OPTIMIZATION METHODS AND HEURISTICS AND THEIR ROLE IN SUPPLY CHAINS AND LOGISTICS

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Abstract: In the past decades, our capability to solve hard and large optimization problems has improved intensely. The paper addresses a review of optimization methods, heuristics, and metaheuristics. Their role in supply chain management, logistics, and transportation is also discussed. The main goal is to update interested readers about an enormous class of prevailing optimization methods and heuristics that have been designed for solving of numerous types of optimization problems. It is assumed that comprehensiveness of the overview of these methods is one of the main contributions of this paper. In the perspective of actual practice, it is also briefly stressed how and where optimization methods can be effectively applied in the field of supply chains and logistics.

Keywords: Optimization Methods, Heuristics, Metaheuristics, Supply Chain Management, Transportation, Logistics.

1. INTRODUCTION

Nowadays, optimization is present practically everywhere, from industrial manufacturing to engineering design, from important decisions of any kind to just routine business transactions, from planning our holidays to choosing our career path, and so on (Yang, 2008). In all these actions or activities, we always have some issues (objectives) that we are trying to optimize, whether they are the optimization of costs, performance, profit, enjoyment, quality, customer-rating, or optimization of something else.

By other words, we make decisions all the time that we believe can minimize or maximize our objectives. Some other typical examples of such decisions are finding a shortcut to minimize the time necessary to reach a specific destination, disclosing the best possible house that can fulfil maximal conditions within certain cost constraints, or finding a lowest-priced item in the store.

Although optimization has been experienced in some form from the early ancient era, this area has significantly erupted during the last five decades. Modern civilization lives not only in an atmosphere of strong competition but is also constrained to plan its
progress in a sustainable fashion with due apprehension for the preservation of resources. Accordingly, it has become authoritative to design, plan, manage, and operate assets and resources in an optimal manner (Chinchuluu et al., 2009).

The formal approach to optimization problems represents the main part of the mathematical optimization, also called *mathematical programming* (Yang, 2008). The themes of mathematical optimization are extensive, and the optimization literature is enormous. It is often a frightening job for beginners to find an appropriate book and to study the right algorithms. Even for lecturers and researchers, it is not trivial to decide what algorithms to teach or apply in a practice since there are so many algorithms we can choose. There are many books about optimization, attributable to some motives. Firstly, the topic itself is mathematically quite rigorous, and there are many solution methods that we need to understand and examine. Namely, no single solution method can be conducted to all types of optimization problems (Arora, 2015). Therefore, a strong understanding of the problem, as well as solution procedures is essential to achieve an appropriate and adequate solution to the optimization problem.

Secondly, with the progression of time, optimization problems have also become more and more complex. It is often necessary not only to find the global optimal solution but also to find local optimum as well (Arora, 2015). Moreover, modern problems are frequently of the multiobjective type, where contradictory objective functions have to be handled. Generally, optimization represents finding the most suitable solution among many feasible solutions available, where all constraints should be fulfilled. The most suitable solution could be the one that minimizes the cost of a certain process or maximizes the efficiency of the certain system (Arora, 2015). The function that is being optimized is usually referred to as the target or objective function, sometimes also called the performance index. The function is some quantity such as profit, cost, size, shape, efficiency, weight, and so on (Arora, 2015). Regarding the companies and other organizations, the profit maximization or cost minimization are usually major considerations.

Optimization is usually described as a *three-step decision-making process*, which includes the following steps (Arora, 2015; Appa et al., 2006): 1. the knowledge of the system, mathematically considered as *modeling the process*; 2. finding a measure of system efficiency (*the objective function*) and setup of all *constraints*; 3. finding a best solution with respect to applied optimization model and appropriately chosen optimization method. By using modeling, we can create the objective function as well as the constraint functions for the given optimization problem. Afterward, we can use various optimization methods for solving such problems.

The modeling of many real systems is ruled by continuous mathematics. Such models are frequently a satisfactory simplification of reality, but the discrete nature of many real processes is often observed at a microscopic level, where continuous modeling might not provide an appropriate simplification. On one side it is true that continuous mathematics is more established and cohesive than discrete mathematics, and the calculus is a quite dominant tool for the optimization of numerous continuous problems. However, on the other side, many systems have a discrete nature (e.g. construction problems, finite element analysis, etc.) and are much more common in decision-making processes (operations research) or information systems (computer science) (Arora, 2015; Appa et al., 2006).
The variables that arise in the objective function are usually symbolized as the **decision (design) variables**. They can belong to a group of real or discrete numbers, often they are binary or integer values. Although a majority of the decision variables are typically real, some of them can also be discrete. In a strict mathematical sense, modeling represents expressing and linking problem's measurement variables into mathematical form by the means of basic mathematics' building blocks such as subtraction, addition, division, multiplication, functions, and certain numbers with proper units (Arora, 2015; Appa et al., 2006). If the applied model does not produce expected results, it has to be polished by accompanying further experiments. Further, many problems do not have closed-form solutions and have to be numerically simulated to reach the proper solutions.

Optimization theory had progressed originally to offer generic solutions to optimization problems regarding the linear, nonlinear, unconstrained, and constrained domains treated within the framework of mathematical programming. At the beginning, the optimization problems were classified into two distinctive categories, linear and nonlinear programming problems. Here, the continuous variables played the main role. However, during the more recent history, various classes of assignment and other discrete-based problems, which required treatment of both continuous and integer variables, have appeared. This fact was leading us to mixed integer linear programming problems (**MILP**) and nonlinear mixed integer programming problems (**MINLP**). Due to their complex nature, these problems were very hard to be efficiently solved in a reasonable time.

