Forecasting and optimization approach for scheduling of order picking in a warehouse

by

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Ákvörðunar- og spálíkan fyrir tínslu pantana í vöruhúsi

Úrdráttur

Að taka saman vörur eftir pöntunum viðskiptavina (vörutínsla) er eitt mikilvægasta ferlið í vöruhúsum. Það kallar á mikið vinnuafl og getur valdið töfum ef það er ekki skipulagt vel. Flest nútíma vöruhús nota vöruhúsatölvukerfi til að hafa yfirsýn á sínum daglega rekstri s.s. gjaldfæra vinnu við pantanir viðskiptavina og tímaskrá verk og færslur á vörum innan vöruhússins. Upplýsingar geymdar í vöruhúsakerfum gefa mikilvægar upplýsingar um rekstur vöruhússins s.s. nýtingu vinnuafls og geymslurýmis.

Í þessari ritgerð er ætlunin að sýna fram á að nýta má upplýsingar sem geymdar eru í vöruhúsakerfum vöruhúsa til að spá fyrir um hversu langan tíma það taki mismunandi starfsmenn að taka saman mismunandi pantanir viðskiptavina. Takist vel að spá til um verktíma má stjórna vörutínslu í vöruhúsum á hagkvæmari hátt en ella. Pantanir koma óreglulega og eru ólíkar hvað varðar vörutegundir, magn og afhendingartíma. Einnig er sett fram bestunarlíkan með það að markmiði að hjálpa yfirmönnum vöruhúsa við að ákvarða niðurröðun vörutínsluverka á starfsmenn. Bestunarlíkanið lágmarkar tafir á afhendingu og sýnt er fram á að hægt sé að bæta nýtingu vinnuafls verulega með notkun þess. Notuð eru gögn frá raunverulegu vöruhúsi þar sem borið eru saman 10 daga af raunverulegri verk niðurraðarnir við 10 daga af verk niðurraðarnir bestaðar af bestunarlíkani.

Forecasting and optimization model for scheduling order picking in a warehouse

Abstract

Retrieving goods for customers (order picking) is one of the most important processes in any warehouse. It is labor intensive and can cause bottlenecks if not scheduled properly. Most modern warehouses use warehouse management systems (WMS) to get overview of the operation, bill the customers and log activities with timestamps into the WMS database. Information stored in WMS databases can be used to indicate how well the warehouse is operated, for example how well the workforce and storage capability are utilized.

In this thesis we show how the information from the WMS database can also be used to build a forecasting model to predict how long it will take each worker to process orders. Accurate prediction on worker performance is a prerequisite for optimizing the schedule of order picking in warehouses. Orders arrive irregularly both during working hours and after, containing different kinds of goods, in different quantities and with different due dates. We also propose an optimization model to assist managers in scheduling orders to workers with the objective of minimizing delayed deliveries of orders. We use actual data from a real life warehouse. We compare the performance of actual schedules from 10 days of operation with 10 days of schedules created by the proposed optimization model.

Key words:

Forecasting, optimization, order picking, scheduling, warehouse management.

The undersigned hereby certify that they recommend to the School of Science and Engineering at Reykjavík University for acceptance this thesis entitled "Forecasting and optimization model for scheduling order picking in a warehouse" submitted by Einar Hrafn Jóhannsson in partial fulfillment of the requirements for the degree of Master of Science.

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1. Introduction

Warehouses play a central role in most supply chains. They store and redistribute goods between every stage of the supply chain as is illustrated in Figure 1. In his book "Fundamentals of Logistics Management"[1], Lambert stated that more than 750,000 warehouse facilities exist worldwide, including state-of-the-art, professionally managed warehouses, as well as company stockrooms and self-store facilities.

According to Lambert [1] the mission of the company is the driving force for the existence of warehouses in the supply chain. For example, to achieve transportation economies (e.g. combine shipment, full-container load) and to support the firm's customer service policies. Warehouses can therefore be owned by companies at all levels in the supply chain. Ownership is dependent on individual company's strategy and market conditions. Figure 1 illustrates where warehouses are located in the supply chain, often between different levels of the supply chain. Many companies choose to outsource their warehouse functions to third party logistics companies (3PL). 3PL are companies that provide their customers with transportation, storage and distribution services [2].Many companies have in recent years outsourced some or all of their logistics to 3PL [3]. 3PL warehouses should be able to utilize their warehouses and workforce better due to the economy of scale and more evenly distributed load that can be obtained with many users. In order to operate efficiently and benefit from the economy of scale, 3PL warehouses have to be able to store and retrieve goods (order picking) for costumers with high level of efficiency.

