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Foreword

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Table of content

FOREWORD.....	I
TABLE OF CONTENT.....	III
TABLES.....	V
TABLE OF FIGURES.....	V
TABLE OF ABBREVIATIONS.....	VI
1 INTRODUCTION	1
2 COMBINATORIAL PROBLEMS.....	2
2.1 TRAVELING SALESMAN PROBLEM	2
2.2 VEHICLE ROUTING PROBLEM	4
2.2.1 <i>Capacitated Vehicle Routing Problem</i>	7
2.2.2 <i>Distance-Constrained Vehicle Routing Problem</i>	8
2.2.3 <i>Vehicle Routing Problem with Time-Windows</i>	8
2.2.4 <i>Vehicle Routing Problem with Backhauls</i>	8
2.2.5 <i>Vehicle Routing Problem with Pickup and Delivery</i>	8
3 SOLUTION METHODS	10
3.1 CLASSICAL HEURISTICS	10
3.1.1 <i>Saving algorithms</i>	11
3.1.2 <i>Sweep algorithm</i>	11
3.1.3 <i>Petal algorithms</i>	11
3.1.4 <i>Cluster-first, route-second algorithms</i>	12
3.1.5 <i>Improvement heuristics</i>	12
3.2 METAHEURISTICS	13
3.2.1 <i>Attributes</i>	13
3.2.2 <i>Simulated Annealing</i>	14
3.2.3 <i>Deterministic Annealing</i>	14
3.2.4 <i>Tabu Search</i>	14
3.2.5 <i>Genetic Algorithms</i>	14
3.2.6 <i>Ant Systems</i>	15
3.2.7 <i>Neural Networks</i>	15
3.3 VARIABLE NEIGHBORHOOD SEARCH	15
4 READY-MIXED CONCRETE	18
4.1 INTRODUCTION	18
4.2 HISTORICAL FACTS	18
4.3 NATURE OF CONCRETE	19
4.3.1 <i>Perishable Material</i>	19
4.3.2 <i>Customized Material</i>	20

4.3.3	<i>Availability of Ingredients</i>	20
4.3.4	<i>Continuous pouring</i>	20
4.3.5	<i>Sequential delivery</i>	20
4.3.6	<i>Ordered and maximum amount</i>	21
4.3.7	<i>Restrictions</i>	21
4.4	CONCRETE PRODUCTION SYSTEM.....	21
4.4.1	<i>Plant Capacity</i>	21
4.4.2	<i>Demand Fluctuation</i>	22
4.4.3	<i>Placement Size</i>	23
4.4.4	<i>Orders</i>	23
4.5	CONCRETE DELIVERY	24
4.5.1	<i>Location</i>	24
4.5.2	<i>Delivery Cycle</i>	24
4.5.3	<i>Timing of Delivery</i>	25
4.5.4	<i>Delivery Process</i>	25
4.6	SPLIT DELIVERY MULTI DEPOT HETEROGENEOUS VEHICLE ROUTING PROBLEM WITH TIME WINDOWS	26
4.7	ORDERS	27
4.8	PLANTS	28
4.9	TRUCKS.....	28
4.10	MODEL	29
4.11	METHODOLOGY BACKGROUND	30
5	EXPERIMENTS	32
5.1	STATIC EXPERIMENT.....	37
5.2	DYNAMIC EXPERIMENT.....	38
5.3	EX-POST EXPERIMENT	39
6	RESULTS	41
6.1	RUN TIME STUDY FOR THE STATIC EXPERIMENT	41
6.2	RUN TIME STUDY FOR THE DYNAMIC EXPERIMENT.....	42
6.3	RESULT VARIATION COEFFICIENT	43
6.4	DYNAMIC EXPERIMENT VERSUS EX-POST EXPERIMENT.....	44
6.4.1	<i>Objective function</i>	44
6.4.2	<i>Value of Information</i>	46
6.5	IMPROVEMENT.....	46
7	CONCLUSION	52
8	BIBLIOGRAPHY	54
	ABSTRACT	57
	ZUSAMMENFASSUNG	58
	CURRICULUM VITAE	59

Tables

Table 1: Grades of changes	34
Table 2: Number of instances	36
Table 3: Mean of the objective function based on the three basic data sets	42
Table 4: Variation coefficient based on the moderate basic data set.....	44
Table 5: Outcome of the moderate basic data set with moderate changes	45
Table 6: Outcome of the large basic data set with large changes.....	45
Table 7: Average solution when setting different run time for the small basic data set with small changes.....	47
Table 8: Average solution when setting different run time for the small basic data set with moderate changes.....	48
Table 9: Average solution when setting different run time for the small basic data set with large changes	49
Table 10: Improvement of the moderate basic data set with all three grades of changes	49
Table 11: Improvement of the large basic data set with all three grades of changes	50

Table of figures

Figure 1: Ulysses odyssey.....	3
Figure 2: Vehicle Routing Problem.....	5
Figure 3: The basic problems of the VRP class and their interconnections.....	7
Figure 4: Delivery process of ready-mixed concrete.....	26
Figure 5: Ordered quantities.....	35
Figure 6: Composition of an experiment	36
Figure 7: Organigram of the static experiment.....	37
Figure 8: Organigram of the dynamic experiment	38
Figure 9: Organigram of the ex-post experiment	40
Figure 10: Mean of the objective function.....	42
Figure 11: Mean of the objective function including minimum and maximum	43
Figure 12: Improvement of the moderate basic data set	50
Figure 13: Improvement of the large basic data set.....	51

Table of abbreviations

Abbreviation	Description
AS	Ant Systems
CPU	Central Processing Unit
CVRP	Capacitated Vehicle Routing Problem
DA	Deterministic Annealing
DCVRP	Distance-Constrained Vehicle Routing Problem
GA	Genetic Algorithm
GAP	Generalized Assignment Problem
GIS	Geographical Information System
ID	Identification Device
MCNF	Multicommodity Network Flow
MIX	Mixed Integer Programming
NN	Neural Networks
PVRP	Periodic Vehicle Routing Problem
RMC	Ready-Mixed Concrete
SA	Simulated Annealing
SC	String Cross
SE	String Exchange
SM	String Mix
SR	String Relocation
SDMDHVRPTW	Split Delivery Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows
TS	Tabu Search
TSP	Travelling Salesman Problem
VNS	Variable Neighborhood Search
VRP	Vehicle Routing Problem
VRPB	Vehicle Routing Problem with Backhauls
VRPBTW	Vehicle Routing Problem with Backhauls and Time Windows
VRPPD	Vehicle Routing Problem with Pickup and Delivery
VRPPDTW	Vehicle Routing Problem with Pickup and Delivery and Time Windows
VRPTW	Vehicle Routing Problem with Time Windows

1 Introduction

For the effective management of goods and services in distribution systems optimization packages are used. These packages are based on operations research and mathematical programming techniques. Real-world applications, which are used in North America and Europe, result in considerable savings (between 5% to 20%) concerning global transportation costs. This is quite significant, as the transportation costs present a major component of the final costs of goods. This success is due to the rising integration of information systems into the productive and commercial procedures.¹

Another aspect which contributed to this success is the creation of modeling and algorithmic tools and their integration in the past years. These models consider all characteristics of distribution models and the analogous algorithm and computer to find an optimal solution.²

The aim of this thesis is a run time analysis of a certain algorithm which is used for vehicle routing problems. This is one of the most challenging problems in the field of combinatorial optimization; however the algorithm can not only solve this problem to near-optimality, but it also improves the given solution over time. This algorithm is applied in a dynamic environment, dynamic, as changes in orders done by customers can occur. The focus lies upon the reaction of the algorithm and on the consequences for the schedulers who have to deal with these matters which often occur on short notice.

This thesis will present the work which has been done to prove that the algorithm not only gives a better solution over time, but also that the solution is a reliable one.

The layout of this thesis is the following: First of all two classical problems in logistics will be outlined, as well as their alternatives. Then the solutions methods will be presented. The next chapter deals with the material ready-mixed concrete itself. It explains the special features of this material, the production system and the delivery system. Moreover it will explain the specific problem in the context of ready-mixed concrete delivery. Afterwards the model used in this thesis is explained as well as the methodology background of the delivery of ready-mixed concrete in scientific papers. The next chapter explains the experiments thoroughly. In the end the results of the experiments will be outlined and the conclusion finishes this thesis.

¹ See Toth/Vigo, 2001, p. 1.

² See Toth/Vigo, 2001, p. 1.

2 Combinatorial problems

Combinatorial problems exist in many areas of computer science and other disciplines where computational methods are relevant, such as operations research, artificial intelligence or electronic commerce. Noted examples are finding the shortest path or the cheapest round trips in graphs.³

Combinatorial problems exist in planning, scheduling, time-tabling, resource allocation, etc. matters. They consist of finding sets, orderings or assignments of discrete, finite objects that satisfy certain constraints.⁴ “Combinations of these solution components form the potential solutions of a combinatorial problem.”⁵

The space of potential solutions for a problem of combinatorial optimization is often at least exponential in the size of that instance.⁶

Two well known combinatorial problems are the Travelling Salesman Problem and the Vehicle Routing Problem, which form the basis of most logistical or transportation related problems in real-world applications.

2.1 *Traveling Salesman Problem*

“The Traveling Salesman Problem (TSP) is a classical combinatorial optimization problem, which is simple to state but very difficult to solve.”⁷ The aim of the TSP is to find the minimum cost tour of several cities which are interlinked.⁸

In a more abstract formulation, the TSP is a directed, edge-weighted graph with the aim to find the shortest path that visits every node exactly once.⁹

The TSP is applied in a lot of branches including Mathematics, Computer Science and Operations Research and was first formulated and solved by Dantzig, Fulkerson and Johnson in 1954.¹⁰

In 1972, the theory of NP-completeness was developed. In that year the TSP was one of the first ones problems to be proven NP-hard by Karp.¹¹

³ See Hoos/Stützle, 2005, p. 13.

⁴ See Hoos/Stützle, 2005, p. 13.

⁵ Hoos/Stützle, 2005, p. 13.

⁶ See Hoos/Stützle, 2005, p. 14.

⁷ Potvin, 1996, p. 339.

⁸ See Hansen/Mladenović, 1999, p. 452.

⁹ See Hoos/Stützle, 2005, p. 21.

¹⁰ See Jünger et al., 1995, p. 225.

¹¹ See Jünger et al., 1995, p. 225.

In 1985 Lawler, Lenstra, Rinooy Kan & Shmoys did considerable research on the TSP. This became apparent at a specialized conference on the TSP in 1990, which took place at Rice University.¹²

The most popular heuristic for solving the TSP is the 2-opt. There, the edges of two cities which are interlinked in a tour are removed and reconnected by adding edges in the only other way possible. However, the 2-opt is a local search heuristic and therefore stops in a local minimum.¹³

An example of the TSP in literature was given by Grötschel and Padberg in 1993. This example is known as Ulysses 16 and refers to the 16 locations where Ulysses is reported to have been during his odyssey. The edge weights account for the geographical distance between the locations, the shortest trip results in 6.859 km and can only be achieved by a “modern Ulysses” using an aircraft. In the picture below the optimal solution is represented by a dashed line whereas the solid line and arrows indicate the original tour undertaken by Ulysses on his odyssey.¹⁴

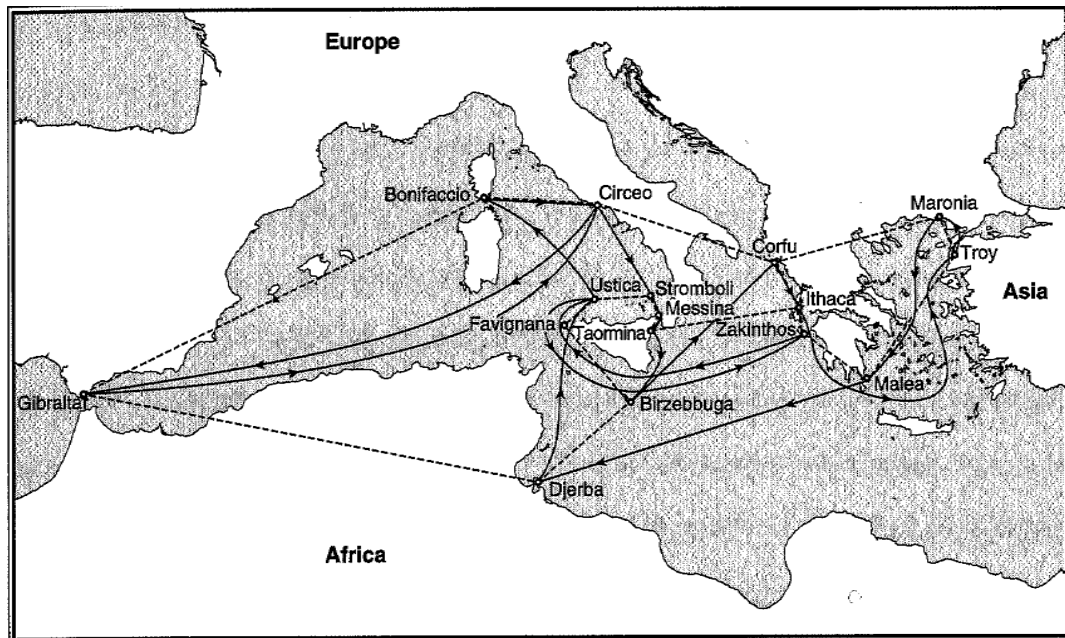


Figure 1: Ulysses odyssey¹⁵

¹² See Jünger et al., 1995, p. 225.

¹³ See Hansen/Mladenović, 1999, p. 452.

¹⁴ See Hoos/Stützle, 2005, p. 22f.

¹⁵ Hoos/Stützle, 2005, p. 23.

2.2 Vehicle Routing Problem

A Vehicle Routing Problem (VRP) describes the distribution problem which arises from transporting goods between depots and customers.¹⁶ It is also one of the most difficult problems in combinatorial optimization. It was first introduced by Dantzig and Ramser in 1959 by presenting a mathematical programming formulation. In 1964 it was improved by Clark and Wright by using an effective greedy heuristic. Until today hundreds of models have been developed for an optimal or approximate solution for the VRP and its variances.¹⁷

Common applications of VRPs are:

- Solid waste collection
- Street cleaning
- School bus routing
- Dial-a-ride systems
- Transportation of handicapped people
- Routing of salespeople
- Maintenance units.¹⁸

A VRP is described through a graph which represents the road network which is used for the transportation of goods. The road sections are represented by arcs and vertices which pose for road junctions, depots and costumers construction sites. Arcs can be directed or undirected depending on the street network. Each arc has a costs resulting from traversing it, as well as a length and travel time.¹⁹

The solution of a VRP consists of designing an optimal set of routes for a fleet of vehicles which serves a given set of customers.²⁰ The following abiding shows how a VRP can look like:

¹⁶ See Toth/Vigo, 2001, p. 1f.

