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The generalization of the Vehicle Routing Problem: Mathematical model, ontology, algorithms, fitness landscape analysis and applications

Booklet

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Miskolc, 2023

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1. Introduction

One of the most important tasks of logistics is the cost-effective delivery of the right products to the right place at the right time. The Vehicle Routing Problem (VRP) is a transportation problem, one of the most common tasks in logistics. The objective of the basic Vehicle Routing Problem (VRP) is to serve the demands of customers in a given position. Vehicles deliver products from one or more depots to customers and then return to the depot. Over the years, several variants (components) of the task have developed, thus adapting to the needs of the industry. Examples of such components are Time Window, Multi-Echelon (when products are first transported from the depot to distribution points - called satellites - and then from there to the customers), Open Route, Multiple Product, Multiple Vehicle, Vehicle Routing with Electric Vehicles, and so on. The Vehicle Routing Problem can be in-plant, out-of-plant transport depending on the components used, but it can even model an entire supply chain. As transport tasks are becoming more and more complex nowadays (simultaneous delivery of several products, several types of vehicles, several types of distribution points, etc.), computer support is necessary for the design and operation tasks.

The aim of the dissertation is to develop a general model and prototype transportation system. Based on the literature, current proposals of this area are focusing only on a subsystem. There is no problem covering a wide area in the literature. The main goal of my research work is an integrated general system. The proposed general system should contain all the major components currently known in practice. Having this general model, almost all types of transportation tasks that appear in logistics systems can be analyzed and solved as a subtype of the general model.

The first part of the dissertation is a literature review, which presents the components of the Vehicle Routing Problem (VRP) and the algorithms with which the Vehicle Routing Problem (VRP) can be solved.

In the next chapter the mathematical model of the Vehicle Routing Problem is presented. The model includes among others the following components: number of levels, number of vehicles, number of product types, periodicity, attributes between nodes (such as distance between nodes, safety factor, etc.), vehicle attributes (such as vehicle capacity limit, charging time, the rental fee for rented vehicles, etc.), time components (packing, unpacking time, time window, etc.), product attributes (such as the capacity limit of the node, fixed order of arrival of products, etc.), costs (such as packing and unpacking costs, quality control cost, etc.) and finally operational parameters (such as inter-depot route, delivery, collection, open route, etc.). Regarding the parameter values the model allows to use static, stochastic, fuzzy, and forecasted data types.

After the mathematical model, I present an ontology knowledge base that helps to design the Vehicle Routing Problem (which types of products can be transported with which vehicles, which types of products can be transported together, what types of products may be needed by each customer, what components should be used in the system design).

Next, I outline the representation related to the applied optimization algorithms and evaluation. The representation used is based on permutations of customers, but I also had to consider other factors in the design, such as different types of products, vehicles, and the levels (Multi-Echelon).

Detailed analyzes of optimization algorithms are also presented in the dissertation in the context of fitness landscape analysis. Algorithms can be divided into two parts: construction and improvement algorithms. Construction algorithms create one possible solution. They take the best steps locally, but global optimum is most often not achieved with their exclusive use. Their running time is usually low. In my dissertation I used 6 different construction algorithms. Improvement algorithms iteratively improve one or more possible solutions. Their running time is usually high. The global optimum can be achieved with their application. In the dissertation, I used 11 different improvement algorithms. Since the model contains several objective functions, I tested 6 different multi-objective optimization techniques. I also implemented the “pre-filtering” of customers, so not all incoming needs must be fulfilled, only those that are economically profitable. This can be done using a classification known in data mining. I have used 5 different classification data mining algorithms.

I have applied the fitness landscape analysis method to extended analysis of the search space. For the generation of the optimum points I used either the optimum of the optimization algorithms or the random selection method. Using the fitness landscape I performed the investigation of the operators and the efficiency of the optimization algorithms. For the analysis I have used 6 different walk techniques. I performed other analyzes for random walk also from the view point of information theory.
In the last chapter I show, that the general system is suitable for solving both in-plant and out-of-plant transport processes. I presented 16 prototype systems to illustrate the versatility of the proposed system. Based on the theoretical and practical test I stated that the proposed model covers wide range of transportation models.

1.1. Research goals

The focus of my research is the generalization of the Vehicle Routing Problem. My goal is to perform a literature review and create a general Vehicle Routing Problem model based on this. Based on the general model, specific transportation tasks can be solved. The advantage of the general model is that it only needs to be created once. It is not necessary to write a new model or a new program for every transportation tasks, it is enough to parameterize the general model. My research covers the followings:

- Performing a literature review on the Vehicle Routing Problem, systematization of the different tasks (components, constraints, objective functions).
- Creation of a general Vehicle Routing Problem model, mathematical description of the model based on the literature and logistics tasks.
- Creation of the ontology of the generalized Vehicle Routing Problem model. The ontology must contain the elements of the mathematical model and the additional elements of the main components (nodes, vehicles, customers). The system should help the user in which of the components and metrics of my generalized VRP model to use during the delivery of a specific product to a specific node with a specific vehicle. I also saw it necessary for the system to help to decide which products can be delivered to the nodes with which vehicles.
- Creation of the representation model of the general VRP model. With the help of the representation, the real problem can be mapped for the optimization algorithm.
- Analysis of the search space of the VRP. The analysis of the search space can be linked to the study of optimization algorithms. The aim of my research is to analyze the effectiveness of optimization algorithms known in the literature. Most of the improvement heuristics use neighborhood operators, so my research goal is also to analyze the efficiency of the operators. The Vehicle Routing Problems may contain several objective function components, so it is also necessary to analyse the multi-objective optimization techniques. My research goal is the application of a wide range of search space analysis techniques in the VRP.
- Developing software that solves the general VRP. Based on the representation, the software can solve the Vehicle Routing Problems with different heuristics, answer the user's questions in connection with the VRP based on the implemented ontology, and analyze the search space.
- The success of a general model lies in how wide a range of problems it covers. I analyze which transportation tasks can be solved with the created general model.

2. Survey of the literature background of the Vehicle Routing Problem (VRP)

The aim of this chapter is to present the informal definition, components and the related literature background of the Vehicle Routing Problem (VRP).
In case of the VRP [1], all (potentially) places to be visited are called as nodes. The node can be a depot, customer, charger station, satellite. Any transport unit that transports products between nodes is called a vehicle.
During the basic Vehicle Routing Problem [1], the customers can be visited by vehicles. Customers have a fix demand for products. All demands must be served; each node can only be visited once. The vehicles start from depot, visit the customers assigned to them and then return to the depot. Vehicles cannot exceed their capacity limit. If the vehicles visited the customers, then they must return to the depot. The objective function is the minimization of the distance travelled by vehicles.

2.1. Literature survey

The Vehicle Routing Problem is a current and important area of logistics. The first Vehicle Routing Problem articles appeared in 1959 by Dantzig & Ramser [1]. After that, in the 60s and 70s, many articles appeared for example [2-3] publications.
The transportation problem may have many parameters. I have selected the followings to perform the categorization of the research topic: the number of nodes, their type (depot, customer, charger station, satellite and their levels). In the case of transportation, it is also necessary to decide on the number of vehicles and products. The types of vehicles to be used may involve the use of several components, such as the use of charger stations, the rental fee (if the vehicles are rented). Types of products can also determine components, the relationship between products and suitable vehicles for transportation, but also that the objective should not be to minimize the distance travelled but to make the vehicle cross the safest route possible. Business logic can also define components such as the time window (only individual nodes can be visited in a certain time interval) or the handling of uncertain (stochastic, fuzzy) or past data (forecasting). I would like to highlight the following Vehicle Routing Problem types:

- Vehicle Routing Problem with Time Window [4],
- Vehicle Routing Problem with Multiple Time Windows [5],
- Vehicle Routing Problem with Soft Time Window [6],
- Vehicle Routing Problem with Single Depot [7],
- Vehicle Routing Problem with Multiple Depot [7],
- Open Vehicle Routing Problem [8],
- Multi-Depot Vehicle Routing Problem with Inter-Depot Routes[9],
- Two-Echelon Vehicle Routing Problem [10],
- Homogeneous Fleet Vehicle Routing Problem [11],
- Heterogeneous Fleet Vehicle Routing Problem [11],
- Capacitated Vehicle Routing Problem [12],
- Vehicle Routing Problem with Pickup and Delivery [13],
- Vehicle Routing Problem with Multiple Product [14],
- Electric Vehicle Routing Problem [16],
- Periodic Vehicle Routing Problem [17],
- Vehicle Routing Problem with Stochastic Demand [20],
- Vehicle Routing Problem with Perishable Food Products Delivery [36],
- Travelling Salesman Problem [46].

3. The mathematical model of the generalization of the Vehicle Routing Problem

It can be seen in Chapter 2., that the Vehicle Routing Problem attracted many researchers over the years. In most of the publications, the mathematical model of the Vehicle Routing Problem was also presented in the articles. These mathematical models were focusing to the investigated transportation problems. The purpose of this chapter is to present generalized mathematical model of a generalized Vehicle Routing Problem.

3.1. Base parameters

Position graph:
The topology of the Vehicle Routing Problem can be described by a graph, where the nodes denote positions (customers, depots, etc.) and edges denote transport relationships between positions.
The graph contains the position components and the relationships between them. I assumed, that the positions can be decomposed into several levels. The levels separate the transportation tasks.

Vehicles:
Different types of vehicles can be used in the system.

Products, services:
In the model, several different products are delivered.

Time:
In the model, the operation is modelled in time. Time is measured at different units. A period is the repetition time. Assume that the plane of the schedule is one-level.

Value:
Different attribute values (properties) can be assigned to the building blocks of the model. Based on the value set, the following attribute types can be distinguished:

- static,
- stochastic,
- fuzzy,
- forecasted.

3.2. Attributes

I have defined the following Vehicle Routing attributes:

- Node attributes: travel time between the nodes, travel distance between the nodes, safety between the nodes, route quality between the nodes and the type of the node.
- Vehicle attributes: the capacity constraint of each vehicle types per product type, fuel consumption, charger time, own vehicle or rented vehicle, rental fee per vehicle types and the maximum distance with a full tank / full charge.
- Time attributes: service time, packing time, unpacking time, loading time, unloading time, product downtime, administration time, quality control time, time window.
- Product attributes: the capacity constraint of the node, product demand of the node, prices- of product, processing order, processing constraint, storage level at the locations.
- Cost attributes: packaging costs, unpacking cost, loading costs, unloading costs, administrative costs, quality control cost.
- Operational parameter attributes: inter-depot route, delivery, pickup, soft time window, open route.

3.3. Decision variable

The decision variable can have a value of 0 or 1. It has 7 indexes which are the followings: i_1: level of the starting point, i_2: level of the ending point, j_1: index of the starting point in level i_1, j_2: index of the ending point in level i_2, k: index of vehicle, t: index of the time, and m: index of the product.

$$\lambda_{j_1,j_2}^{i_1,i_2,k,t,m} = \begin{cases} 1, \textit{if vehicle } k \textit{ in period } t \textit{ after node } j_1 \textit{ in level } i_1 \textit{ travels to} \\ \textit{node } j_2 \textit{ in level } i_2 \textit{ inmediately} \\ \textit{and transport product } m, \\ 0, \textit{else}. \end{cases}$$

3.4. Constraints

Constraints are an important feature of optimization. In order to get a valid solution, various constraints need to be defined.