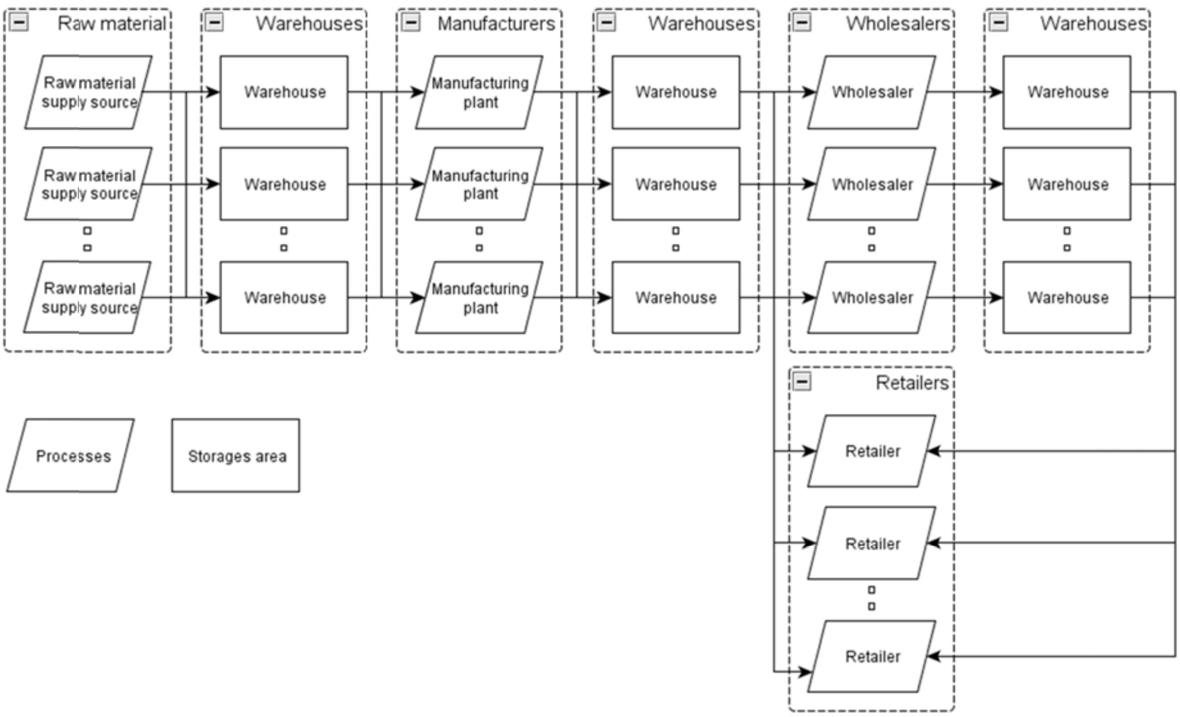

Figure 1: A general flowchart of supply chain from raw material to retailers.

Warehouses have traditionally the role of storing goods and materials in between processes. With more emphasis on limiting cost in the supply chain the warehouses have become more centralized in recent years, taking the role of distribution centers in the supply chain. This has reduced the cost by reducing transportation in the supply chain with the added benefit of reducing complexity (see Figure 2).

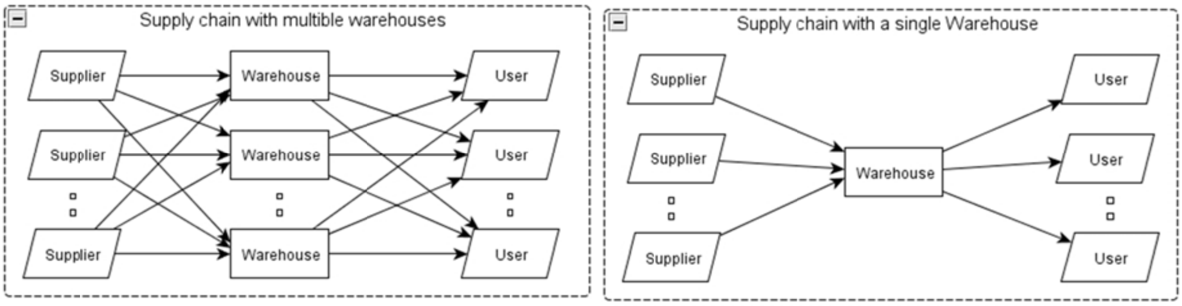

Figure 2: The figure illustrates how the number of transportation legs can be reduced by using fewer warehouses. (Supplier, Warehouse)

A flowchart of the operation of a warehouse is shown in Figure 3. Products are received from suppliers (1) in the receiving area (2). They are then either put into reserve storage (3) or directly put into active storage (4). Order picking is done in active storage and then sorted and packed in accumulating area (5). After packing, the orders are moved to shipping area (6) where they are picked up by forwarding agent.

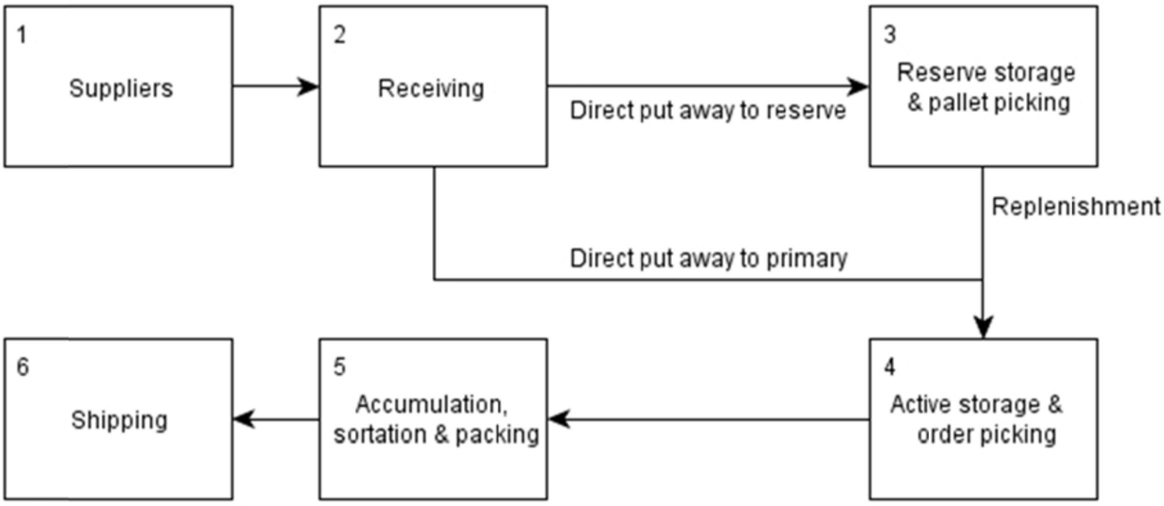

Figure 3: A flowchart of a typical warehouse process [2].

