INTERNATIONAL BLACK SEA UNIVERSITY

FACULTY OF COMPUTER TECHNOLOGIES AND ENGINEERING

PhD PROGRAM

INCREASE OF PERFORMANCE AND EFFECTIVENESS OF THE MULTI DEPOT VEHICLE ROUTING PROBLEM'S SOLUTION (ON THE EXAMPLE OF SOUTH CAUCASIAN LOGISTICS NETWORK)

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CONTENTS

LIST of FIGURES

Abbreviations

- AC – Autonomic Component
- ACE– Autonomic Component Ensembles
- ALNS - Adaptive Large Neighborhood Search
- API - Application Programming Interface
- B&B - Branch and Bound
- BPP - The Bin Packing Problem
- COP - Combinatorial Optimization Problems
- CPRV - Capacitated VRP
- DEECo - Dependable Emergent Ensembles of Components
- EBCS - Ensemble- Based Component Systems
- jRESP - Java Run-time Environment for SCEL Programs
- LNS - Large Neighborhood Search
- MAP - Modified Assignment Problem
- MDVRP - Multiple Depot VRP
- mTSP - multi Travelling Salesman Problem
- POIs - points of interest
- PVRP - Periodic VRP
- QA - Quasi-Assignment
- SCEL - Software Component Ensemble Language
- SDVRP - Split Delivery VRP
- SECs - Subtour Elimination Constraints
- SRD - database of simulation results
- sTSP - symmetric Travelling Salesman Problem
- SVRP Stochastic VRP
- TCMD - travel and congestion management database
- The MATSim - Multi-Agent Transport Simulation)
- TRANSIMS - TRansportation Analysis and SIMulation System
- TSP - The Traveling Salesman Problem
- VRP - Vehicle Routing problem
- VRPTW - VRP with Time Windows
- VRPTW -The Vehicle Routing problem with Time Windows

Introduction

The thesis examines the value of real-time traffic information for optimal vehicle routing in a non-stationary stochastic network. Our goal is to develop a systematic approach to aid in the implementation of transportation systems integrated with real-time information technology. Based on many researches done in the fields of VRP and TSP we can implement them for our heuristics. Finding ways to develop decision making procedures for determining optimal driver attendance times optimal departure times, and optimal routing policies under stochastic time-changing traffic is firsthand goal of our research. With studies based on a road network in Georgia, we demonstrate significant advantages when using this information in terms of total costs savings and vehicle usage reduction while satisfying or improving service levels for just-in-time delivery. With such systems routing and controlling traffic and vehicles should be done more in more precise and easy manner. That means that many sectors of logistics industry can improve their work and make their services cheaper, that will also influence end-user. Our algorithm is adaptive and can react to number of stochastic effects and constrains that can be observed in real logistics networks.

Goals of Research:

Main goal of the following research is to investigate existing approaches in the area of multi depot vehicle routing problem, to reveal its suitability to the practical needs of the Georgian logistic network and to develop new techniques and methods which will satisfy above mentioned needs. In particular, the following issues have to be developed in the thesis:

- A theoretical approach that can manage the uncertainty and stochastic nature of VRP in real life environment.
- Mathematical models which can accurately predict transportation stochastic parameters such as traffic volumes, congestion induced delays etc.
- Combination of models, algorithms and applied technical tools which will ensure the search of practically acceptable optimal routes and usage of advanced technologies. Also the framework to be developed must provide users ability to modify routes in simultaneous and parallel manner.

- Modification of widely used ALNS algorithm (which cannot be directly used for practical needs of logistics networks being under investigation); this modification must be directly applicable to the conditions of Georgian transportation network.
- A suitable programming framework which can effectively implement developed heuristics and algorithms must be accurately selected or developed from scratch.
- Detailed research of all statistical data, which may have important impact on the main traffic characteristics (like types of road congestions, delays, etc.,) on areas of interest. In case of absence of such data, reliable methods of determination and obtaining such information must be developed in the thesis.
- Convenient programming tools which help developed methods to be effectively implemented in practice must be selected.
- Technical implementation of proposed approaches and algorithms must be maximally cost effective.

Importance (significance)

Logistic networks and their tasks are nowadays most important area, from the stand point of vitally importance of Georgian logistic network in the context of increasing demand of international shipments (Silk road). Existing logistics network is not yet developed to satisfy these increasing requirements. Moreover, known to us algorithmic methods and techniques do not cover practical and realistic needs of (Silk road) international shipments. Therefore, there is an urgent need to develop relevant approaches and methods which can fully satisfy above mentioned problems and tasks. Those approaches and methods have to increase throughput of logistic network and generate significant economic effect. Modern society needs a constant increase in the volume of transport, increasing its reliability, safety and quality. This requires increasing the cost of improving the infrastructure of the transport network, turning it into a flexible, highly regulated logistics system. At the same time, the risk of investment increases significantly if the patterns of the transport network development are not taken into account, providing that the distribution of the loading of its sections is taken into account. Ignoring these patterns leads to the frequent formation of traffic jams, overload / underload of certain lines and nodes of the network, increasing the level of accidents, environmental damage. The theory of transport flows was developed by researchers of various fields of knowledge - physicists, mathematicians, operations research specialists, transport workers, economists. A wide experience of studying the processes of motion has been accumulated. However, the general level of research and its practical use is not sufficient.

Theoretical Value

As it is known, large variety of theoretical methods exists in this area. However, they can’t satisfy practical requirement of Georgian logistics network, in particular with increasing impact of new developed intentional Silk Road logistic network. Most of existing nowadays heuristics cannot provide full specter of solutions for real life logistics networks. This theoretical framework will be used as a base for the practical and concrete algorithms. For example, in the existing paradigm, uncertainty and stochastic nature of the VRP is not fully reflected. With this in mind new theoretical approaches (accounting for practical needs of real environment) have been developed in the thesis. The solution of such problems is impossible without mathematical modeling of transport networks. The main task of mathematical models is the definition and forecast of all parameters of the transport network functioning, such as traffic intensity on all network elements, traffic volumes in the public transport network, average traffic speeds, delays and time losses. All the said above was implemented in the approach of the thesis and has great importance for the future researches

Practical Value

As it was pointed out above, practical needs of Georgian logistics network require new approaches to satisfy realistic problems and tasks. Therefore, techniques developed in the thesis will have undoubted practical values and they will be able to bring significant economic effects and contributions. As already pointed above these economic gains will affect end-users in many fields. Transport infrastructure is one of the most important infrastructures in the life of cities and regions. In recent decades, many large Cities are exhausted or close to the exhaustion by the extensive development of transport networks. Therefore, optimal planning of networks, improvement of traffic organization, optimization of the system of public transport routes has a practical importance. All mentioned above results in increasing practical value of the thesis.

Novelty

In the thesis a new set of algorithms and applied tools which combine the application of known algorithms for searching optimal routes (taking into account the actual conditions on the sections of planned routes) and usage of new technology of autonomous components ensembles, has been developed. In particular, the developed program complex allows users to modify promptly current routes based on local information and choose the most accessible routes which reflect local real situation. The originality of the developed complex also lies in the fact that all the necessary calculations are made by the autonomous components, associated with specific cars, in virtual machines of datacenters. This allows users to modify routes in simultaneous and parallel manner without the need to install expensive equipment and software in vehicles. The later significantly reduces the duration and cost of the necessary calculations. The technology developed in the thesis will also help to improve the efficiency and safety of traffic planning for unmanned vehicles.

Research Methods

In the thesis the following methods have been used:

- Collection and classification and estimation of necessary data.
- Modeling and simulation for obtaining required important parameters and characteristics of processes involved in the research.
- Intensive usage of global optimization methods.
- Developing and usage of wide specter of programming solutions.
- Deployment of modern advanced technical solutions to provide maximum effectiveness of proposed models and algorithms, which may result in significant reduction of costs.

Thesis Limitations

Due to the non-availability of data for Armenia and Azerbaijan logistic networks this dissertation is based on realistic information for Georgian logistics network. However, all of the developed methods and algorithms can be applicable to Armenian and Azerbaijan logistics network without significant changes.

Chapter I – Literature Review

1.1 Problem review

Transport logistics is becoming an increasingly important component of many areas of activity. In commerce, the share of transportation costs for a product may be 25-35% of its value. In 2010-2014. The volume of the market for commercial road freight transport has more than doubled. This situation imposes high demands both on representatives of freight services and on producers of goods. Transportation also uses most part of petroleum (Fuglestvedt et al.,2008). Optimization of transportation becomes a serious competitive advantage.

In the past, the compilers of vehicle routes and controllers acted independently of each other and without information exchange, or only with very little. The location of vehicles on the route line was not known, and it was not always possible to establish a good connection with the driver. Recent advances in information and communication technologies have significantly improved the quality of communication between the driver and the dispatch center. Now, information on the arrival of new orders or changes in routes can easily be passed on to drivers, which helps to improve the level of service and reduce costs.

A direct supply chain consists of a producer of a finished product (a focus company), a supplier (level 1), a consumer (level 1), who directly participate in the external and internal flow of products, finance and information. Most often, the focus company determines the structure of the supply chain and management of relationships with business counterparties. The order of interaction of participants in it is determined by the conditions of the external environment (random and deterministic indicators that affect the level of production, the structure of purchases of raw materials, the policy of distribution of finished products to end users, including the transportation policy).

The expanded supply chain includes additional suppliers and second-tier consumers. The extended supply chain is the basis for constructing a reference model of operations in supply chains, since such a basic chain structure is most common in business.

The maximum supply chain consists of a focus company and all its counterparties (down to source suppliers) that determine the resources of the focus company at the entrance, and the distribution networks on the right - down to the end users.

Complex, branched relationships between suppliers and consumers in various industries imply the identification and study of the behavior of the relevant participants in various supply chains. In the modeling of supply chains, the multi-product mix of products, temporary, territorial and cost constraints, the random nature of some logistics processes in supply chains are taken into account.

The need for constant movement of raw materials, semi-finished products, finished products, materials and containers by means of transport between participants in the supply chains of the industry makes for increased requirements for a key logistic function - transportation. The lack of a methodology for transport management at industrial enterprises at the marketing stage leads to a disruption in the schedule of deliveries, uneven exports of finished products, incomplete use of the carrying capacity of vehicles, and therefore increases the costs of rolling stock operation and the price of products. At the procurement stage, untimely delivery leads to an increase in the average level of stocks of raw materials and materials, the creation of increased insurance reserves, the disruption of the production schedule and rhythm and, as a result, an increase in the cost of finished products. The variety of transport links between suppliers and consumers, the use of the rolling stock of transport enterprises of various forms of ownership, necessitates the application of a systematic approach to the choice of ways of interaction between industrial enterprises and suppliers of raw materials, trade and transport organizations. Since the goal of any enterprise in the industry is to increase profit, and in the financial sphere - to shorten the duration of the operational and financial cycles, the choice of rational ways of managing transportation can positively affect the financial performance of enterprises. The tasks of transport and logistics services are being addressed at the strategic, tactical and operational levels. The objectives of the strategic level allow you to design a network for promoting the material flow, determine the location of the main and auxiliary objects of service, identify schemes for the movement of industrial goods between them, determine the tariff policy, and develop strategic transportation plans. At the tactical level, the plans, routes of transportation, the order of service are adjusted, taking into account the unevenness of demand, the availability of rolling stock at the nodes of the supply chains, and so on. At the operational level, the tasks of assigning drivers' crews, the development of routes and schedules of supplies for the next day are being decided. In the event of a change in the results of solving the tasks of the operational level, corrections are also made in the plans for the tactical and strategic levels. To fully satisfy the needs of supply chains in transportation, several types of routing tasks have been identified, which depend on the restrictions and requirements imposed on the delivery system. The application of the appropriate type of task and combination of tasks in the logistics industry depends on such factors as the time range of customer service (the "time window"), the centralization and decentralization of delivery (several senders), the ability to organize the collection and delivery of products for a single transport cycle, For several flights to each consumer, etc. In view of the fact that the dimension of the routing task in logistics is quite large due to the complex marketing network, in practice, heuristic and meta-heuristic methods are often used to obtain a qualitative solution, the use of which allows obtaining acceptable results in a relatively short time. When choosing the type of task, factors such as the planning horizon, the method of controlling the level of stocks, the type of demand for products, the number of types of deliverables in supply chains, the number and carrying capacity of vehicles, routing policies, inventory accounting and management are taken into account. Solving the problems of joint inventory management and routing allows you to obtain results that contribute to making decisions about choosing or changing the strategy of inventory management, building or modernizing transport policy, harmonizing transport and storage processes, integrating them with production processes in order to improve the efficiency of logistics industry enterprises Supply chains.

This dissertation discusses the problem of routing vehicles with time windows and in real-time conditions. To improve the efficiency of operational management, it is expected to use information and communication systems based on mobile technologies. This includes, first of all, mobile communication in real time between the control center and the drivers. Thus, new instructions can be communicated to drivers, even if they have already left the point of departure and are on the way to the client. Secondly, the datacenter can determine the geographic location of the vehicle on the road with the help of modern navigation systems (GPS). At all times, knowledge of the spatial orientation of physical objects or, to put it simply, of their geographical location, were very important for people. For example, primitive hunters always knew the location of their prey, and the life or death of explorers of the pioneers directly depended on their knowledge of geography. Also, modern society lives, works and cooperates, relying on information about who and where is located. Applied geography in the form of maps and information about space helped to make discoveries, promoted trade, increased the safety of human life for at least the last 3000 years, and maps are one of the most beautiful documents that tell about the history of our civilization

This contributes to the efficient operation of the fleet and increases productivity. And, thirdly, modern technology can provide information about the current traffic situation on the road. This makes it possible to consider the timing of transport with a temporary dependency, constantly updated during the day. All the aforementioned possibilities of using mobile technologies allow reacting to certain dynamic events, such as interference on the roads and changing the route of the vehicle in real time.

Routing of shipments to the sender and stepped routes is carried out by scheduling the loading in different directions on certain days. Scheduling allows you to organize routes from cargo trucks by several consignors, when the size of loading for each of them for the route is insignificant. As already mentioned above, for the transport of bulk goods between regular senders and recipients in specific conditions apply special sender routes, which are called ring routes. Such routes are addressed between the stations of their loading and unloading according to strictly established timetables, and from the loading stations they are always sent with the same cargo, and they are returned empty or with a different cargo.

Road transport carries a large number of bulk cargo: construction (land, sand, gravel, crushed stone, brick, panels, farms, timber), agricultural (grain, cotton, sugar, Beetroot, vegetables), fuel (coal, firewood, peat), trade, etc. The production and transportation of bulk goods causes a very intensive turnover associated with the placement of cargo-carrying and cargo-absorbing posts and the establishment of transport links between them.

The location of loading and unloading points in the transport of bulk goods, as a rule, creates a constant, characteristic for the structure and capacity of cargo flows, changing mainly in a planned order. The mass and intensity of cargo flows between the permanent points of departure and arrival create exceptionally favorable conditions for the organization of route traffic carried out by a special group (column) of cars.

Route shipments are made according to the schedule, developed on the basis of the data of the monthly and operational shift-daily plans. With good and precise organization of loading and unloading operations, scheduled transportation is carried out according to the schedule and the schedule of rolling stock movement.

Especially in case of scheduled mass transportations, the use of road trains and special trains to increase the productivity of transportation. If there are enough trailers, loading and unloading facilities, as well as favorable road conditions, the use of road trains is effective for the transport of bulk goods: it allows better use of the traction power of the car and increase the carrying capacity (the total carrying capacity) of the rolling stock. This organization of transportation reduces the cost of transportation by more than 20%.

For this research we assume that we have logistic (distribution) company with fleet of standard cargo vehicles and there are our multiple depots located in different cities and districts of Georgia. The search for optimal transport routes is a key task in the field of logistics. Each depot has individual working hours' schedule. There are many different customers in different cities, each customer has specific demand in goods and specific time window when they need to be served and also other constrains such as start of the working day hours and time that is needed to unload the cargo (service time). Many different constrains should be considered for example, vehicle cargo payload, distance traveled with one tank of gas and so on. Also we consider that problem of congestions is requiring most of the attention. We have to use such algorithm that will make decisions whether to avoid traffics jams or congestions or to wait until road is free, so that this particular vehicle wont violate its scheduled plan and specific time window constrains of the customer. This information about traffic jam and congestions also should be shared to other concerned vehicles so that if their route also lies through congested area their AC should re-plan schedule or routing again not to violate any time windows.

Because of lack of information and statistics about traffic in Georgia and Tbilisi, we have to use different approach. We can't make predictions for routing without knowing real life situation on road and statistical data from database for every street or road in Georgia. It means that firstly planner should be filled with some data, in our case we assume that with the help of MATSim we can run multiple simulations and make statistics for our knowledge bases. MATSim can show bottleneck zones on Georgia map, so we can assume that this areas with high car traffic can be considered as highly congestion danger areas. After receiving basic statistical data algorithm can obtain new information daily from every individual depot and every individual vehicle with help of AC assigned to each. This framework based on ACEs will generate new data and will correct statistical data received from MATSim simulations. It will grant high quality information for planning algorithms to schedule every day plan for whole fleet of vehicles.

Our goal is to maximally automate scheduling and planning routes and further control of vehicles and granting drivers with up-to-date information about possible difficulties in their route. Algorithms and framework have to work stable and fast, while taking in account stochastic nature of traffic flow and possible unplanned delays. Maximal automation means that each vehicle should be equipped with GPS and every driver has to have Smartphone to receive information about routes, plans and possible difficulties ahead on the road and routes to avoid them. So that datacenter can control process flow. As mentioned above each vehicle should be equipped with nowadays gadget and ACE has to have each AC assigned to each individual vehicle and depot. Also such kind of algorithm has to be flexible enough for concerning backhauls vehicle accident and many other unpredicted factors. It is obvious that such a huge framework won't be able to always complete every task that is given due to a stochastic nature of traffic itself. So we consider that it should get closest to optimal solution, to minimize total expenditure of the company and serving highest possible number of customers daily. If still many casualties occur daily algorithm has too find solution for solving this issue for example advising to add vehicles to fleet or maybe to add new depots in different locations.

For that kind of problem specific platform has to be created. Which will include different algorithms and systems. As shown in fig1.

1. This platform has to receive orders from customers.
2. Count minimal possible number of vehicles, to minimize cost of transportation.
3. Plan optimal routes for drivers with minimal travel cost and not violating capacity and time window demands
4. Share the information and give exact route on map to drivers.
5. Based on agent based modeling, agents should distribute duties for each driver.
6. Notify drivers about traffic and possible difficulties on their route. And in case of congestion should give another available route to avoid traffic.

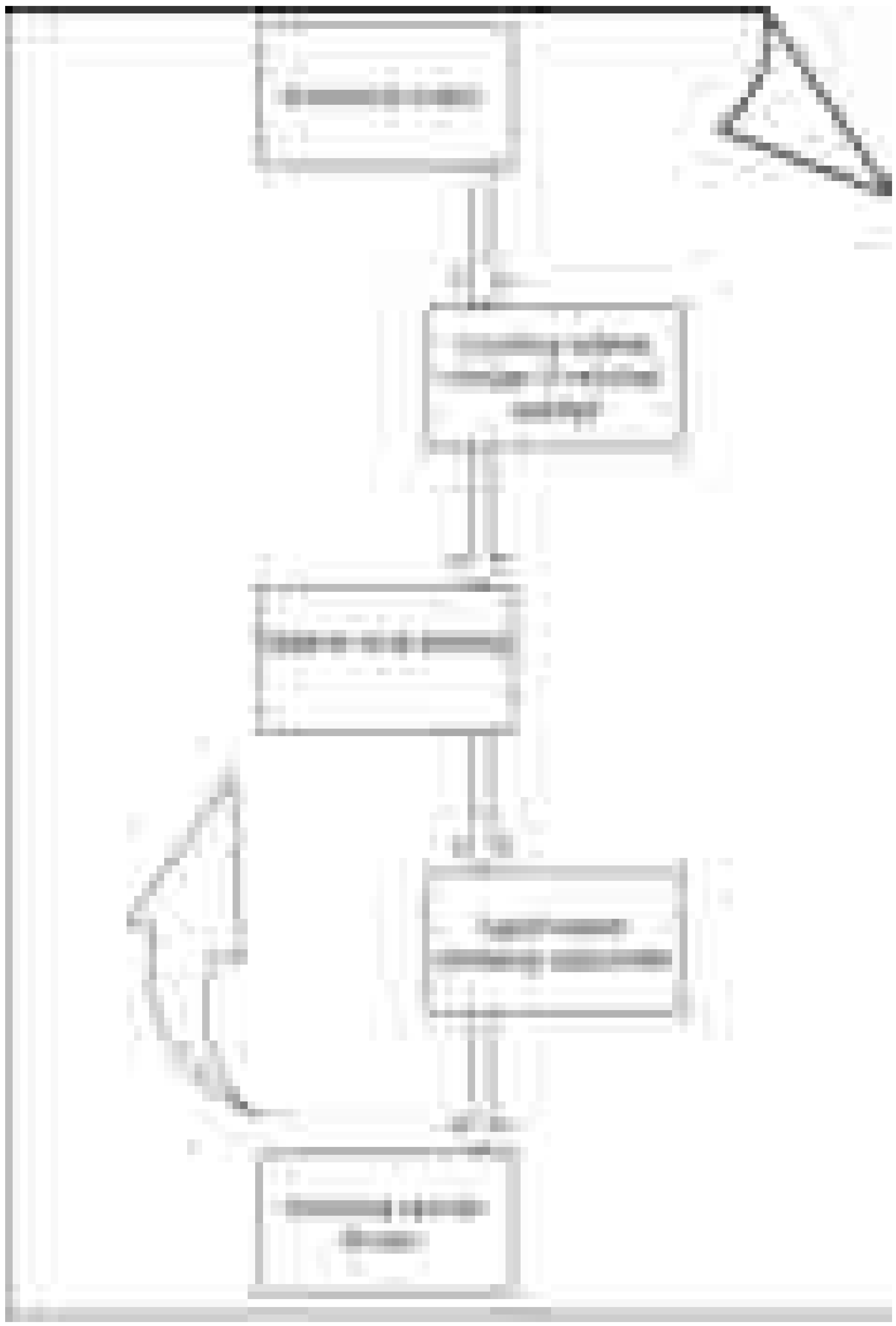


Figure 1 Platform plan

1.2 Vehicle Routing Problem

In the theory of computational complexity, it is customary to consider recognition problems (properties), that is, problems in which the possible answer is "Yes" or "No". For example, is it true that a given graph is a tree? Among the recognition tasks, it is customary to select the classes P and NP. We recall that the class P consists of recognition problems that are solvable in polynomial time. The NP class is broader. It includes all recognition tasks in which the answer "Yes" can be checked for polynomial time. The task belongs to this class, if, even without knowing how to solve it, it is possible to "easily" check the answer, having peeked it or found it on the Internet. Thus it is enough to be able to check only the answer "Yes". Sometimes checking the answer "Yes" may be easier or more difficult than checking the answer "No". We consider the problem of the Hamiltonian property of a graph: given a simple undirected graph, it is required to know whether it contains a Hamiltonian cycle? We show that this problem belongs to the class NP. Suppose that the graph is indeed a Hamiltonian, and someone has given us an answer, indicating one of these cycles. (Harnoor K. 2013)

Modern transport, and in particular the street infrastructure, is increasingly encountering bandwidth limits. The existing system of organizing transportation in conditions of increasing density of the route network does not always satisfy the emerging demand for transport services. As infrastructure expansion activities can hardly meet the uncontrollable growth in the number of transport units on city streets, the planning tasks for transportation are beginning to change. The complexity of the task requires new forms of planning, or at least changes in the emphasis of traffic planning. The task of transport routing can be solved by building one or several ring routes. For their construction, both methods of exact linear programming and approximate heuristic methods are known. It is necessary to take into account that before using these or other methods, they must be tested for applicability depending on certain parameters of the traffic routes.

Can I check this tip for polynomial time? To do this, we need to verify that the specified set of edges forms a simple cycle, and it covers all vertices. Obviously, this is "easy" to do and, consequently, the problem belongs to the NP class. Note that the answer "No" is much harder to check here. It is said that the recognition problem belongs to the class co-NP, if the answer "No" can be checked for polynomial time. It is easy to show that the next problem belongs to the class ω-NP. Given a simple undirected graph, is it true that it is not Hamiltonian? Answer "No" means that the graph is Hamiltonian, and this can be easily verified. In the class P one can check with any polynomial complexity, and therefore $P \subseteq NP$. To prove or refute the reverse inclusion so far no one manages. To date, this is the bottom of the central problems of mathematics - the "Millennium Challenge"

Vehicle Routing problem (VRP) has been delineated along with outlined, quite thirty years past. VRP is the hardest optimization combinatorial problem. (Eberhardt et al., 1991) (Dyckhoff et al., 1997) VRP is represented as “For every specific list of POIs (points of interest) with specific range of vehicles, cargo should be delivered to every customer”. Main challenge is to make minimum (the optimum) list of (routes) for specific range of vehicles. The difficulty in applying this problem to the real life circumstances, is in stochastic behavior of traffic and plenty of additional constrains.

For this extremely complicated combinatorial optimization problem, both exact and approximate algorithms have been proposed.

Interest in such problems is due not only to their great applied value, but also to the complexity of the solution. A number of reviews and monographs on this topic have been published. Of the most significant are the works of P. D. Christofides, G. Laporte, M. Solomon.

Using nowadays technologies and completely different approaches, lots of latest studies were created during this field. Individual still manage to imply novelties in on 1st sight recent problems like VRP. The vehicle routing problem refers to any or all issues where best closed-loop system methods that touch completely different points of interest, like during this case cities and countries.