- <u>Constraint 1</u>: A node at level i only needs to be served maximum once a period by a vehicle with product m.
- <u>Constraint 2:</u> This constraint is optional and should only be considered if a time window has been defined. If a time window is defined, two cases are possible, the hard time window and the soft time window. In the case of a hard time window, the time window must be taken into consideration, while the soft time window is an optimization parameter.
- <u>Constraint 3:</u> Vehicles start from an aggregated level position and then terminate at an aggregated-level position after visiting the lower-level positions. This constraint is optional; it is only not met if there is a single level.
- <u>Constraint 4:</u> This constraint is not optional and should always be considered when transporting products. Vehicles must comply with their capacity limit.
- <u>Constraint 5:</u> This constraint is not optional and always be considered when transporting products. Positions must take into account their capacity limit.
- <u>Constraint 6:</u> For each level the number of transport edges must not exceed the number of vehicles available at each level. This constraint is not optional.
- <u>Constraint 7:</u> This constraint is the subpath elimination constraint, and it is not optional.
- <u>Constraint 8:</u> The constraint is not optional. It relates to route continuity. It says, that the number of incoming must be equal with the number of outcoming edges in each position j.
- <u>Constraint 9:</u> The constraint is not optional. Vehicles require charging after a certain distance, so the vehicles need to visit the charger station.
- <u>Constraint 10:</u> The constraint is optional, only to be considered when defining a fixed order of products. The products arriving in each position can have a fixed order, they must arrive one after the other.
- <u>Constraint 11:</u> The constraint is optional and will only be considered if there are products that cannot be shipped together.

3.5. Metrics, objective function components

Each objective function component can be formed from the metrics. In my case, the goal is to minimize for most metrics. The system contains the following metrics: length of the route, transported value, packaging cost, unpacking cost, loading cost, unloading cost, administrative costs, quality control cost, fuel consumption, vehicle rental fee, safety between nodes, route quality, route time, packaging time, unpacking time, loading time, product downtime, administrative time, quality control time, fuel filling time, waiting time of the nodes, exceeding the time window and the unvisited customers.

4. The ontology model of the generalized Vehicle Routing Problem

Ontology is a standard tool for knowledge representation. The term comes from philosophy, where it means a systematic description of existence. An ontology describes a domain, its concepts, and the relationships between concepts. Its purpose is not only the presentation of information for humans but the machine processing of the content of the information. The most common general ontology language is OWL, developed by the World Web Consortium (W3C). OWL helps automatic machine interpretation of web content to a greater extent than XML, RDF, and RDF Schema (RDF-S). OWL also offers extended vocabulary and formal semantics [48,49].

4.1. The ontology system of the vehicle routing problem

Some of the ontology systems presented in the literature are limited to specific logistics tasks, for example, monitoring service[57], city logistics[58], emergency logistics[61], manufacturing execution system[62], refrigerated goods[63]. Some ontology models can also be found, that try to cover the whole logistics process. I developed a more general system, which is different from these systems. The system should help the user choose which of the components and metrics of my generalized Vehicle Routing Problem model to use when transporting a given product, to a given node, with a given vehicle. I also saw the need for the system to help decide which products can be shipped with which vehicles to nodes.

4.1.1. The main components of the ontology system

The advantage of ontologies is that ontology systems can work together, so my system can be supplemented with a logistics model developed by others. The developed sample system includes the graph descriptive, vehicles, products, period, set of values (static, stochastic, fuzzy, forecasted values) and attributes (nodes, vehicles, period, products, costs, operational parameter) detailed in the mathematical model. Also, metrics are included in the model. In the sample system, ontological concepts allow for a rule-based validation. The main components of the ontology model are followings:

- Node class: products are transported between nodes.
- Product class: the products are transported from one node to another node with vehicles.
- Vehicle class: suitable for transporting products.
- Component class: includes components that can be used during Vehicle Routing Problems. The components can be broken down to according to their main type, but this remains transparent to the user. The following logical resolutions are in the system:
    - CostComponents,
    - FunctionalParameterComponents,
    - NodeComponents,
    - ProductComponents,
    - TimeComponents,
    - VehicleComponents.
- Metrics class: includes metrics that can be used during transportation tasks.

4.1.2. The architecture of the ontology system

The ontology model was also integrated into the optimization module, as the model allows rule-based validation for outdoor material handling tasks. Thus, I made the application of the model known to all programmers, because instead of ontology-specific queries (DL Query, SPARQL Query), the user only needs to specify a JSON descriptor, which is known to all programmers, and is an easy-to-read format for people to read.

The ontology system is created so, that it can be handled by two types of users. One of the users (expert user) who has adequate IT and logistics knowledge. This kind of user performs the following: purpose, scope and requirement identification, then concepts collection, ontology creation and analysis. This user accesses the ontology through the ontology editor, where he can implement it. The other user is the end-user who has adequate logistical knowledge. The user asks questions to the system using a Java program and a JSON descriptor. The query engine layer of the Java program generates SPARQL queries, thereby extracting information from the ontology, and the Java program responds to the user. The ontology layer consists of the RDF / OWL file itself and the reasoner.

The ontology system does not have to specify all the members of the JSON descriptor, it is possible to omit the individual components (Node, Product, Vehicle).
The ontology sample system supports transport tasks. If the user knows what types of nodes to visit during the transport task, the system helps to tell which products can be transported to or from the node and what constraint and objective function components can be used during the transport task. If the user knows which products the delivery is limited to, the system helps to decide what type of vehicles can be used. If the type of vehicles is known during the delivery task, the system tells us in response what products can be delivered with the vehicle, what constraint components and objective function components can be included in the optimization. If the system input parameter is the node and the vehicle type, the response is the type of possible products to be transported to and from the node, the vehicles, the possible vehicle routing components, and the possible objective function components. If the system receives nodes and products as input, it returns other products, vehicle types, vehicle routing components, and objective function components that can be transported to and from the nodes. If a list of vehicles and products are provided, the system returns the products that can be shipped to the node, the products that can be shipped from the node, the list of possible other vehicles, the components, and metrics. If a node, a vehicle, and a product are also specified, the system responses with products, vehicles, components, and objective function metrics.

The presented ontology model was integrated into my Java optimization system. My system thus includes an optimization module and an ontology module. The relationship between the ontology and the optimization module is the followings: the user first uses the ontology module, asking questions to the ontology. The questions are written in JSON format and then answered in a txt format from the system. After that, the optimization module can be used, where the result of the ontology system can be taken into account to create the Vehicle Routing parameters. It then sets the parameters for each optimization algorithm (here too, it specifies a JSON file). Then the system gives the result of the optimization in JSON format.

5. Representation model and operators of integrated Vehicle Routing Problem

In this chapter, I present the representation model and evaluation strategy used by the implemented optimization algorithms for solving the general model of the Vehicle Routing Problem. Using the representation, the real problem can be mapped for the optimization algorithm.
Based on the literature, I developed my own representation method for my general VRP model and I will also detail, what kind of operators can be applied to them.

5.1. Representation model elements

The system contains the following representation model elements:

- Vector describing the order of nodes: A permutation is used to describe the order of nodes in the transportation. In the list the nodes are denoted by position index. The length of the permutation is equal to the number of nodes.
- The matrix describing the assignment of vehicles-nodes-products: Unlike the previous permutation vector, it is an assignment. This means that the individual numbers here indicate the individual vehicles in the line, only here the numbers appear more than once. The length of the assignment is equal to the product of the number of nodes and the number of types of products in the system.
- Vector describing the assignment of vehicle - charger stations: Here it is necessary to determine to which charger station vehicle will belong, so a charger station-vehicle assignment must be introduced. Its length is equal to the number of vehicles.
- Vector describing the vehicle - portal node assignment: The length of the assignment vector is equal to the number of vehicles at the current level since a start node and end node is assigned to the vehicles.
- Vector describing level: It contains vectors describing the order of the nodes, matrices describing the assignment of the vehicle-nodes-products, vectors describing the assignment of the vehicle-charger stations, and vectors describing the assignment of the vehicle - portal node.
- Vector describing period: It contains matrices describing the levels.
- Solution description vector: It contains the vectors describing the period.

5.2. Optimization operators

During optimization, operators create one or more new solutions from one or more existing solutions. The operators used greatly influence the efficiency of the optimization algorithms. I have used the following operators:

- Vector describing the order of nodes: Here, I use a permutation representation mode, the sequence numbers of the nodes are included in the representation mode. Here I used a neighbourhood operator and crossover operators. I have used the 2-opt [70], Partially Matched Crossover (PMX) [71], Order Crossover (OX) [71], Cycle Crossover (CX) [71],
- The matrix describing the assignment of vehicles-nodes-products: A "regeneration" is used here, so the neighbour will be a randomly generated new matrix.
- Vector describing the assignment of vehicle - charger stations: A "regeneration" is used here, so the neighbour will be a randomly generated new vector.
- Vector describing the vehicle - portal node assignment: A "regeneration" is used here, so the neighbour will be a randomly generated new assignment.

6. Fitness landscape analysis

In this chapter, I present the relationship between the representation form and optimization efficiency in search space. Relatively few researchers have addressed this topic in fitness landscape analysis over the years. This is probably because researchers typically focus solely on investigating the surface effectiveness, but they do not analyze the internal optimization processes. Another important reason of topic selection is that in most cases the (local) optimum value is searched by an ad hoc method, do not analyze the quality of the located optimum. In the journal publications, the comparisons are made only practical test. Unfortunately, most researchers do not investigate nor demonstrate why the developed method (algorithm tuning, good choice of parameters, implementation tricks, etc.) is better than the existing methods. This technique is also called "competitive testing". In contrast, behavioural models demonstrate what makes a particular local search metaheuristic more effective than the others. Extensive behavioural models allow us to improve the efficiency of existing local search algorithms. [77]

6.1. Fitness landscape overview

The subject of the fitness landscape analysis is the examination of configuration optimization algorithms, in the search space containing all the allowed configurations.
Optimization metaheuristics are often based on some kind of search or navigation iterations. The body of the iteration cycle is based on the following elements [73,108]:

- Algorithm independent elements:
  - The set of possible states.
  - The distance-based neighbourhood.
  - Fitness, objective function.
  - Encoding and representation.
- Algorithm specific elements:
  - Transition rule (pivoting rule = selection strategy) that selects the next state point from potential neighbouring state points.
  - Termination condition.
  - An initial state point is either a randomly generated solution (state point) or a solution given by some construction heuristic (state point).

Fitness landscape analysis can be used to compare the efficiency of the different search space representation modes. It helps to make the following conclusions [109]:

- Comparison of differences between two search spaces: a problem with two or more different representation methods: different representation, different mutation operator, different objective function, etc.
- Algorithm selection: analysis of the navigation differences of the search space.
- Tuning the parameters: determination of the most appropriate parameters for the selected algorithm (for example the neighbourhood operators, size of populations, number of restarts).
- Controlling parameters during runs: what is the optimal neighbourhood operator based on structure estimation.

6.1.1. Methods of analysis

Analytical methods for investigation of the search space can be divided into two categories, exhaustive search and stochastic, sampling-based techniques [73].

Exhaustive search

This analysis gives the most complete picture of the search space, but they can only be applied to smaller problems (no longer for larger problems) and it is difficult to apply in practice. The main advantage of an exhaustive search is completeness. Search time (runtime) is high, but search space analysis is complete. [73]

Stochastic, sampling-based techniques

Stochastic methods are the most commonly used in analyzes. Their advantage over exhaustive search is their speed. On the other hand the disadvantage is that they are biased, we do not get complete results with their use. [73]
So far, two types of sample generation techniques have been used [73]:

- The trajectory-based sampling, which is the path of optimization methods and produces continuous solution candidates.
- The discovery based sampling strategies which generates scattered samples that can be supplemented with recombination operators or local neighbourhood operators.

Trajectory-based sampling

Sampled trajectories create a path in the search space or, in other words, a sequence of adjacent state points (solution candidates). The method is also called a walk.
The walk starts from a random solution candidate and uses the neighbourhood search to "walk" to neighbouring solution candidates. Depending on the type of neighbourhood search, several different types of walks are possible [74]:

- During the random walk, a state point is randomly selected from a set of neighbours.
- During the adaptive walk, the better state point (neighbour) is selected. Here several strategies can be used to choose which better neighbour state point to choose, for example, any solution (any ascent), steepest ascent, minimum ascent.
- During the reverse adaptive walk, the worse neighbour is selected. This is the reverse of the adaptive walk.
- During the uphill-downhill walk, first, an adaptive walk is performed, and then if a better fitness point (solution) is not found during the step, a reverse adaptive walk is performed until a better state point is found.
- In the neutral walk, a neighbour is selected, whose fitness value is equal to the fitness value of the current state (and try to increase the distance from the starting solution).