¹⁷ See Matsatsinis, 2004, p. 487.

¹⁸ See Toth/Vigo, 2001, p. 1f.

¹⁹ See Toth/Vigo, 2001, p. 2.

²⁰ See URL: <http://neo.lcc.uma.es/dynamic/vrp.html> [07.02.2010].

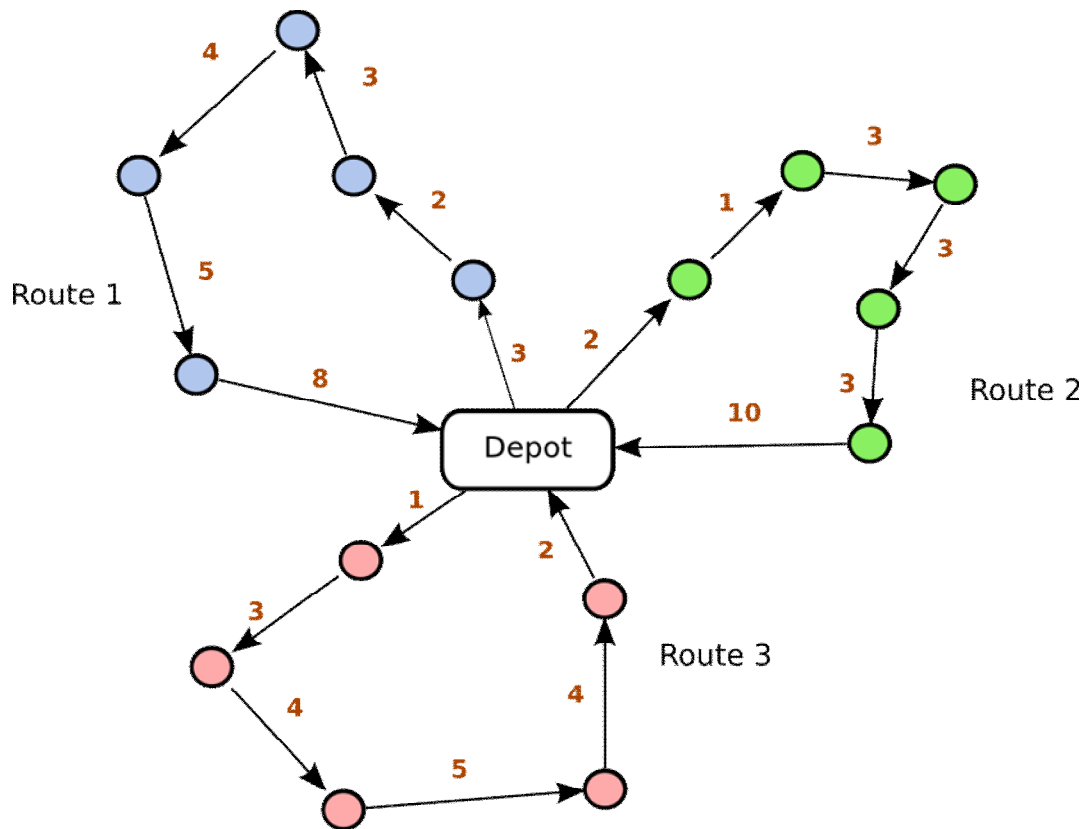


Figure 2: Vehicle Routing Problem²¹

The main components of a vehicle routing problem are the road network, the customers, various depots, vehicles and their drivers, occurring operational constraints and an objective function.²²

- Road network: The road network which is used for the goods transportation is normally described through a graph (as seen above), where arcs represent the road sections and the road junctions, depots and customers locations are described by vertices. The arcs can be either directed or undirected. A directed arc may occur because of one-way streets. Each arc consists of costs which are made up from their length and travel time.²³
- Customers: Customers are located at the vertex of a road graph. They have a demand, which can consist of different types, which has to be either delivered or collected from the customers. Furthermore there are certain periods during the day called time windows where the customers have to be served. Deliveries neglecting the time windows will be penalized. Unloading or loading times

²¹ URL: <http://neo.lcc.uma.es/dynamic/vrp.html> [07.02.2010].

²² See Toth/Vigo, 2001, p. 2.

²³ See Toth/Vigo, 2001, p. 2.

refers to the duration which is required to deliver or collect the goods from the customer's location, this can depend on the vehicle. Occasionally, the demand of the customer cannot be satisfied completely resulting in penalties.²⁴

- Depots: Depots are placed at the vertices of a road graph and the routes which aim to supply the customers either start or end there. A depot is defined by the number and types of vehicles located there and by the total amount of goods which it can handle.²⁵
- Vehicles: The transportation of goods is done by a fleet of vehicles. The size and composition of the vehicles can be defined depending on the customer's prerequisites. A vehicle is defined by several attributes. Each vehicle has a home depot, however there is the possibility to end its tour somewhere else than at its home depot. The capacity of a vehicle can be defined by the maximum weight/volume or number of pallets it can load. Some vehicles may need special tools for loading or unloading processes.²⁶
- Drivers: Drivers are bound to union contracts and company regulations like maximum hours worked per day, a certain number of breaks, a maximum duration of driving, overtime, etc.²⁷
- Operational constraints: Operational constraints depend on the nature of goods delivered, on the service level quality and on customers and vehicles characteristics. All of them have to be satisfied. Some typical constraints can be: the load of a vehicle cannot surpass the vehicle's capacity. A customer served in a route can only require either the delivery or the collection of goods, or both of it. Customers can only be supplied during their time windows and during the working shifts of the serving drivers.²⁸
- Objective functions: Objective functions are either one of the following or a combination of them. Very often a minimization of the global transportation costs is the objective. A minimization of the number of vehicles or penalties can also be searched for. Or the balancing of the routes concerning travel time and vehicle load can also be the objective function.²⁹

²⁴ See Toth/Vigo, 2001, p. 2.

²⁵ See Toth/Vigo, 2001, p. 2.

²⁶ See Toth/Vigo, 2001, p. 3.

²⁷ See Toth/Vigo, 2001, p. 3.

²⁸ See Toth/Vigo, 2001, p. 3.

²⁹ See Toth/Vigo, 2001, p. 4.

Depending on different attributes such as multi depots, time windows or fleet heterogeneity, different VRPs exist. The simplest VRP is the capacitated vehicle routing problem (CVRP), which is the most, studied and researched VRP. Other forms of VRPs are the “Distance-Constrained VRP”, the “VRP with Time-Windows”, the “VRP with Backhauls”, and the “VRP with Pickup and Delivery”.³⁰

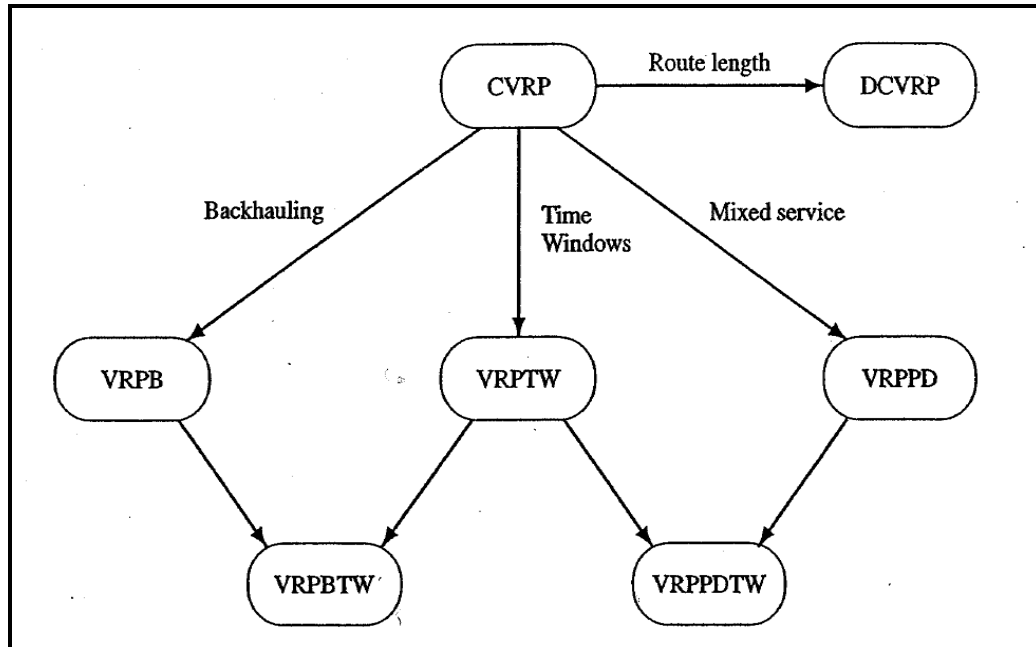


Figure 3: The basic problems of the VRP class and their interconnections³¹

The picture above shows the various enhanced problems of the VRP and their interconnections.

2.2.1 Capacitated Vehicle Routing Problem

A capacitated vehicle routing problem (CVRP) is defined by the customers who correspond to deliveries and deterministic demands (demands are known in advance) which cannot be split. There is a single central depot with identical vehicles. The only constraint concerns the vehicles and their maximum capacity load. The objective function is to minimize the total costs and to supply all customers.³²

The CVRP is a general version of the TSP which has been described above. It is looking for a minimum-cost circuit, visiting all vertices of the graph and occurs when the

³⁰ See Toth/Vigo, 2001, p. 5.

³¹ Toth/Vigo, 2001, p. 6.

³² See Toth/Vigo, 2001, p. 5.

capacity is greater than the demand and the set of vehicles equals one. All relaxation suggested for the TSP stay the same for the CVRP.³³

2.2.2 Distance-Constrained Vehicle Routing Problem

The distance-constrained vehicle routing problem is a variance of the CVRP. Here, the capacity constraint of each route is replaced by a maximum length (or time) constraint. The objective function is to minimize the total length or the duration of the routes. However, this VRP has two additional constraints, namely a restricted vehicle capacity and a maximum distance.³⁴

2.2.3 Vehicle Routing Problem with Time-Windows

The VRP with time-windows is an advanced version of the CVRP with capacity constraints and a certain serving time for customers called time-windows. The supply of a customer has to start within a certain time interval, otherwise penalties might be imposed. There exist two different kinds of time-windows: soft and hard ones, they will be explained in more detail below.³⁵

2.2.4 Vehicle Routing Problem with Backhauls

The VRP with backhauls is another version of the CVRP. Here a set of customers is split into two subsets. One subset consists of “linehaul” customers which demand a certain amount of goods. The other subset contains “backhaul” customers with a certain amount of goods which have to be picked up.³⁶

For this problem a precedence constraint is given. This means that if a route is served which has both types of customers, then the linehaul customers have to be supplied first.³⁷

2.2.5 Vehicle Routing Problem with Pickup and Delivery

For the VRP with pickup and delivery, each customer is linked with two different quantities which represent the demand for homogeneous products. There is a demand for goods given and an amount of goods which has to be picked up. At each customer

³³ See Toth/Vigo, 2001, p. 8.

³⁴ See Toth/Vigo, 2001, p. 8.

³⁵ See Toth/Vigo, 2001, p. 8.

³⁶ See Toth/Vigo, 2001, p. 9.

³⁷ See Toth/Vigo, 2001, p. 9.

location, the delivery is done before the pickup. But it is also possible that only one demand per customer is given.³⁸

The difference to the VRP with backhauls is that in the VRP with pickup and delivery the routes can perform both namely picking up and delivering the goods; however the collected goods from the pickup customers have to be delivered to the corresponding delivery customer using the same vehicle.³⁹

Concerning the VRP with backhauls, one constraint exists whereas all deliveries have to be done before the collection which results from the difficulty of rearranging the vehicle loads along the course and due to loading operations.⁴⁰

In this thesis the ready-mixed concrete problem has been modeled as a VRP. The problem described is a combination of the capacitated VRP and the VRP with time windows. Besides that several constraints exist.

First of all multiple depots from where the ready-mixed concrete is delivered to the customers, exist. Ready-mixed concrete is a perishable material and therefore it has to be processed within 1.5 hours. This makes the delivery a very challenging process. Moreover an order normally consists of more than one delivery. This means that the order is split into several consecutive deliveries.

Another important aspect is the “continuous” delivery of the material. This means that only one vehicle can be unloaded at the construction site and if finished, the next one should be already there for unloading procedures. Therefore, the time between the unloading operations should be small.

Furthermore the vehicle fleet consists of heterogeneous vehicles. Some vehicles have a conveyor belt or pump which are needed for unloading operations. If a special vehicle is needed or not depends on the customer order. If so, the first vehicle has to be equipped with the desired special function, and then help the other trucks with the unloading process until the end of the day.

Therefore the specific model described in this thesis is called: “Split Delivery Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows” (SDMDHVRPTW) and will be explained in more detail in Chapter 4.6.

³⁸ See Toth/Vigo, 2001, p. 10.

³⁹ See Toth/Vigo, 2001, p. 3.

⁴⁰ See Toth/Vigo, 2001, p. 4.

3 Solution methods

Vehicle routing problems are often described through network analysis and mixed integer programming models. These problems can be very complex; consisting of huge dimensions and through the combination of different transportation modes, routing, departure and distribution locations, a high number of variables occur. Due to the complexity of the problems and its large size, the solution finding process with analytical models is either impossible or extremely time-consuming. To be able to find a solution for such complex problems, simulation models and heuristic algorithms are used.⁴¹

Solution methods for VRPs can be defined into two classes, namely:

- Classical heuristics and
- Metaheuristics.⁴²

Classical heuristics have been created between 1960 and 1990 whereas metaheuristics have mainly occurred since the last two decades.⁴³ Of course a VRP can also be solved using exact methods; however this may take longer than classical heuristics or metaheuristics.

The two methods listed above will be explained in more detail in the following two subchapters.

3.1 *Classical Heuristics*

Procedures to solve VRPs belong mostly to the classical heuristics. This is due to the fact that classical heuristics perform a limited exploration of search space and produce good solutions within a fair amount of time. Furthermore they can be easily enhanced so that they meet the requirements for additional constraints which come across in real life.⁴⁴

For determining VRP solutions two main techniques are used: the first possibility merges existing routes using a **savings criterion** and the other possibility assigns vertices to vehicle routes using an **insertion cost**.⁴⁵

⁴¹ See Matsatsinis, 2004, p. 488.

