



Optimization of the feeder assignment for PCB assembly machines

Master of Science Thesis in the Computer science and engineering

KRISTOFFER WIKLUND

Chalmers University of Technology University of Gothenburg Department of Computer Science and Engineering Göteborg, Sweden, April 2010 The Author grants to Chalmers University of Technology and University of Gothenburg the non-exclusive right to publish the Work electronically and in a non-commercial purpose make it accessible on the Internet.

The Author warrants that he/she is the author to the Work, and warrants that the Work does not contain text, pictures or other material that violates copyright law.

The Author shall, when transferring the rights of the Work to a third party (for example a publisher or a company), acknowledge the third party about this agreement. If the Author has signed a copyright agreement with a third party regarding the Work, the Author warrants hereby that he/she has obtained any necessary permission from this third party to let Chalmers University of Technology and University of Gothenburg store the Work electronically and make it accessible on the Internet.

Optimization of the feeder assignment for PCB assembly machines

KRISTOFFER E. WIKLUND

© KRISTOFFER E. WIKLUND, October 2009.

Examiner: DEVDATT DUBHASHI

Chalmers University of Technology University of Gothenburg Department of Computer Science and Engineering SE-412 96 Göteborg Sweden Telephone + 46 (0)31-772 1000

Cover: Machine layout for mounting components onto a PCB, see page 29

Department of Computer Science and Engineering Göteborg, Sweden October 2009 REPORT NO. xxxx/xxxx

Optimization of the feeder assignment for PCB assembly machines

KRISTOFFER WIKLUND

The Department of Computer Science and Engineering CHALMERS UNIVERSITY OF TECHNOLOGY Göteborg, Sweden 2009

Abstract

This report is part of a master thesis done at Chalmers University of Technology in Göteborg and in cooperation with Valor Computerized Systems. The purpose with the report was to compare different algorithms performance in solving a subproblem in PCB assembly. PCB assembly is about to balance the PCB production between different production lines in a factory. For each line one need to balance electrical parts' assembly between the machines in the production line. Finally a minimized sequence of the assembly of components is constructed. The subproblem for this thesis has been the feeder assignment problem, where the problem is come up with setup for how and in which feeder slots the components for the production should be placed, for minimizing the production time. The subproblem has been showed to be NP-hard been proven that the Traveling Salesman problem can be transformed to the subproblem.

We have chosen to compare two versions of Local Search algorithms and two versions of genetic algorithms and a simple heuristic algorithm. To obtain a reliable comparison, the solutions are imported into Valor's software to solve and model a complete assembly machine. Valor's software has enabled us to obtain the simulated production times. To be able to use the chosen algorithm a new and simplified cost function has been developed.

Our approach has showed that is possible to lower the production time compared to Valor's current software. To draw a concussion of which algorithm to use is not possible. All five algorithms have given around one percent improvements. One explanation for that is that the simplified cost function has simplified the problem to much so that it is not possible to separate a good feeder assignment hungry against a less good solution.

Keywords: PCB, Assembly, Optimization problem, Feeder assignment, Local Search, Genetic Algorithm, NP-Hard, TSP

Sammanfattning

Denna rapport är en del av ett examensarbete utfört på Chalmers tekniska högskola i samarbete med Valor Computerized Systems. Syftet med rapporten var att jämföra olika algoritmers förmåga att lösa ett utav delproblemen inom kretskortstillverkning. Kretskortstillverkning handlar om att fördela kretskorts tillverkning mellan olika produktionslinjer i en fabrik. För varje linje handlar det om att fördela komponenternas montering mellan maskinerna i en produktionslinje. Slutgiltigt så ska en minimerad sekvens av montering av komponenter konstrueras. Rapporterns delproblem, matar fördelningsproblemet, har varit att lösa hur och i vilka matare som komponenter ska placeras i, så att produktionstiden är minimerad. Delproblemet är bevisat att vara NP-svårt genom att bevisa att Handelsresandeproblemet kan transformeras till delproblemet.

Vi har valt att jämföra två versioner Local Search algoritmer och två versioner av generiska algoritmer och en enkel heuristik algoritm. För att få en trovärdig jämförelse har lösningarna importeras till Valor's programvara för att lösa och modellera upp en fullständig monteringsmaskin. Genom Valor's programvara har vi kunnat erhålla simulerade produktionstider. För att kunna använda valda algoritmer har också en egen förenklad kostfunktion utvecklats.

Vår tillgångavägsätt sätt har visat på att det går att sänka produktionstiden jämföra med Valors nuvarande programvara. Vilken algoritm som ska användas går inte att dra slutsatser ifrån då de alla fem ligger på runt en procents förbättring. En förklaring till detta har varit den förenklade kostfunktionen vilket trors ha förenklat problemet för mycket och gjort att bra lösningar inte kan skiljas från mindre bra lösningar.

Nyckelord: PCB, Kretskort, Tillverkning, Optimerings problem, Local Search, Generiska algoritmer, NP-Hard, TSP

Content

Abstract	I
Sammanfattning	II
Content	III
Preface	V
Notations and definitions	VI
List of Figures, Tables and Equations	VII
1 Introduction	1
1.1 Background	4
1.2 Purpose	
1.3 Delimitations	
1.4 Local Search	
1.5 Genetic Algorithms	
1.6 Heuristic	19
2 The Traveling salesman problem transformation	
2.1 General TSP	
2.2 Placement TSP	
2.3 Feeder bank assignment	
3 Methods	
3.1 Internal structure	
3.2 Time factors	24
3.3 Cost function for evaluating feeder assignments	
3.4 Revolver setup	
3.5 Algorithms	
3.6 Lower bound	
3.7 Test data	

4 Results	31
4.1 Performance of the algorithms subject to the cost function	32
4.2 Relation between cost function and production time	33
4.3 Performance of the algorithms to solve the whole problem	37
5 Discussion	38
6 Conclusions	40
7 Future Work	41
8 References	42
Appendix 1: Algorithms	44

Preface

This Master Thesis was carried out from April 2009 until October 2009 at the Department of Computer Science and Engineering, Chalmers University of Technology in Göteborg, Sweden. Working place for the thesis has been at the R&D department office in Turku, Finland for Valor Computerized Systems. The work has been formulated and supervised by Ph.D. Mika Johnsson at Valor Computerized Systems. Examiner of the thesis is Prof. Devdatt Dubhashi at Chalmers University of Technology.

A special gratitude is dedicated to Prof. Olli Nevalainen at Turku University who has been helping and supervising me, thanks for reading and correcting my report.

I would like to thank Mika Johnsson and Valor Computerized System for giving me the opportunity to work with this thesis's subject. It has been an interested problem, I am thankful for getting the help concerning my research topic, books and hardware needed when conducting this study.

I also like to thank my loving wife, Marianne, which have supported me during the work.

Turku October 2009

Kristoffer Wiklund

Abbreviations and definitions

Abbreviations

AI	Artificial Intelligence
CAD	Computer-aided design
GA	Genetic algorithm
LS	Local Search
PCB	Printed circuit board
PMX	Partially mapped crossover
RAM	Random-access memory
SMT	Surface-mount technology

Definitions

Component	An electronic element that has one or more connections.					
Part	Type definition of components, all components of the same part					
	have the same form and specification					
Placement	Description that a given component needs to be placed on					
	a given position on the PCB					
PCB job	Description of a set of parts that will be mounted onto the PCB					
Feeder	Component supply mechanism in SMT machines					
Placement head	Mechanical arm of a SMT machine that places the components					
Spindle	Mechanical part attached to the placement head for picking and					
	placing a single component					
Nozzle	Gripping tool for allowing spindles to pick a kinds of components					

List of Figures, Tables and Equations

List of Figures

Figure 1, Example of production line	1
Figure 2, Machine layout	2
Figure 3, Dual Delivery placement machine	6
Figure 4, Turret style placement machine [5]	7
Figure 5, Sequential Pick-And-Place Machine [5]	7
Figure 6, Multi-Head Placement Machine [5]	
Figure 7, Multi-Station Placement Machine [5]	9
Figure 8, Hierarchy of the problems found in PCB assembly	9
Figure 9, Feeder assignment problem	
Figure 10, Roulette wheel	17
Figure 11, Ranked Roulette Wheel	
Figure 12, Flow of the experimental tests	
Figure 14, MachineConfiguration class.	
Figure 13, PCB class	
Figure 15, Algorithms classes	
Figure 16, Graphical presentation of PCB-9 in the developed software	
Figure 17, Relation between procedure S and production time for all PCBs	
Figure 18, Relation between procedure S and production time for PCB-1	
Figure 19, Relation between procedure S and production time for PCB-2	
Figure 20, Relation between procedure S and production time for PCB-5	
Figure 21, Relation between procedure S and production time for PCB-8	

List of Tables

Table 1, PCBs in number	. 31
Table 2, TEST results with procedure S	. 32
Table 3, PCB results with procedure S	. 32
Table 4, TSP problem results	. 33
Table 5, Average difference in production time for exact same feeder assignment	. 33
Table 6, Performance of the algorithms solving the final problem	. 37

List of Equations

Equation 1, Ranked Roulette Wheel formula	17
Equation 2, Total time	
Equation 3, Time for a revolver	24
Equation 4, Pick-up phase	25
Equation 5, Placement phase	
Equation 6, Lower bound	

1 Introduction

Articles about Printed Circuit Board, PCB, [1], [2], almost always discuss the increased demand, new development and increased production volumes in the PCB assembly industry. One common explanation for the rapid development in the field is that citizens own more and more electrical devices and almost each of those devices includes a PCB in it. Design and construction of PCB is very universal and enables almost every possible electrical circuit.