VRP may be a general name that was given to the issues and tasks wherever a listing of finish points or POIs for variety of vehicles positioned at one or multiple depots should be determined for variety of geographically placed customers or cities. There may be one or plenty of cars within the fleet, additionally one or multiple depots, POI and different further factors. Goal is minimizing price of the transportation. whereas satisfying all the customers with their demands minimum vehicles ought to be concerned so as to avoid wasting fuel and cash, however at same time all the constrains ought to be taken into consideration and not desecrated.

This particular challenging combinatorial problem was created from the concepts of two well-known problems such as problem (TSP) and (BPP)

The Traveling Salesman Problem (TSP): In fact, TSP can be transformed in VRP by changing some parameters. There is even multiple Traveling salesman problem which is generalization of original TSP, but with more then, one Salesman.

The Bin Packing Problem (BPP) (Dyckhoff, et al., 1997).: Is described as follows: “Given the set of items and their weights, we have to place all items in minimal number of bins” BPP is also NP-hard problem.

In the fields of transportation, supply chain and logistics main problem to define is The Vehicle Routing problem. Largely in all told market fields, transportation logistics and supply chain adds a major share to the value of the products. Therefore, automation processes for supplying field usually lead to high value economy starting from five percent to twenty of the whole worth. In real world things in VRPs, lots of further constraints appear.

Real world applications of the VRP, in contrast with its accepted definition, often includes two important aspects: evolution of information and quality of information. Quality of information reflects possible uncertainty on the available data, for example when the demand of a client is only known as an estimation of its real demand, that means that in many case planner should behave according to unreliable data. Evolution of information means that while planning initial plan, planner has to consider that during execution of the process, many things can happen. Generally, the points of interest are mentioned as nodes. In our study, the beginning and finish points of a route are identical and are referred to as the depots. several sub issues occur in common Vehicle Routing problem one in all them that we tend to use during this paper is extension of VRP - The Vehicle Routing problem with Time Windows (VRPTW) it's known as non-polynomial hard (NP hard) problem (Lenstra et al., 1981). This VRP involves range of vehicles (fleet) that has to serve given totally different customers with specific demands and distinctive time windows for every. Customers are settled in numerous geographic locations. additionally each vehicle should come at finish point (depot) by the end of the operating day. Objective of the VRPWT is finding greatest optimal solutions to navigate the fleet so as to serve every clients with minimal value (counting gas and salaries in terms of traveled distances) while not violating capacity and time period constraints of every vehicle and distinctive customer demanded time windows.

There are a lot of different cases of VRPs in our paper only few will be used, but to have general knowledge of VRP, there are some most used described with their main goals (objectives):

1.2.1 Capacitated VRP (CPRV)

CVRP may be a Vehicle Routing problem wherever there's outlined range of vehicles with constant capacity should deliver consignment to outlined customer demands for one sort of cargo from a set depot with minimal transportation prices. CPRV considers that there's just one sort of cargo. Main goal is minimizing transportation value for delivering company. And also reducing quantity of vehicles used and considering amount of cargo not to violate capacity constraints. Solution will be feasible if all the above is included.

The CVRP is outlined more exactly as follows. we are given an directionless graph $G = (V, E)$with vertices $V = \{0, \ldots, n\}$ wherever vertex zero is that the depot and therefore the vertices $N = \{1, \ldots, n\}$ are customers. every edge e ∈ E has an associated value C_e. The demand of every customer i ∈ N is given by a positive amount q_i.. Moreover, m uniform vehicles are accessible at the depot and also the capability of every vehicle is up to Q. The goal of the CVRP is to seek out precisely m routes, beginning and ending at the depot, such every client is visited precisely once by a vehicle and such the total of demands of the customers on every route is a smaller amount than or up to Q. The total of the edge worth employed in the m routes should be reduced. (Golden et al., 1998), (Altinel and Oncan 2005) (Toth and Tramontani 2008)

1.2.2 Multiple Depot VRP (MDVRP)

In Multiple Depot VRP (MDVRP) there is company with fixed number of vehicles and has multiple depots. There are different approaches to solve this problem. First one is to assign some concrete customers to each depot, and to solve VRP individually for each depot with its customers. It is feasible if geographically assigned customer demand can be served exclusively with only one depot. But there is also case when planner can distribute customers demand with different depots if they are located reasonably close to each other geographically. In this case algorithms should distribute equally demands and objective to minimize total cost of transportation. (Hadjiconstantinou et al., 1998)

1.2.3 Periodic VRP (PVRP)

Main difference between standard VRP and Periodic VRP is that, in classic VRP schedule and all calculations are made for only one working day while in PVRP palling is done for undefined number of days. A solution is feasible if all constraints of VRP are satisfied. However, a specific vehicle or number of vehicles may not return to the depot in the same day from its departure. Over some undefined period, of course taking into account that individual customer must be visited at least once. (Christofides et al., 1984) (Potvin and Rousseau 1993) (Vidal et al., 2012)

1.2.4 Split Delivery VRP (SDVRP)

SDVRP is type of VPR where each customer is served by different vehicles. Main difference from classic VRP is allowance of vehicles to visit each other’s POIs, if total cost is reduced and if customers demand is as equal or more then the capacity of company’s standard vehicle. A solution is feasible if all constraints of VRP are satisfied excepting allowance of multiple different vehicles to deliver goods to individual customer. (Dror et al., 1994)

1.2.5 Stochastic VRP (SVRP)

Stochastic VRP is one of the most realistic and close to real-life situation (Bertsimas et al., 1997). Stochastics VRP means that one or more variables are completely random. It means that for every day scheduling planner should consider that customers, demand and service times are completely random and stochastic. In fact, it splits problem on two. Firstly, planner should determine all variables and then after getting information it should make standard calculations of VRP.

1.2.6 VRP with Backhauls

The Vehicle Routing Problem with Backhauls (VRPB) is a type of VRP where each individual customer can demand return goods to a depot. Main constrain here is that vehicle capacity should be considered and fact of that the vehicles have rear load also rearranging of goods also leads to additional costs. Solution is feasible if set of routes is found that satisfy the demand and backhauls. While saving total cost.

1.2.7 VRP with Time Windows (VRPTW)

The VRPTW is VRP where additional constrain is added such as time windows. In our paper we consider this constrain along with others. Main problem is to set routes and timing not to violate lower or upper bounds of time windows, while minimizing cost of transportation including waiting time of vehicles because each customer has specific individual time windows. The solution is feasible if all of the constrains are considered. Heuristics for solving was proposed by (Braysy et al., 2005) If customer is served with violation of lower or upper bounds solution becomes unfeasible. Also planning should be done that way, that vehicles minimize waiting time because additional waiting time adds additional cost to total transportation cost.

1.2.8 VRP with Satellite Facilities

An important side of the vehicle routing problem (VRP) that has been for the most part unnoted is that the use of satellite facilities to fill up vehicles throughout a route. once attainable, satellite replenishment permits the drivers to continue making deliveries till the end of their shift while not having to returning to the central depot. this example arises primarily within the distribution of fuels and bound retail items. once demand is random, optimizing client routes a priori could lead to important extra costs for a selected realization of demand. Satellite facilities are a method of safeguarding against sudden demand.

1.3 Traveling Salesman Problem

VRP itself is based on The traveling salesman problem (TSP) which is one of the most intensively studied problems in computational mathematics. TSP main problem to be solved as follows : "*Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?* "

The traveling salesman problem (TSP) is one among the simplest to understand however anyway NP-hard routing problem. The TSP aims to decrease total distances traveled by salesman.
The traveling salesman problem occupies a special place in combinatorial optimization and operations research. Historically, it was one of those tasks that served as an impetus for the development of these areas. The simplicity of the formulation, the finiteness of the set of admissible solutions, the clarity and at the same time the colossal costs of a complete search are still pushing mathematicians to develop new and new numerical methods. In fact, all fresh ideas

are first tested on this task. From the point of view of applications, it is not of interest. Much more important is its generalization for the tasks of transporting goods and logistics, when several vehicles of limited carrying capacity should serve customers by visiting them at specified time windows.

In the classical task of the traveling salesman, all the details of real applications are absent. Only the combinatorial essence is left, a purely mathematical problem that has not been managed for half a century. It is this well-known problem that is devoted to this chapter.2. It includes all the possible routes which cover every city possible on the route.

The TSP is divided in two types as symmetric travelling salesman problem (sTSP), (Gendreau et al., 2005)

and multi travelling salesman problem (mTSP). This section presents description concerning these 2 wide studied TSP.

sTSP: V = { V_1,......, V_n} is a list of cities, A = {(r,s) :r,s ∈V} is list of nodes, and

d_{rs}= d_{sr} is a price attached to a node (r, s)∈ A.

Goal of the sTSP is to look up for the shortest closed tour while visiting each city once. In this case cities v_i∈ V are shown by their geographic coordinates (x_i, y_i) and $d_{rs}$is an Euclidean interval from r to s in this case it is an Euclidean TSP.

aTSP: If d_{rs}≠ d_{sr}be for at least one (r, s) after this the ordinary TSP becomes an asymmetric one.

mTSP: The mTSP is outlined as: during a set of cities, we assume that there are m salesmen settled at a single depot node. The left cities that are not yet visited are in-between cities. After the changes, the mTSP is about looking up for tours for every m salesmen, that all start and end their journeys at the same depot, specified every in-between city is visited exactly once and therefore the end cost of visiting all nodes is decreased. the price metric may be outlined in terms of distance, time, etc.

Possible variations of the problem comes, as follows: Single vs. multiple depots: within the single depot, all salesmen end their tours at one point whereas in multiple depots the salesmen

can either come back to their initial depot or will come back to any depot keeping the initial range of salesmen at every depot remains identical after the travel.

Number of salesmen: the quantity of salesmen within the problem are often fixed or a delimited variable. Cost: once the quantity of salesmen isn't fixed, then every salesperson typically has an associated fixed costs acquisition whenever this salesperson is employed. during this case, the minimizing the wants of salesperson conjointly becomes an objective.

Timeframe: Here, some nodes ought to be visited in a very specific time periods, that is known as time windows, that is an extension of the mTSP, and referred as multiple traveling salesman problem with specified Timewindow (mTSPTW).

The application of mTSPTW are often fine seen within the aircraft planning issues. Other constraints: Constraints are often on the quantity of nodes every salesperson will visits, maximum or minimum distance a salesperson travels or the other constraints. The mTSP is usually treated as a relaxed vehicle routing issues (VRP) wherever there's no restrictions on capacity. Hence, the formulations and resolution ways for the VRP are equally valid and true for the mTSP if an outsized capacity is assigned to the salesmen (or vehicles). However, once there's one salesperson, then the mTSP reduces to the TSP.).

Connections with the VRP: mTSP can be utilized in solving several types of VRPs. discuss several algorithms for VRP, and present a heuristic method which searches over a solution space formed by the mTSP.

In a similar context, the mTSP are often used to calculate the minimum range of vehicles needed to serve a group of consumers in a very distance-constrained VRP. The mTSP additionally seems to be a primary stage drawback during a two-stage answer procedure of a VRP with probabilistic service times. Scientists mentioned that the VRP instances arising in apply ar terribly laborious to resolve, since the mTSP is additionally too complicated. This raises the requirement to expeditiously solve the mTSP so as to attack large-scale VRPs.

The mTSP is additionally associated with the pickup and delivery problem (PDP). The PDP consists of deciding the optimum routes for a group of vehicles to meet the client requests If the purchasers are to be served at intervals specific time intervals, then the matter becomes the PDP with time windows (PDPTW). The PDPTW reduces to the mTSPTW if the origin and destination points of every request coincide.

Exact algorithms for the sTSP once (Dantzig et al., 1954) formulation was initially introduced, the simplex technique was in its infancy and no algorithms were out there to resolve number linear programs. The practitioners thus used a technique consisting of at first reposeful constraints and therefore the integrality needs, that were bit by bit reintroduced when visually examining the answer to the relaxed problem. (Martin, 1966) used an analogous approach. at first he didn't impose higher bounds on the X_{ij}variables and obligatory subtour elimination constraints on all sets S= {i, j } for which j is that the nearest neighbour of i . Integrality was reached by applying the 'Accelerated Euclidean algorithm',an extension of the 'Method of integer forms' (Gomory, 1963). (Miliotis, 1976, 1978) was the primary to plot a completely machine-driven algorithmic program supported constraint relaxation and using either branch-and-bound or Gomory cuts to achieve integrality. (Land, 1979) later puts forward a cut-and-price algorithmic program combining subtour elimination constraints, Gomory cuts and column generation, however no branching. This algorithm was capable of finding 9 Euclidean 100-vertex instances out of 10. it's long been recognized that the linear relaxation of sTSP is strong through the introduction of valid inequalities.

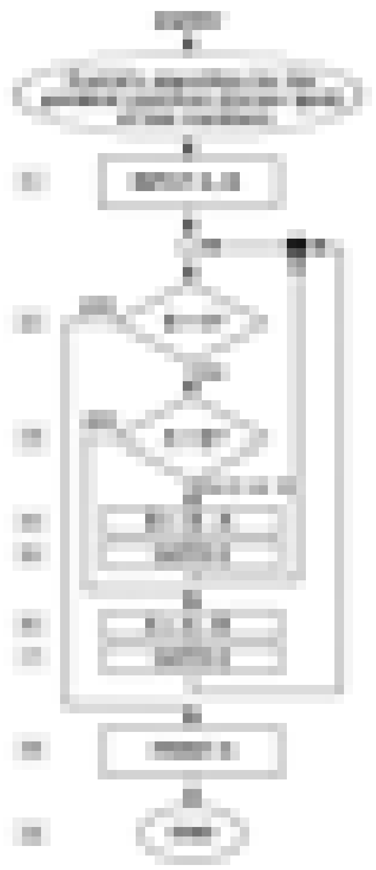


Figure 2 Flow Chart

(Flow chart of an algorithm ('Accelerated Euclidean algorithm') for calculating the greatest common divisor (g.c.d.) of two numbers a and b in locations named A)

Some generalizations of comb inequalities, like clique tree inequalities and path inequalities end up to be quite effective. Many alternative less powerful valid inequalities are represented in (Polyhedral theory and branch-and-cut algorithms for the symmetrical TSP by Naddef, D.). within the Nineteen Eighties variety of researchers have integrated these cuts among relaxation mechanisms and have devised algorithms for their separation. This work, that has fostered the expansion of solid theory and of branch-and-cut. The biggest instance solved by the latter authors was a drilling problem of size n =2392. The end result of this line of analysis is that the development of Concorde by (Applegate et al., 2003, 2006), that is nowadays the most effective out there problem solver for the symmetrical TSP. it's freely obtainable at www.tsp.gatech.edu. This application relies on branch-and-cut-and-price, which means that each some constraints and variables are at first relaxed and dynamically generated throughout the solution method. The rule uses 2-matching constraints, comb inequalities and bound path inequalities. It makes use of subtle separation algorithms to spot violated inequalities.

An interesting feature of aTSP is that relaxing the subtour elimination constraints yields a assignment problem called Modified Assignment Problem (MAP) (Eberhart et al.,1991). By means of aspecialized assignment algorithm the linear relaxation of this problem always has an integer solution and is easy to solve.

Solving the mTSP straightforwardly, without any changing to the initial TSP was initially done by (Laporte & Nobert, 1980), who proposed technique to resolve algorithm based on the relaxation of some constraints of the Multi traveling Salesman Problem. The issue that was considered is an mTSP with a fixed cost f associated with each salesman.

The algorithm consists of solving the problem by initially relaxing the SECs (subtour elimination constraints) and performing a check as to whether any of the SECs are violated, after an integer solution is obtained. The proposed algorithm is a branch-and-bound method, where lower bounds are received from the following Lagrang problem built by relaxing the degree constraints.

With applying a degree constrained minimal spanning tree that spans over all the nodes the Lagrangean problem is solved. The results shows that the integer gap obtained by the Lagrangean relaxation decreases as the problem size increases and turns out to be zero for all problems with n≥400.

Another exact resolution methodology for mTSP was additionally introduced. The algorithmic program is predicated on a quasi-assignment (QA) relaxation obtained by relaxing the SECs, since the QA-problem is resolvable in polynomial time. an additive bounding procedure is applied to strengthen the lower bounds obtained via completely different r-arborescence and r-anti-arborescence relaxations and this procedure is embedded during a branch-and-bound framework. it's determined that the additive bounding procedure features a vital impact in rising the lower bounds, that the QA-relaxation yields poor bounds.
The projected branch-and-bound algorithmic program is superior to the standard branch-and-bound approach with a QA-relaxation in terms of range of nodes, starting from ten percent less to ten times less. symmetrical instances are discovered to yield larger enhancements.

There are primarily 2 ways in which of finding any TSP instance optimally. the primary is to use an exact approach like Branch and bound methodology to search out the length. the opposite is to calculate the Held-Karp lower bound, that produces a lower bound to the best optimum result. This lower bound is employed to guage the behavior of any novelty heuristic projected for the new study of TSP. The methods reviewed here primarily concern with the sTSP, but a number of these heuristics are often changed fitly to resolve the aTSP.

Solving even moderate size of the TSP optimally takes huge computational time, because of this the development of approximate algorithms techniques and applications also has its advantages. The approximate approach never an assures best results but anyway gives close to optimal solution in a less computational time. At this point most known approximation algorithm is (Arora, 1998). The complexity of the approximate algorithm is $O(n(\log_2 n)^{O(C)})$where n is problem size of TSP.

Below are described some different approaches and techniques that are used to solve TSP and its variation.

The ideas of local search have been further developed in the so-called metaheuristics, that is, in general schemes for constructing algorithms that can be applied to almost any problem of discrete optimization. All metaheuristics are iterative procedures, and for many of them the asymptotic convergence of the best solution found to global optimum. Unlike algorithms with estimates, metaheuristics are not tied to the specifics of the problem being solved. These are fairly general iterative procedures using randomization and elements of self-education, intensification and diversification of search, adaptive control mechanisms, constructive heuristics and methods of local search. To metaheuristics it is customary to include Simulation Annealing (SA), Tabu Search (TS), genetic algorithms (Genetic Algorithms (GA)), and evolutionary methods (Evolutionary Computation (EC)), as well as Variable Neighborhood Search (VNS), Ant Colony Optimization (ACO), probabilistic greedy (Greedy Randomized Adaptive Search Procedure

The idea of these methods is based on the assumption that the objective function has many local extrema, and it is impossible to view all admissible solutions, in spite of the finiteness of their number.

In such a situation it is necessary to concentrate the search in the most promising parts of the permissible region. Thus, the task is to identify such areas and quickly view them. Each meta-heuristics solves this problem in its own way. Metaheuristics is usually divided into trajectory methods, when at each iteration there is one permissible solution and the transition to the next one is carried out, and to the methods working with the solution family (population). The first group includes TS, SA, VNS. The trajectory methods leave a trajectory, a sequence of solutions in the search space, where each solution is adjacent to the previous one with respect to some neighborhood. In the methods TS, SA, the neighborhood is determined in advance and does not change during operation. The objective function along the trajectory varies nonmonotonely, which allows us to "get out" of local extrema and find all the best and best approximate solutions. Elements of self-adaptation allow changing the control parameters of algorithms using the search history. More complex methods, for example, VNS, use several neighborhoods and change them systematically for the purpose of diversification. In fact, if you change the neighborhood, the landscape changes. A conscious change in the landscape, as, for example, in the noise method (Noising method, [Charon I., Hudry H 1998]), has a beneficial effect on search results. The study of landscapes, their properties, for example, ruggedness, makes it possible to give recommendations on the choice of neighborhoods. The second group of methods includes GA, EC, ACO, etc. At each iteration of these methods a new solution of the problem is constructed, which is based not on one but on several solutions from the population. Genetic and evolutionary algorithms use crossover and targeted mutations for these purposes. In the ACO methods, another idea is used, based on the collection of statistical information about the most successful

Solutions. This information is taken into account in probabilistic greedy algorithms and prompts which decision components (edge, enterprises, elements of the technical equipment system) most often led to a small error. The methods of this group, as a rule, are based on analogies in living nature. The idea of ACO is an attempt to simulate the behavior of ants that have almost no vision and are guided by the smell, left behind, Previous predecessors. Strongly smelling substance, pheromone, is for them an indicator of the activities of predecessors.

It accumulates in itself the prehistory of the search and prompts the road to the anthill. Attempts to peek at nature ways of solving difficult combinatorial problems find new and new incarnations in numerical methods. For example, in case of infection, the body tries to select (generate, construct) the most effective protection. Observation of this process led to the birth of a new method - artificial immune systems. The study of the life of a beehive, where only one uterus leaves offspring, served as the basis for new genetic methods. However, the greatest progress is observed in the way of hybridization, for example, the construction of hyper-heuristics that automatically selects the most effective heuristics for this example and symbiosis with classical methods of mathematical programming.

• construction of exponential in powers of neighborhoods, in which the search for the best solution is carried out in polynomial time by solving an auxiliary optimization problem;

• study of crossing operators based on the exact or approximate solution of the original problem on a subset determined by the parent solutions;

• Hybridization of meta-heuristics with precise methods, for example, with branch and boundary methods and the method of dynamic programming;

• development of new, accurate methods that use the ideas of local search;

• application of different mathematical formulations of the problem being solved and use of different decision codes etc.

A review of achievements in this area can be found in [Talbi El-G. 2009]. Some of the meta-heuristics, some of which Are trajectory algorithms. Each of them has its own idea and mechanism for its implementation. Despite the fact that this chapter is devoted to the traveling salesman's problem, the reader will easily see the ways of adapting these algorithms to other tasks.

1.3.1 The closest neighbor heuristics

When the solution for the closest neighbor heuristics is found then the algorithm stops and doesn't continue to find better solutions to optimize and improve it. The optimality for this kind of approach is quite low from ten to fifteen percent. The closest neighbor heuristics is quite simple and direct. It is described below. Polynomial complexity of this kind of approach is O(n^2).

When solving easiest TSP this kind of algorithm is most suitable, it is similar to minimum spanning tree. Main idea is to always visit closest unvisited city (Gutin et al., 2002)

Figure 3 *The closest neighbor heuristics*

1.3.2 Greedy heuristic

The Greedy heuristic differs from closest neighbor heuristics by its design, it is described below. The algorithm is created by choosing most shortest edge from the available repeatedly until tour doesn’t create a cycle with no more than N edges. Held-Karp lower bound optimality is kept from 15 to 20 %. Polynomial complexity of this kind of approach is $O(n^2(\log_2(n))$. (Cormen et al., 1990)

Figure 4 *Greedy heuristic*

1.3.3 Insertion heuristic

Insertion heuristics is kind of straightforward to implement conjointly. the concept of insertion heuristics is getting down to construct routes with a set of all cities, and so inserting the remaining. The initial 1st is generally a triangle. Or beginning with an edge as a subtour. Polynomial complexity of this kind of approach is O(n^2).

[illegible]

Figure 5 Insertion heuristic

1.3.4 Christofides heuristic

Christofides heuristics can guarantee a fair near optimal solution.

Polynomial complexity of this kind of approach is O(n^3).

[illegible]

Figure 6 Christofides heuristic

1.3.5 Lin-Kernighan

The Lin-Kernighan heuristic (LK) is a variable k-way exchange heuristic.
It decides the value of suitable k at each iteration. This makes the improvement heuristic quite complex. Polynomial complexity of this kind of approach is O($n^{2.2}$). (Helsgaun et al., 2000)

[illegible]

Figure 7 Lin-Kernighan

An outline of the basic algorithm Fig 1-7 (a simplified version of the original algorithm). t –tour, G_i is the sum g_1 + g_2 + ... + g_i.
Step 1. A random tour is defined as the initial point of the explorations.
Step 3. Chosing link x_1 = (t_1, t_2) on the route. After t_1 is chosen, there are 2 variants for x_1. Anyway, every time an advancement of route is found (in other cases are treated as untried).

Step 6. There are 2 variants of x_i. Anyway, for y_{i-1} (i 2) only 1of them closes the tour (by the adding of y_i). he other alternative ends up as 2 unconnected subtours. Only is one case, however, this kind of an not feasible alternative is admited, namely for i = 2

1.3.6 Tabu search

It is a neighborhood-search algorithmic rule that search the higher result within the neighborhood of the present result. In general, tabu search (TS) uses 2-opt exchange mechanism for searching higher resolution. an issue with easy neighborhood search approach i.e. only 2- opt or 3-opt exchange heuristic is that these will simply mire in an exceedingly local optimum. This can be avoided simply in TS approach. To avoid this TS keeps a tabu list containing unfeasible results with unfeasible exchange. There are many types of implementing the tabu list. The largest issue with the TS is its running time. Most implementations for the TSP typically takes O(n^3), creating it so much slower than a 2-opt native search. (Glover 1986)

1.3.7 Simulated annealing

Simulated annealing (SA) has been with success applied and custom-made to offer an approximate solutions for the TSP. SA is largely a randomised native search algorithmic rule the same as TS however don't permit path exchange that deteriorates the answer. (Johnson &McGeoch, 1995) given a baseline implementation of SA for the TSP. Authors used 2-opt moves to search out neighboring solutions. In SA, higher results will be obtained by increasing the time period of the SA algorithmic rule, and it's found that the results are equivalent to the LK algorithmic rule. because of the 2-opt neighborhood, this specific implementation takes O(n^2) with an oversized constant of proportion (Khachaturyan et al., 1979) (Granville et al., 1994)

1.3.8 Ant colony optimization

In recent years, the scientific direction with the name "Natural Computing" has been intensively developing, combining mathematical methods in which the principles of natural decision-making mechanisms are laid. These mechanisms ensure the effective adaptation of flora and fauna to the environment for several million years.