Nevertheless, with the arrival of computers in the 1980s, which progressed into a very powerful form in the last two decades, the efficient solutions of many large-scale hard optimization problems could be found. Present-day optimization problems are not only multiobjective but also of the multidisciplinary type. Moreover, the solution methods that are conducted today to solve hard optimization problems are not just classical such as the gradient-based and other similar algorithms within the scope of exact mathematical programming methods. Conversely, these methods can also include modern non-traditional methods, **heuristics**, and **metaheuristics** such as ant colony optimization, genetic algorithms, particle swarm optimization, or simulated annealing algorithms, which mimic natural processes (Arora, 2015).

Contrary to the exact methods, the heuristics are techniques consisting of a set of certain rules which seek (and hopefully find) satisfactory solutions at a reasonable computational cost (Maniezzo et al., 2009). They are approximate in the sense that they usually provide good solutions for relatively little-invested efforts, but they do not guarantee optimality. Heuristics just offer a simple mechanism of indicating which among several possible alternatives seems to be the best one (Maniezzo et al., 2009).

These modern methods are particularly useful when we are seeking for global optimums of objective functions since they prevent to stay captured at a local optimum. Namely, this deficiency is typical for many classical mathematical programming methods. On the other hand, for instance, the genetic algorithms that were derived from biology, or simulated annealing that was inspired by optimality of the annealing process, are examples of two quite potent methods, which can effectively seek for global optima without being locally stuck. Moreover, during the last decade, a class of completely new optimization methods called **matheuristics** has appeared. These methods are some
sort of **hybrids** since they combine certain good properties of exact mathematical programming methods on one side, and simplicity of approximate heuristics on the other side. As it turns out, these methods represent another significant milestone in the optimization field, since they provide quite promising results when compared to the other optimization methods.

In the modern era, optimization methods are needed to solve problems from all disciplines, whether being the economic and social sciences, natural sciences, or engineering sciences. Optimization methods are also crucial in the field of logistics, transportation, supply chain management (SCM) and operations research (OR). A whole plethora of difficult problems can be found in these areas, such as different kinds of transportation problems, scheduling and planning problems, vehicle routing problems (VRP), traveling salesperson problems (TSP), location-routing problems, school bus routing problems, and many other combinatorial or discrete optimization problems (Rardin, 1998; Voss and Woodruff, 2006; Parker and Rardin, 1988; Geunes and Pardalos, 2005; Minis, 2011).

The main purpose of this paper is a short review of optimization methods that have been developed for solving of various types of optimization problems. It is believed that an extensiveness of the overview in this paper might serve as one of the major contributions of this paper. In the context of real practice, it is also shortly stressed where and how optimization methods can be efficiently used in the field of logistics, supply chain management, and transportation. We believe that our contribution might not be useful only for the beginners in the field, but also for the optimization experts and researchers.

2. THE LITERATURE REVIEW

2.1 General literature and surveys about optimization

In the last decades, there was an almost uncountable number of different optimization based books published. Some of them are quite general, explaining the basic mathematical principles of optimization methods and algorithms. The other are more oriented to the use of specific program package or language, for instance, statistical program language R, or the language of technical computing Matlab. Some of these books are mainly dedicated to the practical examples and applications, while the others are more focused on certain specific optimization area, for instance on global optimization or discrete optimization. Table 1 shows some of the important books covering the optimization from the general point of view (Arora, 2015; Antoniou and Lu, 2007; Cortez, 2014; Floudas, 2000; Diwekar, 2008; Parker and Rardin, 1988; Sarker and Newton, 2008; Appa et al., 2006; Chinchuluun et al., 2009; Forst and Hoffman, 2010; Grossmann, 1996; Hendrix and G.-Tóth, 2010; Levy, 2001; Nocedal and Wright, 1999; Rao, 2009; Marecek, 2010; Talbi, 2009; Rothlauf, 2011; Maniezzo et al., 2009; Yang, 2008; Venkataraman, 2009; Messac, 2015; Onn, 2010; Kouvelis and Yu, 1997; Wolsey, 1998; Weise, 2009; Williams, 2013; Dréo, 2006). These books are mostly written in engineering style, which means that they are also understandable for the non-mathematicians from any engineering faculty, who have a decent mathematical background. Moreover, these books are written in easy to follow style, but still rigorous enough. Our opinion is that even the beginner can obtain quite good knowledge about the topic after the focused studying of books in Table 1.
Table 1. Some of the typical generally oriented optimization books

