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**"Heuristic algorithms for the optimization of storage
assignment in a log yard"**

Master thesis

by

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Abstract

In this work, heuristic algorithms for the optimization of a log yard roundwood transport and storage problem are presented, and put in the general context of common optimization problems found along the forestry supply chain. The underlying model of the log yard transport and storage optimization was formulated as a mixed integer problem by Rathke et al. (2013), who have also formulated a basic heuristic algorithm for this problem and calculated the optimal results using optimization software. The heuristic algorithms presented here are an extension to the basic heuristic algorithm with the aim of improving the possible solution quality. Finally, the heuristic results are compared to the optimal results of Rathke et al. (2013) in terms of solution quality and necessary time for computation. The research question is whether the implementation of relatively simple and compact algorithms in java can be a satisfying alternative to the optimal but time consuming findings optimization software can deliver.

Kurzfassung

In dieser Arbeit werden heuristische Algorithmen für die Optimierung eines Holzlagerplatz-internen Rundholz Transport- und Lagerungsproblems präsentiert, welche im Kontext von allgemeinen Optimierungsproblemen entlang der Forstwirtschafts-Lieferkette eingebettet sind. Das diesem Problem zugrundeliegende Modell wurde von Rathke et al. (2013) formuliert, außerdem ein grundlegender heuristischer Algorithmus dafür entwickelt sowie auch die optimale Lösung mittels Optimierungssoftware berechnet. Die hier präsentierten heuristischen Algorithmen sind eine Erweiterung zu dem grundlegenden heuristischen Algorithmus mit dem Ziel die mögliche Lösungsgüte zu verbessern. Die Ergebnisse dieser Algorithmen werden anschließend mit den optimalen Ergebnissen von Rathke et al. (2013) verglichen, um Unterschiede in der Lösungsgüte und Berechnungszeit feststellen zu können. Die Forschungsfrage ist, ob die Implementierung von relativ einfachen und kompakten Algorithmen zufriedenstellende Lösungen liefern kann gegenüber den optimalen aber zeitaufwändigen Lösungen welche von einer Optimierungssoftware errechnet werden.

Table of Contents

1.	Introduction.....	1
2.	Log yard activities and functions.....	5
3.	Planning methods to improve forest wood supply chain processes.....	10
3.1	Simulation of forestry supply chain processes.....	11
3.2	Optimization strategies	15
3.3	Applied examples in literature	16
4	Log yard layout planning	20
5	Materials and Methods	21
5.1	Storage Bin Assignment Modelling	22
5.2	Model Formulation.....	22
5.3	Heuristic Methods	26
5.4	Improvement Algorithms	29
6	Numerical Study	31
6.1	Data	31
6.2	Alternative Assortment Distributions.....	34
7	Conclusion	40
	References	42

List of Figures

Figure 1: Schematic connection chart of facilities and material flows in the forestry supply chain. (Gunnarson 2007)	4
Figure 2: Applicability of material handling gear on log yards (Dramm et al. 2002)	6
Figure 3: Schematic overview of a log sort yard (Dramm et al. 2002)	8
Figure 4: Overview of a sawmill with a log yard. Source: https://www.schweighofer.at/en/produktionsstandorte/sebes.html	9
Figure 5: Original layout of the log yard as described by Rathke et al. (2013). Legend: {1} logs are sorted by species {2} identification of optimum cut in length {3} metal detector {4} ejection of logs according to diameter and length {5} full storage bin ready	10
Figure 6: Schematic structure of the model development life cycle according to Nance-Balci. (Wiedenbeck et al. 1994).....	12
Figure 7: Model of the interrelations of simulation and optimization as a solution to stochastic problems. (Juan et al. 2015)	14
Figure 8: Modification of the arrangement of storage bins on a log yard by Rathke et al. (2013).....	21
Figure 9: The distribution of storage volumes V_a in the 42 bin log yard arrangement.	32
Figure 10: The distribution of storage volumes V_a in the 28 bin log yard arrangement.....	32
Figure 11: The original distribution of assortment volumes.....	35
Figure 12: Distribution of the five major assortment volumes, which share a constant proportionality to each two following assortments	36

Figure 13: Examples of volume distribution for each alternative distribution 1 to 8.....	38
Figure 14: Boxplot of the results for the alternative assortment distributions 1-8.....	39

List of Tables

Table 1: Overview of problem solution scope, methods and respective goals selected by author	16
Table 3: Results for the initial stage of heuristic application	33
Table 4: Comparison of optimized results from Rathke et al. (2013) with the best final results of applied heuristics	33
Table 5: Alternative distributions with description of their shape and the number of generated samples	37
Table 6: Comparison of results for alternative distributions 1 to 8	39
Table 7: Optimized and heuristic results for the alternative distributions 9 and 10	40

1. Introduction

In 2014, the global roundwood production was estimated at 1837 million m³, which is an increase of 2.3 percent compared to the estimation of the year 2013. The global trade of sawn wood in 2014 was estimated to be 131 million m³. The five largest producers of roundwood are the USA, the Russian Federation, China, Canada and Brazil. Since the economic downturn of the years 2008-2009 the production of roundwood has widely recovered. (FAO 2014)

In the decades following 1980 the forestry sector has lost shares from the viewpoint of total global economic output, from 1.6% to only about 1% of the world's GDP, while the share of the world's labour force employed in the forestry sector has fallen from 0.7% to a little less than 0.4%. In total, the value added by the forestry sector has risen since, but in comparison to other sectors of the economy the forestry sector has grown considerably slower. A major factor of the weakness of the sector is the isolated nature of the agencies and services, where activities of forestry are separated between public, private and other civil stakeholders. Thus a continued improvement in cooperation between partners in the forestry business is paramount, as well as an intensified interaction with other economic sectors. The deployment of technology is an important factor for the improvement of the processing of forestry products, and can contribute to raise the revenues of the industry. (UNO 2013)

The forestry sector of today is subject to an ongoing progress of globalisation. In between the years of 1985-2005 the states of the European Union have increased the value-added of their forestry exports. A substantial change in the behaviour of the added value is also brought by the intensified and diversified processing of wood and wood products. Apart from critical factors such as wood or energy costs, also know-how, technology and logistics play a dominant role in the competitiveness of the forestry sector and have helped the countries of the European Union to increase their share on global markets. All major forestry and wood product companies around the globe have followed the strategic trend of computerization and heavy machinery in order to stay profitable. (IIASA 2007)

Amongst other factors the scarcity of wood resources can make it necessary to optimize production processes in sawmills to increase efficiency of the output, meaning the optimization of the volume and value yield. (Kambugu et al. 2013)

In the past years the availability and quality of the timber resource have declined in the USA, therefore producers react by trying to recover more value from the resource. (Dramm et al. 2004)

A shift in priority from volume-based to value-based wood processing has therefore taken hold in today's forestry business. Within one tree and in between tree species the properties of the material vary, which makes adaptations in planning and production management necessary. According to observations, 17% of the material of a mature tree are processed into logs and lumber while 74% of the material is used for the production of pulpwood. The 74% of a mature tree which is used for pulpwood include 60% of the tree used for the production of pulp and paper and 14% of the tree used for the production of engineered products. The remaining 9% of the mass of a mature tree not used for pulpwood or logs and lumber is logging residue, which can be used for the production of bioenergy. The modern forestry supply chain is a complex network of actors producing and processing products, with material and information flowing in many directions. A business in this network resembles an agent acting autonomously. One specific aspect distinguishing the supply chain in forestry from other common industrial supply chains is the fact that raw materials are disassembled into separate products along the primary modes of harvest and processing, rather than combined. Increased global networking and interrelations make it necessary to increase the coordination between agents of the forestry supply chain. Operations research and optimization models are important decision tools that can support promising strategies for a higher efficiency. Several studies have examined the performance of parts of the forestry supply chain as well as the performance of the whole system. It is believed that even small improvements in efficiency along the supply chain can gain high profits. Examples have shown that operational management can decrease costs and increase profits in the forest industry. (Shahi et al. 2013)

The logistics in the forest industry are an important element in the optimization of processes. Two key elements of the logistics in any industry as well as forestry are

the placement pattern of vital facilities and the distribution of freight and materials. Locations, information systems, material flows and transportation are determining these main points of concern. In the forestry supply chain in particular, two main flows of material and freight can be distinguished, one that starts initially from the forest itself on to the processing facilities, which in turn is where the second flow of material leaves to enter the final markets. (Troncoso et al. 2005)

The initial nodes of the forestry supply chain are also the source of its raw materials. Important matters of coordination and planning are the rotation times of trees, harvesting schedules and the layout of routes for harvesting and transport operations along these primary nodes of the forestry supply chain. Basic activities at the initial point of the forestry supply chain are planting, cleaning, thinning and harvesting. Harvested timber is then delivered to the sawmills for processing. Optionally, it may first be brought to separate storage terminals before being fed to a mill. The sawmills are the following nodes to the harvesting operations in the forestry supply chain. Sawmills with an efficient process minimize the residue in the production of sawn wood and are well adapted to supplying the demands of the customers. The major products in the forest industry are saw logs, pulp wood and forest residues. These can then be further distinguished and classified into varying assortments according to their quality and respective dimensions. (Gunnarson 2007)

Fluctuating demands are in general one main cause of uncertainty in the forestry supply chain. Other important factors possibly influenced by events of a stochastic nature include the material supply, capacities of production as well as time scheduling of various processes. The resulting uncertainty can heavily influence planning decisions in the supply chain. (Shahi et al. 2013)

Efficient planning and resource optimization have shown to be powerful means to significantly reduce costs. Many efforts in the forest industry are directed towards an increased performance of processes and the reduction of operational costs. Proper utilization of resources and planning are very important for an efficient process in sawmills and still remain a great challenge for many sawmill businesses. (Rahman et al. 2014)[2]

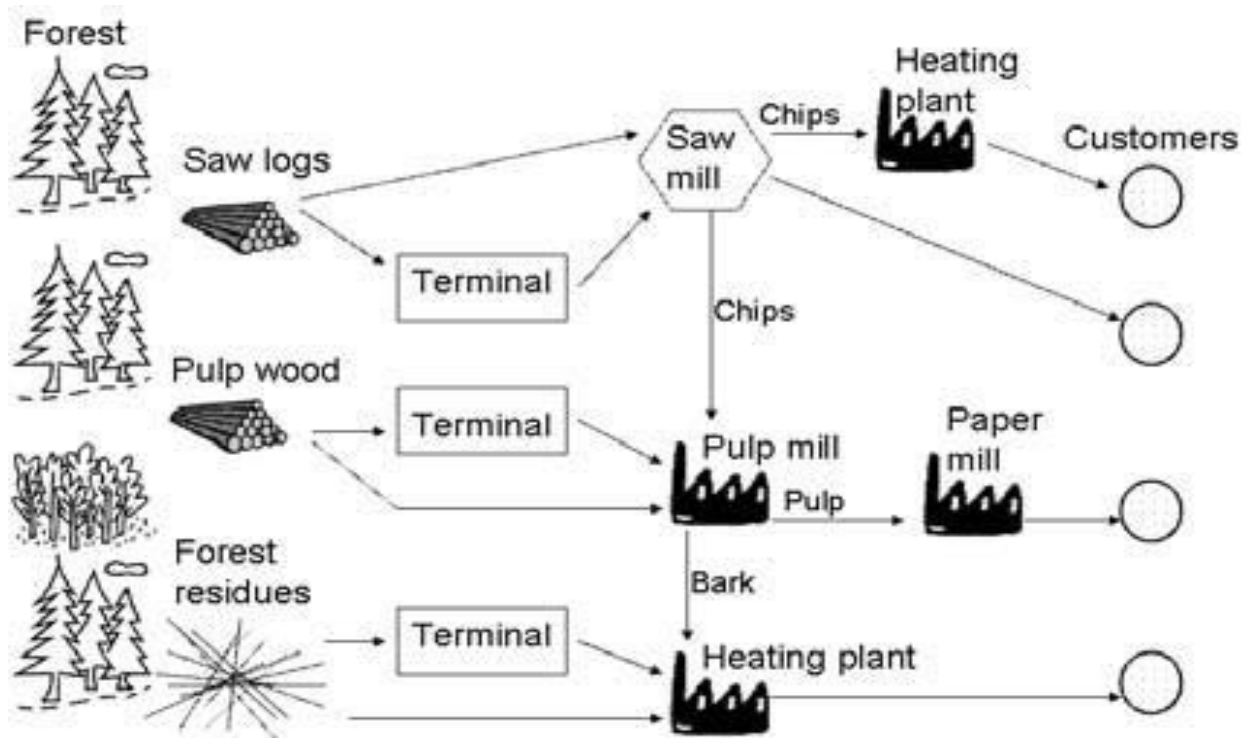


Figure 1: Schematic connection chart of facilities and material flows in the forestry supply chain. (Gunnarson 2007)

The log yard can be considered as a link in the forestry supply chain between the forest operations and the sawmill. (Beaudoin et al. 2013)

A well designed log yard is very important for the efficient operation of a sawmill. A flawed log yard design can result in additional operational costs, raw material shortages, damage of the log yard equipment and other negative effects. (Robichaud et al. 2015)

Log yards may help to improve the recovery of value from the timber resource, thus generating more profit out of the material. Especially the use of biomass and small diameter wood can be improved through log yard operations. (Dramm et al. 2004)

There has been a lot of research on the optimization of processes in the forest industry, such as timber harvesting operations and transportation, however, there is still very little research in the field of log yard design and operation. It is a difficult task to evaluate the design of a log yard, given the complex interactions which take place on the log yard. The question of how to design the layout of a log yard properly leads to many other interrelated problems concerning the planning of a log yard. (Robichaud et al. 2015)

A carefully programmed approach is very important to assess the economic viability of an independent log yard operation. The main objectives for the planning of a log yard include cost saving, risk reduction and improved management of the resources on the yard. Poor log yard design, overstocked inventory and poor handling of the equipment are main causes of inefficiency in log yard operations. A basic relationship of the log cost to the log size is important for economic success. It is recommended to minimize the handling of logs, since material may be damaged and lose value. Other recommendations for the economic success include bundling of low value logs and using equipment at full capacity. (Dramm et al. 2004)

In the following chapters the structure and functionality of a log yard as well as the various types to be distinguished will be characterized. Furthermore, several approaches out of existing literature are presented which can potentially improve the design, planning decisions and operational processes of a log yard. Afterwards an algorithm is shown which has been implemented in order to improve the logistic operations within a case example of an existing log yard.

