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"Enhanced data management techniques for real time logistics planning and scheduling"

Deliverable D4.1 - State of the art in optimization techniques for global optimization of logistic systems

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Executive Summary

This document aims to provide a survey about global optimization methods applied to logistics in the context of the three key topics addressed by the Work Package 4 of the LOGISTAR project: (i) optimization of freight transport networks for horizontal collaboration, (ii) optimization of transhipment planning and (iii) optimization of scheduling in hubs. It is important to mention that the contents of this document cover part of the work and the result of the Task 4.1 (State of the art review in global optimization of logistic systems and definition of benchmarks), within WP4.

The main content of this document can be divided in the following contributions:

- A deep study of the current state of the art related to global optimization of logistic systems and problem models, emphasizing on covering the different alternatives available to model or abstract the processes to be optimized in each of the three key topics of WP4.
- A deep study of the optimization techniques most commonly employed in the mentioned topics, covering exact methods, heuristics and metaheuristics, but with a special focus on metaheuristics.

In order to facilitate the understanding and description of the work, we begin by exposing the problem definition and gradually step into state of the art models and optimization methods.

This review of the state of the art will serve as basis to define the nature of the optimization techniques that will be developed in subsequent tasks of WP4. These techniques have been chosen with the intention of addressing the challenges posed by the services that LOGISTAR will provide. The main results obtained regarding the first objective is a catalogue that orders and categorizes more than 100 bibliographic references about the mentioned topics and that describes the current state of the art regarding global optimization of logistic systems

Additionally, the main results obtained from the activities completed regarding the second objective of the task 4.1 is a set of optimization techniques covering exact methods, heuristics and metaheuristics that will guide the design of the optimization techniques and mathematical models that will be developed in the next stages of this work package.

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1. Introduction

The main objective of the WP4 is the development of the global optimization system of LOGISTAR to improve the state of the art in this field. From this general objective, several particular goals were planned, one of them being the review and update of the state of the art about models and techniques for the optimization of freight transport network for horizontal collaboration and the optimization of transhipment planning and scheduling in hubs.

This deliverable is intended to describe the work done in the field of vehicle routing optimization to give a general view of the current solving techniques and models applied in this regard in scientific literature. One of the main outcomes of the Task 4.1 is the state of the art review for the field of global optimization of logistic systems. This will facilitate the necessary background for Tasks 4.2 ("Design of advance models for global optimization of logistic systems"), 4.3 ("Design of advanced optimization techniques for global optimization of logistic systems") and 4.4 ("Development of the global optimization module"), that is, the design and development of advanced models and techniques that will enable global optimization of logistic systems.

The rest of the document is structured as follows. In Section 2 we provide an overall overview of the background in the field, defining both the types of optimization problems in logistics and also the main metaheuristics used in the literature for their resolution. Section 3 presents the state of the art in optimization of freight transport network by first focusing on the current vehicle routing problems, the main problematic in this area, and then by going deeper in problems associated with the collaboration of multiple agents. For all the problems, considerations about specific restrictions that can be applied are presented. The section finishes with a review of the literature related to methods used to solve the presented vehicle routing problems. Section 4 introduces the state of the art in optimization problems dealing with transhipment planning and scheduling in hubs. In the section, three main issues are addressed: (i) Transhipment planning and scheduling in hubs, (ii) Cross Docking optimization and (iii) Intermodal Hub optimization. For all of them, a review of the state of the art and an overview of the methods used in the literature is provided. Finally, Section 5 provides with extracted conclusions from the whole study.

2. Background

This section provides the background necessary to better understand the following sections of the document. Concretely, we first provide basic concepts about Routing Planning Problems (Section 2.1), that is the framework most commonly used to address the optimization freight transport networks. Next, Section 2.2 describes basic concepts about transhipment, covering aspects such as: transhipment plans, warehouse and hub distribution. Finally, we provide descriptions of canonical versions of the most common optimization algorithms applied to solve this class of optimization problems (Section 2.3).

2.1. Vehicle Route Planning Problems

Vehicle route planning problems in logistics can be broadly divided into two main groups. The first type of problems belongs to the point-to-point route planning problems (Leung et al., 1988), in which the main objective is to find the shortest path between two different points within a graph.

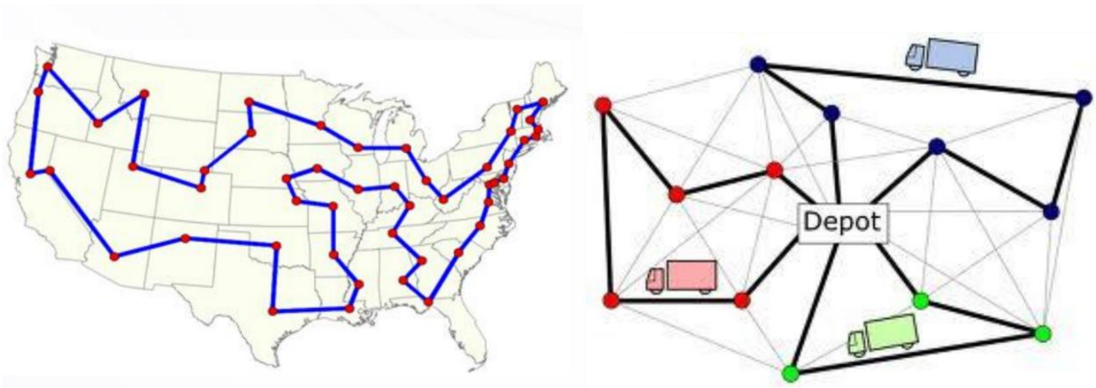

Figure 1 Example of solution of the Travelling salesman problem (left) and the Vehicle Routing Problem (right).

The second type of problems are usually known as multi-point routing problems, the most well-known being the Vehicle Routing Problem (VRP) (Dantzig and Ramser, 1959) and the Traveling Salesman Problem (TSP) (Lawler et al., 1985). In the TSP, there is a set of customers and a single vehicle. The objective of the problem is to find a route that starting and ending at the same point, visit once each and every one of the nodes minimizing the total cost of the trip. On the other hand, the conventional VRP has a set of customers, a fleet of vehicles with a limited capacity and a warehouse. The main objective of the VRP is to find a minimum set of routes with the minimum possible cost that (i) start and end in the established deposit, and in which (ii) each client is visited only once and (iii) the total demand of customers visited on a route does not exceed the capacity of the vehicle that performs it. These problems fall within the field of combinatorial optimization given the fact that are NP-hard problems, whose solution becomes computationally impossible to obtain once the size of the graph increases. Figure 1 presents a solution of shortest route for an instance of the TSP, connecting some of the major cities in the USA (left) and an example of resolution of a simple VRP connecting a warehouse (depot) with 13 customers (right).

The LOGISTAR project focuses on multi-point route planning problems. The determination of optimal paths on road networks is the basic ingredient of driving directions computation as well as for logistic planning. The main purpose of multi-point route planning is to find a route in a graph so that the total travelled distance among all the locations is minimized. Note that as a consequence it may involve minimizing the duration of the paths, the fuel consumption (or, equivalently, the CO2 emissions), or a combination of them (Gendreau et al., 2015) for each one of the actors involved. The interest in this type of problems is crucial, and its wide scope can include, for example, implementation of collaborative tactical and operational decisions.

Recently the number of journal articles published in the field of vehicle routing has grown remarkably. This trend can be seen in Figure 2. Data was obtained from the Scopus bibliographic database.

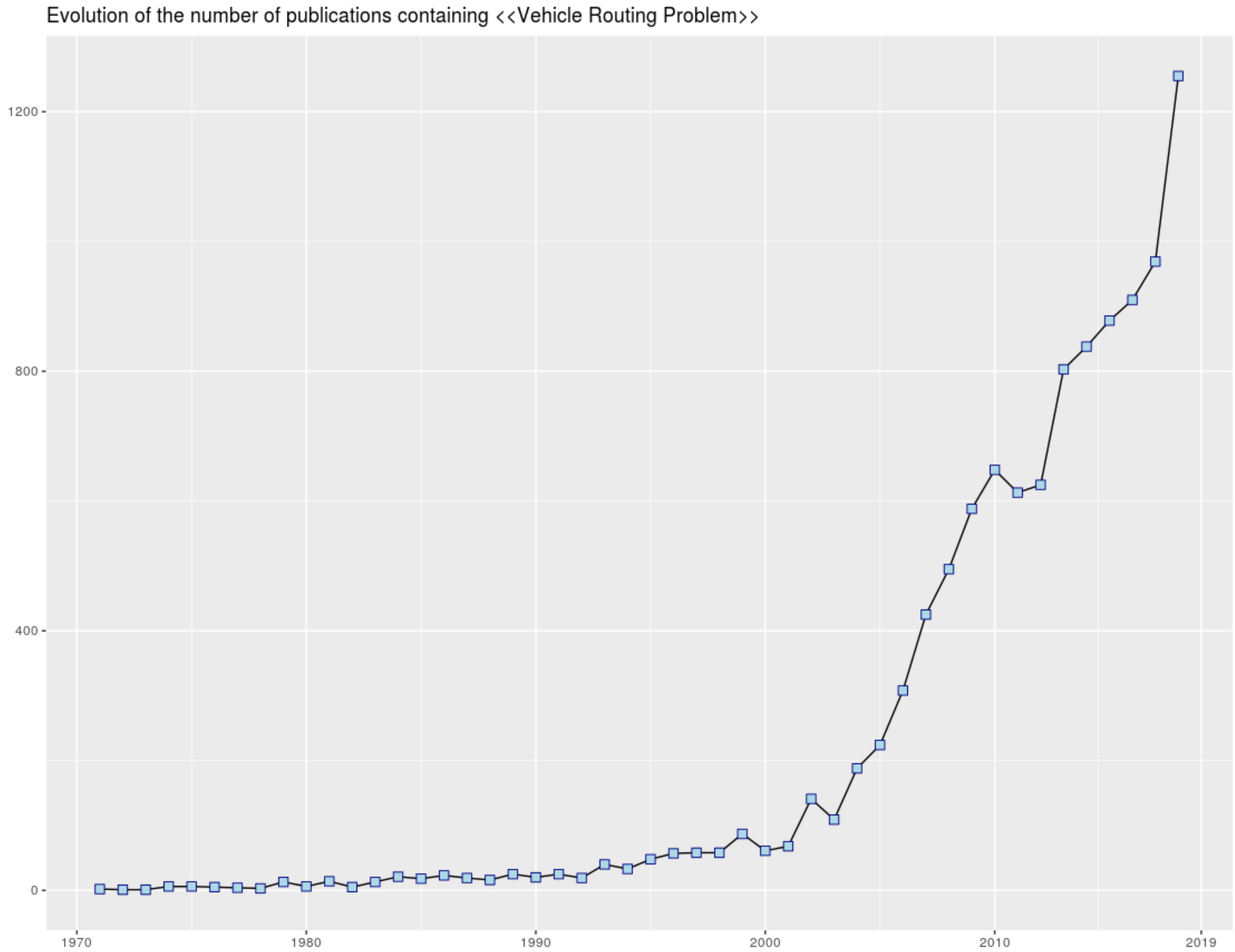

Figure 2 Evolution of the number of publications containing <<Vehicle Routing Problem>> keywords on Scopus on February, 8th 2019.

The reason for the popularity and the importance of such a domain is two-fold: The social and economical interest they generate, and their inherent scientific interest.

- On the one hand, vehicle route planning solutions designed to deal with real-world situations related to transport or logistics entail profits for logistics companies.
- On the other hand, most of the problems arising in this field have a very high computational complexity. For this reason, the resolution of these problems is a major challenge for the scientific community and usually, a testbed for the design of new methods in the field of combinatorial optimization.

2.2. Transhipment and hub scheduling problem

Logistic network warehouse and hub distribution is often a source for different bottlenecks, such as: inbound and outbound flow, pick-up and delivery time windows, dock-door availability, equipment capacity, vehicle availability and capacity, workforce capacity, staging capacity and policy. Moreover, in the context of intermodal hub availability and cross docking or warehousing it is even more complicated and unclear whether journeys are indeed optimised to that they traverse to the most efficient destination, or even if their origin and destination hub is globally optimal.

The objective of transhipment planning and scheduling in hubs is that of optimizing journeys and selecting the placement of best located hubs taking into account not only the starting and ending point of available vehicles, but also the concrete need they must perform. A simple Transhipment Model can help identify proportions and best usage of capacity and proximity. For instance, if one needs to transport some goods with each having distinct supply and demand characteristics, they can gather the requirements and constraints as a linear program that can be solved so to enable the most optimized decisions.