| Author              | Title                                                        |
|---------------------|--------------------------------------------------------------|
| Arora               | Optimization - Algorithms and Applications                  |
| Antoniou and Lu     | Practical Optimization: Algorithms and Engineering Applications |
| Cortez              | Modern Optimization with R                                   |
| Floudas             | Deterministic Global Optimization: Theory, Methods and Applications |
| Diwekar             | Discrete Optimization                                        |
| Parker and Rardin   | Discrete Optimization                                        |
| Sarker and Newton   | Optimization Modelling: A Practical Approach                 |
| Appa et al.         | Handbook on modelling for discrete optimization             |
| Chinchuluun et al.  | Optimization and Its Applications                            |
| Forst and Hofmann   | Optimization - Theory and practice                           |
| Grossmann           | Global Optimization in Engineering Design                    |
| Hendrix and Toth    | Introduction to Nonlinear and Global Optimization           |
| Levy                | Basics of Practical Optimization                             |
| Nocedal and Wright  | Numerical Optimization                                       |
| Rao                 | Engineering Optimization                                     |
| Marecek             | Handbook of Approximation Algorithms and Metaheuristics      |
| Talbi               | Metaheuristics: From Design to Implementation                |
| Rothlauf            | Design of Modern Heuristics: Principles and Application      |
| Maniezzo et al.     | Matheuristics: Hybridizing Metaheuristics and Mathematical Programming |
| Yang                | Introduction to Mathematical Optimization                    |
| Venkataraman        | Applied Optimization with MATLAB Programming                |
| Messac              | Optimization in Practice with MATLAB for Engineering Students and Professionals |
| Onn                 | Nonlinear Discrete Optimization: An Algorithmic Theory       |
| Kouvelis and Yu     | Robust Discrete Optimization and Its Applications            |
| Wolsey              | Integer Programming                                          |
| Weise               | Global Optimization Algorithms – Theory and Application      |
| Dreo et al.         | Metaheuristics for Hard Optimization: Methods and Case Studies |
| Williams            | Model Building in Mathematical Programming                   |

Besides the investigation of optimization books available, we have also examined contributions focusing on general surveys or reviews about extensive generally oriented optimization literature. Surprisingly, the number of these contributions was quite low since we managed to identify only 24 such works (see Table 2 (Addis, 2004; Awad and Chiban, 2015; Beheshti, 2013; Bertacco, 2005; Bianchi et al., 2009; Bixby, 2012; Blum and Roli, 2003; Fernandes and Lourenço, 2007; Floudas et al., 2005; Fu et al., 2006; Genova and Gulia-shki, 2011; Hoffman, 2000; Hu et al., 2012; Jones, 2001; Kallrath, 2000; Koch, 2004; Laguna, 2002; Newman and Weiss, 2013; Osman and Laporte, 1996; Quttineh, 2012; Raidl, 2006; Schichl, 2003; Sergienko et al., 2009; Urli, 2015)). As can be seen from Table 2, the majority of these contributions are papers, while some of them are also doctoral or master theses or chapters in books. From Table 2 can be noticed that the majority of these surveys were focused on global and/or combinatorial
optimization, where the heuristics and metaheuristics have taken a special dedication. Since the majority of works presented in Table 2 penetrate into addressed topics more deeply, it is supposed that the interested reader has a good mathematical understanding of the basic optimization theoretical principles. Furthermore, some of the contributions, for instance, those discussing metaheuristics for stochastic combinatorial optimization, or about model-based randomized methods for global optimization, demand quite advanced understanding about the topic.

Table 2. Surveys or reviews about generally oriented optimization literature

| Author                | Title                                                      |
|-----------------------|------------------------------------------------------------|
| Sergienko et al.      | Classification of Applied Methods of Combinatorial Optimization |
| Awad and Chiban       | Recent Advances in Global Optimization for Combinatorial Discrete Problems |
| Hu et al.             | A Survey of Some Model-Based Methods for Global Optimization |
| Jones                 | A Taxonomy of Global Optimization Methods Based on Response Surfaces |
| Fernandes and Lourenço| Hybrids Combining Local Search Heuristics with Exact Algorithm |
| Raidl                 | A Unified View on Hybrid Metaheuristics                    |
| Bianchi et al.        | A survey on metaheuristics for stochastic combinatorial optimization |
| Beheshti et all.      | A Review of Population-based Meta-Heuristic/Algorithm      |
| Osman and Laporte     | Metaheuristics: A bibliography                             |
| Genova and Gulashki   | Linear Integer Programming Methods and Approaches – A Survey |
| Bisby                 | A Brief History of Linear and Mixed-Integer Programming Computation |
| Laguna                | Global Optimization and Meta-Heuristics (chapter)           |
| Urlì                  | Hybrid Meta-Heuristics for Combinatorial Optimization (thesis) |
| Blum and Roli         | Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison |
| Kallrath              | Mixed Integer Optimization in the Chemical Process Industry - Experience, Potential and Future Perspectives |
| Bertacco              | Exact and Heuristic Methods for Mixed Integer Linear Programs (thesis) |
| Newman and Weiss      | A Survey of Linear and Mixed-Integer Optimization Tutorials |
| Koch                  | Rapid Mathematical Programming (thesis)                     |
| Addis                 | Global optimization using local searches (thesis)           |
| Schichel              | Mathematical Modeling and Global Optimization (habilitation thesis) |
| Floudas               | Global optimization in the 21st Century: Advances and challenges |
| Fu et al.             | Model-Based Randomized Methods for Global Optimization      |
| Quttineh              | Models and Methods for Costly Global Optimization and Military Decision Support Systems (thesis) |
| Hoffman               | Combinatorial Optimization: Current successes and directions for the future |

2.2 Specific literature and surveys about optimization in logistics and SCM

In the next step of our literature review investigation, we had examined how many books were published about the optimization exclusively focused on logistics, supply chain management, or operational research. Surprisingly, we have managed to identify only seven such works, which are given in Table 3 (Voss and Woodruff, 2006; Geunes and Pardalos, 2005; Geunes et al., 2002; Minis, 2011; Puranen, 2011; Rardin, 1998;
These works are more or less dedicated to the majority of typical optimization problems, which can arise in afore-mentioned research fields. Here, the design of various optimization models, as well as the working principles of optimization techniques is also discussed. Besides these six books, the optimization in logistics and SCM is also partially covered in some of the general optimization books from Table 1. Moreover, an interested reader can also find some issues about this topic in several operations research books (Hillier and Lieberman, 1974; Winston and Goldberg, 2004; Taha, 2011), or specialized books about the logistics and SCM (Ghiani and Laporte, 2004).