In the early years, the components were assembled manually. But over time, specialized placement machines have taken over the work. Also the way these machines function has changed. In today's production, the machines often are organized in production lines, where every line comprises of several manufacturing stations.



The stations can include several different or equal assembly machines, inspection stations, oven and more. Duplication of stations can increase the efficiency of production, as shown with the placement machines in Figure 1.

This thesis concentrates on the placement machines and omits the discussion of other machine types. The placement machines can work in different ways, but the main operation principle in all of them is that a mechanical arm picks up an electronic component from the feeder bank and places it on the PCB at a predefined position.

To solve this assembly task is a NP-hard problem. The task is to come up with a setup and a placement order for the placement machines such that the production time is minimized.

The mechanical arm could be built in different ways; the most common types are the inline head and the revolver head. On each head there are one or several spindles which are the mechanical parts that pick and place components. In an inline head the spindles are grouped in one or several lines, and in a revolver head the spindles rotate around a center point. In Figure 2 a photo of a common assembly mount machine with revolver head is showed. It is a collect-and place machine with two feeder banks. At position A, one of the feeder banks is located. Another feeder bank is located just below C. At position B the PCB is fixed stationary on the table. The revolver head and how the



Figure 2, Machine layout

spindles are located around it can be seen at C. In the image, the revolver is picking components at the feeder bank and will later go to the PCB at B and place the components and after that go to the feeder bank at A again to pick up some new components.

Placement machines can be classified into 5 categories [3]. The five classes are: Dual Delivery Placement Machine, Multi-Station Placement Machine, Turret Style Placement Machine, Multi-Head Placement Machine, and Sequential Pick-and-Place Machine. Each of these solves the assembly task in a different way. This thesis will discuss how to solve assembly task for Multi-Head Placement Machines.

PCB assembly control problems have been divided into three subproblems in [2]. The first problem is to group the PCBs by the similarity of the components and then choose the machine group/production line. The next problem is to optimally divide the placements of the components between the machines so that there is no big bottleneck machine in the group. The last problem is to decide the feeder, nozzle and placement sequence for each machine.

All these problems depend on each other when one tries to solve them in a total optimal way. In order to know which components a machine should place it is necessary to group the PCBs and machines. For optimal grouping of the PCBs one has to know how to divide the placements between the machines in the group. It is impossible to solve one of these subproblems without considering its relation to the other problems.

This thesis deals with the last subproblem, the feeder arrangement, nozzle arrangement and placement sequence optimization. The problem will be divided into two subproblems. The first problem is to fix the feeder and nozzle bank setting. The second problem is to optimize the placement order with respect to the components and feeder bank. The task in this thesis is to develop, test and compare different algorithms for fixing the feeder and nozzle bank. In order to see how well the solutions really are, one has to solve also the second subproblem. For solving the second subproblem we will use Valor's planning software to generate a placement sequence and to calculate the total assembly time for that PCB job.

This thesis has the following structure. Chapter 1 explains the background of the PCB assembly research and how PCB assembly works out in the real-life industry. The purpose and delimitations of the thesis is explained and also a description of the algorithms and techniques is given. Chapter 2 will explain how to transform the TSP problem into a PCB assembly problem and show that the PCB assembly problem is NP-hard. Chapter 3 is in detail describing how the problem has been modeled and how we have adapted the algorithms. The heuristics and the formulas we used are presented in this chapter. Chapter 4 describes the results of the practical tests; how well our algorithms run and what works and what does not. Chapter 5 discusses the relation between the methods and the results and how the results relate to the problem. It describes the results and how it refers to the problem. Chapter 6 shows what conclusion one could draw from the results. Chapter 7 discusses how one could do more research on this subject, how to improve the algorithms.

1.1 Background

The desire to connect electronic components in an easy way has existed from the early days of electronics. The technique with PCB was invented by Paul Eisler around the Second World War. After the Second World War the technique was released for commercial use. In this technique, copper traces are printed on a non-conductive board, where the traces connect the different components mounted on the board.

A PCB is as the name says a circuit board with a printed electrical circuit. The board is often green in color and has lots of different components mounted on it and it is placed in a machine behind a plastic cover. One can find PCBs in a broad range of customer products including for example computers, cars, phones, dish washer, clocks and more.

There are many different types of circuit boards. Components can be attached by through-hole construction or by surface-mount construction/ surface-mount technology (SMT). The material for the board and for the electrical traces can differ. This report focuses not on the construction of PCBs; instead, it focuses on the assembly of components on the PCB. The optimization in this thesis will be made for an SMT-machine, but the results can be applied to through-hole technology as well.

Manual assembly of components on the PCB was the first approach of the technology and it is still used for special cases. As machines have been developed and become more advanced, more and more components can be mounted by the machine with greater accuracy, speed and with fewer faults. As the machines get more and more advanced an optimization problem is risen; how to sequence the component placements in an optimal manner. The same problem exists also for manual assembly, but it is not as critical, instead developing of routines and techniques for lowering the risk of human error have been investigated. [4]

One important thing to keep in mind is the difference between part, component and placement. A component is an electronic element that has one or more connection; this is like an atom for electronics. Part is the type definition for components, all components of the same part has the same form and specification. Placement is a word for describing that a component has a fixed placement position on the board. Therefore a PCB consist of a number of parts that each has one or several placements. A PCB consists of the same number of components that it has placements in total.

Some components that are going to be placed on the board need to be visually verified so that the right component is placed and that the component has the right angle. Therefore machines often have a camera to take a picture of the components. The camera might only take black and white pictures, and many times it just examines the shape of the component. Taking pictures of components can be done in different ways; sometime there is a fixed camera station where the mechanical arm verifies the components before placing them. Other machines can have a moving camera station so that the verification of components can be done while the arm is moving. There are even more ways of visual verification of the components that the vendors use.

The mechanical arm, the placement head, can be constructed in several different ways but in most cases they are either of *inline* or *revolver* type. A placements head has one or several spindles. Spindles are the mechanics for picking up a single component, but in order for the spindle to be able to pick up the component it needs a griping tool. For that purpose the industry has developed different kinds of nozzles for picking and placing the components. It works by using a vacuum of air to suck up a component from the feeder slot and air pressure to place the component on the PCBs. Several kinds of nozzles can pick up the same type of components and nozzles can pick up several different component types. The nozzles have different specifications and they set limitations to the placement head in regard to movement and rotation speed. Special components that are hard to hold also affect the selection of the placement head and give it more limitations. The spindles often have the ability to rotate, which makes it possible to have the right angle of the component when placing it on the PCB.

The difference between inline head and a revolver head is that for an inline head the spindles are grouped in one or more lines. This feature makes it possible to do *gangpicks*. In *gang-picks* several spindles pick up components simultaneous. If two spindles are picking components at the same time the time is lowered by 50% for that task and if 6 spindles pick their components at the same moment of times the task consumes 16% of the time it would take to pick them up sequentially. In revolver heads the spindles are located in a rotating circle, so that the spindles are rotating around a center point. Some revolver head types have a camera located at the top of the head. This makes it possible to do the camera verification of the component placed on the top spindle while the bottom spindle is picking up a component.

In order to place the components in exactly the right positions there is a set of *fiducial marks* on the PCBs. After the PCB is loaded to the machine, the head locates the fiducial marks by a camera. This takes some production time at the beginning of processing each PCB but the machines are then able to place components extremely accurately.

SMT machines are equipped with one or several *feeder banks*. They supply the component to the machine. A feeder bank is divided into several feeder slots which are the mechanical places for holding components. Each slot can be populated with a feeding unit. A common industry feeder unit is the tape feeder. Here the components are attached onto a long tape like a movie theater tape. The placement head picks a component and after this the tape is rotated so that a new component can be picked. There are tapes of different widths, and therefore some parts take up several feeder slots. There are also some feeders that can take two or more parts (i.e. component tape reels) in the same feeder slot.

1.1.1 Machine Classification

As mentioned in the introduction, there are several different types of assembly machines. SMT machines have been classified into five classes [3]: Dual Delivery Placement Machine, Multi-Station Placement Machine, Turret Style Placement Machine, Multi-Head Placement Machine, and Sequential Pick-and-Place Machine.

Dual Delivery Placement (Figure 3) has a movable PCB table that can move in x- and y-direction. In the machine there are two placement arms, located on the opposite sides of the table. They can move in y-direction between the placement position and the pickup position over a movable feeder bank. When one arm is placing components the PCB table is moved to its side, and the other arm is picking up components. After the component has been placed, the PCB table moves to the other side there the other arm places its component.



A Turret Style Placement Machine (Figure 4) has a big rotating turret with several spindles on it. On one side of the turret there is a moving feeder bank and on the other side is the PCB table, which moves in the x- and y-direction. The feeder bank is situated on the side of the machine, the spindles pick up components and the moving feeder bank is moved in the x-direction so that the correct part is under the spindle. The PCB table is moved so that the placing position for the component in the spindle is under the spindle and then the component is placed to its proper position.



Figure 4, Turret style placement machine [5]

A Sequential Pick-and-Place Machine (Figure 5) consists of a moving arm. The arm can move over a fixed PCB table, a fixed feeder bank and a fixed nozzle bank. The arm has one spindle that picks up and places components. The placements are done in pick-andplace blocks, where the placement head first moves to the feeder bank, picks up a component, then goes to the PCB table and places the component on its correct position.