Simulation of self-organization of the ant colony forms the basis of ant optimization algorithms.

The colony of ants can be considered as a multi-agent system in which each agent (ant) functions autonomously according to very simple rules. In contrast to the almost primitive behavior of agents, the behavior of the entire system is surprisingly reasonable.

Ant algorithms have been seriously investigated by European scientists since the mid-1990s. To date, good results have already been obtained for the optimization of such complex combinatorial problems as the TSP, the VRP, the task of coloring the graph, the quadratic assignment task, the task of optimizing network schedules, the task of scheduling, and many others.

Especially effective are the ant algorithms for dynamic optimization of processes in distributed non-stationary systems, for example, traffic in telecommunication networks.

Ant algorithms are probabilistic greedy heuristics, where probabilities are established based on information about the quality of the solution obtained from previous solutions. They can be used for both static and dynamic combinatorial optimization tasks.
Convergence is guaranteed, that is, in any case we will get the optimal solution, however, the rate of convergence is unknown.

Researchers are usually making an attempt to mimic nature to unravel complicated issues, and one such example is that the made use of GA. Another attention-grabbing innovation is to mimic the movements of ants. this concept has been quite productive once applied to the TSP, giving best solutions to tiny issues quickly (Dorigo &; Gambardella, 1996). However, as tiny as an ant's brain could be, it's still way too complicated to simulate utterly. However we have a tendency to only want a little part of their behaviour for determination the problem. Ants leave a path of pheromones once they explore new areas. This path is supposed to guide different ants to potential food sources. The key to the success of ants is strength in numbers, and therefore the same goes for ant colony optimisation.
We begin with a bunch of ants, usually twenty approximately. they're placed in random cities, and are then asked to maneuver to a different town. They're not allowed to enter a town already visited by themselves, unless they're heading for the completion of our tour. The ant which picked the shortest tour Will leave a path of pheromones inversely proportional to the length of the tour. This secretion path is taken in account once an ant is selecting a town to maneuver to, making it a lot of liable to walk the path with the strongest secretion trail. This method is continual till a tour being short enough is found.

1.4 Algorithms

1.4.1 Genetic algorithms for VRP

The development of natural systems for many centuries attracted attention of scientists. Repeated attempts have been made to identify and comprehend the fundamental principles and mechanisms underlying the changes occurring in living nature. Many different concepts were proposed, until in 1858 Charles Darwin published his famous work “The Origin of Species”, in which the principles of heredity, variability and natural selection were proclaimed. However, for almost 100 subsequent years, the mechanisms responsible for heredity and variability of organisms remained unclear. In 1944, Avery, MacLeod and McCarthy published the results of their studies, which proved that hereditary processes are responsible for "acid of the deoxyribose type". This discovery served as the impetus for numerous studies around the world

The idea of genetic algorithms was proposed by John Holland in the 60's, and the results of the first studies are summarized in his study "Adaptation in natural and artificial systems" [Holland, 1975], as well as in the thesis of his graduate student Kenneth De Jong [De Jong, 1975]. As already mentioned above, the GA use evolutionary principles of heredity, variability and natural selection.

Genetic algorithm (GA) works in an exceedingly method the same as our environment. A basic GA starts with a randomly generated population of candidate solutions. Some (or all) candidates are then mated to provide offspring and a few undergo a mutating method. every candidate features a fitness worth telling researcher however featable they're. By choosing the foremost match candidates for coupling and mutation the general fitness of the population can increase. Applying GA to the TSP involves implementing a crossover routine, a measure of fitness, and additionally a mutation routine. a decent measure of fitness is that the actual length of the result. completely different approaches to the crossover and mutation routines are mentioned in (Johnson &; McGeoch, 1995)

The difficult strategy within the field of supply chain management and supply industry is to optimize the product supply from shipper to consignee therefore satisfying constraints. Such issues are called VRP, during which, the cars leave the depot, supply and serve clients appointed and after completion of their routes come back to the start point (depot). every client is identified by its own order demand.

Since the problem is said with just one depot, the VRP is additionally named Single-depot VRP. In cases with over one depot, VRPs are called multi-depot VRPs (MDVRP). Single-depot VRPs aren't appropriate for sensible things although they have attracted researchers in a very wide sense. In MDVRP, since there is a big number of depots, it's a troublesome task for decision makers to see that customers are supplied by that depots while not exceeding the capacity constraints. Thence grouping is performed to cluster customers supported on distance between the customers and therefore the depots, before the routing and planning phases. Moreover, since MDVRPs area unit NP hard, precise ways aren't appropriate to get optimum solutions. therefore heuristic algorithms are adopted to resolve the MDVRPs at a quicker rate therefore providing computationally economical solutions. the target of the problem is aimed toward minimizing the entire price of combined routes for a fleet of vehicles. Since price is mostly based on distance traveled, in general, the goal is to attenuate the distance traveled by applying the bio-inspired Genetic algorithm (GA).

Genetic Algorithms (GA) is predicated on a parallel search mechanism, that makes it significantly more efficient than different classical optimisation techniques like branch & bound, tabu search technique also simulated annealing. the essential plan of GA comes as follows to control selected individuals from their population beneath selective pressure. The GA will avoid obtaining cornered in a very native optimum by standardization the genetic operators, crossover and mutation. thanks to its high potential for global optimisation, GA has received quite an attention in solving MDVRPs. GA imitates the mechanism of natural selection and therefore the survival of the fittest as witnessed in natural evolution.

The most common form of GA works next way: a population is formed with a bunch of characters created arbitrarily. The individuals from the population after that are evaluated. The analysis function is provided by the software engineer and provides the individuals a score supported however well they perform at the given task. 2 characters are then elected supported on their fitness, the upper the fitness, the upper an opportunity of being chosen. These characters then "reproduce" to form one or additional offspring, once that the offspring are mutated at random. This continues till an acceptable answer has been found or a definite range of generations have passed, reckoning on the requirements of the scientist.

The GA algorithm

1. Select the initial population.

2. Repeat until the stop criterion is fulfilled.

2.1. Select parents s_1 , $s_2$from the population.

2.2. Construct a new solution s' by solutions s_1 , s_2,.

2.3. Modify s'.

2.4. Update the population.

3. Provide the best solution in the population.

Let us dwell in more detail on the main operators of this algorithm: selection, crossing and mutation. Among the selection operators, the most common are the two probabilistic operators: proportional and tournament selection. With proportional selection, the probability of choosing a solution as one of the parents depends on the quality of the solution: the smaller the value of the objective function, the higher the probability, and the sum of the probabilities is 1. In tournament selection, a random subset of the population elements is formed, and among them one element with The least value of the objective function. Tournament selection has certain advantages. It does not lose its selectivity, when in the course of evolution all elements of the population become approximately equal in value to the objective function. The selection operators are constructed in such a way that, with a non-zero probability, any element of the population could be selected as one of the parents. Moreover, a situation where both parents are represented by the same element of the population is allowed.

Returning to the VNS algorithm, it seems reasonable to take as one of the parents the best element of the population.

Once the two solutions are selected, the probabilistic crossover operator is applied to them. There are many different versions of this operator, among which the simplest, apparently, is a homogeneous operator. On parent solutions, he builds a new solution, assigning to each coordinate of this vector with probability 0.5 the corresponding value of one of the parents. If the parent vectors are the same, say, the first coordinate, then the new vector "inherits" this value. Geometrically, for boolean vectors, the crossing operator randomly selects the vertex s' in the hypercube, which belongs to the minimal face containing the vertices s_1 , s_2,.

You can say that the crossing operator is trying to choose a new solution somewhere between the parents, relying on luck. A more accurate procedure might look like this. The new solution is chosen as the optimal solution of the original problem on the corresponding face of the hypercube. If the distance between s_1 , s_2, is sufficiently large, then the problem of optimal crossing may coincide with the original one. Nevertheless, even an approximate solution of this problem instead of random selection significantly improves the work of the genetic algorithm.

The mutation operator with a given probability $p_m$changes the value of each coordinate by the opposite. For example, the probability that the vector (0,0,0,0,0) during the mutation will go into the vector (1,1,1,0,0) is equal to $p_m p_m p_m(1 - p_m)(1 - p_m)> 0$. Thus, with a nonzero probability, the new solution s' can go into any other solution, which explains the asymptotic properties of the algorithm. Note that the modification of the solution s' can consist not only of a random mutation, but also of a partial reconstruction of the solution by local search algorithms. The use of local improvement allows the genetic algorithm to focus only on local optima. The set of local optima can turn out to be exponentially large, and at first glance such an algorithm variant will not have advantages. However, experimental studies of the distribution of local optima indicate a high concentration of these in the immediate vicinity of the global optimum. This observation partly explains the efficiency of genetic algorithms. If local optimums are accumulated in a population that are concentrated in one place and another solution s' is selected somewhere between two arbitrary local optima, then such a process has many chances to find a global optimum.

1.4.2 Cross entropy in VRP

Optimization is needed for many daily problems. Many operations require to solve hard optimization problems also called combinatorial optimization problems (COP). The TSP, max-cut and quadratic assignment problems are examples of such COP.

CE (cross entropy) method can be referred as a model based search algorithm and it is quite a simple, efficient and decent way for solving and studying difficult kinds of COPs. (Boer et al. 2005) CE method has two phases of application. Firstly it is generating some random data (needed for research such as routes, nodes & etc.) Than changes the specification of stochastic mechanism according to information and resulting more optimal pattern in following iterations.

Created on simulation theory the CE technique is showing good results defining exact mathematical frameworks that derive fast and optimum rules. It is also easy to implement for researcher such an approach already was applied for numerous optimization problems.

In case of VRP stochastic optimization is best resolved by CE based algorithms. For using CE technique for VRP this problem has to be split to rare event estimation problem. After translating the initial VRP into stochastic estimation problem and later applying the rare event simulation machinery. (de Boer et al., 2005)

1.4.3 Branch and Bound algorithm

Vast variety of designing and programing, referred to as combinatorial optimisation issues, are simple to state however typically have giant potential solutions. just in case of VRPTW polynomial algorithms share the properties that no polynomial technique for his or her result is understood like in Minimum Spanning Tree and Short Path issues. (Bard et al.,1995)

Branch and bound (B&B) methodology is today one amongst most generally used approach for determination large scale NP hard issues in combinatorial optimisation. Implementation of bounds for the perform to be optimized combined with the worth of the present best result allows the algorithm to look elements of the answer area solely implicitly. At any purpose while the solution method, the standing of the solution with reference to the search of the solution area is represented by a pool of however undiscovered set of this and also the best solution found to date. At first only 1 set exists, particularly the whole solution area, and therefore the best answer found up to now is ∞. The undiscovered subspaces are portrayed as nodes during a dynamically generated search tree, that at the start solely contains the basis, and every iteration of a classical B&B algorithm processes one such node. The iteration has 3 main components: choice of the node to process, bound calculation, and branching.

B&B methodology relies on 2 main principles. Firstly, branching is splitting search area to lesser areas. Then it eliminates unfeasible solutions by bounds that are cutting the search area. Branch creates 2 or more instances which represent whole subset. Bound computes lower bounds of values of solutions in instance area. Solution checks if instance is a single candidate solution. (Katta et al., 1963)

1.4.4 Evolution Algorithms

In 2000, Professor Toshiyuki Nakagaki, a biologist and physicist from the Japanese University of Hokkaido, took a sample of the yellow mold of the fungus Physarum polycephalum and laid it at the entrance to the labyrinth, which is used to test the intellect and memory of mice. At the other end of the labyrinth, he placed a cube of sugar. Physarum polycephalum felt like a smell of sugar and began to send his sprouts to his search. The mushroom's sprouts split at each intersection of the labyrinth, and those that fell into a dead end unfolded and began to move in other directions. For several hours, the mushroom sprouts filled the labyrinth passages, and by the end of the day one of them found the way to sugar.

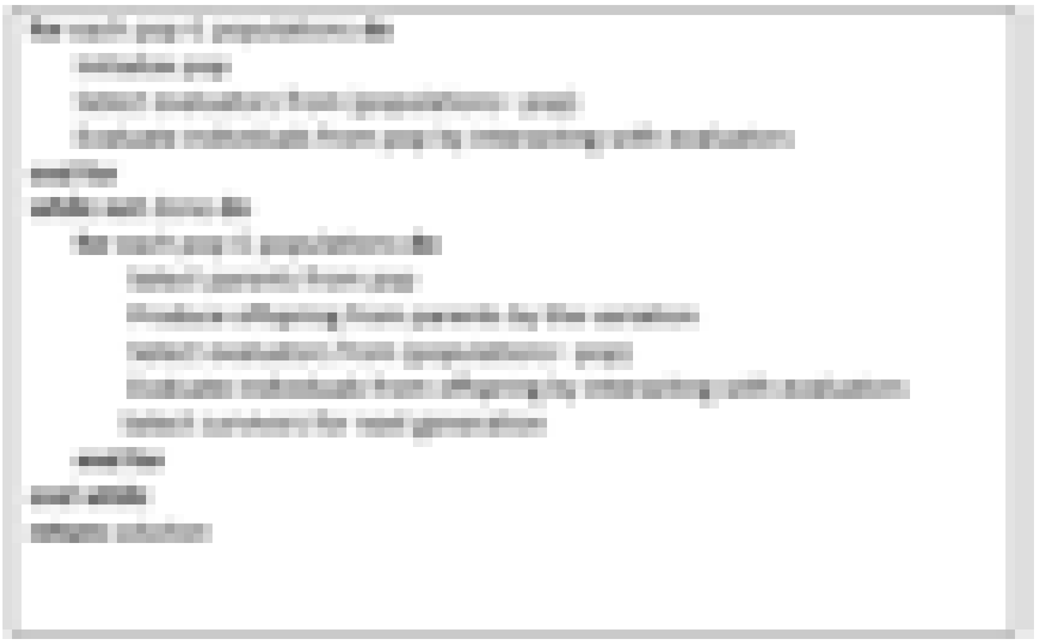
After this, Toshiyuki and a group of his researchers took a piece of spider web of the fungus that participated in the first experiment, and placed it at the entrance of a copy of the same labyrinth, also with a sugar cube on the other end. What happened struck everyone. The web broke into two: one process paved its way to the sugar, without a single superfluous turn, the other - scrambled along the wall of the labyrinth and crossed it directly, on the ceiling, directly to the target. The mushroom spider web not only remembered the road, but also changed the rules of the game. Further studies Toshiyuki found that mushrooms can plan transport routes no worse and much faster than professional engineers.

Toshiyuki took a map of Japan and placed pieces of food in places corresponding to the major cities of the country. He put the mushrooms "in Tokyo." After 23 hours they built a web of cobwebs to all the pieces of food. As a result, almost an exact copy of the railway network in the vicinity of Tokyo. This experiment helped scientists to understand principles of effective planning and for further development of Evolutionary algorithms (EAs).

Evolutionary algorithms are a class of nonlinear random optimization principle. Main Evolutionary algorithm principle is based on our nature itself. These types of algorithms tend to imitate main idea of evolution, survival of the fittest. EA is a consequence of computational approaches to adopt nature laws and evolution to solve difficult optimization problems. Such kind of approach is used in many spheres mainly for the optimization problem and the learning problem. For optimization, finding the optimal solution within the problem area. Optimization problems and learning problems are interconnected with each other. In evolutionary algorithms every individual from the whole population is a potential solution for the problem given. For the problems that are too difficult to be calculated and optimized, for that purpose the learning algorithm could be used to do fitness approximation. Original Evolutionary algorithms, which contain genetic algorithms, evolution strategy, evolutionary programming, and genetic programming are all stochastic solution searching algorithms. EAs are well adapted in many hard engineering problems. EAs strategy is applied to large and complex problems using a “divide-and-conquer” strategy.

Figure 8 pseudo code for evolutionary algorithm approach

A significant difference between the application of an evolutionary algorithm and a co-evolutionary algorithm has to be considered. An evolutionary algorithm would lead to a system optimum, as optimization is applied with a global (or population) fitness function. Instead, the co-evolutionary algorithm leads to a (stochastic) user equilibrium, as optimization is performed in terms of individual scoring functions and within an agent’s set of plans.



```
for each pop ∈ populations do
    initialize pop
    select evaluators from (populations - pop)
    Evaluate individuals from pop by interacting with evaluators
end for
while not done do
    for each pop ∈ populations do
        select parents from pop
        Produce offspring from parents by the variation
        Select evaluators from (populations - pop)
        Evaluate individuals from offspring by interacting with evaluators
        select survivors for next generation
    end for
end while
return solution
```

Figure 9 pseudo code for co-evolutionary algorithm

1.4.5 Adaptive large neighborhood search

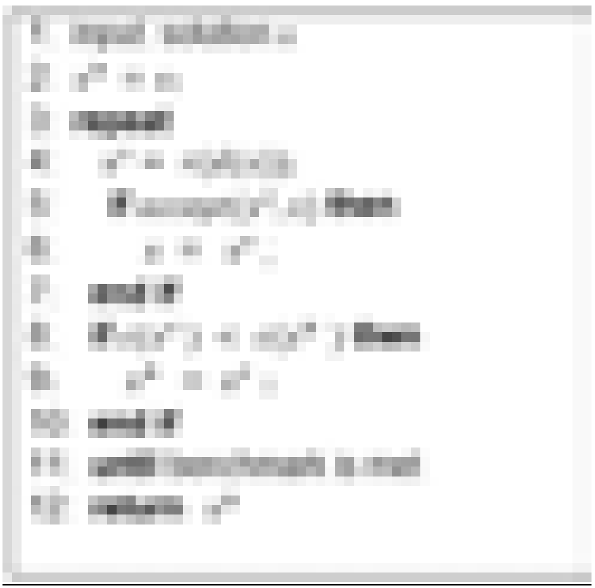
The ideas of local search for solving problems of discrete optimization are, apparently, the most natural and visual. The first steps of their implementation date back to the early 1950s and early 1960s. They are mainly connected with the traveling salesman's problem. Later, these ideas were used for placement, networking, scheduling, etc. However, it quickly turned out that local improvement methods do not guarantee the existence of a global optimum, and the lack of conceptual progress weakened interest in this direction. In the last 20 years, a revival of this approach has been observed. It is connected both with new algorithmic schemes based on analogies with living and inanimate nature, and with new theoretical results in the field of local search. The general view on the construction of local algorithms has changed. The requirement of monotonic improvement in the objective function is no longer dominant.

The most powerful algorithms allow arbitrary degradation, and many of them can be considered as a way of generating finite indecomposable Markov chains on a suitable set of states. This section provides a brief introduction to this rapidly developing field of discrete optimization.

Heuristics supported large neighborhood search have recently shown outstanding results in finding numerous transportation and planning issues. Large neighborhood search techniques explore a big neighborhood by use of heuristics. Using large neighborhoods makes it doable to search out higher candidate solutions in every iteration and therefore traverse a better search path. Ranging from the large neighborhood search technique, we tend to provide an outline of very large scale neighborhood search strategies and discuss recent variants and extensions like variable depth search and adaptive large neighborhood search.

The topic of this chapter is that the metaheuristic Large Neighborhood Search (LNS) projected by Shaw in 1998. In LNS, An initial answer is step by step improved by alternately destroying and repairing the solution. The LNS heuristic belongs to the category of heuristics referred to as very large Scale Neighborhood search (VLSN) algorithms. All VLSN algorithms are created on the observation that looking out a large neighborhood leads to finding local optima of best, and therefore overall a VLSN method could result more suitable solutions. However, searching a large neighborhood is time intense, therefore numerous filtering techniques are used to limit the search. In VLSN algorithms, the neighborhood is usually restricted to a set of the solutions which might be searched expeditiously. In LNS the neighborhood is implicitly outlined by ways (often heuristics) that are accustomed destroy and repair an incumbent answer. The 2 similar terms LNS and VLSN might cause confusion. We tend to systematically use VLSN for the broad category of algorithms that searches very large neighborhoods and LNS for the actual metaheuristic, belonging to the category of VLSN algorithms. Heuristics for solving pick up and delivery problem was introduced by (Masson et al.,2011) (Kritzinger et al., 2015) (P´eton et al., 2014)

<u>Algorithm 1 Large neighborhood search</u>

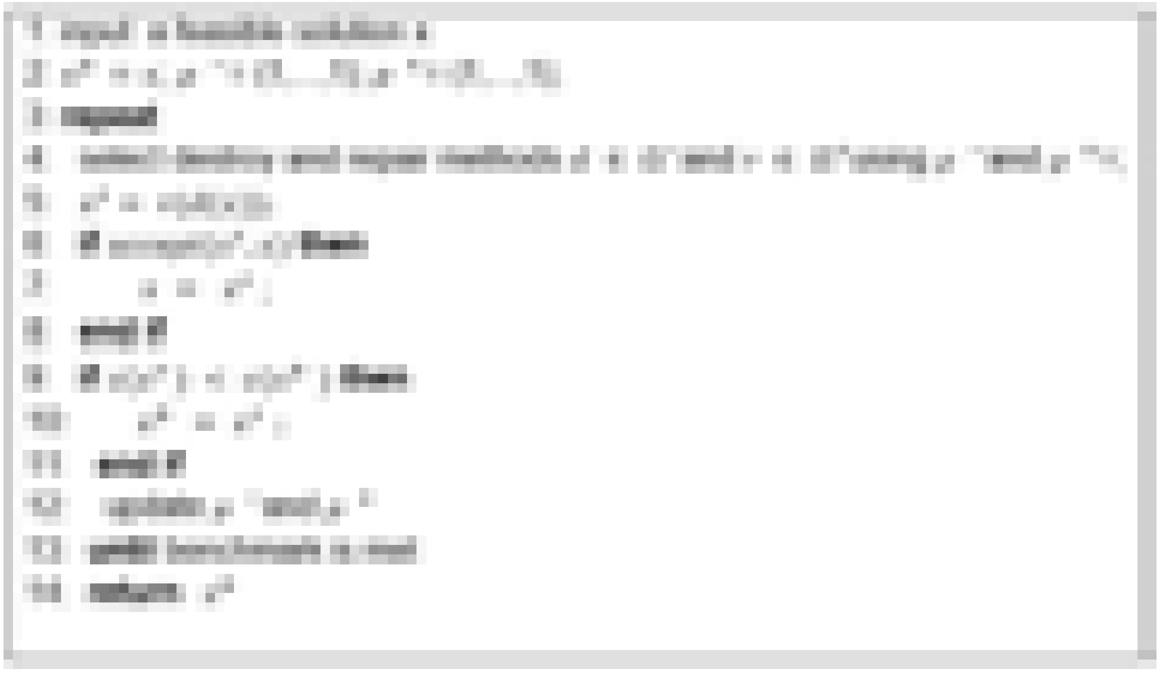


```
input: solution $x$
$x^b = x$;
repeat
    $x^t = r(d(x))$;
    if accept($x^t$, $x$) then
        $x = x^t$;
    end if
    if $c(x^t) < c(x^b)$ then
        $x^b = x^t$;
    end if
until [illegible]
return $x^b$
```

Figure 10 Large neighborhood search

There are 3 variables that are upholded by the algorithm. The x^b means most suitable solution seen while the search, x is the up to now solution and x^t means that it is a momentary solution that can be canceled or changed to the status of current solution. The function $d(\cdot)$ is the destroy method while $r(\cdot)$ is the repair method. More specifically, $d(x)$ returns a copy of x that is partly destroyed. Applying $r(\cdot)$ to a partly destroyed result fixes the solution, after it comes with a feasible answer built from the destroyed one. Line two shows if the global optimal result is initialized. In fourth line the heuristic initially uses the destruction method and then the repair method to gain a new solution x^t . In the line five the new result is checked, and the heuristic decides if this particular solution should become the new current solution (line 6) or whether it should be rejected. The acceptation F(x) can be use in various ways. The easiest way is to only accept improving calculations. Line eight is checking if the current solution is more feasible than the known solution. Here $c(x)$ denotes the objective value of solution x. The optimal solution is changed in line 9 if needed. In line 11 is checked if the benchmark is met. Researcher has to choose the benchmark criterion, but a limit on the number of iterations or a time limit would be typical choices. In line 12 the best solution found is returned. From the pseudocode it can be noticed that the LNS metaheuristic does not search the entire neighborhood of a solution, but just examines given neighborhood.

Algorithm 2 Adaptive large neighborhood search



```
1  input: a feasible solution x
2  $x^b = x$; $\rho^- = (1, ..., 1)$; $\rho^+ = (1, ..., 1)$;
3  repeat
4    select destroy and repair methods $d \in \Omega^-$ and $r \in \Omega^+$ using $\rho^-$ and $\rho^+$;
5    $x^t = r(d(x))$;
6    if accept($x^t$, x) then
7          $x = x^t$;
8    end if
9    if $c(x^t) < c(x^b)$ then
10         $x^b = x^t$;
11   end if
12   update $\rho^-$ and $\rho^+$;
13 until benchmark is met
14 return $x^b$
```

Figure 11 Adaptive large neighborhood search

Pseudo codes for ALNS and LNS heuristics differ. Comparing to the algorithm shown Algorithm 1, Algorithm has had following changes in Pseudo code. There have been lines four and twelve added and as for line two it has been slightly changed. Two sets of destroy and repair methods are marked as $\Omega-$ and $\Omega+$, respectively. 2 new variables are added in line two: $\rho^{-} \in \mathbb{R}^{|\Omega-|}$ and $\rho^{+} \in \mathbb{R}^{|\Omega+|}$, to store the cost of both destroy and repair method, respectively. At the beginning all methods have the same weight. In line four the weight vectors (David Pisinger and Stefan Ropke 2010) $\rho-$ and $\rho+$ are used to select the $\Omega-$ and $\Omega+$, methods using a spin wheel principle. The algorithm calculates probability φ_j^- of choosing the j^{th} destroying method as follows

$$\varphi_j^- = \frac{\rho_j^-}{\sum_{k=1}^{|\Omega-|} \rho_k^-}$$

and the chances for selecting the repair methods are determined in the identical principle.