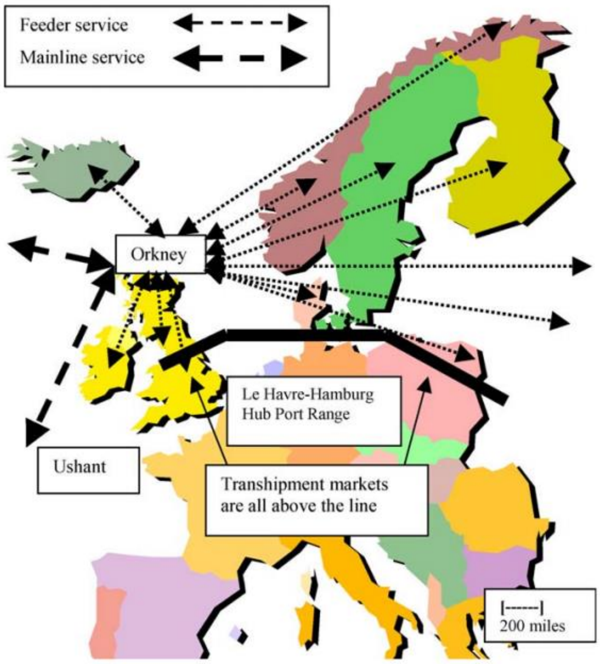

Figure 3 Trade lanes and transhipment plans in Northern Europe for Orkney. Source: (Baird, 2006)

Optimal transhipment plans and hub locations must offer a combination of low mainline transport deviation in time, distance and cost while serving to keep optimal the global objectives that need to be optimized in the system. Usually, transhipment and hub optimization require non-trivial delivery strategies to be implemented, in the state of the art there are four commonly used strategies to configure a firm's distribution activities: (i) direct shipment, (ii) milk-runs, (iii) warehousing, and (iv) cross-docking.

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In a direct shipment strategy, each shipment is sent directly from origin to destination. A milk-run strategy groups shipments into routes visiting multiple origins and destinations sequentially. These two strategies are associated with low implementation costs as they do not involve intermediary logistics facilities. When shipment sizes are small and customers are geographically dispersed, a direct shipment or milk-run strategy results in partially empty trucks and longer transportation lead times as products are stored further away from their demand points. In response to these shortcomings, firms can employ aware housing or cross-docking distribution strategy (Buijs et al., 2014).

Warehousing enables the consolidation of shipments to customers by assembling full truckloads from the products stored in a warehouse or distribution centre. Storage can be efficiently replenished by ordering full truckloads from suppliers. At the warehouse, the main operations are to unload inbound trailers with products from suppliers, store the products, retrieve products and assemble them for shipment upon customer order, and dispatch the consolidated loads onto outbound trailers. The existence of a storage buffer allows local warehouse operations to be considered largely in isolation from activities elsewhere in the distribution network. Hence, warehousing literature primarily addresses local warehouse problems.

Instead of moving partially empty trailers or assembling loads from storage, a cross-docking strategy group shipments from multiple adjacent origins into full truckloads, which are then sent to a cross-dock where they are unloaded and immediately recombined with loads sharing the same destination. As a result, cross-docking can realize transport efficiencies at reduced material handling and storage costs by eliminating the storage and order picking activities from the main warehouse operations. We will further analyze delivery strategies alongside transhipment and hub optimization in Section 4.

Finally, we would like to highlight the relevance of this area of research by displaying evolution of the number of papers related to this published since 1970.

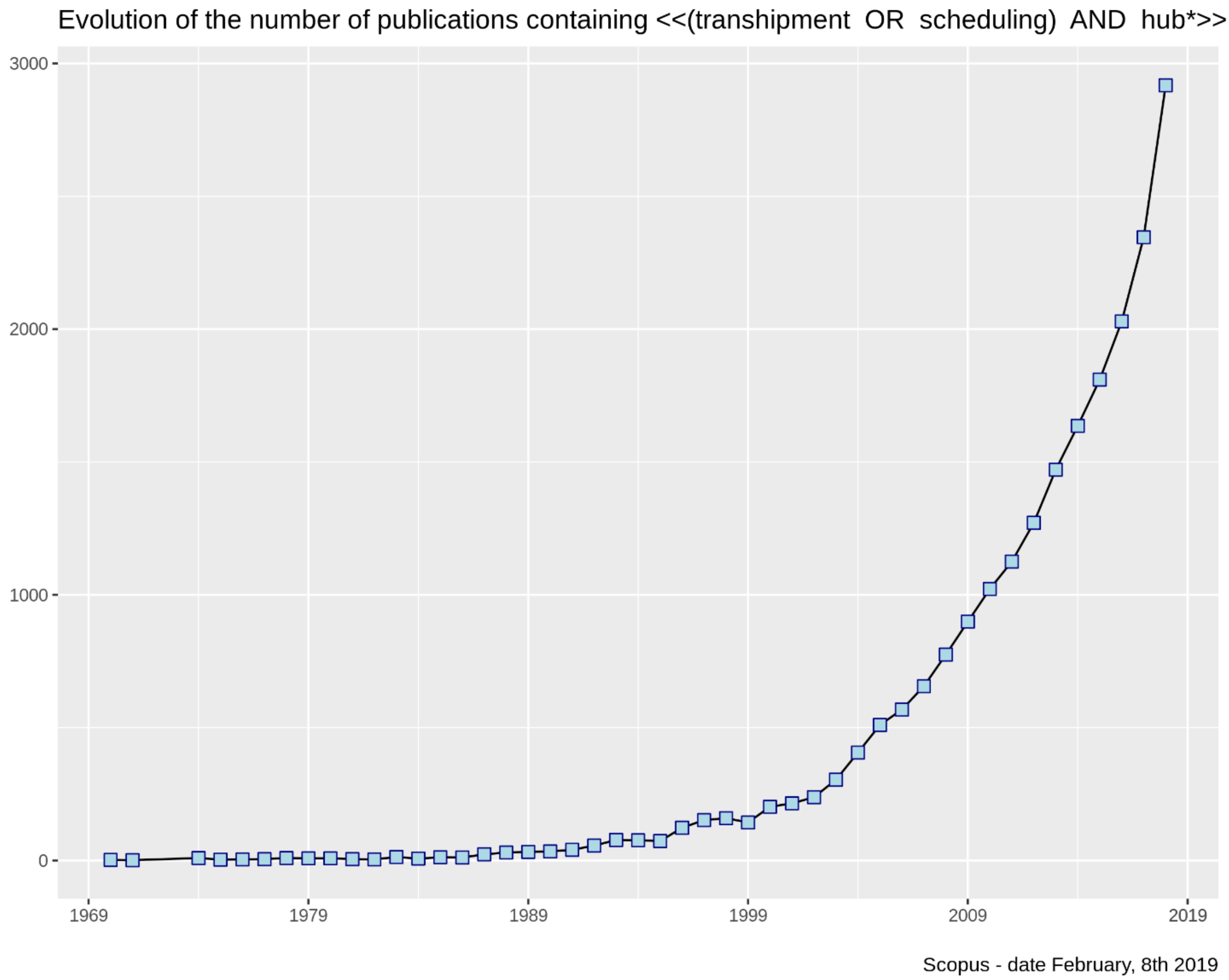

Figure 4 Evolution of the number of publications containing << (transhipment OR scheduling) AND hub>> keywords on Scopus on February, 8th 2019.*

2.3. Common methods applicable to optimization problems in logistic systems

This section covers the background on heuristics and metaheuristics that will be referenced throughout this deliverable. It contains the listing of different methods alongside a short description covering the principles and main ideas of each algorithm.

2.3.1. Branch and cut (Baldacci et al., 2012)

Branch and cut is an exact method of combinatorial optimization for solving integer linear programs (ILPs), that is, linear programming (LP) problems where some or all the unknowns are restricted to integer values. Branch and cut involves running a branch and bound algorithm and using cutting planes to tighten the linear programming relaxations.

2.3.2. Set partitioning (Baldacci et al., 2012)

The set partition problem is the task of deciding whether a given multiset S of positive integers can be partitioned into two subsets S1 and S2 such that the sum of the numbers in S1 equals the sum of the numbers in S2. Although the partition problem is NP-complete, there is a pseudo-polynomial time dynamic programming solution, and there are heuristics that solve the problem in many instances, either optimally or approximately. Based on this approach (Baldacci et al., 2012) defines set partitioning formulations that are exact methods to solve VRPs. The main idea of the formulation is that authors associate a binary variable with each feasible route to search for optimal solutions.

2.3.3. 2-opt heuristic (Toffolo et al., 2018)

2-opt is a simple search algorithm for solving the travelling salesman problem. The main idea behind it is to take a route that crosses over itself and reorders the sequence of nodes to traverse so that it avoids the crossing. A complete 2-opt local search will compare every possible valid combination of the swapping mechanism. This technique can be applied to the travelling salesman problem as well as many related problems. These include the vehicle routing problem (VRP) as well as the capacitated VRP, with minor modification of the algorithm.

2.3.4. Sequencing and assignment heuristic (Toffolo et al., 2018)

The sequencing and assignment heuristic works by decomposing the problem so that it ends up with a list of processes to be sequenced and assigned to specific units over time. The assignment and sequencing procedure is carried out at the same time, since the assignment is done when a process is selected for being sequenced in the future schedule.

2.3.5. Simulated Annealing (Van Laarhoven and Aarts, 1987)

Simulated annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space for an optimization problem. It is often used when the search space is discrete (e.g., all tours that visit a given set of cities). For problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time, simulated annealing may be preferable to alternatives such as gradient descent.

It is implemented using the notion of a cooling temperature interpreted as a slow decrease in the probability of accepting worse solutions as the solution space is explored. Accepting worse solutions is a fundamental property of metaheuristics because it allows for a more extensive search for the global optimal solution. In general, the simulated annealing algorithms work as follows. At each time step, the algorithm randomly selects a solution close to the current one, measures its quality, and then decides to move to it or to stay with the current solution based on either one of two probabilities between which it chooses on the basis of the fact that the new solution is better or worse than the current one. During the search, the temperature is progressively decreased from an initial positive value to zero.

2.3.6. Multiple Temperature Pareto SA (Czyżak and Jaszkiewicz, 1997)

The goal of the procedure is to find in a relatively short amount of time a good fit approximation out of the set of efficient solutions for a multi-objective combinatorial optimization problem. The procedure uses a sample to generate solutions, in such a way that for each of the solutions it explores its neighbourhood in a way similar to that of classical simulated annealing. Weights of the multiple objectives are set in each iteration in order to assure a tendency to approach the efficient solutions set while maintaining a uniform distribution of the generating solutions over this set.

2.3.7. Tabu Search (Glover and Laguna, 1998)

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Tabu Search (TS) is a metaheuristic search method employing local search methods used for mathematical optimization. Local (neighbourhood) searches take a potential solution to a problem and check its immediate neighbours (that is, solutions that are similar except for very few minor details) in the hope of finding an improved solution. Local search methods have a tendency to become stuck in suboptimal regions or on plateaus where many solutions are equally fit.

Tabu search enhances the performance of local search by relaxing its basic rule. First, at each step worsening moves can be accepted if no improving move is available (like when the search is stuck at a strict local minimum). In addition, prohibitions (henceforth the term tabu) are introduced to discourage the search from coming back to previously-visited solutions. The implementation of tabu search uses memory structures that describe the visited solutions or user-provided sets of rules. If a potential solution has been previously visited within a certain short-term period or if it has violated a rule, it is marked as "tabu" (forbidden) so that the algorithm does not consider that possibility repeatedly.

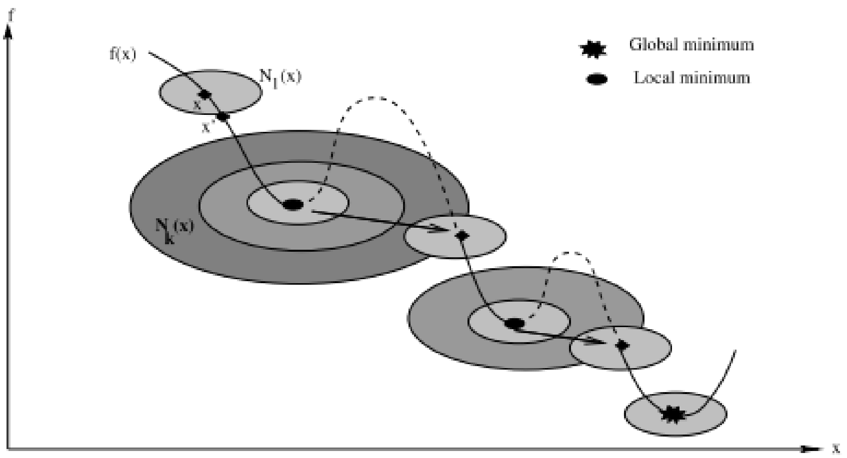

Figure 5 Basic Variable Neighbourhood Search method. Source from (Hansen et al., 2010).

2.3.8. Variable Neighbourhood Search (Hansen et al., 2010)

Variable neighbourhood search (VNS) is a metaheuristic based upon systematic changes of neighbourhoods both in descent phase, to find a local minimum, and in perturbation phase to emerge from the corresponding valley. It was first proposed in 1997 and has since then rapidly developed both in its methods and its applications. VNS embeds a local search heuristic for solving combinatorial and global optimization problems. It allows a change of the neighbourhood structures within the search. In Figure 5, a graphical representation of the search path followed by VNS is presented.

2.3.9. Evolutionary methods (Davis, 1991)

Evolutionary methods are a generic population-based metaheuristic optimization algorithm. An evolutionary method uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the quality of the solutions (also known as fitness function). Evolution of the population then takes place after the repeated application of the above operators. Evolutionary algorithms often perform well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness landscape. Figure 6 presents an illustrative example of the evolution of an initial population over generations.