⁴² See Laporte et al., 2000, p. 286.

⁴³ See Laporte et al., 2000, p. 286.

⁴⁴ See Laporte et al., 2000, p. 286.

⁴⁵ See Laporte et al., 2000, p. 286.

3.1.1 Saving algorithms⁴⁶

The saving algorithm created by Clarke and Wright (1964) is probably the most famous heuristic for the VRP. It works for undirected and directed problems and can be applied for problems where the decision variable denotes for the number of vehicles. There is a parallel and sequential version of the algorithm available:

1. In the first step the savings are calculated.
2. If the parallel version is used, two routes are searched for and if feasible they get merged. Otherwise, if the sequential version is used, each route is considered alone. The first saving is determined which is feasible to merge the current course with another one. Then the merge is done and repeated for the current course. It stops once no further route merge is possible.

An example for the savings algorithm is the 3-opt which was created in 1965 by Lin. The 3-opt tries to improve the vehicle route by repeatedly removing three edges and reconnecting the resulting chains in all feasible ways. It stops once no further improvement is possible.

3.1.2 Sweep algorithm⁴⁷

This algorithm is used for planar instances of a VRP. The vehicle route is calculated by solving each cluster as a TSP. If the clusters are feasible, they are formed by rotating a ray located at the depot. Gillet and Miller (1974) made the sweep algorithm popular.

The steps are as follow:

1. Route initialization: An unused vehicle is chosen.
2. Route construction: The process starts with the unrouted vertex with the smallest angle. From there vertices are assigned to the vehicle as long as either the capacity or the maximum route length is not surpassed. For the remaining unrouted vertices the procedure starts at step 1 again.
3. Route optimization: In the end each route is optimized by using a TSP.

3.1.3 Petal algorithms⁴⁸

The petal algorithm is an enhancement of the sweep algorithm where several routes, called petals, are generated. A final selection is made by solving a partitioning problem set. This algorithm was first used by Balinski and Quandt (1964).

⁴⁶ See Laporte et al., 2000, p. 286f.

⁴⁷ See Laporte et al., 2000, p. 288.

⁴⁸ See Laporte et al., 2000, p. 288f.

3.1.4 Cluster-first, route-second algorithms⁴⁹

The most famous cluster-first, route-second algorithm is probably the Fisher and Jaikumar algorithm. Compared to the previous algorithms, this one solves a generalized assignment problem (GAP) instead of using a geometric method to create the clusters.

The number of vehicle routes is fixed in advance. It consists of four steps:

1. Seed selection: Seed points are chosen to initialize each cluster.
2. Allocation of customers to seeds: For allocating each customer the costs are calculated to each cluster.
3. Generalized assignment: A GAP is solved with costs, customer weights and vehicle capacity.
4. TSP solution: For each cluster a TSP is solved.

3.1.5 Improvement heuristics⁵⁰

Improvement heuristics work by either taking each vehicle route separately or several routes at a time. For the first case, an improvement heuristic for a TSP can be used. For the second case, procedures are developed that exploit the multi-route structure of the VRP.

The λ -opt mechanism by Lin (1965) is widely used for most TSP improvement procedures. There, λ edges are removed from the tour and all λ remaining sections are reconnected in possible ways. It ends when a local minimum is found and no further improvements can be achieved.

Another method obtained by van Breedam(1994) refers to four improvement methods called “string cross”, “string exchange”, “string relocation” and “string mix” which are all special cases of 2-cyclic exchanges.

- String Cross (SC): By crossing two edges of two different routes, two chains of vertices are exchanged.
- String Exchange (SE): Between two routes the two strings with the most customer vertices are exchanged.
- String Relocation (SR): The chain with the most customer vertices is relocated.
- String Mix (SM): A mix of the best move between SE and SR.

⁴⁹ See Laporte et al., 2000, p. 289.

⁵⁰ See Laporte et al., 2000, p. 290f.

3.2 Metaheuristics

Metaheuristics work by doing an exploration of the most auspicious regions of the solution space. To achieve a result they combine memory structures, neighborhood search rules and recombination of solutions. The quality of the solutions is much better than compared with classical heuristics; however, they need more computing time.⁵¹

During the process of finding a solution, metaheuristics even allow intermediary infeasible solutions. A metaheuristic normally identifies a better local optimum than a heuristic which may have been used before.⁵²

Moreover, metaheuristics depends more on the context and finely tuned parameters are needed, making it quite difficult to apply it for other situations. In summary metaheuristics are sophisticated improvement practices and can be seen as improved classical heuristics.⁵³

3.2.1 Attributes

While evaluating metaheuristics, several conflicting criteria have to be taken into account. Therefore, the following attributes should be favored for metaheuristics:⁵⁴

- **Simplicity:** A metaheuristic should follow a simple and clear directive which is also widely applicable.
- **Coherence:** The course of action should follow the principle logically.
- **Efficiency:** The results of the heuristics should provide optimal or near-optimal solutions for most of the instances.
- **Effectiveness:** Optimal solutions should be provided within a moderate CPU time.
- **Robustness:** Heuristics should be able to solve a variety of problems efficiently and effectively. Furthermore the heuristics should be able to give a good solution for several instances, not to work well for one set and failing on the other three sets.
- **User-friendliness:** Heuristics should be easy to understand and easy to use. The best starting position would be if there are no parameters applied.
- **Innovation:** New types of applications should be obtained by either the principle of metaheuristics, by its efficiency or effectiveness.⁵⁵

⁵¹ See Laporte et al., 2000, p. 286.

⁵² See Gendreau et al., 2001, p. 129.

⁵³ See Laporte et al., 2000, p. 286.

⁵⁴ See Hansen/Mladenović, 2001, p. 464.

⁵⁵ See Hansen/Mladenović, 2001, p. 464.

There are six main types which can be used for solving VRPs: namely Simulated Annealing (SA), Deterministic Annealing (DA), Tabu Search (TS), Genetic Algorithms (GA), Ant Systems (AS) and Neural Networks (NN).⁵⁶

3.2.2 Simulated Annealing

Simulated Annealing (SA) starts from the first solution x_1 and takes the solution x_{t+1} with each iteration as a new starting point until a solution which satisfies all constraints is found. Special care has to be taken, as the costs do not necessarily increase with each iteration and to avoid cycling.⁵⁷

3.2.3 Deterministic Annealing

Deterministic Annealing (DA) uses the same approach as SA. It starts from the first solution x_1 and takes the solution x_{t+1} with each iteration as a new starting point until a solution which satisfies all constraints is found. Special care has to be taken, as the costs do not necessarily increase with each iteration and to avoid cycling.⁵⁸

3.2.4 Tabu Search

Tabu Search (TS) uses the same approach as SA and DA. It starts from the first solution x_1 and takes the solution x_{t+1} with each iteration as a new starting point until a solution which satisfies all constraints is found. Special care has to be taken, as the costs do not necessarily increase with each iteration and to avoid cycling.⁵⁹

3.2.5 Genetic Algorithms

Genetic Algorithms (GA) checks for each step various sets of solutions. Each set consists of a mix of the previous best and worst solution.⁶⁰

Genetic Algorithms is a method that takes the information of previous solutions into account, during the process of finding a solution, and applies it to achieve a better solution.⁶¹

⁵⁶ See Gendreau et al., 2001, p. 129.

⁵⁷ See Gendreau et al., 2001, p. 129.

⁵⁸ See Gendreau et al., 2001, p. 129.

⁵⁹ See Gendreau et al., 2001, p. 129.

⁶⁰ See Gendreau et al., 2001, p. 129.

⁶¹ See Gendreau et al., 2001, p. 129.

3.2.6 Ant Systems

Ant systems (AS) takes some of the information which has been gathered at previous iterations and creates new solutions from it. It is a constructive approach.⁶²

Ant Systems is a method that takes the information of previous solutions into account, during the process of finding a solution, and applies it to achieve a better solution.⁶³

3.2.7 Neural Networks

Neural networks (NN) can be compared with a learning method. Here a set of weights is steadily regulated until an optimal solution has been found. The rules differ in each case; however they are modified for each problem. For this method creativity and experimentation is needed.⁶⁴

Neural Networks is a method that takes the information of previous solutions into account, during the process of finding a solution, and applies it to achieve a better solution.⁶⁵

3.3 Variable Neighborhood Search

“Systematic change of neighborhood within a possibly randomized local search algorithm yields a simple and effective metaheuristic for combinatorial and global optimization, called variable neighborhood search.”⁶⁶

Variable neighborhood search (VNS) works by changing the neighborhood in the search. This means that it explores increasingly distant neighborhoods of the current used solution and jumps to a new one if an improvement has been made. By doing this the preferred characteristics of the current solution, e.g. many values have already achieved their optimal value, will remain and are used for further promising neighboring solutions.⁶⁷

VNS presents a simple approach by a systematic change of the neighborhood within the search. The method is largely applicable. Moreover many instances can be solved exactly and for those where it does not it provides solutions very close to the optimum. In the end VNS is also very effective as the solutions are provided within a moderate computing time.⁶⁸

⁶² See Gendreau et al., 2001, p. 129.

⁶³ See Gendreau et al., 2001, p. 129.

⁶⁴ See Gendreau et al., 2001, p. 129f.

⁶⁵ See Gendreau et al., 2001, p. 129.

⁶⁶ Hansen/Mladenović, 2001, p. 449.

⁶⁷ See Hansen/Mladenović, 2001, p. 450.

⁶⁸ See Hansen/Mladenović, 2001, p. 464.

VNS is a very promising metaheuristic, developed by Hansen and Mladenović in 1997 and extended in 2001.⁶⁹

The paper which was written by Mladenović and Hansen in 1997 is the first paper which deals with VNS. They examined a at this moment relatively unexplored area: namely the change of neighborhood in the search –which lead to at this time new approach VNS. To illustrate the effectiveness of their method they showed improvements in the GENIUS algorithm applied for the TSP with and without backhauls.⁷⁰

The second paper written by Hansen and Mladenović was published in 2001 and is an extension of their previous paper. In this paper the authors present the principles of VNS and show possible applications as well as new applications.⁷¹

The next paper written by Kytöjoki et al. was published in 2007. In their paper they present an efficient variable neighborhood search heuristic for the capacitated vehicle routing problem. The objective of their research is a design of the least cost routes for an identically capacitated vehicle fleet which serve geographically scattered customers with known demand. The VNS procedure is used to support a set of heuristics. The developed solution method is especially for solving very large real-life vehicle routing problems. To increase the computation time, new implementation concepts were used. Their result showed that the proposed method is fast, competitive and efficient in finding high-quality solutions for problems with up to 20,000 customers in a reasonable amount of time.⁷²

The next paper is by Fleszar et al. and was published in 2009. Their research focus is a variable neighborhood search for an open vehicle routing problem. The objective of an open vehicle routing problem is to first minimize the number of vehicles, and then minimize the total distance (or time) traveled. The demand of a customer has to be fulfilled by exactly one vehicle. For solving the problem a VNS heuristic was proposed. The neighborhoods in the project are based on reversing the segments of routes and on changing the segments in between routes. The result, which was achieved by using sixteen standard benchmark problem instances, showed that the solution quality of the proposed VNS can be compared to the heuristics mentioned in the article.⁷³

⁶⁹ See Schmid, 2007, p. 49.

⁷⁰ See Mladenović/Hansen, 1997, p. 1097.

⁷¹ See Hansen/Mladenović, 2001, p. 449ff.

⁷² See Kytöjoki et al., 2007, p. 2743.

⁷³ See Fleszar et al., 2009, p. 803.

The topic of the paper published by Hemmelmayr et al. in 2009 is the proposition of a new heuristic concerning the periodic vehicle routing problem (PVRP) without time windows. The PVRP is an extension of the VRP where the planning horizon is extended to a few days and each customer needs a certain number of visits within the time horizon. Thus the visiting days for the customers have to be chosen and for every day a VRP has to be solved. The method used in the paper is based on VNS. Computation results are presented which show that their approach is competitive and even better than existing solutions practices known in the literature.⁷⁴

The algorithm used in this thesis is based on VNS. The advantage of the algorithm is that it does not need any commercial solvers like XPRESS or CPLEX, but it works on any personal computer. It will find a feasible solution and the time it needs to run can be set individually.⁷⁵

⁷⁴ See Hemmelmayr, 2009, p. 791.

⁷⁵ See Schmid, 2007, p. 96.

4 Ready-mixed concrete

4.1 Introduction

“Concrete is one of the most used construction materials.”⁷⁶ It is durable and provides buildings finishes, which are possible through a wide variety of shapes, colors, textures and finishing preferences. Buildings made of concrete are cost-effective and easy to put up. It is also used for factories, industrial and agricultural buildings, as it is perfect for buildings with heavy loads, noise, vibrations and chemicals.⁷⁷

Furthermore, concrete buildings and structures are highly resistant to fire. Concrete can also be quite stable if natural disasters like earthquakes occur. For water retaining structures, reservoirs and sewage channels, which need to resist a constant water saturation or high-velocity waters, concrete is a good option as well.⁷⁸

Concrete is obtained from the earth’s most abundant, naturally occurring materials. To produce concrete, materials like water, cement, sand and gravel are mixed together, adding naturally appearing minerals or recycled products and mixtures. A concrete mix normally consists of, by volume, 10-15% cement, 60-75% aggregates and 15-20% water.⁷⁹

Concrete can also be customized. A concrete mixture will feature the wanted workability in its fresh state and the needed robustness and strength in its hardened state.⁸⁰

4.2 Historical Facts

Concrete has been used in history for over 10,000 years. The first known site which used man-made stone is located in Yiftah’el in Israel. Concrete there consisted of sandy aggregates, limy binder and water. Nearly all cultures which are known for their epochal buildings like Babylonians, Assyrians, Phoenicians, Egyptians and Romans used concrete, though it was made of different mixtures.⁸¹

In the last quarter of the 19th century, an idea of “ready-mixed” concrete emerged. By this time, damp sand and hydrated lime was transported by horses and carts to construction sites in Berlin. Jürgen H. Magens, an architect from Hamburg, did

⁷⁶ ERMCO, 2000, p. 2.

⁷⁷ See ERMCO, 2000, p. 2.

⁷⁸ See ERMCO, 2000, p. 2.