The weights are changed dynamically, based on the recorded performance of each $\Omega-$ and $\Omega+$, method. This is shown in line twelve: after an iteration of the ALNS heuristic is done, a score ψ for the $\Omega-$ and $\Omega+$, used in the steps is computed using the formula

$$\psi = \max \begin{cases} \omega 1 \text{ if the new solution is a new global best,} \\ \omega 2 \text{ if the new solution is better than the current one,} \\ \omega 3 \text{ if the new solution is accepted,} \\ \omega 4 \text{ if the new solution is rejected,} \end{cases}$$

(1)

where $\omega1, \omega2, \omega3$ and $\omega4$ are parameters. A high ψ value means that method is a successful. Normally there are $\omega1 \geq \omega2 \geq \omega3 \geq \omega4 \geq 0$. Let a and b be the pointers of the $\Omega-$ and $\Omega+$, methods that were used in the last steps of the algorithm, respectively. The components corresponding to the selected $\Omega-$ and $\Omega+$, methods in the $\rho-$ and $\rho+$ vectors are updated using the equations

$$\rho_a^- = \lambda \rho_a^- + (1-\lambda)\psi, \quad \rho_b^+ = \lambda \rho_b^+ + (1-\lambda)\psi,$$

(2)

where $\lambda \in [0,1]$ is the decay parameter that is controlling how sensitive the weights are to changes in the performance of the destroy and repair methods. Note that the weights that are not used at the current iteration remain unchanged. The aim of the adaptive weight adjustment is to select weights that work well for the instance being solved. We encourage heuristics that bring the search forward, these are the ones rewarded with the $\omega 1, \omega 2$ and $\omega 3$ parameters in (1). We discourage heuristics that lead to many rejected solutions as an iteration resulting in a rejected solution is a wasted iteration, roughly speaking. This is achieved by assigning a low value to $\omega 4$.

The ALNS heuristic represented up to now is vulnerable to favor complicated repair strategies that more typically reach highly feasible solutions compared to less complicated repair methods. this is often fine if the complicated and straightforward repair strategies are equally lengthy, however that will not be the case. If some strategies are considerably slower than others, one might normalize the score ψ of a way with a measure of the time consumption of the corresponding heuristic. This ensures a correct trade-off between time consumption and resolution quality

One of the key benefits of the LNS heuristic is that a heuristic can be quickly put together from existing components: an existing construction heuristic or exact method can be turned into a repair heuristic and a destroy method based on random selection is easy to implement. Therefore we see a potential for using simple LNS heuristics for benchmark purposes when developing more sophisticated methods.

Large neighborhoods are no guarantee for finding better solutions. Increased complexity of the neighborhood search means that fewer iterations can be performed by a local search algorithm. Gutin and Karapetyan [35] experimentally compared a number of small and large neighborhoods for the multidimensional assignment problem, including various combinations of them. It is demonstrated that some combinations of both small and large neighborhoods provide the best results. This could indicate that hybrid neighborhoods may be a promising direction for future researches.

1.5 Tools

1.5.1 GraphHopper

To visualize routes of vehicles we need to use map, for our case we used GraphHopper. GraphHopper is a young, Germany-based firm that specializes in mapping solutions. It uses the OpenStreetMaps maps to provide services such as geocoding, distance matrix calculation and also solving instances of the vehicle routing problem featured as a web service. For the batch matrix calculation, customers can post a request and using HTTP style requests, can obtain the distance matrix a few instances later.

1.5.2 Openstreetmaps

As for Openstreetmaps it is a project started in Germany that focuses on distributing free geographic data over the world. There are other geographic data sources such as google maps and bing, but the use of their services are not completely free, since technical or legal restrictions exist. This was the incentive for the project to start. Openstreetmaps aims to be 100% free without restrictions, so that people can also use the underlying geographical data of maps, such as geocoding. Openstreetmaps is still expanding their data by contributions and user surveys. Google and Bing have a vast knowledge of geographical data and allow for individual developers and corporate to use this underlying in the form of APIs. An API is an Application Programming Interface, which means a set of definitions which allows applications or programs to communicate with other programs or services. In this sense, a web API allows for a program to communicate with the web service, for example post requests and fetch responses. So for an application to need some sort of data transformation, for example geocoding, where an address string is converted into coordinates, a web API can be used. This and other mapping services are offered by Google Maps as well as by Bing Maps. They invite developers to use the APIs and there is well documented information on how to use the APIs. For small instances or requests, this service is free. However if the service is to be used on a bigger scale, for commercial purposes the companies might require a fee. To safeguard for someone taking advantage of these services, there are some user limits that Google and Bing use per IP-address. Limits cover the times between requests as well as an absolute amount of requests that may be done per IP address per day.

1.5.3 jRESP

This framework was designed to help programmers to develop autonomous and adaptive system in SCEL (Software Component Ensemble Language). (De Nicola et al., 2013) Due to high complexity of nowadays systems, autonomic systems provide more effectiveness. Based on a kernel language SCEL, jRESP (Java Run-time Environment for SCEL Programs) proposes a set of programming abstractions that permit to represent behaviors, knowledge and aggregations according to specific policies, and to support programming context-awareness, self-awareness and adaptation. jRESP basically provides API that allows implementing Java programs to SCEL complex systems.

SCEL itself represents a language that was designed for working with autonomic computing systems. It aids programmers with a complete set of linguistic abstractions for programming the behavior of *Autonomic Components* (AC) and the formation of *Autonomic Component Ensembles* (ACS). SCEL allows specifying autonomic systems in terms of *Behaviors*, *Knowledge* and *Aggregations,* by complying with specific *Policies*.

The interface KnowledgeManager identifies a generic data repository and indicates the high-level primitives to manage items of relevant info coming back from completely different sources. This interface contains the strategies for withdrawing/retrieving/adding piece of data from/to a repository. A SCEL program consists of a group of elements executed over a distributed infrastructure. elements are enforced via the class Node.

Nodes are executed over virtual machines or physical devices providing access to input/output devices and network connections. A node aggregates a data repository, a group of running processes, and a group of policies. Structural and behavioral data about a node are collected into an interface via attribute collectors. Nodes act via ports supporting each point-to-point and group-oriented communications.

Figure 12 SCEL

1.5.4 MatSim

The MATSim (Multi-Agent Transport Simulation) platform created by Kai Nagel, at ETH Zürich, he was interested in his work improvement in, the TRANSIMS (TRansportation Analysis and SIMulation System) the code was designed to be opensource. In Berlin in 2004 Mr.Kay W. Axhausen joined the development team, bringing a new view and personal practice. A collaboration, was productive and succeeded for more than 10 years due to blending a physicist's and a civil engineer's perspective, as well as bringing together competence in traffic flow, large-scale computation, choice modeling and CAS (Complex Adaptive Systems)

MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java. It is open-source and can be downloaded from the Internet (MATSim, 2016; GitHub, 2015)(Bresciani et al., 2004). MATSim is was created for developing massive simulation schemes, meaning that all models' features are stripped down to operate efficiently the aimed functionality; paralyzing has also been very important.

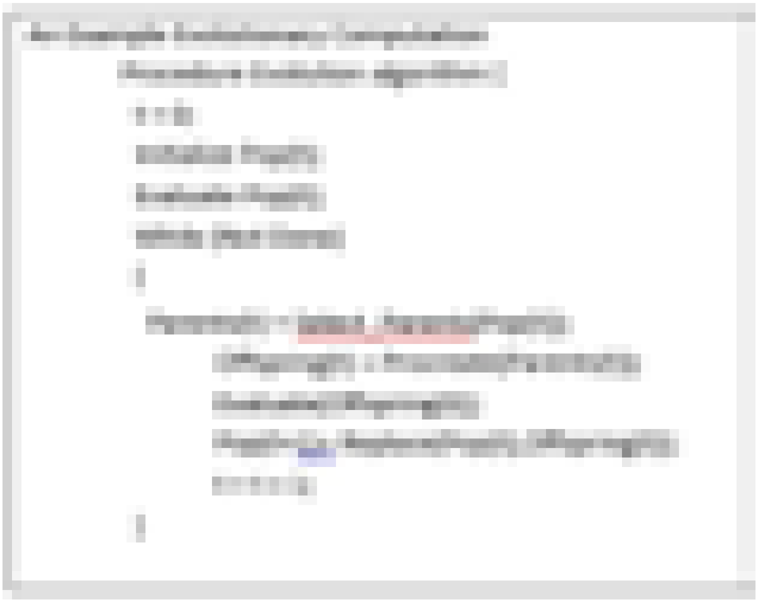
For example, to simulate the load on the network, a queue-based model is realized, excluding very complex and computationally expensive car-following behavior. (Balmer et al., 2007) At this time, MATSim is designed to model a single day, the common unit of analysis for activity-based Models.

The base of MATSim working principle is founded on the co-evolutionary algorithm. Every agent (The modeled persons are called agents) regularly optimizes its daily behavior plan while competing for (space-time) slots with all other agents on the traffic-flow infrastructure. It starts with an initial demand arising from the study area population's daily activity chains. Activity chains are usually derived from empirical data through sampling or discrete choice modeling. During iterations, this initial demand is optimized individually by each agent. Every agent has memory which contains an established number of day plans, where each plan is composed of a daily activity chain and an associated score. The score can be interpreted as an econometric utility.
In every iteration, each individual agent picks a plan from its memory. The selected plan is dependent on the plan scores. For the network loading step, multiple mobsims (mobility simulations) are available and configurable.
Plan modification is performed by the re-planning modules (departure time, route, mode and destination).

MATSim re-planning has various strategies to implement plans, differing from random mutation to approximate suggestions, to best-response answers where, in every iteration, the currently optimal choice is searched. Initial day plans aren't meant to be very exactly defined for the re-planning dimensions included in the optimization process. If an agent has too many plans, the plan with the least score (configurable while planning) is removed from the agent's memory. Agents that didn't have re-planning search among existing plans.
The iterative process is repeated until the average population score stabilizes. The typical score development curve takes the form of an evolutionary optimization progress.
MATSim offers great customizability. In principle, every module of the framework can be exchanged.
Every action in the simulation generates an event, which is recorded for analysis. These event records can be aggregated to evaluate any measure at the desired resolution.

MATSim equilibrium is searched for by a co-evolutionary algorithm. These algorithms co-evolve different species subject to interaction. In MATSim, individuals are represented by their plans, where a person represents a species. With the co-evolutionary algorithm, optimization is performed in terms of agents' plans,i.e., across the whole daily plan of activities and travel. It achieves more than the standard traffic flow equilibria, which ignores activities.

Eventually, an equilibrium is reached, subject to constraints, where the agents cannot further improve their plans unilaterally.



```
An Example Evolutionary Computation:
        Procedure Evolution algorithm()
         t = 0;
         Initialize Pop(t);
         Evaluate Pop(t);
         While (Not Done)
         {
          Parents(t) = Select_Parents(Pop(t));
                Offspring(t) = Procreate(Parents(t));
                Evaluate(Offspring(t));
                Pop(t+1)= Replace(Pop(t),Offspring(t));
                t = t + 1;
         }
```

Figure 13 Pseudo- code for MATSim Coev. principle

For our paper, we decided to implement new approach for detecting bottlenecks in our city (or country) where biggest probability of collisions and congestions may occur. Due to the lack of statistical data from traffic ministry or Google or other systems that can provide any exact statistics for most congested routes, we decided to run simulations in Tbilisi. Which later will be added to knowledge base of ACE’s and datacenters.

With above described principles of MATSim functionality we theoretically can make simulations done in Tbilisi and make plans for 1 million agents (cars in Tbilisi). This plans have to be randomized but close to real life situation. For example, most agents (more than 90%) have to plan their departure and destinations POI (points of interest) times within day, more likely to travel the routes in city center. It means that traffic jams should occur while simulation.

Randomizing plans and making more and more simulations we will receive data and logs that should be analyzed and most problematic zones (routes) will be detected.

Of course stochastic real life situation on road can’t be predicted by simulations, but this statistical data received from MATSim computations will be taken into account for Datacenters. For planning departure time speed limitations of each node (route).

Datacenters and knowledgebase also will receive more information from ACE's assigned to each vehicle, about traffic according on data they will receive from everyday real vehicle maintenance (exploitation). Such as probability of congestion appearance collision possibility on each route and average response time of Police to clear the congested area.

Figure 14 MATSim output of traffic at 07:30 in the MIV (10% sample) example of simulation in city Vorarlberg [38] dots represent vehicles.

Figure 15 Matsim toolkit [46]

The toolkit is based on a well-defined database describing a given scenario which consists of spatial data, transportation networks, survey information, and detailed descriptions of each individual active in the scenario (see Figure 1-15)

1.5.5 DEECo

The latest studies in computation, and mathematics, has shown that many large scale distributed systems are quite influential on our environment. To handle such large scale problems and issues, engineers have to develop very complex systems, that can work dynamically and autonomic. In our work we study VRP, and to improve the algorithm we add new component in particular, Ensemble- Based Component Systems – EBCS, which include fully autonomic components with recursive execution by means of the dynamic component ensembles that are controlling data exchange.

One of the instances of the EBCS is DEECo (Dependable Emergent Ensembles of Components). For our study we observe jDEECo with is Java based framework.

Main concept of the DEECo approach is built on two components. A component and the ensemble. Component is called independent unit of development and ensemble stands for linking list of components and is a dynamic binding mechanism. DEECo framework allows components to interact each other via ensembles.

Component [22]

A component in DEECo comprises knowledge, exposed via a set of interfaces, and processes. Knowledge reflects the state and available functionality of the component. It is organized as a hierarchical data structure, which maps knowledge identifiers to values. Specifically, values may be either (potentially structured) data or executable functions.

A component's knowledge is exposed to the other components and environment via a set of interfaces. An interface thus represents a partial view on the component's knowledge. Specifically, interfaces of a single component can overlap and multiple components can provide the same interface, thus allowing for polymorphism of components. Component processes are essentially soft real-time tasks that manipulate the knowledge of the component.

A process is characterized as a function associated with a list of input and output knowledge fields. Operation of the process is managed by the runtime framework and consists of atomically retrieving all input knowledge fields, computing the process function (with the input knowledge fields as function parameters) and atomically writing all output knowledge fields (retrieved as the return value(s) of the process function).

A process may have side effects in terms of sensing and actuating, however it is not supposed to explicitly communicate with other components or other processes of the same component in any other way than via knowledge. Being active entities of computation, component processes are subject to scheduling, which is again managed by the runtime framework. A process can be scheduled either periodically, i.e., repeatedly executed once within a given period, or as triggered, i.e., executed when a trigger condition is met.

Ensemble

An ensemble embodies a dynamic binding among a set of components and thus determines their composition and interaction. In DEECo, composition is flat, expressed implicitly via a dynamic involvement in an ensemble. Among the components involved in an ensemble, one always plays the role of the ensemble's coordinator while others play the role of the members.

This is determined dynamically (the task of the runtime framework) according to the membership condition of the ensemble. As to interaction, the individual components in an ensemble are not capable of explicit communication with the others. Instead, the interaction among the components forming the ensemble takes the form of knowledge exchange, carried out implicitly (by the runtime framework). Specifically, definition of an ensemble consists of Membership condition and Knowledge exchange.

Definition of a membership condition comprises the definition of the interface specific for the coordinator role – coordinator interface, as well as the interface specific for the member role (and thus featured by each member component) – member interface, and the definition of membership predicate. A membership predicate declaratively expresses the condition under which two components represent a pair coordinator-member of the associated ensemble.

The predicate is defined upon the knowledge exposed via the coordinator/member interfaces and is evaluated by the runtime framework when necessary. In general, a single component can be member/coordinator of multiple ensembles, so that ensembles form overlapping composition layers upon the components.

Knowledge exchange embodies the interaction between the coordinator and all the members of the ensemble i.e., it is a one-to-many interaction (in contrast to the one-to-one form of the membership predicate). Being limited to coordinator-member interaction, knowledge exchange allows the coordinator to apply various interaction policies.

In principle, knowledge exchange is carried out by the runtime framework; thus, it is up to the runtime framework when/how often it is performed. Similarly, to component processes, knowledge exchange can be carried out either periodically or when triggered.

Based on the ensemble definition, a new ensemble is dynamically formed for each group of components that together satisfy the membership condition. In summary, components operate only upon their own local knowledge, which gets implicitly updated by the runtime framework (via knowledge exchange) whenever the component is part of an ensemble. This supports component encapsulation and independence.

In order to bring DEECo abstractions to the practical use during the development of real-life VRP a framework called jDEECo is provided, which is a Java-based realization of DEECo component model. jDEECo delivers the necessary programming abstractions and the runtime environment to deploy and run DEECo-based applications.

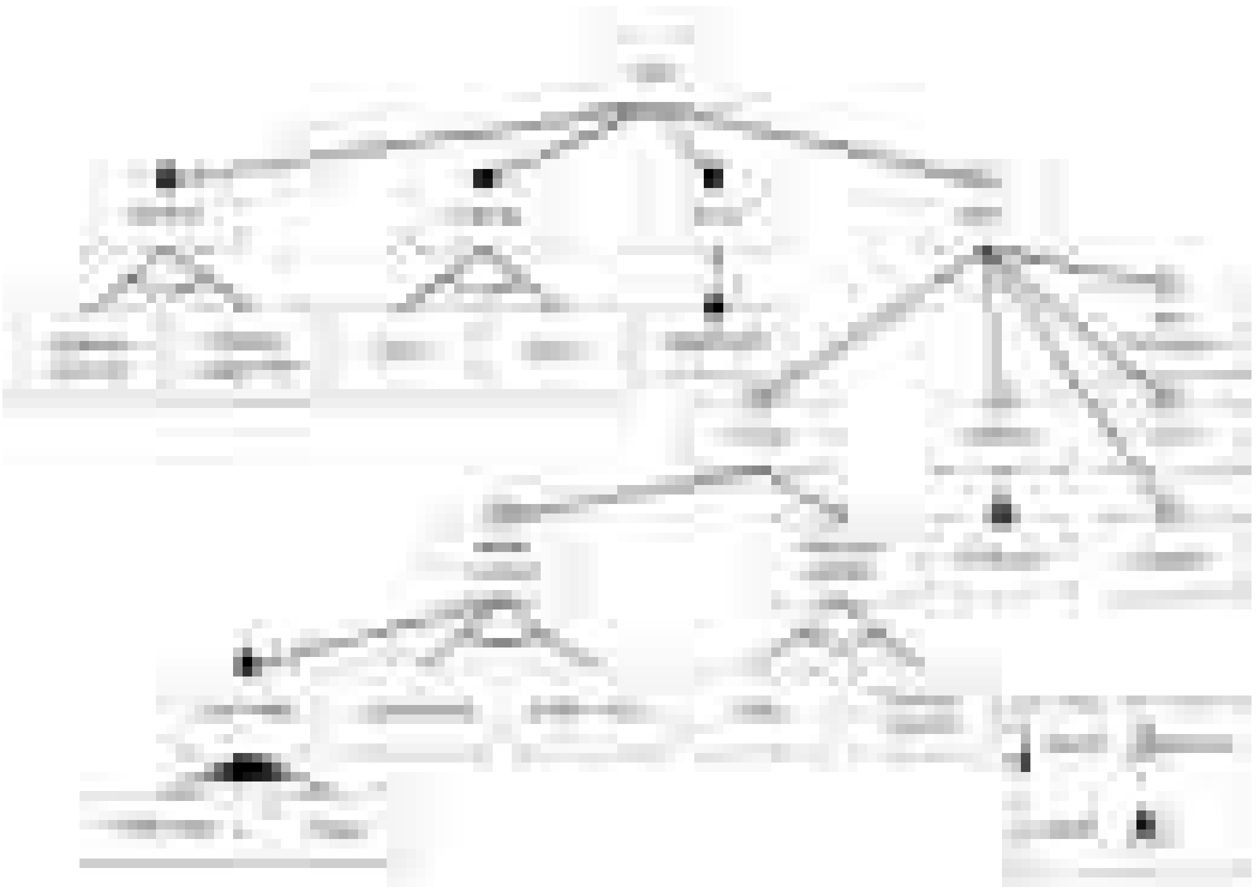


Figure 16 DEECo scheme

Why to use DEECo [23]

- Suitable abstractions.

DEECo abstractions of autonomous components and ensembles allows modeling a dynamic self-adaptive routing model in an intuitive way. Ensembles are established/disbanded dynamically at runtime depending on the state of the environment and the state of the components. They can overlap, reflecting the fact that a component may take on multiple roles and pursue multiple goals at the same time (e.g., the goal of having up-to-date information about unload space and the goal of making sure that selected space is reserved).

- Extensibility and support for design.

DEECo is open to deployment of different adaptation algorithms or strategies. At the same time, it is supported by a dedicated design method that is based on the invariant abstraction.

- Simulations.

JDEECo (the Java implementation of DEECo) provides a simulation framework which allows experimentations with decentralized adaptive behavior of smart CPS. The simulation framework is integrated with OMNeT++ network simulator. All knowledge exchange passed between components is routed through OMNeT++, which provides realistic estimates of network latency w.r.t. to network topology, geographical position of components, network collisions and packet drops, etc. The simulation framework is also integrated with MatSim simulator that provides large-scale agent-based transport simulations.

1.6 Chapter I Summary

In the first chapter problem with logistics network in Georgia is revealed. To start the research, problems should be pointed out and solutions that already exist in this field should be studied and checked if they can help in stated problem. In our case well-known problems such as VRP and TSP were reviewed with their variations and different approaches that already exist to solve them. In the literature review also different algorithms and tools that help to solve them were studied.

Chapter II Methodology

2.1 Planning initial routes

The dissertation uses modern methods of operations research, including the construction of mathematical models, the theory of local search and computational complexity, as well as the methodology of experimental research using computer technology and commercial software packages for solving integer linear programming problems.

The formation of a route network is an important stage in the development of an efficient transport system of the city. The degree to which the route network is rationally developed, how well and harmoniously it is integrated into the transport network of the city, the satisfaction of the population with transportation and the efficiency of the transport companies depend. Under the route network is meant the aggregate of all routes of movement of transport on the territory of the city, district, etc. The route of traffic, in turn, is the path of the vehicle between the starting and ending stopping points in accordance with the schedule.

Simultaneously with the increase in the level of motorization of the population, the load on roads has increased, one of the essential parts of which is the distribution and logistics companies' vehicles fleet

In general, the scheme of work on the routing of cargo transportation consists of a number of stages. First, it is necessary to determine the shortest distances between all the points of departure and receipt of goods and between the road transport enterprises and the specified points, ie, to create a network of shortest distances. Then, taking into account these distances, determine the optimal fastening of consumers of the same cargo to suppliers.

At the last stage, the routes for the transport of different goods in the same rolling stock, the attachment of these routes to motor transport enterprises and the development of tasks for drivers to carry out the transportation of goods along the routes are determined. To do this, it is necessary to select those applications for the carriage of goods that can be carried out on the same rolling stock and which coincide in the time of the transportation. In this case, of course, you need to know the addresses of senders and recipients, the number and name of the cargo to be transported, as well as the distances between all senders and recipients.

By their nature, dynamic routing problems differ from their static equivalent by adding more degrees of freedom for the decision making and introducing new metrics for the objective function. In some contexts, such as the pick-up of express courier, the transport company does not have obligation to service a customer request. As a consequence, it can reject a request, either because it is simply impossible to serve it, or because the cost of serving is too high compared with the company objectives.

Dynamic problems also frequently differ from their static counterparts in their objective function. In particular, while a common objective in static context is to minimize a routing cost, dynamic routing may introduce other notions such as service level, throughout or revenue maximization. Having to answer dynamic customer requests we introduce the notion of response time: a customer might request to be served as soon as possible, in which case the main objective may become to minimize the time between a request and its service (Pillac, 2011).

In dynamic problems critical information is revealed over time, meaning that the complete definition of an instance of a given problem is only known at the end of the planning horizon. As a consequence, an optimal solution can only be found a-posteriori. Therefore, most approaches use fast approximation methods (so called meta-heuristics) that give a good solution in a relatively low computational time, rather than exact methods (dynamic programing, linear programing, Markov processes, etc.) that would only provide an optimal solution for the current state, providing no guarantee that the solution will be optimal once new data becomes available.

As it was expressed already, travel time is taken into account because the problem of high importance and it ought to be taken into account to urge additional sensible and reliable solutions. as a result of a growing quantity of traffic and a restricted capacity of the road network, traffic jam has become a daily phenomenon. Since traffic congestion causes serious delays, it's terribly expensive for intensive road users like supplying service providers and distribution corporations. above all, such delays cause massive prices for hiring the truck drivers and therefore the use of additional vehicles, and if they're not accounted for within the vehicle route plans they will cause late arrivals or perhaps violations of driving hour’s laws. Therefore, accounting for traffic congestion contains a massive potential for price savings (Kok, et al., 2013).