Figure 5, Sequential Pick-And-Place Machine [5]

Multi-Head Placement Machine (Figure 6) is almost of the same technology as the Sequential Pick-And-Place machines. But instead of just one spindle on the placement head it has multiple spindles. These machines are sometimes called collect-and-place machines because they collect a number of components from the feeder bank and then place them on the PCB. Spindles can be arranged into one or several rows or they can be on a rotating revolver. For the revolver head the head needs to rotate the head before picking and placing. Inline heads can perform gang-picks.



Figure 6, Multi-Head Placement Machine [5]

A Multi-Station Placement Machine (Figure 7) consists of several modules or stations. Each module has an arm that can move in x- and y-directions. The arm is picking and placing a limited set of components on the fixed PCB board. When a station has placed all of its components for a certain PCB, the PCB is moved to the next station. This machine is like several Sequential Pick-and-Place Machines in one.



Figure 7, Multi-Station Placement Machine [5]

1.1.2 PCB assembly problem

Mika Johnsson and Jouni Smed [6] have done a hierarchical classification of the PCB assembly problems by looking at it as a combination of one or several machines and one or several PCB jobs.



Figure 8, Hierarchy of the problems found in PCB assembly

Figure 8 shows how they have classified the problem, and how it can be broken down into subproblems. This differs to the classification made before [3] and is another way to describe the PCB assembly task.

One PCB job and one machine (1-1). In this problem we have one machine and want to produce one type of PCB as effectively as possible. The goal is to minimize the assembly time. For this setup we have four subproblems. The feeder assignment problem is to organize the parts to the feeder slots in an optimal way so that the travel time is minimized and gang-picks or other techniques can be used. The placement sequence problem is to solve the order to place the components such that the head movement time is minimized. The nozzle assignment problem is to choose the nozzles to be used. The component retrieval problem exists if the machine has duplications of parts in several feeder slots, and it is optimized how the picks should be done.

Many PCB jobs and one machine (M-1). The goal in this problem is to minimize the time for production, but compared to the Single-machine problem one now has to consider the time to setup the machines. There are two possible way to minimize the setup time, either one minimizes the time it takes to setup the machine or minimizes the number of needed setups. The minimizing of setup time for one machine is about hardware and organization on the factory floor. The second problem has been researched and is about grouping and balancing [7]. As Johnsson and Smed [6] write there are different strategies to solve that problem; unique setup strategy, minimum setup strategy, group setup strategy, and partial setup strategy.

The One PCB job and many Machines problem (1-M) deals with load balancing. The goal is to divide the parts between the different machines such that the production time is as equal and low as possible, because the time to produce a PCB is determined by the machine taking the longest time, the bottleneck machine. For each machine there is the (1-1) problem to be solved with the set of parts that the machine should produce.

Many PCB jobs and many machines (M-M) is the most advanced and difficult version of the problem but it is also the problem that is most common in the industry. Here one has to decide the jobs to the different lines and to decide which PCB jobs each line should produce.

The classification that Johnsson and Smed [6] have done is to classify the problem but M Ayob, P Cowling and G Kendal [3] has done a machine classification. The five machine classification can be described into the hierarchy by looking how they work for a single PCB job. Dual Delivery Placement Machine, Sequential Pick-and-Place Machine, Multi-Head Placement Machine and Turret Style Placement Machine are only facing the (1-1) problem as a single machine. For the Multi-Station Placement Machine there is always the need to solve the (1-M) problem, because every PCB is processed by several stations and each stations is like its own machine.

This thesis concentrates on the one machine and one PCB job (1-1) problem for a Multi-Head Placement Machine. There are many parameters and settings for this problem as mention before, but the goal is here to minimize the production time for a single PCB job. Either one could improve the machine with better hardware, like more feeder slots, faster moving/rotating placement heads or maybe more placements head in the machine. This approach is pushed by the machine vendors and it is often the more expensive way. The other way is that one tries to improve the usages of the available resources. There are studies that show that by optimizing the placement sequence or the planning of production one could get an improvement on 10% and up over 50% [8].

To do a realistic model of the problem can be very hard. This is because the machines can differ in many ways between each model and vendor. The movements made by the machine are also very complex; acceleration and deacceleration are non-linear. The arm movement from point A to point B cannot be expressed by a simple formula, neither do the machine vendors have any movement graph to hand out, as it is treated as a trade secret or they simply don't have it.

But some type of model of the machine is required to solve the problem, and to test the solutions. An important thing to think at is that all machine operations consumes some time. Many times several operations can be done simultaneously which makes that the time for a group of operations is determined by the operation that takes the longest time. As an example; if the placement head needs to moves 4 steps in x-direction and 5 steps in y-direction this movement is done by two moving parts in the machine, one in x-direction and the other in y-direction. The time for this is the maximum of the time to move in the two directions.

One need to do some simplification of the problem but if the simplification is done without research, the results of the model could be really bad, so that a solution of the model seems to be very good but in reality it does not work in practice.

Here is a short list of common tasks in SMT machines that take some time:

- Placement of a component on the PCB
- Pick up of a component in feeder bank
- Movement of the arm into correct position
- Movement of the PCB table (for the machine that have it)
- Rotation of the head
- Preparation of the component in feeder slot
- Changing of the nozzle
- Loading and reading fiducial marks of the PCB
- Rotation of components

Valor Computerized Systems [9] has developed software for PCB manufacturers. Their software helps the manufactures the whole way from PCB design, planning and

assembly. The company has a software tool specialized for line balancing and assembly optimization. In their software one can build up a model of one or several production lines, each line with machines of the markets most common models. Then a production line is created, one or several CAD-drawing of PCB jobs what wants to assembly can be imported. With the help of that software the assembly tasks and components are distributed between the lines and machines. There is also the possibility for letting the software to optimize the distribution of components so that the production time is minimized. The production schedule along with the necessary machine instructions can be sent directly to the SMT machines. The software also produces lists that state there each component is needed. These lists are useful for the workers on the production floor.

In Valor's software one can optimize different segments of the production. One can optimize the production on a particular line by redistributing the components over the production line. Or one can optimize the allocation of the nozzles and the placement order for each machine. Valor is not solving their tasks to optimally, as they are too time consuming/difficult. But they optimize the production step by step for finding better solutions. For knowing when to stop they have some criteria when a final solution is good enough, like; if the improvement after one minute of searching is less than half percent the search is stopped.

1.2 Purpose

The purpose of the thesis is to examine and evaluate different algorithms and heuristics for a Multi-Head Placement Machine with a rotating head, like the Universal Instruments, Genesis GC60 [10]. The focus of the thesis is on the single machine problem (1-1), one machine and one PCB job. The goal is to minimize the total time it takes to process a specific PCB job with a specific machine. The algorithms are evaluated for several PCB jobs.

The task is graphically showed in Figure 9. There is one PCB with a number of parts and each of them with a number of placements. Each part is supplied in a feeder slot. There could be one or several feeder banks. There can be one or several placement head and each of them has a number of spindles. The spindles need a nozzle from the nozzle bank in order to pick components. Each component type needs a specific nozzle type for picking. The task is to minimize the travel time.



Nozzle b

Feeder bank



Figure 9, Feeder assignment problem

We will not try to solve all subproblems, Nozzle arrangement, Feeder assignment, Placement sequence, Component retrieval. We consider the nozzle arrangement and the feeder assignment problems, only. But to know how well our solutions are we need to solve the placement sequence and component retrieval for calculation the total production time, because it is the total production time for a PCB job that's interesting and relevant.

We use Valor's software to solve the placement sequence and the component retrieval and to simulate the total assembly process. We will import a feeder assignment and a nozzle bank setup that the proposed algorithms find, into Valor's software, then the placement sequence and component retrieval is solved, the production time is calculated thru Valor's software. Valor's software also has the possibilities to solve the assignment problem and the proposed algorithms are compared to Valor's solution.

We will not be able to use Valor's software to evaluate each solution candidate as Valor's software takes around 1-10 min to solve the placement sequence and the component retrieval. It is not possible to use so long time in a Local Search algorithm that tests thousands of candidates.

We will therefore develop a simplified cost function for the feeder assignment problem. The cost function should give similar results as the final modeling but it should be faster to calculate. An important thing with the cost function is not that its outcome is precisely the same as the result from the final model, but it should reflect the relation between a good and a bad solution. So that a good final solution will have low value and a bad final solution will have high value of the cost function. One task in creating solution algorithms for feeder assignment problem is therefore to design a good cost function.

This means that this thesis has two goals. The main goal is to compare different algorithms for the nozzle and feeder bank setup. But to get good results a good cost function is needed.

1.3 Delimitations

For not letting the task be too big and hard to examine there is some delimitations. The simplified cost function is one thing, as it models the problem in a simplified way. We will only work with Multi-Head Placement Machine with a revolver head. The assembly is modeled in a perfect world with no miss picks (the nozzle fails in pick up a component), tool malfunction or component shortage. The time for loading a PCB and reading fiducial marks is omitted and we thus support that the PCB is already properly fixed on the table. Rotating of components is also not considered.

The algorithms and models will be just for revolver head machines and not for inline head machines, as production time for inline head machines are very affected by gangpicks which the revolver head model don't capture.

We will just examinate the situation with only one PCB job at a time. So the minimizing is just for one PCB at time not a group of PCB's.