⁷⁹ See ERMCO, 2000, p. 2.

⁸⁰ See ERMCO, 2000, p. 2.

⁸¹ See ERMCO, 2000, p. 9.

intensive research for possible ways of fabricating outside the plant and for transporting fresh concrete over long distances.⁸²

In January 1903, he registered his first patent. This day can also be seen as the birthday of ready-mixed concrete. He continued his studies and four years later, he discovered that the time for transportation could be enhanced by vibrating water. Shortly afterwards first plants were set up in Hamburg and Berlin. The first delivery outside of Germany was done shortly before the First World War to the United States. After the Second World War ready-mixed concrete stretched all over Europe.⁸³

Today, the construction industry is a major player in the European Economy. It is the biggest industrial employer, providing work for 7% of Europe's labor force. To persist this importance in the future, it is important that implemented environmental measures have to be reasonable, economic and proven in practice.⁸⁴

Currently the European ready mixed concrete industry produces more than 300 million m³ in more than 12,000 operating plants. The consumption of ready mixed concrete per person and per year lies between 0.3-1.40 m³.⁸⁵

4.3 Nature of Concrete

The common tasks in the concrete industry are delivering concrete and batching orders. However, some important material-specific considerations have to be taken into account during the planning and delivering process. The following list shows the material-specific features of ready-mixed concrete and the specific features of a smooth delivery.⁸⁶

4.3.1 Perishable Material

Concrete is a perishable material. It consists of aggregates, cement and water, and if specified, admixtures. With the exception of cement which is a perishable material, all the other ingredients, if separated, can be stored for a long time. When mixing the materials together, water plays the important role. Once it has been added, concrete has one and a half hour left to be processed. If not the hydration process forms a gel, which, if disrupted, can endanger the final strength of the concrete. Therefore, there is little room for variability in delivery time and placement after the water has been added.⁸⁷

⁸² See ERMCO, 2000, p. 9.

⁸³ See ERMCO, 2000, p. 9.

⁸⁴ See ERMCO, 2000, p. 3.

⁸⁵ See ERMCO, 2000, p. 4.

⁸⁶ See Tommelein/Li, 1999, p. 100.

⁸⁷ See Tommelein/Li, 1999, p. 100.

Especially unforeseen delays in traffic or at the construction site can jeopardize the state of concrete.⁸⁸

4.3.2 Customized Material

Engineers who perform the structural calculations for an assignment also have to determine the strength and other quality requirements for the concrete. Depending on the project and purpose, different mixtures and quantities of concrete can be needed. Prior to pumping, a priming mix is required as well. However, not all projects need a customized mix of concrete. For public projects like sidewalks or road paving, government agencies prefer standard mixes.⁸⁹

To retain an overview over the hundreds to thousands different recipes, most batch facilities have an online database of mixes which they can download to program their plants. This approach makes it easier to add new mixes, to search mixes that meet the engineer's requirements and to name them based on customers preferences.⁹⁰

4.3.3 Availability of Ingredients

Choosing a suitable mix recipe is easy. However, the availability of aggregate types or admixtures in quantity is not always given. Therefore the contractor has to recognise special ingredients once the project specifications are given and has to notify the batch factory in time, so that the project can be started without any delays.⁹¹

4.3.4 Continuous pouring

Concrete has to be placed in a continuous way. Once delivery of the concrete has started, it has to be continued until all of the required concrete has been placed. This means that it is not a good idea, to let some concrete harden before the rest has not been delivered.⁹²

4.3.5 Sequential delivery

An order normally consists of more than one truckload of concrete. If this is the case, trucks have to arrive sequentially at the customer site. Actually, the customer might demand a particular inter-arrival rate for the trucks.⁹³

⁸⁸ See Durbin, 2003, p. 7.

⁸⁹ See Tommelein/Li, 1999, p. 100.

⁹⁰ See Tommelein/Li, 1999, p. 100.

⁹¹ See Tommelein/Li, 1999, p. 100f.

⁹² See Durbin, 2003, p. 7.

⁹³ See Durbin, 2003, p. 7.

4.3.6 Ordered and maximum amount

The customers hardly ever know the total amount of concrete they need. Therefore they order two amounts, called the *ordered* amount and the *maximum* amount. The difference between maximum and ordered amount is called *bonus load*. During the schedule production, the ordered amount is scheduled. Before one of the last deliveries, a gap is put into the system allowing bonus loads to take place.⁹⁴

Normally, the customer determines during the unloading of the last concrete load if an additional batch is needed. The customer will then calculate the additional amount and informs the truck driver. The amount is then adjusted in the database and a truck delivers the extra amount of concrete.⁹⁵

However, if the customer estimates the needed concrete amount incorrectly, the company has to supply the customer with everything required.⁹⁶

4.3.7 Restrictions

Orders can be restricted to a subset of trucks or plants. Furthermore, only a limited number of trucks can be loaded with concrete at a plant per hour.⁹⁷

Truck drivers have restrictions on their workday enforced by unions and government regulations. These constraints include a maximum number of hours a driver can work, and a certain amount of time which has to be in between working days.⁹⁸

4.4 Concrete Production System

The manufacturing system of concrete depends on the plant owner's equipment, the contractor's placement method, their individual schedules and the coordination of these. Therefore, the production depends on different factors like limited capacity, demand fluctuations, placement size, orders and accuracy in quantity.⁹⁹

4.4.1 Plant Capacity

Today, ready-mixed concrete batch plants are completely automated and computer controlled. This means that recipes can be mixed on demand and very quickly.

⁹⁴ See Durbin, 2003, p. 7f.

⁹⁵ See Durbin, 2003, p. 8.

⁹⁶ See Durbin, 2008, p. 5.

⁹⁷ See Durbin, 2008, p. 5.

⁹⁸ See Durbin, 2003, p. 9.

⁹⁹ See Tommelein/Li, 1999, p. 101.

However, a batch plant only has a limited capacity available, which is either determined by batching capacity or delivery capacity.¹⁰⁰

First of all, a batch plant has a limited capacity,

- Batching capacity: The batching capacity is based on the time needed to measure, dispense, and mix ingredients as well as the loading time. The batch time and quantity mixed are limited by the definite amount needed, the loading area of a truck and weight limitations occurring during transportation or on site.¹⁰¹
- Delivery capacity: The delivery capacity depends on the number of trucks and drivers that serve the batch plant. Normally a batch factory possesses 25 to 30 trucks which will be kept busy at all times. Batch plants may employ a third party to take care of the transportation.¹⁰²

The batching capacity is normally larger than the delivery capacity. The batching can be done in a few minutes. However, the cycle time of a truck which includes the loading time as well, varies between 30 minutes to an hour or two. For example a 30-minute truck cycle with a 2-minute load time, results in 15 trucks which can be served by a plant. A 1-hour cycle would result in 30 trucks which could be served. So the variability of the cycles strongly affects the activity rate of plants. There can be times where the plant remains idle as it is waiting for trucks and other times where trucks will have to wait in line in order to be loaded.¹⁰³

Fixed and variable costs play an important role as well. Fixed costs consist of plants and trucks which bind a lot of capital. Materials, truck operating costs and wages result in variable costs. To minimize costs, the operator will vary the definite numbers of drivers working on a weekend day or vary working hours. Thus, delivery is likely to be a limiting capacity factor.¹⁰⁴

4.4.2 Demand Fluctuation

The demand for ready-mixed concrete can fluctuate during the day, week, and year. Even though the total amount of concrete can be approximated quite well, the timing is

¹⁰⁰ See Tommelein/Li, 1999, p. 101.

¹⁰¹ See Tommelein/Li, 1999, p. 101.

¹⁰² See Tommelein/Li, 1999, p. 101.

¹⁰³ See Tommelein/Li, 1999, p. 101.

¹⁰⁴ See Tommelein/Li, 1999, p. 101.

uncertain as it depends on work which has to be completed prior to the delivery and this can be quite difficult to forecast.¹⁰⁵

Schedule uncertainty is a major factor in ready-mixed concrete delivery as the total amount of concrete might not be known until a day prior to delivery. Unforeseen circumstances like weather conditions can also result in delaying the delivering process. From the plant's point of view, the contractor's orders are demanded randomly, which makes it quite difficult to forecast the actual plant workload for a day.¹⁰⁶

4.4.3 Placement Size

Uninterrupted supply of concrete is very important for large deliveries. To perform an uninterrupted delivery process, a loaded truck could remain at the site as a standby to be available when the previous truck has been emptied.¹⁰⁷

To obtain a certain continuity of delivery, plant and site have to correspond in real time to inform about placements which are delayed and to avoid trucks standing in line at the site. This communication process can be compared with the pull mechanism:

An empty truck which returns to the plant in time is like a kanban, representing successful placement and requesting an additional lot at the same time. If the truck return is delayed, the plant knows it has to hold back further mixing of concrete for that site. However, the pull mechanism can be false if the truck comes across road problems when returning to the plant. For more accurate information and real-time data on truck travel and site circumstances, geographical information systems (GIS) are used rather than satellite-based systems.¹⁰⁸

Large placements require and bind a large number of trucks and consequently a plant's capacity. Therefore a plant needs a backup plan if problems with the production system occur.¹⁰⁹

4.4.4 Orders

To fulfill orders in a timely manner, raw materials like aggregates and cement are replenished daily. Additional deliveries can be arranged if needed. A plant hardly every

¹⁰⁵ See Tommelein/Li, 1999, p. 101.

¹⁰⁶ See Tommelein/Li, 1999, p. 101f.

¹⁰⁷ See Tommelein/Li, 1999, p. 102.

¹⁰⁸ See Tommelein/Li, 1999, p. 102.

¹⁰⁹ See Tommelein/Li, 1999, p. 102.

runs out of material as it has tight connections with its upstream suppliers. When it does happen it is a failure of the equipment rather the fault of the replenishment system.¹¹⁰

Precision is very important for the order quantity as the contractor has to pay for everything including the excess concrete which remains in the trucks after the placement has completed. Additionally, the remainder of the same-day order which is stopped before mixing because it is not needed anymore will be charged to the contractor from the plant. Therefore, contractors are likely to order a little bit less than they actually need, counting on getting an extra truck on short notice if needed. This works only if the plant is able to mobilize concrete. However, this can be complicated for the contractor as a shortage of concrete can result in unwanted construction joints that can impact the strength, the water-tightness, the appearance or the durability of the concrete.¹¹¹

4.5 Concrete Delivery

As already mentioned the delivery of concrete depends on the number of trucks the company owns and how many drivers it employs (compare with Plant Capacity).¹¹² Additionally the location of the plant, the delivery cycle and the timing of the delivery play an important role as well.

4.5.1 Location

As concrete should be placed within 90 minutes after water has been added, the transportation from the plant to the construction site should not take longer than half an hour. Therefore, the operating radius of a plant depends on the nature and condition of the street network.¹¹³

4.5.2 Delivery Cycle

The delivery cycle includes numerous kinds of actions to provide a smooth procedure and to avoid unexpected obstacles. First of all, drivers could wash their vehicle after it got loaded but before leaving the plant to avoid spillages on the road which could lead to major delays. To be aware of different traffic conditions is also important for the planning process. Furthermore, time for finding the site and gaining access, as well as time for testing the mixture has to be added. For improving the cycle time, the operator

¹¹⁰ See Tommelein/Li, 1999, p. 102.

¹¹¹ See Tommelein/Li, 1999, p. 103f.

¹¹² See Tommelein/Li, 1999, p. 101.

¹¹³ See Tommelein/Li, 1999, p. 102.

may assign drivers who are familiar to the site or area as they will arrive faster. Another important unknown variable in the delivery cycle presents the truck release by the contractor. Lastly, the remnants of the previous tour must be washed out of the truck before it can be loaded again.¹¹⁴

To have a cushion in case delivery delays occur, many plants have a 2-hour time slot system where only a limited number of orders are taken per slot. This guarantees on-time deliveries during certain times.¹¹⁵

4.5.3 Timing of Delivery

As already mentioned in the chapter before (see Chapter Delivery Cycle), the on-time delivery is vital for the contractor. Trucks have to arrive within the time window. If a truck arrives too early, the site may not be ready yet. If the truck arrives too late, the employees may stand around doing nothing.¹¹⁶

A typical order lead time starts three to four days before the actual day of placement. This gives the plant enough time to acquire material, reserve capacity and organize drivers and trucks. It is quite simple to add an order to batch in a busy schedule, as a plant is never limited by its batch capacity. The order fulfillment however depends on the truck availability. In busy times orders may be even denied.¹¹⁷

Ready-mixed concrete plants are very busy on Fridays, Saturdays and Sundays. As there is less traffic on the road on weekends, the transportation of ready-mixed concrete can be done more efficiently.¹¹⁸

4.5.4 Delivery Process

The process of delivering concrete consists of several steps. First of all the truck has to be loaded with the requested recipe of concrete defined by the customer. This is done by driving the truck underneath a mixer or loader which is located at the plant. The mixer or loader mixes the ingredients of the concrete thoroughly and then, fills the truck with the concrete. Afterwards the driver has to wash the truck. By doing this, three things have to be checked by the driver. First, the driver makes sure that everything is properly placed in the body of the truck mixer. If the material hasn't been far enough into the body, it gets washed into it by water. Then the driver does a quality test on the concrete. Third, any concrete remainder on the outside of the truck is washed off due to safety

¹¹⁴ See Tommelein/Li, 1999, p. 103.

¹¹⁵ See Tommelein/Li, 1999, p. 103.

¹¹⁶ See Tommelein/Li, 1999, p. 103.

¹¹⁷ See Tommelein/Li, 1999, p. 103.