6.2. Test results

My goal is to investigate different multi-objective optimization techniques, heuristic optimization algorithms, and neighbourhood operators from the view point of fitness landscape characteristics. In generally, the quality and representation of the search space depends on the nature of the optimization task. The task presented in this chapter is a Multi-Echelon VRP with the following properties: 4 levels, 5 nodes in the depot-level, 10 nodes in the first level satellite, 10 nodes in the second level satellite and 15 nodes in the customer level. In total, therefore, the number of nodes is 40. The system contains 1 type of product and I assume, that there is only one period. Each level contains 2-2 vehicles, for a total of 8 vehicles. Among the node properties, the following factors are taken into account: travel time between the nodes, travel distance between the nodes and route quality between the nodes. Among the attributes of the vehicles, I considered the following components: capacity constraint, fuel consumption and rental fee. Among the temporality attributes, the sample system includes the following: loading time, unloading time, administration time. Among the attributes of the products, I used the product demand of the node factor. Among the cost attributes, the following were included in the system: loading costs, unloading costs, administrative costs and quality control cost. The delivery parameter is used in addition to the operational parameters. The following metrics were used: length of the route, fuel consumption, vehicle rental fee, route quality, route time and unvisited customers.

In *Table 1.*, I summarize which are the effective multi-objective optimization techniques and which are the effective heuristics in my measurement. Also, very weak multi-objective optimization techniques and weak heuristics are included in the table. The results show that the simulated annealing and tabu search algorithms provided the best results.

Analysis of multi-objective optimization technique	
Effective multi-objective optimization technique	WGCM, WPM, WESM
Effective heuristics	SA_FI, SA_G, SA_NI, SA_NN, TS_AI, TS_FI, TS_G, TS_NN, FCHC_NN, AS_C, RBVAS_C
Weak multi-objective optimization technique	WSM, PR
Weak heuristics	FA, FA_C, HS, HS_C

Table 1.: Analysis of multi-objective optimization technique

Table 2. shows which heuristics are effective and which are weak heuristics. Efficient iterative heuristic algorithms are effective when the solutions are variable, so space is mapped well. Fitness values vary, with averages of distances between solutions. The results show that the simulated annealing and tabu search and ant algorithms provided the best results.

Iterative heuristic analysis	
Effective iterative heuristic algorithm	ACS, AS, ESAS, FCHC, GA, MMAS, RBVAS, SA, TS
Weak iterative heuristic algorithm	FA, HS

Table 2.: Iterative heuristic analysis

Table 3. shows the analysis of operators with walk techniques. In analyzing each walk operator, I concluded that the 2-opt and partially matched crossover (PMX) operators are much more efficient than the cycle crossover (CX) and order crossover (OX) operators.

Operator analysis (with walks)		
	Effective operator	**Weak operator**
Random walk	2-opt, OX, PMX	
Adaptive walk	2-opt	CX, OX
Reverse adaptive walk	2-opt	CX
Uphill-downhill walk		
Neutral walk	PMX	CX, OX
Reverse neutral walk	PMX, 2-opt	

Table 3.: Operator analysis (with walks)

7. The applications of the generalized model of the Vehicle Routing Problem

In this chapter, case studies are presented to demonstrate the practical applicability of the generalized model for optimization design of the Vehicle Routing Problem. I have investigated the following transportation problems:

- <u>Transport of bakery products:</u> by transporting bakery products, I mean that bread and pastries (non-durable baked products) are delivered from bakeries to shops. The characteristic of this delivery task is that in the case of the tiered system (depot-satellite-customer), only one depot and several customers are distinguished. There is no need for satellites because the bakeries are located near the shops.
- <u>Transport of short-term food:</u> it is very similar to the delivery of baked products, it is characterized by the same attributes, the only difference is that here it is not frequent the pick-up, only delivery, and the period time can be given a higher value e.g. the products are delivered weekly. Fruits and vegetables can be a pick-up if they have remained in the supermarkets.
- <u>Transport of refrigerated products (e.g. dairy products, meat):</u> they are very similar to short-term foods, but here only a special vehicle must transport the products. Furthermore, here the period time is small (e.g. daily transport) because they are perishable products.
- <u>Transport of durable food:</u> this task is also very similar to the delivery of bakery products, the difference here is that there is no collection (pick-up), only delivery, and the period time can be given an even higher value (e.g. monthly or annual transport). Here, however, there is no longer just one depot, but several depots, and the satellites can be also distinguished (even on several levels), for example in the case of products coming from abroad. For the operational parameter, the open route is also possible, this can be mainly for rail transport, and the inter-depot route can therefore also be the inter-depot route.
- <u>Transport of beverages (soft drinks, alcohol):</u> this task is also similar to bakery products and durable foods. There are only a few differences. Here, too, as in the case of bakery products, care must be taken with the combination of pickup and delivery, as well as multi-level transport of products with different types of vehicles.
- <u>Tank transport:</u> during tank transport, products are transported in containers on the liquid. Such liquid products may be water, gasoline, milk, oil, etc. This requires special vehicles. In this type of transport, usually, only one type of products can be transported at a time.
- <u>Transport of durable products:</u> the transport of durable products is the same as the transport of the beverages, the only difference being that most of the time there is only a delivery, the collection (pick-up) is not frequent.
- <u>Treatment of waste:</u> garbage collection is different from previous transportation tasks. This task may mean removing garbage from households or garbage from individual factories and office buildings to the garbage dump.
- <u>Transport of mail items (domestic, foreign):</u> the handling of mail is also a completely different case. This task means that the mail is delivered from the sender to the recipient by the post office.
- <u>Transport of parcels (domestic, foreign):</u> the case of parcels is very similar to the case of the letters. The difference here is that route quality between the locations is a very important case due to the potential for fragile, bulky, valuable packets.
- <u>Money transportation:</u> the transportation of money is a special case of vehicle routing, it may be different from the previous cases. Cash transit means that cash is collected from post offices, shops, banks or just deliver it there. The money must be transported by a special money carrier, with security guards, equipment.

- Transport of advertising papers: in most cases, advertising papers are not delivered by the post office. Here a few levels can be distinguished, depending on what kind of advertising paper it is (e.g. large mall, local store). Advertising papers are delivered periodically, e.g. weekly, monthly. They are usually transported with one type of vehicle.
- Transport of a newspaper: there are two major cases in the delivery of newspapers. One is when you subscribe to the newspaper, it is then delivered to your home. The other case is when the newspaper is delivered to newspaper vendors (or shops).
- Travel agency tour planning: the development of travel agency tour planning can be considered as a completely special vehicle routing. There are no levels (depot-satellite-customer), all nodes are equal, so it is a one-tier case. The travel time between the locations is a key important factor. Safety between the locations is also important, allowing passengers to travel in a safer area. Route quality between the locations can also be important, the better the quality of the road. The node has no type, all nodes are equal.
- In-plant material handling: between warehouse and production: in-plant material handling processes are very different from outdoor material handling processes. Here, the tiered system corresponds to the depot and the individual production sites to the customers. There is no satellite, only material handling between depot and customers takes place.
- In-plant material handling: in the warehouse: in-plant material handling (rearrangement) in the warehouse is similar to material handling between a warehouse and production units but also differs in many ways. There are no privileged nodes here, so there is no level case (neither depot nor satellite), all positions are considered equal because transport can take place from any position to any position
- In-plant material handling: transportation to other locations: this case differs from the transportation of material between the warehouse and the production units in that pickup does not appear here, as the aim here is to transport the products from different places in the warehouse to a specific point from which they will be transported to third party locations.
- Patient transport: patient transport is different from the cases discussed so far, here it is not the transportation of products, but the transport of patients.
- Maintenance: maintenance is also very different from the cases presented so far. Here, each location needs to be visited, it takes a different amount of time for some maintenance activity to be done by the maintenance team.

7.1. Test results

In this section, I present the test results of the program, that implements my general Vehicle Routing Problem model through two case studies. I have tested my model with 2 special cases. I have chosen 2 cases of *postal items* and *in-plant material handling between warehouse and production*. I have chosen these two tasks because both tasks are a common transportation problem and the parameters of the two tasks are very different.

7.1.1. Mail items

Table 4. summarizes the basic parameters of my data set for mail items.

Parameter	Value	Parameter	Value
Number of levels	4	Location of fourth level nodes	[600,700]
Number of nodes belonging to the first level	5	Number of charging stations	2
Location of first level nodes	[0,100]	Location of charging stations	[1000,1100]
Number of second-level nodes	10	Number of periods	1
Location of second level nodes	[200,300]	Number of product types	1
Number of third level nodes	10	Number of vehicles (per level)	2
Location of third level nodes	[400,500]	Number of rented vehicles	0
Number of nodes belonging to the fourth level	15		

Table 4.: Basic parameters data set for mail items

According to *Table 5.*, the nodes are located at four different levels. I have chosen so many levels because each mail (mostly foreign mail) goes through multiple distribution points while being sent from the sender to the recipient. Letters can be delivered by different vehicles, they will definitely be delivered by a car close to the recipient, so a charging station is also needed. The problem does not differentiate between letter types, so the system contains practically only one type of goods.

Parameter	Value	Parameter	Value
Administration cost	static, [10,50]	Quality control cost	static, [10,50]
Loading cost	static, [10,50]	Unloading cost	static, [10,50]

Table 5.: Cost-related parameters of my data set for mail items

Table 6. lists the cost parameters that can occur during a mail delivery. These are administration, loading, unloading and quality control.

Parameter	Value	Parameter	Value
Route quality between nodes	static, [100,500]	Travel time between nodes	static, [10,100]
Travel distance between nodes	static, coordinate based		

Table 6.: Node-related parameters of mail items

The parameters of the nodes are shown in *Table 6*. Distance and time are very important factors in almost every transport task. The condition of the route is mainly important for car transport (not by plane and rail).

Parameter	Value	Parameter	Value
Product demand of the node	static, [10,100]	Loading time	static, [30, 50]
Admininstration time	static, [30, 50]	Unloading time	static, [30, 50]

Table 7.: Product-related parameters of mail items

Of the attributes that can be associated with products (*Table 7.*), the most important is the product demand of the node, i.e., how many letters need to be delivered to a node. Furthermore, the administrative, loading and unloading time at the hub is also very important.

Parameter	Value	Parameter	Value
Capacity constraint of the vehicle	static, [10000, 50000]	Fuel consumption of the vehicle	static, [10, 100]

Table 8.: Vehicle-Related parameters of the data set of mail items

Among the parameters that can be linked to vehicles (*Table 8.*), the vehicle capacity limit is important. The capacity limit is relatively large here because the leaves themselves are small. Fuel consumption is also very important, it can be considered as the main parameter of almost all transport tasks.

Among the metrics (objective function components), my system includes: length of the route range, fuel consumption range, route quality range, route time range, unvisited customers range. These are the parameters that occur during most other transport tasks.

7.1.2. In-plant material handling between warehouse and production

In-plant material handling between warehouse and production is also a common transport task, occurring during all production.

Parameter	Value	Parameter	Value
Number of levels	2	Location of charging stations	[1000,1100]
Number of first level nodes	1	Number of periods	1
Location of first level nodes	[0,100]	Number of product types	1
Number of second-level nodes	25	Number of vehicles (per level)	2
Location of second level nodes	[0,100]	Number of rented vehicles	0
Number of charging stations	2		

Table 9.: Basic parameters of my in-plant material handling data set between warehouse and production

The basic parameters of the task are illustrated in *Table 9*. There are only two levels of the system, the warehouse on the first level and the production units on the second level. Vehicles transporting within the plant may require charging, these may be electric vehicles, so my system also includes a charging station.