2. Log yard activities and functions

The log yard as a node in the forestry supply chain connects the forestry activities with the sawmilling operations. (Beaudoin et al. 2013)

The input flow from a log yard to the sawmill generally consists of logs, which are then processed into the output flow, going to the markets as lumber. The term log yard can be understood in several ways. In general, it comprises the storage and handling of unfinished forestry products. Several different types of log yards can be distinguished according to their respective locality and function. All log yards do, to some degree, sort logs for a higher added value, for a stable supply to mills and factories and to provide an economically desirable mix of logs. Material handling is a central activity at every log yard, which always involves the picking up, moving and laying down of logs and wood products. The following major types of log yards can be distinguished:

- **Sawmill log yard:** a facility adjacent to a sawmill, which traditionally receives and stores raw materials for the sawmill to ensure a continuous flow of operation.
- **Log sort yard:** an independent enterprise in the forestry supply chain. Log sort yards provide their customers, such as sawmills, with a desired mix of logs and concentrate logs into batches which facilitates their transport. Log sort yard can provide all basic services for their customers such as the scaling, grading, storing, bucking and bundling of logs.
- **Concentration yard:** a log yard which concentrates loads of raw materials for shipment and further transport
- **Log reload yard:** a transfer point between different modes of transportation of logs such as truck, rail or barge transport.

	Function and yard size ^b								
	Load and unload logs			Transport and spread logs			Sort logs		
	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
Machine equipment									
Front-end loader, large ^c	—	●	●	◊	●	●	—	—	—
Front-end loader, medium ^d	—	—	◊	—	—	◊	—	—	◊
Front-end loader, small ^e	—	—	◊	—	—	◊	—	◊	●
Log stacker	●	◊	—	●	◊	—	—	—	—
Log loader, tracked	—	—	◊	—	—	—	●	●	◊
Stationary log loader	—	—	—	—	—	—	●	●	—
Log loader, wheeled	—	—	● ^f	—	—	—	—	—	●
Log loader, truck mounted	—	—	◊	—	—	—	—	—	●
Sorting system									
Linear sorting system ^g	—	—	—	—	—	—	●	●	◊ ^h
Transverse sorting table ⁱ	—	—	—	—	—	—	●	●	◊
Log merchandiser, linear	—	—	—	—	—	—	● ^j	● ^j	◊ ^k
Log merchandiser, transverse	—	—	—	—	—	—	● ^l	◊	● ^m

^aAdapted from Sinclair and Wellburn (1984) and Hampton (1981), and information collected from interviews with log sort yard operators.

^b● recommended equipment or system; ◊ acceptable equipment or system; — unsuitable equipment or system or not applicable. Small yard is <25 million board feet (MMBF)/year; medium is 25 to 100 MMBF/year; large is >100 MMBF/year.

^cFor example, CAT988G with log forks (Caterpillar Corp., Peoria, IL).

^dFor example, CAT980G with log forks, good backup machine (Caterpillar Corp., Peoria, IL).

^eFor example, CAT966G with log forks (Caterpillar Corp., Peoria, IL).

^fIn the eastern United States, rubber-tire-mounted log loaders are preferred machines (For example, Prentice 210).

^gGenerally for small-diameter, straight, and uniformly sized logs only.

^hLess expensive linear sorting systems are available for low volume log sort yards.

ⁱTypically for larger grade logs in combination with a stationary grapple boom loader to pull sorts from table.

^jTypically employs optical or laser scanning with computer-optimized bucking systems.

^kLess expensive manual merchandising (that is, manual bucking decisions) systems for small uniform logs.

^lVery high production small-log softwood computer-optimized merchandising.

^mSmaller hardwood log merchandising generally with manual bucking decisionmaking.

Figure 2: Applicability of material handling gear on log yards (Dramm et al. 2002)

The basic equipment of log yards includes various types of log loaders used for transport and sorting logs, as well as sorting tables, linear log-sorting systems and log merchandizers for sorting logs. Large scale log yards use such equipment as log stackers, front-end loaders and log loaders for various handling functions.

Large firms use expensive computerized technology for log sorting. Alternatively, logs can be sorted prior to processing based on optimal sawing patterns according to their diameter classes. With this method, logs are assorted into batches depending on their diameter before processing. Therefore, time is saved when determining the sawing pattern and resetting the saws. An optimal value can be recovered from these assorted logs by using the best sawing pattern for each batch.

Log yards fulfil relevant functions for the efficient operation of sawmills. Log yard activities such as the scaling, grading, bucking, or bundling of logs support the ongoing process of a sawmill and the profitability of the enterprise. The storage of logs and material is oftentimes an important function of log yards. Many small wood product firms particularly depend on a constant supply of logs to retain a profitable margin, therefore log yards can support the material flow through storage, supply and selection of logs. The sorting of logs can also have a relevant influence on the profitability of a sawmilling enterprise. For hardwood mills and pine board mills, the appearance of the lumber determines its value. For pulp mills, it can be more profitable to sort out saw logs and veneer peelers from the wood supply because these logs are more valuable when marketed directly instead of feeding them to the saw line of the pulp mill. The bundling of logs and the combination of logs into a desired log mix is also an important service log yards can provide. Many companies that are processing raw materials in the forest industry, like pulp mills, need a specific log mix due to technical reasons and also laws and regulations. Modern softwood mills are often highly specialized and need a very uniform supply of logs to operate efficiently.

There are several recommendations when it comes to the efficient operation of a log yard which includes the efficient use of the equipment on the log yard. The shorter the distance travelled when moving materials, as well as the greater the weight of the material transported per move, the lower are the resource costs for the log yard. Unnecessary handling of logs should be avoided, as it may potentially

damage logs and decrease their market value. The handling of materials on a log yard can in general be divided into sorting and transporting activities. (Dramm et al. 2002)

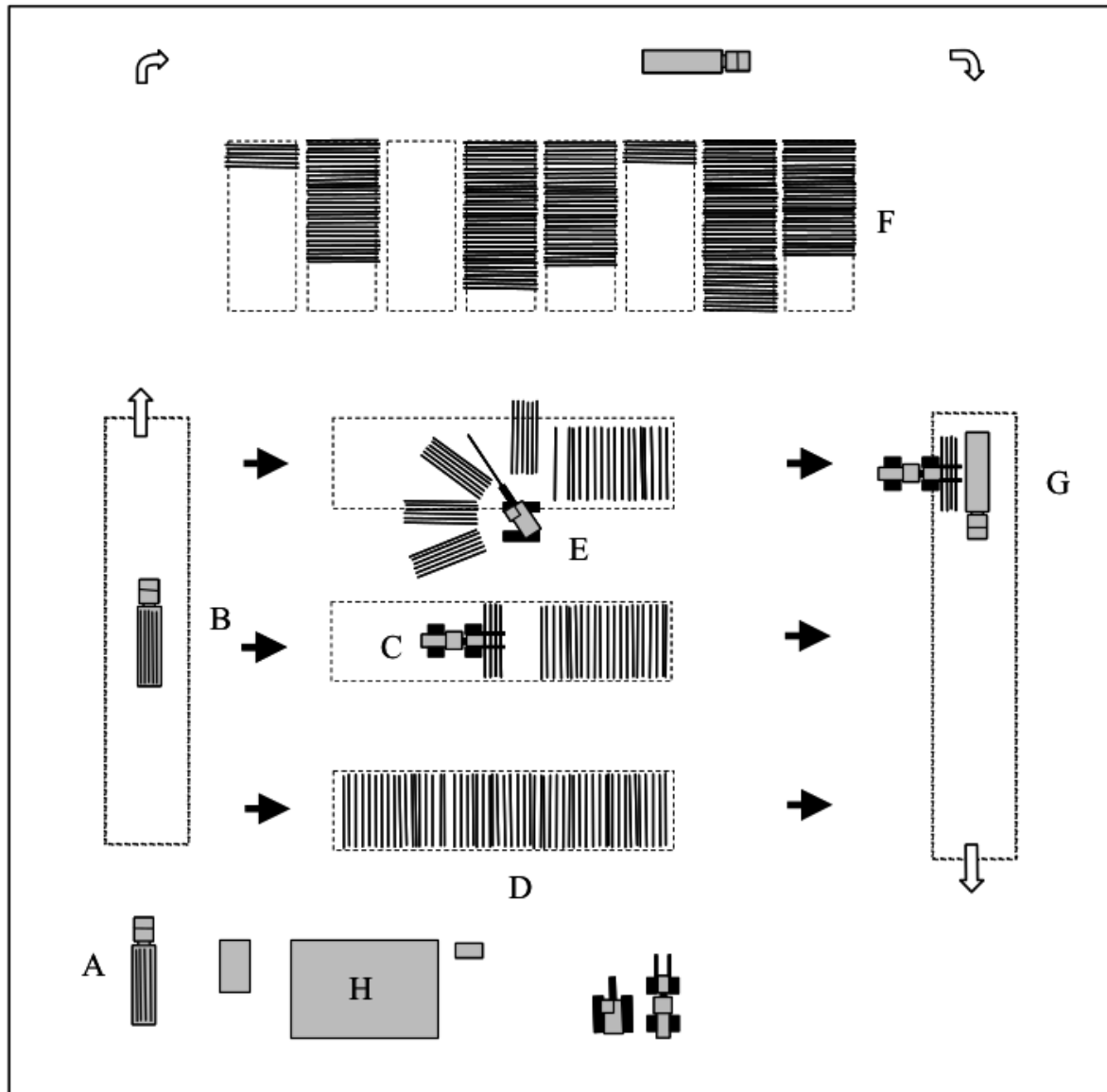


Figure 23—Example of a basic log sort yard layout: (A) log truck waiting in the queue for unloading; (B) log truck unloading with a front-end loader or log stacker; (C) spreading logs in the sorting bay for grading and scaling; (D) grading and scaling functions are decoupled from mobile equipment operations (for example, spreading and sorting logs) for safety; (E) sorting logs with a heel-boom loader—logs are accumulated and transported to temporary storage or reloaded directly onto trucks; (F) temporary sorted log storage for accumulating full truck loads; (G) truck loading with a front-end loader; (H) office, shops, fuel, and mobile equipment deadline.

