, each solution (chromosome) must be uniquely encoded by an adequate structure that facilitates its evaluation, as well as its interrelation with others within their environment. Since the problem assigns at most one type of terminal type $i \in I$ to each region $j,\ j \in N\ (|N| = n)$, each solution has been encoded by an array, A, in which each position (gene) represents a region and the value assigned to that position represents the type of terminal that is located in such region, assigning it the value of 0 if no terminal is located in that region.

	1	2		s		$n-1$	n	← Regions
A	1	0	...	2	...	1	3	

For example, in Figure 3.4 a chromosome encoding a solution of the problem of locating intermodal terminals applied to a territory composed of 5 regions $1, 2, 3, 4, 5$ where no terminal is located in region 1, a type 2 terminal is located in region 2, a type 3 terminal is located in regions 3 and 4, and a type 1 terminal is located in region 5.

1	2	3	4	5
0	2	3	3	1

Figure 3.4 Solution coding

3.4.1.2 **Generation of Initial Population**

The exploration process of the genetic algorithm begins in an initial population, whose composition is modified in each iteration and whose size can also be altered. In the proposed algorithm, the initial population is randomly-generated and its size, $|P|$, is a function of the region's number and is fixed throughout all the iterations of the algorithm for a specific instance.

3.4.1.3 **Fitness Function**

The HGA uses a fitness function, f, which assigns to each chromosome A a fitness value that measures the quality of the chromosome. This measure will serve both to identify the elements of the population set that will survive to the next generation and to choose those parents who will generate offspring.

Firstly, we carry out the freight allocation in the intermodal transport network defined by chromosome A without taking into account the terminal capacity constraint. For this purpose, the freight hauled from an origin to a destination is allocated in its entirety to the route with the lowest cost. The lowest cost route is given by implementing Dijkstra's Algorithm (Dijkstra (1959)). After finishing the freight allocation process, we proceed to calculate the total transportation cost (objective function), OFV. Because terminal capacity constraints are mandatory, we have considered penalizing the objective function every time a terminal does not comply with it, i.e., the penalty in the objective function is proportional to the number of terminals that do not meet the terminal capacity restrictions.

We have considered that the fitness value of a chromosome A, $f(A)$, increases as the sum of the objective function value and the penalty for not complying with the terminal capacity constraints decrease, i.e., chromosomes with a high fitness value are those with a low objective function value and a minimum number of terminals that do not meet the capacity constraints. Thus,

$$f(A) = \frac{1}{OFV + c\ NT}$$

where c is a penalty cost and NT is the number of terminals that do not meet terminal capacity constraints.

3.4.1.4 **Selection Operator**

One of the characteristics of genetic algorithms is the evolution of the population as their individuals interact with one another. Thus, when interacting two individuals of the population (parents) in a generation will produce offspring that could survive in the next generation. Individuals with higher fitness values have a higher probability of being chosen to produce offspring. In the proposed algorithm, the roulette wheel selection method was used for the selection of parents. In this strategy, a discrete probability distribution ψ in the population $\{A_1, A_2, \dots, A_m\}$ is constructed such that each element A of the population is assigned the value $\psi(A)$ given by:

$$\psi(A) = \frac{f(A)}{\sum_{B \,\in\, \text{population}} f(B)}$$

where $f(A)$ is the fitness function value for the chromosome A. Subsequently, an unifrom random number $r \in [0,1]$ is generated either by choosing the first element of the population, A_1, if $r \leq \psi(A_1)$ or by choosing the element of the population located in the position s such that:

$$\sum_{j\,\leq\, s-1} \psi(A_j) \leq r \leq \sum_{j \leq\, s} \psi(A_j), \quad r > \psi(A_1)$$

To exemplify this, let us consider the population $\{A_1, A_2, A_3, A_4\}$ such that $f(A_1) = 2$, $f(A_2) = 1$, $f(A_3) = 4$, $f(A_4) = 3$. Table 3.1 gives a summary of the calculations, showing that element A_1 has a probability of 0.2 of being selected, while element A_3 has the highest probability of being selected (0.4).

Table 3.1 Cumulative probability distribution in a chromosome population

i	A_i	$f(A_i)$	$\psi(A_i) = \frac{f(A_i)}{\sum_j f(A_j)}$	$\sum_{i \leq i} \psi(Ai)$
1	A_1	2	0,2	0.2
2	A_2	1	0,1	0.3
3	A_3	4	0,4	0.7
4	A_4	3	0,3	1

Suppose we generate a random number r between 0 and 1. If r is 0.05, $A_1$is chosen since $r < \psi(A_1)$, while if $r = 0.45$, A_3 is chosen since $\sum_{j\,\leq\, 2} \psi(A_j) \leq r \leq \sum_{j \leq\, 3} \psi(A_j)$.

The process of selecting parents is carried out during a number of iterations defined in advance, with the aim of generating a sufficient number of new offspring that guarantee the diversity of the population.

3.4.1.5 **Crossover Operator**

The crossover operator is a component of the genetic algorithm that allows to mix of the genetic information of the selected parents to generate offspring (new chromosomes). Figure 3.5 shows the pseudo-code of the crossover operator of the HGA. The crossover operator can be delineated as follows: after selecting the two parents to interact with each other, for each gene of each chromosome the genetic information is exchanged if the parameter $crossover\_rate$ is greater than a uniform random number $r \in [0,1]$ i.e., for each region, the type of terminal existing in each selected solution is exchanged.

Algorithm 2 Pseudo-code of the proposed crossover operator

Inputs:

- Let n be the number of regions
- Parents

A_1	a_{11}	a_{12}	...	a_{1i}	...	$a_{1,n-1}$	a_{1n}
A_2	a_{21}	a_{22}	...	a_{2i}	...	$a_{2,n-1}$	a_{2n}

- Crossover rate: $crossover\_rate$

Output: Offspring A_1', A_2'

Initialization: $A_1' = A_1, A_2' = A_2$

For $i = 1$ **to** n

$b_{2i} = a_{2i}$

Generate $r \in [0,1]$

If $r < crossover\_rate$ then

$$a_{2i} \leftarrow a_{1i}$$

$$a_{1i} \leftarrow b_{2i}$$

End

Figure 3.5 Pseudo-code of Crossover Operator of the HGA

Figure 3.6 illustrates this crossover process in a country divided into 7 zones where it is intended to design a network with two types of intermodal terminal. For this purpose, $crossover\_rate = 0.25$ was considered. As can be seen, in genes $1, 2, 4, 7$ of each chromosome the respective contents are exchanged since the generated value of r is less than the value of $crossover\_rate$.

$r =$ 0.1 0.05 0.4 0.2 0.3 0.5 0.1

Parents

a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}
1	2	0	1	0	0	2

a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}
0	1	1	2	1	2	1

Offspring

0	1	0	2	0	0	1
1	2	1	1	1	2	2

Figure 3.6 Example of Crossover Process based on a $crossover\_rate = 0.25$

3.4.1.6 **Mutation Operator**

The mutation operator aims to diversify the chromosome population by randomly modifying a gene of a chromosome i.e. the terminal type located in each region changes when a random number r between 0 and 1 is less than a parameter which we call $mutation\_rate$.

Figure 3.7 illustrates the mutation process in a scenario like that considered in the crossover process. For this purpose, a mutation rate of $mutation\_rate = 0.05$ was considered. As we can see, the mutation is applied to genes $2, 6, 7$ since the generated value of r is less than the value of $mutation\_rate$, altering its content in 1, i.e. the type of terminal located in a region changes randomly to one of greater capacity or less capacity.

$r =$ 0.1 0.02 0.4 0.2 0.3 0.01 0.01

Chromosome

a_1	a_2	a_3	a_4	a_5	a_6	a_7
1	2	0	1	0	0	1

Mutated chromosome

1	2 →1	0	1	0	0 →1	1 →2

Figure 3.7 Example of Mutation Process if $\boldsymbol{mutation\_rate = 0.05}$

The pseudo-code of the mutation operator is shown next.

Algorithm 3: Pseudo-code of the mutation operator

Inputs:

- Chromosome

A_1

a_1	a_2	...	a_i	...	a_{n-1}	a_n

- Rate mutation: $mutation\_rate$

Output: Mutated chromosome

A_1'

a_1'	a_2'	...	a_i'	...	a_{n-1}'	a_n'

Initialization: $A_1' = A_1$

For $i = 1$ **to** n

Generate $r \in [0,1]$

If $r < mutation\_rate$ then

If $a_i = 0$

$$a_i' = 1$$

else

If $a_i = |I|$

$$a_i' = |I| - 1$$

else

$$a_i' \leftarrow a_i + 1 \text{ or } a_i' \leftarrow a_i - 1$$

End

Figure 3.8 Pseudo-code of Mutation Operator

It should be noted that in the proposed algorithm the crossover and mutation operator are applied simultaneously to each gene if the conditions indicated above are met. An example of such application to gene 4 of chromosomes A_1 and A_2 is shown in figure 3.9. After selecting the parents for the crossover process, if the random number r_1 in gene 4 is lower than $crossover\_rate$ then the contents of genes 4 (a_{14} and a_{24}) are exchanged, otherwise each chromosome will maintain its composition (scenario S_4). Additionally, if the random number r_2 is lower than $mutation\_rate$, then two scenarios are presented in the gene enclosed in a circle: its content either increases by one (scenario S_2) or decreases by one (scenario S_1), otherwise its exchange remains unaltered (scenario S_3).

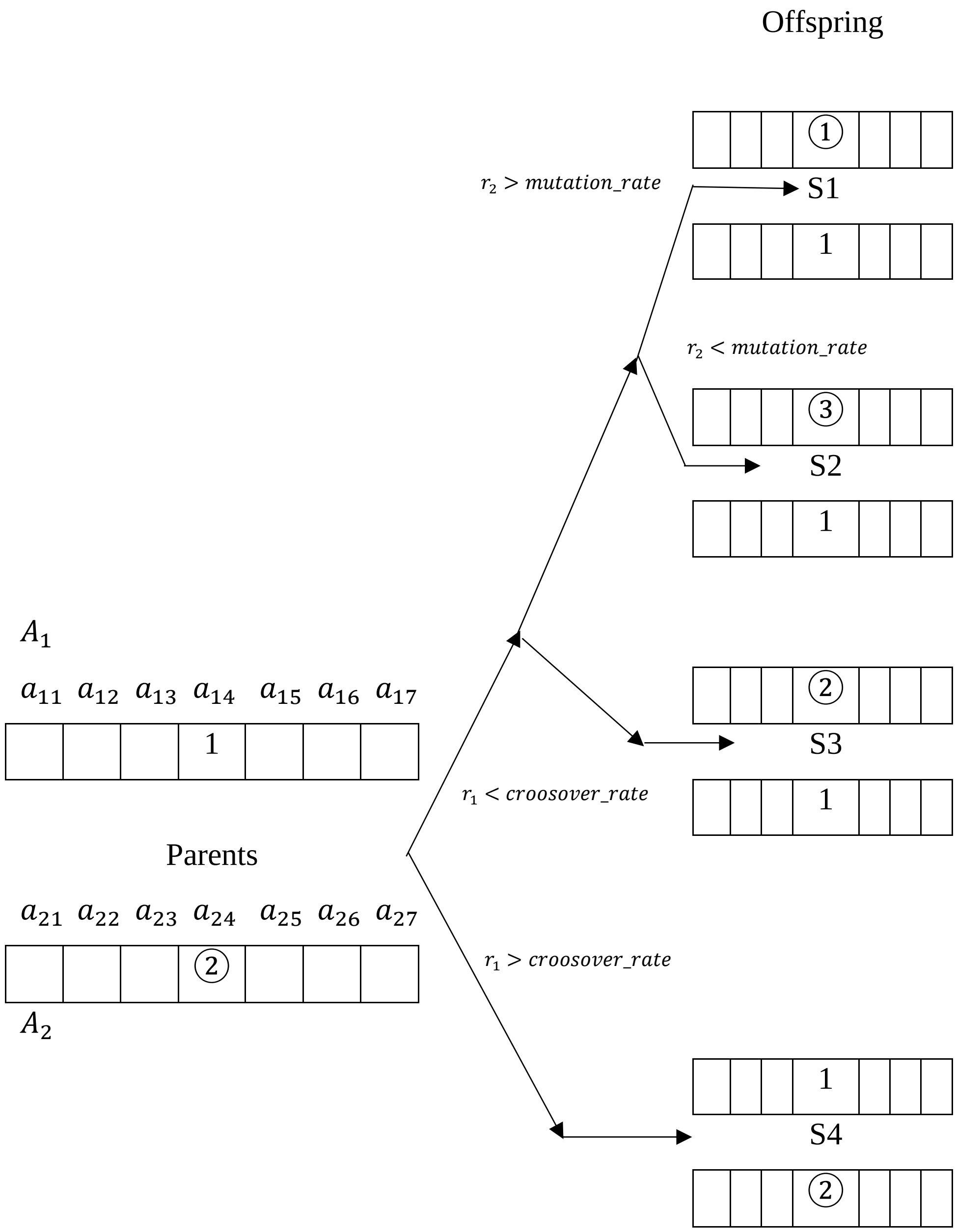


Figure 3.9 Example of Crossover and Mutation Process of HGA

3.4.1.7 **Local Search Process**

Local search is an iterative algorithm that is based on the exploration of the space of solutions of a problem from a current solution to it, making transitions in each iteration to other better solutions that belong to the "neighborhood" of the current solution. Let s be a solution to a given problem, the neighbourhood of s denoted by $\aleph(s)$ is the set of all the solutions that can be generated from a "movement" in s.

In our work, we assumed that the neighborhood of a chromosome (solution) is the set of chromosomes obtained by assigning 1 to only one gene whose content is 0, i.e. in the context of intermodal terminal location, a terminal of lower capacity is located in only one region where no terminal is installed.

Figure 3.10 shows an example of the neighborhood construction of a given chromosome. It is observed that in genes 2, 4, 5 and 7 its content is zero, so that the neighborhood of A is the set of all the chromosomes that alter in 1 the content of these genes.

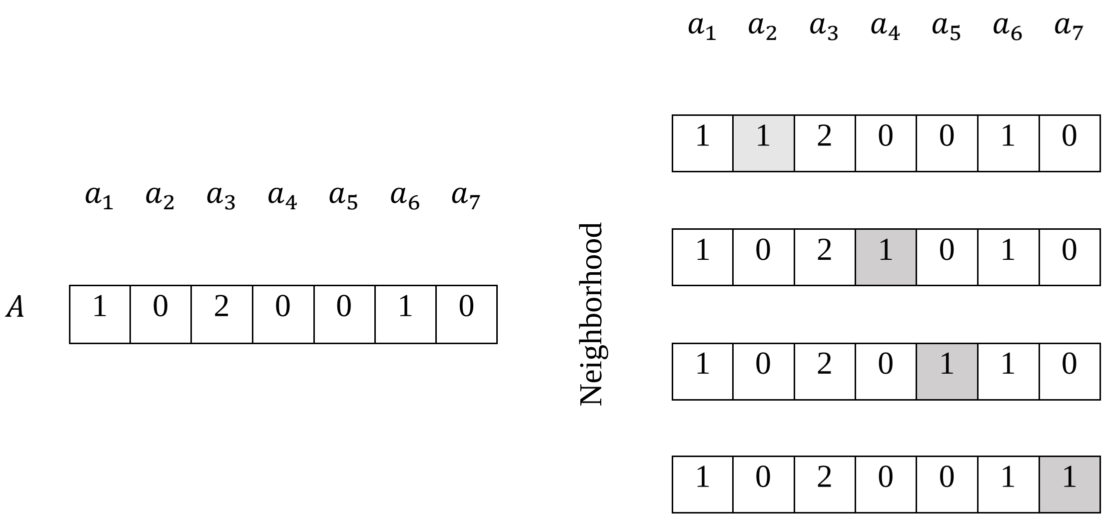


Figure 3.10 Example of the neighborhood of a chromosome A

This procedure is applied to a chromosome if a random number $r \in [0,1]$ is less than a parameter which we call $local\_search\_rate$. The pseudo-code of the local search that will be used as a component of the proposed genetic algorithm is shown in Figure 3.11. In this case, the cost function f is the fitness function defined in Section 3.4.1.3.