1.4 Local Search

Local search algorithms improve a candidate solution of the problem by looking into "nearby" solutions. It is a very general technique that could be used for solving almost any computationally hard problem, [11]. This technique can be found out in real world where it is quite common to improve a solution just by doing small changes that improve the overall performance. For an example, one can make an initial plan of the day and then during the day one can realize that if one buys the food before one picks up the kids from daycare one could earn five minutes of time. Here we did a local search step. It is the same for computationally hard problems. The algorithms work by starting with some initial solution, and then they try different solutions that are just small modifications of the current solution. In some cases the total fitness don't have to be calculated again, like in the day planning example, if the change saves five minutes the whole day don't need to be recalculate to see that the plan is five minutes shorter. But in some other problems this is not as easy as this fitness calculation may be very complicated. Nevertheless this technique has worked very well and it is able to produce good solution in short time. [2].

One problem with local search algorithm is to know what a nearby solution is. When a minimum on a graph is to be found the nearby solution is the position before and after the current position. In other cases the solution may be a list of numbers or a matrix of data that is encoded in different way and a nearby solution might sounds strange. The definition of nearby solution is not strict so one is able to define it as it fits the problem. In the case there the solution is described as a list of number a nearby solution could be such that a position in the list gets a new value or such that two values swap places. In

the case there the solution is a matrix a nearby solution could be a rotation of a group of cells.

With local search the solution eventually reach a local minimum, where every nearby solution is worse than the current one. There is no way for knowing that the solution of a local search algorithm is a global minimum. There are different approaches to get out of local minimum in order to find the global minimum. The easiest way and a rather powerful technique are to run the local search algorithm several times with different initial solution and chose the best local minimum found. Another technique is to give the solution potential energy, where the solution gets more kinetic energy as it moves to better solutions. The algorithm is also able to take a worse solution if it has enough kinetic energy, but in that case the kinetic energy of the solution is decreasing. This is a model how a ball is rolling down a hill and how it comes over some small obstacle in its way to find its lowest potential energy. A more common and used technique is the simulated annealing that Metropolis, Rosenbluth, Rosenbluth, Teller and Teller presented 1953 [12]. The report describes how to model steel annealing and how the energy is described. The key formula is the Boltzmann factor; $e^{\frac{-E}{kT}}$. In local search algorithm that adapts this thought, a better solution is always accepted. A worse solution is accepted with the Boltzmann factor, [13], where E is the solutions fitness, k is a constant and T is the "temperature" that decreases by time.

One problem when choosing nearby solution is to know how many solutions are nearby solutions. If more solutions are examined in every step the algorithms are more likely not to end up in a local minimum. As more solutions are checked it takes more time.

2-opt search or k-opt search is used commonly in local search algorithms. It is an easy technique where the optimal solution is just a permutation of a working solution. The 2-opt search works by switching two nodes/tasks/points, and this can be done for every combination of two nodes/tasks/points. If one has a list of values as the solution a 2-opt step is to swap each pair of two values. The k-opt search is similar to 2-opt search but instead of testing every combination of 2 values, k different values are check in every combination. For some problems a higher k could give better result but for some problems 2-opt search works better because there are possibilities to exanimate more initial solutions in the same amount of time.

1.5 Genetic Algorithms

Genetic algorithm, GA, is used to imitate the nature and its amazing way to adapt to the environment. The technique is to convert a solution into a chromosome like a DNA sequence. After that the genetic algorithm simulates how a population is evolving by letting good solutions survey and bad solutions die.

This is a description on how a standard GA is build [14], but variation often occurs.

Initializes random generated chromosome until the population limit are reach

```
For a number of generation
For a number of new chromosomes
Select two parents according to a parent selection formula
Let the two parents breed a new chromosome thru crossover
Mutate the new chromosome
Add the new chromosome to population
End for
Select which chromosomes that survives until next generation based on theirs
fitness
End for
Return best chromosome as the algorithm solution
```

GA has been mathematically characterized by Holland [15]. He gives the so-called schema theorem. It states that GA is looking thru different combinations of solution space. He also shows how GA finds more fitted schemas over time, but he cannot prove that an optimal solution will be found.

GA is widely used in solving AI problems. It has often been proven to give good experiential results. It has been used for solving assembly mount problem before, [16]. It almost every time has the capacity to find the optimal solution but for the most times it also takes the longest time, therefore it is not perfect for every situation.

1.5.1 Fitness function

GA needs a way to measure its chromosomes and different a good solution and a bad solution. Therefore there is a need of a fitness function, which takes a chromosome and gives a value of how well it works. Sometimes there is a simple function to calculate it but if the GA's task is to find a good chess player the fitness value may be the result then solutions play against other chess players. The fitness value could be on a fixed scale or it could be scaled so that the fitness values for all chromosomes are between fixed values.

1.5.2 Initialization

The first step in GA is initialization. The goal for the initialization is to create a starting population that contains as various chromosomes as possible, because it is from the starting population the optimal solutions is evolving from. New chromosomes are often created purely on random way with no logic; this guarantees that the population is diverse. But a purely randomized chromosome population will in most cases give very bad fitness and it takes more generations for the chromosome population to contain good solutions. Therefore the created chromosome can be made by some greedy approach or heuristics.

1.5.3 Parent selection

For choosing which parents that should be mated there are different approaches. Just picking parents randomly is not working so well, it has been shown that if the better

fitted chromosomes are picked with higher probability the genetic algorithm find the good solutions faster. Roulette wheel is one way to capture this. Each chromosome gets a percent of a roulette wheel according to its percent of the total sum of fitness. This is graphically showed in Figure 10, and now a ball is rotating for a randomized length round the roulette wheel and where it stops that parent is selected. Here a good parent is chosen with a higher probability than others. This technique works well for many applications but it has problems to make difference between chromosomes if the fitness values are close to each other. Further, if one chromosome takes up all space in the Roulette Wheel the diversity is lost. Ranked Roulette Wheel is therefore constructed. Instead of using percent of total the fitness, Equation 1 is used where p is the percent of roulette wheel, r is the rank of the chromosome in the population and n is the number of chromosomes in the population.



Figure 10, Roulette wheel

If the same chromosomes as in Figure 10 are used for Ranked Roulette Wheel the wheel looks like Figure 11. There, the worst chromosome 7 to 10 doesn't get so much percent in the ranked roulette wheel and the top solutions get more percent. This approach is also suited if the chromosomes vary very much. If a chromosome takes up 90% of a Roulette Wheel in the first method, it will get much lower percent in Ranked Roulette Wheel so that more diverse chromosomes can be produced.

$$p = \frac{2 * r}{n * (n+1)}$$

Equation 1, Ranked Roulette Wheel formula

CHALMERS, *Optimization of the feeder assignment for PCB assembly machines*, Master Thesis 2009:



Figure 11, Ranked Roulette Wheel

Tournament selection is another method of selection. As it is describe in [17] the chromosome in the current population is competing to be in the mating pool. A number of chromosomes (usually 2) are selected randomly from the population and the best one of these is added to a mating pool. The same action is repeated until the mating pool is full, and then the parents for mating are selected by random from the pool.

1.5.4 Crossover function

The actually breeding is done in the crossover function. How the crossover is done depends on how the chromosomes are encoded. If the chromosomes are permutations it is a little bit tricky to get permutations as new chromosomes. If the chromosomes are not permutations the easiest way to breed new chromosome is the single point crossover. Take a position by random and for the positions before the random position take the genes from first parent and for the genes after the random position take the genes from the second parent. For example if we breed two parents, $P1 = \{11101101\}$ and P2 = {01010111} and have the single point at three the new child is C = {11110111}, but there is also simple to breed a second child as {01001101}. Instead of a single point crossover, there could be two (or more) point crossover, and for each point switch between the parents. For example with a 2-point crossover with the prior parents the result for crossover point at 2 and 5 would be $C1 = \{11010101\}$ and C2 =**{01**101**111**}. Uniform crossover chooses for each position a gene by random choosing which parent it will be copied from. This makes it possible for every type of combinations of two parents to be found. For the single (and more) point crossover there is a limit. For example the single point crossover could just generate 16 different outcomes from two parents with 8 genes and the Uniform crossover could generate 256 different outcomes. This number is smaller than the two parents have some genes in common. But with Uniform crossover it is more likely that the method destroys a sequence of genes that are good as a group.

The algorithms above don't work if the chromosome is a permutation. For example if $P1 = \{12345678\}$ and $P2 = \{345678123\}$ and a single point crossover at position four the new chromosomes would be $C1 = \{12348123\}$ and $C2 = \{34565678\}$, and this is not a permutation of the solution. A way to overcome this is the Partially Mapped Crossover, PMX, describe in Goldberg and Lingle [18]. This is how it works:

Randomly select a span of genes from P1 and copy them directly to the new
chromosome. Note the indexes of the segment
Looking in the same segment positions in P2, select each value that hasn't
already been copied to the child.
For each of these values (a):
 (i) Note the index of this value in P2. Locate the value, V, from P1 in this
 same position.
Locate this same value in P2
 If the index of this value in P2 is part of the original span
 Go to step i. using this value.
Else
 Insert (a) value into the chromosome in this position.
End for
Copy any remaining positions from P2 to the chromosome.

1.5.5 Mutation

Mutation is sometimes necessary in order to find new chromosomes and nature is using this. It is a simple step where the new chromosome undergoes a small change. So by random a small part is changed or swapped.

1.5.6 Survival

The way to choose which chromosomes survive until the next generation can be done in different ways. One way is that only the two children after each reproduction survive. But a more effective way is the elitism. It says that the best chromosomes always survive. So, if the new chromosomes are worst than the parents, the parents are kept in the population. With the elitism the best (and sometime the optimal) solution is kept to the end.

1.6 Heuristic

Heuristic is the method to do choices based on experience rather than proof [19]. This knowledge is based on knowing the problem and the experiment of what works and don't. This could be used in chess playing to assume that some opening is better than other. For solving the feeder assignment problem heuristic way stats that is better to pack the components in the feeder bank, because that will lower the placement heads movements.