Figure 3: Schematic overview of a log sort yard (Dramm et al. 2002)



Figure 4: Overview of a sawmill with a log yard. Source: <https://www.schweighofer.at/en/produktionsstandorte/sebes.html>

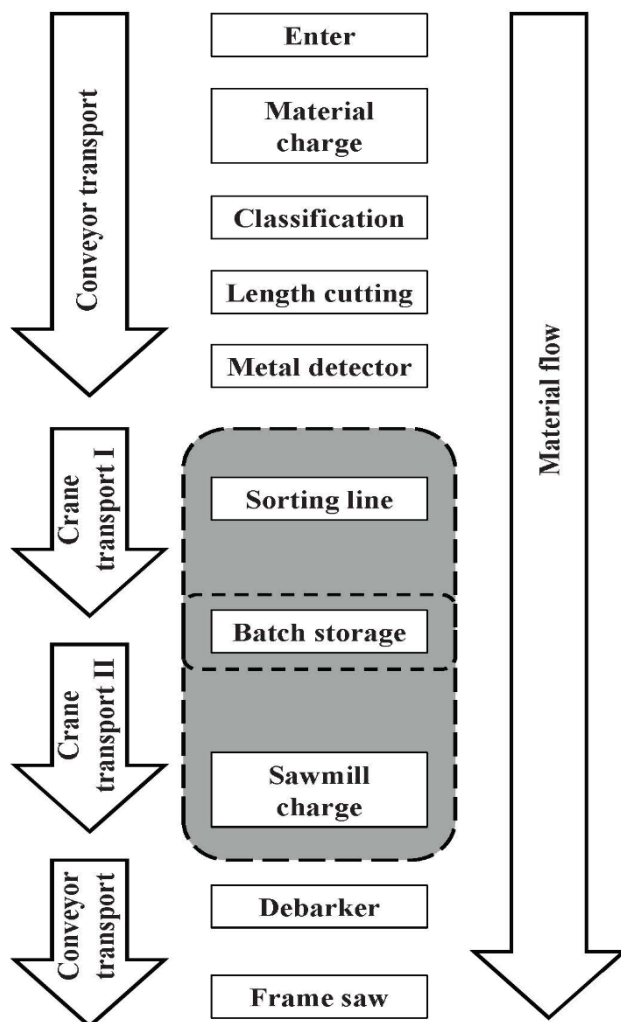


Figure 5: Material flow on a sawmill log yard with yard crane material handling (Rathke et al. 2013)

The log yard Rathke et al. (2013) have described is a sawmill yard of a hardwood sawmill with an annual production capacity of 30,000 cubic meters of round wood. The logs are bundled into assortments according to their diameter. A conveyor belt

delivers the logs to grading and measuring stations before a yard crane moves the logs into storage bins according to the assortment they belong to. Finally, the yard crane moves the round wood assortments from their containing storage bins on to the saw charge. Rathke et al. (2013) have described both the original layout of this yard as well as a modification they have experimentally applied, and implemented both layouts in an optimization model.

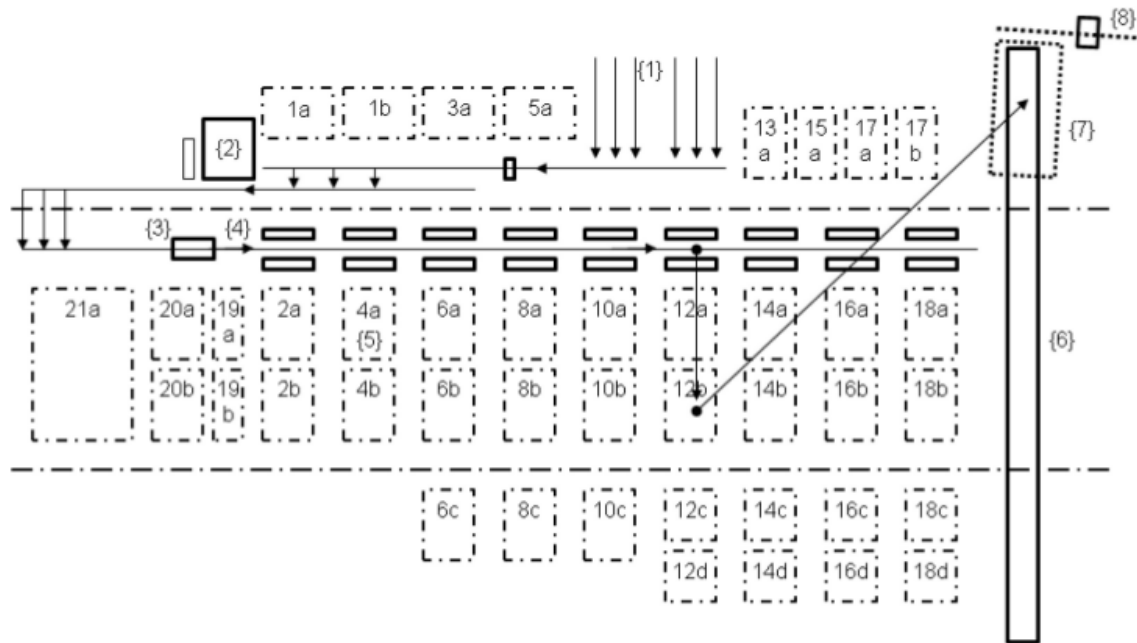


Figure 5: Original layout of the log yard as described by Rathke et al. (2013). Legend: {1} logs are sorted by species {2} identification of optimum cut in length {3} metal detector {4} ejection of logs according to diameter and length {5} full storage bin ready

3. Planning methods to improve forest wood supply chain processes

Optimization studies have been conducted for many individual areas of the forestry supply chain, such as the harvesting, milling and transporting of round wood. The models for optimization in the forestry supply chain usually are linear programming or mixed integer programming models. Optimization models can help to improve the design of production and distribution processes along the supply chain. Optimization strategies for complex processes like those found in a sawmill and other members of the forestry supply chain often use approximate methods like heuristics and metaheuristics in order to find an optimal or near optimal solution.

This is important because with a linear increase in the size of the problem, the computation time needed to calculate an exact result for an optimization model may rise exponentially. Therefore, approximations are a trade-off, possibly delivering a less than optimal solution to a problem with an acceptable use of computation time and effort. Simulation models are used as tools for decision. They are the abstracted design of a real system expressed in a computer model, allowing to support decisions which in turn can mitigate risks and lower costs. A variability in parameters like the diameters of logs in a sawmill can be incorporated easily. It is vital to examine the validity of data and the underlying models for a successful simulation. Simulations can handle a variability of input data and are easier to understand for the end-user in concern. (Shahi et al. 2013)

3.1 Simulation of forestry supply chain processes

In general, modifications to the arrangement of departments and machines on a log yard and the respective itineraries arising can be simulated, avoiding to physically alter any components of the process in real life where it is not desirable. Altering the components of a process in real life may disrupt the steady state of operations. The steady state of a model is defined as the common procedural pattern of continuous process, meaning the continued flow of operations which should not be interrupted in the real world, because any breakdown means a loss of profit during the time it occurs. Systems modelling is a tool which examines the interrelation of single processes in a system, assesses their individual influence on the overall performance of the whole system. It enables the analysis of production methods in respect to output, the identification of bottlenecks in a system and the evaluation of alternative system configurations. Businesses in the forest industry may profit from the outcome of systems modelling, if the quality of the underlying data is sufficient and the assumptions the respective model is based on are correct. The success of a simulation model depends on a complex process of decision making during the life cycle of model building. The life cycle process of a simulation model includes study phases and phases of transition. (Wiedenbeck et al. 1994)

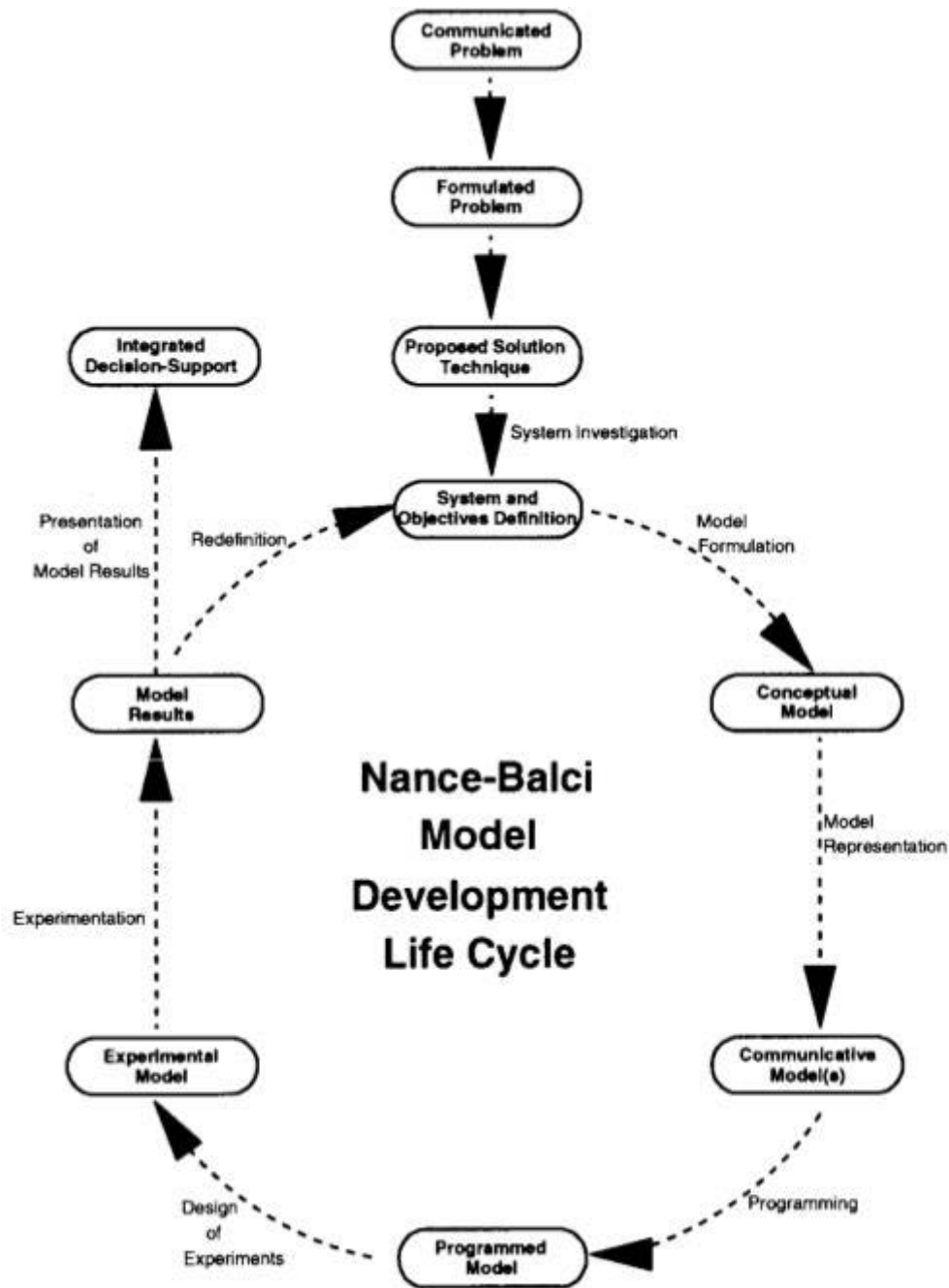


Figure 6: Schematic structure of the model development life cycle according to Nance-Balci. (Wiedenbeck et al. 1994)

This life cycle may experience several iterations until the credibility of a model is established. In the system investigation phase of a model, a system must be analysed including plant layout, material flows and activity relationships. The system is closely examined to identify the most relevant parameters, inputs and outputs for the model. Several modelling runs foster verification. Models with multiple values for the key output allow for a statistical examination of these

values. The predictive validation of a model means to feed historical data into the simulation model and to compare the output results with those of the modelled system in the real world. Integrated decision support systems where simulation data is supporting a process of decision are only feasible when the decision makers understand the simulation and the underlying assumptions. (Wiedenbeck et al. 1994)

One simulation method particularly successful in the application to sawmill processes is Discrete Event Simulation. It is based on events which happen at separate distinct points along the general time line, hence, the proceeding is discrete rather than continuous. These models are among the highest ranking in performance when considering complex stochastic systems. They can be applied to the processes of a sawmill as well as other individual processes in the wider forestry supply chain, and can also be used to model networking relations at the meta level of the forestry supply chain. (Shahi et al. 2013)

Discrete Event Simulation can help to analyse the operational activities on a log yard and identify bottlenecks. (Robichaud et al. 2014)

Linking optimization models and real-time process simulation can also confirm the viability of a production schedule developed for a sawmill. Multi-period production models can be formulated for the daily production activity of the mill. (Mendoza et al. 1991)

In general, the fluctuation of demand and other factors in the forestry supply chain are a great stochastic influence. The combination of optimization strategies and simulation to integrated models is well suited for optimizing under uncertainty. (Shahi et al. 2013)

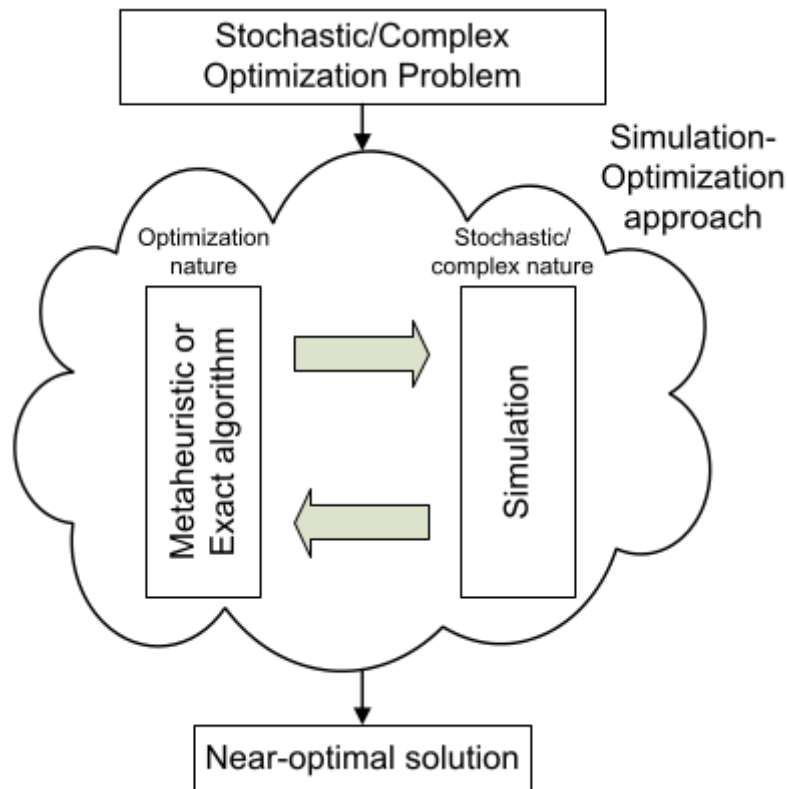


Figure 7: Model of the interrelations of simulation and optimization as a solution to stochastic problems. (Juan et al. 2015)

Mendoza et al. (1991) have shown how schedules and processes in a sawmill can be interactively simulated and dynamically altered during the simulation in progress.