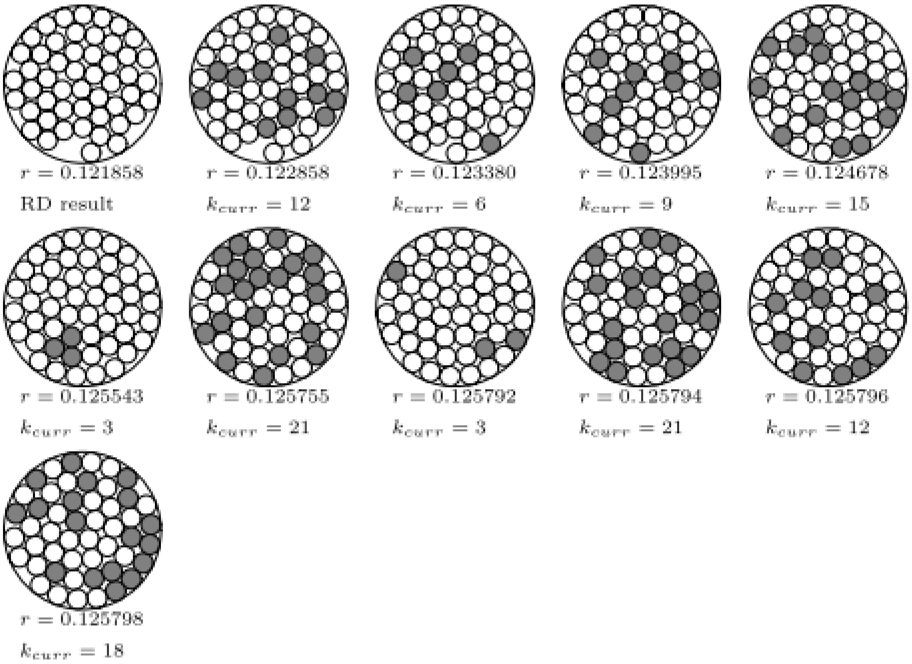

Figure 6 Evolution of an initial population over the generations. Source from (Hansen et al., 2010)

2.3.10. Genetic Algorithm (McCall, 2005)

Genetic algorithms (GA) are a heuristic solution-search or optimization technique, originally motivated by the Darwinian principle of evolution through (genetic) selection. A GA uses a highly abstract version of evolutionary processes to evolve solutions to given problems. Each GA operates on a population of artificial chromosomes. These are strings in a finite alphabet. Each chromosome represents a solution to a problem and has a fitness, a real number which is a measure of how good a solution it is to the particular problem.

Starting with a randomly generated population of chromosomes, a GA carries out a process of fitness-based selection and recombination to produce a successor population, the next generation. During recombination, parent chromosomes are selected, and their genetic material is recombined to produce child chromosomes. These then passes into the successor population. As this process is iterated, a sequence of successive generations evolves, and the average fitness of the chromosomes tends to increase until some stopping criterion is reached. In this way, a GA “evolves” a best solution to a given problem.

2.3.11. Firefly Algorithm (Fister et al., 2013)

The firefly algorithm (FA) is a metaheuristic inspired by the flashing behaviour of fireflies. Fireflies are insects with the characteristic of being able to flash lights. These lights have two fundamental functions, i.e., to attract mating partners and to warn off potential predators. The flashing lights’ intensity decreases as the distance increases according to a mathematical formulation. This phenomenon inspired the firefly algorithm. Results from experiments running FA have shown that the FA is appropriate for solving multi modal problems

2.3.12. Bat Algorithm (Yang, 2010)

The Bat Algorithm (BA) is a metaheuristic based on the echolocation behaviour of bats. The idealization of the echolocation of bats can be summarized as virtual bats randomly flying with some velocity at a given position with a varying frequency or wavelength and loudness. As a bat searches and finds its prey, it changes frequency, loudness and pulse emission rate. This way, the search process is intensified by a local random walk. Selection of the best candidate continues until certain stop criteria are met. This essentially uses a frequency-tuning technique to control the dynamic behaviour of a swarm of bats, and the balance between exploration and exploitation can be controlled by tuning algorithm-dependent parameters in the Bat algorithm. Figure 7 shows the procedure of convergence of a Bat Algorithm.

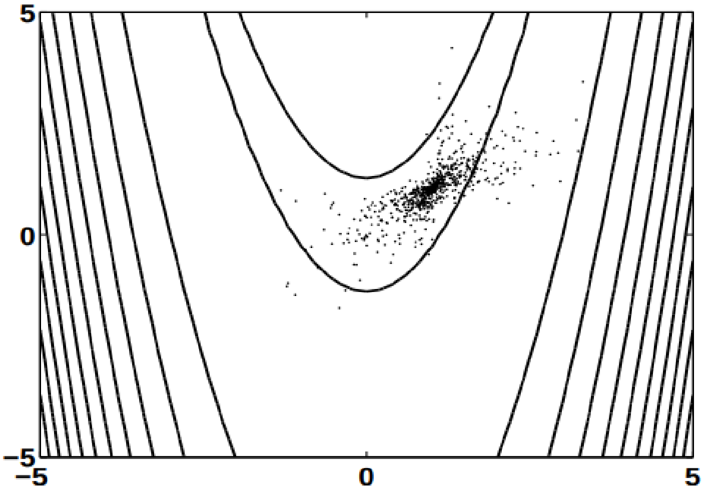

Figure 7 Bat search algorithm converging to an optimal space coordinate. Source (Yang, 2010).

2.3.13. Dragonfly Algorithm (Mirjalili, 2016a)

Dragonfly algorithm (DA) is a recently proposed optimization algorithm based on the static and dynamic swarming behaviour of dragonflies. Due to its simplicity and efficiency, DA has received interest of researchers from different fields. The two swarming behaviours of dragonflies are very similar to the two main phases of optimization using meta-heuristics: exploration and exploitation. Thus, static and dynamic swarming behaviours of dragonflies are modelled mathematically to explore and exploit the search space, respectively. In Figure 8, a schematic representation of the main primitives followed by DA is presented.

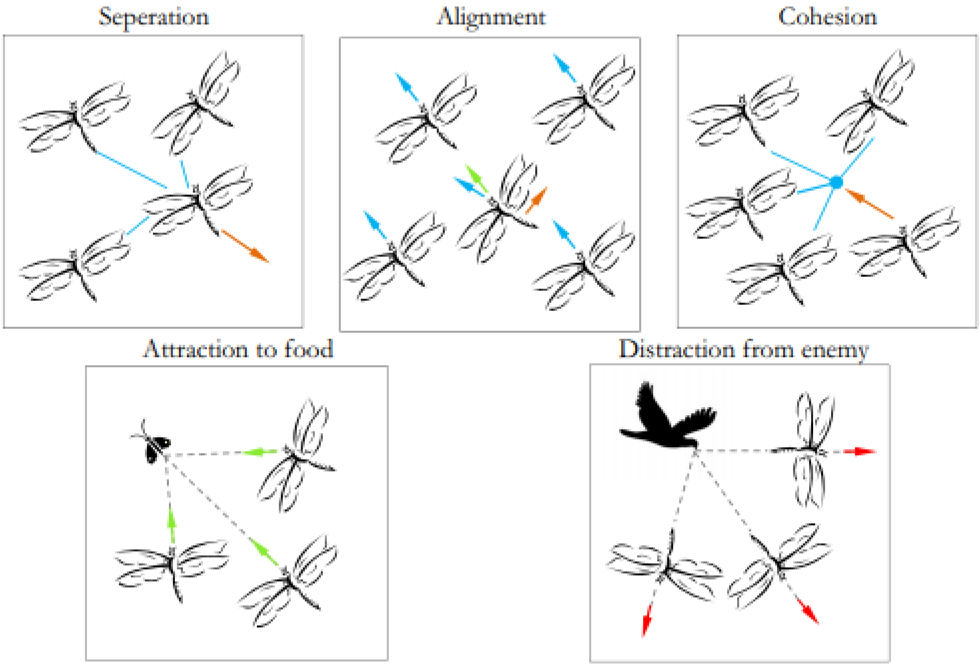

Figure 8 Main primitives of the Dragonfly algorithm. Source from (Mirjalili, 2016a)

2.3.14. Harmony Search Algorithm (Kim, 2016)

The Harmony Search Algorithm (HSA) is a balanced combination of exploration and exploitation and ease of application. The HSA is inspired by musical performance process and consists of three main operators: random search, harmony memory considering rule, and pitch adjusting rule.

In HSA a bunch/group of solutions is randomly generated (called Harmony memory). A new solution is generated by using all the solutions in the Harmony memory and if this new solution is better than the Worst solution in Harmony memory, the Worst solution gets replaced by this new solution. Although HS is a relatively new meta heuristic algorithm, its effectiveness and advantages have been demonstrated in various applications due to the fact that the ways of handling exploration and exploitation with the three operators make the HSA a unique metaheuristic algorithm.

2.3.15. Particle Swarm Optimization (Marini and Walczak, 2015)

Swarm-based algorithms emerged as a powerful family of optimization techniques, inspired by the collective behaviour of social animals. In particle swarm optimization (PSO) the set of candidate solutions to the optimization problem is defined as a swarm of particles which may flow through the parameter space defining trajectories which are driven by their own and neighbours' best performances found. Figure 9 presents the procedure of convergence to a minimum of the PSO algorithm.

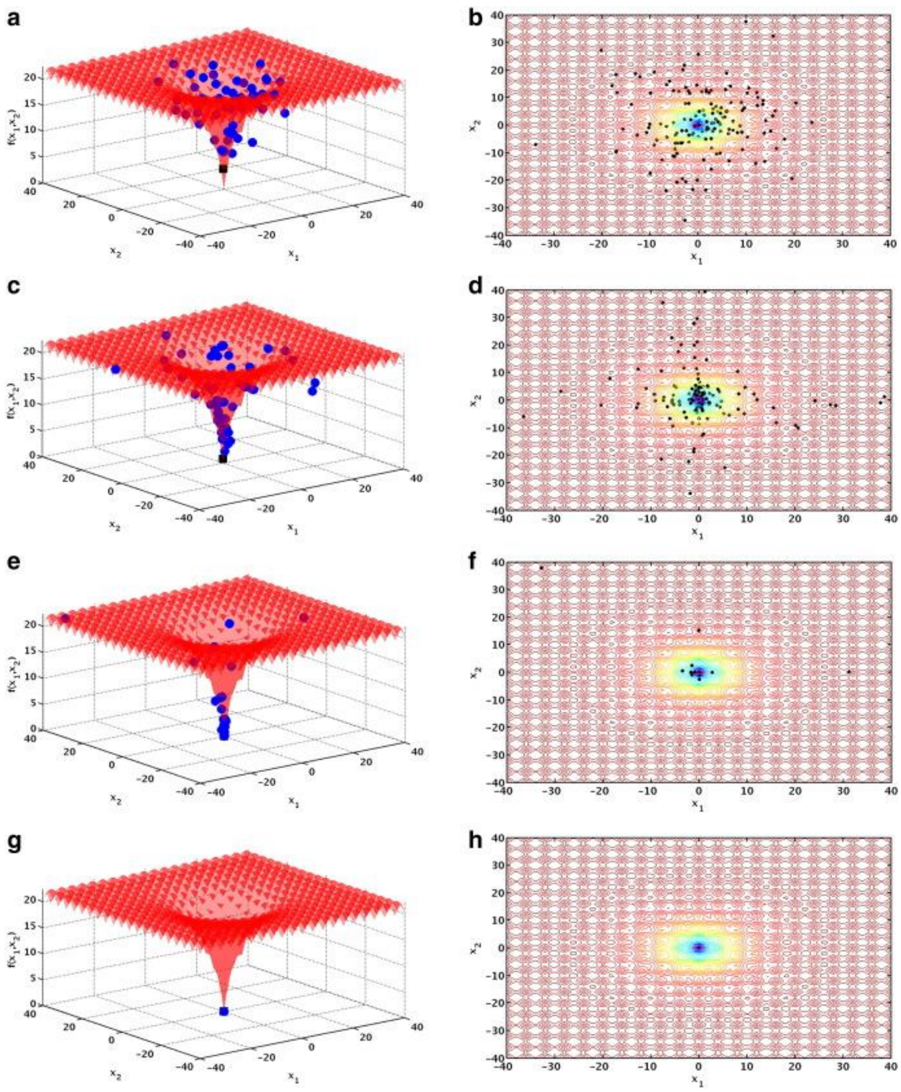

Figure 9 Graphical representation of the Particle Swarm Optimization algorithm. Source from (Marini and Walczak, 2015).

2.3.16. Grasshopper Optimization Algorithm (Saremi et al., 2017)

The Grasshopper Optimization Algorithm is a new multi-objective algorithm inspired from the navigation of grasshopper swarms in nature. A mathematical model is first employed to model the interaction of individuals in the swarm including attraction force, repulsion force, and comfort zone. A mechanism is then proposed to use the model in approximating the global optimum in a single-objective search space. Afterwards, an archive and target selection technique are integrated to the algorithm to estimate the Pareto optimal front for multi-objective problems.

2.3.17. Grey Wolf Optimizer (Mirjalili et al., 2014)

Grey Wolf Optimizer (GWO) is a new meta-heuristic inspired by grey wolves. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. Results show that the GWO algorithm is able to provide very competitive results compared to well-known meta-heuristics. The schematic of the exploration and exploitation approach followed by GWO is shown in Figure 10.