¹¹⁸ See Tommelein/Li, 1999, p. 103.

factors. After the checking has been finished, the driver leaves the plant, driving to the customer. There the truck is moved into an appropriate position, this process is called staging.¹¹⁹

After putting the truck into an appropriate position, the truck begins to place the concrete. Having finished this, the driver pulls the truck away and washes it again. This is also done due to safety reasons and to make sure that no concrete remainders harden in or on the truck. After the washing off has been done the driver returns to the plant to either get a new task or to end the day.¹²⁰

The picture below outlines the described delivery process:

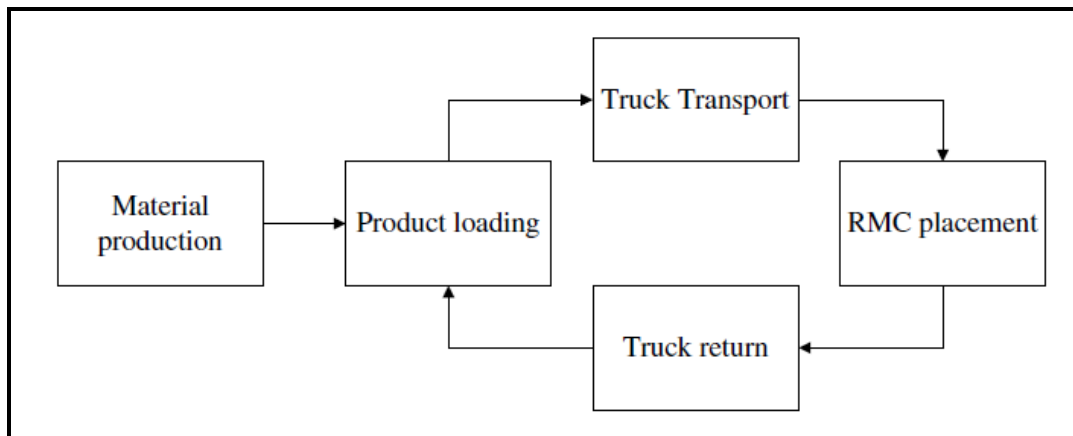


Figure 4: Delivery process of ready-mixed concrete¹²¹

4.6 Split Delivery Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows

The planning and scheduling of ready-mixed concrete delivery has to consider some additional constraints which are not included in standard vehicle routing problems. The following constraints have to be considered:

- Concrete is a perishable product.
- Separated Deliveries.
- Use of a heterogeneous fleet.
- Use of time windows.

¹¹⁹ See Durbin, 2003, p. 5f.

¹²⁰ See Durbin, 2003, p. 6.

¹²¹ Yan et al., 2008, p. 165.

First of all ready-mixed concrete is a perishable product. This leads to numerous consequences, such as concrete can only stay in the concrete mixer vehicle for a certain time before it hardens or loses quality. Furthermore a non-full load of concrete is not recommended as this can lead to an increased rate of hardening. As costumers often need more than one load of concrete, it is essential that the time between two consecutive deliveries (time lags) does not exceed a certain time limit.¹²²

The next constraint concerns the vehicles used for the ready-mixed concrete delivery. The fleet of vehicles used for the ready-mixed concrete delivery are heterogeneous. The vehicles differ in their capacity and in terms of their instrumentation. This means that some of the trucks can be used only for deliveries whilst others are equipped with a pump or a conveyor belt which are used during unloading operations. Whether a pump or conveyor belt is needed or not, depends on the order of the customer.¹²³

Another aspect which differs from a standard VRP is that ready-mixed concrete VRPs use more than one plant. During a normal working day the demand for concrete can be so high, that decisions have to be made which depot to use for which customer.¹²⁴

This leads to the last complication compared to a standard VRP which results in the use of time windows. Every order consists of several attributes, including time windows. A time window describes the starting and ending time of an order, which has to be fulfilled within the time. If an order is delivered not within the time window, it will be penalized.¹²⁵

Therefore this special VRP can be modeled as a “Split Delivery Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows” (SDMDHVRPTW).

In the subchapters below the above mentioned model used for this project is explained. To be able to understand how it works, one needs further knowledge of the orders, plants and trucks that will be mentioned. Therefore, these attributes and their significance are explained below.

4.7 Orders

Orders are known in advance and consist of the requirements of a certain concrete mix defined by a customer, who is located at the construction site. Orders have to be fulfilled on the demanded day; hence they cannot be delayed. The quantity needed by the customer normally surpasses the capacity of a single truck. Therefore a number of

¹²² See Asbach et al., 2009, p.820.

¹²³ See Schmid et al., 2009, p. 71.

¹²⁴ See Asbach et al., 2009, p. 820f.

¹²⁵ See Schmid et al., 2010, p. 561.

deliveries have to be arranged in order to please the customer. It is important to note that a truck can only deliver one order/delivery to one customer at a time; different recipes of ready-mixed concrete cannot be mixed. Moreover, if there is a small order, the truck may only be loaded half.¹²⁶

The construction site requires a steady flow of ready-mixed concrete to build their constructions efficiently. This means that single deliveries should be done just in time, meaning that if one truck is completed, the next one stands already in line. Breaks in between should be avoided, as they result in troubles for the constructor. Furthermore, only one truck can unload at a certain time and they have to leave the construction site after unloading. However they may stay if necessary.¹²⁷

4.8 Plants

The capacity of a plant is classified by the amount of trucks which can be loaded simultaneously. Furthermore each plant has its own predefined loading rate which implies the amount of concrete that gets poured into the trucks. The plant loading rate and the truck capacity define the loading rate of a truck.¹²⁸

4.9 Trucks

Trucks begin their tour every day at their home plant and return at the end of the day. Trucks simply drive between a plant and a construction site fulfilling the orders as needed. A truck cannot serve two customers with one load of concrete. Each order has to consist of fresh concrete. This is due to the heterogeneity of the product which is not simple concrete but consists of various different kinds of recipes, depending on the customer's wishes.¹²⁹

The truck fleet itself is heterogeneous. Trucks are differentiated between the capacity limits, and their type of instrumentation can also be different. A truck with instrumentation (like a pump or conveyor belt) can assist during unloading operations. Moreover hybrid vehicles exist that can be used for the delivery of ready-mixed concrete and provide additional equipment which is needed during the unloading process.¹³⁰

¹²⁶ See Schmid et al., 2010, p. 561.

¹²⁷ See Schmid et al., 2010, p. 561.

¹²⁸ See Schmid et al., 2010, p. 561.

¹²⁹ See Schmid et al., 2010, p. 561.

¹³⁰ See Schmid et al., 2010, p. 561.

Normally trucks can unload the concrete directly and without any help from the construction site. If certain instrumentation is needed, it will be included in the order once it is placed. Then the first truck arriving at the site would have the needed instrumentation. The truck would first unload its load and then stay and assist the later arriving trucks. When the total order amount has been fulfilled, the first truck is allowed to return to its home plant.¹³¹

4.10 Model

The model referred to in this thesis is known as a “Split delivery multi depot heterogeneous vehicle routing problem with time windows” (SDMDHVRPTW) as described in the chapter above. This means that several constraints like a heterogeneous fleet, multiple depots and time windows occur. These constraints have to be taken into account while implementing the task into the algorithm. Furthermore the whole model is set in a dynamic environment. This indicates that changes can have an influence on the problem whilst the algorithm tries to find a solution. Changes can be delays resulting from a traffic jam or a breakdown of a truck, but they can also be cancelled orders, orders with a change in their quantity or new orders.¹³² However all these changes have something in common, they are all unforeseen events that may take place and where the ready-mixed concrete company is challenged to act fast and reasonable. For the experiments this means that there are two different starting times when the algorithm is launched. The static experiments (experiment 1 and 3) start at around 8 o'clock/in the morning whilst the dynamic experiment (experiment 2) gets launched at around 11 o'clock/shortly before lunch time.

The algorithm, which is based on VNS, needs the following input text files for the solution finding process:

- Constructs: Input file which has information concerning the various construction sites. An ID and the name of the construction site are included.
- Distance matrix: Input file with the coordinates of the plants and construction sites as well as their distances in between.
- Orders: This input file is the only file which has been changed and enhanced. Basically the customer orders are getting changed.

¹³¹ See Schmid et al., 2010, p. 561.

¹³² See URL: <http://neo.lcc.uma.es/dynamic/vrp.html> [08.10.2009].

- Plants: Input file includes the ID, the loading rate in m³ per hour and the name of various plants.
- Trucks: Input file consists of the information about the various used trucks. It consists of the truck's ID, their capacity, their instrumentation if available and further specifications.

The objective function of the model is to minimize the total costs. In this case, the total costs arise from two different sources. First, the various transports between the plants and the customers result in so called “real costs”. Second, gaps between consecutive unloading operations result in penalties called “fictional costs” (unless demanded).

4.11 Methodology background

The topic of ready-mixed concrete delivery and its coherent planning issues are widely discussed in the literature. Although hardly any books exist, quite a lot of scientific papers discuss this matter. This chapter will list those which have been a fundamental influence in this thesis and summarizes their focus of research.

A good source of general information about ready-mixed concrete and its production is provided by Tommelein and Li. Not only do they explain the nature of ready-mixed concrete thoroughly, the production system is explained as well as the possibility of applying it in a Just-in-Time system.¹³³

Another paper which deals with ready-mixed concrete in general is the dissertation paper written by Durbin. He gives a good general overview of ready-mixed concrete as well. Furthermore he takes into account the dynamic component of orders and creates a decision-support tool which assists the schedulers and customer service representatives in fulfilling their orders.¹³⁴

The next paper is by Schmid et al. and was published in 2010. A combination of two solution methods are used, namely an exact algorithm, which is based on mixed integer programming (MIP), and a VNS approach. Their problem includes several plants, several customers and a heterogeneous fleet. They compared the two solution methods (hybrid metaheuristic vs. Pure VNS approach) and concluded that the metaheuristic outperforms the VNS approach if applied solely.¹³⁵

Another paper written by Schmid et al. is from 2009. Their research focus lay upon finding a hybrid solution approach for the delivery of ready-mixed concrete. Their

¹³³ See Tommelein/Li, 1999, p. 97.

¹³⁴ See Durbin, 2003, p. 1f.

¹³⁵ See Schmid et al., 2010, p. 559.

approach included optimization and heuristic techniques, namely a multicommodity network flow (MCNF) and a VNS approach were applied. Their hybrid approach on large instances overpassed other approaches by more than 6%.¹³⁶

The next paper is by Durbin and Hoffman, was published in 2008 and can be seen as a shorter version of Durbin's thesis. They designed and implemented a decision-support tool which consists of planning and execution devices. The modules organize orders, drivers and unloading procedures and solve it within 1% of optimality every five minutes throughout the day. Their approach has been successfully implemented by Florida Rock, a ready-mixed concrete company. Moreover this methodology is referred to a "best practice" by the World of Concrete and ConAgg industry conventions.¹³⁷

The next paper is by Asbach et al. and was published in 2009. It deals with the concrete delivery problem itself. Their model used is very similar to the notation of a VRPTW although it does not use time windows. It consists of several depots, several customers and a heterogeneous fleet and it presents a static model. They present a general mixed integer programming model which cannot be solved with an MIP solver due to its size. Therefore the scientists developed a certain local search approach which is able to solve the problem with good quality in a fair amount of time¹³⁸

Another paper which deals with this matter is by Matsatsinis from 2002. His research is based upon a decision support system for a ready-mixed concrete distribution system of a Greek company. The problem which is looked at is a Multi-Depot Multi-Vehicle Routing Problem with Time Windows. The attempt of the paper is to design the specifications for developing a prototype Decision Support System for the distribution of ready(-mixed) concrete. Heuristics are used in particular.¹³⁹

¹³⁶ See Schmid et al., 2009, p. 70f.

¹³⁷ See Durbin/Hoffman, 2008, p. 3.

¹³⁸ See Asbach et al., 2009, p. 820ff.

¹³⁹ See Matsatsinis, 2002, p. 487ff.

5 Experiments

The ready-mixed concrete industry is a very challenging industry. As already mentioned above in chapter 4: Ready-mixed concrete: It is very hard for companies to estimate the order quantities of their customer as it is highly unreliable. Customers tend to order a little bit less than they actually need, in case the lesser quantity is enough and so they don't have ready-mixed concrete leftovers in the end. However, this plan does not always work for them. It happens quite often that further ready-mixed concrete is needed, on a short notice, thus resulting in extreme planning difficulties for the executive ready-mixed concrete company. These planning difficulties are due to the fact that ready-mixed concrete is a highly perishable good with a lifespan of only 1.5 hours and as a customized material it is based on a certain recipe. Therefore, if a customer has bought less but needs more, the ready-mixed concrete company has to be able to fulfill this additional order in short time – this procedure refers to the dynamic environment which is examined thoroughly in this project. Additionally new orders tend to come in during the day, during which the ready-mixed concrete company is also fulfilling other customer's orders and therefore has to plan and accomplish this very fast and accurately.

To be able to fulfill such orders based on a short notice, the algorithm which is used in this thesis has been developed.

However, at this point one cannot be sure how “good” the solution of the algorithm is. Therefore three different experiments have been created and tested. In the end their results will be compared and the significance of the algorithm will be outlined. The three experiments, which are explained in more detail below, are known as “Static experiment”, “Dynamic experiment” and as “Ex-Post Experiment”.

- The static experiment is, as the name describes a static approach where no changes have happened to the initial data.
- The dynamic experiment is the main experiment of this project. It considers various changes which might happen to the orders and therefore result in a dynamic environment.
- The ex-post experiment refers to a hypothesis which never will happen in real life. However it has been tested as well and therefore the value of information could be calculated.

All experiments are based on the same data which itself is based on real time data. Three data sets exist which vary in their order volume. To avoid misconception they are called “basic data sets”. The order volume of the basic data sets can be either small moderate or large.

- The small basic data set consists of 13 orders. Ten relevant construction sites and five plants exist. 15 trucks are available for the delivery. The average order quantity results in 22.16 units. The minimum order quantity accounts to 1 unit and the maximum order quantity accounts to 90 units.
- The moderate basic data set consists of 42 orders. 38 relevant construction sites and 14 plants exist. 736 trucks are available for the delivery. The average order quantity results in 32.5 units. The minimum order quantity accounts to 4 units and the maximum order quantity accounts to 160 units.
- The large basic data set consists of 123 orders. 104 relevant construction sites and 14 plants exist. 736 trucks are available for the delivery. The average order quantity results in 20.05 units. The minimum order quantity accounts to 1 unit and the maximum order quantity accounts to 160 units.

For the various experiments, these basic data sets have been enhanced by including real time information based on real data. Changes, which happen based on short notice, are supposed to happen after 11 o'clock. Orders which take place before this time are excluded from the changes, as they already have been fulfilled. Furthermore three different grades of changes can be possible, namely small, moderate and large changes. This is due to the fact that one cannot predict how many changes will be in one day and how severe they are. Three different modes of changes have been chosen, namely a quantity change, cancelled orders or new orders coming in.

- Quantity change: Based on the original quantity a certain percentage of orders change positively or negatively.
- Cancelled orders: Based on the total amount of orders a certain percentage of orders get cancelled.
- New orders: Based on the total amount of orders a certain percentage of orders get added. These new orders become known during the day or planning horizon.