Rahman et al. (2014)[1] have determined the placement pattern of storage bins on a log yard as one of the main sources of inefficient processing. They recommend Discrete Event Simulation in combination with optimization strategies as a solution, also presenting a case example of the application themselves.

The layout planning of a log yard plays an important part in the management of material flows amongst other affairs. A proper layout is an important factor to determine the success of the log yard operation as a whole and the efficiency of the inherent processes. (Dramm et al. 2004)

Simulation is an important tool when it comes to the planning of the log yard layout. Before entering a simulation, key performance indicators must be specified to give a frame to the simulation model rendering it effective. To compare different scenarios for a log yard layout means to compare the different possible combinations of handling vehicles and their corresponding tasks. Value Stream

Mapping and Quality Function Deployment are supportive tools for planning a log yard layout, however they do not function dynamically to show time-dependent aspects such as machine cycles or supply and demand fluctuations during the process. Varying speeds and inter-arrival times are also crucial parameters for the simulation of a log yard. Logs on the log yard are classified by their raw material profile, which is individually different for each sawmill. Length and diameter of the logs are important attributes for classification. Truck load statistics and volume measurements are important to model the arrival locations and times for every delivery at the log yard. On arrival at the yard, the different types of raw materials will undergo different types of processing and handling. Scaling, measuring and testing are important parts of the handling of logs in the yard. Each activity needs space allocated, therefore raw materials flowing in and out per unit of time is an important parameter to be calculated for each activity. (Robichaud et al. 2014)

3.2 Optimization strategies

While simulation is a good tool in order to handle what-if scenarios, optimization as the application of combinatorial optimization problems on the other hand can help to identify the best scenarios and pathways in a simulation. Discrete Event Simulation can be combined with optimization approaches to make the operational processes on a log yard more efficient and save costs. The placement pattern of the storage bins on a log yard has been identified as one of the main sources of inefficiency in process. Since the enumeration of all possible arrangements soon becomes a heavy task, Rahman et al. (2014)[2] recommend the Genetic Algorithm metaheuristic in combination with an agent based simulation or a Discrete Event Simulation to solve this problem. Rahman et al. (2014)[2] recommend several techniques of optimization and simulation for log yard operations which have previously already been applied to various links in the forestry supply chain, as well as to the other members of the supply chain individually. The most relevant factors to take into account for the optimization in the forestry supply chain are as mentioned: "costs, location, allocation, capacity, routing, agility and transportation." Mathematical programming, which besides other approaches includes integer programming, has often times been applied to optimization problems of the forestry supply chain. Some optimization approaches also

incorporate the probabilistic nature of problems found there. (Rahman et al. 2014)[2]

Rahman et al. (2014)[2] also mention artificial intelligence algorithms as one main tool for the potential optimization of log yard operations, where the optimization model is integrated into a simulation of the log yard operations.

3.3 Applied examples in literature

In this work several authors have been included who have used simulation or a combination of simulation and optimization to find answers to relevant questions relating to the layout planning and/or operation of a log yard. It has to be noted that the availability of literature on the operational process of log yards is very limited. The following table is a selection of available literature on this subject:

Author	Subject	Method	Goal
Rathke et al. 2013	Layout Design - Arrangement of Storage Bins	Mixed Integer Programming - Heuristics	Efficient storage bin arrangement for efficient transport and storage of logs on-site
Mendoza et al. 1991	Material Input - Input Mix	Discrete Event Simulation - SIMAN	Interactive control of log yard's input
Rahman et al. 2014	Layout Design - Arrangement of Storage Bins	Discrete Event Simulation, Simulated Annealing, Genetic Algorithm	Efficient storage bin arrangement
Ramis et al. 2008	Resource Management - Processing Speed Configuration of Stationary Machines, Identification of Bottlenecks	Object Oriented Library Simulation	Identify bottlenecks in Log yard processes
Robichaud et al. 2014	Layout Design - Space Alignment for and Placement of Log Yard Inventory	Discrete Event Simulation	Identify bottlenecks in log yard processes

Table 1: Overview of problem solution scope, methods and respective goals selected by author

Mendoza et al. (1991) have analysed the operational activities of hardwood sawmills. Since processes may vary across sawmills and no method can cover every individual case, Mendoza et al. (1991) have formulated a general sawmill optimization model for an optimal input mix of logs, aiming to satisfy lumber demands. Using the simulation language SIMAN they have created a simulation which supports common procedures in the processing of logs and lumber as event subroutines, modelling the various departments of the log yard with similar equipment as macro-stations. The output of this simulation is: "lumber and volume of logs processed (by species and grade), sawmill operating time, lumber output by species, grade and volume, equipment utilization, anticipated production downtime, and status of buffer decks (queues)."

In their simulation, Mendoza et al. (1991) work with an interactive data interface, which facilitates the real-time creations of schedules for a sawmill.

Robichaud et al. (2014) have analysed the operational activities of a medium sized sawmill in Quebec, Canada, which consumes 500,000m³ of fir every year as an input. They have used an iterative Discrete Event Simulation model to simulate the processes on a log yard. Before the actual simulation, Key Performance Indicators were defined. The simulation itself is based on a static layout not to be modified, concentrating on the resources of the log yard, which is the handling vehicles, and on the resource-processes, which are the respective tasks and schedules for each vehicle. A flow relationship diagram enumerates all possible combinations of handling activities and shows the necessity and frequency of individual process combinations. The process flow diagram shows linked paths in between all stations and departments of the log yard. Each path is evaluated for the relative percentage of the total material flows that need to pass through.

In order to create a viable experimental design of a log yard, Robichaud et al. (2014) have formalized a log yard design procedure into six steps which are the following: " (1) collecting data on relevant activities and resources, (2) modelling material flow, (3) establishing flow relationship diagrams in order to assess flow priorities, (4) determining required space for each activity, (5) developing preliminary plans and finally (6) evaluating said plans, [...]".

Robichaud et al. (2014) have built simulation models with minimum and maximum resource arrivals at the log yard entry, in order to account for seasonal variability known in the real-life situation which they intended to simulate. Their data collection process is described as sub-divided into four different parts: "obtaining information on the raw material profile, quantifying inflow data, understanding the handling activities and comparing the handling and unloading equipment alternatives". The simulation model of Robichaud et al. (2014) has shown that relocation of one processing facility in the log yard is capable of reducing the total distance travelled for a truck-mount loader by more than 75%. Machinery was recommended to be shut down seasonally in order to save costs.

Ramis et al. (2008) have created an object oriented library for the simulation of processes on a log yard. In cooperation with specialists in the field they have established a virtual inventory of all commonly used machines and equipment on the log yard. The minimum number of necessary objects in this inventory was found focusing on three basic questions: which products does the sawmill produce, which types of processes are involved and what resources are used to achieve these tasks.

Ramis et al. (2008) have applied their object oriented library to an existing example of a sawmill with a monthly output of 20,000 cubic meters of round wood. Their simulation model aimed to identify bottlenecks along the production line and test improvements. In their analysis of the results they found that an improvement of 16.6% in productivity could be achieved when implementing the recommendations of their simulated model.

Rahman et al. (2014)[1] have investigated the arrangement of storage bins on a log yard using heuristic algorithms. They state that the absence of a good arrangement of storage bins on a log yard can lead to unnecessary high costs of production, since the storage of round wood in between the delivery and final processing is one of the most relevant parts in the whole supply chain. They see the exponential rise of computing power needed to find exact solutions for models of a linearly increasing scale in the supply chain to be the main reason for the employment of heuristic methods. Their example of reference is the Berkvist Insjötn AB company which owns one of the biggest sawmills in Sweden, with an estimated output of 400,000 cubic meters of timber per year.

Rahman et al. (2014)[1] have used a Discrete Event Simulation to model the operational process of the log yard. The simulation model is compared with results of previous simulations in the field to validate the model and to gain knowledge about the real life situation at the locality. The heuristic algorithms Genetic Algorithm and Simulated Annealing were tested aiming to find a near optimum solution to the model which is also efficient in terms of computation time.

The model of Rahman et al. (2014)[1] includes the arrival of logs at the log yard as well as the assortment, storage and delivery of the logs to their final processing stage. Several assumptions have been made to keep the model simple and practical: only storage bins directly relevant to the process are taken into account, the necessary time of processing is constant for all assortments of round wood, crucial parameters like transporting distances and the capacity of the storage bins are strictly defined and may not fluctuate during the entire process. The goal is to optimize the transporting time the log stacker in the log yard needs to deliver the round wood assortments from their place of arrival to the storage bins and from the storage bins to the final processing stage. The setup of the storage bins is dynamic and can be ordered into any possible arrangement within the area of definition. In the beginning, the simulations start by creating several random solutions where the storage bins are arranged in a random order. The transporting time the log stacker needs for each arrangement in the whole process is then calculated. The heuristic algorithms select a population of the best random solutions and store them for the next round of simulation. The next simulation starts, and again the best of the random solutions are taken into the pool of selected solutions. This process of selection continues iteratively until an ending criterion is met. In the end, only the most optimized of the selected solutions remain.

In their findings, Rahman et al. (2014)[1] describe the heuristic Genetic Algorithm as superior to Simulated Annealing. However, both algorithms are well fit to save production costs. They claim their method has the potential to save roughly 100,000 € of costs a year for the sawmill in question.

Rahman et al. (2014)[1] have used a one-way ANOVA analysis to evaluate their heuristic results against models of purely random choice. They point out that a

critical factor for the success of a simulation in combination with heuristic methods is a careful selection and revision of the modelling parameters in the first place.

4 Log yard layout planning

Rahman et al. (2014)[1] have determined the placement pattern of storage bins on a log yard as one of the main sources of inefficient processing. They have conducted a study to improve the placement of storage bins and thus make log yard processes more efficient. Rathke et al. (2013) have examined a similar problem, presenting individual strategies for the optimization of the layout and processes of a log yard, especially in respect to the material flows.

Comparing the paper of Rathke et al. (2013) with other literature in the field, it can be seen as a notable difference that Rahman et al. (2014) allow the dynamic placement and rearrangement of storage bins on the log yard, while Rathke et al. (2013) have focused on two predefined arrangements of storage bins within their examined log yard. These arrangements were investigated in real life by Rathke et al. (2013), one being the default situation before the study, and another alternative arrangement found when altering the order of storage bins on the log yard and pooling some of them together. Through enlarging some storage bins on the one hand and pooling others together, additional storage capacities were created by including spaces formerly not used for storage. The results of the optimization model are better for this alternative arrangement than for the original arrangement, Rathke et al. (2013) have found.

On the log yard Rathke et al. (2013) have examined a gantry crane transports loads of one assortment from the respective ejection box to the storage bins, and afterwards when the entire assortment is stored the crane transports load by load to the saw charge. It is important to note that the material flow from the conveyor belt to the ejection box has a constant speed and cannot be altered. Therefore, only the itinerary of the yard crane can be subjected to optimization.