Table 3. Identified books about optimization in logistics, supply chain management, or operational research

| Author            | Title                                                                 |
|-------------------|----------------------------------------------------------------------|
| Voß and Woodruff  | Introduction to Computational Optimization Models for Production Planning in a Supply Chain |
| Geunes and Pardalos | Supply Chain Optimization                                           |
| Minis et al.      | Supply Chain Optimization, Design, and Management: Advances and Intelligent Methods |
| Geunes et al.     | Supply Chain Management: Models, Applications, and Research Directions |
| Puranen           | Metaheuristics meet metamodels: a modeling language and a product line architecture for route optimization systems |
| Rardin            | Optimization in operations research                                   |
| MacMohan and Sodhi | Long View of Research and Practice in Operations Research and Management Science: The Past and the Future |

Besides the investigation of optimization books within the scope of logistics, supply chain management, or operational research, we have afterward also reviewed contributions focusing on surveys or reviews about optimization in the context of logistics and SCM. We were surprised again since the number of such kind of contributions was also quite low (only 23 identified works – see Table 4 (Abo-Hamad and Arisha, 2011; Aravendan and Panneerselvam, 2014; Archetti and Speranza, 2014; Bertacco, 2005; De Jaegere N and Kb, 2015; Diaz-Parra et al., 2014; Drexl and Schneider, 2014; Eksioglu, 2002; El-Sherbeny, 2010; Eskandarpour, 2014; Gaze, 2013; Grossmann et al., 2001; Kumar, 2012; Laporte et al., 2015; Ławrynowicz, 2011; Lourenço, 2001; Pino et al., 2011; Respen, 2015; Romero Morales, 2000; Ropke, 2005; Sadrnia et al., 2014; Soysal et al., 2012; Subramanian, 12012)). From Table 4 can be noticed that the majority of these contributions are papers, similarly as in the case of table 2, while we have detected five doctoral or master theses here. From Table 4 can also be seen that seven works are dedicated to the optimization in supply chains from a general point of view. Conversely, the majority of other contributions (even nine of them) are devoted to the routing problems of some kind. The remaining seven contributions cover other optimization problems that can typically arise in logistics and SCM. Regarding the optimization methods (heuristics, exact methods, hybrids), it can be seen from Table 4 that they are on average equally involved in research, perhaps slightly bigger attention is devoted to the modern methods and metaheuristics.
Table 4. Surveys or reviews about optimization in logistics, supply chain management, or operational research

| Author                     | Title                                                                 |
|----------------------------|----------------------------------------------------------------------|
| Drexl and Schneider        | A Survey of the Standard Location-Routing Problem                     |
| Grossmann et al.           | Discrete Optimization Methods and their Role in the Integration of Planning and Scheduling |
| Lawrynowicz                | A Survey of Evolutionary Algorithms for Production and Logistics Optimization |
| Morales                    | Optimization Problems in Supply Chain Management (thesis)            |
| Archetti and Speranza      | A survey on matheuristics for routing problems                        |
| Lourenço                   | Supply Chain Management: An opportunity for Metaheuristics            |
| Sadrnia et al.             | A Review of Nature-Based Algorithms Applications in Green Supply Chain Problems |
| Eksioglu                   | Network Algorithms for Supply Chain Optimization Problems (thesis)    |
| Aravendan and Panneerselvam | Literature Review on Network Design Problems in Closed Loop and Reverse Supply Chains |
| Soysal et al.              | A Review on Quantitative Models for Sustainable Food Logistics Management |
| Eskandarpour               | Generic models and optimization algorithms for sustainable supply chain network design (thesis) |
| Respen                     | From packing to dispatching: supply chain optimization techniques (thesis) |
| Arisha                     | Optimisation Methods in Supply Chain Applications: a Review           |
| Díaz-Parra et al.          | A Survey of Transportation Problems                                  |
| Laporte et al.             | Road-Based Goods Transportation: A Survey of Real-World Applications from 2000 to 2015 |
| Bertacco                   | Two-Echelon Freight Transport Optimisation: Unifying Concepts via a Systematic Review |
| Gaze                       | Exact Optimization Methods for the Mixed Capacitated General Routing Problem |
| Jaegere et al.             | The vehicle routing problem: state of the art, classification and review |
| Subramanian                | Heuristic, Exact and Hybrid Approaches for Vehicle Routing Problems (thesis) |
| Kumar and Panneerselvam    | A Survey on the Vehicle Routing Problem and Its Variants              |
| Ropke                      | Heuristic and exact algorithms for vehicle routing problems           |
| Villanueva et al.          | Heuristic Solutions to the VehicleRouting Problem with Capacity Constraints |
| El-Sherbeny                | Vehicle routing with time windows: An overview of exact, heuristic and metaheuristic methods |

### 3. OPTIMIZATION METHODS

In this section, we will briefly describe some of the important classes of optimization methods related to combinatorial optimization and global optimization. Depending on the complexity of the optimization problem, it may be solved by the means of an exact method or an approximate method (Talbi, 2009). Figure 1 shows the widely accepted classification of combinatorial optimization methods. Exact methods find optimal...
solutions and guarantee their optimality. For NP-complete optimization problems, exact algorithms belong to the class of non-polynomial time algorithms. On the other side, approximate (or heuristic) methods provide high-quality solutions in a reasonable time, but there is no guarantee of obtaining the global optimal solution (Talbi, 2009).