Travel time delays are principally because of the thus known as ‘recurrent’ congestion that, for instance, develops because of high volume of traffic seen throughout peak commutation hours. Incidents, like accidents, vehicle breakdowns, weather condition, work zones, lane closures, special events, etc. are alternative necessary sources of traffic jam. this sort of congestion is labeled ‘non-recurrent’ congestion therein its location and severity is unpredictable. it's reported, that over five hundredth of all travel time delays are because of the non-recurrent congestion (Guner et al. 2012). because it was said, presence of congestions and their time characteristics don't seem to be known beforehand, however are discovered only the conclusion of an initial routing arrange is started. once a vehicle chooses a link (road segment) to traverse, there's fixed likelihood that it'll truly traverse an adjacent link as critical the one chosen. A path from the supply to the destination is chosen a priori. Then there's a fixed likelihood upon inward to at least one of the nodes within the network that consequent link is full and an alternate route ought to be chosen.

To solve the initial stage problem, allow us to take into account a unified heuristic that is able to resolve completely different variants of the vehicle routing problem: the vehicle routing problem with time windows (VRPTW), the multi-depot vehicle routing problem (MDVRP), etc. (Pisinger, et al., 2005). All drawback variants are remodeled to an upscale pickup and delivery model and solved using the Large Neighborhood Search (ALNS) framework. The ALNS framework is an extension of the Large Neighborhood Search framework with an adaptive layer. All problem sorts are remodeled to a rich Pickup and Delivery problem with time windows (RPDPTW) and are resolved using the Adaptive Large Neighborhood Search (ALNS) framework given in (Stefan Ropke, 2009). within the RPDPTW we've got variety of requests to be carried out by a fixed set of vehicles. every request consists of picking up an amount of products at one location and delivering it to a different location.

The objective of the matter is to search out a possible set of routes for the vehicles so all requests are serviceable the general travel distance is reduced. A possible route of a vehicle ought to begin at a given location, service a number of requests in a means that the capacity of the vehicle isn't exceeded, and eventually finish at a given location. A pickup or delivery ought to occur at intervals a given time window. every request, moreover, has an associated pickup precedence variety and a delivery precedence number.

A vehicle should visit the locations in non-decreasing order of precedence’s. Since not all vehicles could also be able to service all requests (e.g. because of their physical size or the absence of some cooling compartments) we need to make sure that each request is serviceable by a given set of vehicles. Between any 2 locations we've got an associated, plus distance and period.

In order to transform the vehicle routing problem with time windows (VRPTW) instance to a RPDPTW instance we map every customer in the VRPTW to a request in the RPDPTW. Such a request consists of a pick up at the depot and delivery at the customer site. The amount of goods that should be carried by the requests is equal to the demand of the corresponding customer. The time window of the pickup is set to [ad, ad] where ad is the start of the time window of the depot in the VRPTW and its service time is set to zero. The time window and service time of the delivery are copied from the corresponding customer in the VRPTW.

As for the multi-depot vehicle routing problem (MDVRP), we cannot use these depots to model the MDVRP. The problem is that we should assign each pickup to a depot and we do not know which depot is going to serve a given request. Instead we create a dummy base location where all routes start and end and where all ordinary requests are picked up.

We also create a dummy request for each vehicle k in the problem. The pickup and delivery locations of these requests are located at the depot of the corresponding vehicle. A dummy request has demand zero, it does not have any service time and it can be served at any time. The set $\boldsymbol{Nk}$ of each vehicle k contains all ordinary requests and the dummy request corresponding to the vehicle. This way, we ensure that each vehicle will carry precisely one dummy request.

The general idea of the ALNS framework (Pisinger, 2005) is to repeatedly remove requests from the solution and to reinsert them at a more profitable position. This is done by special destroy and repair heuristics. In each iteration, a destroy and a repair heuristic are chosen and applied. The selection is based on the past success of the heuristics. Compared to many local search heuristics that only apply very small changes to a solution, ALNS works with a larger search space, the so-called neighborhood N of the current solution. A neighborhood N(s) of the solution s is a set of solutions. The neighborhood contains all the solutions that could be created by changing that part of the solution. The term neighbor refers to the similarity between the solution s and its neighbors in N(s).

A distance measure can be applied to the solutions in the search space, e.g. the Hamming distance. Solutions in N(s) usually have a comparatively low distance to s (Lutz, 2014). A very simple destroy method would select the customers to remove at random. A repair method could rebuild the solution by inserting removed customers, using a greedy heuristic. Such a heuristic could simply scan all free customers, insert the one whose insertion cost is the lowest and repeat inserting until all customers have been inserted.

For the initial construction of traffic routes or their adaptation, after the vehicles left the central warehouse, a series of routing tasks for vehicles with fixed routes is formulated. Each task characterizes a specific problem of static routing of vehicles with a non-uniform fleet of vehicles at a given time. A temporary scheduling method using sliding indicators is used and a re-optimization procedure is started to determine new traffic routes for vehicles each time the voyage time between the two points is updated. For vehicles that are in the process of adjusting the routes on their way to their destination, artificial intermediate vertices are created.

The repeated optimization algorithm is carried out further on the graph, which also includes these artificial vertices. Of course, artificial tops do not have their own demand, and vehicles must immediately leave them.

The theoretical approach (finding the answer of the primary stage: an initial (comprehensive) routing for all depot &; all of the vehicles) mentioned above, is implemented with the open-source toolkit Jsprit. Jsprit - a Java based, open source toolkit for determination rich traveling salesman (TSP) and vehicle routing problems (VRP))

Jsprit will solve issues with pickups and deliveries, back hauls, heterogeneous fleets, finite and infinite fleets, multiple depots, time windows, open routes, completely different begin and finish locations, and initial loads. Jsprit permits to outline services (one stop) and shipments (two stops) with multiple capacity dimensions. in addition, you'll set time windows and needed skills.

Jsprit permits us to feature multiple depots by simply adding vehicles/drivers with completely different start locations. One will specify begin and finish locations explicitly. in addition, one will outline a heterogeneous fleet by distribution completely different vehicle varieties (with different capacities and transportation costs), skills and operation times to your vehicles. Then, one should place it all at once to outline the matter, set the routing prices and specify whether or not you've got a finite or infinite fleet.

Finally, one solves the matter by process and running an algorithmic program. Here it comes out-of-the-box (that is, the solution are going to be elect mechanically based on the problem description).

2.1.1 Counting minimal number of vehicles

Counting minimal number of vehicles is essential in optimizing VRPTW in case of minimizing total cost of shipment lowering fuel emissions to the atmosphere and minimizing total working hours of vehicles. First of all, after receiving orders, datacenter should count whole amount of cargo. We have a fleet of N vehicles. In case if, whole amount of cargo is less the total capacity of vehicles, then there is no need to use all vehicles to deliver the goods. Main idea here is to maximally load every individual vehicle. Every vehicle has some standard capacity. In our case the vehicles are identical but some have more or less capacity (fig17) but they do not play a major role with our set of limitations and constraints. Of course if there is any chance of violating time Windows or planning route for the vehicle which is too long, then the planner has to use one of the free at the moment vehicles. At the strategic level, a fleet of vehicles is determined by the results of the holding's operations for the year. As optimization criteria, the profits of an industry enterprise and the duration of the financial cycle can be considered. The optimal amount of vehicles in the holding companies is significantly affected by the amount of financial resources allocated for transport services to consumers. If these financial resources are limited, the optimal composition of the car fleet changes, the profit decreases and the duration of the financial cycle of the holding company's increases. But for the planning example we assume that there are no such limitations in this case.

Figure 17 Number of vehicles

(shows groups of vehicles from same depots, number of vehicles in each depot, and shows capacity of each vehicle, we consider that each depot has same type of vehicles so that they have standard payload) The number of vehicles cannot be smaller than Nmin. Nmin is the minimum number of vehicles needed to serve all customers counted after determining whole amount of cargo. The total number of vehicles are used daily is influenced by customers' demand.(fig17) After that we focus on a subset of VRP extensions which work with time, i.e., on problems of soft time windows (modeling preferred time of arrival to a customer), multiple time windows (modeling multiple time windows when the customer can be served), plan route with respect to time margin (modeling route robustness with respect to delays) or time-dependent arc cost (modeling variable traffic conditions throughout the day). Every customer specifies the earliest time and the latest time when a vehicle is allowed to arrive to the customer. The depot has a time window with the latest possible departure and the earliest possible arrival.

This kind of time windows are considered as hard time windows, thus the vehicle cannot violate given time window, it cannot arrive to the customer outside its time window. The vehicle is allowed to wait if it arrives earlier. But initial plan has to avoid such circumstances, because, waiting is also a wasting of time and money. Every vehicle starts at the depot at specific time, when depot is open and ready for work.

Figure 18 Service parameters

(service duration stands for time needed to unload cargo, start and end time are specific Time windows and quantity is quantity of boxes of cargo demanded by customer (also can be counted in kilograms or tons instead of boxes)).

There are many different solutions and tools solving the VRP. One of the most appropriate tool is jSprit . It is basically engine toolkit written in Java. It is open source, so we can use it, to integrate algorithms that we need based on metaheuristics to find close to optimal solutions. It is an effective heuristic for some variants of VRPTW, mostly with hard time windows. jSprit basically implements simple linear equations, so that we count minimum vehicles needed, and payloads of each vehicles (fig18) can solve problems with pickups and deliveries, back hauls, heterogeneous fleets, finite and infinite fleets, multiple depots, time windows, open routes, different start and end locations, multiple capacity dimensions, initial loads, skills

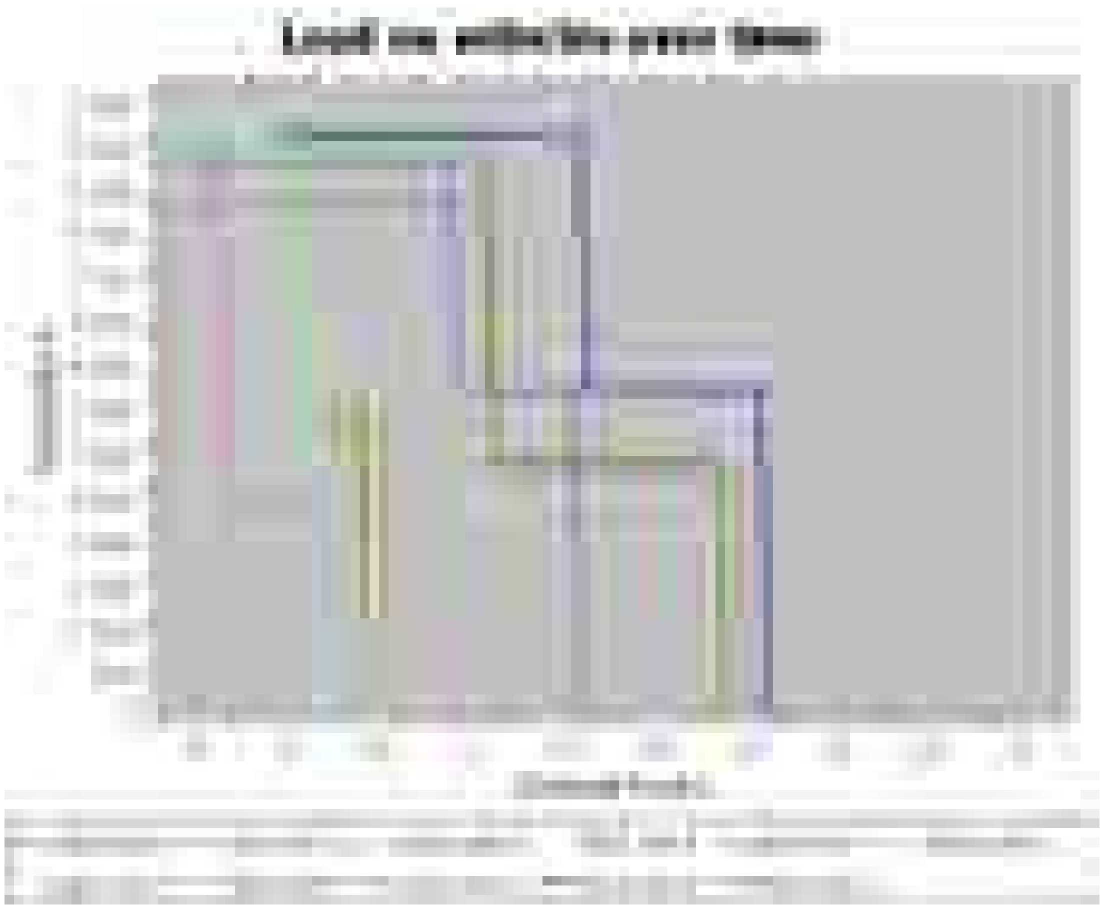


Figure 19 Cargo Load

(Shows overall cargo loaded, in each vehicle, each shown below with different color and show graphs of unloading cargo to customers through time in decimal hours)

So that we need maps for research purposes only we've chosen Openstreetmaps and GraphHopper solutions. With help of these two tools we can use geocoding so we can show location of a specific customer on the map using latitude and longitude parameters. Also we indicate depots (start and end point of vehicles route) on map. Using distance matrix calculation and also instances solving of the vehicle routing problem of GraphHopper which includes basic information of each road in Georgia (in our case) we can use metaheuristics, with help of linear equations and Generic algorithm and Jsprit engine we can find close to optimal routes for vehicles(fig20). Jsprit allows us to add multiple depots by just adding vehicles/drivers with different start locations. One can specify start and end locations explicitly. Additionally, one can define a heterogeneous fleet by assigning different vehicle types (with different capacities and transportation costs), skills and operation times to your vehicles. Then, one has to put it all together to define the problem, set the routing costs and specify whether you have a finite or infinite fleet.

Figure 20 optimal routes general view

Figure 21optimal routes closer look at Tbilisi customers

As shown in fig 20 and fig 21 using above mentioned techniques and tools we have built optimal route solution for 80 customers with 7 depots. We placed customers in different cities and villages in Georgia:

Tskneti,Shindisi,Kodjori,Kiketi,TetriWkaro,Marneuli,Rustavi,Gori,Borjomi,Signaghi,Sagaredjo,Sabatlo,Axalkalaki,Batumi,Kobuleti,Sairme,Zastafoni,Oni,Gudauri,Martkopi,Telavi,Akhmeta,Dusheti,Kaspi,Kareli,Surami,Zestafoni,Vani,Martvili,Sajavakho,Khobi,Zugdidi,Supsa,Ozurgeti,Khala,Sarpi,Bolnisi,Sadakhlo. Also in Tbilisi we consider that there are much more customers located on the next streets:

Dadiani str,Tsereteli ave,Dadiani str,Didube railway station,Zestafoni strt,Guramishvili ave,Sarajishvili strt,Khizanishvili strt,Andronikashvili strt,Zahesi,Vazha Pshavela,Vazha Pshavela ave,Aghmashenebeli Ave,Rustaveli ave,Rustaveli ave,Avlabari strt,Ketevan dedopali ave,Ketevan dedopali ave,Ketevan dedopali ave,Javakheti strt,Kakheti hwy,Moskow ave,Bogdan Khmelnitski,Narikala hill,Europ square,Rose square,Freedom square,Rustaveli ave,Rcheulishvili strt,Barnovi strt,Chavchavadze ave,Dolidze strt,Kazbegi ave,Machavariani strt,Lubliana strt,Aghmashenebeli alley,Aghmashenebeli alley,Rioni strt,Gombori strt,Noneshvili strt,Vanati strt,Cholokashvili strt

Depots are located in Tbilisi,Poti and Batumi and other cities as well. All customer locations and depots are indicated on map via longitude and latitude parameters The geocoding is done using a database file that can couple zip codes to coordinates.(fig2-6)

[illegible]

Figure 22 coordinates

2.2 Example review

To visualize the process of mapping and routing, we need to review one route. As we've seen in fig7 we have 7 depots with total fleet of vehicles – 26. For example, we take vehicle #2 from fourth depot. Fourth depot is located in Tbilisi. As the parameters in this example case are set by us, we consider that depot 4 opens at 8:00 and ends it working day at 23:00 and second vehicle which is unoccupied at this moment has the capacity of 7000 boxes of cargo. Nearest stops, in our case customer's office demands, are generated randomly.

Customer demands are: how much cargo they need daily (boxes) and also working hours of each office. Working hours in our case are hard Time Windows (TW). After randomizing parameters (quantity of boxes, working day start and end time and approximate service duration) we receive that nearest stops that are to be visited by this particular vehicle are in cities Tbilisi and Shindisi. Also this vehicle can serve 2 customers in Tbilisi due to their demand and capabilities of the vehicle.

2.2.1 Parameters

Tbilisi customers demands 2565 for the first customer and 1931 boxes of cargo for the second, and these customer's working hours (TW) are 15:00 – 17:00 and service duration is 7 minutes for Mziuri customer and 15:00 – 17:00 and service duration is 9 minutes for Round square customer. As for Shindisi, its customer demands 2206 boxes of cargo working hours (TW) are 09:30 – 17:00 with service duration – 4 minutes.

2.2.2 Calculation

With this information we compare demanded order of two customers with capacity of vehicle we receive that both customers order 6702 boxes of cargo that doesn't violate capacity restriction of vehicle #2 which has capacity 7000 boxes. After that we begin routing and planning this shipment. With Jsprit engine and simple linear algorithm we can calculate total travel time and traveled kilometers. Traveled kilometers are calculated with OpenStreetmap (or any service that has geocoding and information about roads in Georgia like Google maps or Bing maps). As for planning which way to go first Tbilisi customers or Shindisi we use Nearest Neighbor Algorithm, because in this particular case we don't need too complex solution because we have only one vehicle and only three destinations.

After calculating possible variants of routes, we receive that optimal solution will be to load whole cargo at once and then go first to Tbilisi first stop at Mziuri second at Round Square after that to Shindisi and after that back to the depot.

2.2.3 Travel time and traveled kilometers

According to maps, distance between depot and first stop (Mziuri Chavchavadze Ave) is ~2.9 km, distance between first (Mziuri Chavchavadze Ave), second stop (Round Square Barnovi strt customer) is ~3.7 km and third stop (Shindisi customer) is ~15.62 km and way back to depot will take ~6 km with total traveled kilometers 28.31. As for travel time algorithm calculates average allowed speed on the selected road section with the restriction of maximum allowed speed of loaded vehicle. We receive that total travel time considering service duration is 32:21.

With all this information we apply data to Map (fig 21)

Figure 23 Optimal solution

Above described case is example of methodology to get initial optimal routing and planning with simple demands and small amount of stops. With such planning we can calculate even bigger amount of stops and big amount of restrictions as shown in fig8. With help of Nearest Neighbor algorithm, Branch and Bound algorithm and Adaptive Large Neighbor Search algorithms we get only initial optimal routing and planning for our case.

Optimal solution doesn't mean to be true in real life situation. Many parameters are left uncalculated, in fact optimal solution is only goal to be achieved, stochastic nature of VRP is uninvolved. Road conditions, car accidents, vehicle driver health condition and other parameters need to be involved in calculation. Also every calculation needs to be done in real time, that means that some kind of AI and datacenters need to be created for further research. The developed concept provides for the implementation of transport and logistics services for supply chains based on the principles and objectives of transport logistics, which should be implemented at the strategic, tactical and operational levels. Service processes should be considered inextricably from the processes occurring in the supply chains, in interconnection and interdependence with them as part of a single system. The results of transport and logistics services affect the results of operations and the efficiency of the supply chains.

Every vehicle must be controlled with agent. We count that an agent-based approach performs competitively with an on-line optimization approach. Modeling and solving a VRP by coordinating a set of agents can bring a number of advantages over more established approaches in the field of operations.

Agent advantages include the possibility for distributed computation, the ability to deal with complex sets of data from multiple customers, the possibility to react quickly on local knowledge and the capacity for real time (on-line) planning and routing.

2.3 Chapter II Summary

In the second chapter of our dissertation methodology to solve initial planning route is studied and examples made for Georgian road network were shown. Initial planning and case example are shown and heuristics to obtain the results are also in this chapter

Chapter III Adaptive real-world algorithm of solving MDVRPTW

3.1 Adaptive real-world algorithm of solving MDVRPTW (Multi Depots Vehicle Routing Planning with Time Windows) problem [25]

The adaptive algorithm to solve MDVRPTW problem is projected within the paper. Realistic real-world situations, like presence of varied congestion types on roads, are rigorously thought of and accounted for within the algorithm. To overcome the shortage of realistic and reliable ways of congestion period estimation we have a tendency to use the MatSim large-scale agent-based simulation tool. This tool permits users to compose and run complex simulation models that are very close to the real-world situations. Our approach implements additionally involuntary elements ensembles conception. every vehicle is related to the corresponding autonomic component AC (a virtual machine in datacenter) and exchange on-line data with different vehicles. Besides, ACs will schedule routes so as to search out the suitable alternative routes that alter vehicles to satisfy time windows requirements and, at the same time, avoid the congested roads. The adaptive algorithm is able to reschedule and find alternative routed for several vehicles in parallel, that will increase the performance of proposed approach.

In the introductory in example review solution of the MDVRPTW (Multi Depots Vehicle Routing Planning with Time Windows) was described. The initial daily plan was received by using the Adaptive Large Neighborhood Search (ALNS) and Branch and Bound heuristics. But, this initial plan is only the first step of complex solution. In fact, as already mentioned above, it is just a solution for ideal road traffic, not considering a lots of realistic circumstances as congestions traffic accidents and so on. It cannot be counted as acceptable solution for real life traffic model. Since a fast growing number of vehicles and a limited capacity of the road network, traffic congestion has become a daily problem to overcome.

Due to traffic congestion are a reason for big delays, it is very expensive for companies such as logistic service providers and distribution companies that have to deal with the traffic daily. In specific, such delays cause massive expenses for hiring extra vehicle operators and also the use of additional vehicles, and if they're not accounted for within the vehicle route plans they'll cause late arrivals at customers or perhaps violations of driving hour’s regulations. Therefore, accounting for traffic jam includes a massive potential for value savings. We have developed a modification of the ALNS algorithm (written in the Jsprit framework).

One of the key functions of decision support systems in the field of transport logistics is the ability to calculate and construct efficient from the point of view of the cost of detour routes for various purposes on the transport network

Our algorithm considers a probability of links' congestion, estimation of probability of their release of busy route sections. Our modification of the algorithm can plan routes for any starting and finishing nodes. To provide the real-time adaptability the proposed heuristics uses the concept of autonomic components (AC) and autonomic component ensembles (ACE). ACs are entities with dedicated knowledge units and resources that can cooperate while making different computations. ACs are dynamically organized into ACEs. AC members of an ACE are connected by the interdependency relations defined through predicates (used to specify the targets of communication actions). The functional description of an AC and ACE is shown on Fig.24

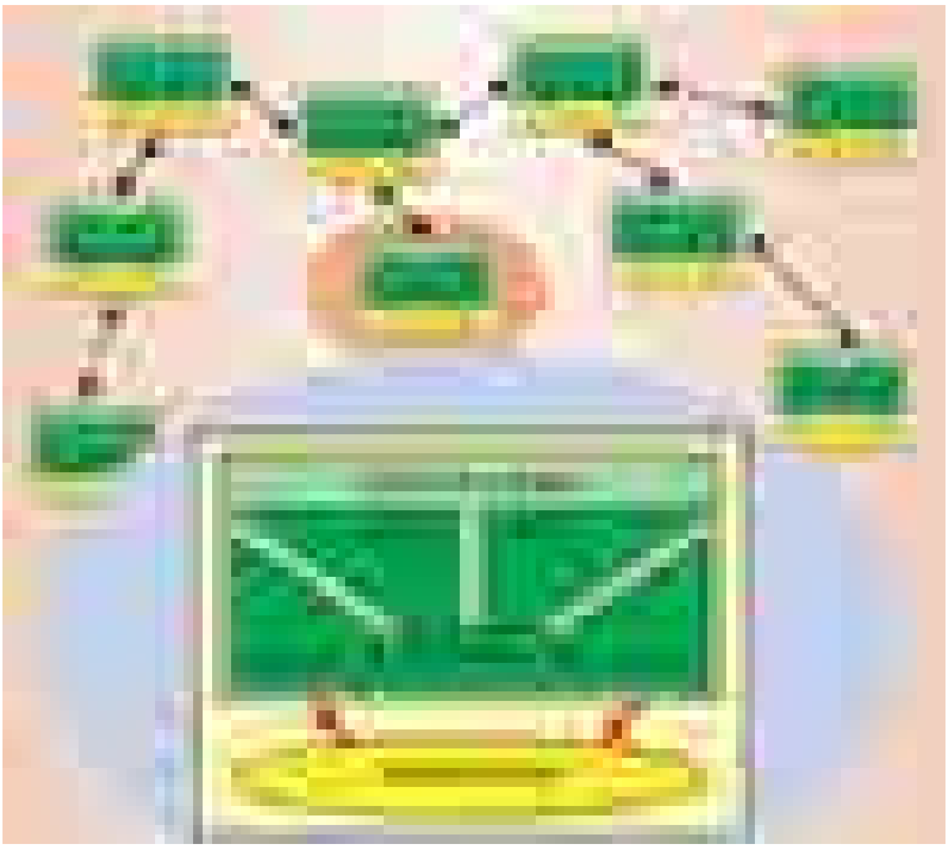


Figure 24 Functional description of a component

The process part of a component is split into an autonomic manager controlling execution of a managed element. The autonomic manager monitors the state of the component, as well as the execution context, and identifies relevant changes that may affect the achievement of its goals or the fulfillment of its requirements.

It also plans adaptations in order to meet the new functional or non-functional requirements, executes them, and monitors that its goals are achieved, possibly without any interruption.