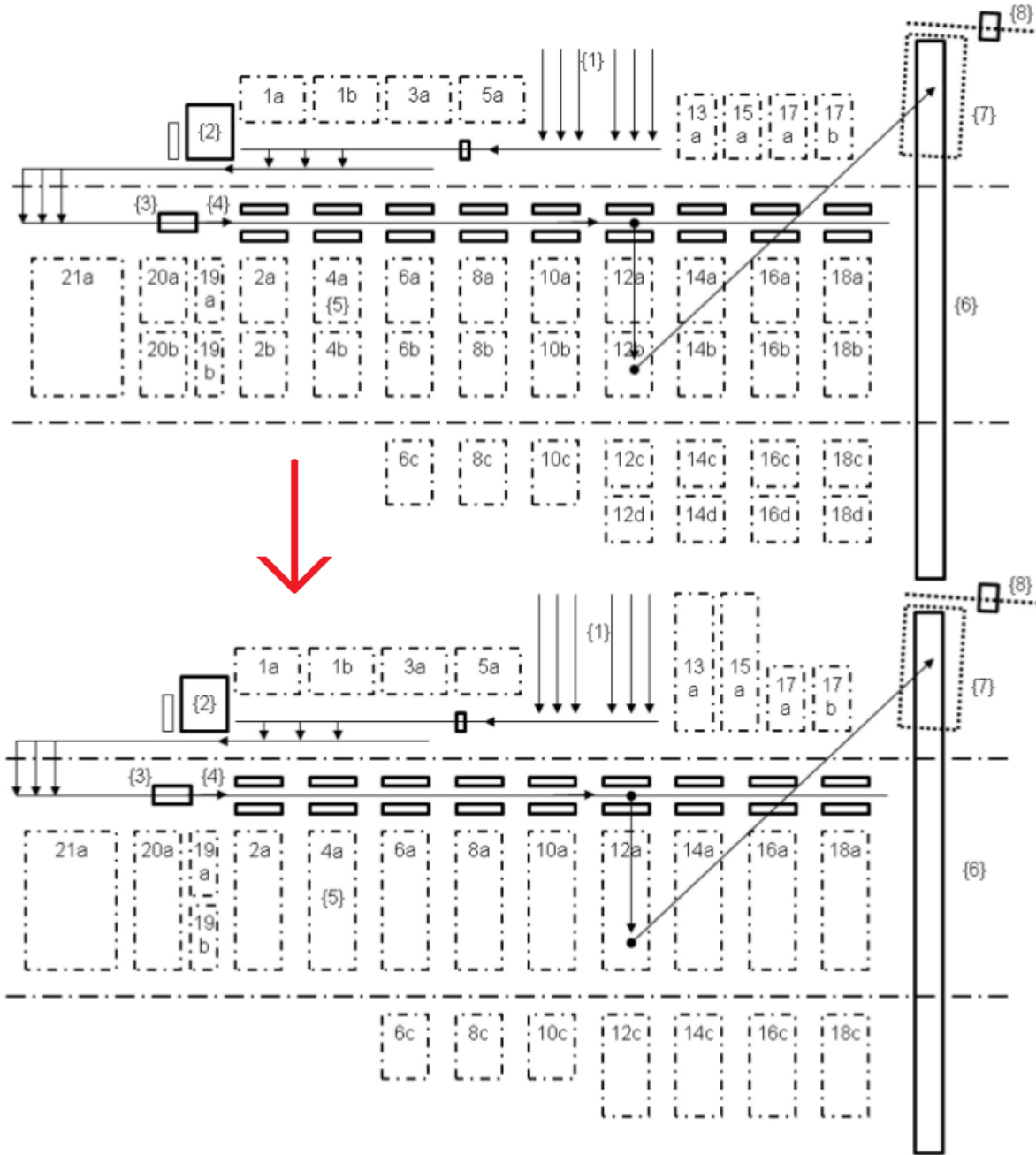


Figure 8: Modification of the arrangement of storage bins on a log yard by Rathke et al. (2013)

5 Materials and Methods

Rathke et al. (2013) have formulated an optimization problem with the objective of minimizing overall transportation time and distances on a log yard. Basic data like the feeding volume of logs, the size of assortments, and the storage capacity of the storage boxes have been retrieved and parameters calculated.

5.1 Storage Bin Assignment Modelling

Rathke et al. (2013) have investigated the transport and storage process on a log yard and modelled the process accordingly as two mixed integer problems. Additionally to the basic arrangement of storage boxes on the log yard, Rathke et al. (2013) have experimentally joined storage boxes together. This has effectively reduced the number of storage boxes on the yard and increased the average storage capacity by combining the capacities of boxes and including the spaces in between as new capacities. Also, some of the boxes were simply enlarged. In this way, an alternative arrangement of storage box placement was created.

The "double stage" model of Rathke et al. (2013) is an optimization model in two stages: first the optimized transportation time for the assortments from the chosen storage boxes to the final destination, the material charge, is calculated. In the second stage, an ejection box is chosen for each assortment as an initial point of storage before being transported to the storage boxes. Transportation and storage parameters refer to the storage box arrangement that Rathke et al. (2013) have themselves created and investigated. In this model, no splitting of loads is allowed for the containment of assortments, therefore each assortment must be contained within exactly one storage box of choice.

In the "partition" model of Rathke et al. (2013), an assortment of round wood can be split into separate loads and distributed to more than one storage box. However, a storage box may only be filled with one type of assortment. It is not possible to store parts of two or more different assortments in one storage box. The model can be used for both the original storage box arrangement of the log yard as well as the experimental arrangement of Rathke et al. (2013).

5.2 Model Formulation

The following indices, parameters and variables for the mixed integer models will be used throughout this paper:

Indices

A Set of assortments a

E Set of ejection boxes e

S Set of storage boxes s

Parameters

N_a Number of necessary trips to deploy one whole assortment a

TM_s Transporting time from a storage box s to the material charge of the sawmill

TS_{es} Transporting time from an ejection box e to a storage box s

TT_{es} The combined transporting time from an ejection box e to a storage box s and from a storage box s to the saw line

C_s Storage capacity of a storage box s

V_a Total volume of an assortment a

Variables

x_{as} 1 if assortment a is assigned to storage box s , 0 if no assignment exists between assortment a and storage box s

y_{ae} 1 if assortment a is assigned to ejection box e , 0 if no assignment exists between assortment a and ejection box e

w_{es} 1 if storage box s has been delivered to from ejection box e , 0 otherwise

v_{aes} filling factor of assortment a delivered from ejection box e in storage box s

Rathke et al. (2013) have formulated two mixed integer models for their task. The first is the double stage model. This model comes in two parts or stages where the models are solved sequentially. In the first part the transportation time of the distinguished round wood assortments from the chosen storage bins to the saw is minimized and constraints for the storage bins and ejection boxes are defined. Note that in this model, each storage bin in the log yard may only contain one whole assortment of round wood:

Stage 1

$$(1) \min \sum_{a \in A, s \in S} N_a \times x_{as} \times TM_s$$

$$(2) V_a \times x_{as} \leq C_s \quad \forall a \in A, s \in S$$

$$(3) \sum_{s \in S} x_{as} = 1 \quad \forall a \in A$$

$$(4) \sum_{a \in A} x_{as} \leq 1 \quad \forall s \in S$$

$$(5) x_{as} \in \{0, 1\} \quad \forall a \in A, s \in S$$

The objective function (1) minimizes the transportation time from storage box s to the material charge, taking into account the numbers of trips per assortment a . The first constraints (2) ensure that the available storage volume is not exceeded by the assortment. Under the very restrictive assumption that every assortment fits into even the smallest storage box without having to divide it, these constraints are redundant. The constraints (3) guarantee that every assortment is assigned to exactly one ejection box. Whereas the next constraints (4) make sure that not more than one assortment can be placed in one ejection box and not every ejection box has to be used. The last constraints (5) define the binary decision variables. (Rathke et al. 2013)

Stage 2

$$(6) \sum_{a \in A, e \in E, s \in S} N_a \times y_{ae} \times x_{as} \times TSes$$

$$(7) \sum_{e \in E} y_{ae} = 1 \quad \forall a \in A$$

$$(8) \sum_{a \in A} y_{ae} \leq 1 \quad \forall e \in E$$

$$(9) y_{ae} \in \{0, 1\} \quad \forall a \in A, e \in E$$

Again, the objective function (6) minimizes the transportation time from ejection box e to storage box s taking into account the optimal assignment of assortment a to storage box s , x_{as} from stage 1. Constraints (7) and (8) make sure that the assignment of assortment to ejection box is performed correctly. The last constraint (9) is the binary constraint. The second model is the partition model. Here, the constraints differ, because every single assortment of round wood may

be separated into parts and disseminated among several storage bins, hence the greater complexity of the model formulation. (Rathke et al. 2013)

Partition

$$(10) \sum_{a \in A, e \in E, s \in S} \frac{N_a}{V_a} \times v_{aes} \times TT_{es}$$

$$(11) \sum_{a \in A} y_{ae} \leq 1 \quad \forall e \in E$$

$$(12) \sum_{e \in E} y_{ae} = 1 \quad \forall a \in A$$

$$(13) \sum_{e \in E} w_{es} \leq 1 \quad \forall s \in S$$

$$(14) \sum_{e \in E, s \in S} v_{aes} = V_a \quad \forall a \in A$$

$$(15) \sum_{s \in S} v_{aes} \leq y_{ae} \times V_a \quad \forall a \in A, e \in E$$

$$(16) \sum_{s \in S} v_{aes} \leq w_{es} \times \max_{a \in A} \{V_a\} \quad \forall e \in E, s \in S$$

$$(17) \sum_{a \in A, e \in E} v_{aes} \leq C_s \quad \forall s \in S$$

$$(18) y_{ae} \in \{0, 1\} \quad \forall a \in A, e \in E$$

$$(19) w_{es} \in \{0, 1\} \quad \forall e \in E, s \in S$$

Objective function (10) minimizes the total transportation time. Constraints (11) and (12) guarantee the right assignment of every assortment a to exactly one ejection box e . Whereas constraints (13) ensure that each storage box s is used at most one time. The next two constraints (14) and (15) make sure that the whole volume of every assortment a is assigned to exactly one ejection box e . Whilst constraints (16) manage the filling over all assortments a into storage boxes s and ejection boxes e . The filling cannot exceed the largest volume of an assortment if volume is transported from ejector box e to storage box s at all. The next constraints (17) make sure that the capacity of each storage box s is not exceeded. Constraints (18) and (19) define the binary variables. (Rathke et al. 2013)

5.3 Heuristic Methods

Rathke et al. (2013) have formulated a heuristic algorithm that was implemented in Excel. It solely applies to the "double stage" model.

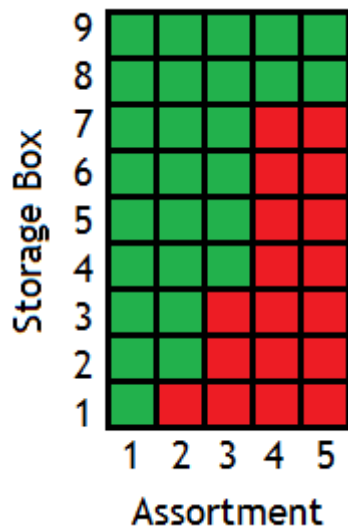
The heuristic algorithm consists of the following methodical steps:

- 1: order A according to N_a
- 2: choose a with $\max_{a \in A} \{N_a\}$ and s with $\min_{e \in E, s \in S} \{TM_{es}\}$
- 3: Assign a to s
- 4: Remove a from A and s from S
- 5: if set $A \neq \{\}$ go to step 2

Rathke et al. (2013) have based the application of this algorithm on a grid of all possible ways to transport the round wood from the ejection box to the storage box (TT_{es}) and from the storage box to the sawmill (TM_s). Initially, all possibilities in the grid which would violate the given constraints of the double stage model are ruled out, before the algorithm starts. A constraint is violated if the volume of an assortment a exceeds the capacity of a storage box s .

In the beginning of this algorithm, the assortments of round wood are ordered decreasingly according to their respective number of necessary trips N_a . For the implementation in Java it is necessary to add an extension to the algorithm. The reason lies in the fact that when ordering the assortments of A according to a priority other than their respective volume V_a , assortments of a smaller volume with multiple possibilities of storage box choice will use up all valid options for other assortments with a lower priority but a higher volume V_a .

Therefore, a sub algorithm was added to the method implementation in Java to foresee potential conflicts when choosing any storage box s for any assortment a :

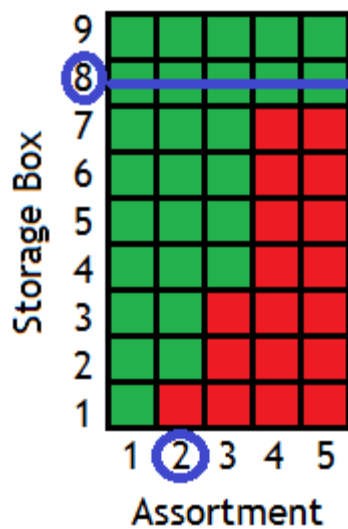


x-axis: assortments, ordered increasingly from 1 to 5 according to their volume V_a

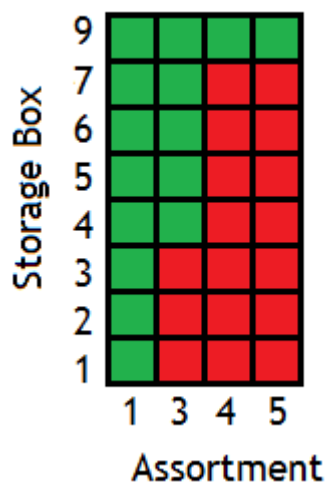
y-axis: containers, ordered increasingly from 1 to 9 according to their capacity C_s

green rectangle: assortment fits to storage box because $C_s \geq V_a$

red rectangle: assortment does not fit to storage box because $C_s < V_a$



Storage box s_8 has been chosen to contain the assortment a_2 . The blue line illustrates that storage box s_8 is now out of choice for further containment decisions.