Algorithm 4: Local Search

Input: Chromosome A,

Output: Chromosome A'

- **Initialization:** $Flag$ = 1

While $(Flag \neq 0)$

- $Flag = 0$
- To generate $\aleph(A)$
- Calculate $f(A) =$ fitness value

Repeat

Choose $x \in \aleph(A)$

If $f(x) >$ fitness value then

$$A' \leftarrow x$$

$$\text{fitness value} \leftarrow f(x)$$

$$Flag \leftarrow 1$$

Until $f(x) \leq f(A'), \forall x \in \aleph(A)$

- $A = A'$

End

Figure 3.11 Pseudo-code of local search on the HGA

Basically, the local search process applied to a chromosome explores the entire neighborhood of the chromosome in order to find another chromosome with the greatest fitness value, after which the initial chromosome is updated and then the process is applied to the updated chromosome again. This process is carried out until the current chromosome cannot be improved.

3.4.1.8 **Stopping Criterion**

The stopping criterion is a condition that allows an algorithm to finish its execution. In the literature, some of the criteria that have been used in genetic algorithms as stopping conditions consist of setting a maximum number of generations or a maximum number of iterations in which the best solution found in the execution of the algorithm has not been improved. This latter strategy is the basis of the stopping criterion adopted in our algorithm.

Thus, during the execution of our algorithm the feasible solution with the lowest cost is stored. If the number of iterations after which this best solution is not improved reaches the parameter $stopping\_criterion$ then the execution of our algorithm ends.

3.5 Automatic Algorithm Configuration

Generally, the performance of both heuristics and metaheuristics depends on the parameter values that have been defined in them. For instance, population size, mutation rate and crossover rate directly affect efficiency and effectiveness of genetic algorithms (Reeves (2003), Aytug et al. (1996)). The process of assigning values to the parameters of an algorithm is generally known as algorithm configuration (or parameter tuning). The complexity of the parameter tuning not only lies in the computational effort used but, in some cases, trying to adjust a parameter to improve the effectiveness of the algorithm results in a decrease in its efficiency.

A usual way to perform the parameter tuning is by trial and error until the performance of the algorithm is adequate. A weakness of this procedure is that it is usually performed for a specific instance so that an algorithm with a specific configuration might be not suitable (in terms of performance) for other instances. An alternative approach is to determine an algorithm configuration that is suitable for all the analyzed instances regardless of its characteristics e.g. the number of regions in the problem we are addressing.

Formally, let A be a parametrized algorithm, ϕ a configuration of the algorithm that belongs to the space Φ of the all feasible configurations of the algorithm, I a benchmark instance set. Let $g(A, \phi, \iota)$ be a value of the performance of the algorithm A under a specific configuration $\phi \in \Phi$ applied in an instance $\iota \in \mathrm{I}$. Thus, the algorithm configuration problem aims to find a configuration $\phi^* \in \Phi$ such that it produces the optimal performance of the algorithm in the instance set I.

The complexity of the algorithm configuration problem depends on the number and type of parameters (ordinal, categorical, continuous, discrete) since they directly affect the space of all feasible configurations; an exhaustive exploration of this space is thus not appropriate in many cases. Therefore, this section focuses on designing an algorithmic strategy to determine a configuration of the HGA within the space of all possible configurations, so that the performance of the HGA in a benchmark instance set is close to the optimum. This strategy is based on an adaptation of the work done by Hutter et al.

(2009). They proposed an algorithm based on an iterative local search for getting near-optimal configuration to the algorithm configuration problem.

3.5.1 Iterated Local Search Algorithm for Automatic Algorithm Configuration

In the classical local search algorithm (CLSA) the exploration of the solution set, S, of a given problem proceeds as follows: the neighbor of a current solution s, which consists of all the solutions that can be generated from a movement applied to s, is explored to select a new current solution that improves the objective function value of the current solution. This process is performed iteratively until no improvement can be made.

Let S^* be the set of locally optimal solutions obtained by applying the CLSA to each element of S. Unlike the CLSA, the exploration process in the iterative local search algorithm (ILSA) is done in S^* instead of S, as follows: first, the CLSA is applied to an initial solution $s \in S$ to get the solution $s^* \in S^*$; then a perturbation process is applied to s^* to get the solution $s' \in S$. The CLSA is applied to s', producing the solution $s^{*\prime} \in S^*$, which is chosen if an acceptance criterion is satisfied. Schematically, this process is shown in Figure 3.12.

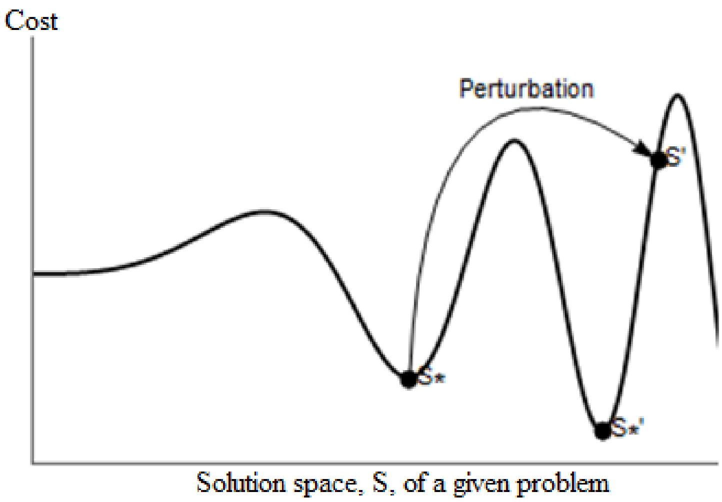


Figure 3.12 Scheme of iterated local search

Given the proposed HGA, a benchmark instances set I, the pseudo-code of the algorithm based on iterated local search for achieving a near-optimal configuration of the HGA is shown below:

Algorithm 5: Iterated local search algorithm for algorithm configuration problem

Input: HGA, an initial configuration parameter ϕ_0, a benchmark instance set I

Output: The best configuration parameter ϕ^* throughout the execution of the algorithm

- **Initialization**

  $\phi^* \leftarrow \boldsymbol{ClassicalLocalSearchProcedure}(HGA, \phi_0, \mathrm{I})$

While Stop Criterion is not met **Do**

- $\phi' \leftarrow \boldsymbol{DisturbProcedure}(\phi^*)$
- $\phi^{*\prime} \leftarrow \boldsymbol{ClassicalLocalSearchProcedure}(HGA, \phi', \mathrm{I})$
- $\phi^* \leftarrow \boldsymbol{EvaluationProcedure}(\phi^*, \phi^{*\prime})$

End

Figure 3.13 Pseudo-code of iterated local search for algorithm configuration problem

As can be seen, the algorithm proposed for the automatic configuration of the HGA consists of the following procedures:

• Classical local search

• Disturbance

• Evaluation

3.5.1.1 Classical Local Search Procedure

The classical local search embedded in the iterated local search algorithm for the algorithm configuration problem is similar to that presented in Section 3.4.1.7 (Figure 3.11). Substantial differences lie in the objective function to be optimized and the neighborhood structure of a current solution.

Given that the HGA is a stochastic algorithm, it is executed for a fixed number of running K over a specific instance. Let $C_\kappa^\iota(\phi)$ be the performance of the HGA at a run $\kappa \in \mathrm{K}$ over an instance $\iota \in \mathrm{I}$ under the configuration ϕ, then the performance of the HGA is the average value, $\overline{C}^\iota(\phi)$, of all the values C_κ^ι after executing K iterations over the instance $\iota \in \mathrm{I}$.

Based on the above, the $CLSA$ aims to determine a near-optimal configuration of HGA through an exhaustive exploration of the neighborhood of a current configuration.

To schematize the neighborhood of a configuration of the HGA, suppose that the performance of the algorithm depends on 5 parameters (A, B, C, D, E) and that a configuration ϕ of the HGA can be represented by the vector $\{a, b, c, d_m, e\}$, where each element of this vector represents a value of the parameter that belongs to its domain, i.e. feasible values of the parameter. Also, suppose that the domain of parameter D is the set $\{d_1, \ldots, d_{m-1}, d_m, d_{m+1}, \ldots\}$ then the neighborhood of ϕ, $\aleph(\phi)$, considering the fixed parameter D is the set formed by all the configurations that are obtained by replacing the current value of the fixed parameter (d_m) with the adjacent value in its domain i.e. $\aleph(\phi) = \{\{a, b, c, d_{m-1}, e\}, \{a, b, c, d_{m+1}, e\}\}$, provided that some of these configurations have not been analyzed previously, in which case the next adjacent one is taken.

3.5.1.2 **Disturbance Procedure**

After performing the classical local search procedure considering a discrete change in a fixed parameter, the disturbance procedure of a parameter vector consists of modifying the content of another parameter chosen randomly by a value of its domain

3.5.1.3 **Evaluation Procedure**

Let S^* be the set of locally optimal solutions obtained by applying the CLSA to each element of S. The evaluation procedure determines the way in which a solution $\phi^* \in S^*$ is updated to another feasible solution $\phi^{*\prime} \in S^*$.

A first criterion is that the configuration ϕ^* is updated by $\phi^{*\prime}$, which is obtained at the end of the classical local search procedure applied to an algorithm configuration with the configuration that results from disturbing ϕ^*, if the performance of the HGA with the configuration $\phi^{*\prime}$ is better than the performance of the HGA with the configuration ϕ^*. This criterion is linked to an intensification process. However, to explore other regions of S^*, ϕ^* can be updated by $\phi^{*\prime}$ with a given probability, although the performance of the HGA with the configuration $\phi^{*\prime}$ does not improve the performance of the HGA with the configuration ϕ^*. This criterion allows a diverse exploration of S^*(diversification process).

For the above, and in order to balance the intensification and diversification processes in the exploration of S^*, the evaluation procedure is defined as:

$$EvaluationProcedure(\phi^*, \phi^{*\prime}) = \begin{cases} \phi^{*\prime}, & \bar{C}^\iota(\phi^{*\prime}) < \bar{C}^\iota(\phi^*) \quad \text{or} \quad r < e^{\left(\frac{\bar{C}^\iota(\phi^*) - \bar{C}^\iota(\phi^{*\prime})}{AP}\right)} \\ \phi^*, & \text{otherwise} \end{cases}$$

with r being a random number which belongs to $[0,1]$, and AP is an adaptative parameter in terms of the iteration number executed.

3.6 Computational Results

In this section, we analyze the performance of the HGA proposed in Section 3.4 for the problem described in Chapter 2. For this purpose, the HGA and the iterated local search algorithm for the automatic algorithm configuration were coded using MATLAB R2018a on an Intel Core™ i5-7400 processor (3.0 GHz) and 8Gb RAM.

3.6.1 Computational Results of Automatic Algorithm Configuration

Several parameters were included in the design of the HGA such as a threshold that defines the execution or not of a procedure in the algorithm, for instance, $crossover\_rate$, $mutation\_rate$ and $local\_search\_rate$. Other parameters that affect the performance of the algorithm are the size of the population and what is defined as the stopping criterion. Some authors have proposed different criteria to define these parameters (Ghoreishi et al. (2017)). For instance, a maximum number of iterations in which the best solution is not improved is a criterion used as a parameter to stop executing the algorithm. Aytug et al. (1996) state that number depends, among other factors, on the length of the chromosome. Based on the above and taking T as the maximum number of iterations in which the best solution is not updated, then we have considered that $T = factor\_stop\ |N|$, with $|N|$ being the number of regions of the analyzed instance and $factor\_stop$ is a parameter that must be adjusted. A similar approach has been adopted to define the size of the population. Thus, let $|P|$ be the population size then $|P| = factor\_size\ |N|$.

Based on the above, it was established that the parameters vector $[mutation\_rate, crossover\_rate, local\_search\_rate, factor\_size, factor\_stop]$ will be adjusted automatically using the algorithm proposed in Section 3.5.1.

Due to the continuous nature of the parameters to be calibrated, a suitable discretization of the domain of each one has been defined, as shown in Table 3.2. Based on this discretization, there are 768 feasible configurations for the HGA. Evaluating the performance of the algorithm in each of the possible configurations is practically an exhausting task despite the relaxation of the domain of each parameter.

Table 3.2 Definition and discretization of parameters.

Parameter	Discretized domain
mutation_rate	{0.025, 0.05, 0.1, 0.2}
crossover_rate	{0.2, 0.4, 0.6, 0.8}
local_search_rate	{0.05, 0.10, 0.20, 0.40}
factor_size	{1, 2, 3}
factor_stop	{0.125, 0.25, 0.5, 1}

The performance of the HGA under a configuration over an instance is evaluated based on three characteristics of the set of local optimal solutions found at the end of 10 runs of the HGA: quality (in terms of the average total cost); robustness (in terms of dispersion level relative to the average total cost); and computational time taken to find the last local optimal solution in each run. Thus, the automatic algorithm configuration consists of determining a configuration that produces, for each instance, a minimum average total cost with a minimum level of dispersion and at a minimum computational cost.

However, this multi-objective approach is only manageable for a fixed instance since all generated instances differ in their topology and it is impossible to compare the performance of the algorithm in two different instances. An alternative approach is to apply iterated local search (ILS) to the automatic algorithm configuration on minimizing the average total cost of 10 instances (each of them composed of 20 regions) generated randomly as indicated in Appendix B. For each instance, it keeps track of all the locally optimal configurations found in the exploration of the ILS. Thus, a first criterion to establish a near-optimal configuration in the benchmark instances space is to choose the one that is locally optimal in many instances. However, the robustness criterion must complement the analysis.

Figure 3.14 shows 8 of the parameter configurations that are repeated more than once in the execution of the ILS over the 10 benchmark instances which were generated according to guidelines described on Appendix B. The number of times in which each configuration is represented in the diagram is equal to the frequency of occurrence in the execution of the ILS. For instance, the configuration represented by an orange square is a local optimal in 4 of the 10 benchmark instances, as is the configuration represented by the green diamond. The difference in the performance of the algorithm under both configurations is that in the first configuration the locally optimal solution obtained after running each instance 10 times is achieved in less time than the locally optimal solutions obtained with the second configuration. In terms of robustness, the range of variability coefficient values is similar for both configurations, however the set of locally optimal solutions after running the algorithm 10 times under the first configuration (orange squares) have, in two instances, lower values of the variability coefficient than is obtained under the second configuration (green diamond).

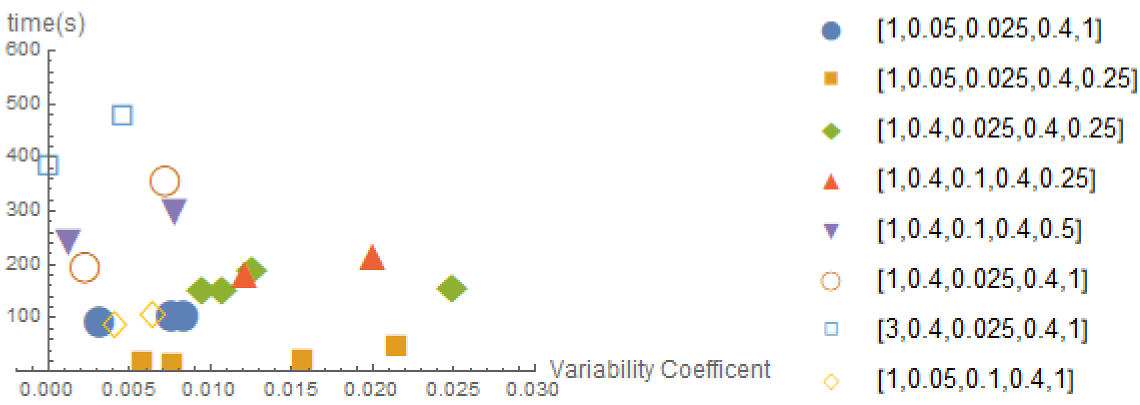
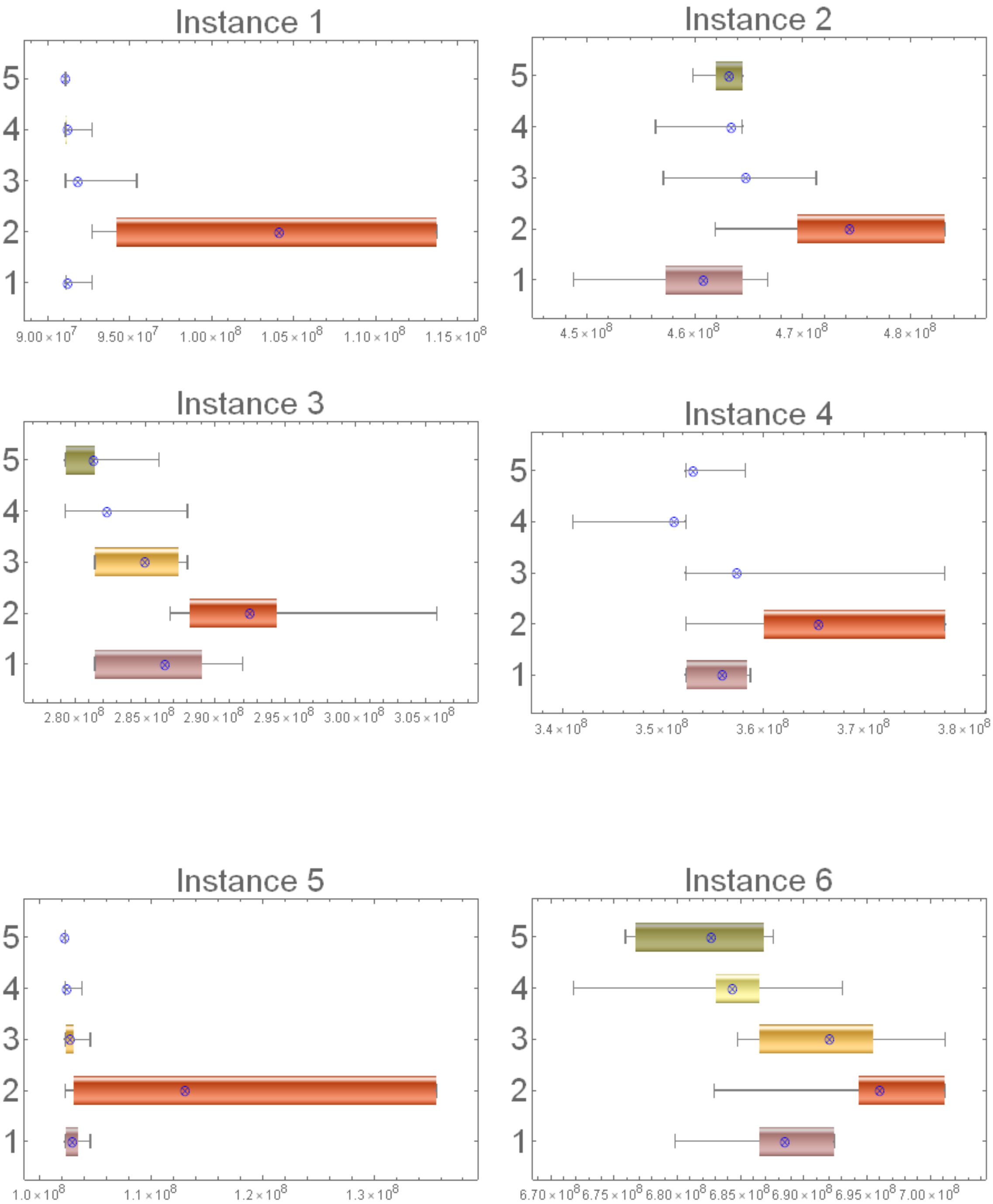