A managed element can be seen as an empty “executor" which retrieves from the knowledge repository the process implementing a required functionality and bounds it to a process variable, the retrieved process for execution and waits until it terminates.

The ACs in an ACE may be implemented as virtual machines (VMs) in datacenters (ACE). Each AC is associated with the concrete vehicle and comprehensive information of the current location of the vehicle on the route, relevant data on its current state and etc. In our approach the knowledge repository is used to store these data and exchange them with other ACs.

Occasionally so called spatial temporal event (that is, a vehicle arrives to a certain service point at a certain time) occurs. The equipment in the car (GPS receivers and GSM telephones (or some similar wireless communications technology)) determines location using the GPS receiver and sends the coordinates and other relevant data to the Web server.

The general infrastructure of our approach id shown in the Fig.2 The base virtual machine VM_0 hosts all main structural components of proposed system: JSpirit, MatSim, travel and congestion management database (TCMD), database of simulation results (SRD), web servers for connection with vehicles, GPS, etc.

Although VM_0 is permanently used and maintained, it is convenient to represent it as a virtual machine because it will intensively interact and exchange data with other virtual machines, each of which represents autonomic component (AC).

As it will be shown later, autonomic components are associated with concrete vehicles and constitute an Autonomic Component Ensemble (ACE). The base VM_0 executes the initial solution of MDVRPTW problem and generates the initial set of routes RI. The input parameters, such as time windows for each service points, are held at VM0 as well.

After generating the initial set of routes, new virtual machines, enumerated from 1 to $\boldsymbol{nr}$ (where nr is the amount of routes in the initial set RI), are created. The recourses of the datacenter’s servers are dynamically allocated to virtual machines.

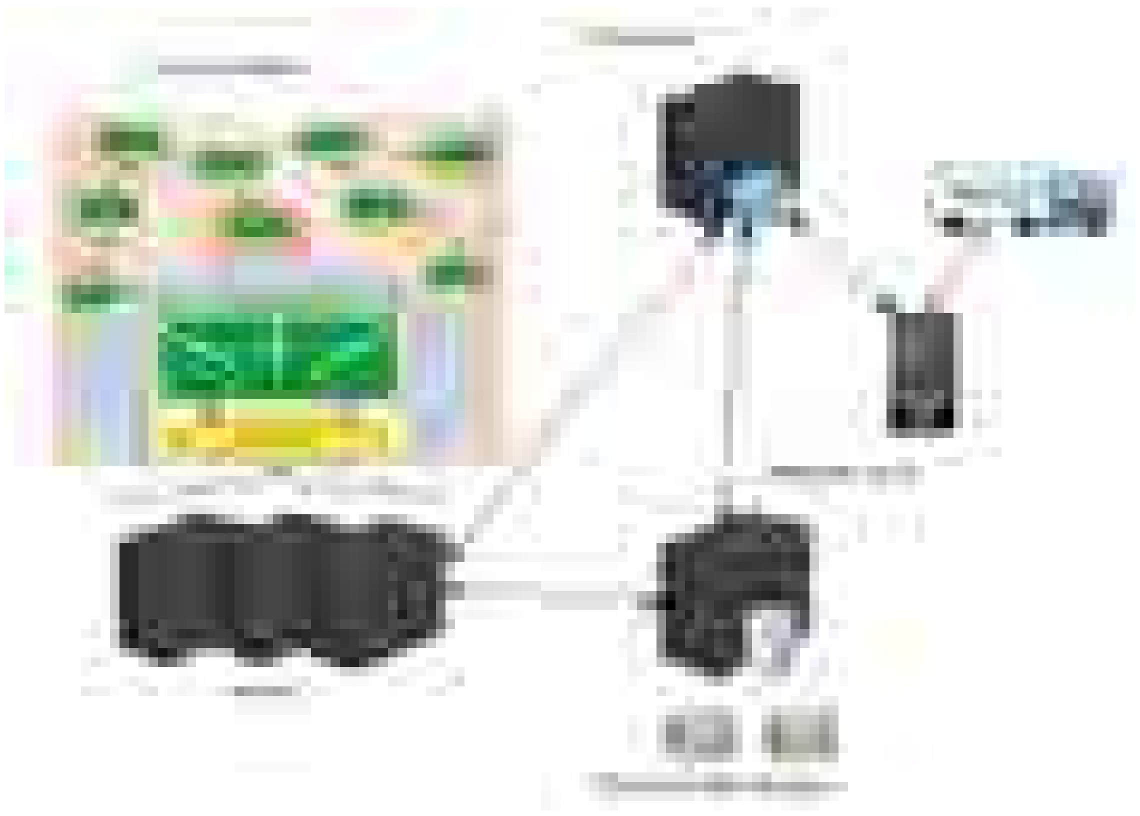


Figure 25 General infrastructure

As it was said earlier, congestions are the most, important critical factors for the successful and, practically acceptable solution of the MDVRPTW, problem. The congestion duration is defined as the, total of detection/reporting, response, and clearance, times. Due to the nature of most incident response, mechanisms, the longer the incident has not been, cleared, the more likely that it will be cleared in the, next period. For example, the probability of an, incident being cleared in the 15th min, given that it, has lasted 14 min, is greater than the probability of, it being cleared in the 14th min given that it has, lasted 13 min [26, 27].

This is because it is more likely, that someone has already reported the congestion, and a congestion response team is either on its way or has already responded. Let $\boldsymbol{t}$ be the time to unload the congested segment. Then, we have the increasing, hazard (failure) rate (in our case – clearance rate), property, e.g., $\lambda(t+1) > \lambda(t),$ where $\lambda(t) = \frac{f(t)}{1-F(t)},$ is the hazard rate of congestion clearance in duration, $\boldsymbol{t}$, and $f_{(t)}$and $F_{(t)}$are the density and cumulative, density functions of the clearance duration,, respectively. The Weibull distribution with increasing hazard rate is chosen to model the, congestion clearance duration [26].

We assume that, its starting time t^0_{cong}, current status (i.e., cleared/not cleared), expected duration (μ), and, standard deviation (σ) are available through the, travel and congestion management database,(TCMD). However, this kind of real-world data is, rarely available, especially at the beginning phase of VRPTWMD planning. In the case when these, data does not yet exist for the current spatial-temporal unit, the responsibility of the corresponding AC of the ACE is to determine and register these, parameters for the current vehicle and update the, local copy of the TCMD.

This action is performed, in the following manner. If after arriving to the, service point (with observed congestion in its, outgoing arc) either of 3 above-said congestion, types are observed, the decision whether to wait or, reschedule and select an alternative acceptable route, is to be made by using the algorithm described in, details later in the paper text. If the decision to wait, has been made, then the actual congestion-induce, delay time is available (this is equal to the difference, between time when the vehicle continued the, movement on the arc and the starting time of, congestion occurrence t^0_{cong}; this time t^0_{cong} can be, find out by interview with responsible persons,(incident response team or road police) or got from, available GSM data).

This value is stored to the, local copy of the TCMD. If the decision not to wait and reschedule has been made, then two possible, solutions may be considered. The first one is to, retrieve the relevant information from other ACs, that corresponds to vehicles visited the service, point of interest at subsequent time intervals. Of, course, only visits associated with the congestion, event under consideration (current spatial-temporal, event) must be accounted for. This action is, executed by the AM of the current AC by, generating the SCEL query statement $\boldsymbol{qru}$ with the, input arguments: current service point, current route, current vehicle, current time unit, congestion state).,The $\boldsymbol{qru}$ is addressed to all relevant ACs that meet, conditions[28].
The output of the statement $\boldsymbol{qru}$ is, defined by the group-oriented communication, predicate:
$\Omega(X)=(X.\text{Vehicle}_{\text{ID}} = \text{List}(\text{Vehicles}(\text{Routes}$ [illegible] $SP_i) \wedge X.\text{Arc}(i,k) \wedge X.\text{Time}\ (\text{Time}<\text{CurrentTime}))$

In other words, this predicate yields IDs of all relevant vehicles (if any). Additionally, congestion states at arrival times of all vehicles met input arguments' conditions, arrival times of all relevant vehicles can be obtained. We assume that these attributes are provided by the interface of each component and obtain dynamically updated values from corresponding probes (sensors) as a result of constant monitoring (sensing) of the ACE environment.

If at the arrival time of any of these vehicles to the service point (whose outgoing arc was earlier in congestion state) the arc is free of congestion, then the congested-induced time (see below in the text) is computed by the current AC and the corresponding record is stored to the local copy of the TCMD. The second solution of the problem (in the case when no vehicles visited the service point of interest) is to use results of simulation of the MatSim (Multi-Agent Transport Simulation) – a highly productive and efficient large-scale multi-agent simulation framework implemented in Java.

These results can be found in the special database of simulation results (SRD). The MatSim allows users to compose and run complex simulation models that are extremely close to the real-world situations. In particular, this language allows to enter various input parameters, obtain process simulation outputs and a great lot of parameters and distributions functions of simulated processes. Namely, we have simulated a large number of situations with various amounts of vehicles, roads, routes, service points, depots, loads, speeds, etc.

The main types of possible congestions and incidents (cases, which are most characteristic for the actual conditions of Georgia - there are totally 18 cases (both recurrent and non-recurrent congestions)) – have been simulated.

As a result, numerous characteristics, such as possible congestion durations (and their various distributions and parameters), congestion clearance times, road non-congested capacities, road congested capacities, vehicles' arrival rates, etc. for all roads and service points of Georgia, have been obtained and stored to the special simulation results database (SRD).

These data can serve as a good approximation of real-world parameters and be used for preliminary estimation of processes of interest. It is to be pointed out that the Matsim simulation study of roads and service points in modes, which are maximally close to real conditions and comprehensively cover all possible states of the transport system, is the first and indispensable stage of the successful MDVRPTW problem solution. Careful consideration and identification of all the factors and parameters affecting the actual behavior of the transport system, inclusion them in the simulation models, statistically justified processing of simulation outputs and storing them to the special database of simulation results (SRD) is the key to successful real-world solution of MDVRPTW problem with maximum consideration of the actual conditions.

It is also to be pointed out that the MatSim simulation study is periodical and is invoked whenever the current situations lack the reliable data from the TCMD database and, therefore, running of simulation to obtain some approximated to the real changed circumstances information is necessary. In the later stages, when the database is already filled with real data, the MatSim's function should be minimized (to save computing power)., In addition to the above cases it is necessary to take into consideration one particular case.

When a vehicle arrives to a service point whose outgoing arc is congested, it generates the query $\boldsymbol{qru}$. This query is addressed to all vehicle executing other planned routes and having to visit in subsequent time intervals the service point indicated in the $\boldsymbol{qru}$'s input arguments (and, additionally, being travelled on the arc incoming the service point under consideration). This query is received by all relevant ACs of vehicles. In this case the decision for these vehicles (which met conditions of the $\boldsymbol{qru}$'s input parameters) whether to continue travelling on the remaining part of the arc or reschedule and select some alternative route is made by using the algorithm described below in the paper., Hence, we can estimate the parameters of the Weibull distribution φ of the congestion clearance duration using TCMD or SRD databases. The congestion-induced delay function $\Theta(\cdot)$ is based on the congestion duration φ, road non-congested capacity denoted with c (vehicle per hour, or vph in short), road capacity during the congestion denoted with $\rho(vph)$, and arrival rate of vehicles to the congested arc denoted with $q(vph)$. Given these parameters for an congestion started at t_{cong}^{0}, the vehicle arriving to the congested arc at time t experiences the following expected congestion-induces delay:

[illegible]

Figure 26 expected congestion-induces delay

We assume again that parameters c, ρ, q (or their approximations) and distribution function $\varphi(t)$ are available at any current moment and at any current location of the vehicle i by querying the TCMD or SRD database in response of requirement of the corresponding AC_i

Recall that the algorithm ALNS of finding the initial solution generates the set of routes RI; the amount of initial routes is $\boldsymbol{nr}$. Besides, the main priority of the proposed approach is non-violence of time windows for each service point of each generated routes. These time windows are defined before execution of the algorithm and entered as parameters to the matrix TW[nr, nsp], where $\boldsymbol{nsp}$ is the total amount of service points (nodes of the graph). In each row $\boldsymbol{i}$ an element $\boldsymbol{j}$ is equal to the given time window for the service point $\boldsymbol{j}$ only if this service point belongs to the route $\boldsymbol{r} \in RI$**,** otherwise it is 0.

Suppose that the vehicle V_i arrives to the service point SP_j. Suppose also that the vehicle V_i travels along the route RI_r which was initially generated by the algorithm ALNS. The time of arrival is assumed equal to t_{ij}^{r}. The communication equipment on the board of V_i sends the message to the autonomic component AC_i associated with the vehicle V_i . The message delivers the above information to the AC_i, the information is stored to the knowledge database of the $AC_i$and to the TCMD. Upon arrival the driver of V_i finds out (by direct observation or by interviewing a congestion response team or road policy) the current situation: congestion status (congested or not) $Cong_{jk}$of the next segment of the route RI_r (the arc A_{jk} connecting the current service points SP_j and the next service points SP_k, both SPs belong to the route RI_r), the type of congestion (if any), starting time of the congestion occurrence $tcong_{jr}^{0}$ (i.e. the congestion that occurred on the arc A_{jk} during execution of the route RI_r), the expected time $tcong_{jr}^{clear}$ of congestion clearance. We assume that the latter time can be clarified during the interview with the staff (congestion response team or road police) and with a certain probability; if this probability (in the staff's opinion) exceeds 0.5 (practically the most reliable and acceptable threshold), that time is taken as the base for further application in the algorithm. If the staff cannot determine that time even approximately or its confidence is below 0.5, the decision on generating an alternative route is made. The autonomic component AC_i receives the above described information and retrieves also the additional information (the congestion duration φ, road non-congested capacity c, road capacity during the congestion ρ, and arrival rate of vehicles to the congested arc q) from the TCMD or SRD (see the explanation of details above). The AC_i computes the expected congestion-induces delay by using formulas (29) and determines the following important costs:

• CDW_{jr} – cost to pay the driver that waits at the service point SP_j and executes the route r (based on the computed expected congestion-induces delay)

• CTW_{kr} –cost (penalty) of violation the time windows assigned to the SP_k when executing the route r (k is the end node of the arc)

If $CDW_{jr} \leq CTW_{kr}$ then the decision to stay at the SP_j is made. Otherwise the decision of rescheduling and selecting an alternative route is made (the destination point of the route is the same as the destination point of the "old" route r). Rescheduling is executed by the autonomic manager AM of the AC_i. Before executing the algorithm all already traversed service points are excluded, however, arcs, which income in and outgo from the excluded service point, are concatenated. It is necessary also to point out that by the moment of rescheduling (generating an alternative route) the complete picture of congestion states of all arcs at the current moment must be available. It can be obtained from congestion map received from GSM (as a rule, this information is available in real-time scale and is updated dynamically).

Congested arcs must be marked and cannot be used when planning alternative routes. For this reason the congestion matrix MCong[m,n] (where m=1÷ NSP, n=1÷ NSP) is created and periodically updated. The values of elements of MCong are as follows: MCong[j,k]=-1 if the A_{jk} does not exist, MCong[j,k]=0 if the arc A_{jk} is not congested, MCong[j,k]=1 if the arc A_{jk} is congested). Moreover, the partial rescheduling can be executed for several service points in parallel, because corresponding ACs of the ensemble ACE can run the rescheduling algorithms simultaneously and independently of each other. This is one of the advantages of the proposed approach.

After rescheduling it may turn out that there is no alternative route (the algorithm ALNS failed to find the alternative route for the current state of the system and given time windows); in this case the vehicle V_i must simply wait at the SP_j.

Regardless of whether the vehicle continued along the “new” or “old” route’s segment , or it waits at the service point SP_j, we assume that service of the SP_j is completed. The actual service time is registered. If this time is equal or less of the required time window for the SPj, then we increment the amount of successfully served service points: NSSP++, otherwise we increment the amount of overdue (delayed) serviced service point: OSSP++.

At the end of planning horizon (as a rule, starting time of planning is 8:00 of each day, ending time is 24:00) the number of successfully and overdue service points is displayed and stored to the TCMD (for statistical processing and performance evaluation).

Now consider another option. As it was mentioned, the vehicle V_i upon arrival at the SP_j sends the message to the autonomic component AC_i associated with the vehicle V_i. Then the AC_i by implementing the query statement qry propagates information to all relevant ACs, defined by the group-oriented communication predicate (30). The arrival time of those vehicles are less than the arrival time t_{ij}^{r}. Hence, at the moment of receiving the propagated message vehicles are somewhere on the corresponding arcs. The decision whether to continue travelling on the remaining part of the arc or reschedule and select some alternative route is made similarly to the algorithm described above. The only difference is that the costs of travelling along the remaining part of the arcs are computed (instead of computing the cost of travelling along the whole arc A_{jk}, connected the current service points SP_j and the next service points SP_k).

Pseudo-code of proposed adaptive algorithm:

input: nsp: number of service points; RTW[nsp]: required time windows array;

PH[29]: planning horizon (starting and ending times);

nv: amount of available vehicles; np: amount of given characteristics of vehicles;

VP[nv,np]: vehicles characteristics array;

TCMD: travel and congestion management database ;

SRD: MatSim simulation results database;

Output: nr: amount of generated routes; RI[r]: set of generated routes;

NSSP: amount of successfully served service points;

OSSP: amount of overdue (delayed) serviced service points

```
1. while CurrentTime < PH[29] do:
2. spatial-temporal event occurs (a vehicle arrives to a service point at a certain time)
3.     t← current time
4.     i← number of a vehicle arrived to some service point at time t

5.     j← number of service point SP at which the vehicle $V_i$ arrived at time t
6.     r← number of route along which the vehicle $V_i$ travels at time t
7.     k← number of SP, connected to $SP_j$ in route r
8.     MCong[j,k] ← congestion status of arc $A_{jk}$
9.     TW[r,j] ← required time window for the service point j in the route r
10.    $CT_{jr}$ ← type of congestion;
11.      $tcong_{jr}^{0}$ ← starting time of congestion occurrence
12.      $tcong_{jr}^{clear}$ ← expected time of congestion clearance
13.          $\varphi$ ← congestion duration; $c$← road non- congested capacity; $\rho$← road capacity
             during the congestion; $q$ ← arrival rate of vehicles to the congested arc
14.      Autonomic component $AC_i$ receives a message from vehicle $V_i$
15.          $CDW_{jr}$← cost to pay the driver that waits at the service point $SP_j$ and executes the route r
               (see formula 1)
16.          $CTW_{kr}$← cost (penalty) of violation the time windows assigned to the $SP_k$ when executing
               the route r (see formula 1)
17.            if $CDW_{jr} \leq CTW_{kr}$ then
18.              decision: wait at $SP_j$
19.            else
             decision: reschedule and generate new route r*
             (by using the modified ALNS algorithm)
21.            end if
22.            if r* is null then
23.                decision: wait at $SP_j$
24.            end if
25.            NSSP++ or OSSP++
23.            store obtained results to TCMD
24. end while
25. display obtained results
```

In this chapter we described the adaptive algorithm to solve MDVRPTW problem. The algorithm is aimed to account for realistic real-world situation, such as presence of various congestion types.

The congestions are the most important critical factors for the successful and practically acceptable solution of the MDVRPTW problem. Since the realistic estimation of congestion duration is rather difficult and non-standard problem, we use the MatSim large-scale agent-based simulation tool which allows users to compose and run complex simulation models that are extremely close to the real-world situations. In particular, this language allows to enter various input parameters, obtain process simulation outputs and a great lot of parameters and distributions functions of simulated processes.

Another distinctive feature of our approach is the use of autonomic components ensembles. Each vehicle is associated with the corresponding autonomic component AC (implemented as a virtual machine in datacenter) and exchange on-line information with other vehicles. This allows a vehicle to notify other vehicles about expected and actual congestion. Besides, ACs can reschedule routes in order to find the acceptable alternative routes that enable vehicles to meet time windows requirements and, at the same time, avoid the congested roads. It is necessary to point out that the algorithm of adaptation is able to reschedule and find alternative routed for several vehicles in parallel. The latter significantly increases the performance of proposed approach.

3.2 Chapter III Summary

In chapter III Adaptive real-world algorithm of solving MDVRPTW (Multi Depots Vehicle Routing Planning with Time Windows) problem is proposed. This tool permits users to compose and run complex simulation models that are very close to the real-world situations. Our approach implements additionally involuntary elements ensembles conception. every vehicle is related to the corresponding autonomic component AC (a virtual machine in datacenter) and exchange on-line data with different vehicles.

Chapter IV Application Of DEECo

4.1 Application Of DEECo Framework To MDVRPTW Problem

In the work the idea of Autonomic Components Ensembles (ACE), that are applied to the real-world Multi-Depots Vehicle Routing Planning with Time Windows (MDVRPTW), is proposed. Every vehicle is applied to each corresponding autonomic component AC (a virtual machine in datacenter) and share on-line data with every other vehicle. Moreover, ACs can reschedule routes in order to find the acceptable alternative routes that enable vehicles to meet time windows requirements and, at the same time, avoid the congested roads. Implementation of DEECo (Distributed Emergent Ensembles of Components) model to create dynamic ensembles of vehicles and non-congested route segments is also proposed in the paper. Detailed description of components, components' knowledge, processes and interfaces is given.

In previous part we described the adaptive algorithm to solve Multi Depots Vehicle Routing Planning with Time Windows (MDVRPTW) problem. The heuristics is aimed to account for realistic real-world scenario, like presence of varied congestion varieties. The congestions are the foremost vital essential factors for the productive and practically acceptable solution of the MDVRPTW problem. Traffic jams cause serious delays.

To provide the real-time adaptability the proposed approach uses the concept of *autonomic components (AC) and autonomic component ensembles (ACE).* Each vehicle is associated with the corresponding autonomic component AC (implemented as a virtual machine in datacenter) and exchange on-line information with other vehicles. This allows a vehicle to notify other vehicles about expected and actual congestion. Besides, ACs can reschedule routes in order to find the acceptable alternative routes that allows vehicles to meet time windows requirements and, at the same time, avoid the congested roads. It is necessary to point out that the algorithm of adaptation is able to reschedule and find alternative routed for several vehicles in parallel. The latter significantly increases the performance of proposed approach.

As described in first chapter DEECo has concept of two main concepts: component and ensemble [22]. A component is an independent and self-sustained unit of development, deployment and computation. An ensemble acts as a dynamic binding mechanism, which connects a group of components and controls their interactions. A grounding idea in DEECo is that the only way components bind and communicate with one another is through ensembles. An integral part of the component model is also the runtime framework providing the necessary management services for both components and ensembles.

A *component* in DEECo comprises *knowledge*, exposed via a set of *interfaces*, and *processes*[22]. Knowledge reflects the state and available functionality of the component (lines 6-19). It is organized as a hierarchical data structure, which maps knowledge identifiers to values. Specifically, values may be either potentially structured data or executable functions. In this context, the term *belief* refers to the part of a component's knowledge that represents a copy of knowledge of another component, and is thus treated with a certain level of uncertainty as it might become obsolete or invalid.

A component's knowledge [22] is exposed to the other components and environment via a set of interfaces (lines 5, 60). An interface (e.g., lines 1-2) thus represents a partial view on the component's knowledge. Specifically, interfaces of a single component can overlap and multiple components can provide the same interface, thus allowing for polymorphism of components.

Component processes are essentially soft real-time tasks that manipulate the knowledge of the component. A process is characterized as a function (lines 23-27) associated with a list of input and output knowledge fields (line 21,22). Operation of the process is managed by the runtime framework and consists of atomically retrieving all input knowledge fields, computing the process function, and atomically writing all output knowledge fields [22].