Parameter	Value	Parameter	Value
Administration cost	static, [10,50]	Quality control cost	static, [10,50]
Loading cost	static, [10,50]	Unloading cost	static, [10,50]
Packaging cost	static, [10,50]	Unpackaging cost	static, [10,50]

Table 10.: Cost parameters of my in-plant material handling data set between warehouse and production

The cost parameters are illustrated in *Table 10*. There may be administration, loading and unloading costs, and quality control costs during transportation.

Parameter	Value	Parameter	Value
Travel distance between nodes	static, coordinate based	Travel time between nodes	static, [100,500]

Table 11.: Node parameters of the in-plant material handling data set between warehouse and production

Of the node parameters (*Table 11.*), I considered only two (these are important for all transport tasks): distance between nodes and route time.

Parameter	Value	Parameter	Value
Product demand of the node	static, [10,100]	Quality control time	static, [30,50]
Admininstration time	static, [30,50]	Service time	static, [30,50]
Loading time	static, [30,50]	Unloading time	static, [30,50]
Packing time	static, [30,50]	Unpacking time	static, [30,50]

Table 12.: Node parameters of the in-plant material handling data set between warehouse and production

The parameters related to the products are shown in *Table 12*. Here, too, I considered the classic transportation-related parameters. Demand for products, administration, loading and unloading time, quality control. The time of service actually means the time of production.

Parameter	Value	Parameter	Value
Capacity constraint of the vehicle	static, [10000,50000]	Maximum distance with full tank / full charge	static, [50000,100000]
Fuel consumption of the vehicle	static, [10,100]	Charger time of the vehicle	static, [10,30]

Table 13.: Vehicle parameters of the in-plant material handling data set between warehouse and production

In relation to vehicles (*Table 13.*), the parameters that can be used in classical transport tasks were also included. Vehicle capacity limit, fuel consumption (delivered with smaller vehicles within the plant), distance to be filled with tank (fuel level), and charging time.

Of the metrics, I considered only the length of the route.

8. Summary

The focus of my dissertation is on a logistics task, the Vehicle Routing Problem (VRP). In the case of the basic VRP, the objective is to fulfil the demands of customers in a transportation network. Vehicles deliver products from one or more depots to customers and then return to the depot. Based on the literature many variants of the task were investigated over the years and many solution variants were developed for the special cases. In the first part of my dissertation, I conducted a literature search, where I presented the Vehicle Routing Problem components published so far. In the next section I analyzed and presented a general requirements against a general model. I presented the mathematical model of the problem including the variables, constraints, objective functions. After the mathematical model, I presented an ontological knowledge to design the control of the optimization of the VRP task. Ontology can be used among others to describe which types of products can be transported with which vehicles, which types of products can be transported together, what types of products may be needed by each customer, what components should be used in designing the system. Next, I outlined the formalism related to the applied optimization algorithms and evaluation. In the thesis I have analyzed the efficiency of different optimization algorithms. Heuristic algorithms can be divided into two parts: construction and improvement algorithms. Construction algorithms create one possible solution. They take the best steps locally, but most often the global optimum cannot be reached with their exclusive use. Their running time is usually low. The following construction algorithms are used in the dissertation: Arbitrary Insertion, Cheapest Insertion, Farthest Insertion, Greedy, Nearest Insertion, Nearest Neighbor. Improvement algorithms iteratively improve one or more possible solutions. Their running time is usually high. The global optimum can be achieved with their application. In the dissertation, I used the following improvement algorithms: Ant Colony System, Ant System, Elitist Strategy of Ant System, Firefly Algorithm, First Choice Hill Climbing, Genetic Algorithm, Harmony Search, MAX-MIN Ant System, Particle Swarm Optimization, Rank Based Version of Ant System, Simulated Annealing, Tabu Search. In this step I analyzed the efficiencies of each multi-objective optimization technique and the heuristic algorithms several of my objective functions are possible, I used the following multi-objective optimization in the dissertation: Bounded Objective Function Method, Pareto Ranking, Weighted Exponential Sum Method, Weighted Global Criterion Method, Weighted Product Method, Weighted Sum Method. I also performed the analysis of each neighbourhood operator (2-opt, order crossover, cycle crossover, partially matched crossover). The analysis showed that improving construction algorithms proved to be better than improving randomly generated solutions. In the analysis of operators, the 2-opt and partially matched crossover operators proved to be more efficient than cycle crossover and order crossover. I have also demonstrated, that the proposed general model is able to manage a wide range of transportation task. I obtained result solutions that meet the right quality, result for practice.
I summarized the scientific results in 5 theses.

Thesis 1:
I have developed a novel general Vehicle Routing Problem model that is suitable (both in terms of objective function and constraints) for solving different types of transportation problems. In the model, there are 4 basic components between which different attributes can be defined. The basic components are graph descriptors, vehicles, products, services, and time. I defined the relations between the basic components with functions. In this novel model the relations can be assigned to 6 large groups, including nodes, vehicles, time, products, costs, and operational parameters. The novelty of this complex VRP model is the one complex decision variable, which includes a wide range of decision variables of conventional VRP models. The solutions of the defined complex VRP problems are limited by different constraints. The model includes 11 constraints and 23 metrics.
Related publications: [P/1], [P/5], [P/6], [P/8], [P/16], [P/17], [P/22], [P/23], [P/24], [P/25].

Thesis 2.:

I have proposed a novel ontology system approach for the generalized Vehicle Routing Problem using the OWL modelling language. The generated ontology system was used for rule-based validation. The system contains the basic components of the general model of the Vehicle Routing Problem, the possible relations between them and the metrics. I extended the basic components of the system with additional subclasses (subcategories of product types, vehicle types and node types). I have created an ontology system, which supports flexibly and effectively the decision in the following topics:

1. ***Selection of Vehicle Routing components that can be used during transport to/from nodes.***
2. ***Selection of products, which can be transported to the nodes.***
3. ***Selection of Vehicle Routing metrics, which can be used during transport to/from nodes.***
4. ***Selection of products, which can be transported from nodes.***
5. ***Selection of vehicles, which can transport each product.***
6. ***Selection of products, which can be delivered together.***
7. ***Selection of Vehicle Routing components, which can be used when using each vehicle.***
8. ***Selection of Vehicle Routing metrics, which can be used when using each vehicle.***
9. ***Selection of products, which can be delivered by the given vehicles.***

Related publications: [P/2], [P/24].

Thesis 3.:

I created a novel representation of the general model of the Vehicle Routing Problem. The representation model includes the following main components:

1. ***Vector describing the order of nodes (depot, satellite, customer).***
2. ***The matrix describing the assignment of vehicles-nodes-products.***
3. ***Vector describing the assignment of vehicle - charger stations.***
4. ***Vector describing the vehicle - portal node assignment.***
5. ***Vector describing the level.***
6. ***Vector describing the period.***

I introduced and analyzed the search operators of heuristic algorithms.
Operators applied to the vector describing the order of the nodes (based on the literature) are the followings:

1. ***2-opt,***
2. ***Partially Matched Crossover – PMX,***
3. ***Order Crossover – OX,***
4. ***Cycle crossover – CX.***

Operator applied to the matrix describing the assignment of vehicles-nodes-products, vector describing the assignment of vehicle - charger stations and the vehicle - portal node assignment vector:

1. ***Regeneration operator.***

I also created an evaluation of the representation of the general model of the Vehicle Routing Problem.
Related publications:[P/1], [P/5], [P/6], [P/8], [P/10], [P/15], [P/16], [P/17], [P/21], [P/22], [P/23].

Thesis 4.:

I analytically analyzed the search space belonging to the optimization task of the generalized model of the Vehicle Routing Problem and I made a detailed analysis. In the search space study, I first analyzed the efficiency of multi-objective optimization techniques and heuristic algorithms. After I analyzed the efficiency of the operators (2-opt, cycle crossover, order crossover, and partially matched crossover). During the analysis of the operators I used different walk techniques like the random walk, adaptive walk, reverse adaptive walk, uphill-downhill walk, neutral walk and the reverse neutral walk. I also analyzed the search space based on information theory, which is also used to analyze the efficiency of operators. For the analysis of the operators, I also prepared the fitness cloud analysis.

Based on the examined sample, it can be concluded that the following multi-objective optimization techniques are effective: Weighted Global Criterium Method (WGCM), Weighted Product Method (WPM), Weighted Exponential Sum Method (WESM). Based on the performed analyzes, it can be concluded that the following heuristics are effective for Vehicle Routing Problems: Simulated Annealing (SA), Tabu Search (TS), First Choice Hill Climbing (FCHC), Genetic Algorithm (GA), Rank Based Version of Ant System (RBVAS). During the measurements, I also observed that the improvement of the solutions provided by the construction algorithms proved to be more effective than the improvement of the purely randomly generated solutions. In the measurements, I also found that the 2-opt and partially matched crossover operators are more efficient than the order crossover and cycle crossover operators.

Related publications: [P/3], [P/4], [P/7], [P/9], [P/11], [P/12], [P/13], [P/18].

Thesis 5:

I have demonstrated, that the proposed general model is able to manage a wide range of transportation task. I obtained result solutions that meet the right quality, result for practice.

Related publications: [P/1], [P/2], [P/15].

Literature

[1] Dantzig, G. B., & Ramser, J. H. (1959). The Truck Dispatching Problem. Management Science, 6(1), 80–91
[2] Stricker, R. (1970). Public sector vehicle routing: the Chinese Postman Problem (Doctoral dissertation, Massachusetts Institute of Technology).
[3] Christofides, N. (1976). The vehicle routing problem. Revue française d'automatique, informatique, recherche opérationnelle. Recherche opérationnelle, 10(V1), 55-70.
4] Cordeau, J. F., Laporte, G., & Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. Journal of the Operational research society, 52(8), 928-936.
[5] Belhaiza, S., Hansen, P., & Laporte, G. (2014). A hybrid variable neighborhood tabu search heuristic for the vehicle routing problem with multiple time windows. Computers & Operations Research, 52, 269-281.
[6] Taillard, É., Badeau, P., Gendreau, M., Guertin, F., & Potvin, J. Y. (1997). A tabu search heuristic for the vehicle routing problem with soft time windows. Transportation science, 31(2), 170-186.
[7] Salhi, S., & Nagy, G. (1999). A cluster insertion heuristic for single and multiple depot vehicle routing problems with backhauling. Journal of the operational Research Society, 50(10), 1034-1042.
[8] Brandão, J. (2004). A tabu search algorithm for the open vehicle routing problem. European Journal of Operational Research, 157(3), 552-564.
[9] Crevier, B., Cordeau, J. F., & Laporte, G. (2007). The multi-depot vehicle routing problem with inter-depot routes. European journal of operational research, 176(2), 756-773.
[10] Hemmelmayr, V. C., Cordeau, J. F., & Crainic, T. G. (2012). An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics. Computers & operations research, 39(12), 3215-3228.
[11] Gendreau, M., Laporte, G., Musaraganyi, C., & Taillard, É. D. (1999). A tabu search heuristic for the heterogeneous fleet vehicle routing problem. Computers & Operations Research, 26(12), 1153-1173.
[12] Ralphs, T. K., Kopman, L., Pulleyblank, W. R., & Trotter, L. E. (2003). On the capacitated vehicle routing problem. Mathematical programming, 94(2-3), 343-359.
[13] Ai, T. J., & Kachitvichyanukul, V. (2009). A particle swarm optimization for the vehicle routing problem with simultaneous pickup and delivery. Computers & Operations Research, 36(5), 1693-1702.
[14] Kabcome, P., & Mouktonglang, T. (2015). Vehicle routing problem for multiple product types, compartments, and trips with soft time windows. International Journal of Mathematics and Mathematical Sciences, 2015.
[15] Soysal, M., Bloemhof-Ruwaard, J. M., & Bektaş, T. (2015). The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations. International Journal of Production Economics, 164, 366-378.
[16] Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. Transportation Science, 48(4), 500-520.
[17] Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., & Rei, W. (2012). A hybrid genetic algorithm for multidepot and periodic vehicle routing problems. Operations Research, 60(3), 611-624.
[18] Stavropoulou, F., Repoussis, P. P., & Tarantilis, C. D. (2019). The Vehicle Routing Problem with Profits and consistency constraints. European Journal of Operational Research, 274(1), 340-356
[19] Huang, Y. H., Blazquez, C. A., Huang, S. H., Paredes-Belmar, G., & Latorre-Nuñez, G. (2019). Solving the Feeder Vehicle Routing Problem using ant colony optimization. Computers & Industrial Engineering, 127, 520-535
[20] Bertazzi, L., & Secomandi, N. (2018). Faster rollout search for the vehicle routing problem with stochastic demands and restocking. European Journal of Operational Research, 270(2), 487-497
[21] Fernández, E., Roca-Riu, M., & Speranza, M. G. (2018). The shared customer collaboration vehicle routing problem. European Journal of Operational Research, 265(3), 1078-1093
[22] Nucamendi-Guillén, S., Angel-Bello, F., Martínez-Salazar, I., & Cordero-Franco, A. E. (2018). The cumulative capacitated vehicle routing problem: New formulations and iterated greedy algorithms. Expert Systems with Applications, 113, 315-327
[23] Archetti, C., Fernández, E., & Huerta-Muñoz, D. L. (2017). The flexible periodic vehicle routing problem. Computers & Operations Research, 85, 58-70
[24] Reihaneh, M., & Ghoniem, A. (2019). A branch-and-price algorithm for a vehicle routing with demand allocation problem. European Journal of Operational Research, 272(2), 523-538
[25] Baniamerian, A., Bashiri, M., & Tavakkoli-Moghaddam, R. (2019). Modified variable neighborhood search and genetic algorithm for profitable heterogeneous vehicle routing problem with cross-docking. Applied Soft Computing, 75, 441-460