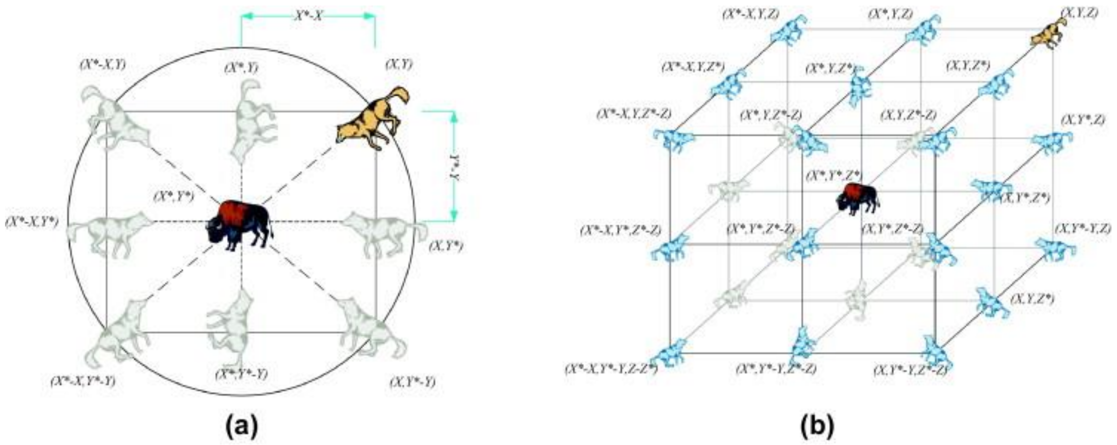

Figure 10 2D (a) and 3D (b) representation of the exploration and exploitation approach of the Grey wolf optimizer. Source: (Mirjalili et al., 2014).

2.3.18. Moth Flame Optimizer (Mirjalili, 2015a)

The Moth-Flame Optimization (MFO) algorithm is a nature-inspired optimization paradigm. The main inspiration of this optimizer is the navigation method of moths in nature called transverse orientation. Moths fly in night by maintaining a fixed angle with respect to the moon, a very effective mechanism for travelling in a straight line for long distances. MFO mathematically models this behaviour to perform optimization. The results of the real problems demonstrate the merits of this algorithm in solving challenging problems with constrained and unknown search spaces. The search trajectory followed by MFO is presented in a visual way in Figure 11.

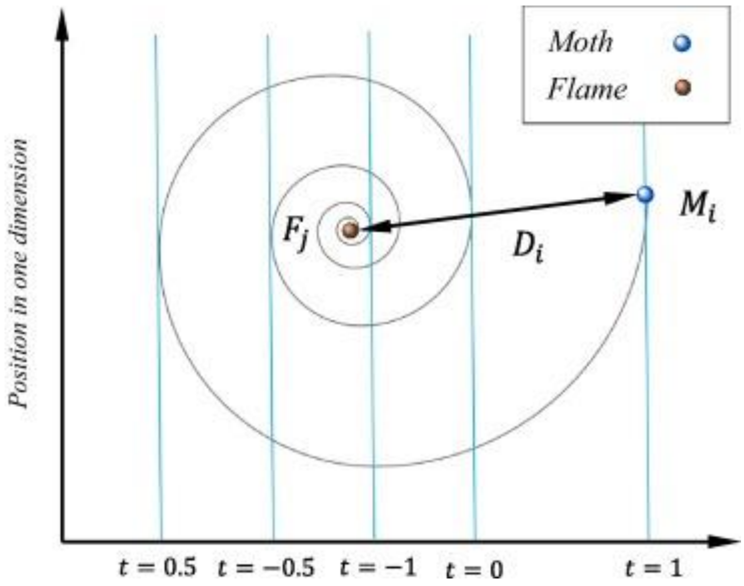

Figure 11 Graphical representation of the Moth Flame optimization process. Source (Mirjalili, 2015a).

2.3.19. Sine Cosine Algorithm (Mirjalili, 2016b)

Sine Cosine Algorithm (SCA) is an optimization algorithm for solving optimization problems. The SCA creates multiple initial random candidate solutions and requires them to fluctuate outwards or towards the best solution using a mathematical model based on sine and cosine functions. Several random and adaptive variables also are integrated to this algorithm to emphasize exploration and exploitation of the search space in different milestones of optimization. The results of test functions and performance metrics have proven that SCA is able to explore different regions of a search space, avoid local optima, converge towards the global optimum, and exploit promising regions of a search space during optimization effectively. The convergence method of the SCA is presented in Figure 12.

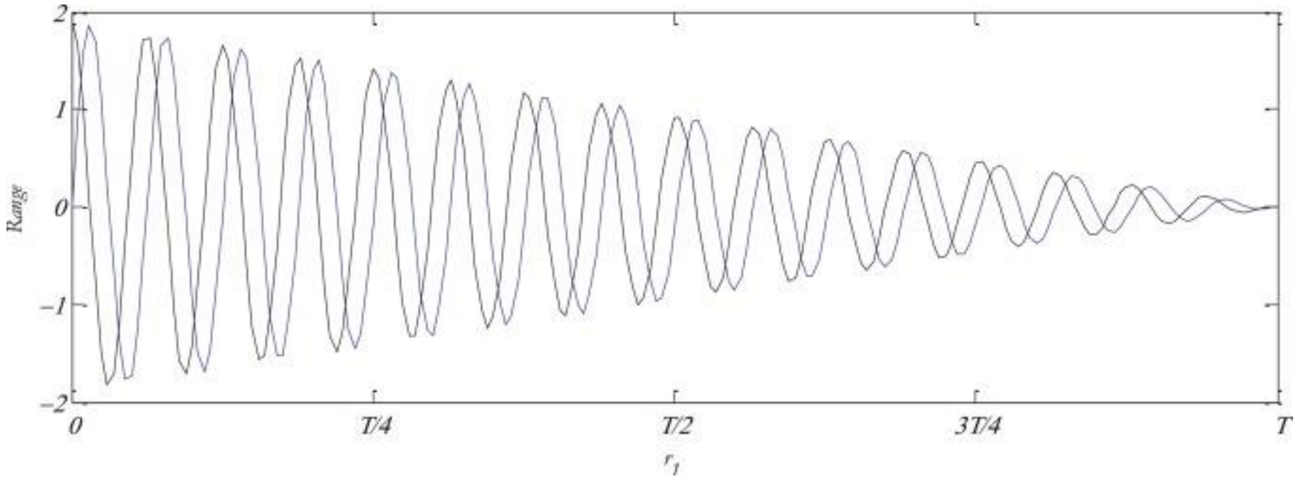

Figure 12 Graphical representation of the Sine Cosine Algorithm convergence method. Source: (Mirjalili, 2016b).

2.3.20. Whale Optimization Algorithm (Mirjalili and Lewis, 2016)

The Whale Optimization Algorithm (WOA) is a novel nature-inspired meta-heuristic optimization algorithm that mathematically mimics the social behaviour of humpback whales. High exploration ability of WOA is due to the position updating mechanism of whales. This equation requires whales to move randomly around each other during the initial steps of the iterations. In the rest of iterations, however, high exploitation and convergence are emphasized. This mathematical model allows the whales to rapidly re-position themselves around or move in spiral-shaped path towards the best solution obtained so far. Since these two phases are done separately and in almost half of iterations each, the WOA shows high local optima avoidance and convergence speed simultaneously during the course of iterations. Optimization results prove that the WOA algorithm is very competitive compared to the stateof the art meta-heuristic algorithms as well as conventional methods.

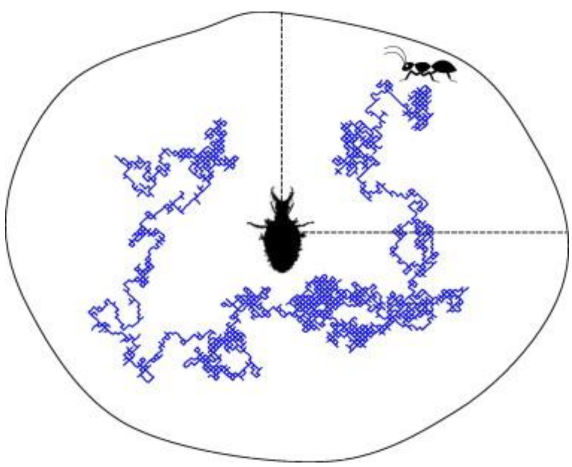

Figure 13 Graphical representation of the exploration strategy of the Ant Lion Optimizer. Source: (Mirjalili, 2015b)

2.3.21. Ant Lion Optimizer (Mirjalili, 2015b)

Ant Lion Optimizer (ALO) is a novel nature-inspired algorithm that mimics the hunting mechanism of antlions in nature. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented. The ALO algorithm mimics interaction between antlions and ants in the trap. To model such interactions, ants are required to move over the search space, and antlions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk mathematical model is implemented for modelling ants' movement. Results of the test functions prove that ALO is able to provide very competitive results in terms of improved exploration, local optima avoidance, exploitation, and convergence. Figure 13 presents a graphical representation of the exploration strategy followed by the ALO.

2.3.22. Ant Colony Optimizer (Dorigo and Birattari, 2010)

Ant colony optimization (ACO) is a population-based metaheuristic for the solution of difficult combinatorial optimization problems. In ACO, each individual of the population is an artificial agent that builds incrementally and stochastically a solution to the considered problem. Agents build solutions by moving on a graph-based representation of the problem. At each step their moves define which solution components are added to the solution under construction. A probabilistic model is associated with the graph and is used to bias the agents' choices. The probabilistic model is updated on-line by the agents so as to increase the probability that future agents will build good solutions.

2.3.23. Large Neighbourhood Search (Pisinger and Ropke, 2004))

Large Neighbourhood Search (LNS) is a meta-heuristic in which the neighbourhood of a solution is defined implicitly by destroy and repair operators. A destroy operator destroys part of the current solution while a repair operator rebuilds the destroyed solution. Typically, the destroy method contains some randomness such that different parts of the current solution are modified so that enabling exploration of the solution search space. This exploration technique enables larger neighbourhoods to be visited in comparison to standard neighbourhoods of classical local search methods. This property has made this method became the state of the art in many variants of the vehicle routing problem (Ghilas et al., 2016; Grangier et al., 2016; Mancini, 2016; Wen et al., 2016) and that is also why it is the method most commonly implemented in many software libraries and packages related to this field (e.g. or-tools[1], jsprit[2]).

[1] https://developers.google.com/optimization/routing/
[2] https://github.com/graphhopper/jsprit

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3. State of the art in optimization of freight transport networks for horizontal collaboration

This section is devoted to gather the stateof the art in the optimization of freight transport networks in general, with a special focus on horizontal collaboration, the first of our two key areas regarding the global optimization of logistic systems. For the task, we deepen into distinct alternatives to model vehicle routing problems, described in Section 2.2, which is the most common modelling framework in freight transport network optimization. To follow up, Section 2.3 focuses on the benefits and drawbacks of Collaborative VRP that is the closest model to the scenario that we aim at facing in LOGISTAR in order to foster horizontal collaboration among logistic agents. Finally, we describe the optimization methods that have been applied to solve VRP problems, with a special mention to those applied for Collaborative VRP in Section 2.4.

3.1. VRP Modelling

As mentioned above, among Multi-point Routing Problems, probably the most well-known problem in this field are the TSP (Osvald and Stirn, 2008) and the VRP (Hashimoto et al., 2008). In the canonical version of the VRP, there is a set of customers, a fleet of vehicles with a limited capacity and a warehouse. The main objective of the VRP is to find a minimum set of routes with the minimum possible cost that (i) start and end in the established deposit, and in which (ii) each client is visited only once and (iii) the total demand of customers visited on a route does not exceed the capacity of the vehicle that performs it.

In addition to the basic versions of the VRP, in the literature you can find different variants of them, mainly imposing different types of constraints, with the aim of making the models closer to situations found in the real problems. We now describe some of the common variants and constraints found in the domain of VRP, as well as those more related to the problems we will address in LOGISTAR. Concretely, we will review constraints related to time window, depot, capacity, co-loading, pickup and delivery, multi-depot, backhauling and dynamic re-planning constraints, as well as other two relevant VRP variants for LOGISTAR as time-dependant VRP and Robust VRP.

- **Time window constraints (Chang and Chen, 2007)**

In the context of this kind of constraints, the service of a particular customer or warehouse must be satisfied within a specified time frame. The restriction imposed is that the truck must not arrive to a location neither before nor after the window is opened. Figure 14 represents the solution of a simple VRP with time windows.

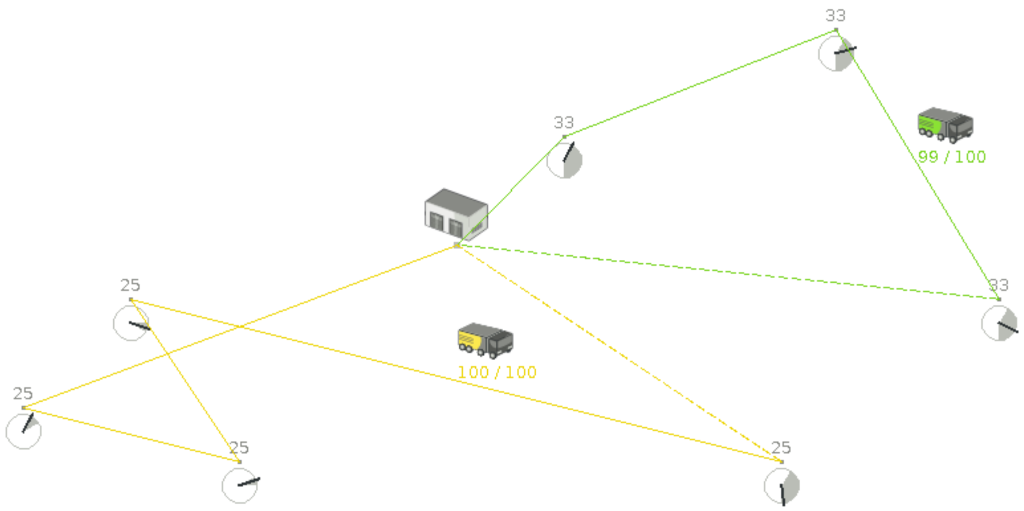

Figure 14 Time window constrained VRP.