![Classification of combinatorial optimization methods](image)

**Fig. 1: Classification of combinatorial optimization methods adopted from (Talbi, 2009)**

### 3.1 Classification of Applied Methods for Combinatorial Optimization

The subjects considered in combinatorial optimization (CO) are usually (Sergienko et al., 2009): subsets, graphs, integers, arrangements, permutations, and other structures that can be generalized under the concepts of the combinatorial object. In general, CO covers tree types of methods (see Fig. 1): the exact algorithms, the approximate (approximation) algorithms, and the heuristics or metaheuristics. As aforementioned, the exact algorithms guarantee a computation of optimal solution in a finite time. They can also conclude that the optimal solution does not exist in the case of an unsolvable problem. According to (Sergienko et al., 2009), exact algorithms can be divided into two categories: general and special methods. Most popular general methods are: the branch-and-bound algorithm, exhaustive search, branch-and-cut method, dynamic programming, sequential analysis, and elimination of alternatives (Sergienko et al., 2009). A typical example of special methods is the Balazs Hungarian method applied to solve a linear assignment problem.

On the other hand, the approximate algorithms return an alternative solution in a finite time, while their accuracy can be estimated via a priori or posteriori estimates. The a priori estimate is a guaranteed estimate that should be specified before the solving of the optimization problem, while a posteriori estimate is computed during or after the problem-solving process.

Conversely, when the heuristic algorithms are taken into consideration, their accuracy estimate is absent or not known. The latter means that for a specific problem, the heuristics may return a “bad” solution (considering the objective function) or even no solution. However, on the other side, the heuristics are correct in the sense that they do not provide alternative solutions when these are not feasible (Sergienko et al., 2009).
Approximate and heuristic algorithms belong to the group of approximate ("inexact") methods. Such algorithms have shown to be effective for many real-world problems. On the other side, in many cases, the exact methods are not always applicable. Namely, they can usually be conducted only for small-dimensional optimization problems, while they cannot be applied for more complex problems such as dynamic or uncertainty-based problems (Sergienko et al., 2009).

As claimed by (Sergienko et al., 2009), all the approaches for solving complex combinatorial optimization problems can be defined as search procedures, which iteratively generate and estimate the alternative solutions. He adopted seven approximate CO algorithms. The first three classes (Sequential algorithms, Deterministic local search, Stochastic local search) have been used for a long time and are in detail explained in the literature. On the other hand, the evolutionary methods represent a wide class of algorithms that engage the basic principles of biological evolution for solving of optimization problems (Sergienko et al., 2009). Conversely to the other algorithms, swarm intelligence algorithms represent a class of decentralized algorithms. Here we are dealing with decentralized systems of simple agents that locally cooperate with certain medium and with each other (Sergienko et al., 2009). Despite the lack of a centralized control structure, local interactions between the agents result in a global behavior of the entire system.

The approximate CO methods can also be classified concerning the following characteristics (Sergienko et al., 2009): 1. The decision-making principles; 2. The complexity of the structure; 3. The type of used spaces; 4. The type of formed trajectory; 5. The influence on the search landscape; 6. The use of memory; 7. The presence of adaptation or training; and finally: 8. The presence of the special model.

3.2 Heuristics and Metaheuristics

The main characteristic of heuristic algorithms is that they can find a “good” solution to large-size problem instances (Talbi, 2009). These algorithms provide acceptable performance at acceptable costs for a wide range of different optimization problems. Generally, the heuristics can be classified into two major classes: specific heuristics and metaheuristics. The methods of the first class are specially tailored and designed to solve a specific problem. Conversely, the metaheuristics are general-purpose methods that can be conducted to solve almost any optimization problem (Talbi, 2009).

Polya firstly introduced the heuristic concept for solving the optimization problems in the year 1945. The simplex algorithm, designed by Dantzig in the year 1947, can be treated as a local search algorithm for linear programming optimization problems. Edmonds was the first who applied the greedy heuristic for combinatorial optimization in the year 1971 (Talbi, 2009). Further development of different heuristics can be seen in (Talbi, 2009), where the years of introducing of the individual algorithms are also represented. Moreover, Talbi (2009) precisely illustrates the genealogy of the various metaheuristic algorithms in his work.

Perhaps even more accurate, updated and in some details slightly different chronology of major metaheuristic algorithms is given by Beheshti and his colleagues (Beheshti, 2013). They indicated the list of 35 most important metaheuristic algorithms during the last four decades, their creators, and the dates of their appearance.
Metaheuristics can be classified in many ways. Talbi (2009) classified metaheuristics according to some of the typical criteria for the classification of metaheuristic algorithms: Nature inspired versus nonnature inspired, Memory usage versus memoryless methods, Deterministic versus stochastic, Population-based search versus single-solution based search, Iterative versus greedy.

An excellent representation of the classification of metaheuristic algorithms is also given by (Beheshti, 2013). The main criterion borders to divide algorithms are settled in the following directions: nature-inspired versus non-nature inspired, population-based versus single point search, single neighborhood versus various neighborhood structures, dynamic versus static objective function, and memory usage versus memory-less algorithms.