[26] Atefi, R., Salari, M., Coelho, L. C., & Renaud, J. (2018). The open vehicle routing problem with decoupling points. European Journal of Operational Research, 265(1), 316-327
[27] Archetti, C., Savelsbergh, M., & Speranza, M. G. (2016). The vehicle routing problem with occasional drivers. European Journal of Operational Research, 254(2), 472-480
[28] Sabar, N. R., Bhaskar, A., Chung, E., Turky, A., & Song, A. (2019). A self-adaptive evolutionary algorithm for dynamic vehicle routing problems with traffic congestion. Swarm and evolutionary computation, 44, 1018-1027
[29] Ran LIU, Yangyi TAO, Xiaolei XIE (2019): An adaptive large neighborhood search heuristic for the vehicle routing problem with time windows and synchronized visits Computers & Operations Research Vol 101, 250-262
[30] Poonthalir, G., & Nadarajan, R. (2018). A fuel efficient green vehicle routing problem with varying speed constraint (F-GVRP). Expert Systems with Applications, 100, 131-144.
[31] Bodin, L., Mingozzi, A., Baldacci, R., & Ball, M. (2000). The rollon–rolloff vehicle routing problem. Transportation Science, 34(3), 271-288.
[32] Salavati-Khoshghalb, M., Gendreau, M., Jabali, O., & Rei, W. (2019). An exact algorithm to solve the vehicle routing problem with stochastic demands under an optimal restocking policy. European Journal of Operational Research, 273(1), 175-189
[33] Toffolo, T. A., Christiaens, J., Van Malderen, S., Wauters, T., & Berghe, G. V. (2018). Stochastic local search with learning automaton for the swap-body vehicle routing problem. Computers & Operations Research, 89, 68-81
[34] Hu, Z. H., Sheu, J. B., Zhao, L., & Lu, C. C. (2015). A dynamic closed-loop vehicle routing problem with uncertainty and incompatible goods. Transportation Research Part C: Emerging Technologies, 55, 273-297
[35] Pop, P. C., Kara, I., & Marc, A. H. (2012). New mathematical models of the generalized vehicle routing problem and extensions. Applied Mathematical Modelling, 36(1), 97-107
[36] Song, B. D., & Ko, Y. D. (2016). A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery. Journal of Food Engineering, 169, 61-71
[37] Talarico, L., Sörensen, K., & Springael, J. (2015). Metaheuristics for the risk-constrained cash-in-transit vehicle routing problem. European Journal of Operational Research, 244(2), 457-470
[38] Bae, H., & Moon, I. (2016). Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles. Applied Mathematical Modelling, 40(13-14), 6536-6549
[39] Defryn, C., & Sörensen, K. (2017). A fast two-level variable neighborhood search for the clustered vehicle routing problem. Computers & Operations Research, 83, 78-94
[40] Drexl, M. (2013). Applications of the vehicle routing problem with trailers and transshipments. European Journal of Operational Research, 227(2), 275-283
[41] Bektaş, T., Gouveia, L., Martínez-Sykora, A., & Salazar-González, J. J. (2019). Balanced vehicle routing: Polyhedral analysis and branch-and-cut algorithm. European Journal of Operational Research, 273(2), 452-463
[42] Ke, L., & Feng, Z. (2013). A two-phase metaheuristic for the cumulative capacitated vehicle routing problem. Computers & Operations Research, 40(2), 633-638
[43] Talarico, L., Springael, J., Sörensen, K., & Talarico, F. (2017). A large neighbourhood metaheuristic for the risk-constrained cash-in-transit vehicle routing problem. Computers & Operations Research, 78, 547-556
[44] Cheng, R., Gen, M., & Tozawa, T. (1995). Vehicle routing problem with fuzzy due-time using genetic algorithms. Journal of Japan Society for Fuzzy Theory and Systems, 7(5), 1050-1061
[45] Bent, R. W., & Van Hentenryck, P. (2004). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. Operations Research, 52(6), 977-987
[46] Lin, S. (1965). Computer solutions of the traveling salesman problem. Bell System Technical Journal, 44(10), 2245-2269.
[47] Caceres-Cruz, J., Arias, P., Guimarans, D., Riera, D., & Juan, A. A. (2014). Rich vehicle routing problem: Survey. ACM Computing Surveys (CSUR), 47(2), 1-28.
[48] Matthew Horridge, Holger Knublauch, Alan Rector, Robert Stevens, Chris Wroe, Simon Jupp, Georgina Moulton, Nick Drummond, Sebastian Brandt (2011): A Practical Guide To Building OWL Ontologies Using Protege 4 and CO-ODE Tools, Edition 1.3, The University Of Manchester.
[49] OWL: http://www.w3c.hu/forditasok/OWL/REC-owl-features-20040210.html (Last accessed: 2022.12.30.)
[50] IRI, URI, URL, URN and their differences https://fusion.cs.uni-jena.de/fusion/blog/2016/11/18/iri-uri-url-urn-and-their-differences/ (Last accessed: 2022.12.30.)
[51] OWL: http://www.w3c.hu/forditasok/OWL/REC-webont-req-20040210.html (Last accessed: 2022.12.30.)
[52] Smith, S. F., & Becker, M. A. (1997, March). An ontology for constructing scheduling systems. In Working Notes of 1997 AAAI Symposium on Ontological Engineering (pp. 120-127). AAAI Press.
[53] Himoff, J., Rzevski, G., & Skobelev, P. (2006, May). Magenta technology multi-agent logistics i-Scheduler for road transportation. In Proceedings of the fifth international joint conference on Autonomous agents and

multiagent systems (pp. 1514-1521).
[54] Lian, P., Park, D. W., & Kwon, H. C. (2007, December). Design of logistics ontology for semantic representing of situation in logistics. In Second Workshop on Digital Media and its Application in Museum & Heritages (DMAMH 2007) (pp. 432-437). IEEE.
[55] Dong, H., Hussain, F. K., & Chang, E. (2008, October). Transport service ontology and its application in the field of semantic search. In 2008 IEEE International Conference on Service Operations and Logistics, and Informatics (Vol. 1, pp. 820-824). IEEE.
[56] Hoxha, J., Scheuermann, A., & Bloehdorn, S. (2010, September). An approach to formal and semantic representation of logistics services. In Proceedings of the Workshop on Artificial Intelligence and Logistics (AILog), 19th European Conference on Artificial Intelligence (ECAI 2010), Lisbon, Portugal (pp. 73-78).
[57] Xu, D., Wijesooriya, C., Wang, Y. G., & Beydoun, G. (2011). Outbound logistics exception monitoring: A multi-perspective ontologies' approach with intelligent agents. Expert Systems with Applications, 38(11), 13604-13611.
[58] Anand, N., Yang, M., van Duin, J. R., & Tavasszy, L. (2012). GenCLOn: An ontology for city logistics. Expert Systems with Applications, 39(15), 11944-11960.
[59] De Oliveira, K. M., Bacha, F., Mnasser, H., & Abed, M. (2013). Transportation ontology definition and application for the content personalization of user interfaces. Expert Systems with Applications, 40(8), 3145-3159.
[60] Daniele, L., & Pires, L. F. (2013). An ontological approach to logistics. Enterprise interoperability, research and applications in the service-oriented ecosystem, IWEI, 13, 199-213.
[61] Zhang, L., Jiang, D., Zeng, Y., Ning, Y., & Wang, Q. (2014). Exploring Ontology-driven Modeling Approach for Multi-agent Cooperation in Emergency Logistics. JCP, 9(2), 285-294.
[62] Fumagalli, L., Pala, S., Garetti, M., & Negri, E. (2014, September). Ontology-based modeling of manufacturing and logistics systems for a new MES architecture. In IFIP International Conference on Advances in Production Management Systems (pp. 192-200). Springer, Berlin, Heidelberg.
[63] Wang, Y., Yi, J., Zhu, X., Luo, J., & Ji, B. (2015). Developing an ontology-based cold chain logistics monitoring and decision system. Journal of Sensors, 2015.
[64] Glöckner, M., & Ludwig, A. (2017). LoSe ODP-an ontology design pattern for logistics services. Advances in Ontology Design and Patterns, 32, 131.
[65] Li, S. T., Hsieh, H. C., & Sun, I. W. (2003, May). An Ontology-based Knowledge Management System for the Metal Industry. In WWW (Alternate Paper Tracks)
[66] Kachitvichyanukul, V., Sombuntham, P., & Kunnapapdeelert, S. (2015). Two solution representations for solving multi-depot vehicle routing problem with multiple pickup and delivery requests via PSO. Computers & Industrial Engineering, 89, 125-136.
[67] Wang, S., Lu, Z., Wei, L., Ji, G., & Yang, J. (2016). Fitness-scaling adaptive genetic algorithm with local search for solving the Multiple Depot Vehicle Routing Problem. Simulation, 92(7), 601-616.
[68] Wang, S., Wang, X., Liu, X., & Yu, J. (2018). A bi-objective vehicle-routing problem with soft time windows and multiple depots to minimize the total energy consumption and customer dissatisfaction. Sustainability, 10(11), 4257.
[69] Zhou, L., Baldacci, R., Vigo, D., & Wang, X. (2018). A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution. European Journal of Operational Research, 265(2), 765-778.
[70] Englert, M., Röglin, H., & Vöcking, B. (2007, January). Worst case and probabilistic analysis of the 2-Opt algorithm for the TSP. In SODA (pp. 1295-1304).
[71] Hussain, A., Muhammad, Y. S., Nauman Sajid, M., Hussain, I., Mohamd Shoukry, A., & Gani, S. (2017). Genetic algorithm for traveling salesman problem with modified cycle crossover operator. Computational intelligence and neuroscience, 2017.
[72] Wright, S. (1932). The roles of mutation, inbreeding, crossbreeding, and selection in evolution (Vol. 1, pp. 356-366).
[73] Erik Pitzer (2013): Applied Fitness Landscape Analysis, PhD dissertation, JOHANNES KEPLER UNIVERSITÄT LINZ, Technisch-Naturwissenschaftliche Fakultät
[74] Pitzer, E., & Affenzeller, M. (2012). A comprehensive survey on fitness landscape analysis. In Recent advances in intelligent engineering systems (pp. 161-191). Springer, Berlin, Heidelberg
[75] Mattfeld, D. C., Bierwirth, C., & Kopfer, H. (1999). A search space analysis of the job shop scheduling problem. Annals of Operations Research, 86, 441-453.
[76] Ventresca, M., Ombuki-Berman, B., & Runka, A. (2013, April). Predicting genetic algorithm performance on the vehicle routing problem using information theoretic landscape measures. In European Conference on Evolutionary Computation in Combinatorial Optimization (pp. 214-225). Springer, Berlin, Heidelberg.