Being active entities of computation implementing feedback loops, component processes are subject to cyclic scheduling, which is again managed by the runtime framework [22]. A process can be scheduled either periodically (line 74), i.e., repeatedly executed once within a given period, or as triggered (line 28), i.e., executed when a trigger condition is met.

```
1. interface RouteSegmentsCongestionAware:
2.      initialSP, routeSegment, congestionStatus,  expectedCongestionInducedDelay

3. interface RouteSegmentAvailabilityAggregator:
4.           position, timetable, routeSegmentsAvailability

5. component  Vehicle  features RouteSegmentAvailabilityAggregator:
6.        knowledge:
7.            position = GPS(…),
8.            currentSP=(position, …),
9.            routeSegmentsAvailability=List<segmentsStatus>
10.           timetable = List<TimeWindowsForSPs>,
11.               route = {
12.                             List<SPs>,
                    onSchedule=TR
                     isFeasible=TRUE
                 },
        expectedCongestionInducedDelay=(…),
        vehicleParameters=List<Parameters>,
         costDriverWaitPayment=(….),
         costViolationTimeWindows=(….)

   process computeNewRoute:
           in routeSegmentsAvailability, in timetable,
           inout   route
         function:
               if (!route.isFeasible ∧ (costDriverWaitPayment
                     >costViolationTimeWindows))
                 route ← ME.ALNS.computeRoute (position, timetable,
                                          routeSegmentsAvailability)
          scheduling: periodic(2000)


   process checkRouteFeasibility:
           in route,  in position, in  timetable, in routeSegmentsAvailabilities,
           out   route.isFeasible
        function:
           route.isFeasible ← ME.checkRouteFeasibility (route, position, timetable,
                                                routeSegmentsAvailabilities)
        scheduling: triggered(changed(routeSegmentsAvailabilities) ⋁
                                         changed(onSchedule))

   process  computeCostDriverWaitPayment:
          in routeSegment,
          in  CongestionInducedDelay,
          in  vehicleParameters,
          out CostDriverWaitPayment
       function:
           CostDriverWaitPayment← ME.computeCostDriverWaitPayment(routeSegment,
                                       vehicleParemeters,  CongestionInducedDelay)
       scheduling: triggered(changed(changed(routeGenerated.isFeasible)  ⋁
                                 changed(onSchedule) ⋁
                                 changed(routeSegmentsAvailabilities) )

    process  computeCostViolationTimeWindows:
          in routeSegment,
          in  CongestionInducedDelay,
          in  vehicleParameters,
          out costViolationTimeWindows
      function:
          costViolationTimeWindows ←
               ME.computeCostViolationTimeWindows(routeSegment,
                    CongestionInducedDelay, vehicleParameters)
      scheduling: triggered(changed(changed(routeGenerated.isFeasible)  ⋁
                                 changed(onSchedule) ⋁
                                 changed(routeSegmentsAvailabilities) )

component  RouteSegmentsCongestion features RouteSegmentsCongestionAware:
   knowledge:
      initialSP=(…),
      endSPs =List<adjacentSPs>,
      routeSegment =(initialSP, endSP ∈endSPs),
      segmentAvailability=(…),
      congestionStatus=[congestionStatus, type,  startingTime,
                      expectedCongestionClearanceTime,
                      congestionClearanceProbability],
       expectedCongestionInducedDelay=(….)

    process observeSegmentAvailability:
           out  segmentAvailability
       function:
           segmentAvailability ← MessageFromVehicle.getSegmentCurrentAvailability
      scheduling: periodic(1000)

   process computeCongestionInducedDelay:
           in routeSegment,
           in congestionDuration, in segmentNonCongestedCapacity,
           in segmentCongestedCapacity, in arrivalRate,
           out CongestionInducedDelay
       function:
           CongestionInducedDelay ←
                  ME.computeCongestionInducedDelay(routeSegment,
                  congestionDuration, segmentNonCongestedCapacity,
                  segmentCongestedCapacity)
          scheduling: triggered(changed(congestionStatus) )
```

Figure 27 RouteSegmentAvailabilityAggregator

Referring to the MDVRPTW running example, the components (each occurring in multiple instances) are the *Vehicle* and the *RouteSegmentsCongestion*. A Vehicle maintains a belief over the availability of the relevant *RouteSegmentsCongestion* (routeSegmentsAvailability, line 9). It uses an Adaptive Large Neighborhood Search (ALNS) library to (re-) compute its route according to the availability belief
and its timetable (lines 20-28) every time the availability belief or route feasibility changes (line 28).

The Vehicle also checks if its route remains feasible, with respect to the corresponding *routeSegmentsAvailabilities* and its route's *onSchedule* propertycurrent position (lines 29-36). A *RouteSegmentsCongestion* just keeps track of its available route's segment availability and computes the expected Congestion Induced Delay time (lines 60-85).

An *ensemble* (see the description below) implements a dynamic binding among a set of components and thus determines their composition and interaction [3]. In DEECo, composition is flat, expressed implicitly via a dynamic involvement in an ensemble. Among the components involved in an ensemble, one always plays the role of the ensemble's coordinator while others play the role of the members. This is determined dynamically (the task of the runtime framework) according to the membership condition of the ensemble.

```
ensemble UpdateRouteSegmentAvailabilityInformation
    coordinator: RouteSegmentAvailabilityAggregator
    member: RouteSegmentsCongestionAware
    membership:
          ∃ vehicle ∈coordinator. routeSegmentsAvailability:
                    isAvailable(member.routeSegmentsAvailability)==TRUE
    knowledge exchange:
          coordinator: routeSegmentsAvailability ← member. routeSegmentsAvailability
          coordinator: expectedCongestionInducedDelay ← member.
                          expectedCongestionInducedDelay
     scheduling: periodic(2000)
```

As to interaction, the individual components in an ensemble are not capable of explicit communication with the others [22]. Instead, the interaction among the components forming the ensemble takes the form of *knowledge exchange.* Specifically, definition of an ensemble consists of:

- *Membership* condition. Definition of a membership condition includes the definition of the interface specific for the *coordinator* role – coordinator interface (line 2), as well as the interface specific for the member role (and thus featured by each member component) – member interface (line 3), and the definition of a *membership predicate* (lines 4-6). A membership predicate declaratively expresses the condition under which two components represent a coordinator-member pair of the associated ensemble. The predicate is defined upon the knowledge exposed via the coordinator/member interfaces and is evaluated by the runtime framework when necessary.

- *Knowledge exchange.* Knowledge exchange embodies the interaction between the coordinator and all the members of the ensemble (lines 7-8); i.e., it is a one-to-many interaction (in contrast to the one-to-one form of the membership predicate). Being limited to coordinator-member interaction, knowledge exchange allows the coordinator to apply various interaction policies. In principle, knowledge exchange is carried out by the runtime framework; thus, it is up to the runtime framework when/how often it is performed. Similarly, to component processes, knowledge exchange can be carried out either periodically or when triggered (line 11). Based on the ensemble definition, a new ensemble is dynamically formed for each group of components that together satisfy the membership condition.

The only ensemble of the running example is the *UpdateRouteSegmentAvailabilityInformation* ensemble. Its purpose is to aggregate the route segments availability information of the members, i.e. $RouteSegmentsCongestions$, on the side of the coordinator, i.e., Vehicle (lines 9-10). The ensemble is formed only when a route segment is available and the expected congestion induced delay time is acceptable.

By building on Java annotations, the mapping of DEECo concepts relies on standard Java language primitives and does not require any language extensions or external tools [22].

An examples of a *component* definition has the form of a Java class:

```
1.   @DEECoComponent
2.   public class Vehicle extends ComponentKnowledge {
3.         public Position position;
4.         public ServicePoint currentSP
5.         public List< TimeWindowsForSPs >  timetable;
6.         public Map<ID, segmentsStatus >  routeSegmentsAvailability
7.         public  Route  route;
8.         public  Delay expectedCongestionInducedDelay;
9.         public   List <vehicleParameters>  vehicleParameters
10.        public   Cost  costDriverWaitPayment,
11.        public    Cost  costViolationTimeWindows

12.   public Vehicle() {
 13.       // initialize the initial knowledge structure reflected by the class fields
 14.      }

15. @DEECoProcess
16. public static void  computeNewRoute(
17.        @DEECoIn("routeSegmentsAvailability ") @DEECoTriggered Map<…>
18.                                                       routeSegmentsAvailability
19.        @DEECoIn("timetable") List< TimeWindowsForSPs > timetable,
20.        @DEECoInOut("route") Route   route
21.      ) {
22.           // re---compute the vehicle's route  if it's infeasible
23.     }

24. @DEECoProcess
25. @DEECoPeriodScheduling(2000))
26. public static void checkRouteFeasibility (
27.             @DEECoIn("route") Route route,
28.             @DEECoIn("timetablel") List< TimeWindowsForSPs >   timetable,
29.             @DEECoIn("position") Position position,
 30.            @DEECoOut("route.isFeasible") OutWrapper<Boolean> isRouteFeasible
 31             ){
 32.                    // determine feasibility of the route
 33.              }
 34                . ...
 35.        }
```

A component definition has the form of a Java class (see the above code). Such a class is marked by the @DEECoComponent annotation and extends the ComponentKnowledge class. The initial knowledge structure of the component is captured by means of the public, non-static fields of the class (lines 3-11). At runtime, this initial knowledge structure is initialized either via static initializers or via the constructor of the class (lines 12-14). The component processes are defined as public static methods of the class, annotated with @DEECoProcess (e.g., lines 15-23).
The input and output knowledge of the process is represented by the methods' parameters.

The parameters are marked with one of the annotations @DEECoIn, @DEECoOut or @DEECoInOut, in order to distinguish between input and output knowledge fields of the process (e.g., lines 17-20). Each annotation also includes an identifier of the knowledge field that the associated method parameter represents.

When a non-structured knowledge field constitutes an inout/out knowledge of a process, the associated method parameter is for technical reasons (related to Java immutable types) passed inside an OutWrapper object (e.g., line 30). Periodic scheduling of a process is defined via the @DEECoPeriodicScheduling annotation of the process's method, which takes the period expressed in milliseconds in its parameter (line 25). Triggered scheduling is defined via @DEECoTriggered annotation of the method's parameter, change of which should trigger the execution of the process (lines 17-19).

Below the example of an ensemble definition Java (jDEECO) is given:

```
1. @DEECoEnsemble
2. @DEECoPeriodicScheduling(2000)
3. public  class UpdateRouteSegmentAvailabilityInformation extends Ensemble {
4.
5.          @DEECoEnsembleMembership
6.          public static Boolean membership (
7.                  @DEECoIn("coordinator.routeSegmentsAvailability ")
                                       List< segmentsStatus>,
8.                  @DEECoIn("member.routeSegmentsAvailability ")  SegmetStatus,
9.                   @DEECoIn("member. expectedCongestionInducedDelay ") Delay
10.          ) {
11.                  for (RouteSegment rs : segmentRoute)) {
12.                       if (isAvailable(rs.routeSegmentsAvailability)==TRUE
13.                   return true;
14.                  }
15.             return false;
16.     }
17.
18.
19.  @DEECoEnsembleKnowledgeExchange
 20. @DEECoPeriodScheduling(2000))
21. public static void knowledgeExchange (
22.     @DEECoOut("coordinator. routeSegmentsAvailability ") Map <…> SegmentStatus,
23.     @DEECoOut("coordinator. expectedCongestionInducedDelay ")  Delay,
24.     @DEECoIn("member. routeSegmentsAvailability]") Map <…> SegmentStatus,
25.     @DEECoIn("member. expectedCongestionInducedDelay "") Delay,,
26.   )
27.  }
```

The ensemble definition takes also the form of a Java class [22]. In particular, the class is marked with the @DEECoEnsemble annotation and extends the Ensemble class (see the above example). Both the membership predicate and the knowledge exchange are defined as specifically-annotated static methods of this class. While the method representing the membership predicate is annotated by @DEECoEnsembleMembership (line 5), the method representing knowledge exchange is annotated by @DEECoEnsembleKnowledgeExchange (line 19).

The jDEECo runtime framework is primarily responsible for scheduling component processes, forming ensembles, and performing knowledge exchange. It also allows for distribution of Components [22].

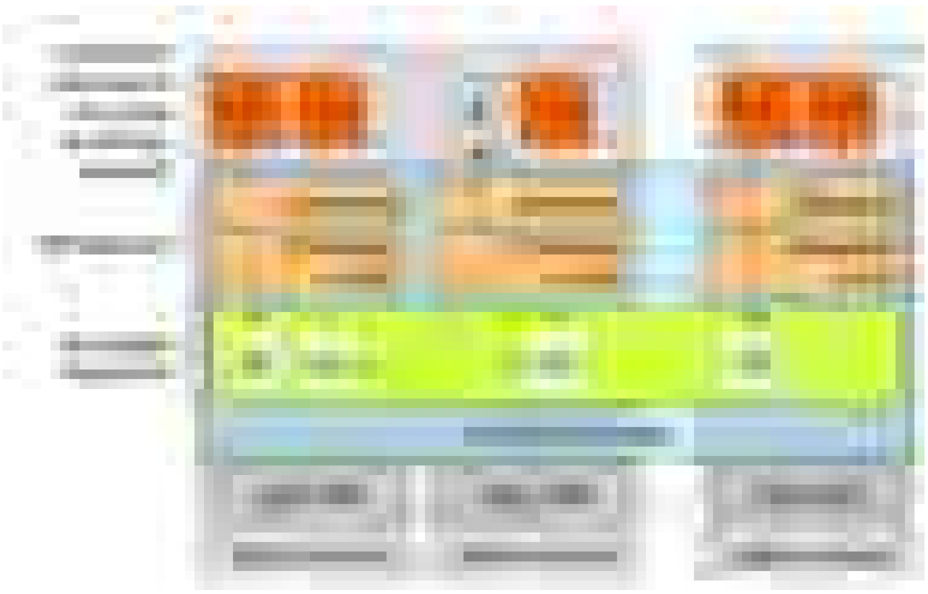


Figure 28 jDEECo runtime framework architecture.

As illustrated in Figure 28, it is internally composed of the management part and the knowledge repository. The management part is further composed of two modules. One is responsible for scheduling and execution of component processes and knowledge exchange of ensembles. The other is responsible for managing access to the knowledge repository. Exploiting the fact that all modules of the runtime framework implementation are loosely coupled, we are able to introduce implementation variants for each of them. As a result, different variants can be selected in order to reflect specific requirements imposed to the platform [22].

The role of the knowledge repository is to store the component’s knowledge (e.g., CK1 – knowledge of component C1 – in Figure 28). Its responsibility is also to provide component processes and knowledge exchange of ensembles with access to this knowledge. In fact, we provide a local and a distributed implementation of the knowledge repository; the former is employed for simulation and verification of the code) while the latter is used in case the runtime framework needs to run in a distributed setting (i.e., the distribution is achieved at the level of knowledge repository).

Specifically, the distributed implementation of the knowledge repository allows each component to run in a different Java virtual machine (as illustrated in Figure 28).
The approach described above was implemented by using cloud computing service provider *Google Cloud Platform*. Namely, *IaaS* (Infrastructure-as-a-Service) was used for creation and deployment Virtual Machines (VM), associated with the vehicles (totally 17 VMs) and the Virtual Machine, associated with the **base** Virtual machine VM_0 [1].
The VM_0 hosts all main structural components of proposed system: JSpirit, MatSim, ALNS, travel and congestion management database (TCMD), database of simulation results (SRD), web servers for connection with vehicles, GPS, etc. VMs, associated with vehicles, run local reduced copies of ALNS algorithm, and local copy of TCMD and SRD databases.

Payments Pay-as-you-go for consumed resources of the Google Cloud Platform datacenter are on average 60% less for many compute workloads than other clouds. Implementation of Autonomic Components Ensembles (ACE) on Google Cloud Platform (and, in general, on other cloudproviders platforms) shifts most of the costs from *capital expenditures* (or buying and installing servers, storage, networking, and related infrastructure) to an *operating expenses* model, where customers pay only for usage of these types of resources.

4.2 Cloud computing [34]

Cloud computing is a general term for the delivery of hosted services over the internet.
Cloud computing is an information technology concept that implies the provision of ubiquitous and convenient network access on demand to a common pool of configurable computing resources (for example, data networks, servers, storage devices, applications and services - as Together, and separately), which can be promptly provided and released with minimal operating costs or calls to the provider.
Consumers of cloud computing can significantly reduce the cost of information technology infrastructure (in the short and medium term) and flexibly respond to changes in computing needs, using the properties of computational elasticity (English elastic computing) of cloud services.

The use of real infrastructures, like Amazon EC2 and Microsoft Azure, for benchmarking program performance (throughput, price benefits) underneath variable conditions (availability, employment patterns) is commonly forced by the rigidity of the infrastructure. Hence, this makes the replica of results which will be relied upon, an especially tough endeavor. Further, it's tedious and time overwhelming to re-configure benchmarking parameters across a massive-scale Cloud computing infrastructure over multiple check runs. Such limitations are caused by the conditions prevailing within the Cloud-based environments that don't seem to be within the management of developers of application services. Thus, it's impossible to perform benchmarking experiments in repeatable, dependable, and scalable environments using real-world Cloud environments.

Self-service on demand (self-service on demand) - the consumer independently identifies and changes computing needs, such as server time, access and processing speed, the amount of stored data without interacting with a representative of the service provider;

Universal access over the network - services are available to consumers over the data network, regardless of the terminal device used;

Resource pooling - a service provider integrates resources to serve a large number of consumers in a single pool for dynamic redistribution of capacity between consumers in a constantly changing demand for capacity; While consumers control only the basic parameters of the service (for example, data volume, access speed), but the actual distribution of resources provided to the consumer is performed by the supplier (in some cases, consumers can still manage some physical parameters of redistribution, for example, specify the desired data center For reasons of geographical proximity);

Elasticity - services can be provided, expanded, narrowed at any time, without additional costs for interaction with the supplier, usually in automatic mode;

Consumption accounting - the service provider automatically calculates the consumed resources at a certain level of abstraction (for example, the amount of data stored, bandwidth, the number of users, the number of transactions), and on the basis of these data estimates the volume of services provided to consumers.

From the vendor's point of view, due to the pooling of resources and the volatile nature of consumer consumption, cloud computing allows economies of scale, using less hardware than would be required with dedicated hardware for each customer, and by automating the procedures for modifying resource allocation, costs are significantly reduced To subscription service.

From the customer's point of view, these characteristics allow you to get services with high availability and low risks of inoperability, to provide rapid scalability of the computing system due to elasticity without the need to create, maintain and upgrade your own hardware infrastructure.

4.2.1 Private cloud

Private cloud is an infrastructure intended for use by one organization, including several consumers (for example, units of the same organization), possibly also customers and contractors of this organization. A private cloud can be owned, managed and operated by both the organization itself and a third party (or some combination thereof), and it can physically exist both within and outside the owner's jurisdiction.

4.2.2 Public cloud

The public cloud is an infrastructure designed for free use by the general public. A public cloud can be owned, managed and operated by commercial, scientific and government organizations (or some combination thereof). A public cloud exists physically in the jurisdiction of the owner-provider of services.

The public cloud is an infrastructure type intended for use by a specific community of consumers from organizations with common tasks (for example, missions, security requirements, policies, and compliance with various requirements). A public cloud may be co-operative (co-owned), managed and operated by one or more of the community organizations or a third party (or any combination thereof), and it can physically exist both within and outside the owner's jurisdiction.

4.2.3 Hybrid Cloud

A hybrid cloud is a combination of two or more different cloud infrastructures (private, public or public) that remain unique objects, but are interconnected by standardized or proprietary data and application technologies (for example, short-term use of public cloud resources For load balancing between clouds)

4.2.4 Software as a Service

Software as a Service (SaaS, Software-as-a-Service) is a model in which the user is given the opportunity to use the application software of a provider operating in the cloud infrastructure and accessible from various client devices or through a thin client, for example, from a browser (For example, web mail) or through the program interface. Control and management of the basic physical and virtual infrastructure of the cloud, including the network, servers, operating systems, storage, or even individual application features (except for a limited set of custom application configuration settings) is provided by the cloud provider.

4.2.5 Platform as a service

The platform as a service (PaaS, Platform-as-a-Service) is a model where the user is given the opportunity to use the cloud infrastructure to place the basic software for subsequent placement on it of new or existing applications (own, custom-built or purchased replicated applications). Such platforms include tools for creating, testing and executing application software - database management systems, middleware, runtime programming languages provided by a cloud provider.

Control and management of the basic physical and virtual infrastructure of the cloud, including the network, servers, operating systems, storage is carried out by the cloud provider, with the exception of developed or installed applications, and, if possible, environment configuration parameters (platform).

4.2.6 Infrastructure as a Service

Infrastructure as a service (IaaS, Infrastructure-as-a-Service) is provided as an opportunity to use the cloud infrastructure for self-management of processing, storage, networks and other fundamental computing resources, for example, a user can install and run arbitrary software that can Include operating systems, platform and application software. The consumer can monitor operating systems, virtual storage systems and installed applications, and also have limited control over the set of available network services (for example, a firewall, DNS). Control and management of the basic physical and virtual infrastructure of the cloud, including the network, servers, types of operating systems used, storage systems is provided by the cloud provider

4.2.7 CloudSim

In the process of development and operation of distributed computing systems, especially cloud computing systems, issues arise related to the change in the structure of these systems, the algorithms of their operation and architecture. Of particular interest is the study of the impact of these changes on the key parameters of a distributed computing system: performance, security, fault tolerance, scalability, etc. Currently, many studies are under way to study the behavior of large distributed systems, and software is being created to carry out these studies.

Simulation is an approach in which a model application is executed within the framework of a computing environment model. Simulation allows you to focus the process on modeling a certain part of the environment, abstracting from the rest of the system. This approach allows us to achieve a high level of repeatable results within a wide range of different platforms and experimental conditions, allowing us to evaluate the behavior of Algorithms under changing conditions and, based on this, to optimize the strategies for managing task flows. The main advantage of this approach is the flexibility of the system, since both the application and the computing environment are models, it is possible to easily change the experimental conditions. The downside, however, is the extremely high complexity of developing application models and the computing environment.

CloudSim [41] is a framework for modeling and simulation of cloud computing infrastructures and services. Originally built primarily at the Cloud Computing and Distributed Systems (CLOUDS) Laboratory, The University of Melbourne, Australia, CloudSim has become one of the most popular open source cloud simulators in the research and academia. CloudSim is completely written in Java. (Calheiros et al.,2011, 2014)

The core of CloudSim is based on the SimJava engine, which supports such basic functions like the use of queues when processing events, the creation of cloud entities (services, nodes, data centers, resource brokers and virtual machines), the interaction between the elements of the system and the management of the flow of the simulation. When developing a cloud environment model, the user needs to refine the key components for his model to achieve results that are as close to reality as possible.

The main entities of the platform for modeling are Virtual Machine and Task. These components are specific for different groups of cloud systems. For example, for cloud systems like PaaS, it will be common to deploy several applications on the same virtual machine.

The most important components in the modeling are the components responsible for resource management policies. The tasks that these components solve include the following:

- Allocation of processor capacities, operative memory and other resources for various entities of the simulated system;
- Deployment of virtual machines on the nodes of the simulated system;
- Distribution of tasks between virtual machines of the simulated system.

The principle of the model based on the CloudSim platform implies the completion of the necessary basic components of the platform and a preliminary description of the simulated system and the simulation scenario in the form of source code. After starting the simulation, all data about the simulated system is transferred to the core of CloudSim, where the simulation is performed.

It should be noted that the CloudSim platform does not imply changes in the simulated system or simulation scenarios directly during the operation of the model, which imposes some limitations on the platform's capabilities.

For initial test of the algorithms and heuristics we used CloudSim platform to get close to real life scenario of the behavior of the cloud computing.

CloudSim offers the subsequent features: support for modeling and simulation of huge scale Cloud computing environments, as well as data centers, on one physical computing node;

- A self-contained platform for modeling Clouds, service brokers, provisioning, and allocation policies;
- Support for simulation of network connections among the simulated system elements;
- Facility for simulation of united Cloud environment that inter-networks resources from each non-public and public domains, a feature essential for analysis studies associated with Cloud-Bursts and automatic application scaling.

A number of the distinctive options of CloudSim are:

- Accessibility of a virtualization engine that aids within the creation and management of multiple, independent, and co-hosted virtualized services on a knowledge center node
- Flexibility to switch between space-shared and time-shared allocation of process cores to virtualized services.

These compelling options of CloudSim would speed up the event of recent application provisioning algorithms for Cloud computing.

Figure 29 Class design diagram for CloudSim

The recent development of Cloud technologies focuses mainly on defining nowadays methodologies, policies and techniques to manage Cloud infrastructures. For testing these newly developed methods and policies, researchers need tools that allow them to evaluate the hypothesis before a real deployment in an environment, where they can reproduce tests.

Simulation-based approaches in evaluating Cloud computing systems and application behaviors offer significant benefits, because they allow Cloud developers to test the performance of their provisioning and service delivery policies in a repeatable and controllable environment free of cost and also to tune the performance bottlenecks before real-world deployment on commercial Clouds.

Resource planning is a critical aspect of cloud resource management. Accordingly, the ability to model different approaches and resource planning algorithms is a necessary feature of any distributed computer system modeling system.