Now that the assigned storage box s_8 and assortment a_2 have been removed from the matrix, a conflict becomes evident: the assortments a_4 and a_5 have each only a single storage box left that has the capacity C_s to contain the Volume V_a of either assortment. It is now impossible to have all assortments adequately contained.

The full algorithm, adapted for use in Java:

Initial algorithm A:

- 1: order A according to N_a decreasingly
- 2: choose a with $\max_{a \in A} \{N_a\}$ and s, e with $\min_{e \in E, s \in S} \{TT_{es}\}$
- 3: if $V_a \leq C_s$ go to step 4
 else temporarily remove s from S until step 6
- 4: if $\sum_{s \in S, a \in A} [C_s \geq \max \{V_a\}] < \sum_{s \in S, a \in A} [[C_s \geq V_a] = [C_s \geq \max \{V_a\}]]$
 temporarily remove s from S until step 6
 else go to step 5
- 5: Assign a to s and e , remove a from A and s from S
- 6: if $A \neq \{\}$ go to step 2

When the assortments are ordered according to their volume V_a instead of necessary number of trips N_a initially, the problem of conflicting choices does not occur. The algorithm is simpler in this case:

Initial algorithm B:

- 1: order A according to V_a decreasingly
- 2: choose a with $\max_{a \in A} \{V_a\}$ and s, e with $\min_{e \in E, s \in S} \{TT_{es}\}$
- 3: if $V_a \leq C_s$ temporarily remove s from S until step 6, go to step 2
- 4: Assign a to s and e
- 5: remove a from A , s from S and e from E
- 6: if set $A \neq \{\}$ then go to step 2

An algorithm was found to be applied for the partition model as well. The algorithm is similar to the previous one, yet slightly altered to fit the constraints given in the partition model.

In this model, multiple assignments of an assortment a to more than one storage box s are possible. Like in the previous examples the assortments of A can be either ordered according to their N_a or V_a .

A conflicting storage box choice when ordering set A according to N_a is not possible in the partition model by definition, therefore, no adaptation for the algorithm like for the "double stage" model is necessary.

The only difference between the initial algorithms A and B is the initial order of assortments according to either N_a or V_a , apart from this step all other steps are identical for both algorithms:

- 1: order A according to N_a/V_a decreasingly
- 2: choose a with $\max_{a \in A} \{N_a\}$ and s, e with $\min_{e \in E, s \in S} \{TT_{es}\}$
- 3: Assign a to e , remove e from E
- 4: assign a to s , decrease V_a by C_s and remove s from S
- 5: If $V_a > 0$ then choose s with $\min_{e \in E, s \in S} \{TT_{es}\}$ and go to step 4
- 6: remove a from A
- 7: if set $A \neq \{\}$ go to step 2

The process of assigning an assortment a to storage boxes in S is iterative and continues until the entire volume V_a of a has been assigned. The choice of an ejection box e for the assortment a is determined in the first iteration of the process and remains unaltered for the following iterations.

5.4 Improvement Algorithms

Two improvement algorithms have been formulated to improve the solution quality for the previous algorithms. For the improvement algorithm A, the sets A, E, S which contain all assortments a , ejection boxes e , and storage boxes s are duplicated. This is done in order to swap the assigned ejection box e and storage box s of any assortment a with the assignments of each other assortment of A and itself. In this way, better assignments in between the sets may be found. Improvement algorithm B is identical to improvement algorithm A except that only sets A and S are duplicated, because the assignments of ejection boxes are never exchanged in between assortments. In this algorithm only the assignments of storage boxes are potentially exchanged.

Improvement algorithm A:

```
1: Z=A,Y=A,X=E,W=E,V=S,U=S
2: pick v with  $\min_{v \in V} \{\text{index}_v\}$  v ∈ S
3: pick u with  $\min_{u \in U} \{\text{index}_u\}$  u ∈ S
4: if  $[(N_z \times y_{zx} \times x_{zv} \times TT_{xv}) + (N_y \times y_{yw} \times x_{yu} \times TT_{wu})] >$ 
 $[(N_z \times y_{zx} \times x_{zu} \times TT_{xu}) + (N_y \times y_{yw} \times x_{yv} \times TT_{wv})]$  then  $x_{zv}=0, x_{yu}=0, x_{zu}=1, x_{yv}=1$ 
5: if  $[(N_z \times y_{zx} \times x_{zv} \times TT_{xv}) + (N_y \times y_{yw} \times x_{yu} \times TT_{wu})] >$ 
 $[(N_z \times y_{zw} \times x_{zu} \times TT_{xu}) + (N_y \times y_{yx} \times x_{yv} \times TT_{wv})]$  then  $x_{zv}=0, x_{yu}=0, x_{zu}=1, x_{yv}=1,$ 
 $y_{zx}=0, y_{yw}=0, y_{zw}=1, y_{yx}=1$ 
6: remove u from U
7: if set  $U \neq \{ \}$  go to step 3
8: remove v from V
9: if set  $V \neq \{ \}$  go to step 2
```

(4) Two storage boxes are examined: storage box v containing assortment z and storage box u containing assortment y . The overall transportation times TT_{es} are calculated for both assortments z and y and added up with each other as the combined transportation time of both assortments. Then the combined transportation time is calculated for both assortments that results if the assortments exchange their respective storage box assignment. Both combined transportation times are compared. If the combined transportation time for both assortments with their original storage box assignments is greater than the combined transportation time for both assortments when they exchange their respective storage box assignments, it means the exchange is desirable and will therefore be executed. Otherwise, if the original storage box assignments of the two assortments lead to a more desirable combined transportation time, it means the exchange will not result in an improvement and therefore the assignments are left unaltered.

(5) This step is identical to step 4 except that not only the storage box assignments are exchanged between two assortments for the comparison of combined transportation times, but simultaneously also the assignments to the respective ejection boxes are exchanged. If exchanging both assignments in between the two assortments leads to a better combined transportation time, those exchanges are

executed accordingly. Otherwise if the exchanges are not desirable, the original configuration will be left unaltered.

The algorithm iterates through all possible pairs of storage boxes, in search of an improvement to the present solution.

Both improvement algorithms are applied iteratively until no further improvement can be found.

6 Numerical Study

In this chapter, the results of the heuristic algorithms will be compared to the optimal results of Rathke et al. (2013). The original arrangement of storage boxes in the log yard as described by Rathke et al. (2013) is called " C_{42} ", because it consists of 42 storage boxes, each with a pre-defined storage capacity and position on the log yard. The experimental arrangement of Rathke et al. (2013) is called " C_{28} ", as the 42 storage boxes of the original arrangement were joined together into only 28 storage boxes, also with clearly defined positions and capacities.

The results of the algorithms shown in this chapter refer to the arrangement where the assortments are ordered according to their number of necessary trips N_a , because the solution is always superior to the solution of the algorithms where the assortments were ordered according to their volume, V_a .

6.1 Data

The following graphics illustrate the capacity distributions of the storage boxes in both arrangements:

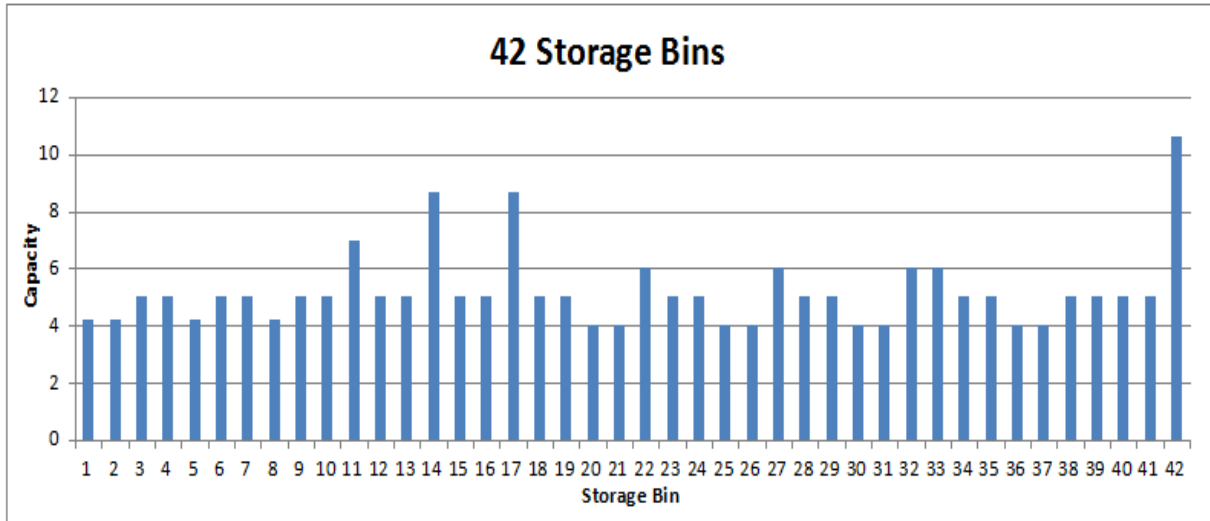


Figure 9: The distribution of storage volumes V_a in the 42 bin log yard arrangement.

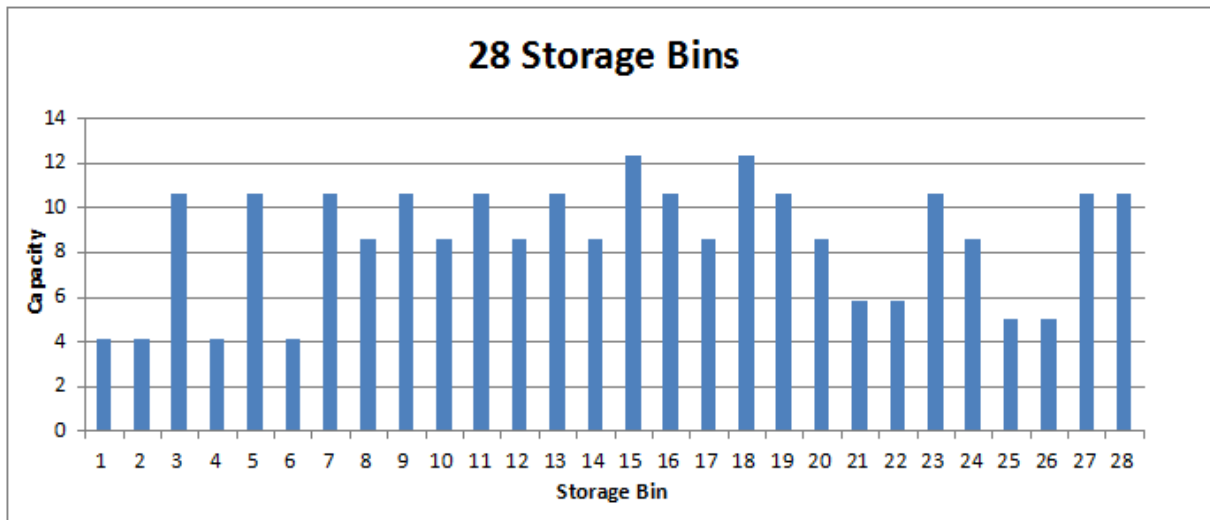


Figure 10: The distribution of storage volumes V_a in the 28 bin log yard arrangement

The C_{28} arrangement includes storage boxes with a bigger capacity than the C_{42} arrangement. For this reason, the double stage model is only applicable to the C_{28} arrangement, because some of the assortment volumes are bigger than any storage box capacity found in the C_{42} arrangement, and therefore cannot be fully contained as the double stage model requires.

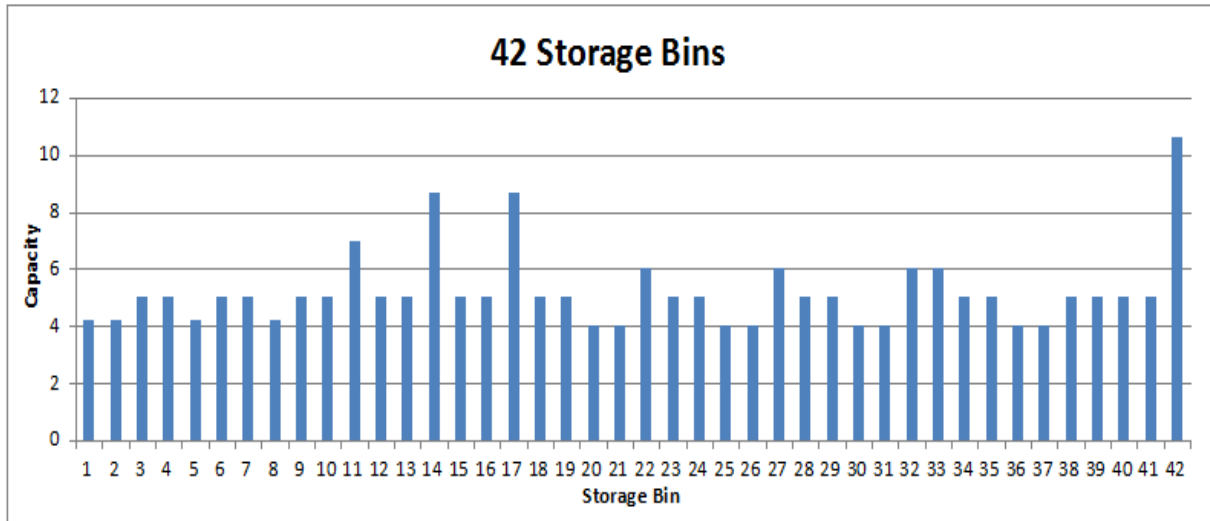


Figure 9: The distribution of storage volumes V_a in the 42 bin log yard arrangement.