[77] Watson, J. P. (2010). An introduction to fitness landscape analysis and cost models for local search. In Handbook of metaheuristics (pp. 599-623). Springer, Boston, MA.
[78] Humeau, J., Liefooghe, A., Talbi, E. G., & Verel, S. (2013). ParadisEO-MO: From fitness landscape analysis to efficient local search algorithms. Journal of Heuristics, 19(6), 881-915.
[79] Merz, P., & Freisleben, B. (1999). Fitness landscapes and memetic algorithm design. New ideas in optimization, 245-260.
[80] Hordijk, W. (1996). A measure of landscapes. Evolutionary computation, 4(4), 335-360.
[81] Verel, S., Collard, P., & Clergue, M. (2007). Measuring the evolvability landscape to study neutrality. arXiv preprint arXiv:0709.4011.
[82] Ochoa, G., Tomassini, M., Vérel, S., & Darabos, C. (2008, July). A study of NK landscapes' basins and local optima networks. In Proceedings of the 10th annual conference on Genetic and evolutionary computation (pp. 555-562).
[83] Marmion, M. E., Dhaenens, C., Jourdan, L., Liefooghe, A., & Verel, S. (2011, January). On the neutrality of flowshop scheduling fitness landscapes. In International Conference on Learning and Intelligent Optimization (pp. 238-252).
[84] Ochoa, G., Qu, R., & Burke, E. K. (2009, July). Analyzing the landscape of a graph based hyper-heuristic for timetabling problems. In Proceedings of the 11th Annual conference on Genetic and evolutionary computation (pp. 341-348).
[85] Vassilev, V. K., Fogarty, T. C., & Miller, J. F. (2000). Information characteristics and the structure of landscapes. Evolutionary computation, 8(1), 31-60
[86] Tavares, J., Pereira, F. B., & Costa, E. (2008). Multidimensional knapsack problem: A fitness landscape analysis. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 38(3), 604-616.
[87] Pitzer, E., & Affenzeller, M. (2012). A comprehensive survey on fitness landscape analysis. In Recent advances in intelligent engineering systems (pp. 161-191).
[88] Stadler, P. F. (2002). Fitness landscapes. In Biological evolution and statistical physics (pp. 183-204). Springer, Berlin, Heidelberg
[89] Uludağ, G., & Uyar, A. Ş. (2009, September). Fitness landscape analysis of differential evolution algorithms. In 2009 Fifth International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control (pp. 1-4).
[90] Merz, P., & Freisleben, B. (2001). Memetic algorithms for the traveling salesman problem. Complex Systems, 13(4), 297-346
[91] Merz, P. (2004). Advanced fitness landscape analysis and the performance of memetic algorithms. Evolutionary Computation, 12(3), 303-325
[92] Chicano, F., Daolio, F., Ochoa, G., Vérel, S., Tomassini, M., & Alba, E. (2012, September). Local optima networks, landscape autocorrelation and heuristic search performance. In International Conference on Parallel Problem Solving from Nature (pp. 337-347).
[93] Pitzer, E., & Affenzeller, M. (2012). A comprehensive survey on fitness landscape analysis. In Recent advances in intelligent engineering systems (pp. 161-191).
[94] Tayarani-N, M. H., & Prügel-Bennett, A. (2016). An analysis of the fitness landscape of travelling salesman problem. Evolutionary computation, 24(2), 347-384.
[95] Mathias, K., & Whitley, D. (1992). Genetic operators, the fitness landscape and the traveling salesman problem. In PPSN (pp. 221-230).
[96] Fonlupt, C., Robilliard, D., & Preux, P. (1997, April). Fitness landscape and the behavior of heuristics. In Evolution Artificielle(Vol. 97, p. 56).
[97] Wang, S., Zhu, Q., & Kang, L. (2006, May). Landscape properties and hybrid evolutionary algorithm for optimum multiuser detection problem. In International Conference on Computational Science (pp. 340-347).
[98] Lu, G., Li, J., & Yao, X. (2011, April). Fitness-probability cloud and a measure of problem hardness for evolutionary algorithms. In European Conference on Evolutionary Computation in Combinatorial Optimization (pp. 108-117).
[99] Wang, S., Zhu, Q., & Kang, L. (2006, May). Landscape properties and hybrid evolutionary algorithm for optimum multiuser detection problem. In International Conference on Computational Science (pp. 340-347).
[100] Tayarani-N, M. H., & Prügel-Bennett, A. (2016). An analysis of the fitness landscape of travelling salesman problem. Evolutionary computation, 24(2), 347-384.
[101] Belaidouni, M., & Hao, J. K. (2000, September). An analysis of the configuration space of the maximal constraint satisfaction problem. In International Conference on Parallel Problem Solving from Nature (pp. 49-58).
[102] Collard, P., Verel, S., & Clergue, M. (2007). Local search heuristics: Fitness cloud versus fitness landscape.

[103] Müller, C. L., & Sbalzarini, I. F. (2011, April). Global characterization of the CEC 2005 fitness landscapes using fitness-distance analysis. In European Conference on the Applications of Evolutionary Computation (pp. 294-303).
[104] Preux, P., Robilliard, D., & Fonlupt, C. (1997). Fitness Landscapes of Combinatorial Problems And The Performance Of Search Algorithms
[105] Czech, Z. J. (2008, April). Statistical measures of a fitness landscape for the vehicle routing problem. In 2008 IEEE International Symposium on Parallel and Distributed Processing(pp. 1-8).
[106] Jones, T., & Forrest, S. (1995). Fitness distance correlation as a measure of problem difficulty for genetic algorithms. In Proc. 6th Internat. Conf. on Genetic Algorithms.
[107] Merz, P., & Freisleben, B. (1998, September). Memetic algorithms and the fitness landscape of the graph bi-partitioning problem. In International Conference on Parallel Problem Solving from Nature (pp. 765-774).
[108] Fonlupt, C., Robilliard, D., Preux, P., & Talbi, E. G. (1999). Fitness landscapes and performance of meta-heuristics. In Meta-Heuristics (pp. 257-268).
[109] Sébastien Verel (2013): Fitness Landscapes and Graphs: Multimodularity, Ruggedness and Neutrality, Université Nice Sophia Antipolis / CNRS, France, DOLPHIN team - INRIA Lille-Nord Europe, http://www-lisic.univ-littoral.fr/~verel/talks/2tut16-verel.pdf (Last accessed: 2022.12.30.)
[110] HEURISTIC OPTIMIZATION, Search Space Analysis http://iridia.ulb.ac.be/~stuetzle/Teaching/HO12/Slides/Lecture12.pdf (Last accessed: 2022.12.30.)
[111] Rogier Hans Wuijts (2018): Investigation of the Traveling Thief Problem, Utrecht University, Master Thesis
[112] Smith, T., Husbands, P., & O'Shea, M. (2002). Fitness landscapes and evolvability. Evolutionary computation, 10(1), 1-34.
[113] Lokketangen, A., Oppen, J., Oyola, J., & Woodruff, D. L. (2012). An attribute based similarity function for VRP decision support. Decision making in manufacturing and services, 6(1-2).
[114] Wang, K. P., Huang, L., Zhou, C. G., & Pang, W. (2003, November). Particle swarm optimization for traveling salesman problem. In Proceedings of the 2003 international conference on machine learning and cybernetics (IEEE cat. no. 03ex693) (Vol. 3, pp. 1583-1585). IEEE.
[115] Moustafa, A., Abdelhalim, A. A., Eltawil, A. B., & Fors, N. (2013). Waste collection vehicle routing problem: case study in Alexandria, Egypt. In The 19th International Conference on Industrial Engineering and Engineering Management (pp. 935-944). Springer, Berlin, Heidelberg.
[116] Golden, B. L., Assad, A. A., & Wasil, E. A. (2002). Routing vehicles in the real world: applications in the solid waste, beverage, food, dairy, and newspaper industries. In The vehicle routing problem (pp. 245-286). Society for Industrial and Applied Mathematics.
[117] Boonkleaw, A., Suthikarnnarunai, N., & Srinon, R. (2009, October). Strategic planning and vehicle routing algorithm for newspaper delivery problem: Case study of morning newspaper, bangkok, thailand. In Proceedings of the world congress on engineering and computer science (Vol. 2, pp. 1067-1071).
[118] Osaba, E., Yang, X. S., Diaz, F., Onieva, E., Masegosa, A. D., & Perallos, A. (2017). A discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy. Soft Computing, 21(18), 5295-5308.
[119] Boonkleaw, A., Suthikarnnarunai, N., & Srinon, R. (2010). Strategic planning for newspaper delivery problem using vehicle routing algorithm with time window (VRPTW).
[120] Maden, W., Eglese, R., & Black, D. (2010). Vehicle routing and scheduling with time-varying data: A case study. Journal of the Operational Research Society, 61(3), 515-522.
[121] Hsu, C. I., Hung, S. F., & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. Journal of food engineering, 80(2), 465-475.
[122] Chen, H. K., Hsueh, C. F., & Chang, M. S. (2009). Production scheduling and vehicle routing with time windows for perishable food products. Computers & operations research, 36(7), 2311-2319.
[123] Song, B. D., & Ko, Y. D. (2016). A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery. Journal of food engineering, 169, 61-71.
[124] Osvald, A., & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. Journal of food engineering, 85(2), 285-295.
[125] Zhang, Y., & Chen, X. D. (2014). An optimization model for the vehicle routing problem in multi-product frozen food delivery. Journal of applied research and technology, 12(2), 239-250.
[126] Talarico, L., Sörensen, K., & Springael, J. (2015). Metaheuristics for the risk-constrained cash-in-transit vehicle routing problem. European Journal of operational research, 244(2), 457-470.
[127] Ghannadpour, S. F., & Zandiyeh, F. (2020). A new game-theoretical multi-objective evolutionary approach for cash-in-transit vehicle routing problem with time windows (A Real life Case). Applied Soft Computing, 106378.