2 The Traveling salesman problem transformation

When this problem was investigated and constructed, two different approaches for transforming the travel salesman problem (TSP) into assembly mounted problem were found. TSP is known to be a NP-hard problem [20]. The following description proves that the surface mounted PCB problem is NP-hard in two different aspects.

2.1 General TSP

The TSP problem is an old problem about a salesman's travel. It is not known when it was first introduced but there are writings about the problem from the 1800 century [20]. The problem is to visit n different cities where the distance between the cities are known and the goal is to minimize the total length to visit every city once and only once and then back to the starting city.

2.2 Placement TSP

For transforming a TSP problem into a placement problem the revolver capacity is set to n, so that the revolver has n spindles. Now, locate a feeder slot at the first cities position, for the rest of the positions set them as a placement position for one particular part. The assembly problem is now to pick n-1 components in the feeder slot and then place the components in the different placement positions. If the problem can be solved optimally in the assembly problem the solution could easily be transformed back as a solution to the TSP problem. Therefore if it exist a polynomial time algorithm for the assembly problem, a TSP could be solved in polynomial time, this shows that the assembly problem is at least as hard as TSP, in other word it is NP-hard.

2.3 Feeder bank assignment

In assembly mount problem, a revolver needs to pick-up components in different feeder slots and then place them at the PCB. Each component has a required nozzle that needs to be in the revolver head in order for the revolver to pick up the component.

In order to transform the TSP problem to a feeder bank assignment problem create n components each with a unique part number and one placement each. Each of the components has a unique nozzle which means that the revolver head will be populated with n nozzles. Make the revolver head fixed so that the nozzles in the spindles are always the same which leads to that the pickup order of the components will be the same for ever feeder assignment. Create n feeder slots and give the feeder slots the same positions as the cities. There will therefore be n feeder slots spread out as the cities.

With the assembly cost function there is a small modification. The calculation for the placements of components will not be included, just the pickups. So the pickup order and cost is calculated as:

Move head to feeder banks slot for the components which requires the nozzle in the last spindle head For every spindle head Find feeder slot that have the component that require the nozzle that's in
the current head
Increase the Cost with the Euclidean 2D distance between previous position
and position for the feeder slot related to current head.
Update position to the current feeder slot
End for loop

With this procedure the cost of a TSP problem is possible to calculate. Each feeder slot has a component that indicates in which order it will be visit. So instead of a list in which the cities should be visit (as usually with the TSP) each feeder slot will have a component (number) which tells in which order it will be visit.

Therefore if an optimal solution is found in the feeder bank assignment problem the result can be transformed back to a TSP solution. The assignment problem is NP-hard because it is as hard as TSP to solve.

3 Methods

The algorithms for feeder assignment problem are compared by making a set of experimental tests. These tests follow the flow of Figure 12.



Figure 12, Flow of the experimental tests

The first four steps are done in the new proposed optimizing program and the last three steps are preformed in the existing software from Valor. The whole test procedure is scripted in Valor's software but the actually feeder optimizing is done thru a binary file outside Valor's software. This test procedure of the system model is repeated for every setting of the parameter.

3.1 Internal structure

The model of the problem instances consists of three blocks / classes. The MachineConfiguration model contains all the information needed to describe a machine. Second the PCB model describes the PCBs. Third the Optimizing is a class that is inherited by each algorithm. Figure 14 shows how the MachineConfiguration is modeled. MachineConfiguration is the main class that implements a machine having a number of NozzleBanks, Revolvers and FeederBanks, each with its own attributes. MachineConfiguration contains the information on how to populate the feeder banks for Valor's software.



Figure 14, MachineConfiguration class.



Figure 13, PCB class

The PCB structure is described in Figure 13. A PCB has several components and each of them is of a specified Part type. Each component can be described as a placement and all components have a RefDes, Reference Description, which is the unique name for its placement. This description is sometimes printed in text on the PCB. The algorithms are build around an Optimizer class from where they inherit functions and also overload the Each optimize function, see Figure 15. algorithm is loaded with MachineConfiguration for description the setup to optimize. If a certain part already has been placed in the feeder slots or the revolver head is populated, this is considered by the proposed algorithms. After the optimization is done the results are exported. Except for these classes there is also a data structure that records static relations and lookup tables. That data structure states what type of nozzle each part needs to be picked with, what kind of feeder group a part is stored in and also some other look up tables for speeding up the optimization. The cost function has its own class for calculating the feeder assignment cost. The cost function takes a MachineConfiguration as parameter and calculated the cost for determinate how well a solution is. How the cost is calculated is described below.



Figure 15, Algorithms classes

3.2 Time factors

As mention in the introduction, there are several time factors in an assembly machine model to consider. This is a list of known time factors.

- Loading of the bare PCB
- Head movements
- Recognition of the fiducial marks
- Component Pick-up
- Component Checking
- Component Placements
- Change time for nozzles

In the model of this thesis there are some simplifications, but the core thoughts originates from Kallio et al. [21] on a realistic simulator of placement machines. Loading of the PCB and the recognitions of fiducial marks are not considered as this is the same operation for every setup. The total production time for a machine setup is given by Equation 2. Here we recognize that the slowest revolver is the bottleneck of the

Equation 2, Total time

production time. For the calculation of time used by a revolver head, let G be the number of *task blocks*, number of times the revolver goes from picking components in feeder bank to placing components on the PCB, CC_j the time for picking components

Time for revolver
$$=\sum_{j=1}^{G} (CC_j + CP_j)$$

Equation 3, Time for a revolver

CHALMERS, *Optimization of the feeder assignment for PCB assembly machines*, Master Thesis 2009:

for task block *j*, and *CPj* the time of placing components for task block *j*. Then, the time for each revolver can be calculated as Equation 3. CC_j can be given as Equation 4 where *A* is number of components to place, MP_{ij} is the time to move to the pickup position of component *i* in task block *j* and P_{ij} is the pick-up time for component *i* in task block *j*. CP_j can be describe as Equation 5 where *A* is number of components to place, MI_{ij} is the movement time to the placement position for component *i* of task block *j* and I_{ij} is the placement time for component *i* in task block *j*.

$$CC_j = \sum_{i=1}^{A} MP_{ij} + P_{ij}$$

Equation 4, Pick-up phase

$$CP_j = \sum_{i=1}^A MI_{ij} + I_{ij}$$

Equation 5, Placement phase

3.3 Cost function for evaluating feeder assignments

The quality of the feeder assignment is evaluated by a cost function. As the main focus of this thesis is the solution of the feeder assignment problem the cost function looks on that part of the PCB assembly problem. Therefore the cost function considers the feeder setup, the settings of the revolver heads and the PCB and calculates a cost for it. The cost function does not suppose that the placement problem has been solved optimally. In contrast to that a greedy approach is used. This simple procedure creates a placement order and then calculates the cost for it using the time functions mention above. The reason to trust on a greedy approach for placement order is sufficient due to the simple nature of the cost function. The procedure for evaluating the cost is described as the following pseudo-code and is called *S*.

```
ComponentToPlace = Number of components to place for revolver
Cost = 0
CurrentPosition = Center of PCB
While ComponentToPlace is greater than zero
For every spindle in Revolver
If first spindle then
F = Component, with matching nozzle as spindle, in feeder bank with most
placements left
Else
F = Closest feeder bank with matching nozzle between spindle and component
End if
Increase Cost with movement time from CurrentPosition to feeder slot F
```

CHALMERS, *Optimization of the feeder assignment for PCB assembly machines*, Master Thesis 2009:

```
Increase Cost with pick-up time for component in F
   Increase Cost with placement time for component in F
   Increase Cost with an average time for moving between placements
   Update CurrentPosition to feeder slot F.
   Decrease ComponentToPlace
 End for
 If revolver needs to verify some components in a camera station
   Increase Cost with movement to camera Station
   Update CurrentPosition to camera station
 End if
 Increase Cost with movement to average position for component in the first
 Nozzle
 Update CurrentPosition to average position for component
 Increase Cost with movement to center of PCB
 Update CurrentPosition to center of PCB
End while
```

As can be seen there is no consideration of the placement position in *S* except for the first component in every task block. This is because the placements can be done in many different ways and therefore that sequence is excluded. The average time for moving between placements is analyzed by Valor's software using several different PCB job.

The time for placements head movements is determinate by the longest axial distance, because the head moves independently in the x- and y-directions. The time in millisecond for the particular machine is the distance in millimeters times 0.5 plus 132. This has been verified from the movement graphs given by Valor, it is not a perfect match but close in the general case.

For evaluating the performance of the algorithms in solving the TSP problems an optimized version of the cost function was developed, named STSP. It is almost the same as the previous cost function, S, but there are some simplifications and the distance calculation are modified to reflect the TSP. The pick-up order in procedure STSP is same as procedure S for TSP problems. The cost is calculated as this:

```
Find component that needs the nozzle for the last spindle in revolver
Set CurrentPosition to that component's feeder slot
Set Cost to zero
For every spindle in head
Find component that needs the nozzle for current spindle
Set F to feeder slot for that component
Increase Cost with Euc2D between CurrentPosition and F
Update CurrentPosition to F
End for
```

Distance between positions is calculated with Euclidean distance function for 2D, which is based on Pythagorean formula, $distance = \sqrt{(\Delta x)^2 + (\Delta y)^2}$ which is used in general TSP problems.