When constructing a metaheuristic, two conflicting criteria must be taken into consideration (Talbi, 2009):

- exploration of the search space (diversification),
- exploitation of the best solutions found (intensification).

Promising regions of the search space are those regions that are determined by the revealed “good” solutions. In the intensification process, the promising regions are discovered more exhaustively by using local search methods in the hope to find even better solutions. Conversely, in the diversification process, non-explored regions should be visited to be certain that all regions are equally explored and that the search is not limited to only an incomplete number of regions. While doing the diversification, the random search algorithms are applied in the sense of the exploration. As it turns out, in general, the single-solution metaheuristics (S-metaheuristics) are more exploitation oriented, while the population metaheuristics (P-metaheuristics) are more exploration oriented (Talbi, 2009).

It is presumed that the metaheuristic algorithms will become more and more popular in the future since the optimization problems will remain to increase in size and complexity. Talbi, (2009) summarizes the main characteristics of optimization problems that justify the use of metaheuristics. Naturally, it is clear that the metaheuristics should be used only in the cases when other methods or even powerful optimization solvers (e.g. Lindo, CPLEX, XPRESS-MP) fail to complete their tasks efficiently. Sometimes it is even impossible to unambiguously define an appropriate analytical mathematical formulation of the objective function. This happens in simulation-based optimization problems, when the objective function may be a completely black-box based function without any mathematical formulation. Namely, many engineering problems in logistics, production, finance, computational biology, telecommunications, etc., are based on simulation to assess the quality of solutions. Here, metaheuristics can be of great use since they have, unlike mathematical programming, a restrictive assumption in formulating the model (Talbi, 2009).

As it turns out, the evaluation of the objective function is the most time-intensive part in metaheuristics for many optimization problems. To avoid this, we can often approximate the objective function, which means that we can replace it with its approximation function. Such an approach is known as meta-modeling approach (Talbi, 2009). There are several meta-modeling techniques available to employ for expensive objective functions. Typical examples of such approximate models are the
neural network models and response surface models. Sometimes we can also apply the Gaussian processes, support vector machines, or Kriging models. Once the meta-model is designed, it can be used in combination with the original objective function. This way, we can switch between the original model and the approximated one with respect to different management strategies of meta-models.

3.3 Global optimization

In many nonlinear optimization problems, the objective function contains a big number of local minimums and maximums. Finding the global optimum (minimum or maximum) of a function is far more difficult than finding its local optimum. A classification of GO methods in deterministic and stochastic methods is the most common in the existing literature (see (Weise, 2009, Addis, 2004; Awad and Chiban, 2015; Floudas, 2000; Floudas et al., 2005; Fu et al., 2006; Grossmann, 1996; Hendrix and G.-Tóth, 2010; Hu et al., 2012; Jones, 2001; Laguna, 2002; Neumaier et al., 2005; Pinter, 2009; Quttineh, 2012; Schichl, 2003; Weise, 2009)). In these works, an interested reader can find more details about GO methods and their working mechanisms.

If we are using local search techniques, we can easily get stuck in the local minimum. To avoid this and to escape from the local minimum, many alternative methods have been developed. In general, if we restrict ourselves to S-metaheuristic family of algorithms for GO, we have four different approaches that can be adopted to avoid the local optimum (Talbi, 2009):

- Iterating from different initial solutions;
- Accepting non-improving neighbors;
- Changing the neighborhood; and
- Changing the objective function and/or the input data of the optimization problem.

“Accepting non-improving neighbor” methods also enable moves that are allowed to worsen the current solution temporarily. In “Changing the neighborhood” methods, the neighborhood structure can be changed, which also changes the landscape of the problem. The latter can also be changed by using the “Changing the objective function and/or the input data of the optimization problem” methods. Here, the problem can be converted by applying perturbations of the objective function, input data of the problem, or the constraints. By doing such perturbing, we hope that we can solve the original problem more efficiently (Talbi, 2009).

4. OPTIMIZATION IN LOGISTICS AND SUPPLY CHAIN MANAGEMENT

Optimization also plays an essential role in practically all fields of logistics, SCM, and transportation. Here, the reduction of all kinds of unnecessary costs and maximization of a profit of all the major SCM players are of particular importance. Moreover, the performance of SCM members should be synchronized in the largest possible manner to make information flows and material flows maximally fluent.

There exist many books and almost a countless number of papers that are addressing optimization problems in logistics, SCM, and transportation. However, regarding the books, there are only several of them containing a really good representation and consistent explanation of the mentioned problems (e.g. (Ghiani and Laporte, 2004; Wolsey, 1998; Sarker and Newton, 2008; Williams, 2013)). Moreover, authors define a
classification of optimization problems in logistics in several different ways, which can perhaps cause even some confusion, particularly for the beginners from the field. By our opinion, a far best classification is given by Ghiani and his colleagues in (Ghiani and Laporte, 2004). According to (Ghiani and Laporte, 2004), we can classify typical problems that arise in logistics and SCM as it is shown in Fig. 2 (Ghiani and Laporte, 2004).