[128] Bocewicz, G., Nielsen, P., & Banaszak, Z. (2018, September). Declarative modeling of a milk-run vehicle routing problem for split and merge supply streams scheduling. In International Conference on Information Systems Architecture and Technology (pp. 157-172). Springer, Cham.
[129] Keskinturk, T., & Yildirim, M. B. (2011, June). A genetic algorithm metaheuristic for bakery distribution vehicle routing problem with load balancing. In 2011 International Symposium on Innovations in Intelligent Systems and Applications (pp. 287-291). IEEE.
[130] Tunjongsirigul, B., & Pongchairerks, P. (2010, May). A genetic algorithm for a vehicle routing problem on a real application of bakery delivery. In 2010 2nd International Conference on Electronic Computer Technology (pp. 214-217). IEEE.
[131] Derigs, U., & Grabenbauer, G. (1993). Intime-A new heuristic approach to the vehicle routing problem with time windows, with a bakery fleet case. American Journal of Mathematical and Management Sciences, 13(3-4), 249-266.
[132] Privé, J., Renaud, J., Boctor, F., & Laporte, G. (2006). Solving a vehicle-routing problem arising in soft-drink distribution. Journal of the Operational Research Society, 57(9), 1045-1052.
[133] Stolk, J., Mann, I., Mohais, A., & Michalewicz, Z. (2013). Combining vehicle routing and packing for optimal delivery schedules of water tanks. OR Insight, 26(3), 167-190.
[134] Hollis, B. L., Forbes, M. A., & Douglas, B. E. (2006). Vehicle routing and crew scheduling for metropolitan mail distribution at Australia Post. European Journal of Operational Research, 173(1), 133-150.
[135] Wasner, M., & Zäpfel, G. (2004). An integrated multi-depot hub-location vehicle routing model for network planning of parcel service. International journal of production economics, 90(3), 403-419.
[136] Pérez, E. S., Yepez, L. A., & de la Mota, I. F. (2010, July). Simulation and optimization of the pre-hospital care system of the National University of Mexico using travelling salesman problem algorithms. In SummerSim (pp. 364-370).
[137] Xiao, L., Dridi, M., Hajjam El Hassani, A., Fei, H., & Lin, W. (2018). An improved cuckoo search for a patient transportation problem with consideration of reducing transport emissions. Sustainability, 10(3), 793.
[138] Li, J., Li, T., Yu, Y., Zhang, Z., Pardalos, P. M., Zhang, Y., & Ma, Y. (2019). Discrete firefly algorithm with compound neighborhoods for asymmetric multi-depot vehicle routing problem in the maintenance of farm machinery. Applied Soft Computing, 81, 105460.
[139] Rashidnejad, M., Ebrahimnejad, S., & Safari, J. (2018). A bi-objective model of preventive maintenance planning in distributed systems considering vehicle routing problem. Computers & Industrial Engineering, 120, 360-381.
[140] Dhahri, A., Zidi, K., & Ghedira, K. (2015). A variable neighborhood search for the vehicle routing problem with time windows and preventive maintenance activities. Electronic Notes in Discrete Mathematics, 47, 229-236.
[141] Xie, B., Li, Y., & Jin, L. (2013). Vehicle routing optimization for deicing salt spreading in winter highway maintenance. Procedia-Social and Behavioral Sciences, 96, 945-953.
[142] Kizilateş, G., & Nuriyeva, F. (2013). On the nearest neighbor algorithms for the traveling salesman problem. In Advances in Computational Science, Engineering and Information Technology (pp. 111-118). Springer, Heidelberg.
[143] Rosenkrantz, D. J., Stearns, R. E., & Lewis, II, P. M. (1977). An analysis of several heuristics for the traveling salesman problem. SIAM journal on computing, 6(3), 563-581.
[144] Nilsson, C. (2003). Heuristics for the traveling salesman problem. Linkoping University, 38, 00085-9.
[145] Braun, H. (1990, October). On solving travelling salesman problems by genetic algorithms. In International Conference on Parallel Problem Solving from Nature (pp. 129-133). Springer, Berlin, Heidelberg.
[146] Zhou, J., Xiao, H., Wang, H., & Dai, H. N. (2016, July). Parallelizing simulated annealing algorithm in many integrated core architecture. In International Conference on Computational Science and Its Applications (pp. 239-250). Springer, Cham.
[147] Tsubakitani, S., & Evans, J. R. (1998). Optimizing tabu list size for the traveling salesman problem. Computers & Operations Research, 25(2), 91-97.
[148] Marini, F., & Walczak, B. (2015). Particle swarm optimization (PSO). A tutorial. Chemometrics and Intelligent Laboratory Systems, 149, 153-165.
[149] Wang, K. P., Huang, L., Zhou, C. G., & Pang, W. (2003, November). Particle swarm optimization for traveling salesman problem. In Proceedings of the 2003 international conference on machine learning and cybernetics (IEEE cat. no. 03ex693) (Vol. 3, pp. 1583-1585). IEEE.
[150] Zhang, L., Liu, L., Yang, X. S., & Dai, Y. (2016). A novel hybrid firefly algorithm for global optimization. PloS one, 11(9), e0163230.
[151] Osaba, E., Carballedo, R., Yang, X. S., & Diaz, F. (2016). An evolutionary discrete firefly algorithm with novel operators for solving the vehicle routing problem with time windows. In Nature-Inspired Computation in Engineering, pp. 21-41. Springer, Cham.

[152] Jati, G. K. (2011). Evolutionary discrete firefly algorithm for travelling salesman problem. In Adaptive and intelligent systems, pp. 393-403. Springer, Berlin, Heidelberg.
[153] Bouzidi, M., & Riffi, M. E. (2014). Adaptation of the Harmony Search Algorithm to solve the Travelling Salesman Problem. Journal of Theoretical & Applied Information Technology, 62(1), pp. 154-160.
[154] Boryczka, U., & Szwarc, K. (2019). The adaptation of the harmony search algorithm to the ATSP with the evaluation of the influence of the pitch adjustment place on the quality of results. Journal of Information and Telecommunication, 3(1), 2-18.
[155] Blum, C. (2005). Ant colony optimization: Introduction and recent trends. Physics of Life reviews, 2(4), 353-373.
[156] Stützle, T., & Dorigo, M. (1999). ACO algorithms for the traveling salesman problem. Evolutionary algorithms in engineering and computer science, 4, 163-183.
[157] Bullnheimer, B., Hartl, R. F., & Strauss, C. (1997). A new rank based version of the Ant System. A computational study.
[158] Ökonometria /Elméleti jegyzet/ Nagy Lajos, Balogh Péter (2013): https://dtk.tankonyvtar.hu/xmlui/handle/123456789/3619 (Last accessed: 2022.12.30.)
[159] Barta Gergő: Idősorok elemzése, http://www.cs.bme.hu/nagyadat/timeseries-gergo_barta.pdf (Last accessed: 2022.12.30.)
[160] Nwogu, E. C., Iwueze, I. S., & Nlebedim, V. U. (2016). Some tests for seasonality in time series data. Journal of Modern Applied Statistical Methods, 15(2), 24.
[161] Applied Time Series Analysis, https://online.stat.psu.edu/stat510/ (Last accessed: 2022.12.30.)
[162] Tratar, L. F., & Strmčnik, E. (2016). The comparison of Holt–Winters method and Multiple regression method: A case study. Energy, 109, 266-276.
[163] Genre, V., Kenny, G., Meyler, A., & Timmermann, A. (2013). Combining expert forecasts: Can anything beat the simple average?. International Journal of Forecasting, 29(1), 108-121.
[164] Ostertagová, E., & Ostertag, O. (2011, September). The simple exponential smoothing model. In The 4th International Conference on Modelling of Mechanical and Mechatronic Systems, Technical University of Košice, Slovak Republic, Proceedings of conference (pp. 380-384).
[165] Rasmussen, R. (2004). On time series data and optimal parameters. Omega, 32(2), 111-120.
[166] Bai, Y., Jin, X., Wang, X., Su, T., Kong, J., & Lu, Y. (2019). Compound autoregressive network for prediction of multivariate time series. Complexity, 2019.
[167] Géczi-Papp Renáta: Autoregresszív és mozgóátlag folyamatok, http://gtk.uni-miskolc.hu/files/8791/D%C3%B6nt%C3%A9sel%C5%91k%C3%A9sz%C3%ADt%C3%A9s+m%C3%B3dszertana+2.pdf (Last accessed: 2022.12.30.)
[168] Wei, W. W. (2018). Multivariate time series analysis and applications. John Wiley & Sons.
[169] Jason Brownlee: A Gentle Introduction to Autocorrelation and Partial Autocorrelation, https://machinelearningmastery.com/gentle-introduction-autocorrelation-partial-autocorrelation/
[170] Prof. Dr. habil. Kosztyán Zsolt Tibor: Kvantitatív módszerek, https://kmt.gtk.uni-pannon.hu/kzst/oktatas/km/levelezo/KM01.pptx (Last accessed: 2022.12.30.)
[171] Wei, W. W. (2006). Time series analysis. In The Oxford Handbook of Quantitative Methods in Psychology: Vol. 2.
[172] Jason Brownlee: Time Series Forecasting Performance Measures With Python, https://machinelearningmastery.com/time-series-forecasting-performance-measures-with-python/ (Last accessed: 2022.12.30.)
[173] Adhikari, R., & Agrawal, R. K. (2013). An introductory study on time series modeling and forecasting. arXiv preprint arXiv:1302.6613.
[174] Bodon Ferenc, Buza Krisztián (2014): Adatbányászat, http://www.cs.bme.hu/nagyadat/bodon.pdf (Last accessed: 2022.12.30.)
[175] Pang-Ning Tan, Michael Steinbach, Vipin Kumar. Bevezetés az adatbányászatba. https://gyires.inf.unideb.hu/KMITT/a04/ (Last accessed: 2022.12.30.)
[176] Safavian, S. R., & Landgrebe, D. (1991). A survey of decision tree classifier methodology. IEEE transactions on systems, man, and cybernetics, 21(3), 660-674.
[177] Szabó Adrienn: Random Forests - Véletlen erdők, https://docplayer.hu/11299587-Random-forests-veletlen-erdok.html (Last accessed: 2022.12.30.)
[178] Zhao, Y., & Zhang, Y. (2008). Comparison of decision tree methods for finding active objects. Advances in Space Research, 41(12), 1955-1959.
[179] Zhang, S., Li, X., Zong, M., Zhu, X., & Wang, R. (2017). Efficient knn classification with different numbers of nearest neighbors. IEEE transactions on neural networks and learning systems, 29(5), 1774-1785.

[180] Ren, J., Lee, S. D., Chen, X., Kao, B., Cheng, R., & Cheung, D. (2009, December). Naive bayes classification of uncertain data. In 2009 Ninth IEEE International Conference on Data Mining (pp. 944-949). IEEE.
[181] Powers, D. M. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. arXiv preprint arXiv:2010.16061.
[182] Cheng, R., Gen, M., & Tozawa, T. (1995). Vehicle routing problem with fuzzy due-time using genetic algorithms. Journal of Japan Society for Fuzzy Theory and Systems, 7(5), 1050-1061.
[183] Bansal, S., & Katiyar, V. (2014). Integrating Fuzzy and Ant Colony System for Fuzzy Vehicle Routing Problem with Time Windows. arXiv preprint arXiv:1411.3806
[184] Dror, M., & Trudeau, P. (1986). Stochastic vehicle routing with modified savings algorithm. European Journal of Operational Research, 23(2), 228-235.)
[185] Balogh Sándor (2009) Többszempontú gazdasági döntéseket segítő Genetikus Algoritmus kidolgozása és alkalmazásai, Phd értekezés, Kaposvári Egyetem, Gazdaságtudományi Kar, Informatika Tanszék
[186] Kuang-HuaChang (2015) Chapter 5 - Multiobjective Optimization and Advanced Topics, Design Theory and Methods Using CAD/CAE, The Computer Aided Engineering Design Series, 325-406
[187] Arora, J. S. (2004). Multiobjective Optimum Design Concepts and Methods. Introduction to Optimum Design, 543-563.
[188] Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. Structural and multidisciplinary optimization, 26(6), 369-395.
[189] Ghoseiri, K., & Ghannadpour, S. F. (2010). Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. Applied Soft Computing, 10(4), 1096-1107.