For the previous estimation of the real cloud implementation of the developed adaptive real-world algorithm of solving MDVRPTW we have performed the detailed simulation of the system. The characteristics of the simulated system are as follows:

- 1 datacenter
- 1 broker that allocates the cloudlets between the virtual machines, and implements allocation of virtual machines among the physical hosts
- 20 virtual machines which simulated routes planning for 20 vehicles
- 20 cloudlets which represent local execution of the adaptive algorithms
- The size of the cloudlet (the program representing the adaptive algorithm) is estimated as 40000 MI (million instructions); this estimation was made by using the special program which converts the length of any program written in high level programming language into the machine language of the hosts on which the virtual machines run

```
package org.cloudbus.cloudsim.examples;

import java.text.DecimalFormat;
import java.util.ArrayList;
import java.util.Calendar;
import java.util.LinkedList;
import java.util.List;

import org.cloudbus.cloudsim.Cloudlet;
import org.cloudbus.cloudsim.CloudletSchedulerTimeShared;
import org.cloudbus.cloudsim.Datacenter;
import org.cloudbus.cloudsim.DatacenterBroker;
import org.cloudbus.cloudsim.DatacenterCharacteristics;
import org.cloudbus.cloudsim.Host;
import org.cloudbus.cloudsim.Log;
import org.cloudbus.cloudsim.Pe;
import org.cloudbus.cloudsim.Storage;
import org.cloudbus.cloudsim.UtilizationModel;
import org.cloudbus.cloudsim.UtilizationModelFull;
import org.cloudbus.cloudsim.Vm;
import org.cloudbus.cloudsim.VmAllocationPolicySimple;
import org.cloudbus.cloudsim.VmSchedulerTimeShared;
import org.cloudbus.cloudsim.core.CloudSim;
import org.cloudbus.cloudsim.provisioners.BwProvisionerSimple;
import org.cloudbus.cloudsim.provisioners.PeProvisionerSimple;
import org.cloudbus.cloudsim.provisioners.RamProvisionerSimple;

/**
 * The simulation program  showing how to create a data center with 20 host and run 20
cloudlets on it.

 */
public class CloudSimMDVRPTW {
	/** The cloudlet list. */
	private static List<Cloudlet>cloudletList;
	/** The vmlist. */
	private static List<Vm>vmlist;

	/**
	 * Creates main() to run this example.
	 *
	 * @paramargs the args
	 */
	@SuppressWarnings("unused")
	public static void main(String[] args) {
		Log.printLine("Starting CloudSimExample1...");

		try {
			// First step: Initialize the CloudSim package. It should be called before
creating any entities.
			intnum_user = 1; // number of cloud users
			Calendar calendar = Calendar.getInstance(); // Calendar whose fields have
been initialized with the current date and time.
			booleantrace_flag = false; // trace events

			/* Comment Start - Dinesh Bhagwat
			 * Initialize the CloudSim library.
			 * init() invokes initCommonVariable() which in turn calls initialize() (all
these 3 methods are defined in CloudSim.java).
			 * initialize() creates two collections - an ArrayList of SimEntity Objects
(named entities which denote the simulation entities) and
```

```
			 * a LinkedHashMap (named entitiesByName which denote the
LinkedHashMap of the same simulation entities), with name of every SimEntity as the key.
			 * initialize() creates two queues - a Queue of SimEvents (future) and
another Queue of SimEvents (deferred).
			 * initialize() creates a HashMap of of Predicates (with integers as keys) -
these predicates are used to select a particular event from the deferred queue.
			 * initialize() sets the simulation clock to 0 and running (a boolean flag) to
false.
			 * Once initialize() returns (note that we are in method
initCommonVariable() now), a CloudSimShutDown (which is derived from SimEntity) instance
is created
			 * (with numuser as 1, its name as CloudSimShutDown, id as -1, and state
as RUNNABLE). Then this new entity is added to the simulation
			 * While being added to the simulation, its id changes to 0 (from the earlier
-1). The two collections - entities and entitiesByName are updated with this SimEntity.
			 * the shutdownId (whose default value was -1) is 0
			 * Once initCommonVariable() returns (note that we are in method init()
now), a CloudInformationService (which is also derived from SimEntity) instance is created
			 * (with its name as CloudInformatinService, id as -1, and state as
RUNNABLE). Then this new entity is also added to the simulation.
			 * While being added to the simulation, the id of the SimEntitiy is changed
to 1 (which is the next id) from its earlier value of -1.
			 * The two collections - entities and entitiesByName are updated with this
SimEntity.
			 * the cisId(whose default value is -1) is 1
			 * Comment End - Dinesh Bhagwat
			 */
			CloudSim.init(num_user, calendar, trace_flag);

			// Second step: Create Datacenters
			// Datacenters are the resource providers in CloudSim. We need at
			// list one of them to run a CloudSim simulation
			Datacenter datacenter0 = createDatacenter("Datacenter_0");

			// Third step: Create Broker
			DatacenterBroker broker = createBroker();
			intbrokerId = broker.getId();

			// Fourth step: Create one virtual machine
			vmlist = new ArrayList<Vm>();

			// VM description
			intvmid = 0;
			intmips = 250; // Million Instruction Per Second – MIPS
```

```
                        long size =10000; // image size (MB),
                        int ram = 1024; // vm memory (MB)
                        long bw = 1000;
                        intpesNumber = 1; // number of cpus
                        String vmm = "Xen"; // VMM name

                        // create VM
                        Vm vm1 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size,
vmm, new CloudletSchedulerTimeShared());
Vmid++;
Vm vm2 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;


Vm vm3 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;


Vm vm4 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;


Vm vm5 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
        Vmid++;

        Vm vm6 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;


Vm vm7 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;

Vm vm8 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
Vmid++;

Vm vm9 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());
```

```
Vmid++;

Vm vm10 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm11 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm12 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm13 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm14 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm15 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm16 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm17 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm18 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm19 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());

Vm vm20 = new Vm(vmid, brokerId, mips, pesNumber, ram, bw, size, vmm, new
CloudletSchedulerTimeShared());



                        // add the VM to the vmList
                        vmlist.add(vm1);
                        vmlist.add(vm2);
vmlist.add(vm3);
vmlist.add(vm4);
vmlist.add(vm5);
vmlist.add(vm6);
vmlist.add(vm7);
vmlist.add(vm8);
vmlist.add(vm9);
vmlist.add(vm10);
                    vmlist.add(vm11);
                    vmlist.add(vm12);
vmlist.add(vm13);
vmlist.add(vm14);
vmlist.add(vm15);
vmlist.add(vm16);
vmlist.add(vm17);
vmlist.add(vm18);
vmlist.add(vm19);
vmlist.add(vm20);


                    // submit vm list to the broker
                    broker.submitVmList(vmlist);

                    // Fifth step: Create one Cloudlet
                    cloudletList = new ArrayList<Cloudlet>();

                    // Cloudlet   properties
                    int id = 0;
                    long length = 40000;
                    long fileSize = 35000; //this size has to be considered the program + input
data sizes ( in bytes)
                    long outputSize = 35000; // the output file size of this Cloudlet after
execution (in bytes)
                    UtilizationModelutilizationModel = new UtilizationModelFull();

                    Cloudlet cloudlet1 =
                        new Cloudlet(id, length, pesNumber, fileSize,  outputSize,
utilizationModel, utilizationModel, utilizationModel);
                    cloudlet.setUserId(brokerId);
                    cloudlet.setVmId(vmid);
                         id++;

Cloudlet cloudlet2 =
 new Cloudlet(id, length, pesNumber, fileSize, outputSize, utilizationModel, utilizationModel,
utilizationModel);
cloudlet.setUserId(brokerId);
cloudlet.setVmId(vmid);
```

```
id++;

Cloudlet cloudlet3 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                          cloudlet.setUserId(brokerId);
                          cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet4 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                          cloudlet.setUserId(brokerId);
                          cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet5 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                          cloudlet.setUserId(brokerId);
                          cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet6 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                          cloudlet.setUserId(brokerId);
                          cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet7 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                          cloudlet.setUserId(brokerId);
                          cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet8 =
                        new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet9 =
                           new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet10 =
                           new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);

Cloudlet cloudlet11 =
                                     new Cloudlet(id, length, pesNumber, fileSize,  outputSize,
utilizationModel, utilizationModel, utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);
 id++;
id++;

Cloudlet cloudlet12 =
                           new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet13 =
                           new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                              cloudlet.setUserId(brokerId);
                              cloudlet.setVmId(vmid);
id++;
```

```
Cloudlet cloudlet14 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                             cloudlet.setUserId(brokerId);
                             cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet15 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                             cloudlet.setUserId(brokerId);
                             cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet16 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                             cloudlet.setUserId(brokerId);
                             cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet17 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                             cloudlet.setUserId(brokerId);
                             cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet18 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                             cloudlet.setUserId(brokerId);
                             cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet19 =
                          new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                cloudlet.setUserId(brokerId);
                cloudlet.setVmId(vmid);
id++;

Cloudlet cloudlet20 =
              new Cloudlet(id, length, pesNumber, fileSize,
outputSize, utilizationModel, utilizationModel,
utilizationModel);
                cloudlet.setUserId(brokerId);
                cloudlet.setVmId(vmid);



                // add the cloudlet to the list
                cloudletList.add(cloudlet1);
cloudletList.add(cloudlet2);
cloudletList.add(cloudlet3);
cloudletList.add(cloudlet4);
cloudletList.add(cloudlet5);
cloudletList.add(cloudlet6);
cloudletList.add(cloudlet7);
cloudletList.add(cloudlet8);
cloudletList.add(cloudlet9);
cloudletList.add(cloudlet10);
cloudletList.add(cloudlet11);
cloudletList.add(cloudlet12);
cloudletList.add(cloudlet13);
cloudletList.add(cloudlet14);
cloudletList.add(cloudlet15);
cloudletList.add(cloudlet16);
cloudletList.add(cloudlet17);
cloudletList.add(cloudlet18);
cloudletList.add(cloudlet19);
cloudletList.add(cloudlet20);

                // submit cloudlet list to the broker
                broker.submitCloudletList(cloudletList);
//bind the cloudlets to the vms. This way, the broker
                // will submit the bound cloudlets only to the specific VM
                broker.bindCloudletToVm(cloudlet1.getCloudletId(),vm1.getId());
broker.bindCloudletToVm(cloudlet2.getCloudletId(),vm2.getId());
                broker.bindCloudletToVm(cloudlet3.getCloudletId(),vm3.getId());
                broker.bindCloudletToVm(cloudlet4.getCloudletId(),vm4.getId());
```

```
			broker.bindCloudletToVm(cloudlet5.getCloudletId(),vm5.getId());
broker.bindCloudletToVm(cloudlet6.getCloudletId(),vm6.getId());
			broker.bindCloudletToVm(cloudlet7.getCloudletId(),vm7.getId());
			broker.bindCloudletToVm(cloudlet8.getCloudletId(),vm8.getId());

			broker.bindCloudletToVm(cloudlet9.getCloudletId(),vm9.getId());
broker.bindCloudletToVm(cloudlet10.getCloudletId(),vm10.getId());
			broker.bindCloudletToVm(cloudlet11.getCloudletId(),vm11.getId());
			broker.bindCloudletToVm(cloudlet12.getCloudletId(),vm12.getId());
			broker.bindCloudletToVm(cloudlet13.getCloudletId(),vm13.getId());
broker.bindCloudletToVm(cloudlet14.getCloudletId(),vm14.getId());
			broker.bindCloudletToVm(cloudlet15.getCloudletId(),vm15.getId());
			broker.bindCloudletToVm(cloudlet16.getCloudletId(),vm16.getId());
			broker.bindCloudletToVm(cloudlet17.getCloudletId(),vm17.getId());
broker.bindCloudletToVm(cloudlet18.getCloudletId(),vm18.getId());
			broker.bindCloudletToVm(cloudlet19.getCloudletId(),vm19.getId());
			broker.bindCloudletToVm(cloudlet20.getCloudletId(),vm20.getId());



			// Sixth step: Starts the simulation
			CloudSim.startSimulation();

			CloudSim.stopSimulation();

			//Final step: Print results when simulation is over
			List<Cloudlet>newList = broker.getCloudletReceivedList();
			printCloudletList(newList);

			Log.printLine("CloudSimExample1 finished!");
		} catch (Exception e) {
			e.printStackTrace();
			Log.printLine("Unwanted errors happen");
		}
	}

	/**
	 * Creates the datacenter.
	 *
	 * @param name the name
	 *
	 * @return the datacenter
	 */
	private static Datacenter createDatacenter(String name) {

		// Here are the steps needed to create a PowerDatacenter:
		// 1. We need to create a list to store
		// our machine
		List<Host>hostList = new ArrayList<Host>();

		// 2. A Machine contains one or more PEs or CPUs/Cores.
		// In this example, it will have only one core.
		List<Pe>peList = new ArrayList<Pe>();

		intmips = 1000;

		// 3. Create PEs and add these into a list.
		peList.add(new Pe(0, new PeProvisionerSimple(mips))); // need to store Pe id and
MIPS Rating

		// 4. Create Host with its id and list of PEs and add them to the list
		// of machines
		inthostId = 0;
		int ram = 4096; // host memory (MB)
		long storage = 1000000; // host storage
		intbw = 10000;

		hostList.add(
			new Host(
				hostId,
				new RamProvisionerSimple(ram),
				new BwProvisionerSimple(bw),
				storage,
				SpaceShared,
				new VmSchedulerTimeShared(SpaceShared)
			)
		); // This is our machine

		// 5. Create a DatacenterCharacteristics object that stores the
		// properties of a data center: architecture, OS, list of
		// Machines, allocation policy: time- or space-shared, time zone
		// and its price (G$/Pe time unit).
		String arch = "x86"; // system architecture
		String os = "Linux"; // operating system
		String vmm = "Xen";
		double time_zone = 4.0; // time zone this resource located
		double cost = 1.0; // the cost of using processing in this resource
		double costPerMem = 0.05; // the cost of using memory in this resource
		double costPerStorage = 0.001; // the cost of using storage in this
									// resource
		double costPerBw = 0.001; // the cost of using bw in this resource
		LinkedList<Storage>storageList = new LinkedList<Storage>(); // we are not
adding SAN
															//
devices by now

		DatacenterCharacteristics characteristics = new DatacenterCharacteristics(
				arch, os, vmm, hostList, time_zone, cost, costPerMem,
				costPerStorage, costPerBw);

		// 6. Finally, we need to create a PowerDatacenter object.
		Datacenter datacenter = null;
		try {
			datacenter = new Datacenter(name, characteristics, new
VmAllocationPolicySimple(hostList), storageList, 0);
		} catch (Exception e) {
			e.printStackTrace();
		}

		return datacenter;
	}

	// We strongly encourage users to develop their own broker policies, to
	// submit vms and cloudlets according
	// to the specific rules of the simulated scenario
	/**
	 * Creates the broker.
	 *
	 * @return the datacenter broker
	 */
	private static DatacenterBrokercreateBroker() {
		DatacenterBroker broker = null;
		try {
			broker = new DatacenterBroker("Broker");
		} catch (Exception e) {
			e.printStackTrace();
			return null;
		}
		return broker;
	}
	/**
	 * Prints the Cloudlet objects.
	 *
	 * @param list list of Cloudlets
	 */
	private static void printCloudletList(List<Cloudlet> list) {
		int size = list.size();
		Cloudlet cloudlet;

		String indent = "    ";
		Log.printLine();
		Log.printLine("========== OUTPUT ==========");
		Log.printLine("Cloudlet ID" + indent + "STATUS" + indent
				+ "Data center ID" + indent + "VM ID" + indent + "Time" + indent
				+ "Start Time" + indent + "Finish Time");

		DecimalFormatdft = new DecimalFormat("###.##");
		for (inti = 0; i< size; i++) {
			cloudlet = list.get(i);
			Log.print(indent + cloudlet.getCloudletId() + indent + indent);

			if (cloudlet.getCloudletStatus() == Cloudlet.SUCCESS) {
				Log.print("SUCCESS");

				Log.printLine(indent + indent + cloudlet.getResourceId()
						+ indent + indent + indent + cloudlet.getVmId()
						+ indent + indent
						+ dft.format(cloudlet.getActualCPUTime()) + indent
						+ indent + dft.format(cloudlet.getExecStartTime())
						+ indent + indent
						+ dft.format(cloudlet.getFinishTime()));
			}
		}
	}
}
```

The simulation program has yilded the following output:

```
Starting CloudSimMDVRPTW...
Initialising...
Starting CloudSim version 3.0
Datacenter_0 is starting...
Broker is starting...
Entities started.
0.0: Broker: Cloud Resource List received with 20 resource(s)
```

```
0.0: Broker: Trying to Create VM #0 in Datacenter_0
0.1: Broker: VM #0 has been created in Datacenter #1, Host #0
0.1: Broker: Sending cloudlet 0 to VM #0
0.1: Broker: Cloudlet 0 received
0.1: Broker: Trying to Create VM #1 in Datacenter_0
0.1: Broker: VM #1 has been created in Datacenter #1, Host #1
0.1: Broker: Sending cloudlet 1 to VM #1
……………………………………………………………………………………………..

0.1:  Broker: Trying to Create VM #20 in Datacenter_0
0.1:   Broker: VM #20 has been created in Datacenter #1, Host #20
0.1:  Broker: Sending cloudlet 20 to VM #20
160.1: Broker: Cloudlet 0 received
160.1: Broker: Cloudlet 1 received
……………………………………………………………………………………………..

160.1: Broker: Cloudlet 20 received

160.2: Broker: All Cloudlets executed. Finishing...


160.3: Broker: Destroying VM #0
160.3: Broker: Destroying VM #1
…………………………………………………………………………………………..
160.3: Broker: Destroying VM #20

Broker is shutting down...
Simulation: No more future events
CloudInformationService: Notify all CloudSim entities for shutting down.
Datacenter_0 is shutting down...
Broker is shutting down...
Simulation completed.
Simulation completed.

========== OUTPUT ==========
Cloudlet ID    STATUS    Data center ID    VM ID    Time    Start Time    Finish Time
   0       SUCCESS       0          0       160       0,1       160,1
   1       SUCCESS       0          1       160       0,1       160,1
………………………………………………………………………………………………………
………………………………………………………………………………………………………
……………………
   20      SUCCESS       0          20      160       0,1       160,1
CloudSimExample4 finished!
```

So, the total time of executing the adaptive algorithm MDVRPTW on the virtual machines (the extreme case, when all 20 vehicles require the rescheduling of their routes, was considered) is 160 sec. The additional time required for sending the information of rescheduled routes to the vehicles (through GPS tools and WEB server) is added.
The results of simulation proved that the proposed in the thesis approach can be effectively implemented by using autonomic component ensembles and cloud computing methodologies.

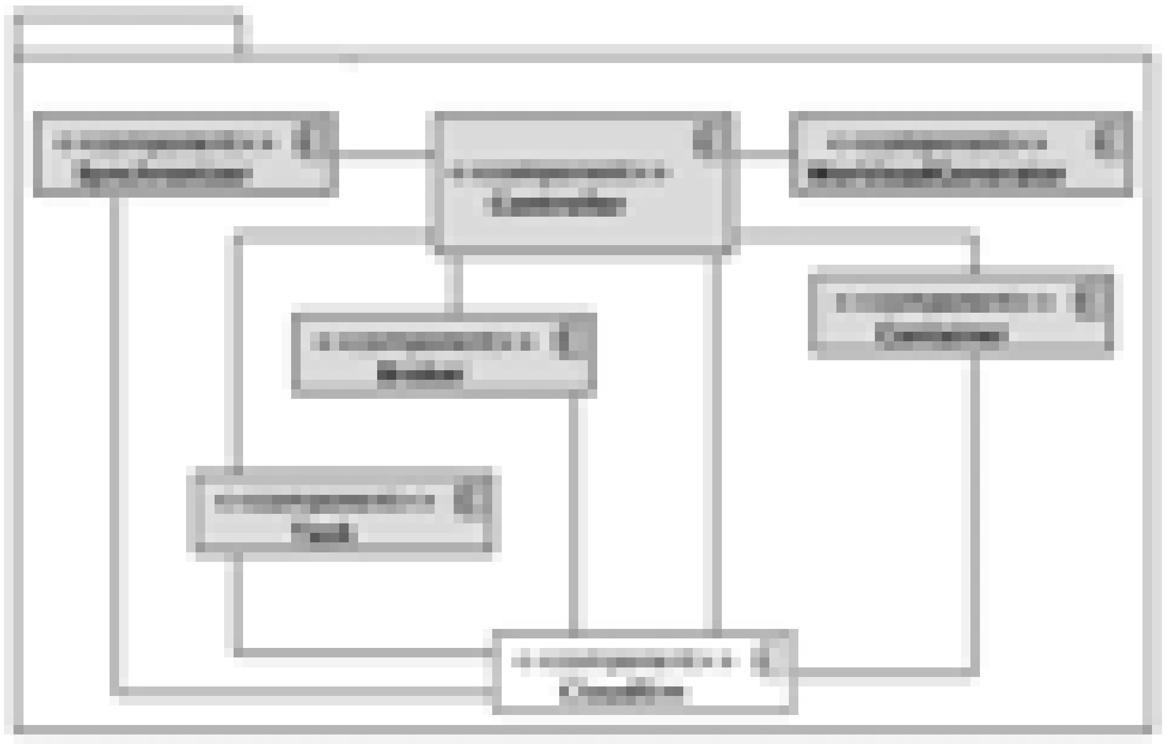


Figure 30Components of the software system for modeling private cloud PaaS-systems

The system of modeling of private cloud PaaS-systems consists of six components (Figure 4-5):

- Task - a component that describes the structure and features of the tasks that the system simulates. This component provides the ability to simulate the execution of nested subtasks, as well as the ability to specify the application by which this task should be performed.

- Container - a component that provides the functionality of the virtual machine within the simulation. Provides the ability to simulate the deployment of applications, as well as managing their lifecycle.
- WorkloadGenerator - a component that generates real-time load during the simulation. This component provides the periodic addition of tasks to the modeling subsystem of the simulated system, which allows you to simulate a predictable dynamic load on the system.
- Synchronizer - component that ensures correct modification of the simulated system during the simulation run. During simulation, the need for synchronization arises when simulating a spontaneous load, as well as using a decentralized approach to planning, in which resource schedulers are responsible for resource scheduling
- Broker - a component that implements the management of the resources of the simulated system during the simulation. The tasks of this component include the distribution of virtual machines on the nodes available in the simulated system, the distribution of applications by virtual machines, the distribution of tasks by applications.
- Controller - a component that prepares the essence of the simulated system based on the content of the configuration file prepared by the user.
- Cloudlet: this component represents the application service whose complexity is modeled in CloudSim in terms of the computational requirements.
- CloudCoordinator: this component manages the communication between other CloudCoordinator services and brokers, and also monitor the internal state of a data center which will be done periodically in terms of the simulation time.

Figure 31 Components CloudSim[45]

The main for modeling the cloud system is the configuration file of the model - JSON document, which contains a detailed description of the hardware infrastructure of the simulated system, as well as the simulation scenario. The configuration file consists of two blocks:

- datacenter - contains a description of the infrastructure of the system being simulated;
- workload - description of the simulation scenario.

The datacenter block describes the physical nodes (hosts block), virtual machines (vms block), task scheduling algorithms, and application distribution (block brokers). Each described physical node in the hosts block has a number of attributes:

- quantity - the number of nodes with the described characteristics;
- ram - memory of the node;
- storage - available disk storage;
- bandwidth - network bandwidth;
- CPUs - a list of available processors with the processing power specified in the millions of processor instructions per second (mips).

The description of virtual machines in the vms block has a structure similar to the description of physical nodes:

- quantity - the number of virtual machines with the characteristics described;
- cpu - the number of required cores;
- size - the size of the image;
- ram - required RAM;
- bandwidth - network bandwidth;
- mips - the required processing power in millions of processor instructions per second.

The brokers block specifies the paths to the files that contain the scheduling algorithms for tasks and distribution of applications in the simulated cloud environment. The developed system of modeling of private cloud PaaS-systems provides the possibility of implementing own algorithms for managing tasks and distributing applications.

The description of the simulation scenario in the workload block contains a list of tasks for the simulated system, the number of re-adding tasks to the queue and the time delay before re-adding tasks. The task description has the following structure:

- quantity - number of tasks with the same description;
- length - the number of processor instructions required to complete the task;
- fileSize - the size of the job file in megabytes;
- outputSize - the size of the result of the task in megabytes;
- app - the application that should perform the task;
- subtasks - an optional block describing the list of tasks that will be added to the queue after the simulation of the task of the owner is completed.

4.3 Chapter IV Summary

Application Of DEECo Framework To MDVRPTW Problem is reviewed and Cloud computing is described this approaches we use for our dissertation. Payments Pay-as-you-go for consumed resources of the Google Cloud Platform datacenter are on average 60% less for many compute workloads than other clouds. Implementation of Autonomic Components Ensembles (ACE) on Google Cloud Platform (and, in general, on other cloudproviders platforms) shifts most of the costs from *capital expenditures* (or buying and installing servers, storage, networking, and related infrastructure) to an *operating expenses* model, where customers pay only for usage of these types of resources.

Conclusion and Future Works

As the main goal of MDVRP is reducing the distances and on the basis of reducing distances also shortening total costs of whole travel, some effective heuristics should be applied to this given problem. There exist multiple techniques of solving VRP and TSP in exact methods which are described in this thesis. But with such methods optimal solutions cannot be obtained due too many constrains and complexity of real life environment. Such constrains as human factor and traffic congestions are not considered in most heuristics. Earlier in this thesis LNS and ALNS and their extensions were briefly explained. Both methods have great potential, but anyway there not enough for implementing of real world transportation problems. However, in general, this given heuristics work well with partitioning decisions. A number of powerful metaheuristics as Tabu search and genetic algorithm have also been proposed. But only by adopting and incorporating many approaches and heuristics we can get desired results. In our dissertation we proposed heuristics that can get close to optimal solutions. We believe that our approach can help in fields of logistic applied to our country's situation in this field.

In our thesis the following items have been studied and developed:

- Theoretical approach that considers uncertainty and stochastic nature of VRP real life environment in transportation fields
- Mathematical models which define and forecast all of the parameters of the transport network functioning, such as traffic intensity on all network elements, traffic volumes in the public transport network, average traffic speeds congestion conditions (congestion induced delays), have been proposed and developed.
- A set of algorithms and applied tools which combine the application of known algorithms for searching optimal routes and usage of new technology of autonomous components ensembles, has been developed. The developed program complex allows users to modify promptly current routes based on local information and choose the most accessible routes which reflect local real situation. The complex also allows users to modify routes in simultaneous and parallel manner without the need to install expensive equipment and software in vehicles.
- The modification of well-known algorithm ALNS which allows planning of partial routes by autonomic components (on virtual machines) has been proposed and implemented.

- The JSprit framework for modification of the proposed algorithms was used. Based on Java language this framework allows to conveniently describe and generate required solutions.
- To overcome the shortage of realistic and reliable ways of congestion period estimation we have a tendency to use the MatSim large-scale agent-based simulation tool. This tool has permitted us to compose and run complex simulation models that are very close to the real-world situations.
- Implementation of DEECo model to create dynamic ensembles of vehicles and non-congested route segments has been proposed and developed in the thesis.
- Extensive use of cloud computing framework allowed us to significantly reduce cost of calculations; besides cloud computing framework is the most suitable and effective tools for the methods proposed in the thesis.

The work is of a theoretical and experimental nature. New properties of various routing problems are obtained, known mathematical models are modified and new mathematical models are constructed, numerical methods of solution are developed. The developed methods are implemented as a set of programs. They have shown their effectiveness and can be used in solving practical problems of large dimension

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