Warehouse management systems (WMS) play a central role in managing the warehouse. More advanced systems keep track of movement and storage of material within the warehouse by using barcodes, wireless LANs and mobile computer (MC) with barcode scanners. Every movement of material within the warehouse is logged into WMS database with timestamps.

WMS can receive orders directly from costumers electronically or they can be manually put into the WMS through its user interface. Orders consist of order lines, each line containing a unique stock keeping unit (SKU) in a specific quantity. WMS system splits order lines based on quantity in pallet picks, case picks and broken case (units) picks.

Order picking is the process of collecting SKUs from storage to fulfill the costumer's orders, based on information from the WMS. There are many types of order picking systems, the most commonly used are *Picker-to-parts* order picking systems that are used in the majority of warehouses around the world [4]. There are two types of picker-to-parts systems: *low-level* picking and *high-level* picking. In low-level order picking systems, the worker retrieves requested items from storage racks, while traveling along the storage corridor by foot or driving a forklift. High-level order picking or automatic storage and retrieval systems (AS/RS) are mostly used in corridor bound cranes that retrieve one or more units and bring them to a pick position. There are several other organization variants of high and low pick-to-part systems. The two basic ones are picking by article (batch picking) and picking by order (discrete picking). In batch picking multiple customer orders are picked simultaneously by a worker. In discrete picking one order is picked per picking tour.

80% of warehouses in the world use low-level *picker-to-parts* systems where the worker drives or walks along the warehouse corridors to pick items [4]. Figure 4 describes the low level order picking process (discrete picking) that starts with the release of an order from the warehouse foreman to the floor where the workers locate the orders SKUs in active storage locations and put correct number of units on pallets.

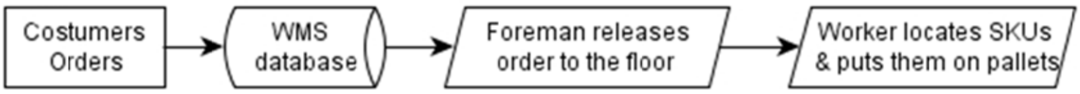

Figure 4: A simple flow chart of order picking.

Warehousing contributes to about 20% of logistics cost [5] and order picking is estimated to account for 55% of the total warehouse operation expense [1]. This implies that the total cost of retrieving goods accounts for about 10% of all the cost in the supply chain which emphases the importance of order picking.

In this thesis we will study real world problems from a 3PL warehouse with the goal of optimizing its order picking scheduling. According to the management of the warehouse the main goal of the warehouse is to maximize customer satisfaction. To be able to schedule order picking we have to know the time each worker takes to perform each order picking task before the worker is assigned to that task. All order picking is done by human workers and it is therefore necessary to estimate how much time it takes each worker to pick each order.

We propose a forecasting method based on our case study foreman's suggestions and compare it to another forecasting method that is based on a standard way of measuring order picking performance in warehouses.

Chapter 2 will explain further the problem we are working with. In Chapter 3 we propose a solution approach for the problem and in Chapter 4 we show results from testing the approach with several actual problem instances. Finally in Chapters 5 and 6 we draw conclusions from our work and discuss future work and software implemented.

2. Description of the case study's warehouse

Our case study warehouse is located in the main shipping port area in Iceland. The warehouse storage can keep up to 12 thousand full size pallets (Euro pallets) and has 12 thousand active storage locations of mixed sizes. The main materials that are normally stored are food (frozen and dry), chemicals and goods that have not been taken through custom, mainly beverages.

2.1 Workers, order arrival and delivery

There are 25 employees that work in the warehouse, both workers and managers doing jobs like order picking, transportation and managing. The warehouse uses low level order picking system. There are 9 to 11 workers that are responsible for the order picking process and they are organized into two overlapping shifts. Shift one begins work at 08:00 and ends work at 16:30 and shifts two begins work at 09:30 and ends work at 18:00.

On an average workday 114 orders arrive and 171 pallets are used to store items on. On average it takes 23 minutes to complete an order picking task. The average number of boxes picked in a day is 5.537 and the average number of SKUs picked per day 3.138.

The warehouse foreman's role is to assign order picking tasks to his workers. With the help of the WMS and mobile computers (MC) the workers are directed to right locations to pick up the ordered SKUs. Normally the first available worker selects the oldest order picking task that he sees, see Figure 5. The foreman monitors the workers progress and assigns a specific worker to a critical order if he feels that delivering time will possibly not be met.