- **Depot constraints**

In logistics a depot is considered a facility dedicated to logistical centre operations. A logistics centre might be a warehouse, freight forwarder, or a repair depot. The availability of goods and types of depots is a primary constraint in VRP optimization as methods need to optimize the route plan according to the depot stations, which are usually treated as nodes in a graph.

- **Capacity and type of good constraints**

In logistics the capacity constraint is associated with the variation of freight forwarders (i.e. the number of different vehicle models available). The fleet variation is a primary constraint in collaborative VRP optimization as heuristics need to take into account the distinct capacity of vehicles that are simultaneously optimizing a global goal. It is also a great matter of concern for dynamic re-planning of routes as the capacity of the new vehicles must be able to deal with the freight transported previously before assuring the replacement is feasible.

In addition, constraints related with the type or characteristics of goods that a particular truck can move increases the realism of the problems that can be solved.

- **Co-loading constraints (Hartman, 2018)**

One technique for reducing logistics costs is to load items into multiple compartment vehicles, which have several spaces within that can be set for different item necessities. These vehicles allow better consolidation of loads and cost reduction. However, constructing the optimal load is a difficult problem, requiring heuristics for solution. In addition, the cost determined must be allocated to the different items being shipped, most often with different owners who need to pay for the service.

- **Pickup and delivery constraints (Fan, 2011)**

The vehicle routing problem with simultaneous pickup and delivery considering customer satisfaction is based on a time window at each customer location. In such a problem, the transportation requests must be performed by vehicles, each request having to be met as early as possible. The customer satisfaction is inversely proportional to the waiting time for the vehicle from the lower bound of the time window. The goal is to minimize the total length of vehicles' paths to reduce cost, and to maximize the sum of all customer satisfactions to improve service quality.

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- **Multi-depot constraints (Mirabi et al., 2016)**

Multi-depot vehicle routing problem defines a problematic in which each vehicle starts from a depot and there is no need to return to its primary depot after serving customers. This modelling adds up complexity to the original VRP in that it aims to minimize the transportation costs including the global travelled distance, constrained by the fact of having to end the current route in an optimal depot in sight of possible future requests of vehicles.

- **Backhauling constraints (Goetschalckx and Jacobs-Blecha, 1989)**

The Vehicle Routing Problem with Backhauls (VRPB) is an extension of the classical Vehicle Routing Problem that includes both a set of customers to whom products are to be delivered, and a set of vendors whose goods need to be transported back to the distributioncentre. In addition, on each route all deliveries have to be made before any goods can be picked up to avoid rearranging the loads on the vehicle.

- **Dynamic replanning constraints (Hvattum et al., 2006)**

The problem of the standard vehicle routing cannot always capture all aspects of real-world necessities. As a result, extensions or modifications to the model are warranted. VRP with dynamic replanning considers the case when customers can call in orders during the daily operations or daily plans get altered by unavoidable factors or issues in the development of the agreed plan. In this scenario we consider that both customer locations and demands may be unknown in advance.

- **Time-dependant VRP (Osvald and Stirn, 2008)**

An especially interesting variable of the VRP is the so-called VRP with dependent times (TDVRP). In the great majority of the problems of the TSP and VRP family it is assumed that the times, or costs, involved in travelling between the different points of visit are invariable. This characteristic is difficult to be represented in situations that arise in the real world, in which travel times can vary stochastically due to various reasons such as traffic congestion, weather conditions, or road accidents. This is why TDVRP tries to deal with this problem by adding some uncertainty in travel times. This variant of the VRP is especially effective to deal with situations such as those that will arise in the present project. Recently the TDVRP has been applied to fields such as the distribution of perishable foods (Osvald and Stirn, 2008), and with premises such as the reduction of the emission of polluting gases (Franceschetti et al., 2013; Jabali et al., 2012) . Among the techniques that have been applied for the resolution of the TDVRP can be found the iterative local searches (Hashimoto et al., 2008), the ant colony systems (Balseiro et al., 2011), the simulated annealing (Lecluyse et al., 2009) and linear programming methods (Franceschetti et al., 2013). It is interesting to mention that this type of characteristic can also be applied to the TSP (Taş et al., 2016).

- **Robust VRP (Toklu et al., 2013)**

Uncertainty in the field of problems of assigning routes to vehicles is a factor that is gaining importance in the literature year after year. This uncertainty can be described as the inability to know the data of a problem accurately. The fact of not taking into account this factor can make apparently good solutions lose quality when applied to real transport and logistics situations. To deal with this type of situation, two branches of knowledge can be used: stochastic programming (Birge and Louveaux, 2011), where information cannot be predicted accurately, but information about its probability distribution is available, and robust optimization, where information cannot be predicted and the probability distribution is unknown. In the field of problems of assignment of routes to vehicles, multiple have been the works that have treated this type of optimization. In the work presented in (Toklu et al., 2013), for example, a multiple ACO is presented for the resolution of a robust VRP, in which the travel time has a certain level of uncertainty. Another example can be found

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in (Agra et al., 2013), in which the authors model a problem of maritime transport, a sector in which delays are very frequent as a robust VRPTW. In this problem it is also assumed that travel times are not known with precision. In (Solano-Charris et al., 2015), on the other hand, a set of meta-heuristics of local search is presented to face a robust VRP in which the journey times are also uncertain, and they take into accountdifferent scenarios. The authors consider a scenario, for example, of the journey time observed in a certain way in a specific time. Finally, in (Ordóñez, 2010) an interesting study about robust VRP can be found.

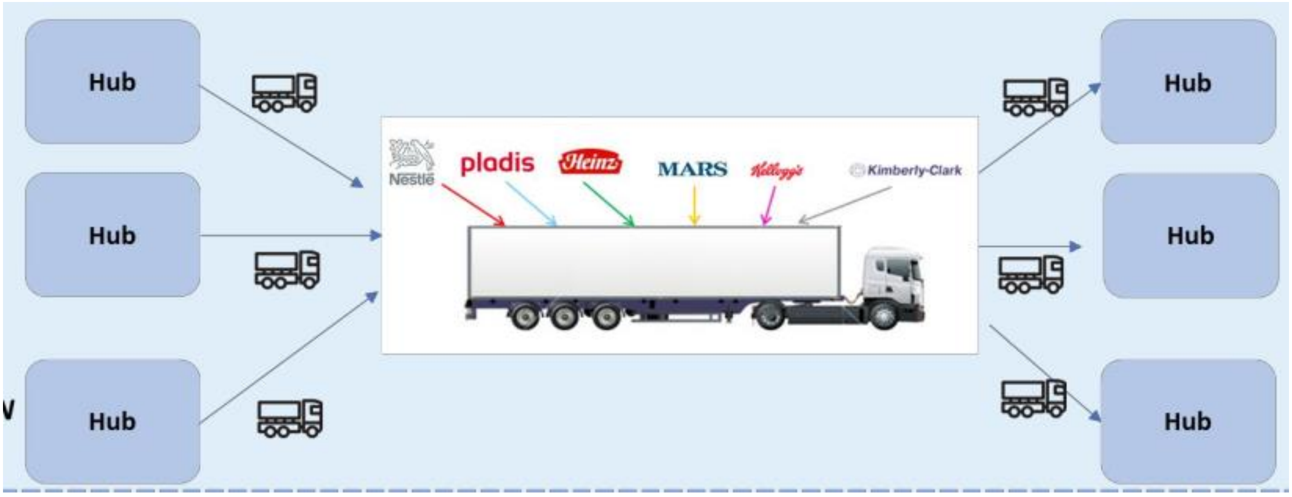

Figure 15 Example of tactical horizontal collaboration in the scope of the LOGISTAR project.

3.2. Collaborative VRP

With the EU facing the challenge to maintain and increase its economic growth and cope with the problem of freight transport efficiency in Europe point-to-point routing problems are starting to become overseed by more efficient alternatives that integrate larger volumes of transport modes and cooperation. Better use of capacity, flexibility, resource efficiency and cooperation between all actors along the logistic chain are some of the benefits attached to horizontal collaboration strategies (Serrano-Hernández et al., 2017).

Collaborative VRP or Collaborative Transportation Management (CTM) is an emerging model of collaboration in the transportation area (Okdinawati et al., 2015) that is expected to bring all parties together in the supply chain to drive inefficiencies out of the transportation planning and execution process. Horizontal collaboration improves the operating performances of all parties involved through optimization of collaborative objectives for parties involved rather than for individuals (Mason et al., 2007; Simatupang and Sridharan, 2002). Despite few research has been performed in the field of horizontal collaboration corroborated benefits include reduction of unused load capacity, reduction of travelling time and reduction in transportation costs (particularly back-hauling costs) (Browning, 2000). These research studies suggest that collaborative transportation models should be incorporated into logistics to reduce logistic bottlenecks, inefficiency and provide mutual benefits for all collaborative parties (Bishop, 2002; Min et al., 2005).

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Due to the lack of collaborative transportation modelling literature issues regarding behavioural aspects that arise from the collaborative transportation have not been yet explored in the state of the art. Altogether, (Okdinawati et al., 2015) establishes four dimensions of collaborative categories enumerating thepotential risks for each dimension:

- Collaborative Structure
- General characteristics
- Collaborative planning level
- Solution methodologies

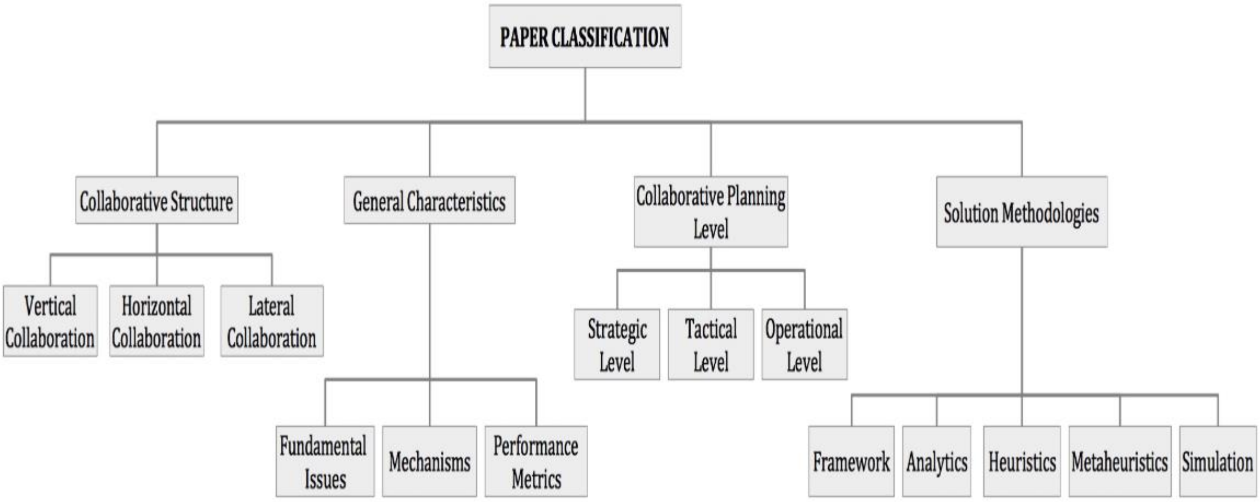

Figure 16 Classification of CTM dimensions according to (Okdinawati et al., 2015)

In this project we focus on the Collaborative Planning level and consider the following scenarios for strategic, tactic and operational horizontal collaboration:

1. **Consolidation of shared centres:** Determining the best location for the distribution centres of an agent, is a typical example of such a strategic decision. Figure 17 describes an illustrative case in which firms must serve all the customers placing orders to them. In a collaborative scenario, some consolidation centres are selected to distribute products among nearby customers.

2. **Co-joint routing:** In this case, two or more companies pool their customers to serve them from a shared depot. Therefore, clients' orders are exchanged to get a better match between customers and depots. Most articles start with a non-collaborative scenario, after which they analyse the potential benefits that could be obtained if a collaborative scenario was used instead. Figure 18 shows a scenario in which co-joint routing is applied.

3. **Back-hauling:** Usually, customers are widespread over the geography, which generates long empty back-hauls after deliveries. Thus, load factors can be easily improved by collaborating to reduce empty back-hauls when companies share their logistics operations. Sharing the vehicle capacity can significantly increase load factors, since it generates the potential to gain revenue on non-full haul trips. Figure 19 presents a scenario in which this strategy is applied.