Figure 3.14 Scatter plot of the local optimal of the variability coefficient during exploration of the parameter configuration space

Since there is no configuration that is locally optimal for the 10 analyzed instances, the robustness and computational time criteria are incorporated to select a subset of promising configurations. These promising configurations should, to a great extent, provide for each instance a set of locally optimal solutions with low coefficient of variability (robustness), in reasonable computational time.

Based on the above, the configurations $[1, 0.4, 0.025, 0.4, 0.25]$ and $[1, 0.05, 0.025, 0.4, 0.25]$ are selected due to their greater frequency with respect to the other configurations, $[1, 0.05, 0.025, 0.4, 1]$ is selected for having an adequate frequency (three out of ten instances), low computational time and variability, $[1, 0.4, 0.025, 0.4, 1]$ due to its low variability coefficient and good computational time and, $[3, 0.4, 0.025, 0.4, 1]$ due to its low variability coefficient. The set of local optimal solutions obtained when executing the HGA with each of the promising configurations in the 10 benchmark instances must be analyzed with the objective of choosing the best configuration of the HGA.

The set of local optimal solutions at the end of ten executions of the HGA for each benchmark instance and for each promising configuration is represented visually by a boxplot (Figure 3.15). For each instance and for each configuration the total cost average is represented by a blue mark.



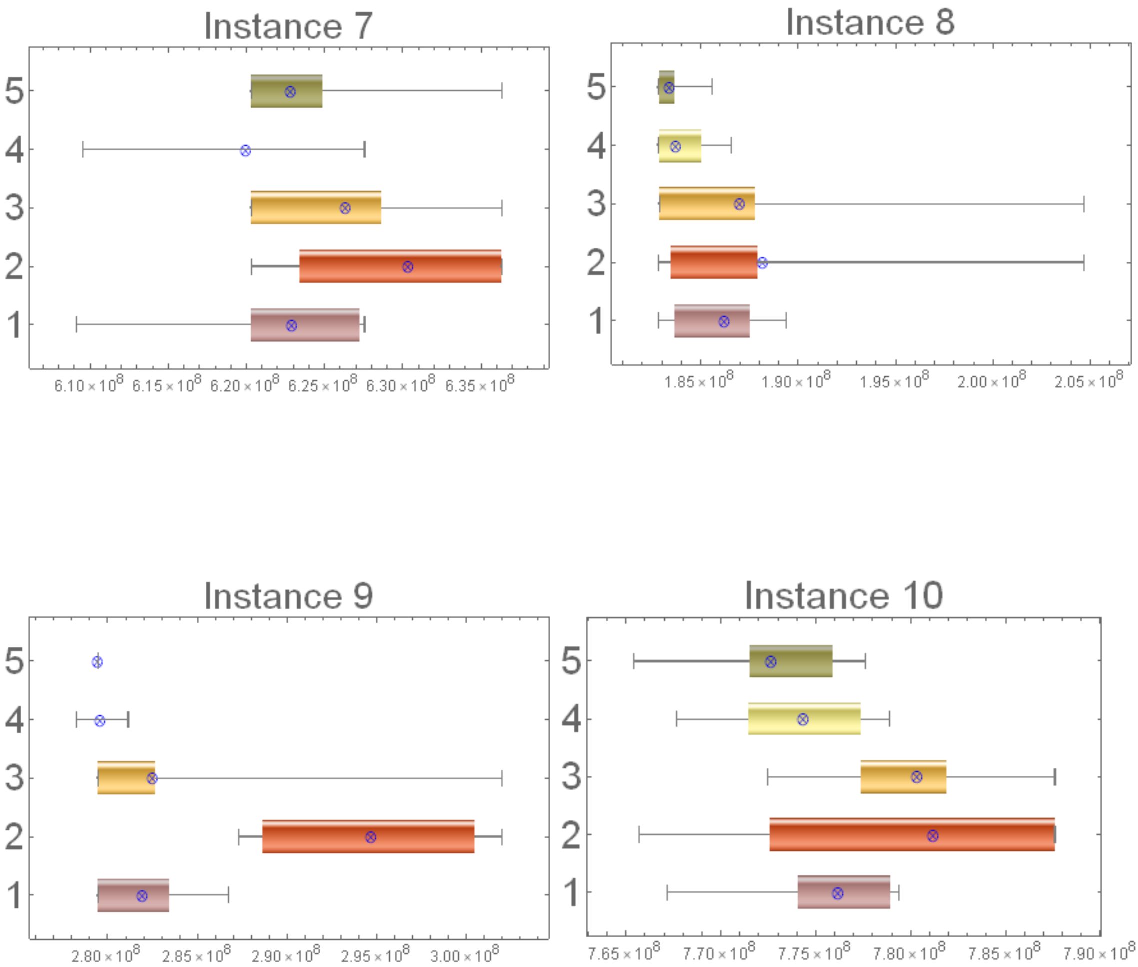


Figure 3.15 Boxplot of locally optimal solution set after 10 runs for each benchmark instance.

Parameter Configuration $\mathbf{1}$: $[\mathbf{1}, \mathbf{0.05}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$ $\mathbf{2}$: $[\mathbf{1}, \mathbf{0.05}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{0.25}]$

$\mathbf{3}$: $[\mathbf{1}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{0.25}]$ $\mathbf{4}$: $[\mathbf{1}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$ $\mathbf{5}$: $[\mathbf{3}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$

As can be seen in Figure 3.15, configuration $[1, 0.05, 0.025, 0.4, 0.25]$ does not provide locally optimal solutions of good quality, since in all the instances evaluated the average total cost is higher than those obtained in the other configurations. A similar performance of the algorithm occurs if the parameters configuration $[1, 0.05, 0.025, 0.4, 1]$ is used. In fact, only in one instance is the total cost average is lower than those obtained with the other instances. On the other hand, in 7 of the 10 benchmark instances, the minimum average total cost of the set of local optimal solutions at the end of 10 runs is obtained by setting the HGA with the parameters configuration $[3, 0.4, 0.025, 0.4, 1]$, while if the parameter configuration $[1, 0.4, 0.025, 0.4, 1]$ is used, the proportion decreases to 2 out of the 10 instances. By contrast, if we analyze the frequency that the minimum total cost in the set of local optimal solutions is reached with each parameter configuration, we observe that highest frequencies occur with the configurations $[3, 0.4, 0.025, 0.4, 1]$ and $[1, 0.4, 0.025, 0.4, 1]$ (5 and 7 respectively).

Since the analysis carried out so far is based on instances of 20 regions and because the performance of the HGA with the configurations $[1, 0.4, 0.025, 0.4, 1]$ and $[3, 0.4, 0.025, 0.4, 1]$ is adequate in terms of the quality and robustness of the set of local optimal solutions, the analysis will be expanded to higher cardinality instances. For this purpose, two sets of instances of 50 and 100 regions were generated (according to guidelines described on Appendix B), each one of cardinality 5.

The performance of the HGA in each group of instances was evaluated in terms of the quality of the set of local optimal solutions found during 12 hours of execution of the algorithm. As can be seen in Figures 3.16 and 3.17, if the HGA is configured with the vector $[1, 0.4, 0.025, 0.4, 1]$, the value of the objective function, as well as the computational time in which the last locally optimal solution is found, is lower in most instances with 50 regions (Figure 3.16-blue line) compared to values obtained when configuring the algorithm with the vector $[3, 0.4, 0.025, 0.4, 1]$ (Figure 3.16-orange line). Similar performance of the algorithm is observed for instances of 100 regions (Figure 3.17).

On the other hand, we can see from Figures 3.16 and 3.17 that the number of locally optimal solutions found in each instance decreases as the number of regions increases. Partial experiments performed in the HGA show that, proportionally, the time spent in the exhaustive exploration of the neighborhood in the local search process is high with respect to other processes which could affect the quality of locally optimal solutions. Based on the above, one aspect to investigate is the impact of changing the neighborhood exploration approach in the local search process. For this purpose, the exploration of the neighborhood of a current solution is carried out until the first feasible solution improves the current solution performance within a maximum time limit for executing this sub-routine.

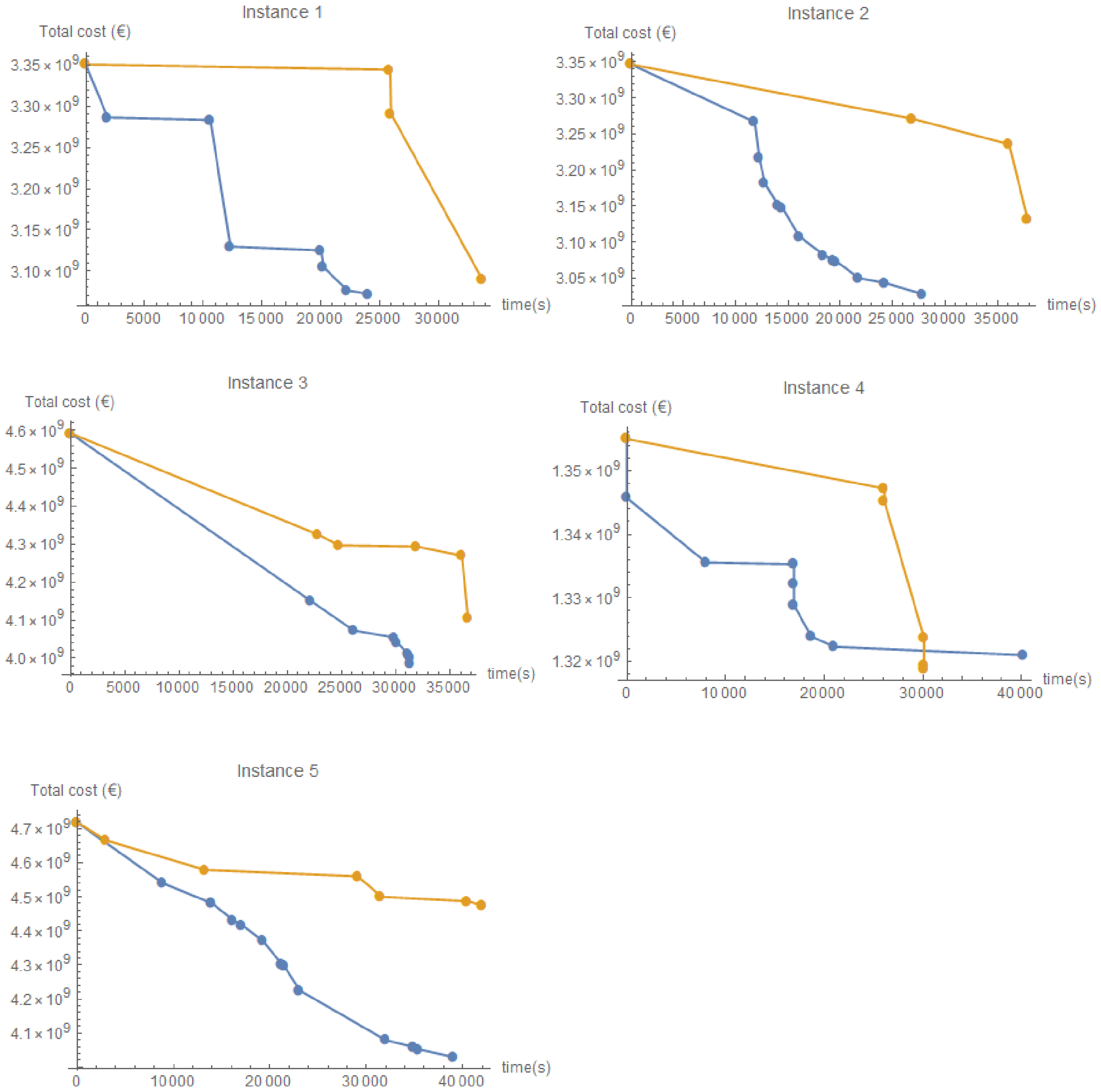


Figure 3.16 Scatter-Plot: Total cost trend during the execution of the algorithm in instances with 50 regions using 2 promising parameter configurations.

. $\boldsymbol{Blue\ Line}: [\mathbf{1, 0.4, 0.025, 0.4, 1}]$ $\boldsymbol{Orange\ Line}: [\mathbf{3, 0.4, 0.025, 0.4, 1}]$

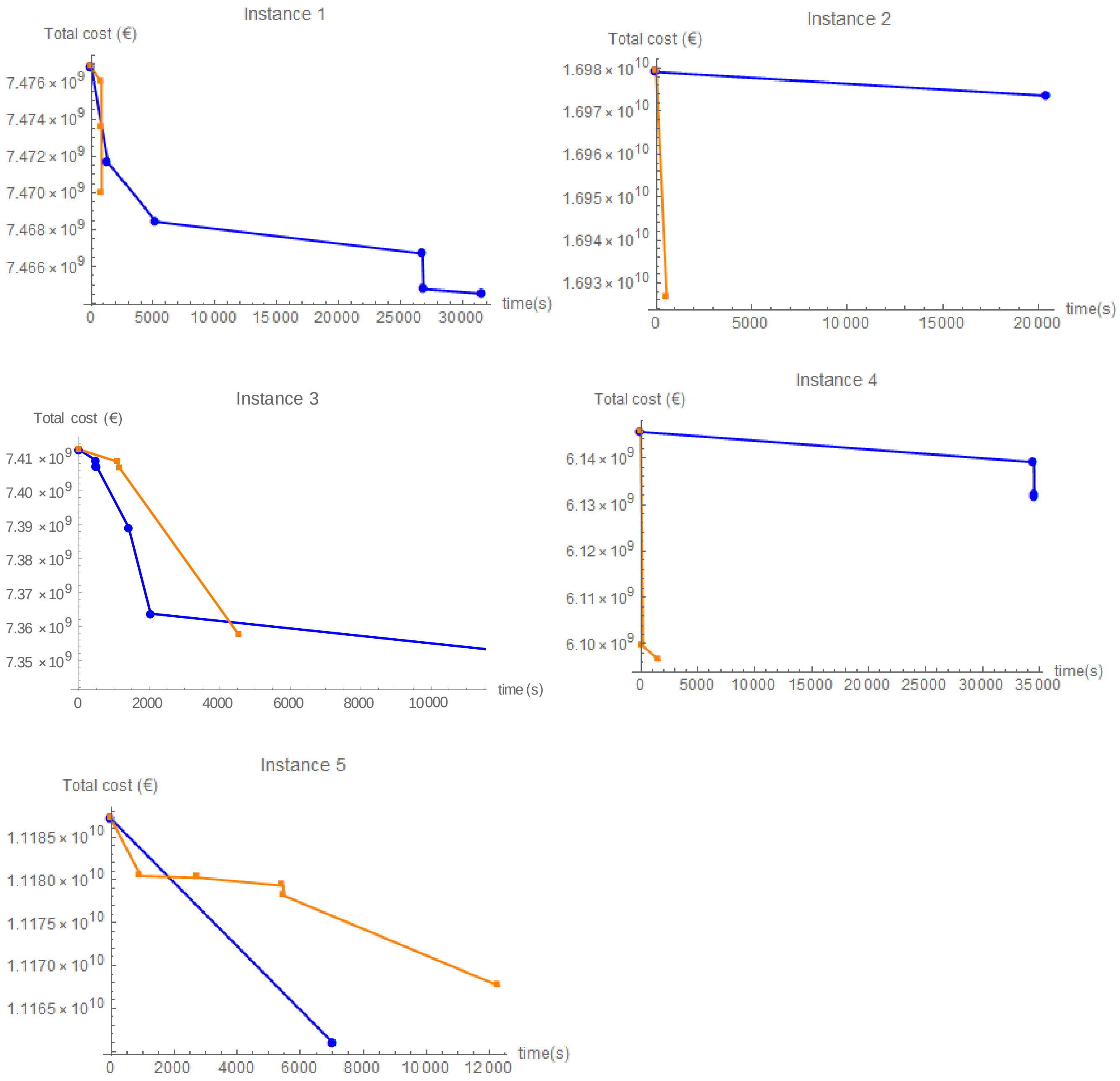


Figure 3.17 Scatter-Plot: Total cost trend during the execution of the algorithm in instances with 100 regions using 2 promising parameter configurations.