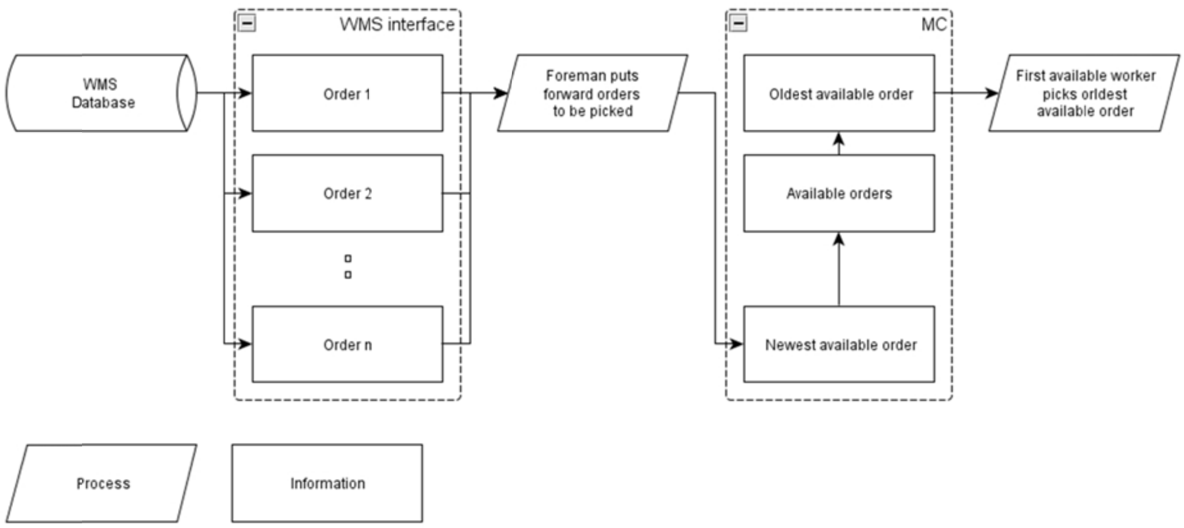

Figure 5: The flow of order picking tasks from the WMS to the foreman an than to the worker.

If delivery time is not met or wrong SKUs are picked it can result in customer's dissatisfaction and possibly break up a business relationship which then directly affects the profits of the company as well as its reputation.

The main rule of order delivery is that orders that come before noon have to be delivered the same day. Orders that come after noon have to be completed before noon the day after. Many of the orders are dependent on carriages time plan so if an order comes before noon and there is no trip until the day after the delivering time is set for the next day according to carriages time plan. Orders can arrive around the clock but most of them arrive during working hours 8:00-18:00.

2.2 Warehouse Management System (WMS)

Our case study warehouse uses a Warehouse Management System (or WMS) supplied from Manhattan associates' [6]. They are a leading company in supplying companies with warehouse management systems. The WMS system is supplied with mobile computers (MC) to direct workers and for tracking of SKUs physical location. WMS accepts two kinds of locations for SKUs, on pallets (case) or in active storage. WMS also tracks the pallets' physical locations. Pallets can be in reserve storage, in accumulation or as part of order picking task. Whenever worker performs any action on SKU, order or pallet, the action is logged with timestamps into the WMS database.

2.3 The order picking process

The order picking process in our case study warehouse is shown in Figure 6. The first step is to open an order picking task (1). After that the worker assigns a pallet to the task (2). Next the worker locates the first SKU in active storage (3) and after that he assigns correct number of items on the pallet (4). If the task is not completed (5) and the pallet is not full (6) the worker then locates the next SKU and puts it on the pallet (3), (4). If the pallet is full the worker puts the pallet into the accumulation area (7) and assigns a new pallet to the order picking task (2). When the order picking task is completed the last pallet is assigned to the accumulation area (8) and the task is completed (9).

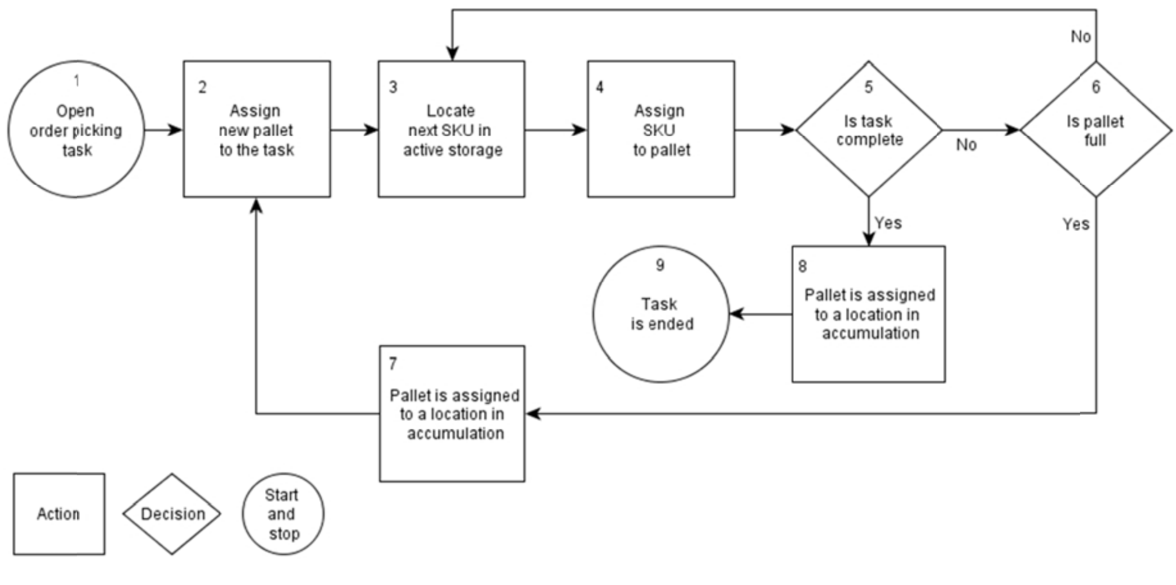

Figure 6: Flowchart of order picking.