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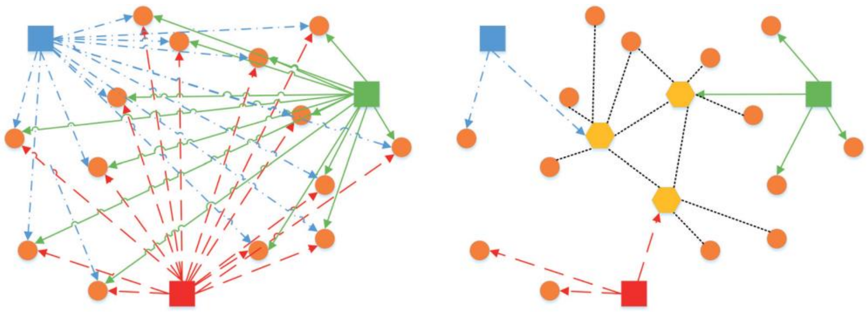

Figure 17 Non-collaborative (left) vs. collaborative scenarios (right) for consolidation of shared centres

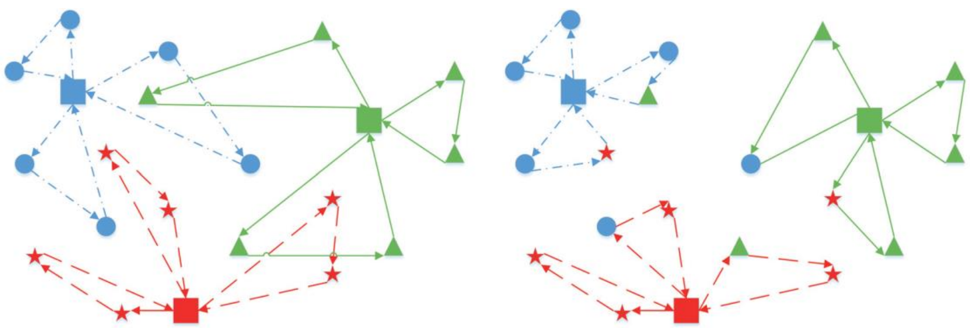

Figure 18 Non-collaborative (left) vs. collaborative (right) scenarios for conjoint routes.

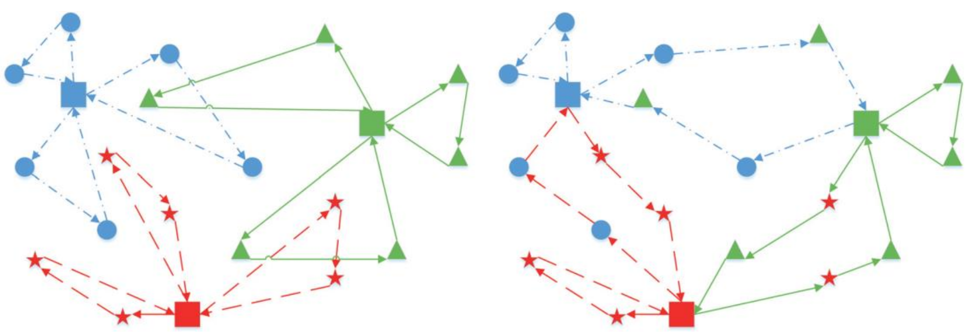

Figure 19 Non-collaborative (left) vs. collaborative (right) scenarios for back-hauling.

The work of (Gansterer and Hartl, 2018) define collaborative vehicle routing as an increasingly active research area of high practical importance. In the case of centralized planning the total profit is maximized jointly across the actors participating in the collaboration. The actors or players involved in the collaboration might be the carriers, shippers or freight forwarders. Carriers are assumed to be the operators of transportation equipment and joint route planning is typically assumed by these players, while shippers are expected to supply shipments. When shippers consider collaboration, they identify attractive bundles of lanes, helping carriers to reduce empty trips in return of better rates.

In our scenario, LOGISTAR defines the role of a central authority having full information regarding the strategical, tactical and operational level. Under this schema of full information (centralized collaborative planning) the decision-making process has to tackle a standard optimization problem taking into account shared centre locations and possibilities for sharing carrier resources. Centralized authorities typically face huge and highly complex optimization problems, since they have to plan operations for several interconnected players. In this context, sophisticated solution techniques are required. Yet, the majority of papers finds that horizontal collaborations can improve the non-cooperative solution by around 20-30%.

In centralized horizontal collaborative planning problems, there are several decisions that have to be taken. Typically, not only the routing but also the assignment of customers to depots has to be considered. In order to approximate optimal solutions even for large real-world instances, many authors propose decomposition strategies (Buijs et al., 2016; Dai and Chen, 2011; Nadarajah and Bookbinder, 2013). While a popular assumption is that in horizontal collaborations the VRP is the underlying planning problem, also collaborative Arc Routing Problems (ARP) or Minimum Cost-Flow Problems (MCFP) have been investigated. The optimal hub routing problem of merged tasks is investigated by (Weng and Xu, 2014). This problem allows all requests to pass up to two hubs within limited distance. The underlying problem is formulated as multi-depot ARP. Solutions are generated using two heuristics based on Lagrangian relaxation and Benders decomposition.

The time-dependent centralized multiple carrier collaboration problem is introduced by (Nadarajah and Bookbinder, 2013). The authors assume a setting where carriers either provide or consume collaborative capacity. Capacities are time-dependent but known a priori, and demand is fixed. The problem is modelled as a binary multi-commodity MCFP and solved using a branch-and-cut algorithm. (Liu et al., 2010) define the multi-depot capacitated ARP aiming for a solution with minimized empty movements of truckload carriers. A two-phase greedy algorithm is presented to solve practical large-scale problems.

One of the first studies to systematically assess the potential of collaborative vehicle routing was presented by (Cruijssen et al., 2007). The authors considered a system with multiple companies, each having a separate set of distribution orders. Goods are picked up at a single distribution centre and delivered to customer sites. Both, a non-cooperative setting, where each company solves the planning problem independently, and a cooperative setting, where routes are planned jointly are investigated.

It is shown that joint route planning can achieve synergy values of up to 30%. Many other studies confirm the observation of (Cruijssen et al., 2007), that centralized collaborative planning has the potential to improve total profits by around 20-30% of the non-cooperative solution(Montoya-Torres et al., 2016; Soysal, 2016). A real-world setting, where a local courier service of a multinational logistics company is investigated by (Lin, 2008). It is shown that the cooperative strategy, where courier routes are planned jointly, outperforms the non-cooperative setting by up to 20% of travel cost.

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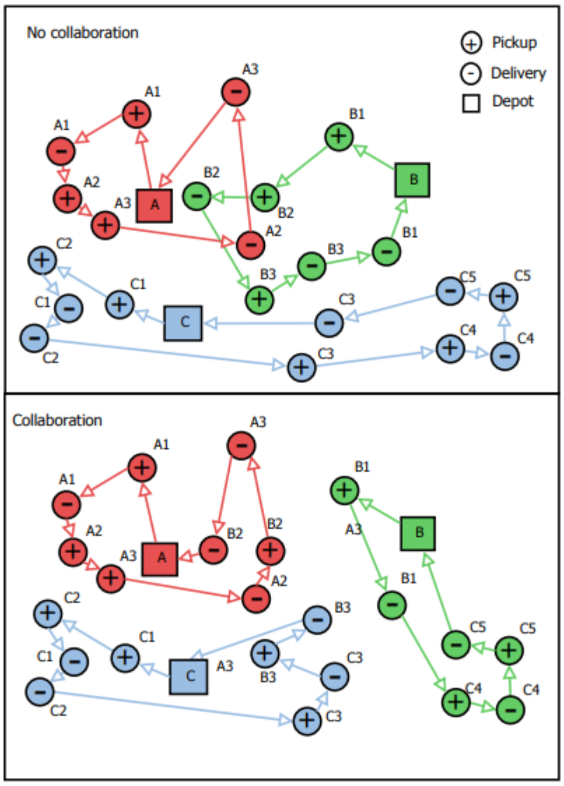

Figure 20 Example for non-collaborative and collaborative vehicle routes of three LTL carriers with pickup and delivery requests. (Gansterer and Hartl, 2018).

Collaboration potentials in stochastic systems has also been assessed by (Sprenger and Mönch, 2014). The authors investigate a real-world scenario found in the German food industry, where products are sent from manufacturers to customers via intermediate distribution centres. They are the first to show that the cooperative strategy clearly outperforms the noncooperative algorithms in a dynamic and stochastic logistics system. A large-scale collaborative planning is obtained for the delivery of the orders, capacity constraints, maximum operating times for the vehicles, and outsourcing options. This problem is decomposed into rich route planning subproblems and solved by an algorithm based on ant colony systems. The proposed heuristics is tested in a rolling horizon setting using discrete event simulation. (Quintero-Araujo et al., 2016) discuss the potential benefits of collaborations in supply chains with stochastic demands. A simheuristic approach is used to compare cooperative and non-cooperative scenarios. The authors find costs reduction around 4% with values rising up to 7.3%.

Horizontal collaboration not only follows economical but also ecological goals like reducing road congestion, noise pollution, and emissions of harmful substances. Public authorities are encouraging companies to collaborate. The city of Zurich, for instance, funded a research project aiming at improved logistic cooperation by an IT-based collaboration platform (Schmelzer et al., 2014). In order to solve real-world instances from the city of Bogota (Montoya-Torres et al., 2016) quantify the effect of collaborative routing between different transport companies. For the task, the authors centralized the problem and decomposed it into an assignment part and a routing part. By means of this decomposition, the non-cooperative solution was improved by 25.6% of the travel distance.

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The Vehicle Routing Problem with time windows (VRPTW) and with carbon footprint as a constraint is proposed by (Sanchez et al., 2016). Using this model, the reduction of carbon emissions in a collaborative setting, where different companies pool resources, is investigated. The authors find that the total greenhouse gas emissions can be reduced by 60%, while cost savings were nearly 55%. (Soysal et al., 2018) model and analyse the IRP in a collaborative environment, which accounts for perishability, energy use (CO2 emissions), and demand uncertainty. According to their experiments, the cost benefit from cooperation varies in a range of about 4-24%, while the aggregated total emission benefit varies in a range of about 8-33%.

3.3. Methods to solve multi-point route planning problems

Metaheuristics have been widely used for the solving of multi-point routing problems in the last decades, becoming the state of the art in the resolution of many of the variants of these problems. One of the first metaheuristics applied in this context was Simulated Annealing(Laarhoven van PJM, 1987). For example, in (Solano-Charris et al., 2015), Marek et al. presented a serial and parallel SA for solving the TSP. Other example of the application of this technique for route planning is the work published by Chiang and Rusell(Chiang and Russell, 1996), in which the VRP with Time Windows is solved using a SA.

More recently, Baños et al. developed a parallel variant of SA, called Multiple Temperature Pareto SA in (Baños et al., 2013), to also solve the VRP with Time Windows with very successful results. Another well-known stochastic local search, Tabu Search, which has been also frequently used for solving route planning problems. A recent work on this topic is the one presented by Escobar et al. in 2014 (Escobar et al., 2014), in which they proposed a hybrid granular TS for tackling the challenging Multi-Depot VRP. Briefly explained, the proposed method considers different neighbourhoods and diversification strategies, with the aim of improving the initial solution obtained by a hybrid procedure.

The Variable Neighbourhood Search has also demonstrated its efficiency in this area. An interesting example is the work presented in (Carrabs et al., 2007), in which Carrabs et al. proposed a VNS for solving a multi-attribute version of the TSP: a Pickup and Delivery TSP with LIFO Loading. More concretely, the authors of this paper introduce three new local search operators, which are then embedded within a VNS. In a more recent publication, Sarasola et al. (Sarasola et al., 2016) developed a VNS for facing a stochastic and dynamic VRP. This version of the VRP contemplates two different features. The first one is stochastic demand, which is only revealed when the vehicle arrives at the customer location. The second feature is the dynamic request, meaning that new orders from previously unknown customers can be received and scheduled over time. Furthermore, evolutionary methods have also shown a great performance for this sort of problems, genetic algorithms being one of the most successful ones.The work presented by Vidal et al. in 2013 is an example of this fact (Vidal et al., 2013). In this research, a hybrid genetic algorithm with adaptive diversity management is implemented for tackling the VRP with time windows.

Another example is the survey paper published by Karakati and Podgorelec in 2015 (Karakatič and Podgorelec, 2015), which collects some of the most important works focused on the application of the GA to the multi-depot VRP. Additionally, since the appearance of GA in the early 1970s, a wide variety of nature-inspired metaheuristics have also appeared in literature. Some of these recently proposed methods are the Firefly Algorithm and the Bat Algorithm. The FA was proposed by Yang in 2008 (Yang, 2010). This meta-heuristic has been applied to a wide range of optimization fields and problems since its proposal (Yang and He, 2013), and it has also shown a promising performance for routing problems. In (Jati, 2011), for example, Jati et al. presented the first application of the FA for solving the TSP. In order to do that, authors adapt the FA, which was firstly proposed for tackling continuous problems, providing it with an evolutionary and discrete behaviour. Another interesting example of application is the one presented in (Alinaghian and Naderipour, 2016) by Alinaghian et al., in which a hybrid version of the FA is proposed to solve a time-dependent VRP with multi-alternative graph, in order to reduce the fuel consumption. The developed hybrid version of the FA is a Gaussian Firefly Algorithm. The most interesting part of this paper is the real-world use case that authors presented, focused on a distribution company, established in Esfahan, Iran. Additionally, in (Osaba et al., 2016a) Osaba et al. also shown that the FA is able to face complex routing problem, such as the asymmetric and clustered VRP with simultaneous pickup and deliveries, variable costs and forbidden paths. Finally, in (Cruz et al., 2010) , the authors presented a evolutionary discrete FA with a novel operator to deal with VRP with time windows with successful results.