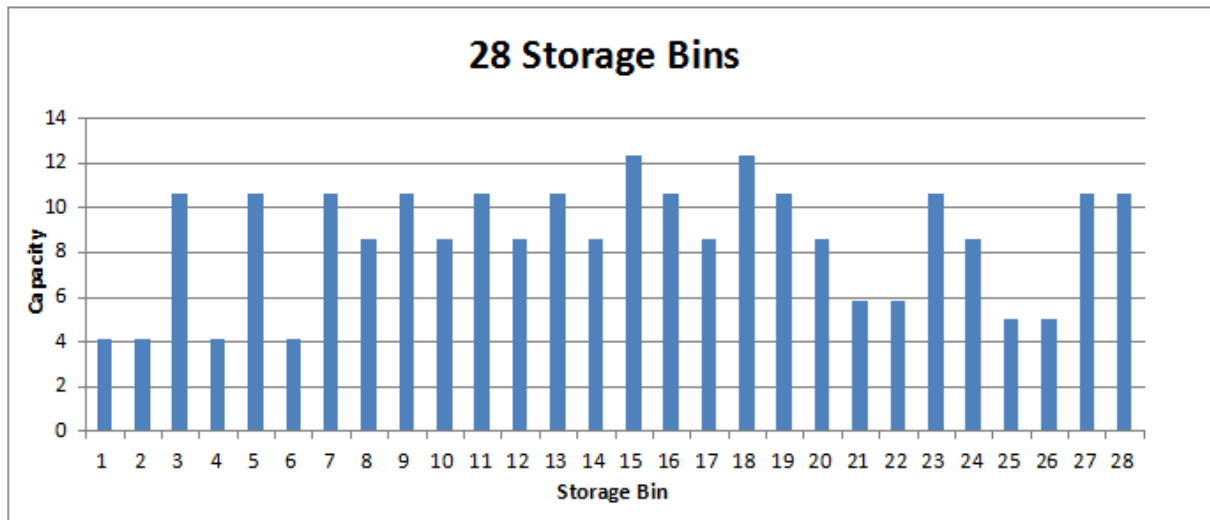


Figure 10: The distribution of storage volumes V_a in the 28 bin log yard arrangement

The C_{28} arrangement includes storage boxes with a bigger capacity than the C_{42} arrangement. For this reason, the double stage model is only applicable to the C_{28} arrangement, because some of the assortment volumes are bigger than any storage box capacity found in the C_{42} arrangement, and therefore cannot be fully contained as the double stage model requires.

The implemented results for the initial heuristic algorithm A:

Model	Double stage	Partition	Partition
Bin arrangement	C_{28}	C_{28}	C_{42}
Initial algorithm A result (min)	305.6	305.5	340.1

Table 2: Results for the initial stage of heuristic application

These results are the initial solutions, which are to be improved by one of the two improvement algorithms A or B. While improvement algorithm A was always superior to its counterpart when applied to the Double Stage model, improvement algorithm B was always superior to its counterpart when applied to the Partition model. Below, the best results of the heuristic algorithms are compared to the optimal results Rathke et al. (2013) have found in their study. The heuristic improvement algorithms show slightly improved results when undergoing more than one iteration. In the results shown in table 5, the number of iterations is shown until the best result for the algorithm was found. After this number of iterations, the next 200,000 iterations do not improve the solution any further.

Model	Double stage	Partition	Partition
Bin Arrangement	C_{28}	C_{28}	C_{42}
Iterations	3	3	4
Improvement algorithm solution(min)	305.2	298.3	314
optimal solution (min)	301.5	288.1	293.6
optimal result-computing time	0.0 sec	106.3 sec	approx. six days
Heuristic efficiency	-1.23%	-3.54%	-6.95%

Table 3: Comparison of optimized results from Rathke et al. (2013) with the best final results of applied heuristics

Clearly, a partitioning of assortment loads as well as the reduction of storage boxes and enlargement of storage spaces are factors for a more efficient storage process. The best performing model for both the heuristic and the optimization of Rathke et al. (2013) is the partition model with the C_{28} storage box arrangement on the log yard. The partition model is more efficient than the double stage model since it applies one optimization to the whole problem, while the double stage model splits the problem into two separate problems of optimization.

The heuristic results were computed with a hp probook 4730s with an Intel CORE i5-2450M CPU and 4GB RAM, the computation time for all of the results was equal to or below one second.

It can be seen that the necessary computing time for the optimized solutions can vary greatly, rising exponentially with the complexity of the problem, in this case the storage box arrangement and the mixed integer model. For the partition model with the storage box arrangement C_{42} , the computing time for an optimal result is as high as six days, however after 20 minutes a solution can be found with a gap lower than 1% to the lower bound. Here a very sharp rise of necessary computation time in between a near optimal solution and a fully optimal solution is clearly visible. For this example, the heuristic algorithm shows the weakest performance with a low solution quality compared to the application to the other configurations. Rathke et al. (2013) have used this example to demonstrate the superiority of a storage box arrangement with a reduced number of storage boxes.

6.2 Alternative Assortment Distributions

In order to test the overall efficiency of the heuristic algorithms against the optimized solutions of Rathke et al. (2013), alternative distributions of assortment Volumes V_a were created.

In the example of Rathke et al. (2013), the original set of assortments A contains 15 assortments. These 15 assortments are based on 5 classes of volume per transport and 3 standardized lengths of logs in each of the 5 classes.

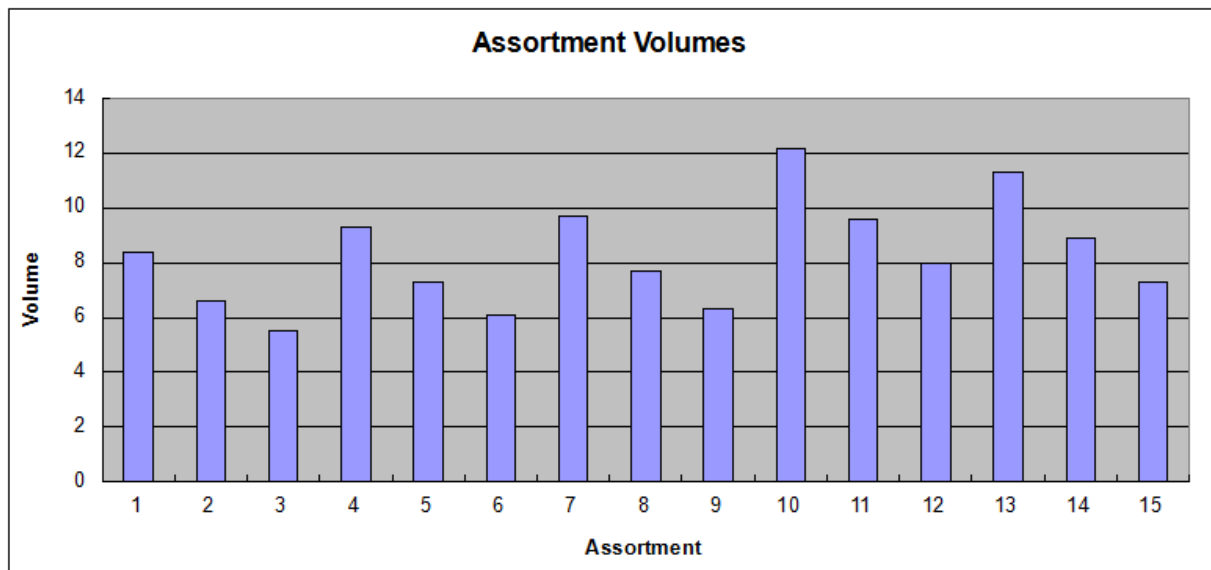


Figure 11: *The original distribution of assortment volumes*

The original volume of an assortment is the total volume of logs that can be transported during an entire shift. The respective number of necessary trips to process the entire batch of an assortment can be calculated by dividing the overall assortment volume through the volume of a single log, or alternatively by dividing the total number of logs of an assortment processed in one shift by the number of logs that can be transported in one single transportation process.

The volumes are different between each class, but the proportions of the assortment volumes within one class to each other are identical for all classes. If the volume of one assortment within a class is known, the volumes of the other assortments in this class can be retrieved by calculation. Thus knowing the volume of every assortment of one standardized length, which is one assortment in each class, allows to calculate the volumes of all other assortments. The major assortments 1, 4, 7, 10 and 13 initiate the beginning of each class, with three assortments contained in every class.

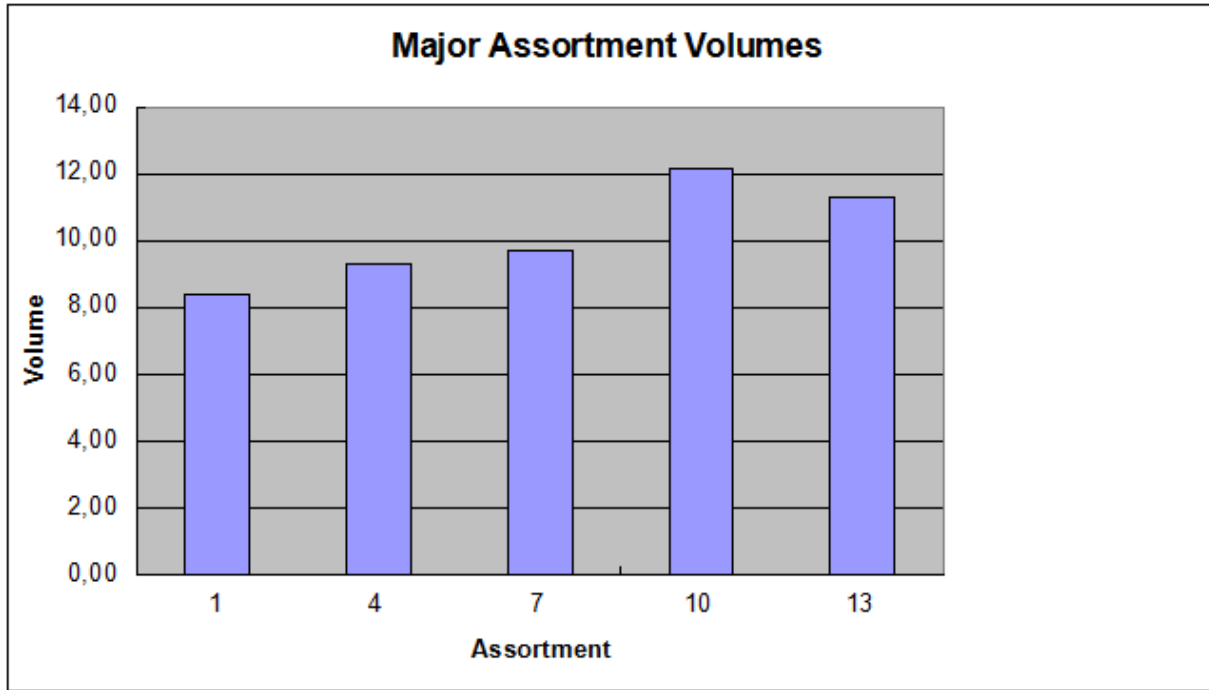


Figure 12: Distribution of the five major assortment volumes, which share a constant proportionality to each two following assortments

Several distributions were generated in order to additionally test the solution quality of the best performing heuristic algorithm against the optimized solutions calculated with the FICO Xpress Optimization Suite.

The model for the test is Partition with the storage box arrangement C_{28} , the conditions where the initial heuristic algorithm in combination with improvement algorithm B and the study of Rathke et al. (2013) yielded the best results. For the heuristic algorithm, the assortments were ordered according to their N_a in a decreasing order.

The conditions for creating the alternative distributions was that the sum of volumes must be equal to the sum of volumes in the original distribution of A, and the ratio of the number of necessary trips for complete delivery to the volume of an assortment, $N_a:V_a$, must remain unaltered.