The major challenge for the warehouse foreman is having an overview of orders based on importance and with regards to delivery time. All decisions are based on intuition and the experience of the foreman. There are no proper tools that assist the foreman with allocating orders based on delivery time according to the workload on his workers. This can lead to worse utilization of workers, delayed deliveries, and worsening relationships with customers that affect the profits of the company.

2.4 Optimization of scheduling

The most common objective of order-picking systems is to maximize the service level subject to resource constrains such as labor, machine and capital [7]. The service level is usually composed of factors such as the average and the variation of order delivery time, order integrity and accuracy. Constraints because of workers shifts schedules, order arrivals and delivering also have to be met. The optimization model will give the foreman recommendation on how he can directly allocate order picking to workers and enable him to monitor order picking better.

In the context of traditional mathematical programming classifications for scheduling problems (see e.g. [8]), the problems machine environment is defined as unrelated machines in parallel (Rm). In our context workers are considered "machines". The processing characteristics are different processing times of job j on machine i (p_{ij}), different release date for job j (r_j), different due date of job j (d_j) and preemptions (prmp) are allowed. Preemption means that it is not necessary to keep a job in a machine once it has started, until it is completed. The scheduler is allowed to interrupt the processing of job and put it on another machine without losing the amount of processing the job has already received. Our objective is to minimize lateness of job j (L_j) and number of times preemptions are performed. Completion time of job j on last machine on which process is denoted by C_j so the lateness is $L_j = C_j - d_j$. In short, $Rm|p_{ij}, r_j, d_j, prmp|\alpha * \sum L_j + \beta * \#prmp$.

Another aspect of our optimization problem is that orders can come at any time during working hours and therefore optimization has to be done several times over working hours. This is called rolling horizon in the scheduling literature [8]. As shown in Figure 7, orders can come at any time during the working hours and have to be scheduled after their arrival. The figure shows how 6 different orders arrive and how they are scheduled for two workers during one and a half working days.

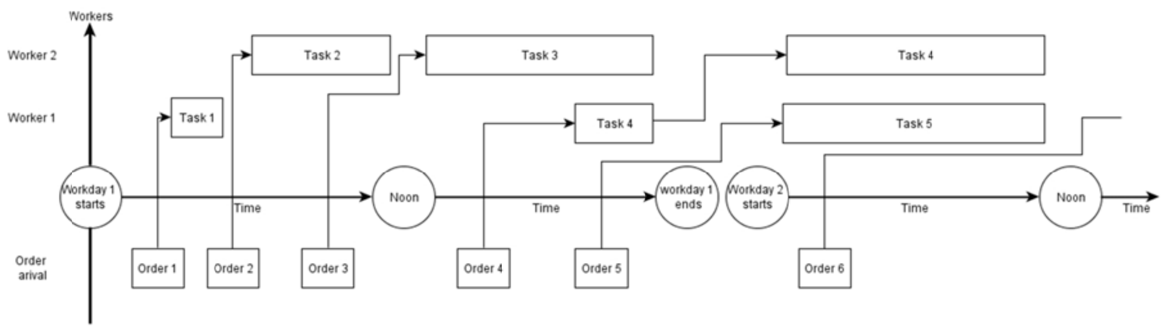

Figure 7: Chronological illustration of order arrival and order picking scheduling.

Mixed Integer Linear Programming (MILP) is a widely used method for scheduling problems because of its meticulousness and flexibility which makes it useful for modeling and solving real world problems [9]. Scheduling problems usually involve discrete decisions such as equipment assignment and task allocation over time and therefore require integer variables. Thus MILP is used rather than the more efficient but less accurate Linear Programming methods (LP). A good introduction to operations research models for scheduling is given by Pinedo in the book "Scheduling: Theory, Algorithms and systems" [8] .

When solving mathematical programs special problems arise from integer variables. The combinatorial explosion of possible solutions makes the scheduling of real world processes a complex combinatorial optimization problem that belongs to the class of NP-hard problems [10]. Consequently there exists no known solution algorithms of polynomial complexity with regard to the problem size and all known solution algorithms scale exponentially in the worst case. Therefore a small increase in the problem size may result in a significant increase in the computational complexity and the solution time.

Branch & Bound [11] is a common way to find an optimal solution in discreet optimization and combinatorial optimization. Branch & Bound is a systematic way to divide the feasible set of solutions into subsets by bounding the optimal cost to avoid exploring certain parts of the set of the feasible solution. We then compare the optimal solution of the sub-problem, and select the best one. If the sub-problem is as difficult as the original problem, the sub-problem is also divided into sub-problems, branching the original problem into a tree of sub-problems. It is often much easier to obtain the lower bound of the sub-problem than the optimal solution. The goal is then to find the sub-problem with the highest lower bound before the optimal solution is obtained. When solving MILP sub-problems are obtained by relaxing the integer conditions. When exact methods such as MILP are used, it is in some cases not even possible to find integer solutions because feasible integer solutions exist often only very deep in the Branch & Bound tree. The scheduling problems often also suffer from poor LP relaxations and in many cases it is very difficult to derive useful upper and/or lower bounds for the optimal solution [12] .