If the problems in designing the logistics network are considered, facility location and allocation problems are here particularly important. Regarding inventory management problems, we could classify them into two major categories: deterministic problems and stochastic problems. Here, the optimal inventory policies must be built on the basis of deterministic or stochastic inventory models used to minimize the inventory cost function. As shown in Fig. 2, problems in designing and operating warehouses primary consist of the following problems: the warehouse design problems, order picker routing problems, and packing problems. Freight transportation is another essential category within the field of logistics planning and control. According to (Ghiani and Laporte, 2004), freight transportation can be divided into two major categories: long-haul freight transportation and short-haul freight transportation. In the case of long-haul freight transportation, goods are relocated over relatively long distances, for example between terminals or other important facilities (warehouses, plants, etc.). Moreover, commodities can be transported by rail, trucks, ships, or by any combination of different modes. Conversely, in the case of short-haul freight transportation, goods are usually moved by trucks on the routes between pick-up and delivery points located in the same area (e.g. between a terminal, or a warehouse, and a set of customers). Such jobs are usually executed during a shorter duration, while vehicle tours are carried out via a sequence of tasks (Ghiani and Laporte, 2004).

Careful investigation of the relevant literature shows that different kinds of transportation problems have received particularly big attention in studying and solving various problems in the logistics. Moreover, probably the far most research has been dedicated to the different types of the Vehicle routing problems (VRP), the Traveling salesperson problems (TSP), Arc routing problems (i.e. Chinese postman), and the School bus routing problems (SBRP) (see Fig. 2) (Dragan et al., 2016; Hertz, 2005; Kramberger et al., 2013; Kramberger and Žerovnik, 2008; Kramberger et al., 2012). Within the scope of the SBRP problems, some works were also dedicated to a research of how the reduced driving kilometers (i.e. the reduced total vehicles’ distance travelled) influence on the decrease of emission gasses (Dragan et al., 2016; Kramberger et al., 2013).

We have a whole plethora of approaches to solve problems introduced in Fig. 2. We can solve them by adopting a certain optimization method from the set of methods shown in Fig. 1 to 5. For instance, if we are taking into consideration the VRP problems, the historic-based evolution of methods for their solving can be represented as given in Fig. 3.

While introducing Table 4, we have already briefly discussed about the contributions focusing on the surveys or reviews about the optimization in the context of logistics and SCM. As we have had seen, seven works in Table 4 are dedicated to the optimization in the supply chains from a general point of view; nine are devoted to the routing problems
of some kind, while the remaining seven cover other optimization problems that can typically arise in logistics and SCM. An interested reader can get a more in-depth insight into these works in the corresponding references. At this place, we will only take a brief overview of the papers detected in an interesting study (Laporte et al., 2015). Here, a survey of real-world applications from 2000 to 2015 is conducted for road-based goods transportation. Table 5 shows the collected papers, their authors, journals in which these papers were published, and applied optimization algorithms (Laporte et al., 2015) (see also references therein). The estimated improvements after applied optimization (see a far-most right column of Table 5) are typical evidence how the optimization can play an essential role in logistics and transport.

Fig. 2: Classification of typical problems that can arise in logistics and SCM (adopted from (Ghiani and Laporte, 2004))

Fig. 3: Historic-based evolution of algorithms for Vehicle routing problem (adopted from Mikio, 1994)
Table 5: Collected papers in the survey of real-world applications from 2000 to 2015 conducted for road-based goods transportation (adopted from (Laporte et al., 2015) – see also the references therein)

| Author                  | Year | Journal | Algorithm                                      | Product/Company/Location                    | Estimated improvement                      |
|-------------------------|------|---------|------------------------------------------------|---------------------------------------------|--------------------------------------------|
| Avella et al.           | 2004 | EJOR    | Set partitioning and branch-and-price          | Fuel                                        | 22-25% reduction in total costs.          |
| Belenguer et al.        | 2005 | JFE     | Constructive heuristic with tabu search        | Meat/Vallencia, Spain                       | 8.96% distance deduction                  |
| Belfiore and Yoshizaki  | 2009 | EJOR    | Scatter search                                 | Supermarkets/Brazil                         | 7.5% cost reduction                       |
| Caramia and Guerriero   | 2010 | INTER   | Mathematical programming and local search multi-start | Milk/ASSO. La. C./Italy                   | 14.4% distance reduction                  |
| Cheong et al.           | 2002 | APJ     | Tree search, column generation over a set covering formulation | Soft drink/Singapore                       | Consistent reduction in the maximum number of vehicles required |
| Chiang and Russell      | 2004 | EJOR    | Set partitioning and tabu search               | Propane/One of the largest USA distributor/Illinois and Michigan | 9.4% reduction in total cost and 21.5% in number of vehicles. |
| Cohn et al.             | 2007 | TS      | Column generation and enumeration based heuristics | Courier/UPS/USA                             | Cost reduction of about 5%                |
| Cornillier et al.       | 2009 | COR     | Heuristic based on arc and route preselection  | Fuel/Easters Quebec, Canada                 | 22% reduction in distance.               |
| Cornilliet et al.       | 2008 | JORS    | Matching and column generation                 | Fuel/Easters Quebec, Canada                 | 17.2% reduction in distance and 1.16% increase in quantitie delivered. |
| Day et al.              | 2009 | OME     | Three-phase heuristic                          | Carmon dioxide/Indiana                      | 30% reduction in driver labor cost        |
| Faulín                  | 2003 | IJL     | Heuristics and linear programming              | Canning/Alimentos Congelados S.A./Navarra, Spain | Average of 4.6% distance reduction        |
| Faulín                  | 2003 | OME     | Heuristics and linear programming              | Canning/Alimentos Congelados S.A./Navarra, Spain | Average of 4.6% distance reduction        |
| Faulín et al.           | 2005 | INTER   | DSS based on savings and sweep algorithm       | Frozen goods/Frilac/Pamplopa, Spain         | 13.5% distance and 10.8% in cost reduction |
| Gaur and Fisher         | 2004 | OR      | Mathematical programming and matching          | Supermarket/Albert Heijn/ The Netherlands    | 4% cost reduction                         |
| Hollis et al.           | 2006 | EJOR    | Set covering with column generation            | Mail/Australia Post/ Australia              | Potential cost savings of 10%             |
| Ioannou                 | 2005 | JFE     | DSS with GIS, look ahead heuristic             | Sugar/Greece                                | About 25% in total transportation cost    |
| Ioannou et al.          | 2002 | JORS    | DSS with GIS, look ahead heuristic             | Packaged goods and beverages/Athens         | Lower number of routes and vehicles       |
| Kant et al.             | 2008 | INTER   | ORTEC software based on and local search       | Soft drinks/Coca-Cola/USA                   | Annual cost saving of $45 million         |
| Lahyani et al.          | 2015 | OME     | Branch-and-cut                                 | Olive oil/Tunisia                           | 11.7% distance reduction                  |
| Martínez and Amaya      | 2012 | JORS    | Insertion, tabu search and bin packing heuristics | Spanish paella                             | 25.5% in total trip time over a set of 19 instances |
Table 5: Collected papers in the survey of real-world applications from 2000 to 2015 conducted for road-based goods transportation (adopted from (Laporte et al., 2015) – see also the references therein) (continued)