According to Rathke et al. (2013), the logs are transported within the yard by a gantry crane with a speed of 80m /min and trolleys moving orthogonally with a speed of 100m/min. The gantry crane is able to transport loads with a maximum of 7.3 tons. The maximum load of an assortment the gantry crane can carry in a single take is restricted both by the diameter of the logs and by the weight of the load. The relative density of logs differs across the assortments. Therefore, the

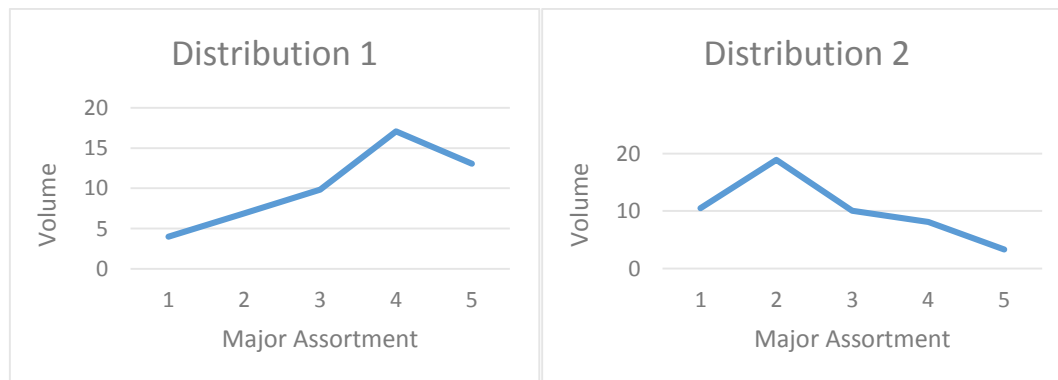
proportion between the overall volume of an assortment and the necessary number of trips to transport the whole batch is different for each assortment.

The following table describes the alternative distributions by shape and lists the number of respective samples taken. The 5 major assortments of the original order 1, 4, 7, 10 and 13 are listed as d_1 to d_5 for practical purposes. The proportion of the major distributions to their two consequent distributions does not change for the generated alternative distributions.

Distribution	Shape	Samples
1	d_1 to d_4 ascending, d_4 to d_5 descending	24
2	d_1 to d_2 ascending, d_2 to d_5 descending	24
3	d_1 to d_4 descending, d_4 to d_5 ascending	24
4	d_1 to d_2 descending, d_2 to d_5 ascending	24
5	d_1 to d_5 ascending	24
6	d_1 to d_5 descending	24
7	d_1 to d_3 ascending, d_3 to d_5 descending	10
8	d_1 to d_3 descending, d_3 to d_5 ascending	10
9	equal value for d_1 to d_5	1
10	equal value for all 15 assortments	1

Table 4: Alternative distributions with description of their shape and the number of generated samples

The following graphs show an example for each of the alternative distributions 1 to 8:



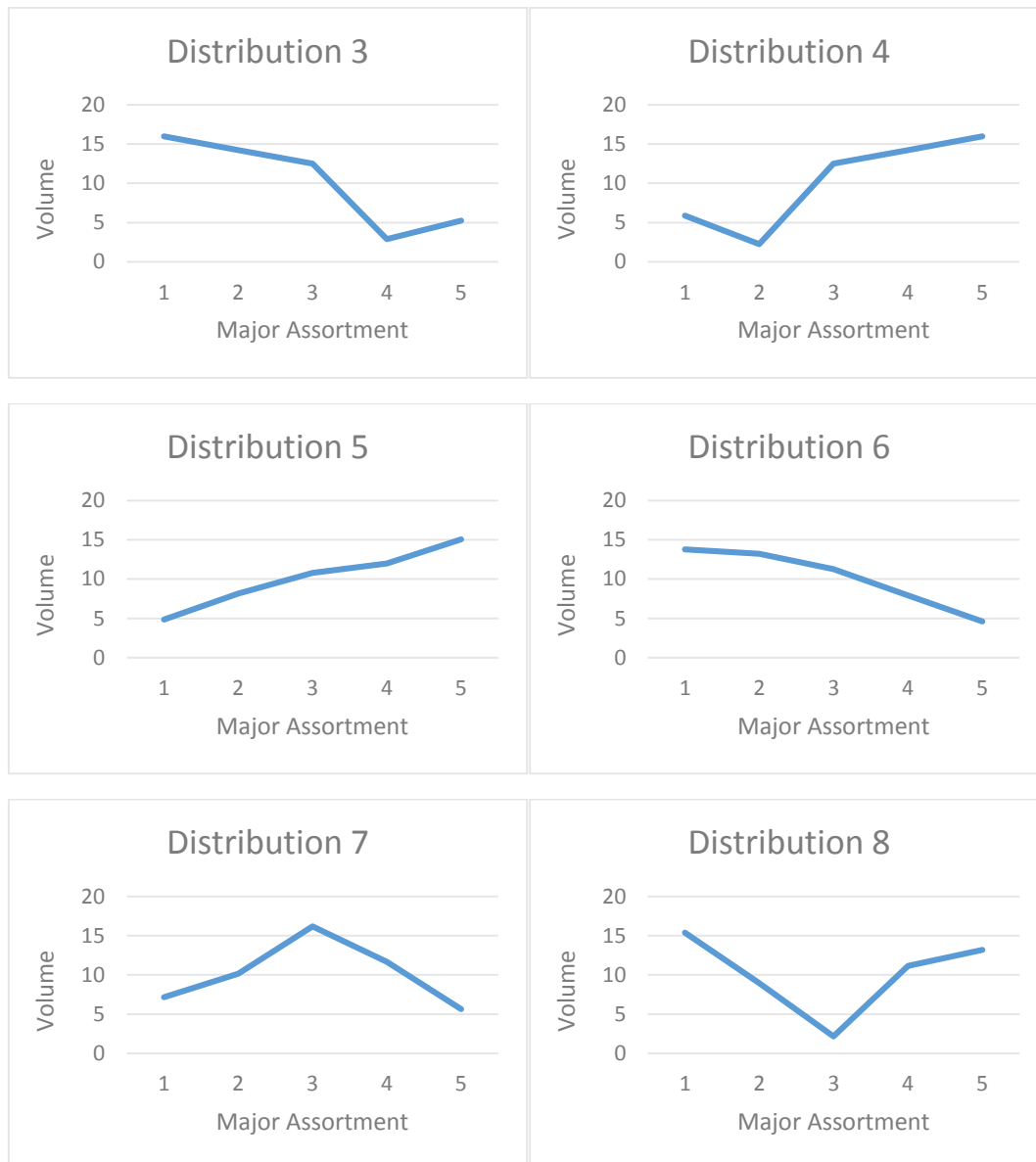


Figure 13: Examples of volume distribution for each alternative distribution 1 to 8

In the following table, a comparison is drawn between the results of the optimized solution and the heuristic algorithm respectively, giving the mean and median results for alternative distributions 1 to 8:

Distribution	Optimized Mean	Optimized Median	Heuristic Mean	Heuristic Median	Mean heuristic efficiency	Median heuristic efficiency
1	278.80	282.47	303.32	305.83	92%	92%
2	312.56	314.51	332.55	328.45	94%	94%
3	316.85	318.19	340.83	344.71	93%	93%
4	274.85	275.50	298.30	299.12	92%	92%

5	282.67	283.15	302.45	305.42	93%	93%
6	316.65	313.67	341.41	330.86	93%	94%
7	293.65	293.73	319.01	321.02	92%	91%
8	300.71	297.14	317.72	316.60	95%	96%

Table 5: Comparison of results for alternative distributions 1 to 8

The following box plot graph shows the distribution of heuristic efficiency values across the alternative distributions 1 to 8:

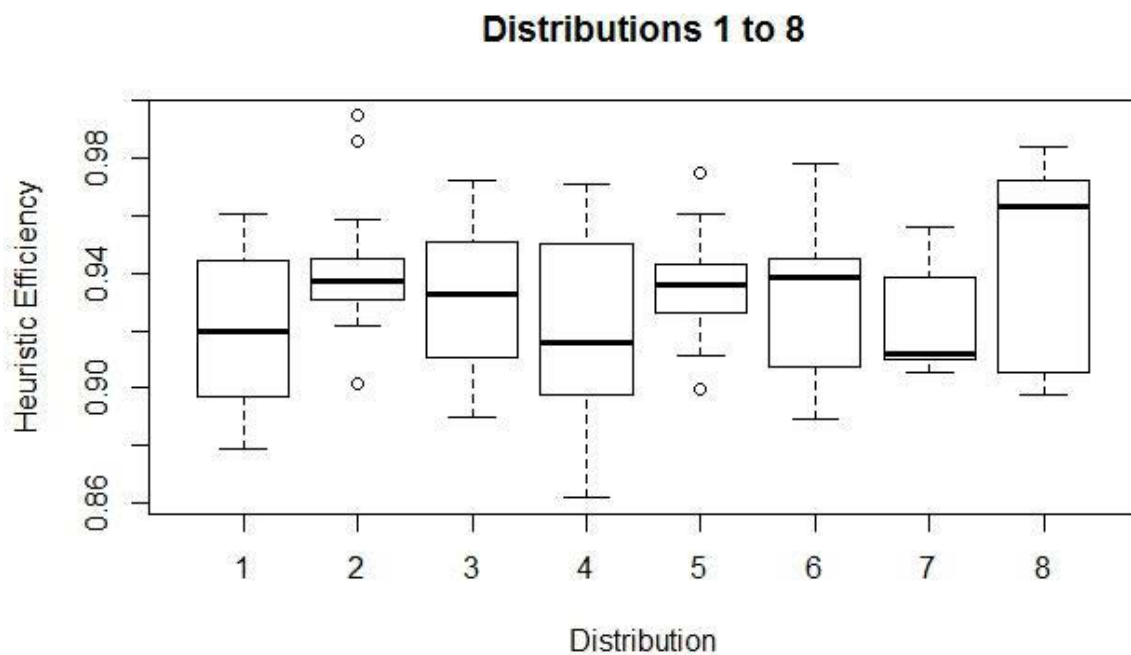


Figure 14: Boxplot of the results for the alternative assortment distributions 1-8.

The boxplots in Figure 11 show the distributions of heuristic efficiency across the alternative assortment distributions 1-8. It is obvious that the volume distribution of an assortment can influence the quality of the heuristic solution approach presented in this work. Distribution 1 is the distribution most similar to the original distribution of assortments. The results for this distribution vary greatly around the median result, however there are no outliers and the range of results from the minimum to the maximum shows an almost perfectly even distribution around the median. The results of distribution 3 resemble distribution 1 in all aspects, except the algorithm performs slightly better for this distribution and the results are distributed a little less even around the median. Distribution 2 on the other hand shows the lowest variability of results, although there are three outliers, two of

them even coming close to an optimal solution! The algorithm performs very well for this distribution, as the narrow interquartile range of the results here fits into the upper end of the upper quartile of most of the other distributions. The results of this distribution only vary little. It can be assumed the solution quality of algorithm results for this distribution is well predictable. Surprisingly distribution 5 shows a similar structure of results with slightly less algorithm performance and slightly more variety on the lower end. Distribution 8 has the highest variability of results. The upper quartile of distribution shows the best results of all distributions and is clearly much higher than in any other distribution. The range of the lower quartile however is very wide, the lower end of the interquartile range goes lower than 5 other distributions. For this distribution the resulting solution quality is not easily predictable.

The two alternative distributions 9 and 10 with only a single incident each have yielded the following results:

Alternative distribution	Optimized result	Heuristic result
9	301.609	309.17
10	303.772	308.34

Table 6: Optimized and heuristic results for the alternative distributions 9 and 10

7 Conclusion

Obviously, a relatively simple heuristic method like it is presented in this work is able to achieve a solution quality of over 90% using only negligible time for computation. An improvement algorithm has proven to be a good tool to improve the results of an opening algorithm, also using very little time for computation. Depending on the standards of someone employing such algorithms for a certain problem and the size of the problem instance, heuristic algorithms like these can be a useful tool to find acceptable solutions to a given problem quickly, using very little resources. However, to determine the solution quality a heuristic algorithm can deliver, an optimal result must be already known in advance.

An increased performance of heuristic optimization is often possible using additional heuristics and tools. However, an important question for any optimization undertaking is the relationship between the time and effort needed to

implement and apply the optimization method and the cost it will save or the additional profit it may gain. For many optimization problems, a linear increase in the size of the problem means an exponential rise of computation time needed to find an optimal result.

A heuristic algorithm as presented in this work can certainly be applied to other layouts of log yards as well. Of course, an algorithm needs to be based on a model that takes important constraints into account, which may vary depending on the size of a log yard, the resources used for material handling and other tasks, seasonal factors and individual site restrictions that constrain the operational process on the yard. Existing algorithms may also be modified to fit a new purpose or to be applied to a different process layout.

As can be seen in the available literature, not only the operational process on a given layout of a log yard can be optimized. It is also possible to simulate alternative layouts and find new efficient solutions for a log yard by relocating or replacing machinery and equipment, although this option demands much bigger expenses in time and resources than simply relocating storage.

The question remaining is whether the solution to a certain problem will be needed only once or once in a while or whether delivering solutions with an acceptable quality is continuously necessary within short periods of time. If the composition and dimensional features of the assortments in the case of the log yard Rathke et al. (2013) have examined do not change regularly, the solution method will not be needed very often and therefore, a high computation time may not be an intolerable obstacle for the solution of such a problem.

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