3.4 Revolver setup

How to populate the revolver head with nozzles in an optimal way is a hard problem, because this depends on two NP-hard problems, the placement problem and the feeder assignment problem. The task in this thesis is to evaluate the performance of our proposed algorithm in Valor's software. Therefore, the nozzle to head assignment technique that is used in this thesis is the same as in Valor's software. The technique aims at minimizing the number of task blocks. The algorithm works in following ways:

```
Populate revolver with one nozzle of each type that is needed for placing the
components
While space left in revolver
Find nozzle with highest ratio, placements with that nozzle / nozzles of that
type already in revolver
If two or more nozzle has the same ratio choose the one with the most
placements
Add that nozzle to Revolver
Decrease space left in revolver
End while
Sort revolver by first nozzle type count and second nozzle name
```

For an example, if a revolver with 10 spindles should place 12 components with nozzle A and 5 components with nozzle B and 7 components with nozzle C and 1 component with nozzle D the revolver will look like this; 4 of A, 3 of C, 2 of B, 1 of C.

This algorithm does not guarantee the finding an optimal placement order. It is said that it will minimize the number of task blocks to the optimal but this has not been proven.

3.5 Algorithms

Three different algorithms have been developed for solving the feeder assignment problem and also a variation of two of them is tested. The first algorithm is a simple randomized setup algorithm with heuristics, the second applies local search technique and the last one is a genetic algorithm. In order to do a fair comparison of the algorithms, they are run for a limited period of time. This will be achieved by adjusting the number of generations and the number of new starts.

3.5.1 Randomized

The algorithm consist of a loop to generate a randomized feeder assignment and then the feeder banks are packed, meaning that every component is moved towards the center of the feeder bank so that no spaces exist between the components. After that the cost for the feeder setup is calculated and the best solution is kept. See Appendix 1 for pseudo-code.

3.5.2 Local Search

Local search is performed in a straight forward manner. The neighborhood is rather large; swapping of each pair of feeder slots is tested. If a better solution is found it is kept and the same is iterated until no more single swaps produce a better solution. After that the local search is restarted from a new randomized feeder setup. The algorithm is terminated when the given time limit of the running time is reach. A pseudo-code of the algorithm can be found in Appendix 1. An extended version of local search was also developed, it has the same basic idea as the ordinary local search but after no improvement could be found by swaps, the algorithm tries to invert the order of the components of a group of feeder slots. For an example if we have components in the order <1,2,3,4,5,6,7,8> and we invert the order of components from position 2 to 5 the result should be <1,5,4,3,2,6,7,8>. This operation is done for every position and the length from two to the end of feeder bank.

3.5.3 Genetic Algorithm

The genetic algorithm applies the PMX crossover and ranked roulette wheel selection method. The mutation step consists of randomized swapping of components. One problem that was discovered with an ordinary PMX is that it could not handle the situation where several parts can be stored in the same feeder slot. Therefore a modification of PMX was developed, see Appendix 1. The idea is to use the PMX crossover method and if this creates conflicts they are postponed and solved later. The Uniform crossover method was also tested as a second version. The Genetic Algorithms are run with a population of 100 and with 80 children. The mutation rate is set to 5%.

3.6 Lower bound

For knowing how well the results are, a lower bound algorithm has been developed. The goal was to produce a lower bound function that gives as high value as possible. Let n be the number of components to place, pp the time to rotate revolver head one step plus the minimum time to place a component, t the number of needed task blocks, c the closest distance between a feeder slot and the center of board, r the number of revolver heads and m the number of placements for the part that have most placements. Then the lower bound can be calculated as in Equation 6.

Lower bound =
$$Max\left\{\frac{(n*pp+t*c*2)}{r}, m*pp+t*c*2\right\}$$

Equation 6, Lower bound

3.7 Test data

For test data we had several PCB products to choose from. Some PCB products where with rather few parts and others have more parts than the capacity for the machine. Therefore we constructed PCB jobs with a few parts up to the limit for the machine. For some PCB jobs we have used subsets of the required parts for the PCB products as a job. Theses setups are labeled by PCB-X. In Figure 16 a graphical presentation of instance PCB-9 is showed, this is from the developed program. The dotted red lines on top and bottom of the image indicate the feeder slots, the big green rectangle in center of the image is the PCB, between the feeder banks and the PCB is a bunch of blue dots, this is nozzle bank slots. The white dotes on the PCB mark the component placements.



Two PCB assembly tasks were also constructed such that the optimal solution is easy to calculate. TEST-1 includes 60 parts with one placement of each and the placements are all in the center of the board. The 60 parts are divided by seven different nozzles needed for the pickup. Here the optimal solution is that we have 30 components in each feeder bank. The parts are ordered so that the revolver head is picking up the first component

in slot one and the second component is picked up in slot two and so on. Is means that the revolver goes to the feeder bank and do a straight line move over the feeder bank and then go to the placements in the middle of the board. TEST-2 consists of 11 parts with a total of 240 placements. The optimal solutions is such that 5 parts are in one feeder bank and 6 parts in the other and each revolver head has 120 placements and they are done in exactly four task blocks.

4 Results

The test results can be divided into three categories. The first category answers to the question on how well the algorithms are to solve the optimizing problem according to the simplified cost function. The second category tells how well is the relation between the cost function and the production time from Valor's software. The last and the most interesting question is how well the algorithms are to solve the whole problem. We make the following abbreviations; R stands for the random algorithm, LS standard local search algorithm, LSE extended version of local search with the inversion step, GAPMX genetic algorithm with PMX crossover and GAU genetic algorithm with uniform crossover. In order to give a fair comparison each algorithm was run for the same time, preferably 40 seconds but no more than 50 second. The tests are performed on an ordinary laptop with a 1.7 GHz processor and 1 GB of RAM. Each algorithm is run ten times and the average values of these runs are displayed. We focus on the average cost or production time instead of the lowest cost or production time, this is because there are lots of random decisions in our approach and some problem instances could be easy by luck, so we are interested in the average case. Because of the time limit and the different size of problem the algorithms has different number of new starts and generation for the different problem. Algorithm R did 60'000 to 120'000 new starts. Algorithm LS did 2 to 190 new starts depending on problem, algorithm LSE did 1 to 110 new starts and the generic algorithms did 700 to 2700 generations. For generating the production time from Valor's software the feeder setup is imported to the software and the placement order optimizing is done three times and after that the average productions time is calculated. From the final results it is observed that the order optimizing gives in average production time 0.68% from the lowest production time for the same feeder assignment. In Table 1 the data of the different PCB jobs are showed along with the best production time observed, lower bound and the best cost observed by the cost function. The last column is the average production time for Valor's feeder optimization after ten runs. This shows that there are some improvements available to

PCB name	PCB number	Parts / Placements	Lower Bound	Best Cost Observed	Best prod. Time Observed	Valor
PCB-1	73-10400-03	8 / 78	15238	15494	15815	15913
PCB-2	73-10412-01	36 / 256	38610	41039	44959	48009
PCB-3	73-10400-03	32 / 345	51991	54746	55298	58837
PCB-4	73-10412-01	35 / 252	38052	40622	44024	47772
PCB-5	73-10098-05	62 / 487	73410	77637	86615	91358
PCB-6	73-10098-05	105 / 201	30293	33740	42653	44038
PCB-7	73-10412-01	13 / 509	76479	79048	76956	80486
PCB-8	73-10142-52	32 / 109	16493	17937	24212	25720
PCB-9	73-10142-52	45 / 409	61563	64855	70725	75892

Table 1, PCBs in number

do for Valor's software. The improvements that can be done are from 0.62% to 7.85% with an average of 5%.

4.1 Performance of the algorithms subject to the cost function

Table 2 shows the results of the TEST runs. The results are given as percentage from the known optimal solution using procedure S. TEST-1f and TEST-2f is the same as TEST-1 and TEST-2 but here the revolver is fixed to the nozzle that is used in the optimal solution. Here we can observe that the algorithms don't have any problems to find the optimal solution for the setup with just a few parts but with lots of placements. The optimal solution has been compared also to the lower bound. For TEST-1 the algorithms showed worse performance in finding good solutions. For TEST-1 the optimal solution is 28.47 % higher than the lower bound and for TEST-2 the optimal solution is 7.28 % higher than the lower bound.

	R	LS	LSE	GAPMX	GAU
TEST-1	3,52 %	0,00 %	0,00 %	1,12 %	1,46 %
TEST-2	0,14 %	0,00 %	0,00 %	0,08 %	0,20 %
TEST-1f	6,80 %	8,24 %	6,92 %	3,31 %	4,08 %
TEST-2f	0,16 %	0,00 %	0,00 %	0,02 %	0,03 %
				- ~	

Table 2, TEST results with procedure S

The performance in solving the PCB jobs of the algorithms of the present studies is compared to each other in Table 3. The optimal solution is not known here. The percent ratio is compared to the best algorithm. The last column in Table 3 is the ratio between the best solution observed and the lower bound. It turns out that the different algorithms

PCB	R	LS	LSE	GAPMX	GAU	Best
PCB-1	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	1,68 %
PCB-2	1,47 %	0,75 %	0,64 %	0,35 %	0,00 %	6,29 %
PCB-3	0,79 %	0,33 %	0,39 %	0,00 %	0,04 %	5,30 %
PCB-4	1,23 %	0,39 %	0,40 %	0,38 %	0,00 %	6,75 %
PCB-5	1,94 %	0,67 %	0,50 %	0,11 %	0,00 %	5,76 %
PCB-6	3,71 %	0,42 %	0,00 %	0,15 %	1,59 %	11,38 %
PCB-7	0,00 %	0,06 %	0,16 %	0,23 %	0,21 %	3,36 %
PCB-8	0,85 %	0,28 %	0,12 %	0,37 %	0,00 %	8,76 %
PCB-9	1,21 %	0,34 %	0,19 %	0,09 %	0,00 %	5,35 %
Average	1,24 %	0,36 %	0,27 %	0,19 %	0,21 %	
		Table	3. PCB resul	ts with proce	dure S	

are almost equal in producing good result except for R. For PCB-1 an exhaustive search was done and the best solution found by the algorithms is also the optimal solution subject to cost function. The performance of the algorithms to solve the TSP problem for feeder bank assignment problem with procedure STSP was also tested, see Table 4. Problem instances r4 and r11 are small TSP problems with 4 and 11 cities placed by random and the optimal solution is calculated by testing every combination. Problem instance wi29, dj28, xqf131 has been taken directly from Georgia Tech's TSP homepage [22] where the optimal solution is known.