. $\boldsymbol{Blue\ Line}: [\mathbf{1}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$ $\quad$ $\boldsymbol{Orange\ Line}: [\mathbf{3}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$

Computational experiments (Figures 3.18 and 3.19) showed that by updating a current solution for the first feasible solution that satisfied the selection criteria, a higher quality of the locally optimal solutions was obtained in instances of 100 regions than was obtained by exhaustively exploring the neighborhood of a current solution (60 % of the analyzed instances). This suggests that this approach should be considered for large-scale instances.

Based on the exhaustive analysis carried out previously, it can be established that the best configuration for the HGA is $[1, 0.4, 0.025, 0.4, 1]$. Next, we apply the proposed algorithm with the selected configuration at medium-scale instance to evaluate its performance.

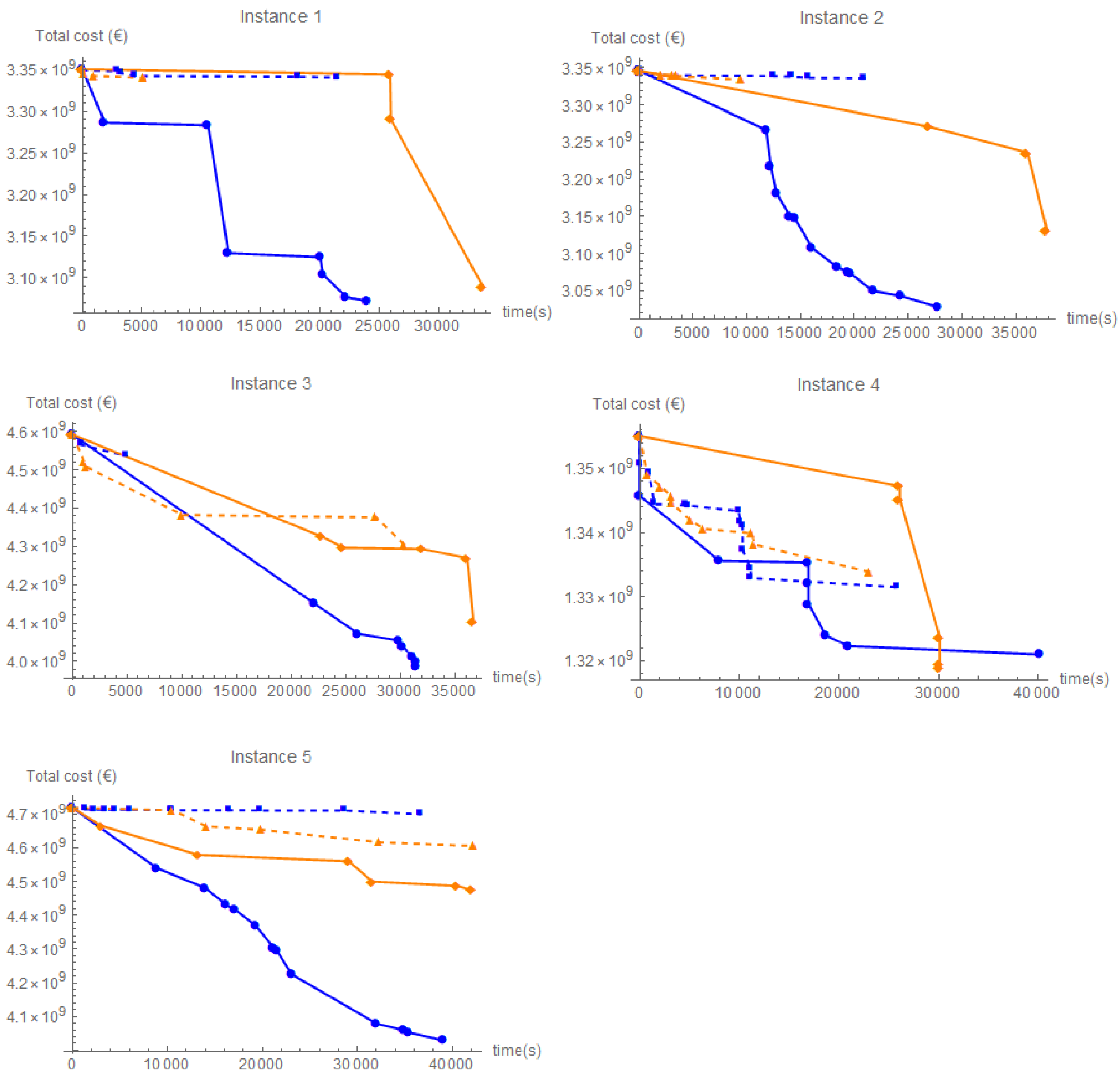


Figure 3.18 Scatter-Plot: Total cost trend during the execution of the algorithm in instances with 50 regions using 2 promising parameter configurations.

. $\boldsymbol{Blue\ Line}: [\mathbf{1, 0.4, 0.025, 0.4, 1}]$ $\boldsymbol{Orange\ Line}: [\mathbf{3, 0.4, 0.025, 0.4, 1}]$

Dashed line: Non-exhaustive exploration of the neighborhood

Continuous line: Exhaustive exploration of the neighborhood

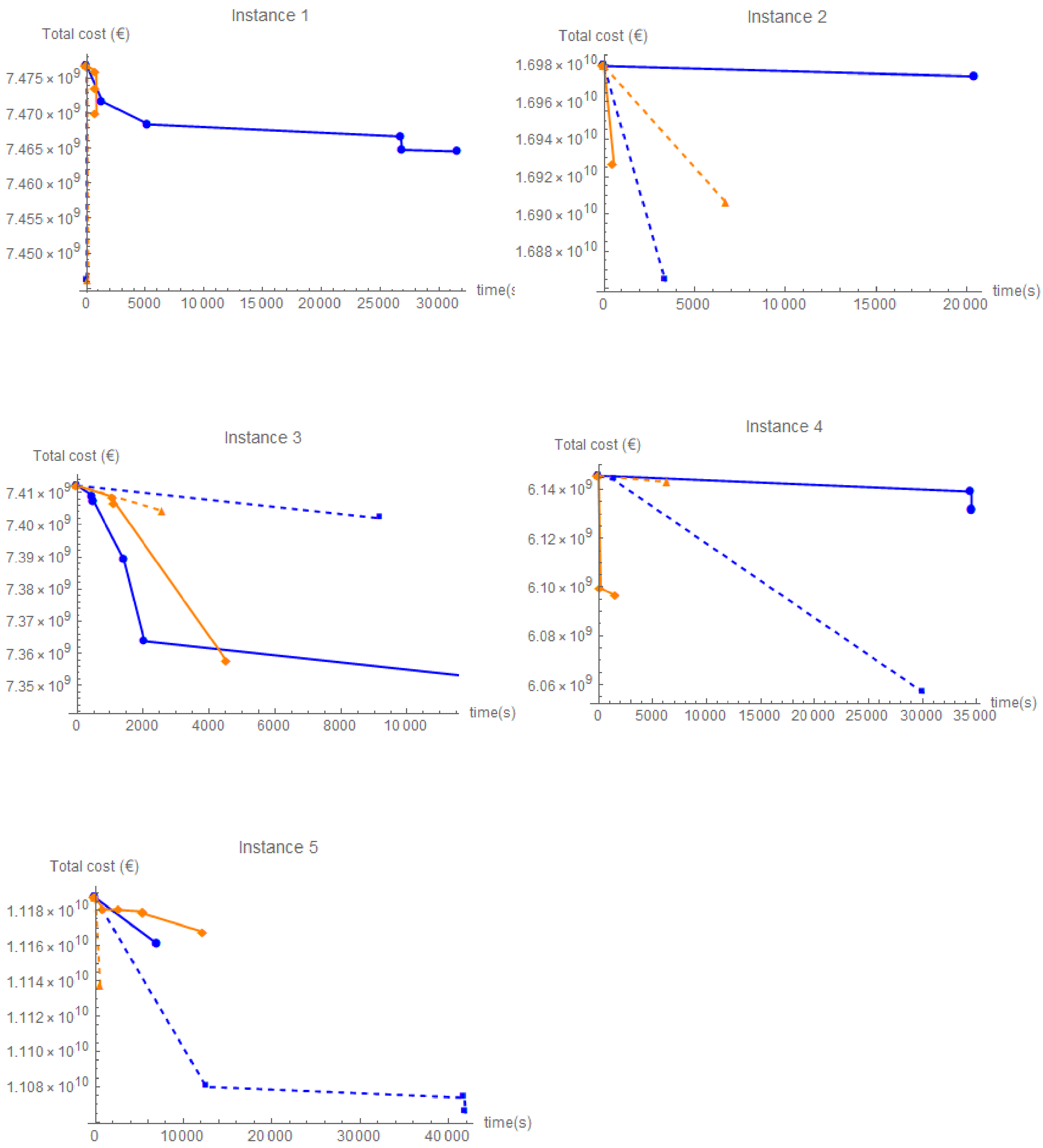


Figure 3.19 Scatter-Plot: Total cost trend during the execution of the algorithm in instances with 100 regions using 2 promising parameter configurations.

$\boldsymbol{Blue\ Line}$: $[\mathbf{1}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$ $\boldsymbol{Orange\ Line}$: $[\mathbf{3}, \mathbf{0.4}, \mathbf{0.025}, \mathbf{0.4}, \mathbf{1}]$

Dashed line: Non-exhaustive exploration Continuous line: Exhaustive exploration

3.6.2 Computational Experiments

In this section, we analyze the performance of the algorithm, considering separately the Portugal case and the 10 instances generated randomly according to the guidelines in Appendix B, with each one comprising 20 regions. In all cases, the HGA has been configured with the best configuration obtained in the previous section.

3.6.2.1 **Case Study**

In this first experiment, we compared the results provided by the HGA with those given by the exact method and using the Portuguese case described in Section 2.6. Because the HGA is a stochastic algorithm, it was executed 10 times in order to analyze the behavior of the solutions in each iteration.

Table 3.3 summarizes the computational results of HGA in the Portugal case. The solution quality is measured in terms of the percentage of deviation from the optimal value (GAP). As can be seen, the optimal solution is achieved 7 out of 10 of the runs made by the algorithm.

Table 3.3 Comparative analysis of the computational results between the exact method and HGA on Portugal case.

Exact results		Heuristic results			
Optimal cost (x 10^8 €)	Computational time (s)	Optimal is reached (%)	Average gap (%)	Maximum gap (%)	Average computational time (s)
4.7901	113	70	0.39	1.34	231

Although the effectiveness of the heuristic has been demonstrated (by the percentage in which the optimum is reached), in terms of efficiency the heuristic is not adequate in this instance since in the average time to reach the optimum it is greater compared to the time spent in the exact method. Despite this apparent weakness, the efficiency of the heuristic improves on large-size instances scale, as will be shown in the following section.

3.6.2.2 **Computational Results on Random Instances**

Other computational experiments were carried out to measure the performance of the HGA. For this purpose, we generated 10 instances according to the guidelines described on Appendix B each with 20 regions. We compared the best solution obtained by exact method within a maximum execution time of 12 hours and the best solution obtained by performing 10 runs of the HGA on each generated instance.

Computational results are shown in Table 3.4. As can be seen, in 2 instances the optimal solution was reached within the limit time (12 hours) using the exact method, which to some extent shows the complexity of the mathematical model for the problem under study. On the other hand, in all the analyzed instances, the results obtained by the proposed heuristic have improved the results obtained by exact methods in significantly shorter computational times.

Table 3.4 Comparative analysis between exact method and the HGA results on a benchmark instance set of 20 regions.

Instance	Exact method results			Heuristic results		Percentage difference
	Total cost of the best integer solution found (x 10^8 €)	GAP (%)	Computational time (s)	Total cost of the best integer solution found (x 10^8 €)	Computational time (s)	(%)
1	0.9109	0	3197	0.9109	70.38	0
2	4.8112	22.06	43200*	4.5947	243.85	4.50
2	3.0579	22.48	43200*	2.8142	63.14	7.97
4	2.7518	19.69	43200*	2.4996	408.48	9.16
5	1.0229	0	8304.25	1.0229	64.71	0
6	6.9952	20.42	43200*	6.8679	437.82	1.82
7	6.3474	21.66	43200*	6.2029	400.48	2.28
8	2.0467	20.99	43200*	1.8283	353.69	10.67
9	3.0197	18.70	43200*	2.7946	102.20	7.45
10	7.8478	21.05	43200*	7.7317	333.89	1.48

* Maximum time of running

3.7 Conclusions

In this part of our work, we focused on the design and implementation of an algorithm based on metaheuristics in order to find near-optimal solutions in a reasonable computational time. The computational experiments carried out led us to the conclusion that the implementation of a local search procedure embedded in a classical genetic algorithm gave solutions of acceptable quality when compared with the optimal solution in a benchmark instances set.

However, an initial weakness of our proposal was the excessive computational effort in a large-scale instance, to some extent due to the exploration strategy of the neighborhood executed in the local search procedure. The initial strategy consisted of the exhaustive exploration of the neighborhood of a current solution. This strategy was modified to stop the exploration once the first solution is found that "improves" the current solution or the exploration time exceeds a predefined threshold. The solutions found when applying the second strategy were of higher quality than those obtained with the initial strategy, in large-scale instances.

The computational experience described above led us to evaluate other variants in the implementation of the various procedures in the proposed algorithm in order to improve its computational performance for the intermodal terminal location problem in a decentralized management context, based on an all-or-nothing approach; for instance, we could analyze the impact on the quality of the solutions found in the execution of the algorithm if the quality of the set of initial solutions is improved (in our work this set was generated randomly).

In line with the works related to the design of heuristic algorithms that have been reviewed in the present work, the performance of our algorithm depends to a great extent on the algorithm configuration. The parameter tuning was carried out in an automated way by means of an iterated local search algorithm, which, as with any local search algorithm, depends on the neighborhood of a current solution. Otherwise, due to the nature of each parameter to be adjusted (each of them belongs to the set of positive reals), one of the challenges in this process was to define a discretization of each parameter, both in cardinality and in figures. This situation leads us to think that previous computational experiments are required for getting a suitable parameters discretization.

Despite the initial difficulties in defining a suitable discretization of the parameters to be adjusted, the results obtained in the automatic algorithm configuration of the HGA have shown that the performance of the HGA is satisfactory in a set of benchmark instances.

In the literature review carried out, it was observed that the works focused on the aims of the automatic algorithm configuration to optimize the algorithm performance, measured in terms of computational effort, or the objective function value within a maximum time defined in advance in a set of reference instances. An innovative aspect considered in this work is to measure the performance of our algorithm in terms of other factors, namely, the quality and robustness of the set of feasible solutions found in its execution and the computational effort used to obtain them. One difficulty of this approach is that the benchmark instances differ in their main characteristics (spatial distribution and GDP of each region), so it was decided to apply a heuristic procedure to evaluate the performance of the hybrid algorithm of each factor separately. Undoubtedly, other approaches may be open to exploration in future research.