| Author            | Year | Journal | Algorithm                                      | Product/Company/Location                          | Estimated improvement                     |
|-------------------|------|---------|-----------------------------------------------|--------------------------------------------------|--------------------------------------------|
| Ng et al.         | 2008 | JORS    | Heuristic and programming with multiple objectives integer | Information is not given                          | Better route design and increased volume delivered. |
| Nuortio et al.    | 2006 | ESA     | Guided variable neighborhood thresholding metaheuristic | Municipal waste/Jätekukko Ltd/Finland             | 12% distance reduction on average          |
| Prins             | 2002 | JMMA    | Construction, improvement and tabu search algorithm | Furniture/Nantes, France                         | Reduction in distribution times of 11.7%   |
| Privé et al.      | 2006 | JORS    | Constructive and improvement                  | Soft drink/Distribution J. Dubois/Quebec, Canada  | 23% in distance reduction                  |
| Repoussis et al.  | 2009 | EJOR    | DSS with hybrid metaheuristics                | Lube oil/Greece                                  | 25% to 30% reduction in per unit cost      |
| Ruiz et al.       | 2004 | EJOR    | B&B with Lingo                                 | Animal food/Nanta S.A./Spain                     | Reduction of up to 11% in cost and 12% in distance |
| Sahoo et al.      | 2005 | INTER   | Iterative two-phase algorithm                 | Waste/Waste Management Inc./USA                  | 984 fewer routes, saving $18 million      |
| Sungur et al.     | 2010 | TS      | Insertion based and tabu search                | Courier/UPS/USA                                  | Up to 20% over a weighted objective function |
| Tarantilis and Kiranoudis | 2001 | JFE    | Backtracking adaptive threshold accepting      | Milk/Athens                                      | 28% distance reduction                     |
| Tarantilis and Kiranoudis | 2002 | JFE    | List-based threshold accepting                 | Meat/Athens                                      | 17% distance reduction                     |
| Teixeira et al.   | 2004 | EJOR    | Three-phase heuristic                          | Glass, paper, plastic, metal/Portugal            | 29% reduction in distance                  |
| Tung and Pinnoi   | 2000 | EJOR    | Heuristic route construction and improvement   | Household and street solid waste/Urenco/Hanoi, Vietnam | 4.6% operating cost reduction            |

5. CONCLUSIONS

The paper addressed a comprehensive and systematic review of optimization methods with a particular focus on applications in logistics, supply chain management, and transportation. Nowadays, optimization plays an essential role in all areas of natural sciences, social sciences, and engineering. Moreover, optimization software has become much more accessible and reliable, while the hardware has essentially improved in the sense of a larger speed and lower prices. The high-level optimization languages have been considerably improved, which has significantly facilitated all efforts invested in modeling of the complex optimization problems.

The main purpose of this work was to provide an interested reader with the key information about a quite huge class of existing optimization methods that have been designed for solving of various types of optimization problems. When optimization methods are taken into consideration, they can generally be classified into exact and
approximate methods. Among the latter, various heuristic and metaheuristic methods are particularly gaining in popularity in the last two decades. Metaheuristics like genetic algorithms, ant colony, simulated annealing, iterative local search or tabu search are just some of the methods, which became essentially important in many research fields, particularly for the case of solving the combinatorial or global optimization problems.

While analyzing real-world applications from the field of logistics, SCM, and transportation, we can see that advanced and sophisticated optimization methods should be used practically in all serious applications. The main reason is a high complexity of the optimization problems, which usually contain a massive number of decision variables and/or constraints, while the objective functions are often quite complicated.

To the best of our knowledge, there have not been published a lot of scientific papers, which would include such a comprehensive review of optimization methods as it was done in our paper. So we hope that this work will contribute to the fastest possible absorption of this exciting topic, particularly for those who are beginners or less experienced researchers.

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