The table below shows the grades of changes as well as the various percentages which have been chosen for this project.

	Small	Moderate	Large
Quantity change	3% change by 15%	10% change by 20%	20% change by 40%
Cancelled orders	5%	6%	7%
New Orders	10%	20%	40%

Table 1: Grades of changes

The percentages in the table above were chosen arbitrarily but illustrate the daily life in the ready-mixed concrete business. There, changes in orders take place every day, are very random and hard to foresee. Therefore the three different modes of changes mentioned above were created, so to be able to illustrate the real life situation as best as possible. However one can never foresee all the changes but should try to react as fast and best as possible.

To be able to depict the real life situation as best as possible, nine combinations have been created. They are based on the three different basic data sets and on the three different grades of changes. The resulting matrix leads to nine possible combinations (like one instance is based on a small basic data set with small changes or an instance is based on a moderate basic data set with large changes).

For the enhancement of the existing orders, several calculations were executed using spreadsheets in MS Excel. The changes mentioned above were then implemented in the order files. The change in quantity and the cancelled orders were able to be done in the existing files. However, for the new orders, an extra data file was created. The first step in doing so was to evaluate the quantity of the various orders. A histogram was used to show the order pattern and to be able to achieve random values which were needed to enhance the data set. To be able to do so, the distribution function of the order quantities was estimated. As seen below the histogram indicates an exponential distribution. The final values of the order quantities were drawn from the exponential distribution.

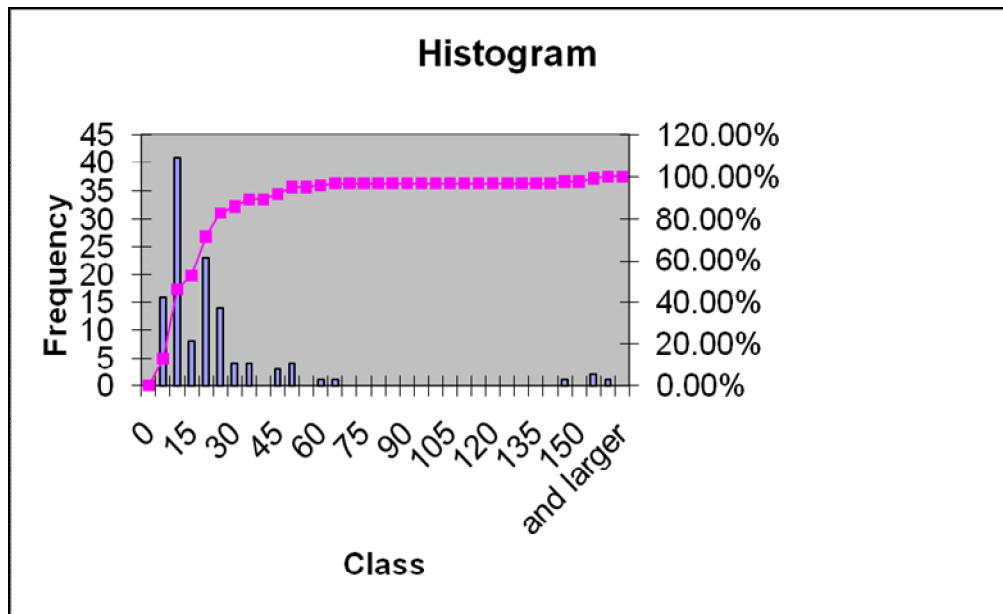


Figure 5: Ordered quantities

The enhanced order text file looks basically the same as the old order text file. However, as the name already suggests, new orders were added. These new orders were created using random values. The attributes ordered quantities and the time windows were derived by using a histogram. A random percentage of 36% was chosen for the instrumentation which may apply on a truck. A random percentage of 50% was chosen for the unload rate of a truck. Furthermore the number of the various construction sites was derived from the original order file. Then these changes were applied and the percentages as given in the grades of changes were applied for the new orders, hence all the changes were done properly.

Through using various mathematical functions the input data sets have been changed and enhanced, when needed. However, these changes only occur in the dynamic experiment and the ex-post experiment. Therefore new data files, due to the changes, have been created only for the last two experiments.

The normal composition of an Experiment looks like this:

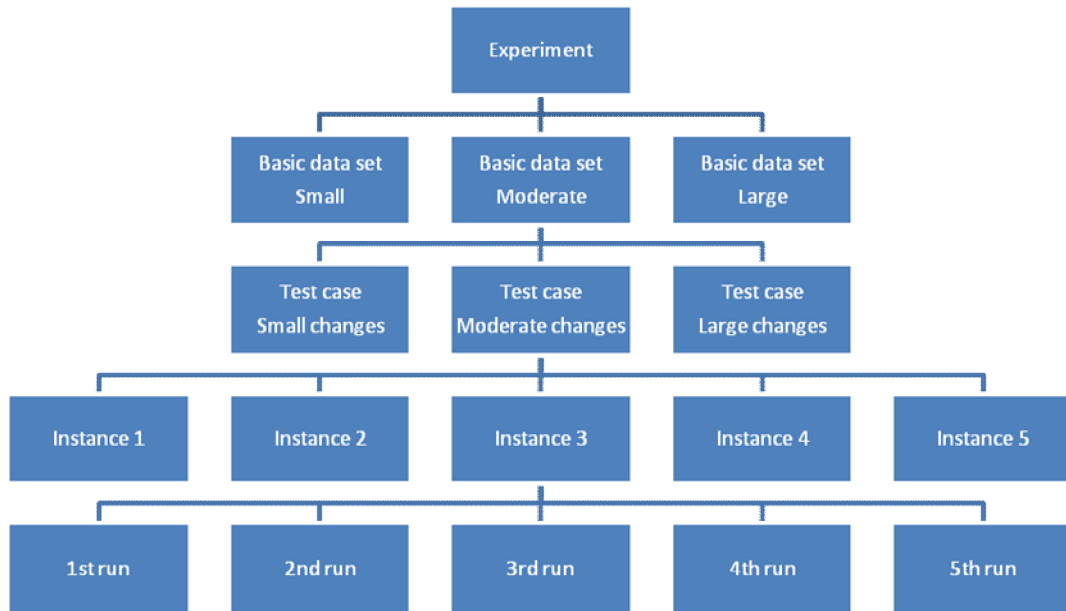


Figure 6: Composition of an experiment

As one can see in the figure above, an experiment consists of four levels. The first level consists of the basic data sets which vary, depending on their order volume, from small to large. Each basic data set consists of three test cases which depend on their grade of changes. Each test case itself consists of five instances, and each instance is run five times. Due to shortage of space, the picture above outlines only the course of one instance. In this case it outlines Instance 3, which belongs to the test case with moderate changes. However, the course is the same for all other instances.

As already mentioned before, three Experiments have been tested. The following table gives a short overview over the three experiments, whereas the numbers in the boxes refer to the number of instances a test case consists of:

	Static Experiment	Dynamic Experiment			Ex-Post Experiment		
Basic data set		Small	Moderate	Large	Small	Moderate	Large
Small	1	5	5	5	5	5	5
Moderate	1	5	5	5	5	5	5
Large	1	5	5	5	5	5	5
	Optimization	Re-optimization			Ex-Post		

Table 2: Number of instances

The aim of the three experiments is to compare the solutions with each other and to interpretate them thoroughly. As one can see in the table above the static experiment is an optimization where no changes in orders have taken place. On the other side the dynamic experiment represent, as the name already suggests, a dynamic approach with small to large changes in order quantity and numbers of orders. The ex-post experiment poses as a hypothesis and is needed for the value of information. The experiments are explained in more detail in the chapters below.

5.1 Static Experiment

The first experiment represents an optimization of the input data concerning a whole day of a ready-mixed concrete company. The input data is known in advance and consists of the three, already mentioned, basic data sets. Its aim is to achieve an optimal solution for the objective function by minimizing the travel and penalty costs. As no changes take place, this experiment could also be run over night, resulting in a longer running time for the algorithm.

This is the only experiment where the basic data set more or less equals an instance, not in their meaning but in their content. As one can see above an experiment normally consists of four levels, however the static experiment (pictured below) is an exception as it only consists of two levels. This is due to the fact that no changes in orders take place.

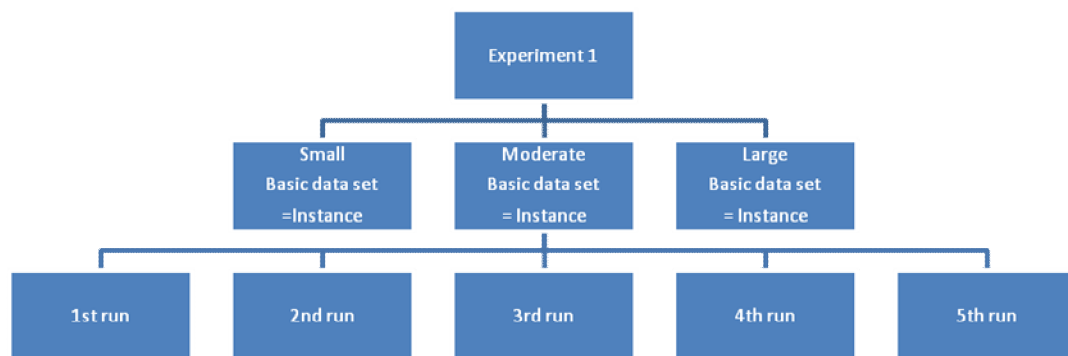


Figure 7: Organigram of the static experiment

This experiment consists of the three basic data sets in small, moderate and large. In this special case the basic data set poses as instance as well, as no alterations were done to

the order files. Each instance was tested five times. These independent five test runs check the probabilistic nature of the underlying algorithm.

5.2 *Dynamic Experiment*

The second experiment presents a re-optimization. In this case several things have happened. First of all new orders become known for the company. Those additional orders were not predicted but they have to be fulfilled within the working day. Furthermore, some orders have been cancelled as they are not needed anymore. And last, the quantity in some orders has changed as well. Some customers need more, others need less ready-mixed concrete.

Those changes are assumed to become known around 11 o'clock and the re-optimization takes place afterwards. The changes mentioned above happen in real life as well and result in a very difficult planning and scheduling approach.

Below, an exemplary course of the dynamic experiment is outlined:

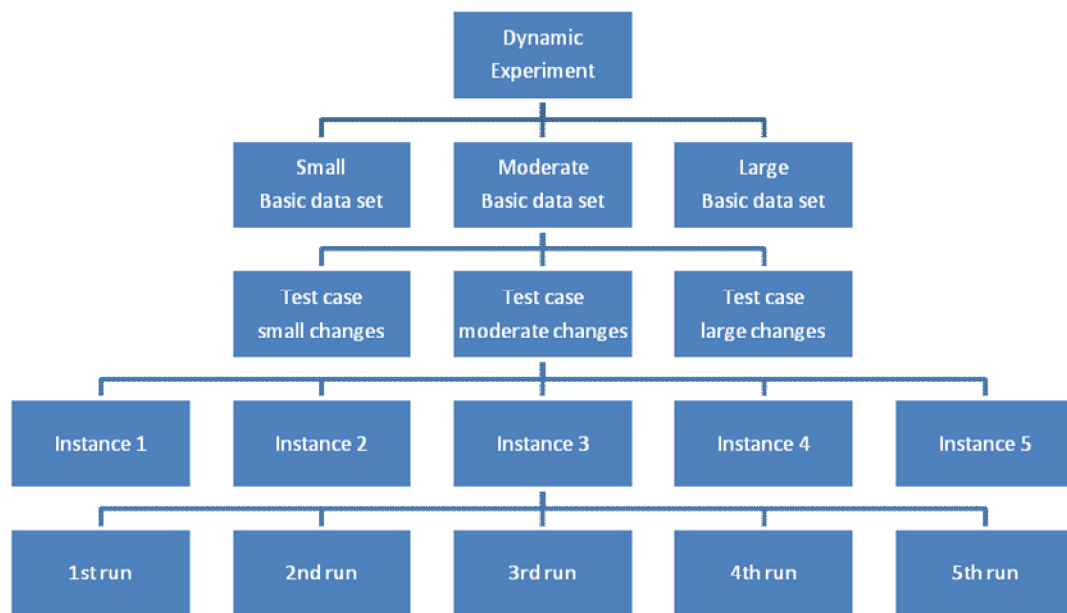


Figure 8: Organigram of the dynamic experiment

The dynamic experiment consists of the three different basic data sets: small, moderate and large. Each basic data set consists of three different test cases with various changes. Each test case consists of five instances where every instance has been solved five times.

The differences to the first experiment are that in this case there is very little time for the re-optimization. Furthermore the trucks are already either on the road or at the customer's construction site whereas in the static experiment the trucks are located on the plant's site. Due to the fact that ready-mixed concrete is custom made, trucks which have been already loaded with ready-mixed concrete cannot be reloaded or off-loaded. Furthermore, this experiment has to consider the current position, destination and travelling time of the trucks still on the road. This leads to a rescheduling of the trucks. Finally, in this experiment some of the orders are already fulfilled or partially fulfilled, where only the remainder of the day will be optimized, as this experiment is situated during the day.

5.3 Ex-post Experiment

The third experiment has more of a hypothesis than of a real case as it will never happen in real life. However, the solution is still interesting as it shows a "what if" scenario. So what would have happened, if the company would have had the information from the dynamic experiment at the beginning of the planning horizon?

Furthermore it has been compared with the dynamic experiment, to figure out how much a company loses because of its unreliable customers (who cancel orders, change orders or orders are known too late) as well as (dynamic) changes throughout the day.