Regarding the other nature-inspired method mentioned above, the BA, it was proposed by Yang in 2010 (Yang, 2010). As can be read in several surveys (Jati, 2011), the BA has been successfully applied to different optimization fields and problems since its proposal. Focusing in routing problems, several recent papers have shown that the BA is a promising technique in vehicle route planning. For example, in (Taha et al., 2015), Taha presented an adapted version of this algorithm for solving the well-known Capacitated VRP. The Adapted BA developed in that study allows a large diversity of the population and a balance between global and local search. Zhou et al. addressed the same problem in (Zhou et al., 2016). In that paper an hybrid BA with path relinking is described. This approach is constructed based on the framework of the continuous BA, in which the greedy randomized adaptive search procedure and path relinking are effectively integrated. Additionally, with the aim of improving the performance of the technique, the random subsequences and single-point local search are operated with certain probability. In (Osaba et al., 2016b), Osaba et al. presented an improved adaptation of the BA for addressing both symmetric and asymmetric TSP. The results show that the improved version of BA could obtain promising results, in comparison with some reference techniques, such as an evolutionary simulated annealing, a genetic algorithm, a distributed genetic algorithm or an imperialist competitive algorithm. We want to highlight that the meta-heuristics referenced in this section form a small part of all different approaches that can be found in current literature.

We are aware that many other interesting and efficient techniques are available in the scientific community, such as the Harmony Search (Karakatič and Podgorelec, 2015), or Gravitational Search (Precup et al., 2013, 2014), which also show good performance when they are applied to routing problems. Additionally, different classical methods have also shown a great performance for this kind of problems, such as the Particle Swarm Optimization (Yao et al., 2016), the Ant Colony Optimization (Reed et al., 2014) or Large Neighbourhood Search (Pisinger and Ropke, 2010). This last method is considered currently the state of the art for solving VRP problems and it is implemented by many commercial solvers.

4. State of the art in optimization of transhipment planning and scheduling in hubs

This section is devoted to review the state of the art in transhipment planning and scheduling in hubs, the second key area covered by this deliverable.

LOGISTAR project has received funding from European Union's Horizon 2020 research and innovation programme under grant agreement no. 769142.

This section is structured as follows. Section 4.1 is dedicated to give a general view of problems that may arise in the area of transhipment planning and scheduling in hubs as well as the optimization methods applied. Section 4.2 focus on one of the problems that will be addressed in LOGISTAR that is the optimization of cross docking operations. Finally, in section 4.3 we analyse intermodal hub optimization covering the problematic and proposed approaches to deal with this problem.

4.1. Transhipment planning and hub scheduling

This section presents a research analysis that centres on the transhipment planning for collaborative entities, enumerating alternatives to optimize the use of means available in hubs.

Due to the representation of the problematic linear Programming has been extensively used to optimize journeys and selecting the placement of best located hubs, for instance, (González et al., 2008) used linear programming to effectively automate container transhipment plans for train-train transhipment in the Spanish-French border by letting the algorithm determine the best usage of routes by optimising vehicle availability, distance and capacity. The authors also show how their model could be transferred both to other transhipment terminals and to cargo terminals in general to improve performance minimizing cost or distance.

A transhipment model could also determine which yards are strategically placed to support loaded and unloaded and help keeping vehicles moving along the busy mainlines. For instance, (Brewer, 2014) defined a transhipment model created out of hub distance data to identify which ports and coal mines were used optimally. Additionally, the work contributed to better understand how the resources were being used. In the railway domain, (Mu and Dessouky, 2011) also obtained improvements on scheduling and timelines by modelling the US Railroad by means of a transhipment model based on optimization-based mathematical approaches: greedy heuristics and global neighbourhood search algorithms. Out of the scope of the railway research, transhipment planning has also been extensively used for optimization, for instance, (Shang and Kokossis, 2004) successfully used the transhipment model for optimising multiperiod operations using multi-period mixed-integer linear programming (MILP) and (Wiles and van Brunt, 2001) developed a model to identify the optimum location for transhipment depots.

Other mathematical models have also been used to optimize the decision-making process, for instance, (Sharma and Jana, 2009) exploited fuzzy goal programming (FGP) combined with genetic algorithms to find flexible solutions for different values of the same goal at the same time in a petroleum refinery industry study.

With continuously increasing attention in the area of Intermodal freight transport distinct planning problems are starting to emerge. In this context, (Caris et al., 2008) proposes an organized overview of planning issues and solution methods in the scientific literature. In this work, planning problems are classified according to the type of decision maker and decision level. The authors also define conclusions and subjects for the applicability of methods.

4.2. Cross Docking Optimization

Cross-docking is a logistics strategy used by many companies in different industries. The basic idea behind cross-docking is to transfer incoming shipments directly to outgoing vehicles without storing them in between (Van Belle et al., 2012). This practice can serve different goals: the consolidation of shipments, a shorter delivery lead time, the reduction of costs (warehousing costs, inventory-holding costs, handling costs, labour costs), improved customer service, reduction of storage space, faster inventory turnover, fewer overstocks and so on. These objectives requires a correct synchronization of incoming (inbound) and outgoing (outbound) vehicles. However, a perfect synchronization is difficult to achieve so usually constraints are in some manner relaxed by most authors. A graphical representation of cross-docking can be observed in the following figure.

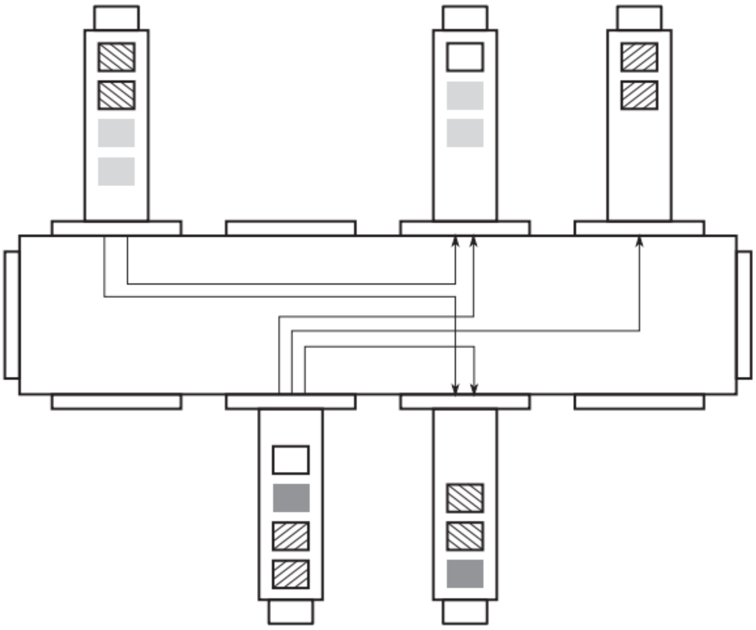

Figure 21 A graphical representation of cross-docking with the objective of minimizing the storage rate between inbound and outbound traffic. Source (Van Belle et al., 2012).

Cross-docking is generally considered an interesting logistic strategy that can potentially give companies considerable competitive advantages. Furthermore, cross-docking is extremely suitable for the environments in which products have a stable demand rate and low unit stock-out cost. The traditional warehousing is still preferable for the opposite situation with an unstable demand and high unit stock-out costs. For the two other cases, cross-docking can still be used when proper systems and planning tools are in place to keep the number of stock-outs to a reasonable level.

Some other factors that can influence the suitability of cross-docking are the distance to suppliers and customers (higher distances increase the benefits of consolidation), the product value and life cycle (a larger reduction in inventory costs for products with a higher value and shorter life cycle), the demand quantity (a larger reduction in inventory space and costs for products with a higher demand), the timeliness of supplier shipments (to ensure a correct synchronization of inbound and outbound trucks) (Apte and Viswanathan, 2000)

The first decisions that have to be taken during the planning process are strategic decisions: where will a cross-dock (or cross-docks) be located and what is the best internal layout of a cross-dock. Once the cross-dock is available, it will be part of a supply network (with one or more cross-docks). A tactical decision that has to be made then is how the goods will flow through the network to minimize the costs, while making supply meet demand.

The modelling of the cross-docking problem is NP-hard, thus, global optimization search strategies are employed to find optimal solutions.For instance, (Sung and Song, 2003)propose a tabu search-

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based algorithm to solve the problem in which the solutions determine how the goods flow through the network. Based on this flow, the number of vehicles can be derived by solving a subproblem. The authors also perform some computational experiments on generated test instances and indicate that the proposed algorithm finds good feasible solutions within a reasonable time.

A different approach is taken (Jayaraman and Ross, 2003). In this work the authors employ a simulated annealing heuristic study a multi-echelon problem in which goods (from multiple product families) have to be transported from a central manufacturing plant to one or more distribution centres. From there, the goods are moved via cross-docks to the customers. The problem is tackled in two stages. In the first stage, a strategic model is used to select the best set of locations for the distribution centres and cross-docks. The authors provide an integer programming formulation that aims to minimize the fixed costs associated with operating open distribution centres and cross-docks.

Some authors do not study problems concerning a single cross-dock but consider a network that contains one or more cross-docks. The aim is to determine the flow of goods through such a network in order to reduce costs, while making supply meet demand.

The research of (Lim et al., 2005) extends the traditional transhipment problem. The transhipment problem consists of a number of supply, transhipment and demand nodes (crf. Section 4.1). The arcs between these nodes have different capacity limits and costs. The objective is to find a minimum cost flow that meets all demands and the capacity constraints. In the extended transhipment problem, storage is allowed at the transhipmentcentres. These centres can be considered as cross-docks because the aim of the model is to minimize or eliminate holdover inventory. Moreover, this problem takes supplier and customer time windows into account and considers the capacity and holding costs of the cross docks. All shipments have to pass via a cross-dock, so no direct shipments are considered. Similar to the original problem, the objective is to minimize the total cost (transportation costs and holding costs) while meeting demand and respecting the time windows and capacity constraints. If multiple departures and deliveries within a time window are allowed (multiple shipping–multiple delivery), the authors show that a time-expanded network can be used to formulate the problem as a minimum cost flow problem which can be solved in polynomial time. For other cases, the authors prove that the problem is NP-hard.

In addition to the basic problematic of cross docking, the literature defines different cross docking classes by imposing distinct definitions to the initial problem. These extended problems aim to make the models closer to situations found in real scenarios. We now describe some of the common variants found in the domain of cross docking, as well as those more related to the problems we will address in LOGISTAR. Concretely, we will review the following dimensions of cross docking problem classes: cross dock planning, cross dock scheduling, network design, network planning and network scheduling (Buijs et al., 2014).

4.2.1. Cross dock planning

Cross dock planning decisions address local cross dock operations on the medium-term. A typical objective used by cross dock managers is to minimize the material handling effort required for moving incoming freight from strip to stack doors. The decision specifying dock doors as either strip or stack door dictates the aggregated freight flows through the cross-dock. More precise freight flows are determined by the dock door assignment, i.e. demining at which dock door a trailer is served. Cross docks serving a fixed set of origins and destinations with relatively constant freight flows tend to assign dock doors over a planning horizon of 3-6 months. In situations with volatile freight flows, stack doors are sometimes assigned from night to night. A more dynamic assignment of docks doors requires contemporary information technology (e.g., RFID) supporting the material handlers in locating the stack doors associated with shipments.

Another important cross dock planning decision is concerned with determining the appropriate workforce and material handling equipment to efficiently handle all freight within the limited time available. Cross dock operations start and terminate with little or no shipments in the staging area and usually take place during apart of the day, e.g., overnight.

4.2.2. Cross dock scheduling

Cross dock scheduling decisions specify the allocation of resources at the cross dock over time. Scheduling decisions for serving individual trailers at the cross-dock are aimed at facilitating a smooth flow of freight from the strip to the stack doors. As opposed to the assignment of dock doors, trailer scheduling decisions consider highly capacity constrained dock doors, i.e., the number of trailers to be served far exceeds the number of available dock doors.

Accordingly, detailed timing and sequencing aspects are taken into account in order to minimize the waiting times of shipments and trailers on-site. Trailer schedules can be completed before the start of operations or developed dynamically during ongoing operations, which is referred to as offline or online trailer scheduling, respectively. In order to align the inbound and outbound activities at the cross dock, the internal workforce that unloads and reloads trailers and moves freight through the cross-dock has to be scheduled as well.

The utilization of the staging areas (i.e., how shipments are placed in the staging area) influences the total travel distance of the material handling equipment and determines the accessibility of shipments. Lastly, some cross-docks receive inbound shipments that are not yet assigned to a particular outbound trailer. Cross dock scheduling then involves the assignment of shipments to outbound trailers, i.e., assembling consolidated trailer loads.

4.2.3. Network design

Network design decisions determine the physical infrastructure of the cross-docking network such that transportation demand is met at the lowest possible cost. Each transportation order is associated with particular costs, which are incurred depending on how that order is routed through the cross-docking network. An important network design decision is concerned with shaping the general structure of the network and defining the types of logistics facilities that are established. The structure of the network consists of a set of possible facility locations and routes to transport freight. The facility type definitions describe for each type, e.g., the fixed costs to operate the facility, the maximum capacity, and the distribution functions performed. Opportunities for outsourcing may also emerge and are evaluated at the strategic level when shaping the network structure and defining the facility types. Based on the network structure and the expected transportation demand, the appropriate number and locations of facilities in the cross docking network are determined as part of the network design.