3. Solution Approach

3.1 General structure

Scheduling of order picking tasks can be a challenging task among other reasons since picking times for available orders are not known in advance. Skilled foremen often have good intuition on how well workers will do and will monitor the order picking and allocate critical picking tasks to good workers if it is needed. However, it is too difficult for the foremen to allocate effectively every single picking task, each with different arrival, delivering and processing time to several workers. To further complicate things the individual processing time of the same order is different between workers.

Our goal in this thesis is twofold. The first goal is to find out if it is possible to forecast how long it will take each worker to complete each order picking task with reasonable good accuracy. Forecasting has to be as accurate as possible to guarantee the reliability of the optimization model. The result of the optimization model is a proposal for the foreman, telling him which worker should be responsible for which order picking and when they should perform the picking during their shift. The second goal of the thesis is to use the forecasted times for order picking processing as an input into an optimizing model that optimizes the scheduling of order picking. To optimize scheduling for the order picking process in the warehouse several factors must be taken into account. Available workers and their shift schedule are used as constrains in the model because the workers have to complete all their order pickings during their shifts. Each worker can only work on one order at a time. Orders are picked up as they arrive from the customers and important orders, based on delivery time, have to be completed earlier than others.

The idea is to provide useful and effective tools for supporting the decisions of the foremen so they will have more than their intuition to rely on when they schedule which worker performs which order picking task at which time.

Figure 8 shows the flow of the data and tasks of the overall solution approach. The WMS database contains information about which workers are available and which shift schedule they are on. We also get information on available order arrival and delivering time. Estimation on order/worker process time comes from the forecasting model. From the order schedule optimization we get information about which worker picks which order at what time.

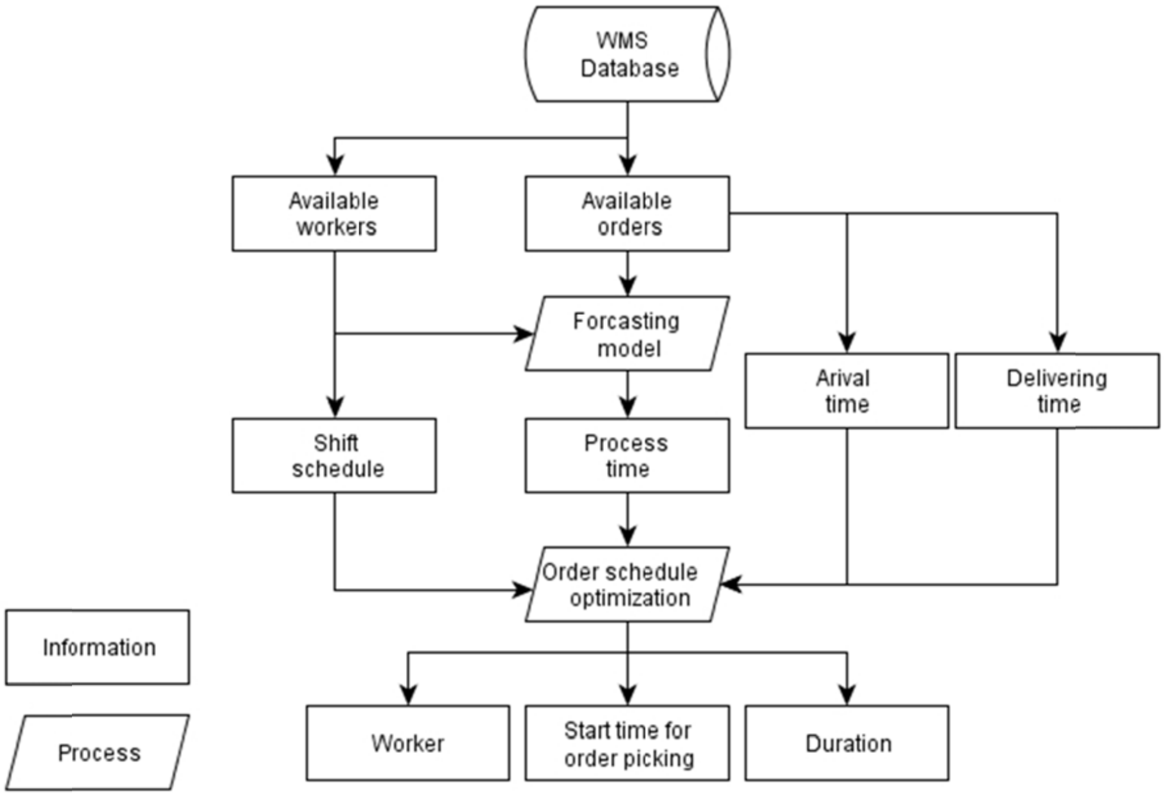

Figure 8: A flowchart of the flow of the data and tasks of the overall solution approach.

In the following sections we will further describe the two main components of the solution approach, i.e. the forecasting procedure and the optimization procedure.