Author's scientific works

Publications related to the dissertation

I. Scientific journal article:
in international journal:

[P/1] A Agárdi, L Kovács, T Bányai (2022). Mathematical Model for the Generalized VRP Model, SUSTAINABILITY 14 (18) Paper: 11639 **SCOPUS INDEXED Q1, IF=3,889**
[P/2] A Agárdi, L Kovács, T Bányai (2022). Ontology Support for Vehicle Routing Problem, APPLIED SCIENCES-BASEL, 12(23), Paper:12299, **SCOPUS INDEXED Q2, IF=2,838**
[P/3] L Kovács, A Agárdi, T Bányai (2020). Fitness Landscape Analysis and Edge Weighting-Based Optimization of Vehicle Routing Problems, PROCESSES 8 (11), Paper: 1363 **SCOPUS INDEXED Q2, IF=2,753**
[P/4]A Agárdi, L Kovács, T Bányai (2021). An Attraction Map Framework of a Complex Multi-Echelon Vehicle Routing Problem with Random Walk Analysis, APPLIED SCIENCES-BASEL, 11 (5), Paper: 2100 **SCOPUS INDEXED Q2, IF=2,474**
[P/5] A Agárdi, L Kovács, T Bányai (2019). Two - Echelon Vehicle Routing Problem with Recharge Stations, TRANSPORT AND TELECOMMUNICATION 20 (4), 305–317 **SCOPUS INDEXED Q2**
[P/6] A Agárdi, L Kovács, T Bányai (2019). Optimization of Multi-Depot Periodic Vehicle Routing Problem with Time Window, ACADEMIC JOURNAL OF MANUFACTURING ENGINEERING 17 (4), 96-108 **SCOPUS INDEXED Q3**
[P/7] A Agárdi, L Kovács, T Bányai (2021). Comparision of the walk techniques for fitness state space analysis in vehicle routing problem, ACTA POLYTECHNICA 61, 672-683. **SCOPUS INDEXED Q3**
[P/8] A Agárdi, L Kovács, T Bányai (2021). Ant Colony Algorithms For The Vehicle Routing Problem With Time Window, Period And Multiple Depots, MANUFACTURING TECHNOLOGY 21, 422-433. **SCOPUS INDEXED Q3**
[P/9] A Agárdi, L Kovács, T Bányai (2021). The Fitness Landscape Analysis of The Ant Colony System Algorithm in Solving a Vehicle Routing Problem, ACADEMIC JOURNAL OF MANUFACTURING ENGINEERING 19 (2), 85-89. **SCOPUS INDEXED Q3**
[P/10] A Agárdi, L Kovács, T Bányai (2021). Using Time Series and Classification in Vehicle Routing Problem, INTERNATIONAL JOURNAL OF PERFORMABILITY ENGINEERING 17 (1), 14-25. **SCOPUS INDEXED Q4**
[P/11] A Agárdi (2023). Fitness Landscape Analysis of Population-Based Heuristics in Solving a Complex Vehicle Routing Problem, LECTURE NOTES IN MECHANICAL ENGINEERING Vehicle and Automotive Engineering 4, 667-677. **SCOPUS INDEXED Q4**
[P/12] A Agárdi (2023). Analysis of the Multi-Objective Optimisation Techniques in Solving a Complex Vehicle Routing Problem, LECTURE NOTES IN MECHANICAL ENGINEERING Vehicle and Automotive Engineering 4, 678-693. **SCOPUS INDEXED Q4**
[P/13] A Agárdi, L Kovács, T Bányai (2021). Neutrality of Vehicle Routing Problem, INTERNATIONAL JOURNAL OF PERFORMABILITY ENGINEERING 17 (10), 848-857. **SCOPUS INDEXED Q4**

in hungarian journal in a foreign language:

[P/14] A Agárdi, L Kovács, T Bányai (2019). Investigation of Convergence Properties of Ant Colony Based Algorithms, ADVANCED LOGISTIC SYSTEMS: THEORY AND PRACTICE 13 (2), 5-20.
[P/15] A Agárdi (2022). Software for the generalization of the Vehicle Routing Problem, PRODUCTION SYSTEMS AND INFORMATION ENGINEERING 10 (3), 41-52.

in hungarian journal in hungarian:

[P/16] A Agárdi, L Kovács, T Bányai (2019). Időablakos járatszervezési probléma megoldása populációs heurisztikus algoritmusokkal, GÉPGYÁRTÁS 58 (1-2), 17-25
[P/17] A Agárdi, L Kovács, T Bányai (2018). Az időablakos járatszervezési probléma optimalizálása, GÉPGYÁRTÁS 57 (1-2), 6-14
[P/18] A Agárdi, L Kovács, T Bányai (2020). Fitness landscape elemzési technikák áttekintése, MULTIDISZCIPLINÁRIS TUDOMÁNYOK: A MISKOLCI EGYETEM KÖZLEMÉNYE 10 (4), 214-218.
[P/19] A Agárdi (2019). A többlerakatos időablakos járatszervezési feladat matematikai és ontológiai modellje, MULTIDISZCIPLINÁRIS TUDOMÁNYOK: A MISKOLCI EGYETEM KÖZLEMÉNYE 9 (4), 293-300.
[P/20] A Agárdi (2018). A többügynökös utazó ügynök probléma megoldása lokális optimalizálással MULTIDISZCIPLINÁRIS TUDOMÁNYOK: A MISKOLCI EGYETEM KÖZLEMÉNYE 8 (1), 3-8.

II. Conference paper
in a foreign language:

[P/21] A Agárdi, L Kovács, T Bányai (2019). Optimization of Complex Vehicle Routing Problems, 12th International Doctoral Students Workshop on Logistics, 107-112.
[P/22] A Agárdi, L Kovács, T Bányai (2019). Optimization of automatized picking process, SACI 2019 : IEEE 13th International Symposium on Applied Computational Intelligence and Informatics : PROCEEDINGS, 364-369.
[P/23] A Agárdi, L Kovács, T Bányai (2019). Vehicle routing in drone-based package delivery services, Solutions for Sustainable Development: Proceedings of the 1st International Conference on Engineering Solutions for Sustainable Development (ICESSD 2019), 151-159.
[P/24] A Agárdi, L Kovács, T Bányai (2020). The mathematical and ontology model of the Two-Echelon Vehicle Routing Problem with Time Window, 13th International Doctoral Students Workshop on Logistics, 23-30.

in hungarian:

[P/25] A Agárdi, L Kovács, T Bányai (2019). A hangya kolónia optimalizáció hatékonyságának vizsgálata a járatszervezési probléma megoldásában, Műszaki tudomány az Észak-kelet Magyarországi Régióban 2019 : konferencia előadása, 5-8
[P/26] A Agárdi (2018). A többlerakatos járat szervezési probléma optimalizálási lehetőségei, 15 éves PEME XVI. PhD - Konferenciájának előadásai, 5-14
[P/27] A Agárdi (2018). Optimális lerakat meghatározása a több ügynökös egy lerakatos utazó ügynök probléma megoldásában, Tavaszi Szél 2018 = Spring Wind 2018 : Tanulmánykötet, 525-534

III. Other scientific works:

[P/28] A Agárdi (2019). A járatszervezési probléma megoldása autonóm, elektromos járművek esetén, DIÁKTUDOMÁNY: A MISKOLCI EGYETEM TUDOMÁNYOS DIÁKKÖRI MUNKÁIBÓL XII, 50-55
[P/29] A Agárdi (2018). A több ügynökös utazó ügynök probléma megoldása lokális optimalizálással, DIÁKTUDOMÁNY: A MISKOLCI EGYETEM TUDOMÁNYOS DIÁKKÖRI MUNKÁIBÓL XI, 53-58
[P/30] A Agárdi (2018). A több lerakatos, periodikus, időablakos járatszervezési probléma optimalizálása, Diplomamunka, Miskolci Egyetem
[P/31] A Agárdi (2017). Klaszterezési és evolúciós technikák alkalmazása az utazó ügynök probléma megoldásában, Szakdolgozat, Miskolci Egyetem

Author's web resources

Appendices:

[A/1] Meaning of the components of the general Vehicle Routing Problem model, the ontology model and evaluation of the representation mode:
https://drive.google.com/file/d/1qBL1AiwFd1U4wQ6kgEML0o7Amzj_cja1/view?usp=sharing
[A/2] Additional components of the ontology system:
https://drive.google.com/file/d/1fg2aXSRKkgkS_w9TG-VsgqqZDdxVTbfI/view?usp=sharing
[A/3] Test results of the ontology knowledge base:
https://drive.google.com/file/d/1MFMryefOadfkCDoheFZxnAYrIH9b1h_Z/view?usp=sharing
[A/4] The representation of the Vehicle Routing Problem in the literature:
https://drive.google.com/file/d/1wb-H6gUJiCTWeeY1wQmkbCXzPwnLaS5n/view?usp=sharing
[A/5] The representation of the generalized route description model of the Vehicle Routing Problem (examples):
https://drive.google.com/file/d/13R8yHlaf81NbPUOWOsZ65Cj51u5axhRU/view?usp=sharing
[A/6] Optimization algorithms:
https://drive.google.com/file/d/1NlmQD2DfKnYfmc9mcPzhlRwn2BJ8OBhs/view?usp=sharing
[A/7] Time series algorithms:
https://drive.google.com/file/d/1VKL_3stlJy_4VHDAiFycVHQBo86Z_f3e/view?usp=sharing
[A/8] Classification algorithms:
https://drive.google.com/file/d/1k3gdSaW8zCGDoUM93mc90m9iBtzF6YYC/view?usp=sharing
[A/9] Handling fuzzy and stochastic data:
https://drive.google.com/file/d/1A63gQHhb796TZ-flX8b7_tlNOqEXy5ft/view?usp=sharing
[A/10] Single - and Multi-Objective Optimization:
https://drive.google.com/file/d/1RJRLei6kxC87GQZoPbsSuqcz67OsOx59/view?usp=sharing
[A/11] Applications of the general model of the Vehicle Routing Problem: tables:
https://drive.google.com/file/d/1PjtEiBdrr29MCgEy8Qx3qoeOXvctNHL4/view?usp=sharing
[A/12] The tables of the analysis of fitness landscape:
https://drive.google.com/file/d/1fZFQujHEdX3hita-ivDRKxW6HcZhGAVJ/view?usp=sharing
[A/13] Overview of ontology systems:
https://drive.google.com/file/d/1HHbRFCwHzlO7yDJmLptxpeRispsWt3ls/view?usp=sharing

Test results:
[W/1] Multi-Objective Optimization:
https://drive.google.com/file/d/1gy-5n8TBwT8IwcthYJN-4Y1HmhYyUWOl/view?usp=sharing
[W/2] Analysis of the solutions of heuristic algorithms:
https://drive.google.com/file/d/1x48Nbdo2_bF6iNin5fZ9zNLSKTunRBSZ/view?usp=sharing
[W/3] Analysis of the iteration of the iterative heuristic algorithms:
https://drive.google.com/file/d/1SnLvoznz0lBkto0XDn9jZsLcufzHXDZx/view?usp=sharing
[W/4] Analysis of the iteration of the iterative heuristic algorithms:
https://drive.google.com/file/d/1c2EMGmu2UtxjR13R6bKdzUIuGtRlYE05/view?usp=sharing
[W/5] Operator analysis (with walks):
https://drive.google.com/file/d/1ZQisWItH9NUcbj8REhBtNAQbGNQ7b4tc/view?usp=sharing
[W/6] Operator analysis (with walks):
https://drive.google.com/file/d/1VKUL5nhpdxd-ACdQMABcXUdBAp_FXu4L/view?usp=sharing
[W/7] Random walk analysis (with information content analysis):
https://drive.google.com/file/d/1MQFVW1GNhC-o_pa-l4zx6aZHs8OBn99l/view?usp=sharing
[W/8] Analysis of the filtered search space:
https://drive.google.com/file/d/1mPXBOa-8oB1oOoZJvNt7wHDsNv-wWgNf/view?usp=sharing
[W/9] Fitness Cloud:
https://drive.google.com/file/d/1S_Jk9hGA7huE9-M6beRB5-0BAAvOF6rW/view?usp=sharing