4 Intermodal Terminal Location Problem under a Decentralized Approach based on a Discrete Path Choice Model

4.1 Introduction

The mathematical formulation of the problem described in chapter 2 was based on the fact that the users of the freight transport system constitute a homogeneous group who choose the lowest cost route when transporting the freight demand between two regions. However, in practice other factors can influence when making the modal choice. For instance, one of the factors that affects the market share of the rail-road intermodal system is the location and type/capacity of the intermodal terminals, especially with respect to their proximity to the supply and demand points (Niérat P. (1977)).

Other factors that could affect the attractiveness of a rail-road intermodal transport system include rail-hauled distance, price per ton transported, delivery time, reliability, frequency and accessibility (Ben-Akiva M. et al. (2013)), which enable carriers to evaluate and select a transport mode and/or route according to their own best interest. Nevertheless, two carriers do not always make the same choice in the same scenario because they might assess any of the distribution options differently. This implies that the freight flows between each pair of regions can be simultaneously distributed in multiple ways.

Left-Figure 4.1 shows a distribution example of three freight flows represented by red, blue and green lines in a system which is composed of three regions (A, B, C) and four potential terminals (1, 2, 3, 4), each with a maximum capacity of 100 units. The demand between each pair of regions is shown along each line. The absence of intermodal terminals means that the shipments are done by road (solid line). Now suppose that terminals 1, 2 and 3 are operative. If freight distribution is managed in a centralized way (i.e. regardless of the individual decisions of the carriers) using intermodal infrastructure, freight flow is routed to minimize the total cost of the system. However, this situation is not realistic because each carrier, under its own assessment of the "utility" of each routing option, chooses the best route so that the total freight flow will be split proportionally according to the "utility" of each routing option between each region pair (right-Figure 4.1). For instance, freight flow from region B to region C is, according to the figure in brackets, proportionally split between the rail/road route B-1-3-C (40 units) and road B-

C (10 units). Otherwise, freight flow from region A to region B is completely carried out by road.

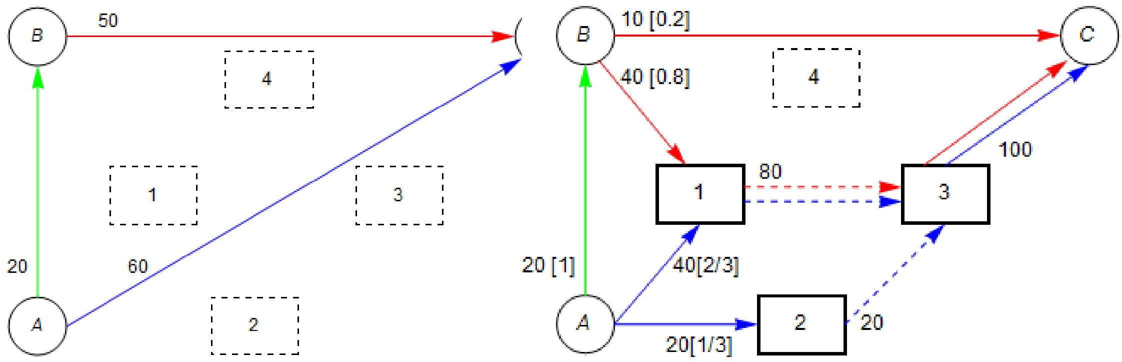


Figure 4.1 **An instance of an intermodal transport network in a decentralized approach context based on a discrete path choice model. (Based on figure in Sörensen et al. (2013))**

The difference between the problem described in chapter 2 and the one addressed in this chapter is circumscribed in the way freight is allocated in the network i.e. in chapter 2 the demand between two regions is completely allocated to the lowest cost route between them while in this chapter the demand is split proportionally among the various route options between the two regions according to a discrete path choice model.

Thus, a first objective of this chapter is to formulate an optimization model for the intermodal location problem under a decentralized context based on a discrete choice model.

The problem addressed in this chapter has a high computational complexity, so that the implementation of heuristics becomes vital for getting near-optimal solutions in large-scale instances. Thus, a second objective is to adapt the hybrid heuristic algorithm designed in chapter 3 to the problem proposed in this section.

The remainder of this chapter is organized as follows. First, we describe in detail the problem to be addressed and key related modeling work reported in the literature. This is followed by the presentation of the optimization model we developed to address the problem, where we highlight the constraints required to cope with a decentralized management context based on a discrete path choice model. The behavior of the model is then discussed, with reference to a hypothetical example. After that, we show the results of several computational experiments that measure the performance of an adaptation of the hybrid algorithm proposed in chapter 3 in a benchmark instance set and; an application in mainland Portugal and the Iberian Peninsula. Finally, we summarize the research done so far and indicate directions for our future work on intermodal terminal location problems

4.2 Problem Description

The addressed problem in this section is a variant to that described in Chapter 2. This variant is focused on modifying the way in which the demand between regions is allocated to the transport network. In fact, an adopted assumption in the problem addressed on Chapter 2 is that users of the freight transport network will choose the route with the lowest transport cost between each pair of regions.

However, carriers are rational individuals who belong to a heterogeneous group and value each of the transport options in different ways, pondering other factors such as cultural and social aspect, reliability, frequency and others. This behavior lead that the freight transport between two regions is not necessarily carried out by the least-cost route but the freigth is hauled between the different feasible routes.

On the other hand, the behavior of the users in the modal (or routes) decision process is not usually completely known by a analyst. Therefore, the analyst can only draw inferences regarding the behavior of users. Thus, specifically, the problem addresses in this section consists to formulate a mathematical model for designing an intermodal terminal network by a government entity that includes the multiple factors that users weigh in the decision process of the appropriate route for them.

4.3 Related Works

Intermodal terminal location has been tackled from a number of angles. A few works have focused on applying a multi-criteria approach (Mateus et al. (2008), Awad-Núñez et al. (2014), Nguyen L.et al.(2016)) to a potential set of intermodal terminal locations. Other contributions have addressed this issue by applying a mathematical model that includes a few terminal operational characteristics. For instance, some works deal with a limit on the capacity handled by a terminal (Ernst et al. (1999), Rodriguez et al. (2007), Hoff et al. (2017), Stanojević et al. (2015), Sörensen et al. (2012)). However, the mathematical models they present do not consider a lower limit in the operating capacity of each terminal. This constraint aims to ensure economic sustainability in the operation of each terminal. Other authors tackle the multiple-allocation hub location problem, in which different routes can be used to transport from one region to another (Ebery et al. (2000), Ernst et al. (1998)). These last works assume that a centralized authority establishes the distribution in order to minimize the total cost of the system. However, in practice the carriers make their own decisions based on their own interests, and thus choose the best way of distribution to meet their requirements.

This issue can be analyzed in a scenario where competition between the different forms of distribution (unimodal or intermodal) is possible. Vasconcelos et al. (2011) formulate a mathematical model for an uncapacitated hub location problem. Another approach is proposed by Sörensen et al. (2012)) based on a bi-objective model. Sörensen et al. (2012)) devise a mathematical model for the capacitated multiple-allocation intermodal location problem with two objectives: the first one aims to minimize the fixed charge for installing the new intermodal terminals, i.e. a government policy or a private institution which would build the terminals, and the second one aims to minimize the total distribution cost, i.e. a strategy employed by users.

Another contribution linked to the facilities' location in a competitive environment was proposed by Marianov et al. (1999). They formulated a mathematical model to locate new hubs in a competitive environment, i.e. in which hubs already exist that are operated by another firm. The objective function is to maximize market share on the assumption that customers will choose the firm that provides the lowest cost (all-or-nothing allocation approach). In the same context, Sasaki et al. (2001) incorporate a logit model in the customer decision process. In addition to the use of a discrete choice model to characterize the choice of the decision maker, Lüer-Villagra et al. (2013) include a pricing problem for the services provided by a firm with the objective of maximizing the profits of the firm.

An alternative approach to characterize the decision process of carriers is provided by Teye et al. (2017) in an intermodal terminal location problem. Teye et al. (2017) formulate a mathematical model for locating an intermodal terminal set taking into account that carries have multiple freight distribution options. The objective of the model is to maximize the entropy that will allow the establishment of the most likely feasible state of the variables. Unlike the other models presented in this literature review, the total system cost is restricted to a maximum budget in the planning horizon.

4.4 Optimization Model

In the formulation of the optimization model for the location of intermodal terminals under a decentralized management based on a discrete path choice model, it is necessary to augment the centralized model (section 2.5.1) with constraints guaranteeing that the freight between each pair of regions to be split among the different routes between them. The new parameters, parameter, decision variables and constraints to include in the model are as follows:

Parameters

$c_{jk}^{gh} \geq 0$ – observable generalized transport cost from region j to region k using terminals located in regions g and h

$\theta \geq 0$ - The scale parameter of Gumbel distribution

Decision variables

$p_{jk}^{gh} \geq 0$ – Freight proportion from j to k that is sent through terminals g and h. In the case of direct shipments by road from j to k, it is represented by p_{jk}^{jj};

s_{gh}= 1 if at region g and at region h are located an intermodal terminal, otherwise $s_{gh} = 0$;

Constraints

The following constraints allow assigning 1 to the variable s_{gh} if at region g and at region h are located an intermodal terminal i.e., if no terminal is located at h or no terminal is located at g, then s_{gh} takes 0.

$$2s_{gh} \leq \sum_{i \in I} y_g^i + \sum_{i \in I} y_h^i, \qquad \forall g, h, g \neq h \ \in N \tag{31}$$

$$s_{gh} \geq 1 + 2\left(\sum_{i \in I} y_g^i + \sum_{i \in I} y_h^i - 2\right), \forall g, h, g \neq h \in N \tag{32}$$

The following constraints (33 and 34) define the freight proportion sent from region j to region k through every possible route between them. Constraints (33) quantify the freight proportion sent from region j to region k through intermodal terminals located at g and h, whereas constraints (34) define the freight proportion sent from region j to region k

directly by road. In both cases, the freight proportion is based on a multinomial logit model being $-c_{jk}^{gh}$ the value of the observable utility of the path $j-g-h-k$ determined by the analyst. This utility results from the weighted combination of a factors set that users take into account when choosing how to transport freight. (see Appendix A).

$$p_{jk}^{gh} = \frac{\mathrm{e}^{-\theta c_{jk}^{gh}} s_{gh}}{\mathrm{e}^{-\theta c_{jk}^{jj}} + \sum_{h' \in N} \sum_{g' \in N: g' \neq h'} \left(\mathrm{e}^{-\theta c_{jk}^{g'h'}} s_{g'h'} \right)}, \forall j,k,g,h \in N: g \neq h \tag{33}$$

$$p_{jk}^{jj} = \frac{\mathrm{e}^{-\theta c_{jk}^{ro}}}{\mathrm{e}^{-\theta c_{jk}^{jj}} + \sum_{h' \in N} \sum_{g' \in N: g' \neq h'} \left(\mathrm{e}^{-\theta c_{jk}^{g'h'}} s_{g'h'} \right)}, \forall j,k \in N \tag{34}$$

The following constraints (35 to 38) define freight proportion aggregation. Constraints (35) define that the freight proportion sent from region j to a terminal located at region g (u_{jg}^{i}) is equal to the sum of the freight proportions allocated to all intermodal routes that have as its first leg the path from region j to region g. Constraints (36) and (37) play a similar role. Constraints (36) calculate the freight proportion sent from a terminal located at region g to a terminal located at region h which is originated at region j, whereas constraints (37) quantity the freight proportion sent from a terminal located at region h to region k which is originated at region j. On the other hand, constraints (38) quantity the freight proportion sent directly by road.

$$\sum_{i \in I} u_{jg}^{i} = \sum_{k \in N} \sum_{h \in N: h \neq g} \frac{q_{jk}}{q_j^{TOT}} p_{jk}^{gh}, \qquad \forall j,g \in N \tag{35}$$

$$\sum_{i \in I} w_{jgh}^{i} = \sum_{k \in N} \frac{q_{jk}}{q_j^{TOT}} p_{jk}^{gh}, \qquad \forall j,g,h \in N: g \neq h \tag{36}$$

$$v_{jhk} = \sum_{g \in N: g \neq h} \frac{q_{jk}}{q_j^{TOT}} p_{jk}^{gh}, \qquad \forall j,h,k \in N \tag{37}$$

$$x_{jk} = \frac{q_{jk}}{q_j^{TOT}} p_{jk}^{jj} \tag{38}$$

Given that constraints (33) and (34) are non-linear constraints, we proceed with its linearization based on the work by Aros-Vera et al. (2013).

The following constraints ensure that if a terminal does not operate in the region g or in the region h, the freight proportion sent from region j to k through the terminals located at g and h is zero, otherwise this freight proportion does not exceed the value of one.

$$p_{jk}^{gh} \leq s_{gh}, \forall j,k,g,h,g \neq h \in N \tag{39}$$

The following constraints ensure that freight demand between region j and region k is completely split among all feasible routes.

$$p_{jk}^{jj} + \sum_{g \in N} \sum_{h \in N: q \neq h} p_{jk}^{gh} = 1, \forall j,k \in N \tag{40}$$

The following constraints ensure that freight shipments between the different possible routes follow a multinomial logit model.

$$p_{jk}^{gh} \leq \frac{e^{-\theta c_{jk}^{gh}}}{e^{-\theta c_{jk}^{g'h'}}} p_{jk}^{g'h'} + (1 - s_{g'h'}) \tag{41}$$

$$, \forall j,k,h,g\ h',g' \in N: g' \neq h', g \neq h, h \neq h', g \neq g'$$

$$p_{jk}^{jj} \leq \frac{e^{-\theta c_{jk}^{jj}}}{e^{-\theta c_{jk}^{g'h'}}} p_{jk}^{g'h'} + (1 - s_{g'h'}), \quad \forall j,k,\ h',g' \in N: g' \neq h' \tag{42}$$

$$p_{jk}^{gh} \leq \frac{e^{-\theta c_{jk}^{gh}}}{e^{-\theta c_{jk}^{jj}}} p_{jk}^{jj}, \qquad \forall j,k,h,g \in N: g \neq h, \tag{43}$$

Finally, the following constraints represent the domain of the variables:

$$p_{jk}^{gh} \geq 0, \forall j,g,h,k \in N \tag{44}$$

$$s_{gh} \in \{0,1\}, \forall\ g,h \in N \tag{45}$$

Thus, a linear model for the intermodal terminal location problem under a decentralized management based on a multinomial logit model is given by:

min (1)

s.t.

(2)-(15), (31)-(32),(35)-(45)

4.4.1 Application Example

To exemplify the impact of the proposed model, we apply it in an instance of 10 regions, which is generated according to the guidelines established in Appendix B. Figure 4.2 shows the spatial distribution of the centroids and GDP distribution for the region set. Each centroid is represented by a circle colored according to the level of GDP. For instance, regions 1 and 9 have a high GDP, i.e. the incoming and outgoing freight levels are higher. In contrast, region 5 has the lowest GDP figure. As can be seen, there is a large concentration of regions with a GDP value around the average (approximately € 17000).

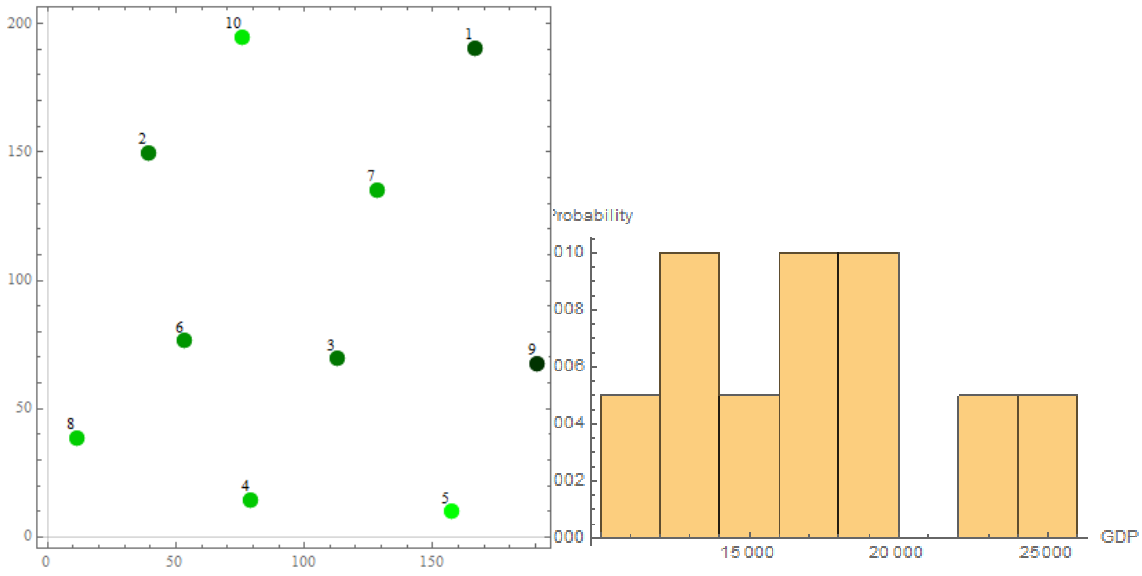


Figure 4.2 Spatial distribution and GDP probability distribution of the generated instance for the application example

Next, we carried out a comparative analysis of the results of the intermodal transport network design in a decentralized management context, based on both an all-or-nothing allocation approach (carrier chooses the lowest cost route between each pair of regions), and on a multinomial logit model. Firstly, the intermodal terminal network under a decentralized management context based on an all-or-nothing allocation approach is shown in Figure 4.3. This shows that 4 type L terminals and two type M terminals should be installed. Otherwise, shipments between each pair of regions can only be undertaken by one route; for instance, shipments from region 1 to region 9 are carried by rail. Also, shipments from region 10 to region 5 can be carried first by rail to the terminal located in 3, and then transported by road to region 5.