3.2 Forecasting procedure

3.2.1 Multivariable regression model with numeric and factor variables

To build up the forecasting model we use multivariable regression model (MR) which is a standard way of making such models [13]. We use MR because it determines a relationship between a set of variables and how this variable affects the order picking processing time that we are trying to predict. There are two types of variables used in MR models, response variable **Y** = $[Y_1,..,Y_n]^T$ or dependent variable which depends on value of inputs. The other one is called an independent variable.

$$\boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1k} \\ 1 & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nk} \end{bmatrix}$$

The simplest type of a relationship between the dependent variable and the independent dependent variables is a linear relationship with coefficients $\alpha = [\alpha_0,...,\alpha_k]^T$ as shown in equation (1) [14].

$$\boldsymbol{Y} = \boldsymbol{X} \cdot \boldsymbol{\alpha} \quad (1)$$

Since independent variable, like worker, has no numeric value of any meaning for our forecast we have to use it as a factor in our forecasting model [15]. This is done by adding dummy variables (R) to the regression model and corresponding vector of coefficients ($ß^D_{ij}$) for the dummy variables. In the general case we have t systems of classification, of which the i-th contains k_i mutually exclusive classes. We define t sets of dummy variables $R_{ij}(i = 1,..,t; j = 1,..,k_i)$ so that R_{ij} = 1 if the item belongs to the j-th class of the i-th system; in all other cases R_{ij} = 0. We cannot use the unit matrix for R_{ij} because it will make the estimation of the coefficients indeterminate [15]. This is solved by dropping one of the dummy variables from each set; i.e. select a j_i for each system of classes I, and pre-assign $\beta^D_{ij_i}$ $(i = 1,..,t)$. Equation (2) shows how variable R_{ij} is built up for three workers.

$$\boldsymbol{R}_{i=1..t,j=1..k} = \begin{matrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{matrix} \quad (2)$$

The general regression model can be seen in equation (3)

$$\boldsymbol{Y} = \boldsymbol{\beta_{ij}} \cdot \boldsymbol{R_{ij}} + \boldsymbol{X} \cdot \boldsymbol{\alpha} \quad (3)$$

3.2.2 Selection of independent variables

We propose two forecasting models that differ by the choice of independent variables. In model 1 we use the number of boxes as an independent variable. Number of boxes picked in an hour is a widely used industrial standard for measuring performance in warehouses. Workers are also used as factor variable in model 1. In model 2 we add the number of pallets and also the number of SKUs in each order to model 1. Fetching a new pallet takes time but the number of SKUs is the real number of stops that the worker has to make as he picks up the SKUs. This can affect the order picking time and therefore it is of interest to compare models 1 and 2. Workers and types of orders are also used as factor variables in our forecasting model 2.

The dependent variable, order picking processing time, and all of the proposed numeric independent variables, number of pallets, number of SKUs and number of boxes can be considered as counted data that takes non-negative integer values. On that basis the Poisson regression (see Equation 4) is our best choice to estimate coefficients in our forecasting model [16], and not regression based on normal distribution which is more suitable for continuous normally distributed values that can take negative values.

$$\log \boldsymbol{Y} = \boldsymbol{\beta_{ij}} \cdot \boldsymbol{R_{ij}} + \boldsymbol{X} \cdot \boldsymbol{\alpha} \quad (4)$$

As shown in Figure 10 we also have taken log of the independent variables to get a liner relationship between dependent and independent variables. So our final model shown in Equation 5.

$$\log \boldsymbol{Y} = \boldsymbol{\beta_{ij}} \cdot \boldsymbol{R_{ij}} + \log \boldsymbol{X} \cdot \boldsymbol{\alpha} \quad (5)$$