Below, an exemplary course of the ex-post experiment is outlined:

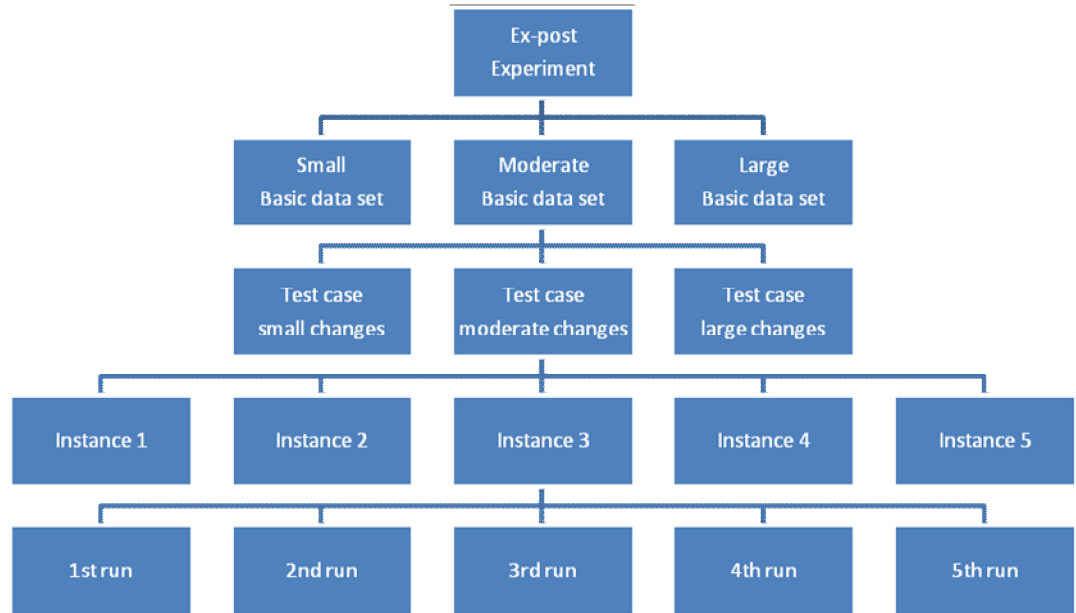


Figure 9: Organigram of the ex-post experiment

The ex-post experiment is in its composition basically the same as the dynamic experiment. It consists of the three different basic data sets: small, moderate and large. Each basic data set consists of three different test cases with various changes. Each test case consists of five instances where every instance has been solved five times. As already mentioned above, the only purpose of this experiment lays in its comparison with the dynamic experiment.

6 Results

This chapter presents the results given by the algorithm. The results have been determined in excel using pivot tables. Pivot tables are a useful way of showing results which are derived of a great amount of data, by collecting the data and breaking it down into various aspects.

The intention of the algorithm is to minimize the objective function. The objective function includes the travel time and penalty for delays, as well as the gaps between consecutive orders.

The results of the three experiments turned out as expected. The static experiment presents no major surprise; this is due to the fact that no variations exist. The next experiment represents a dynamic solution where diverse changes in orders (quantity change, cancelled orders, new orders) have taken place. As expected, the ex-post experiment turned out better than the dynamic experiment. This is no surprise, as the last experiment presents a hypothesis which has a better starting position as all the information is known in advance. Moreover, the greater the dynamic changes are, the greater are the changes in between the two experiments.

In general the first experiment cannot be compared with the other two as the data is not the same. The first one only consists of the basic data set with no grades of changes being applied to, whereas the dynamic and ex-post ones have been enhanced by using several modifications. These modifications have been explained thoroughly in Chapter 5: Experiments.

6.1 Run time study for the static experiment

The aim of this thesis was a run time analysis of the algorithm. To see how the algorithm reacts if changes occur, several experiments have been created. The maximum run time was set to 1800 seconds.

Due to the probabilistic nature and random number in use, each instance has been ran five times (this can be seen in the organigram above). All results are averaged over five independent runs.

The table below shows the result of the objective function depending on the imposed run time limit for the static experiment. There one can perfectly see how the solution improves over time.

Run time	Small	Moderate	Large
10	6,003	8,179	23,047
30	5,892	6,967	16,975
50	5,775	6,632	15,228
60	5,772	6,527	14,688
100	5,680	6,314	13,519
120	5,680	6,235	13,208
150	5,680	6,143	12,966
300	5,607	5,982	12,153
600	5,604	5,858	11,726
1200	5,604	5,829	11,400
1800	5,604	5,799	11,264

Table 3: Mean of the objective function based on the three basic data sets

Furthermore, this solution also implies that the mean converges over time. Nevertheless a smaller data set converges faster than a larger data set.

The improvement of the algorithm if it is only ran for 60 seconds instead of 1800 seconds can be seen in the chapter 6.5: Improvement.

6.2 Run time study for the dynamic experiment

The table shows the outcome of the objective function. The result of the objective function depends on the grades of changes as well, as one can see below. The test case with small changes does not improve as much as the test case with large changes. This can be seen in Table 3: Mean of the objective function as well. For the small basic data set, which consists of 13 orders, its improvement has not been such intense compared with the other two basic data sets.

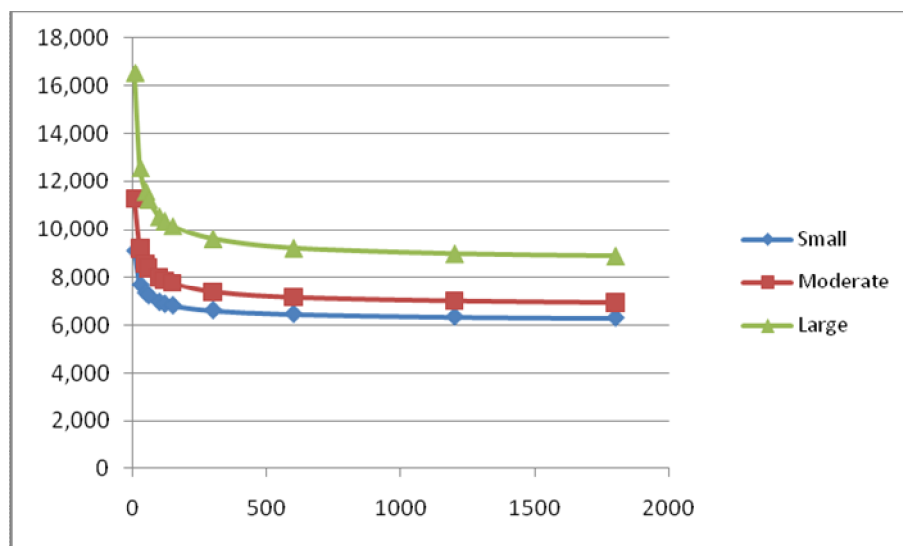


Figure 10: Mean of the objective function

Therefore an improvement depends on the size of the basic data set as well as the grade of changes implied. The greater the changes are the better is the improvement.

However, the mean of the objective function alone is not enough to show the functionality of the algorithm. Therefore the maximum and minimum values of the run time have been evaluated as well. The aim of this computation is to show how much the mean oscillates per run time. The graph below shows such an outcome. As one can see the result is similar to the mean of the objective function. The longer the algorithm runs, the better the solution turns out. The solution also gets more stable over time and converges. Furthermore the absolute minimum and maximum values are also getting better over time.

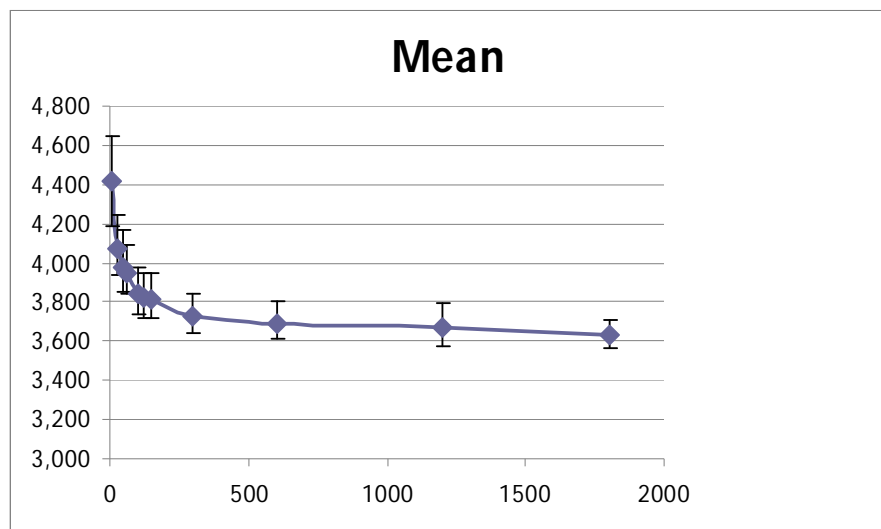


Figure 11: Mean of the objective function including minimum and maximum

This figure has been taken from the dynamic experiment and shows the results of the moderate basic data set with moderate changes. This result is exemplary for all the other results.

6.3 Result variation coefficient

The variance is a measurement of distribution. If the variance is large, the algorithm is not very reliable. On the other side, a solution is credible if the variance of the results is small. However, as the different basic data sets provide different means, the variance alone is not enough to compare so many different solutions of such big size.

Therefore the variation coefficient has been estimated. It is used for a better comparison and it is able to scales the results.

Run time	Static Experiment	Dynamic Experiment	Ex-post Experiment
10	3.3%	3.0%	3.9%
30	2.2%	2.5%	2.8%
50	2.1%	2.3%	2.2%
60	1.7%	1.8%	2.1%
100	1.4%	1.8%	1.7%
120	1.3%	1.7%	1.6%
150	1.8%	1.7%	1.5%
300	1.6%	1.5%	1.7%
600	1.5%	1.4%	1.5%
1200	1.6%	1.4%	1.5%
1800	1.3%	1.1%	1.4%

Table 4: Variation coefficient based on the moderate basic data set

For example the table above shows the variation coefficient of the three experiments of the moderate basic data set when run time is increased from 10 to 1800 seconds. Please note that for the last two experiments the mean of the five instances has been taken. The result shows clearly that the solution of the algorithm is reliable, as the values of the variation coefficient are low. The picture above is the same for the small and large basic data sets.

6.4 Dynamic Experiment versus Ex-post Experiment

As already mentioned before, the dynamic experiment and the ex-post experiment have been derived of the same data. Moreover the last experiment is the ex-post view of the dynamic experiment. Therefore those two experiments have been compared, in order to achieve a significant solution.

6.4.1 Objective function

Concerning the objective function, the outcome of the last experiment was expected to be better than the dynamic experiment. This is due to the fact that the ex-post experiment presents a hypothesis where all the information, especially about the changes, is known in advance.

The following tables present the outcome of the comparison. One can clearly see that the ex-post experiment results in a better objective function than the dynamic experiment.

Run time	Dynamic Experiment	Ex-post Experiment
10	4,418	4,319
30	4,071	3,850
50	3,980	3,761
60	3,946	3,729
100	3,844	3,678
120	3,826	3,665
150	3,811	3,630
300	3,732	3,594
600	3,692	3,558
1200	3,668	3,539
1800	3,629	3,532

Table 5: Outcome of the moderate basic data set with moderate changes

As one can see in the table above, the results refer to the moderate basic data set with moderate changes where the ex-post experiment is slightly better than the dynamic experiment. Concerning the other grades of changes, the picture is pretty much the same.

Run time	Dynamic Experiment	Ex-post Experiment
10	16,563	17,278
30	12,588	12,458
50	11,601	11,097
60	11,271	10,761
100	10,563	9,983
120	10,377	9,777
150	10,154	9,528
300	9,621	9,030
600	9,235	8,702
1200	9,002	8,539
1800	8,911	8,457

Table 6: Outcome of the large basic data set with large changes

The table above shows the results of the large basic data set with large changes. Again, the ex-post experiment is better than the dynamic one. Furthermore this solution depicts the outcome for the other two grades of changes as well. Another aspect which can be seen in the tables above is the impact of the grades of changes on the outcome. Namely, the greater the grades of changes are, the greater is the difference between the solutions.

6.4.2 Value of Information

The question which has to be considered is how much money a company loses because of its unreliable customers orders. For this question the comparison between the two experiments can be taken into consideration as well.

As the ready-mixed concrete industry is very busy and highly unreliable, new orders may come in during a day and have to be accomplished on the same day. Therefore a company has to act fast, resulting in higher costs and lesser gain for them. Even though the company may be able to fine the customers for their late orders, there is still a loss in profit.

Nevertheless the question how much the company loses still resides. For this the results of the mean of the two experiments were compared and their percentage and absolute values were calculated. The profit loss ranges between 1%-6% depending on the size of the order volume and the grades of changes applied to the basic data set.

In the beginning the dynamic experiment achieves a better result than the ex-post experiment. This is due to the fact that the dynamic experiment starts at around 11 o'clock when some of the orders or parts of them, have already been fulfilled. Nonetheless the longer the algorithm runs the better the latter experiment gets and in the end the difference between the outcomes results to:

Moderate basic data set

- 0.8% for the moderate basic data set with small changes.
- 2.7% for the moderate basic data set with moderate changes.
- 1.7% for the moderate basic data set with large changes.

Large basic data set

- 2.5% for the large basic data set with small changes.
- 5.9% for the large basic data set with moderate changes.
- 5.1% for the large basic data set with large changes.

The outcomes of the small basic data sets have not been listed, as, due to the small order volumes (which does not depict the real life) no effect exists.

6.5 Improvement

The next aspect which arises is the running time of the algorithm. One has to take into account that all the cases have been tested with a running time of 1800 seconds. This

may not sound like a long time but a company will not always have the time to run the algorithm half an hour considering that it has to fulfill and calculate more than one order. Therefore there is a need for a proper time period which gives a good solution within it. Therefore the following question has to be asked:

1. What is a proper running time for the algorithm?

To achieve a satisfying solution for the questions asked above, two things have been done. First of all, the differences in percent of the running time of the algorithm have been calculated. This means that some certain time periods have been chosen. Based on these time periods the savings have been calculated. The table below clarifies this method.

Small basic data set with small changes					
Run time	Mean	Running time of algorithm			
10	3,893				
30	3,876				
50	3,868				
60	3,853	60	100	120	150
100	3,850	0.10%			
120	3,849	0.12%	0.03%		
150	3,845	0.21%	0.11%	0.09%	
300	3,845	0.21%	0.11%	0.00%	0.00%
600	3,838	0.39%	0.29%	0.18%	0.18%
1200	3,819	0.90%	0.80%	0.51%	0.69%
1800	3,813	1.04%	0.94%	0.14%	0.83%

Table 7: Average solution when setting different run time for the small basic data set with small changes

As seen in the table above, the example refers to the small basic data set with small grades of changes. As possible running time 60, 100, 120 and 150 seconds have been chosen. Based on the results which have been achieved already, percentages have been calculated. This percentages show how much the solution could have been better, if it would have been runned longer.

This means that if 60 seconds would have been chosen as a proper running time:

- The best solution would be 3,853.
- However if the algorithm would have been runned 40 seconds longer, so 100 seconds in total, the solution would have been 0.10% better.

- However if the algorithm would have been runned 60 seconds longer, so 120 seconds in total, the solution would have been 0.12% better.
- ...
- However if the algorithm would have been runned 1740 seconds longer, so 1800 seconds in total, the solution would have been 1.04% better.