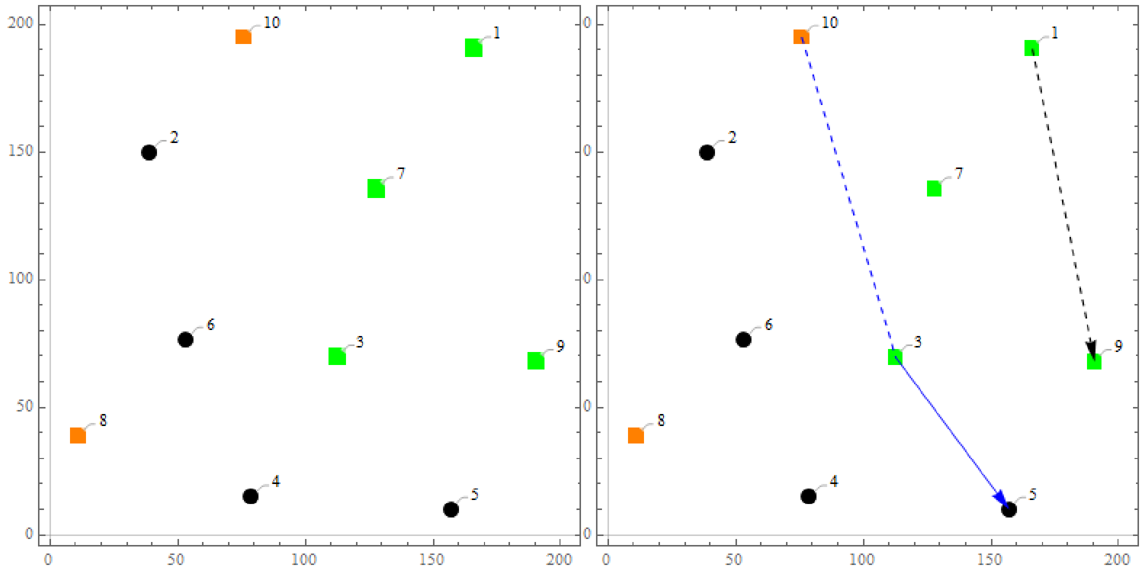


Figure 4.3 Intermodal terminal network of the application example under a decentralized approach based on an all-or-nothing strategy.

Orange rectangle is a type M terminal. Green rectangle is a type L terminal. Dashed line: rail. Solid line: road

If the demand flow between each pair of regions is allocated to each feasible route between them according to a multinomial logit model, the optimal intermodal terminal network shown in Left-Figure 4.3 might be not feasible. In fact, if we characterized the choice of carrier by a multinomial logit model, the path utility measured as the negative of the generalized cost of the path and a θ value (sensitivity to changes on the utility of a path) of 0.01, the freight handled in 3 of the 4 type 1 terminals is below the minimum value at which their operations are economically sustainable. Also, the freight handled in terminal 10 exceeds its maximum operational capacity.

Assuming the path utility is measured as the negative of its generalized cost, and the θ value (sensitivity to changes on the utility of a path) is 0.01, we show below the impact on the design of the intermodal terminal network, considering the variability in the decision making of the carriers.

The freight distribution in the initial network (without intermodal terminals) produces a total transportation cost of approximately 1.26×10^8 € and the cost of freight transported by road of $3.49 \times 10^7 (TEU - Km)$. In this context, the objective is to reduce the total transportation cost by installing a set of facilities that allow intermodal freight transport and hence reduce freight transportation by road.

The results of applying the model in this example show that the new terminals must be established in regions 1, 2 and 9. This network design would allow a market share of intermodal transport of about 10.55 % and a decrease in the transportation total cost of about 2%. On the other hand, freight transported by road which includes freight pre-hauled from regions to terminal, freight post-hauled from terminal to regions and direct shipments is about $3.08 \times 10^7 (TEU - Km)$ which represents a decrease of about 11.75 % with respect to that achieved in the initial network.

The design of the network under a decentralized management context based on a multinomial logit model influences how the freight is distributed in the network. For instance, shipments from region 1 to region 9 are made using two ways: 73.1% of the demand from region 1 to region 9 is shipped by rail (dashed line in Left-Figure 4.4), and 26.9% is done by road (solid line in Left-Figure 4.4). Otherwise, shipments from region 10 to region 5 are made using three ways (Right-Figure 4.4): 11.6% of the demand is transported using the terminals located in regions 1 and 9, 13.9% of the demand is transported using the terminals located in regions 2 and 9, and finally 74.5% of the demand is carried directly by road.

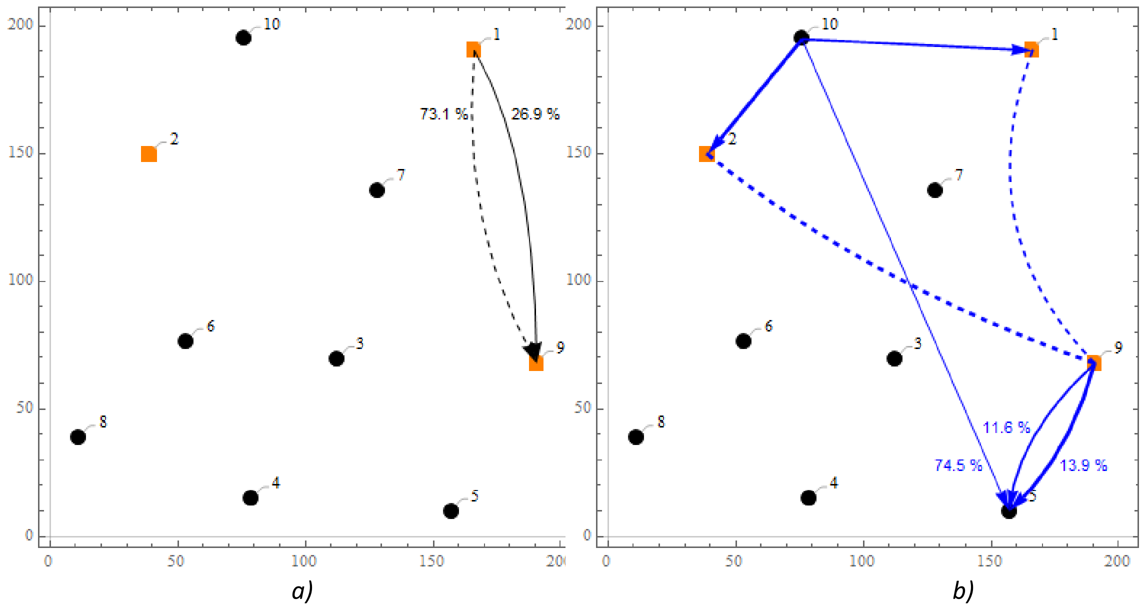


Figure 4.4 Scheme of distribution in the network design of the application example a) from region 1 to region 9 and b) from region 10 to region 5 in a decentralized management context based on a multinomial logit model

Orange rectangle is a terminal type M. Dashed line: rail. Solid line: road.

This example shows that the individual decisions made by the multiple carriers, each sometimes favoring each transport option (both modal choice and path choice) differently, directly affect not only the method of distribution but also the capacity of the terminals.

One aspect to include in the analysis of the model is the impact on the optimal solution for variation in the sensitivity to changes in the utility of a path, θ. For this purpose, we consider a variation in θ of $\pm 25\%$ in the value initially assumed for running the proposed model ($\theta = 0.01$), i.e. we analyze the variation in the initial solution if we set $\theta = 0.0075$ and $\theta = 0.0125$. Table 4.1 shows a summary of the optimal solutions under the sensitivity values described above. One aspect to note is the increase in the market share of intermodal transport and the terminal numbers as sensitivity to path costs increases. Otherwise, freight transported by road decreases as sensitivity to path costs increases.

Table 4.1 Comparative analysis between optimal solution under different θ values.

	ϴ=0.0075	ϴ=0.01	ϴ=0.0125
Terminals	1, 7	1, 2, 9	1, 2, 8, 9
Market share of intermodal transport (%)	8.06	10.55	14.56
Freight transported by road ($\times 10^7$ TEU-KM)	3.33	3.08	2.86

Various computational experiments were performed to ascertain the computational complexity of the proposed model. For this purpose, 4 groups of instances were generated according to the guidelines established in Appendix B, each with 10, 15, 20, and 25 regions. Each instance was executed in a maximum time of 4 hours. Table 4.2. shows a summary of the results obtained:

Table 4.2 Summary of model size of a benchmark instance

Number of regions	Minimum execution time	Average execution time	Maximum execution time	Number of Constraints	Number of Variables	Number of Discrete	Minimum GAP (%)	Average GAP (%)	Maximum GAP (%)
10	689.41	1588.35	2086.48	59646	12758	120	0	0	0
15	14400	14400	14400	616869	59033	255	17.92	65.35	96.06
20	14400	14400	14400	3655274	178908	440	96.28	96.73	97.3
25	14400	14400	14400	14138115	426383	675	96.71	97.20	97.81

As can be seen, as the number of regions in the instance increases, the number of variables and equations in the model increases. Similar behavior can be seen with respect to the computational time-effort and the quality of the feasible solutions obtained at the end of the 4 hours of execution. It is important to note that in the instances of 30 or more regions it was impossible to obtain a feasible solution due to lack of memory in its execution.

This evidence and related work on intermodal location problems for large-scale instances led us to design an algorithm based on metaheuristics for getting near-optimal solution to the problem described in Section 4.2. Given the similarities between the problem analyzed in section 4.2 and that of chapter 2, the proposed heuristic will be the result of adapting the hybrid algorithm described in chapter 3 to the intermodal location problem under a decentralized management based on a multinomial logic model. For this purpose, the freight allocation procedure (freight demand between two regions is allocated to the lowest cost route between them) in the hybrid algorithm described in section 3.4 was modified in such a way the allocation of freight demand between two region is proportionally split according to a multinomial logic model. In the next section, we present some computational results of this modified heuristic which we will identify as $HGADC$.

4.5 Computational Results

In this section, we present different results from applying the $HGADC$ to solve the intermodal terminal location problem in a decentralized management context based on a multinomial logit model. In the first part, we analyzed the performance of the $HGADC$ on a set of 20 instances which were generated according to the guidelines set out in Appendix B, with each instance having 10 regions. In the second part of this section, we apply the $HGADC$ in two case studies based on a mainland Portugal and the Iberian Peninsula.

4.5.1 Computational Experiments on Random Instances

A comparative analysis was carried out to evaluate the quality of solutions provided by $HGADC$ by comparing them to an optimal solution obtained from the mathematical model in Section 4.4. Due to the stochastic nature of the algorithm, each instance was executed over 20 runs, applying $HGADC$.

The computational experiences carried out in section 3.6 have served as a reference for the algorithm configuration, which has been performed by trial and error. Finally, the parameters of the hybrid algorithm defined in section 3.4 for the computational analysis were $factor\_stop = 4$, $factor\_size = 3$, $local\_search\_rate = 0.4$, $mutation\_rate = 0.035$, $crossover\_rate = 0.4$

Computational results are shown in Table 4.3. As can be seen, results show that in all instances the $HGADC$ reached the optimal solution. However, in 9 out of 20 instances (instances $1-6, 11, 12, 20$) the optimal solution was not obtained in all the runs of the algorithm; for example, in instance 20 only for 55% of 20 runs was the optimal solution reached. On the other hand, its percentage deviation from the optimum value (GAP) in those cases is low (less than 1%). Also, we achieved an average GAP of 0.077% and a maximum GAP of 1.403%. Furthermore, the computational time spent on obtaining feasible solutions from $HGADC$ is much shorter relative to those obtained by exact methods.

Table 4.3 Comparative analysis of the HGADC performance over a benchmark instance set

Instance	Exact method results		Heuristic results			
	Optimal value (x 10^8 €)	Computational time (s)	Optimal is reached (%)	Average GAP (%)	Maximum GAP (%)	Average Computational time (%)
1	2.062	2744	80	0.031	0.283	12.94
2	1.981	2820	95	0.002	0.047	3.66
2	2.344	2720	50	0.118	0.248	17.17
4	2.221	1819	80	0.279	1.403	16.55
5	3.271	3124	60	0.118	0.365	10.50
6	2.353	3557	90	0.016	0.156	3.10
7	1.233	1849	100	0	0	5.29
8	0.952	2450	100	0	0	3.46
9	1.264	3595	100	0	0	3.59
10	1.868	2587	100	0	0	4.72
11	2.260	1699	55	0.074	0.236	11.04
12	2.769	4152	85	0.046	0.350	2.58
13	1.258	2721	100	0	0	3.35
14	1.235	3463	100	0	0	2.96
15	1.334	3663	100	0	0	2.40
16	0.795	1812	100	0	0	3.74
17	1.812	3439	100	0	0	3.96
18	2.102	4228	100	0	0	9.21
19	0.756	1929	100	0	0	3.41
20	1.916	3573	55	0.856	2.037	19.96

4.5.2 Case Studies

This section includes the application of heuristics to the problem addressed in two case studies: the first addresses the Portuguese case which has been described in section 2.6. In addition, it is intended to contrast the results obtained based on the two decentralized approaches (all-or-nothing and discrete path choice model). The second case is based on the Iberian Peninsula.

4.5.2.1 **Mainland Portugal**

A detailed description of this case and study data has been presented in section 2.6. It should be emphasized that study data have been estimated based on some assumptions, so the results shown may not be completely adjusted to reality. However, it serves as an illustrative example of the application of the model.

Prior to the execution of the algorithm, calibration of the scale parameter of the Gumbel distribution (θ) defined on the multinomial logit model (section 4.4) was necessary. This process took as reference the market share of freight transport by rail in the current network of intermodal terminals in Portugal (about 3% section 2.6.1) e.g. various θ value were analysed and the one in which the freight allocation in the network according to a multinomial logic model produces a market share of freight transport by rail close to 3% was chosen. In this case, the θ value was 0.33.

Next, we proceed to carry out a comparative analysis between the overall results of the application of the exact model if the current terminals were operating optimally in a decentralized management context based on a multinomial logic model and the results obtained when applying the heuristic adaptation of section 3.4. It is important to indicate that the heuristic was executed 20 times and the results shown correspond to the best solution found in the 20 runs.

The results of this case study are shown in Figure 4.5 and Table 4.4. These results present a set of intermodal system utilization rates in terms of road and rail transport (TEU and TEUxKm) and the respective costs for both the situation current as the best feasible solution obtained by heuristics. Although the optimality of the feasible solution obtained through heuristics has not been guaranteed, it should be noted that the number of terminals that should be installed is smaller than in the optimal configuration of terminals obtained in the decentralized context based on all- or nothing allocation (section 2.6.2). Indeed, 3 new terminals of type L should be built in Tâmega e Sousa, Douro and Leiria (figure 4.5)

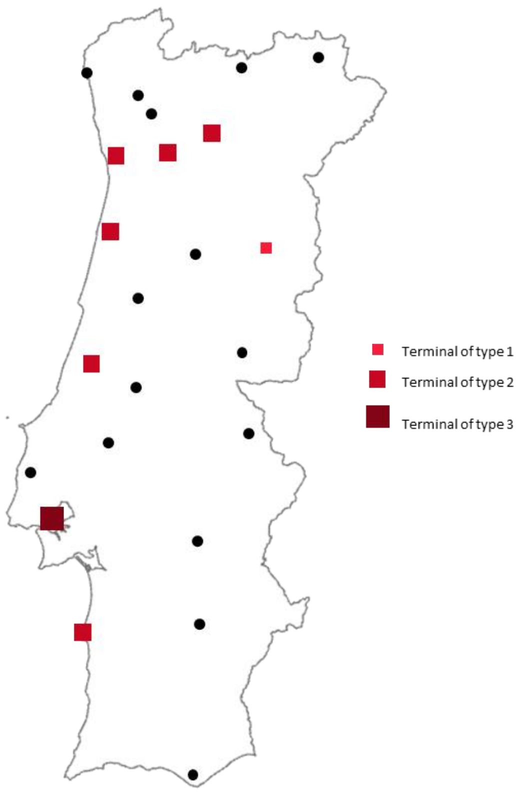


Figure 4.5 Near-optimal location and type of intermodal terminals under a decentralized management context based on a multinomial logic model.