4.2.4. Network planning

Network planning decisions are concerned with allocating and utilizing network-wide logistics resources in order to attain economic and customer service level objectives. A primary network planning decision assigns transport capacity (e.g., a fixed number of trailers) to each route in the cross-docking network and, thereby, specifies which of the potential network routes will actually be used to provide transport services. A closely related network planning decision allocates freight to the available transport services.

Collectively, the network planning decisions determine how freight is routed through the network, and thus where opportunities for consolidation occur. If transportation demand is characterized by origin-destination pairs, the destination for each shipment is known prior to solving the network planning problems. Alternatively, transportation demand is expressed by supply and demand figures for one or more product types. The decision to assign a destination to each shipment is then part of the network planning. This is often the case for cross docking networks in a retail-distribution setting where each retail store demands a certain range of products. Provided that the correct product range is send to each retailer, products from the same type are interchangeable. The decision latitude that may arise as a result of product interchangeability, effectively, enables additional opportunities for consolidation.

4.2.5. Network scheduling

In contrast to network planning decisions, network scheduling considers detailed temporal constraints in routing freight through the cross-docking network. The capacity and time windows for transport services in the cross-docking network are often determined in advance of the scheduling decisions. Network scheduling decisions are then concerned with dispatching shipments, i.e., specifying if and how many shipments are dispatched onto a given transport service. In the local region of a cross dock, network scheduling may include vehicle routing to collect and deliver shipments from and to the cross-dock. In this specific variant of the vehicle routing problem, there is an emphasis on aligning the resulting inbound and outbound freight flows at the cross-dock.

4.3. Intermodal hub optimization

Intermodal containers are large standardized shipping containers, designed and built for intermodal freight transport. Intermodal freight transport involves the transportation of freight using multiple modes of transportation (e.g., rail, ship, and truck) without any handling of the freight itself when changing modes. This means that intermodal containers are used across different modes of transport without unloading and reloading their cargo, and, as a consequence, it offers an efficient and effective solution to share transportation costs across the supply chain based on cooperation and integration between companies. Intermodal containers are primarily used to store and transport materials and products efficiently across intermodal hubs during the long-haul transportation chain segment (SteadieSeifi et al., 2014).

A transportation chain is basically partitioned in three segments: pre-haul (the pickup process), long-haul (door-to-door transit of containers), and end-haul (delivery process). In most cases, the pre-haul and end-haul transportation is carried out via road, but for the long-haul transportation intermodal freight transportation is considered. Among the key points for containerization we can mention an increase in the safety of cargo, reduction of handling costs, standardization, and accessibility to multiple modes of transportation, as described in (Crainic and Kim, 2007).

In order to successfully apply intermodal transportation strategies intermodal terminal locations around the globe are a matter of great concern so that companies are able to take advantage of the flexibility and the economies of scale of using multiple modes. Nevertheless, state of the art analysis shows that the design of intermodal networks is sensitive to the network parameters, especially to the cost ratio of transportation modes and this modal connectivity cost. Better insight in the cost structure of intermodal transport chains is one way to find necessary and effective policy actions for realizing modal shift. Capacity constraints, modal connectivity costs, scheduling issues, uncertainty issues, decentralized decision making are also to be taken into account when optimizing intermodal freight transport.

The objective of intermodal hub optimization is to select intermodal routes and determine container flow assignments over the network hubs such that a user-supplied objective function given by intermodal freight transport operators is minimized, while considering a number of transport demands, the physical capacities of transport connections, the transport network properties, and the traffic conditions (Li et al., 2015).

Solving intermodal hub optimization problems at the strategical level is difficult due to the large amount of variables involved (e.g. infrastructure, modal choice and capacity allocation on each service, service frequencies, the timetables of vehicles and barges, equipment planning, and container flow assignment among others). That is why most solution methodologies involve using heuristics or metaheuristics to approximate the global optimum (SteadieSeifi et al., 2014). Among the methodologies involved, Tabu Search seems to be a popular metaheuristic employed in several articles (Crainic and Kim, 2007).

On the operational planning level, the aim still resides in finding the best choice of services and associated transportation modes, best itineraries and allocation of resources to the demand. However, the search requires to answer the real-time requirements of all multimodal operators, carriers and shippers. Operational planning deals with dynamicity and stochasticity that are not explicitly addressed at strategic and tactical levels. These characteristics make operational planning problems remarkably complex. Hence, designing accurate and fast solution algorithms is essential. Indeed, these problems usually require solving mixed integer optimization problems in which individual containers are directly modelled and scheduled. This problem is NP-hard and requires huge computational efforts to solve it as the number of shipments or the size of the intermodal network increase (Li et al., 2015)..

As an example, in (Li et al., 2015) the authors investigate intermodal freight transport planning problems among deep-sea terminals and inland terminals in hinterland haulage for a horizontally fully integrated intermodal freight transport operator. They model the behaviour of the network capturing characteristics, such as: modality changes at intermodal terminals, capacities of physical infrastructures, time-dependent transport times on freeways, time schedules for trains and barges and dynamic transport demands and traffic conditions in the network for intermodal freight transport. By solving this approach as an integer linear problem, the authors are capable to find solution to large-sized networks and outperform greedy approaches in terms of the total delivery cost in the simulation study. They also explore different demand scenarios and different prediction error levels on transport demands and traffic conditions.

4.4. Methods to solve transhipment planning and scheduling in hubs

In this subsection we will review some of the main optimization methods that have been applied in different problems in the are of transhipment planning and scheduling in hubs. Concretely, we will first review optimization methods for cross docking, and subsequently for intermodal hub optimization.

Cross docking is a warehouse management concept, in which items delivered to a warehouse by inbound trucks are immediately sorted out, reorganized based on customer demands, routed and loaded into outbound trucks for delivery to customers without the items being actually held in inventory at the warehouse. This way, the turnaround times for customer orders, inventory management cost, and warehouse space requirements are reduced. One of the objectives for cross docking systems is how well the trucks can be scheduled at the dock and how the items in inbound trucks can be allocated to the outbound trucks to optimize on some measure of system performance.

Previous research on cross docking mainly investigates one of the following decision problems: (1) location of cross docks and other kinds of intermediate warehouses (Abdinnour-Helm and Venkataramanan, 1998), (2) layout of the dock (Bartholdi and Gue, 2004), (3) mid-term assignment of outbound destinations to dock doors . Only very few research papers deal with the short-term scheduling problems arising during the daily operations of cross docking terminals

To optimize cross-docking systems, (Yu and Egbelu, 2008) presents six heuristic algorithms designed to minimize the number of matching pairs of receiving and shipping trucks. Each heuristic uses a specific selection criterion to match a proper pair, as follows: (1) maximum flow between pairs, (2) maximum ratio between pairs, (3) maximum fitness between pairs, (4) maximum flow with priority assignment, (5) maximum ratio with priority assignment, and (6) maximum fitness with priority assignment. These heuristic methods indicate the minimum number of matching pairs of receiving and shipping trucks, which should reduce the makespan value. Because in a cross-docking system, the best sequence of truck pairs is desirable, and changing the sequence of pairs does not affect the value of make span, the need to define a powerful objective is sensible. Furthermore, because minimizing the time trucks spend at DCs to pick up or deliver their items is the goal, the mean flow time criterion is adopted for meta-heuristic approaches.

The computational complexity of the problem, which increases as the number of inbound and outbound trucks and product type increase, makes heuristic methods inapplicable, whereas meta-heuristic methods offer a better alternative. The encoding scheme for the proposed meta-heuristic algorithms uses to be represented with a string of matching pairs of inbound and outbound trucks. In literature, each meta-heuristic operates in two phases: in the first phase, the initial solution of each meta-heuristic connects through the heuristic methods listed previously, and in the second phase, this solution gets improved by the proposed hybrid meta-heuristics. TS, a modified version of SA and a modified version of VNS is tested in (Vahdani and Zandieh, 2010), proving the good performance of meta-heuristics based on VNS to optimize the problem. In other hand, (Boloori Arabani et al., 2010) put their emphasis on a cross-docking system in which a multi-criteria scheduling problem with a just-in-time approach is processed by three meta-heuristics: GA, PSO and DE.

One of the most common optimization problems that arise in transhipment optimization in hubs is the planning of crane operations. In (Souffriau et al., 2009) the authors proposed a Variable Neighbourhood Descent metaheuristic to optimize train-to-train container transhipment. The problem is subdivided in three subproblems: assignment of destination to train, determination of container positions and the operation sequence of the cranes. The experimentation done over simulated instances show the good performance of the proposed method.

Another interesting work can be found in (Hu et al., 2018) where the authors design a tabu search to optimize the planning of inter-terminal transport using a new approach that integrated container and vehicle movement with rail yard operations. The results obtained over problems with different complexity showed that the tabu search provided similar or better results than a local search and CPLEX.

Braekers et al. addressed a drayage optimization problem in intermodal terminals in (Braekers et al., 2014). In this case the authors. They use a bi-objetive optimization model that integrates both allocation and routing decisions. For optimizing the bi-objective model they proposed three metaheuristic methods based on deterministic annealing: an iterative method, a two-phase deterministic annealing algorithm and a two-phase hybrid deterministic annealing and tabu search algorithm. The authors concluded that the last of the three methods proposed outperformed the other two, which is a proof of the general good performance of hybrid metaheuristics for this sort of problems.

In (Dotoli et al., 2017), the authors presented a decision support system to optimize two important activities in intermodal terminals, freight train composition and allocation of containers in the terminal storage yard. Concretely, the authors modelled these two problems as integer linear programming models and they solve it using the tool GLPK[3]. The methodology proposed was tested on a real case study in Italy with satisfactory results.

More recently, in (Guo et al., 2018), a new fix and optimizing method is proposed for granty crane scheduling in railroad intermodal hubs, where containers are transferred from trains to trucks and vice versa. The optimization algorithm proposed, that can be considered a metaheuristic (hybridization between metaheuristics and mathematical methods) decomposes the problem to a set of smaller subproblems using an approach similar to that of large neighbourhood search. The algorithm is able to solve large instances with reasonable quality.

5. Conclusions

As mentioned in the Introduction, this deliverable “D.4.1 State of the art in optimization techniques for global optimization of logistic systems” describe the main part of the work done in Task 4.1. State of the art review in global optimization of logistic systems and definition of benchmarks. More specifically, it focuses on the review of the state of the art in global optimization of logistic systems in the two key topics of the Work Package 4 of the LOGISTAR project: (i) freight transport networks for horizontal collaboration, (ii) transhipment planning and scheduling in hubs.

The main content of the paper can be divided in three parts. In the first part we have provided an overall overview of the background in the field of optimization in freight transport networks and transhipment planning and scheduling in hubs, showing the basic description of the problematic addresses, the most common mathematical models used as well as the most usual optimization methods employed for its resolution.

In the second part of the document we have reviewed the state of the art in routing problems that is the most common framework used to address optimization of freight transport networks. In a more specific way, we have started with a general view of this models to then going deep into deep in those models more related to the variant of the problem that will arise in LOGISTAR, with a particular focus on the collaborative VRP. Then, we have reviewed the main optimization methods applied to

[3] https://www.gnu.org/software/glpk/

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solve these problems focusing particularly on metaheuristics. The principal conclusions of this task have been the following:

- The collaborative VRP is the most appropriate model to address the optimization of horizontal collaboration in freight transport network.
- We will need to take into account constraints related to time window, depot, capacity, co-loading, pickup and delivery, multi-depot and backhauling.
- Regarding optimization methods, metaheuristics are by far the best algorithm for addressing this type of problems in real scenarios, and particularly, large neighbourhood search is the reference method in both scientific literature and commercial products.

Finally, in the last section of the document, we have done an overview of the state of the art in optimization problems related with transhipment planning and scheduling in hubs. Concretely, we have given a general view about the optimization problems that may arise in this field, and after that we have centred in the specific problem that we will address within the LOGISTAR project that is the optimization of cross-docking and intermodal hub operations. The main conclusions drawn from this part of the review of the state of the art are the following:

- The most appropriate models for cross docking optimization are those related with planning and scheduling.
- For intermodal hub optimization, transhipment planning (truck to train and train to truck) and resources scheduling (e.g. vehicles, cranes or yards) are the models that better fit to the LOGISTAR requirements.
- Regarding the optimization method, metaheuristics are also the most appropriate algorithms to deal with this type of problems in real scenarios.
- Within the different optimization methods applied, Tabu Search, Large Neighbourhood Search and Hybrid Metaheuristics are the one with a better performance.

List of abbreviations and acronyms

ACO Ant Colony Optimizer

ALO Ant Lion Optimizer

ARP Arc Routing Problems

BA Bat Algorithm

CTM Collaborative Transportation Management

DA Dragonfly Algorithm

FA Firefly Algorithm

FGP Fuzzy Goal Programming

GA Genetic Algorithms

GWO Grey Wolf Optimizer

HSA Harmony Search Algorithm

HLP Hub Location Problem

LNS Large Neighbourhood Search

MCFP Minimum Cost-Flow Problems

MFO Moth-Flame Optimization

MILP Multi-period Mixed-Integer Linear Programming

PSO Particle Swarm Optimization

SA Simulated Annealing

SCA Sine Cosine Algorithm

TS Tabu Search

TSP Traveling Salesman Problem

VNS Variable Neighbourhood Search

VRP Vehicle Routing Problem

VRPB Vehicle Routing Problem with Backhauls

TDVRP VRP with Dependent Times

WOA Whale Optimization Algorithm

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