	R	LS	LSE	GAPMX	GAU
r4	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
r11	2,65 %	0,00 %	0,00 %	0,00 %	0,00 %
wi29	134,70 %	5,25 %	5,23 %	9,89 %	8,27 %
dj38	191,27 %	22,21 %	28,16 %	33,42 %	19,71 %
xqf131	581,66 %	97,48 %	104,90 %	399,02 %	247,94 %

Table 4, TSP problem results

4.2 Relation between cost function and production time

In Figure 17 results of all test runs for all the algorithms are displayed using the cost from procedure S in the y-axis and the actual production time from Valor's software in x-axis. The groups of dots are the repeated runs for each PCB job. The straight line is the trend line regression for the result. The relation is almost linear and not far away from a 1:1 match. One thing to mention is that the loading of PCB is not a part of the procedure S and this is typically of the size 2500 milliseconds. In the case with PCB-1 (Figure 18) we can see that the actual production time can vary up to 423 milliseconds for the same cost calculated by procedure S. As mention earlier it has been observed that the average difference in production times is 0.68% for the same feeder assignment. In the worst case it has been observed that the production time could differ 7.5% from the best production time to the worst case for the exactly same feeder assignment. The average different in production time for ten runs compared to the lowest production time found in the ten runs for each PCB is summarized in Table 5

PCB-1	PCB-2	PCB-3	PCB-4	PCB-5	PCB-6	PCB-7	PCB-8	PCB-9
0,22 %	0,68 %	0,61 %	0,90 %	0,80 %	1,00 %	0,48 %	0,49 %	0,98 %
Table 5. Average difference in production time for exact same feeder assignment								

The production time is therefore not treated as a fixed value instead it is an indication of how well the final production time can be after the placements order has been solved. For PCB-2 (Figure 19) and PCB-5 (Figure 20) it is observed that the trend line is not as good as in Figure 17, and the line is almost horizontal for PCB-2. Two interesting observation can be done from the figures; the instance which gives the lowest cost

according to procedure S also gives the lowest production time. For PCB-8 (Figure 21) the trend line points in the right direction but the relation between the cost function result and the production time is not perfect. The instance that gives the lowest cost, by procedure S, gives not the lowest production time neither is it in the top ten production time and the best production time is not in the top ten instances with lowest cost by procedure S.



Figure 17, Relation between procedure S and production time for all PCBs



Figure 18, Relation between procedure S and production time for PCB-1



Figure 19, Relation between procedure S and production time for PCB-2

CHALMERS, *Optimization of the feeder assignment for PCB assembly machines*, Master Thesis 2009:



Figure 20, Relation between procedure S and production time for PCB-5



Figure 21, Relation between procedure S and production time for PCB-8

CHALMERS, *Optimization of the feeder assignment for PCB assembly machines*, Master Thesis 2009:

4.3 Performance of the algorithms to solve the whole problem

The performance of the algorithms is summarized in Table 6. Here we can see how well the feeder assignments actually are in the real production after the placement order optimizations has been done. Each algorithm is compare to the result of Valor's feeder optimization. The production time for Valor's software is the average production time after ten runs of feeder optimization from a random start and the placements order optimization. As can been seen in the table, every algorithm manage to get better production times than Valor's software. The best algorithm in an average turns out to be the genetic algorithm with Uniform crossover but it is not the best algorithm for every PCB jobs. The results differ a lot between different PCB jobs. Some PCB jobs gets up to 3.5 percent improvements against Valor's optimization but some other will have just under a percents improvement and for the first PCB job the results are even worse. The best algorithm is only slightly better than the others. Interested things are that the next best algorithm is the random based algorithm, because it operates very badly in the task to find the lowest cost by procedure S.

РСВ	Valor	R	LS	LSE	GAPMX	GAU
PCB-1	100,00 %	101,62 %	101,39 %	101,31 %	101,09 %	100,98 %
PCB-2	100,00 %	97,29 %	98,67 %	98,47 %	98,84 %	96,92 %
PCB-3	100,00 %	97,25 %	99,42 %	99,97 %	98,46 %	97,67 %
PCB-4	100,00 %	97,22 %	96,93 %	97,64 %	96,42 %	97,08 %
PCB-5	100,00 %	98,89 %	99,47 %	98,73 %	98,31 %	97,64 %
PCB-6	100,00 %	100,73 %	99,67 %	100,71 %	100,93 %	100,82 %
PCB-7	100,00 %	97,18 %	97,52 %	97,93 %	97,90 %	98,27 %
PCB-8	100,00 %	98,92 %	99,04 %	99,10 %	100,04 %	99,39 %
PCB-9	100,00 %	99,88 %	98,15 %	98,46 %	98,91 %	96,50 %
Average	100,00 %	98,78 %	98,92 %	99,15 %	98,99 %	98,36 %

Table 6, Performance of the algorithms solving the final problem

5 Discussion

The first step for this thesis was to develop a machine model software where it is possible to import, optimize and export the results to Valor's software. This has been working well with some minor problems that have been solved. It has also been shown that there are improvements to be done in Valor's software and some more production seconds to earn. In the task for solving the problem subject to the cost function the algorithm had different success rates. For constructed problems and the PCB job where the optimal solution could be calculated, the proposed algorithms of the present work found the optimal solution for the most cases, as seen in Table 2. For TEST-1 where we have 60 parts in every feeder bank the task is more complicated and it is almost to solve two TSP problem with 30 cities. This is not all true because we don't have unique nozzle need for each part, therefore some parts can swap places and we still have an optimal solution, this is not possible for TSP. TEST-2 is an simpler problem to solve as we have fewer components to place in the feeder banks. For TEST-1f the algorithms have more difficulties to find the optimal solution. One theory why this happens is because the nozzles are fixed in the revolver head some solution have a greater number of task blocks than if the nozzles were repopulated in the revolver head for each feeder assignment in order to minimize the task blocks. This leads to more local minima and local search algorithms have more difficulties than GA to get out of local minima and find the global minimum.

The algorithms performance, Table 3, to find good solutions where the optimal solution is unknown is not so diverted. The algorithms are equally good but the random based algorithm somewhat worse. GA solves the task better than LS but the difference is too small in order to say some conclusions from that. For the most PCB jobs and in special for PCB-7 the best solution is not far away from the lower bound. The algorithms solve the task well and produce solutions near optimal solution or the optimal solution for the feeder assignment problem subject to the cost function. One factor that affects the solution is the running time for the algorithm. We have chosen a rather short running time because industry manufactures work daily with planning PCB production and they can't wait on the computer for long time. The randomized based algorithm gives not much better results by increasing their running time. As it is now the randomized based algorithm checks around 80 000 feeder assignments in 40 seconds. If the time is double so that 80 000 more feeder assignments are checked the probability to find a better solution then is found so far is not high. But for the genetic algorithm is takes a longer time before the population converts to a good solution and its results improve then the running time is increased.

In the case of the TSP relaxation problem the algorithm has big difficulties for bigger problem instances. It founds the optimal solution for smaller problems but the bigger ones the results are not good. The theory is that the LS has difficulties to find a good solution as the relaxation of the problem makes the 2-opt step work in a different way.

Also the relaxations of the problem produces lots of local minima. LS has been proven to work well for TSP problems only when the starting setup has some potential.

The cost function that has been developed in this thesis has been proven to work well. We have an almost 1:1 relation when considered all the PCBs. But it is not as good for the last percentage from optimal solution. This can be seen in Figure 18 to Figure 21. For the case with PCB-1 it is clear that the cost function fails to model the small difference in the production time caused by the changes in the feeder assignment. Two hypotheses why these errors occur success themselves. The first is that the simplified placement order has not been good. The actual placements order differs much from the simplified. The information of the actual placements is not considered in model. The second hypothesis is that the cost function is omits some important time factors that affects the production time. However, if we look the best solutions found by our optimizer their real production time may be worse than those of some other not as good solutions. This mirrors in accuracy of our model.

One problem in generating placement order is the big variation of the production time, because one feeder assignment could give results that differ up to 7%. Therefore it is important that the placement order optimization is run several times in order to find the best solution when the product is used in real industrial production environment.

It was observed the approach of the present study that (splitting the problem and applying well known algorithm) produces better solutions than the industrial solution. The approach has lowered the production time by 1.67% with GAU. It also showed up that there is more space to explore the solution method for revolver head machines and in this way lowers the production time. With a better algorithm and cost function there is a possibility to lower the production time to 5% below current average production time in Valor's software. It was also shown that even though GA with PMX crossover solved the optimizing problem subject to the cost function equally well as with Uniform crossover, the feeder setup from GAU had better feeder assignment structures that allow better placement orders and production times. The random based algorithm was the second best algorithm according to the production time and this algorithm have more parts by random and are not tuned for matching the cost function. Because of this, one can draw conclusion that the cost function is not perfect for the placement order because the random algorithm sometime beats the local search algorithm.