The installation of these new terminals has an important impact on the market share of freight transport by rail. Indeed, its operation allows that the market share increase from 3.2% to 6.28%. This greater market share causes savings in the system of approximately 17 million euros annually. Disaggregating these savings (table 4.5), it can be seen the greatest savings occurs in the regions in which a new terminal must operate e.g. Douro (with cost savings of 3.89%), Leiria (3.45%) and Tâmega e Sousa (2.76). Likewise, the operation of the terminals in Douro and Tâmega e Sousa affects significant savings in the surrounding regions e.g. Ave (1.85%) and Trás-os-Montes (1.77%).

Table 4.4 Main features of the current and near-optimal intermodal terminal networks under a decentralized management based on a multinomial logic model.

Solution features		Intermodal terminal network under decentralized management based on:		
		Multinomial Logic Model		All-or-nothing
		Current	Near-Optimal	Optimal
Number of new terminals	XL	-	0	0
	L	-	3	2
	M	-	0	4
Freight tonnage (10^6TEU/year)	Intermodal	0.137 (3.2%)	0.266 (6.28%)	0.281 (6.6%)
	Road-only	4.103	3.974	3.959
Freight tonnage × km (10^6TEU×km/year)	Rail	36.1 (4.7%)	53.58 (6.9%)	68.24 (8.8%)
	Road	736.78	719.64	709.27
Annual-equivalent terminal investment costs (10^6 €/year)		-	9.17	8.58
Total terminal revenues (10^6 €/year)		13.73	26.61	28.12
Total terminal and transport costs (10^9 €/year)		2.724	2.707	2.698

On the other hand, in table 4.6 the values of the handled freight in the existing terminals are contrasted both in the current network and in the best feasible solution obtained by heuristics. As can be evidenced, in all terminals there is an increase in the freight tonnage which shows that competition for the operation of new terminals does not necessarily impair the operations of current terminals.

Table 4.5 Freight transport costs of NUTS 3 before and after the implementation of the near-optimal intermodal terminal network under decentralized management based on a multinomial logic model

Region	Transport costs (10^6 €/year)		Transport cost savings (%)
	Current network	Near-Optimal network under decentralized management	
Alentejo Central	103.76	103.68	0.08
Alentejo Litoral	172.09	171.42	0.39
Algarve	27.91	27.89	0.07
Alto Alentejo	112.64	112.59	0.04
Alto Minho	104.84	103.99	0.81
Alto Tâmega	92.61	91.75	0.93
Ave	83.13	81.59	1.85
Aveiro	130.73	129.43	0.99
Baixo Alentejo	136.06	135.97	0.07
Beira Baixa	153.11	153.03	0.05
Beira e Serra da Estrela	122.16	120.77	1.14
Cávado	85.47	84.71	0.89
Coimbra	108.94	108.15	0.73
Douro	85.02	81.71	3.89
Leiria	132.86	128.27	3.45
Lezíria do Tejo	85.35	84.94	0.48
Lisbon	316.75	314.96	0.57
Médio Tejo	110.74	110.44	0.27
Oeste	136.09	134.42	1.23
Oporto	95.75	94.17	1.65
Tâmega e Sousa	64.42	62.64	2.76
Tras-os-Montes	146.11	143.52	1.77
Viseu Dão-Lafões	117.96	117.82	0.12
Portugal	2724.6	2697.9	0.98

Table 4.6 Freight handled by the intermodal terminals on a decentralized management based on a multinomial logic model.

Region	Current network		Near-optimal network under decentralized management	
	Terminal type	Freight handled (10^3TEU/year)	Terminal type	Freight handled (10^3TEU/year)
Alentejo Litoral	L	35.2	L	38.3
Aveiro	L	55.6	L	63.1
Beira e Serra da Estrela	M	27.5	M	29.2
Douro	-	-	L	91.9
Leiria	-	-	L	73.3
Lisbon	XL	91.1	XL	98.4
Oporto	L	65.3	L	69.4
Tâmega e Sousa	-	-	L	68.6

Regarding the freight distribution, we take as reference the Douro region where an intermodal terminal of type L should be installed. Although Douro is close to some regions in the northern part of Portugal, freight shipments from Douro is not predominantly by road due to the approach taken in this section. For example, 85.10% of the freight shipments from Douro to Alto Minho is hauled by road; 6.71% with connection by rail to the terminal located in Porto and 8.17% with connection in Tâmega e Sousa. Indeed, 86.87% of freight shipments from Douro to Cávado is hauled by road, 12.98% with connection in Tâmega e Sousa and almost 1% with connection in Porto. On the other hand, shipments from Douro to some central regions are diversified between the different routes that the new terminals provide e.g. shipments from Douro to Alto Alentejo are made in 87.14% by road, and with connection to Port by rail in 0.72%, Aveiro in 9.95% and Leiria in 1.97%. Otherwise, there are predominant routes in the freight shipment between some regions, for instance, 99.98% of the demand from Douro to Trás-os-Montes is hauled by road.

4.5.2.2 **Iberian Peninsula**

This case study is inspired by the Iberian Peninsula reality. The Iberian Peninsula has been defined as having 70 NUTS-III subdivisions, each represented by a centroid according to its importance at the region. Currently, twenty-nine intermodal terminals are operating in the Iberian Peninsula (5 in Portugal and 24 in Spain (ADIF 2017)). As our study area is divided into NUTS-III subdivisions, and given that in Spain a few terminals operate in the same NUTS-III subdivision, e.g. Barcelona, we consider that the operation of these terminals is carried out by a single terminal located at the centroid. Based on this relaxation, we can deal with 24 intermodal terminals in the Iberian Peninsula which are geographically distributed as shown in Figure 4.6. It can be seen that in the north and south regions of Spain there is a concentration of intermodal terminals. In contrast, there are very few in the central region of Spain. Otherwise, intermodal terminals in Portugal are predominantly in the coastal regions.

On the other hand, we needed to identify a set of feasible regions where it is possible to locate an intermodal terminal. Access to a railway and road network was the only criterion taken into account to analyze the feasibility of a region. Thus, there are 44 feasible regions in which an intermodal terminal (of any type of terminal (M-L-XL)) could be installed, since there are no railway links in Alto Tâmega and Trás-os-Montes.

Regarding connection between Portugal and Spain, it has been considered that first leg connection by road and rail between Portugal and Spain is only made between Alto Minho and Pontevedra; Beira and Serra da Estrela and Salamanca and; Alto Alentejo and Badajoz. Also, connection between Algarve and Huelva is only possible by road. The freight tonnage to be sent between each pair of regions was assumed to be proportional to the product of their GDP and inversely proportional to the distance between them. However, the freight demand between regions of different countries was adjusted in such a way that the aggregate freight demand between Portugal and Spain fit to the data published by INE. The other study data (terminal costs, usage rate, rail and road transport unit costs and capacity limits of each type of intermodal terminal) are the same considered in section 4.5.2.1.

Figure 4.6 Geographical location of the current intermodal terminals in the Iberian Peninsula. (Orange circle: Type-M terminal. Green circle: Type-L terminal. Blue circle: Type-XL terminal)

We proceeded to analyze the current situation of freight transport in the Iberian Peninsula situation if the freight demand is allocated in the transport network based on a multinomial logic model. The results in this scenario show that the freight transported by rail is about $1.34 \times 10^8 (\mathrm{TEU} - \mathrm{Km})$ with a market share of about 5.33%. On the other hand, the freight transported by road is about $15.42 \times 10^8 (\mathrm{TEU} - \mathrm{Km})$.

A detailed analysis of the current situation shows that Segovia, Toledo and Guadalajara direct about 50% of the incoming freight to the intermodal terminal of Madrid to be distributed to other regions. In addition, it is observed that at a greater radial distance from Madrid the attractiveness of the intermodal terminal decreases, e.g. Ciudad Real, Cuenca and Avila direct about 30% of the incoming freight to the terminal. Figure 4.7 shows the area of influence of the intermodal terminal located at Madrid

Likewise, in Teruel about 94.15% of demand for other regions is transported by road. However, intermodal terminals located in Zaragoza, Madrid and Burgos gather approximately 87% of the freight first transported to Teruel.

Figure 4.7 Influence area of intermodal terminal in Madrid

We applied the proposed algorithm to the case of the Iberian Peninsula. Figure 4.8 shows a redesigned intermodal terminal which is the best solution obtained when applying the algorithm. A total of 13 new terminals of type M must be established in the Iberian Peninsula in order to reduce total transportation costs. This configuration of intermodal terminals would lead to a reduction of approximately 0.88% of the current transportation cost (40 million Euros by year) and an increase in the market share of intermodal transport up to 7.35%. Otherwise, the freight transported by road is about $15.06 \times 10^{8}(TEU -$

Km) which represents a decrease of 2.34% of the freight transported in the current conditions.

Figure 4.8 Redesigned Network under a decentralized approach based on a multinomial logit model.

(Orange circle: Type M terminal. Green circle: Type L terminal Blue circle: Type XL terminal)

Otherwise, most of the new terminals should be in the central region of the Iberian Peninsula. Also, a terminal should be installed in Baixo Alentejo, which to some extent becomes relevant in the current times when the governments of Spain and Portugal boost intermodal freight trade. A summary of the overall results of the case study is shown in Table 4.7

Table 4.7 Main features of the current and near-optimal intermodal terminal networks on Iberian Peninsula

Solution features		Intermodal terminal network	
		Current	Near-Optimal
Number of new terminals	XL	-	0
	L	-	0
	M	-	13
Freight tonnage (10^6TEU/year)	Intermodal	0.347 (5.33%)	0.478 (7.35%)
	Road-only	6.162	6.03
Freight tonnage × km (10^8TEU×km/year)	Rail	1.34 (8.00%)	1.73 (10.30%)
	Road	15.42	15.06
Annual-equivalent terminal investment costs (10^6 €/year)			8.03
Total terminal revenues (10^6 €/year)		34.7	47.8
Total terminal and transport costs (10^9 €/year)		5.82	5.78

The redesign of the intermodal terminal network produces savings in transportation costs in each NUTS 3 (Table 4.8), being more significant in regions where a new terminal operates e.g. Albacete (4.82%), Alicante (3.30%), Baixo Alentejo (2.50%), Zamora (3.73%) among others. However, in other regions, savings are not significant because access to new terminals is not economically profitable e.g. Trás-os-Montes.

Table 4.8 Freight transport costs of NUTS 3 before and after the implementation of the near-optimal intermodal terminal network under decentralized management

Region	Transport costs (10^6 €/year)		Transport cost savings (%)
	Current network	Near-optimal network under decentralized management	
A Coruña	67.35	66.92	0.63
Álava	128.71	127.88	0.64
Albacete	70.41	67.01	4.82
Alentejo Central	85.69	85.68	0.01
Alentejo Litoral	142.24	142.01	0.16
Algarve	28.30	28.20	0.36
Alicante	62.74	60.67	3.30
Almería	54.61	54.45	0.28
Alto Alentejo	91.45	91.44	0.01
Alto Minho	85.18	85.05	0.15
Alto Tâmega	74.65	74.55	0.13
Asturias	78.87	78.72	0.19
Ave	69.01	68.87	0.20
Aveiro	106.94	106.57	0.35
Ávila	78.08	77.47	0.77
Badajoz	60.21	59.95	0.44
Baixo Alentejo	110.60	107.84	2.50
Barcelona	86.07	85.62	0.53
Beira Baixa	123.44	121.08	1.91
Beira e Serra da Estrela	98.77	98.57	0.20
Bizkaia	100.23	99.67	0.56
Burgos	90.46	89.70	0.84
Cáceres	64.60	63.98	0.96
Cádiz	59.81	59.68	0.22
Cantabria	80.91	80.39	0.65
Castellón	69.21	67.08	3.08
Cávado	70.59	70.46	0.19
Ciudad Real	69.01	65.91	4.49
Coimbra	89.44	89.42	0.02
Córdoba	57.72	57.28	0.75
Cuenca	66.50	66.05	0.68
Douro	69.65	69.58	0.10
Gipuzkoa	108.02	107.50	0.49
Girona	68.49	68.20	0.42
Granada	64.37	63.77	0.93
Guadalajara	90.42	88.26	2.39
Huelva	55.94	55.63	0.56
Huesca	82.53	81.98	0.66
Jaén	56.41	55.17	2.19
La Rioja	85.23	84.77	0.55
Leiria	108.37	108.34	0.03
León	77.05	76.84	0.27
Lezíria do Tejo	70.90	70.80	0.13
Lisbon	251.94	249.87	0.82
Lleida	75.71	75.29	0.56
Lugo	58.10	57.62	0.83
Madrid	118.61	117.66	0.80
Málaga	62.73	62.56	0.27
Medio Tejo	90.30	90.29	0.02
Murcia	64.54	64.22	0.50
Navarra	103.30	102.79	0.49
Oeste	109.62	109.28	0.31
Oporto	79.54	79.38	0.21
Ourense	58.83	57.05	3.03
Palencia	84.24	83.87	0.44
Pontevedra	62.96	62.22	1.18
Salamanca	84.60	81.58	3.57
Segovia	85.68	85.20	0.57
Sevilla	68.53	68.06	0.70
Soria	82.31	81.83	0.57
Tâmega e Sousa	53.10	53.00	0.19
Tarragona	75.25	74.74	0.67
Teruel	77.39	75.82	2.03
Toledo	72.42	71.03	1.92
Trás-os-Montes	116.72	116.67	0.05
Valencia	73.26	72.68	0.79
Valladolid	93.39	92.86	0.57
Viseu	95.74	95.66	0.08
Zamora	76.63	73.77	3.73
Zaragoza	85.99	85.25	0.86
Mainland Iberian Peninsula	5820.6	5769.3	0.88

One aspect to highlight is that the new terminals in central Spain capture a percentage of freight handled by the intermodal terminal in Madrid (approximately 25%). Other impacts of the freight demand redistribution can be seen in regions where there was no terminal in the current situation. For instance, based on the current situation, shipments from Salamanca to Madrid are carried out almost entirely by unimodal transport (road). However, given the new intermodal network, 13.42% of freight demand from Salamanca to Madrid is transported by rail, 85.47% by road, 0.5% by rail/road transport using the new terminal located at Guadalajara and the rest is carried on other rail/road routes. Likewise, in Teruel, there is a noticeable decrease in the freight demand transported by road. In fact, about 82.57% of total demand for other regions is carried out unimodally by road. This can be explained by the new terminal that must be installed there.

4.6 Conclusions

The specific objective of this section was to incorporate the variability in the decisions adopted by the carriers into the strategic planning of the intermodal terminal network. For this purpose, the formulation of a mathematical model for the design (redesign) of the intermodal terminal network was based on the assumption that the errors generated, either in obtaining the information or in identifying the significant variables in the valuation of the utility of each routing option, follows a Gumbel probability distribution. This distribution is a function of a parameter, θ, which measures, in the context of this section, the sensitivity in decisions made by carriers to changes in the utility of a path. In practice, this parameter is obtained from the preferences revealed by the carriers. The impact on the design of the intermodal terminal network, both in the number of terminals to be installed and in their geographical location, should be evident from the computational experiments due to variations in this parameter. Thus, future research should focus on the formulation of models robust to variations of the parameter described above.

However, the incidence of the freight allocation approach (all-or-nothing vs multinomial logit model) in the intermodal transport network was marked. Basically, the impact occurred in the sizing of the terminals as well as in the number of terminals to be installed, which in some cases could affect the economic sustainability (if the handled freight is lower than the operational minimum) or generate congestion problems (if the handled freight exceeds the operational maximum) in the terminals.