So the maximum improvement is around 1% concerning the small basic data set. To be able to give a recommendation one has to take a closer look on the small basic data set with moderate/large changes.

The table below shows the outcome for the basic data set with moderate changes. Here the missed improvement of the algorithm with a running time of 60 seconds accounts to 2.07%. Again this number is quite low and does not present an enormous loss.

Small basic data set with moderate changes					
Run time	Mean	Running time of algorithm			
10	4,760				
30	4,724				
50	4,714				
60	4,712	60	100	120	150
100	4,694	0.38%			
120	4,685	0.58%	0.19%		
150	4,680	0.67%	0.29%	0.09%	
300	4,652	1.27%	0.89%	0.70%	0.61%
600	4,629	1.77%	1.39%	1.20%	1.11%
1200	4,616	2.04%	1.66%	1.48%	1.38%
1800	4,614	2.07%	1.69%	1.50%	1.41%

Table 8: Average solution when setting different run time for the small basic data set with moderate changes

The next table shows the outcome for the small basic data set with large changes. The outcome is very similar to the other two grades of changes of the same basic data set. For 60 seconds the result account to 1.39% seconds.

Small basic data set with large changes					
Run time	Mean	Running time of algorithm			
10	4,933				
30	4,910				
50	4,898				
60	4,898	60	100	120	150
100	4,876	0.45%			
120	4,874	0.49%	0.04%		
150	4,871	0.55%	0.10%	0.07%	
300	4,863	0.70%	0.25%	0.22%	0.15%
600	4,852	0.93%	0.48%	0.45%	0.38%
1200	4,838	1.21%	0.77%	0.73%	0.66%
1800	4,829	1.39%	0.95%	0.91%	0.85%

Table 9: Average solution when setting different run time for the small basic data set with large changes

In summary the improvement for the small basic data set is quite low. It oscillates between 0-2% (as seen in the three tables above). The recommendation for this case, a data set with a small amount of orders, therefore is that a running period of 60 seconds is okay and that the missed improvement does not compensate the waiting time of the algorithm.

However, the situation for the other two cases looks totally different. There the order volume of the data set is significantly higher than in the case described above. The next focus lies upon the moderate basic data set which consists of about 40 orders, so compared to the one described above it is already a little bit larger. The following table shows the outcome of the algorithm with a shorter running period and the resulting missed improvement:

Run time				
Moderate basic data set	60	100	120	150
Small	2.0%	1.2%	1.1%	1.1%
Moderate	8.0%	5.6%	5.2%	4.8%
Large	4.9%	3.3%	2.9%	2.1%

Table 10: Improvement of the moderate basic data set with all three grades of changes

As seen in the table above, for the moderate basic data set, the percentages are a little bit higher than compared to the small one. Especially interesting is the course of the one

with the moderate changes (middle line) as it is compared to the other two considerably higher. The diagram below shows the percentages:

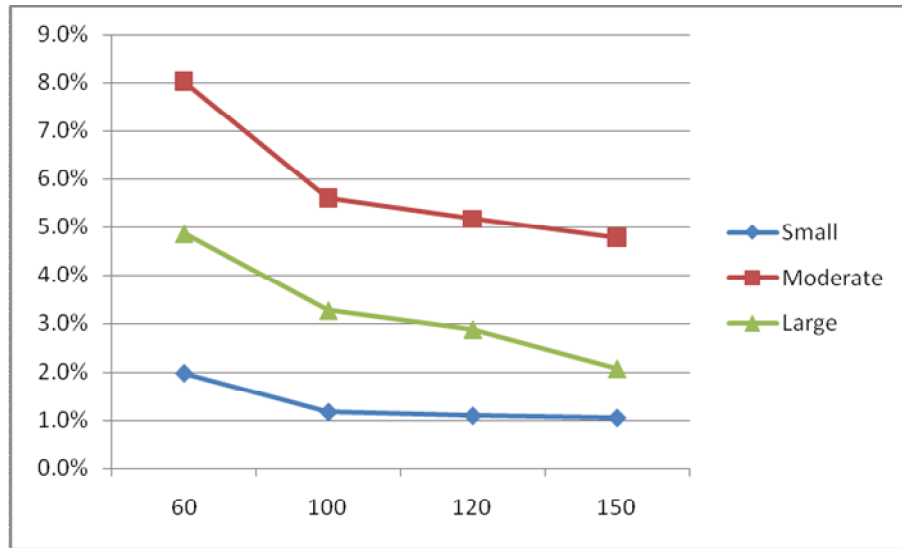


Figure 12: Improvement of the moderate basic data set

The last data set shows the outcome of the large basic data set. This data set consists of about 120 orders and is the one with the largest volume. This set is also the one which depicts the situation in real life at best. The table below shows the percentages of the improvement and how much a company would lose if the running period would be shorter.

Run time \ Large basic data set	60	100	120	150
Small	12.7%	9.3%	8.3%	7.5%
Moderate	17.4%	13.4%	12.0%	10.6%
Large	20.9%	15.6%	14.1%	12.2%

Table 11: Improvement of the large basic data set with all three grades of changes

As seen in the table above this test case consists of the most dramatic improvements. Especially the results of the first column and moreover the total results of the large basic data set with large changes are compared to the other two basic test cases impressive. The diagram below shows the percentages as well:

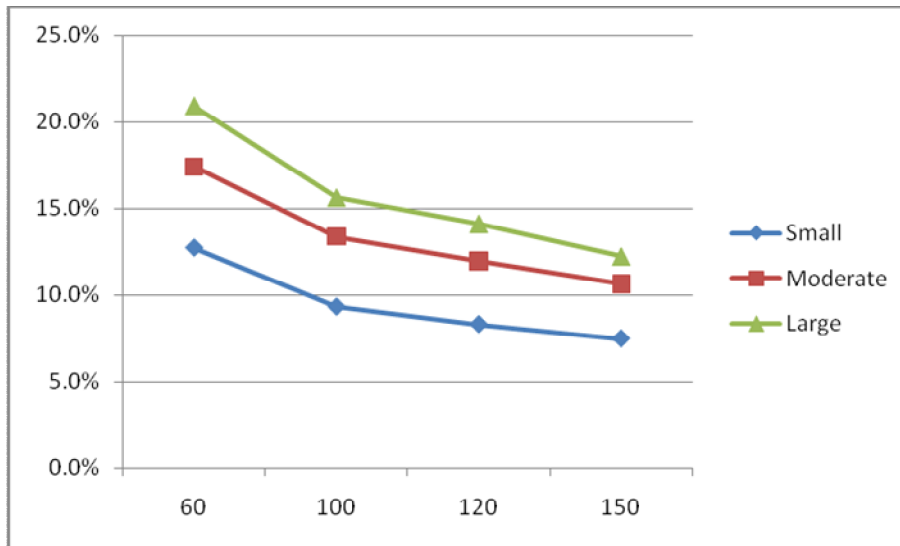


Figure 13: Improvement of the large basic data set

In general one can say that the larger the order volume of a basic data set is the greater the improvement of the running time. Moreover the greater the changes are per basic data set, the greater the improvement of the running time.

7 Conclusion

As seen above ready-mixed concrete is an important and widely used material in the field of construction. However, due to its characteristics the production and transportation of this material is a very challenging process. Especially the delivery plays a tricky part as ready-mixed concrete hardens very fast and if the material is handled wrong the results can be tremendous. Besides the fact that the material itself is highly unstable, the planning and scheduling process of the material is challenging as well. In addition to this problem one has to take into account any changes with the customers and their orders, which consist of several deliveries. For the customers it is not always clear how much ready-mixed concrete is needed and therefore they tend to order a little bit less than they might actually need. Then, if they need more the producer company has to react fast to complete the order, adding more deliveries to it. Considering the changes in orders which might happen, schedulers have to take into account the distance between construction plants and customers, the road composition and the readiness of the construction plant itself. This all leads to several factors, each which weight differently, making it an extremely challenging work for the responsible performers.

The algorithm which has been used in this project tries to support the planners of the construction site in scheduling a usual day. Based on mathematical functions and calculations it solves the problem to near-optimality.

To figure out whether the solution of the algorithm is actually a good one and can be relied on, different experiments were created and compared. However, due to various input data, only the results of the dynamic experiment and the ex-post experiment have been able to be compared efficiently. Nevertheless all of the results showed the same outcome, namely the longer the algorithm runs the better the solution, in this case the mean of the objective function, gets. Moreover the maximum and minimum values of the results also improve over time. To show that the solution is reliable the variation coefficient had been calculated, which was very low in all cases. Thus this results in a reliable solution.

Then the two experiments have been compared each of them posing as a situation which may or may not arise in real life cases. The one case depicts the real life of ready-mixed concrete companies where changes happen throughout the day and the company has to react to them to be able to fulfill additional orders whereas the other experiment poses as a hypothesis which never will happen in real life as it starts in the morning knowing

and considers changes which actually have not happened so far. Nonetheless this comparison is helpful to figure out how much profit a company loses because of the information which is needed in advance, but received too late.

However one question still remains unanswered so far in this project, namely what is an optimal running time of the algorithm. First of all the use of the algorithm depends on the number of orders a company has to deal with. As seen in the small basic data set, if the order volume is quite low, the use of the algorithm is not needed as, due to the small order volume and the considered possible changes, the work can be done by the planners itself and still leads to a successful solution. However this changes once the company faces more than at least ten orders as seen in the moderate and large basic data sets which consist of far more than ten orders. There the information known in advance, results in a far better result of the objective function in the ex-post experiment than in the dynamic experiment. In the chapter concerning the profit loss one can see the improvement separated into different time steps as well as the lost profit if the algorithm would have stopped earlier. There one can make an assumption as when to stop or not. Of course this decision depends on two factors, namely the order size volume and the grades of changes. Therefore, depending on these factors, a running time of 60-120 seconds should be considered if this algorithm is used in real life.

Another aspect which has arisen so far but has not discussed further concerns the possible use of the algorithm. It is clear that when only a small order volume exists, there is no need for the algorithm. However this is not always the case in real life. Often the size of the order volumes cannot be counted on two hands. Therefore, to figure out for what order volume the use of the algorithm is beneficiary could be another research topic.

The planning and scheduling of ready-mixed concrete delivery remains a very difficult process in the daily life of a company. Nonetheless the algorithm supports the decision makers very well. However the focus should not only lie upon the schedulers, the customers should be taken more into account as well. A company should offer incentives for their customers which should result in a lower rate of changes based on short notice. This could also be done in another project.

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Abstract

This thesis deals with the delivery of ready-mixed concrete in a dynamic environment. Its aim is a run time analysis of a certain algorithm which is used for vehicle routing problems, a problem which is in the field of combinatorial optimization problems one of the most challenging ones, which can not only solve this problem to near-optimality, but also improves the given solution over time. For this case the algorithm is applied on three generated experiments set in a static/dynamic environment. The focus lies upon the reaction of the algorithm and on the consequences for the schedulers who have to deal with this matters which often occur on short notice.

The thesis consists of three main parts. The first part takes a deeper look at the theory behind this problem. Two combinatorial optimization problems have been explained, and their solutions methods were presented. Then the material itself was presented, its special features and how this inflicts the production system and delivery of ready-mixed concrete. The last part consists of the experiments and the results of the study.

To be able to depict the real life situation and to figure out whether the solution of the algorithm is a good one and can be relied on, three experiments, based on real-time data have been generated. These experiments present a static approach, a dynamic approach and an ex-post approach. Especially the dynamic experiment has been of great value for this project. Furthermore the dynamic and the ex-post experiment have been compared and analyzed concerning their results of the objective function as well as the value of information.

With the help of the experiments several questions concerning the use of the algorithm were able to be solved. First of all the algorithm provides a good and reliable solution. This was supported by a low variation coefficient. Furthermore the solution improves over time. By comparing the last two experiments the value of information could be calculated as well. In the end a recommendation for an optimal running time of the algorithm was given as well.

Zusammenfassung

Das Thema dieser Magisterarbeit behandelt die Auslieferung von Fertigbeton in einem dynamischen Umfeld. Das Ziel der Arbeit ist mit einem bestehenden Algorithmus eine Laufzeit-Analyse durchzuführen.

Die Arbeit besteht aus drei Hauptteilen. Der erste Teil befasst sich mit dem theoretischen Hintergrund. Der zweite Abschnitt beschreibt die spezifischen Eigenschaften und Anforderungen an Fertigbeton. Zum Abschluss der Arbeit werden die drei Experimente genauer beschrieben und die Ergebnisse präsentiert.

Die Auslieferung von Fertigbeton stellt eine logistische Herausforderung dar und wird in der Literatur durch ein *VRP (Vehicle Routing Problem)* beschrieben. Ein VRP, in diesem Fall mit unterschiedlichen Bedingungen, ist eines der schwierigsten Aufgabenstellungen aus dem Bereich der Kombinatorik. Mit Hilfe des Algorithmus kann das VRP jedoch fast optimal gelöst werden, gleichzeitig verbessert sich auch die Lösung über einem längeren Zeitraum. Anhand von drei unterschiedlichen Experimenten soll die Anwendbarkeit und Lösungsgüte des Algorithmus untersucht werden. Dabei werden verschiedene Auftragsszenarien unter statischen, dynamischen bzw. hypothetischen Bedingungen generiert. Der Fokus liegt in der Reaktionsfähigkeit des Algorithmus und den damit verbundenen Auswirkungen auf den Planungsprozess.

Um die Situation möglichst detailgetreu darzustellen wurden drei Experimente generiert die auf Echtzeitdaten basieren. Mit Hilfe dieser Experimente lässt sich genaueres über die Lösungsgüte des Algorithmus aussagen. Die Experimente stellen einen statischen, einen dynamischen und einen hypothetischen Ansatz dar. Der Fokus liegt hierbei vor allem auf dem dynamischen Experiment, welches unter anderem auch mit dem hypothetischen Experiment verglichen werden kann.

Mit Hilfe der Experimente konnten einige Fragen hinsichtlich der Lösungsgüte des Algorithmus geklärt werden. Der Algorithmus bietet eine gute und zuverlässige Lösung. Diese Aussage kann mit einem niedrigen Variationskoeffizient-Wert gestützt werden. Des Weiteren verbessert sich die Lösung über einen längeren Zeitraum. Durch den Vergleich der beiden Experimente konnte auch genaueres über den *Value of Information* wiedergegeben werden. Am Ende wurde noch eine Empfehlung für eine optimal Laufzeit des Algorithmus abgegeben.

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