6 Conclusions

This thesis has proposed and evaluated different algorithms and heuristics for the feeder assignment problem. The results show that the algorithms are capable to produce good results that are near optimal subject to the cost function. The algorithms also found solutions that are better than the exiting algorithm in Valor's software. The algorithms are almost equally well to solve the task compared to each other. The random based algorithm is a little bite worse than the others but the inaccurately of the cost function makes the final results similar. The crossover function for the genetic algorithm affects the algorithms performance and for this model the Uniform crossover gives slightly better results.

The expected improvements in the local search algorithm for extending the neighborhood didn't appear. In the end it didn't matter too much which algorithm one used, they all give almost the same result. Therefore, the task to get better production times is to improve the cost function. This approach with the current cost function gives a slightly better result than Valor's software but as has been seen previous the improvements could be around 5%.

How big the real improvements are on the production floor is hard to predict, because the placement order optimization solve the problem with some percentage difference. Further, the production simulation that is used in Valor's software also has some percentage difference to the real production time by the machine. Therefore it is not possible to say that the production is improved in the factories.

7 Future Work

As mention earlier the cost function needs more research. Is it possible to define a good cost function without solving the placement ordering or is it possible to solve the placement order in the same procedure as solving the feeder assignment problem? One interested idea is to solve the placement order problem first with all parts pickup position in the middle of the feeder bank and then after the placement order has been solved to spread the parts out in the feeder bank. The placement order affects the final production time and it omission will never give good solution. Therefore this part needs to be understood and researched more.

The pick-up time in feeder slots, the rotating of revolver head and preparing a new component in the feeder slot are sometimes done simultaneously in a machine. This and other complex movements need to be modeled more exactly in order to improve the cost function.

For the local search algorithm it has been proven that they are affected by the initial solution. Therefore a future work is to come up with a good initial solution to the feeder assignment problem.

Future work with heuristic algorithms can involve a doing some more precalculations on where the parts should be in the feeder banks. Instead of just packing the components also move them as a group up and down the feeder bank.

The generic algorithms have been tested with implementation of a local search step, but this has not showed better results. Therefore future work would be to improve and research on how to implement local search steps to the generic algorithms for better results.

8 References

1. Volgenant, A and de Waal, A. *A heuristic for multiple-feeder PCB manufacturing*. s.l. : Journal of the Operational Research Society 57, pp. 1134–1141, 2006.

2. Grunow, M, et al. Operations planning for collect-and-place machines in PCB assembly. s.l. : Computers & Industrial Engineering 47, pp 409–429, 2004.

3. Ayob, M, Cowling, P and Kendal, G. Optimisation for Surface Mount Placement Machines. s.l. : Proceedings of the IEEE ICIT'02, Bangkok, 11-14 Dec, pp 498-503, , 2002.

4. Leipälä, Timo, Johnsson, Mika and Nevalainen, Olli. Determining the Manual Setting Order ofComponent on PCB Boards. s.l.: Journal of Manufactoring Systems Vol. 15 / No. 3 pp 155-163, 1996.

5. Ayob, Masri. Optimization of Surface Mount Device Placement Machine in Printed Circuit Board Assembly. s.l. : University of Nottingham, 2005.

6. Johnsson, M and Smed, J. Observations on PCB Assembly Optimization. s.l.: Electronic Packaging & Production, Vol. 41, No. 5, pp. 38–42, 2001.

7. **Smed, Jouni, et al.** *Job Grouping Surface Mounted Component Printing.* s.l. : Robotics and Computer Integrated Manufacturing, Vol 15, No. 1, pp 39-49, 1999.

8. Johnsson, Mika. Operational and tactical level optimization in printed circuit board assembly. s.l. : Turku Center for Computer Science, 1999.

9. Valor Computerized Systems. Valor Computerized Systems. [Online] http://www.valor.com.

10. **Universial Instruments.** Genesis Platform. [Online] [Cited: September 2, 2009.] http://www3.uic.com/wcms/WCMS2.nsf/index/Products_17.html.

11. Kleinberg, Jon and Tardos, Éva. *Algorithm Design.* s.l. : Pearson Education Inc, pp 661-671, 2006.

12. **Metropolis, N., et al.** *Equation os state calculations by fast computing machines.* s.l.: J. Chem. Phys. 21, 1087-1092, 1953.

13. **Kittel, Charles and Kroemer, Herbert.** *Thermal Physics, 2nd ed.* s.l. : Freeman & Co.: New York, 1980.

14. Mitchell, Tom M. Machine learning. s.l. : McGraw Hill, 1997.

15. Holland, J.H. Adaptation in natural and artigicial systems. s.l.: University of Michigan Press, 1975.

16. Ho, W. and Ji, P. A genetic algorithm to optimise the component placement process. s.l. : Int J Adv Manuf Technol, pp 1397–1401, 2005.

17. Yang, Jiaping and Soh, Chee Kiong. *Structural Optimization by Genetic Algorithms with Tournament Selection.* s.l. : Journal of computing in civil engineering, pp 195-200, 1997.

18. **Goldberg, D.E. and Lingle, R.** *Alleles, Loci, and the Traveling Salesman Problem.* s.l. : Proc. of the 1st Int. Conf. on Genetic Algorithms, pp 154-159, 1985.

19. **Janlert, Lars-Erik.** Nationalencyklopedin. [Online] [Cited: September 7, 2009.] http://www.ne.se/lang/heuristik.

20. Schrijver, Alexander. On the history of combinatorial optimization (till 1960). *Handbook of Discrete Optimization, pp 1-68.* 2005.

21. Kallio, Kai. Joustavan ladontakoneen suoritusajan arvioinnista. s.l.: Turun Yliopisto, 2008.

22. Office of Naval Research, National Science Foundation and Georgia Tech. Traveling Salesman Problem. [Online] School of Industrial and Systems Engineering at Georgia Tech, August 8, 1991. http://www.tsp.gatech.edu.

Appendix 1: Algorithms

Randomized algorithm

Set BestSolution to Ø
While time left
Create a randomized feeder assignment F
Pack F by moving parts toward center of feeder bank so that there is no empty
feeder slot between parts
If F has lower cost than BestSolution
Update BestSolution to F
End

Return BestSolution

Local Search

```
Set BestSolution to Ø
While time left
Create a randomized feeder assignment F
Repeat
For every feeder slot
Swap feeder slot with every other feeder slot
If swap lower the cost
Keep it and update F
Else
Undo swap
Until no improvements has been done to F
If F has lower cost than BestSolution
Update BestSolution to F
End
Return BestSolution
```

Local Search Extended

```
Set BestSolution to Ø
While time left
Create a randomized feeder assignment F
Repeat
Repeat
For every feeder slot
Swap feeder slot with every other feeder slot
If swap lower the cost
Keep it and update F
Else
Undo swap
Until no improvements has been done to F
For every feeder slot, P
For value 2 to the length of feeder bank, L
```

```
Invert the span of feeder slot from P and length L
If swap lower the cost
Keep it and update F
Else
Undo Swap
End for
End for
Until no improvements has been done to F
If F has lower cost than BestSolution
Update BestSolution to F
End
```

Return BestSolution

Genetic Algorithm

```
Initializes random generated chromosome until the population limit are reach
For a number of generation
Pre-calculate Ranked roulette wheel
For a number of new chromosomes
Select two parents using Ranked Roulette Wheel
Let the two parents breed a new chromosome thru crossover
Mutate the new chromosome
Find worst chromosome in population
If worst chromosome is worse than new chromosome
Replace chromosome with the new one
End for
End for
Return best chromosome in population
```

Genetic Algorithm - Ranked Roulette Wheel pre calculation

```
Set r to one
Set n to number of chromosome in population
Loop n times
Find worst chromosome what don't have be ranked
Set chromosomes rank to 2*r/(n*(n+1))
Increase r by one
End
```

Genetic Algorithm - Ranked Roulette Wheel selection

```
Set Rand to a random floating number between 0 and 1
For every chromosome, C, in population
If Rand is lower than the sum of every chromosome's rank so far
Return C and break
End for
```

Genetic Algorithm - PMX crossover

```
Set Conflicts to \emptyset
```

```
CHALMERS, Optimization of the feeder assignment for PCB assembly machines, Master Thesis 2009:
```

```
Set Child to Ø
 Randomly select a span of genes from P1 and copy them directly to the Child.
 Note the indexes of the segment
 Looking in the same segment positions in P2, select each value that hasn't
 already been copied to the child.
 For each of these values (a):
   (i) Note the index of this value in P2. Locate the value, V, from P1 in this
   same position.
   Locate this same value in P2
   If the index of this value in P2 is part of the original span
    If this value have been visit before
      Add (a) to Conflicts
    Else
      Go to step i. using one of the values from the index position by random
   Else
    Insert (a) value into Child in this position.
 End for
 Copy any remaining positions from P2 to Child.
 For every components in Conflicts
   Add component at a empty feeder slot by random in Child
 Return Child
Genetic Algorithm – Uniform crossover
 Set P1 and P2 to two different parent chromosomes by Ranked Roulette Wheel
 Set Child to Ø
 Set Conflicts to Ø
 For every component, C
   Set P to one of P1 and P2 by random
   Find C's position in P
   If that position is empty in Child
    Add C to Child by position in P
  Else
    Add C to Conflicts
 End
 For every components in Conflicts
   Add component at a empty feeder slot by random
 Return Child
```