When analyzing the impact of installing terminals in central Spain, it was evident that these terminals would capture a percentage of the freight handled at the Madrid terminal. Undoubtedly, this situation could affect the economic sustainability of the terminal in Madrid. Therefore, the strategic planning of the intermodal transport network should not only be concerned with installing new terminals but also examine the possibility of changing the type of a terminal that is operative. This process clearly includes an extensive analysis because the initial investment made in the existing terminals will be difficult to recover.

Finally, the high computational complexity of the problem tackled in this section bore out the reports in some publications related to the hub location problem. This was a limiting factor for obtaining optimal solutions for large-scale instances such as the Iberian Peninsula. A hybrid algorithm was proposed to achieve near-optimal solutions to large-scale instance problems. The results obtained were satisfactory, but one weakness of the proposed algorithm was the excessive computational effort required for these problems.

5 Conclusions

A multimodal transport system is a feasible alternative in freight transportation, but despite its economic and ecological advantages, unimodal transport by road still has a greater market share in freight transportation. One aspect that affects the performance of the system is the location of the terminals. The review of the literature made it possible to report multiple approaches used to design a network of intermodal terminals. Some of these contributions focus on providing optimization-based tools for the optimal location of intermodal terminals in a centralized management context. However, in some cases it is the interaction between the supply of services and the demand by users that regulates the flows within an intermodal terminal network. From the above, the general objective of this thesis is formulated: to provide a government entity with optimization-based decision support tools for the strategic planning of a rail/road intermodal terminal network in a context where freight transport is under decentralized management.

The fulfillment of the general objective of this research is carried out through five specific objectives. Two of the five specific objectives concern the development of optimization-based models for the optimal location of intermodal terminals in a decentralized context i.e. in a context in which users decide whether or not to use the terminals based on their own interests. To the best of our knowledge, those objectives address a problem that has not been widely explored in the literature.

It is obvious that the design of the intermodal terminal network is influenced by the information available to the analysts involved in planning the strategy. For that, a first approach taken in a decentralized context is that both the analyst and the terminal users are rational individuals who possess perfect information, so that the analyst has full knowledge of the utility that users assign to each transport. This problem was extensively addressed in Chapter 2 and allows the fulfillment of our first specific objective. Chapter 2 focused on the formulation of an optimization model that allows to a governmental entity defining the optimal location of intermodal terminals in order to minimize the total transportation costs taking into account the decisions made by users who choose the lowest cost route between them (all-or-nothing approach). This optimization model was applied to a case study inspired by the Portuguese reality. We have shown both the economic impact and the market share of the intermodal transport due to the context (centralized vs decentralized) in which the strategic planning is carried out. There is no doubt that deciding on the location and type of intermodal terminals is a long-term problem, and therefore the context in which the planning is carried out is crucial, because of the high initial investment. In addition to the economic advantages of intermodal transportation, its use promotes an appreciable reduction in road transport which was evidenced in the overall results of the application of the model in the case study. Likewise, it was verified that the savings were not only focused on the regions in which a new intermodal terminal should operate but also in the surrounding regions. This network effect is also reflected in the freight handled in each current terminal e.g. freight handled in the terminal located in Oporto would decrease on the optimal redesign of the current network under a decentralized management based on an all-or-nothing allocation by the operation of the new terminals in north of Portugal.

The computational experiments carried out on different instances on chapter 2 have shown the computational complexity of the intermodal terminal location problem under a decentralized context, which is in line with the reports found in the literature review. Because of this, it became necessary to design heuristic algorithms to obtain near-optimal solutions to large-scale instances of the problem in question. This in line with our second specific objective which is addressed on Chapter 3.

Based on the reports found in the literature review that show the advantages of designing hybrid algorithms, our algorithm approach was focused on to embed a local search procedure in an evolutionary algorithm. Although the hybrid algorithm performance in terms of quality of the solutions found for locating an intermodal terminal in the benchmark instance set was adequate, the computational effort is not very encouraging for large-scale instances. Computational experiments showed that an exhaustive neighborhood exploration of a solution in the local search was not suitable for large-scale problems. Thus, a variant that was implemented was a non-exhaustive exploration limited by the execution time of the local search showing significant improvements in large-scale problems.

In line with research related to the design of heuristic algorithms that have been reviewed during the present work, the performance of our algorithm depends to a great extent on the algorithm configuration. This process allows tuning a parameter set of the algorithm in order to optimize its performance. As explained in chapter 3, this process may require excessive computational effort and only be suitable for one instance. For that, additionally in chapter 3 we designed a strategy to find an algorithm configuration automatically in order to optimizing the algorithm performance of a benchmark instances set which allows the fulfilment of our third specific objective.

The adopted approach was based on an iterated local search algorithm. However, the nature of each parameter to be adjusted (each of them belongs to the set of positive reals) meant that one of the challenges in this process was the definition of the domain of each parameter, both in cardinality and in figures. This situation leads us to think that previous computational experiments are needed to define the domain of real parameters.

In the literature review carried out, it was noted that the works focused on the automatic algorithm configuration aim to optimize the algorithm's performance, measured in terms of computational effort or the objective function value within a maximum time specified in advance in a set of reference instances. An innovative aspect considered in this work is to measure the performance of our algorithm in terms of other factors, namely, the quality and robustness of the set of feasible solutions found in its execution. One difficulty of this approach is that the benchmark instance sets differ in their main characteristics (spatial distribution and GDP of each region), so it was decided to apply a heuristic procedure to evaluate the performance of the hybrid algorithm of each factor separately. The computational experiences have allowed to demonstrate the advantages of this strategy to determine a suitable algorithm configuration for getting near-optimal solutions of several instances.

The last two specific objectives are addressed in Chapter 4. Chapter 2 to some extent reflects the way in which decisions are taken by both a government entity, who must make decisions about the location and type of terminals, and by the possible users of the terminals, who decide whether or not to resort to terminals. However, users make up a heterogeneous group, who value in different ways each feasible route all feasible routes between each pair of regions. Also, the analyst does not know specifically the way in which users make their decisions. Advantageously, several researches identify multiple factors that affect the modal and routing choices made by users and to understand that they can weigh those factors in different ways when evaluating their options. This allows the analyst to infer about the behavior of the terminal users and therefore calculate the demand of terminals. An assumed assumption in this research is that the freight demand between each pair of regions is split proportionally according to a multinomial logic model. Based on this assumption, in chapter 4 we shown an optimization model for the intermodal location problem under a decentralized context based on a multinomial logic model.

Computational experiences have evidenced the computational complexity of the problem in question even in small-scale instances such as the Portuguese case. For that and given that the difference between the problems described in chapter 2 and chapter 4 lies in the way in which the freight is allocated in the freight transport network, we modify this procedure in the hybrid algorithm of chapter 3, to obtain near-optimal solutions for the problem the intermodal location problem under a decentralized context based on a multinomial logic model. The algorithm was validated by comparing the optimal solution of the model applied to instances of 10 regions and the solutions obtained by the hybrid algorithm. The results were satisfactory in terms of effectiveness and efficiency. One aspect worth mentioning is that the design of the intermodal terminal network was clearly affected by the approach taken in decentralized management. Unfortunately, it was impossible to perform a similar comparative analysis in instances of greater cardinality.

In spite of that, we did a comparative analysis of the overall results of the optimal solution of the intermodal terminal location problem under a decentralized management based on an all-or-nothing approach and the best heuristic solution found when applying the variant to the hybrid algorithm in the Portuguese case. It is to be expected that the overall results of the optimal network in the first approach (all-or-nothing allocation) are better than in the second approach, however, this second approach is undoubtedly more in line with reality.

Likewise, we present an analysis of the overall results of the best solution obtained by applying the hybrid algorithm in a case study inspired by the Iberian Peninsula. Although it is complex to carry out a comparative analysis between the Portuguese and the Iberian Peninsula cases, the savings (in percentage terms) generated by the redesign of the current network are similar in both cases. On the other hand, regardless of the approach adopted in the freight allocation on the network, its impact is significant in the reduction of road transport and the increase in the market share of rail transport.

Although these decision-support tools for a government entity is inspired by real situation, they suffer from some shortcoming. For instance, the sensitivity analyses carried out on the formulated mathematical models have shown that small variations in demand, as well as transportation costs, produce significant changes in the design of the intermodal transport network, especially in the types of terminal. Future work should focus on formulating robust models before changing the parameters indicated above.

A significant contribution to the state of the art of this research is, in fact, that it incorporates the variability in the decisions of the terminal users in the strategic planning, which was characterized by a multinomial logit model. However, this approach requires that users perceive that the routing options are completely different from one another. Therefore, a gap to be explored is the impact on the strategic planning of the intermodal terminal network if terminal users believe that all the routes through the terminals are similar in that they share certain attributes. This new approach could be characterized by a Single-Level Hierarchical Logit Model.

Finally, government entities should not only focus on providing infrastructure to boost the use of a sustainable transport. The installation of a new terminal in a region not only benefits the stakeholders of the transport sector but also in the quality of life of people living in the region e.g. increases employment positions due to the need for skilled labor, increases the consumption of food that is usually provided by the neighbors of the zone among others. Thus, social aspects such as such as equity or the accessibility of terminals in certain regions in order to promote their economic and social development, should be considered in future research.

Appendix A

The amount of freight handled in each intermodal terminal is the result of multiple individual decisions taken by decision makers (carriers) with respect to freight distribution. Choices regarding a route and/or transport mode depend on the attractiveness of the option's offer. Generally, attractiveness is represented by a utility measure ("which is a convenient theoretical construct defined as what the individual seeks to maximise" (Ortuzar et al. (2011)), which is composed of an observable utility and an unobservable component. As a rule, the observable utility is a linear combination of a few carrier characteristics (e.g. equipment), a few attributes of route choice (e.g. transport cost, distance traveled, delivery time, reliability, accessibility and so on), as well as a few freight characteristics (e.g. price, type, and so on). The unobservable component captures a series of errors that can be committed by analysts when they try to predict the value of the utility assigned by the carriers to each available transport option. Thus, let j be an available alternative in available options set J for the decision maker q then the utility of j to q denoted by U_j^q is:

$$U_j^q = V_j^q + \varepsilon_j^q$$

with V_j^q being the observed utility and ε_j^q the unobservable component, which includes dismissed variables, measurement error and any characteristics unobserved or non-measurable by the decision maker. An assumption considered here is that the decision maker is a rational individual who will choose the option that has greater utility for their own interests, i.e. given a choice j, the decision maker q will select choice j in the set of available options J if $U_j^q > U_k^q,\ \forall k \in J$ which implies that:

$$V_j^q + \varepsilon_j^q > V_k^q + \varepsilon_k^q, \forall k \in J \quad \rightarrow V_j^q - V_k^q > \varepsilon_k^q - \varepsilon_j^q, \forall k \in J$$

Since the value of $\varepsilon_k^q - \varepsilon_j^q$ is not known by the analyst, it is possible to establish a probability value of choosing the option j as $p_j^q\left(V_j^q - V_k^q > \varepsilon_k^q - \varepsilon_j^q, \forall k \in J\right)$. It is possible to get an explicit expression for the probability of choosing option j if some assumptions regarding the probability distribution of random variables $\varepsilon_s^q, \forall s \in J$ are considered. Thus, if we assume that the random variables are independent and identically distributed (I.I.D.) Gumbel, the probability distribution of choosing option j by decision maker q is given by:

$$p_j^q = \frac{e^{\left(\theta\, V_j^q\right)}}{\sum_{k \in J} e^{\left(\theta\, V_k^q\right)}}$$

where θ is a scale parameter of the Gumbel distribution. In the context of intermodal terminal location, each alternative is an available route either by unimodal road transport or by intermodal transport (road/rail) and θ, to a certain extent, quantifies the impact on the freight allocation by variation in the utility of each transport option.

Appendix B

With respect to the location of hubs, several instances have been generated to evaluate the performance of multiple algorithms. However, the analyzed problem in this thesis includes several types of terminal with different capacities that do not accommodate the available instances such as the CAB (Civil Aeronautics Board) and AP (Australia Post) instances. Therefore, to broaden the analysis of the performance of the HGA, a set of instances with different topologies have been generated, but with each of them keeping certain facts of the European reality.

Once the number of regions of a random instance has been defined, we proceed to size the study area in which the set of centroids will be randomly generated. To size the study area and adjust it to the European reality, one adopted assumption is for the ratio between the width and the height of the study area to follow the probability distribution shown in Table 5.1, and for its area to be equal to the number of centroids generated multiplied by the average surface of a NUTS-III subdivision of Portugal (approximately 3874 km^2).

Table 5.1 Probability distribution of ratios between width and height of study areas.

Ratio	**Probability**
$1:3$	0.15
$1:2$	0.20
$1:1$	0.25
$2:1$	0.20
$3:1$	0.20

An additional constraint incorporated in the process of placing the centroids in the study area is that they must be at least 50 km apart.

Regarding the flows between each pair of regions in each instance, we consider that it follows a gravity model that depends on the generalized costs and gross domestic product in both the origin and destination regions. Let q_{jk} and c_{jk} be the flow and generalized transportation costs between each pair of regions $j, k \in N$. Also, let GDP_j be the gross domestic product of region $j \in N$, thus:

$$q_{jk} = \rho \frac{GDP_j^{\lambda} GDP_k^{\kappa}}{c_{jk}^{\delta}}$$

with $\rho, \lambda, \kappa, \delta$ being parameters to be determined from the freight flow in the Portuguese case.

Another assumption in the process of generating reference instances is that the GDP in each region follows a probability distribution of extreme values. The choice of this distribution is based on a characterization of the economic behavior of a country, in which there are few regions with high GDP values. (Right-Figure B1).

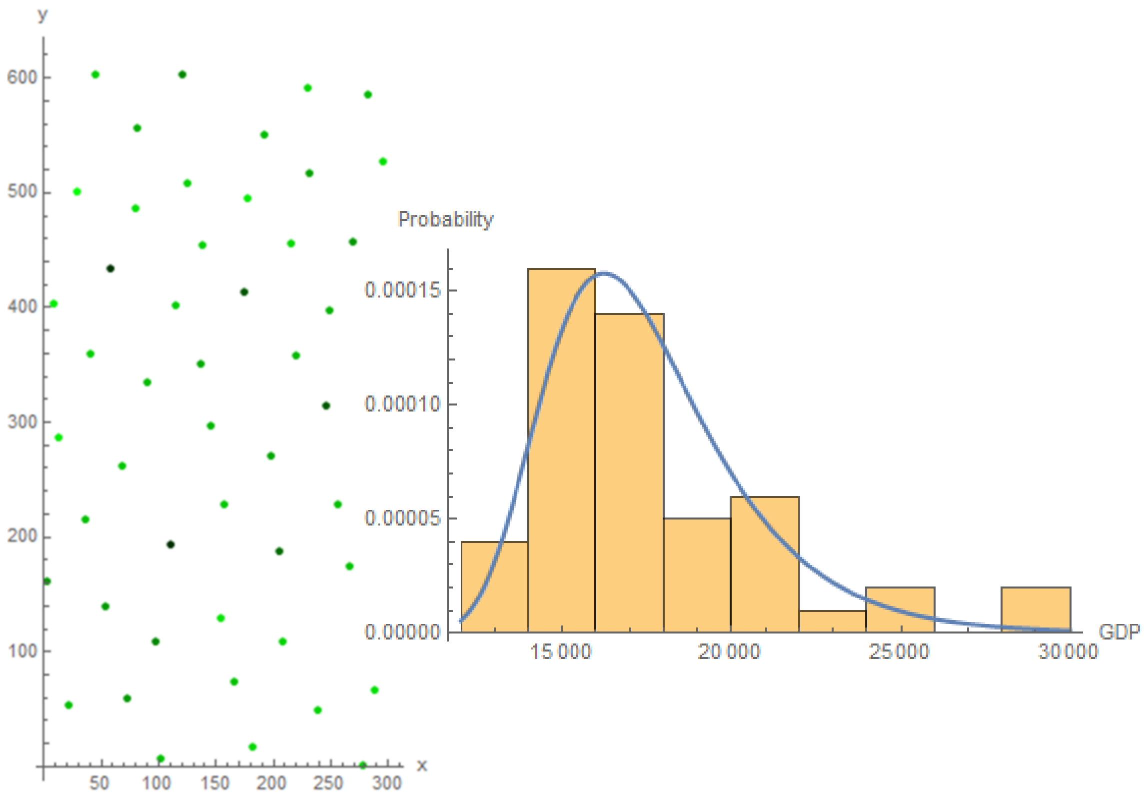


Figure B1 Scatter-Plot of a randomly generated instance of 50 regions.

Regarding the characteristics of the intermodal terminals, their capacity and installation costs amortized annually, the transportation costs per unit of freight and distance by road and rail, and the flat-rate usage are the same as those established in the Portuguese case which is described on chapter 2.

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