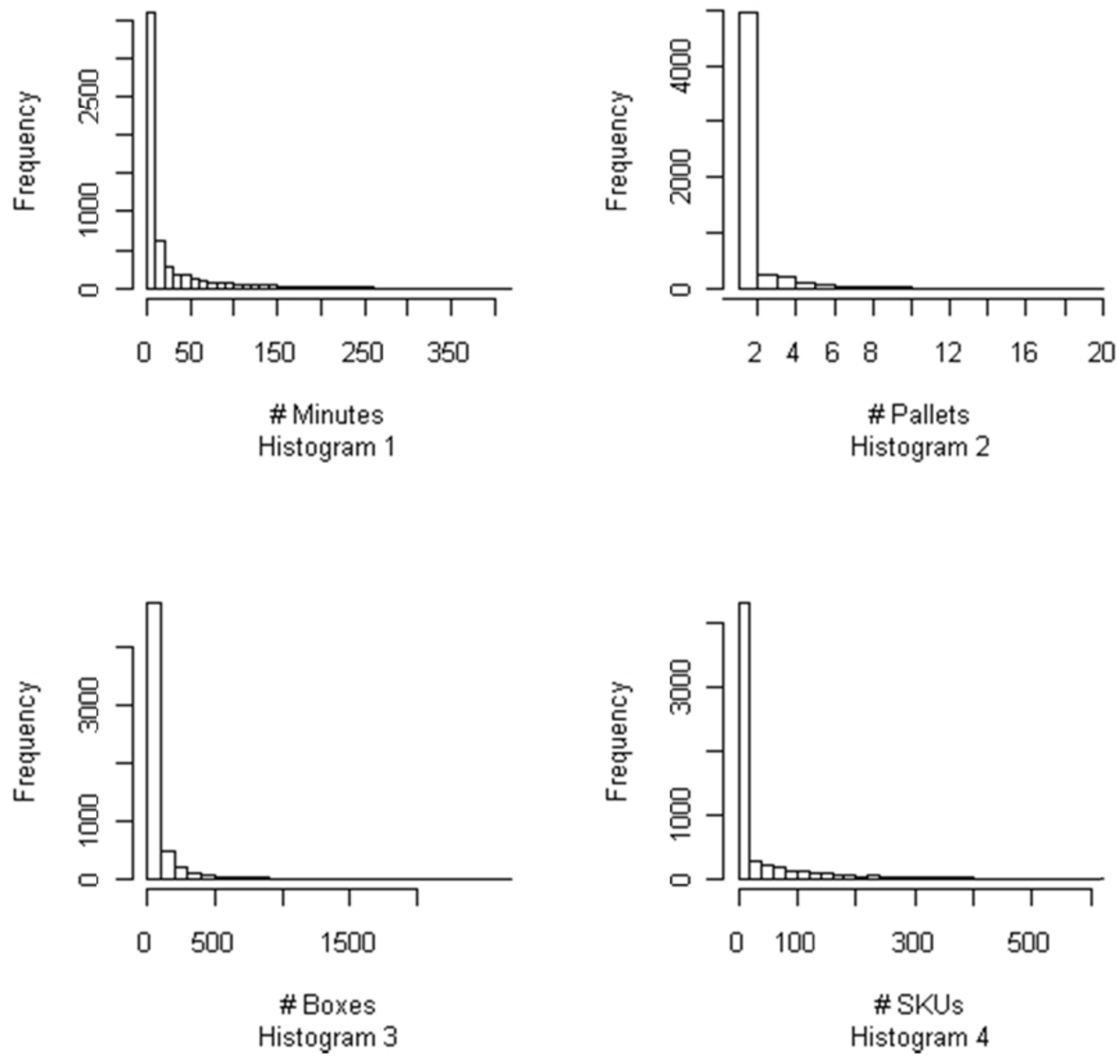

Figure 9: Histogram 1 shows the frequency of our dependent variable, order picking duration. Histogram 2 shows the frequency of number of pallets in orders. Histogram 3 shows the frequency of number of boxes in orders. Histogram 4 shows the frequency of number of SKUs in orders.

From scatter plots 1 to 3 (in Figure 10) we can see that there is a correlation between the log of our dependent variable and the log of all the independent variables in the data. Correlation between the log of #pallets and the log of time is 0.73, correlation between the log of #boxes is and the log of time is 0.86 and correlation between the log of #SKU's and the log of time is 0.86. This indicates that we should use them in our forecasting model.

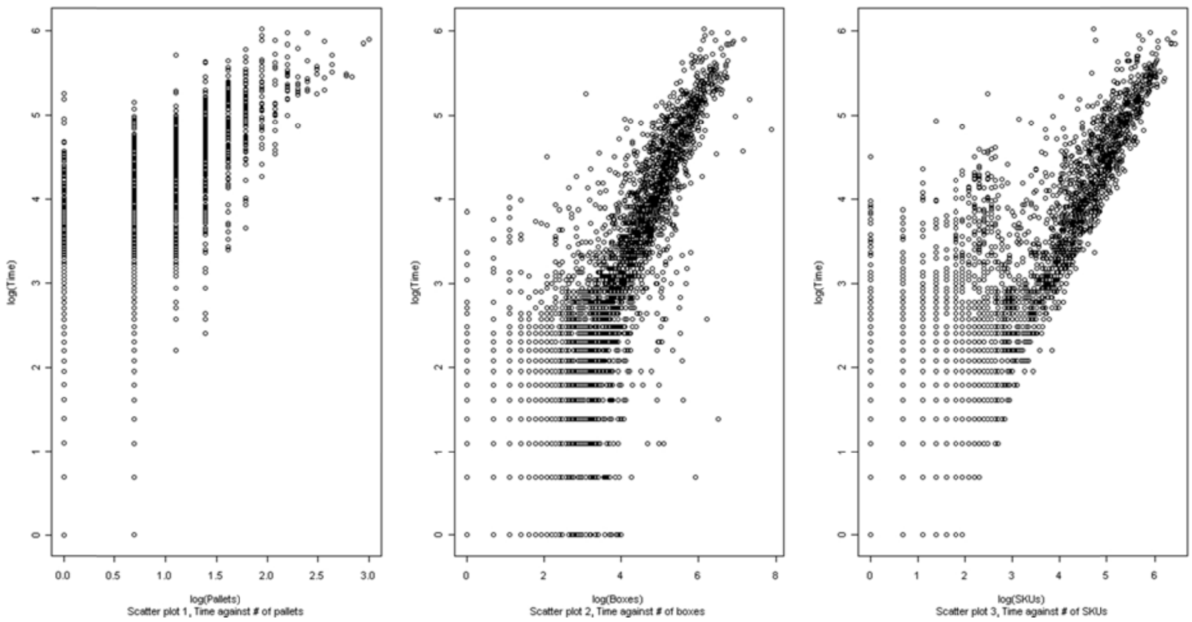

Figure 10: Scatter plot 1, log of number of pallets against log of order picking processing time. Scatter plot 2, log of number of boxes against log of order picking processing time. Scatter plot 3, log of number of SKUs against log of order picking processing time.

Box plot 1 and 2 in Figure 11 shows that non-numeric factor variables, workers and type of orders, have variations in their average processing time so we have a reason to think that they can have an effect in our forecasting model.

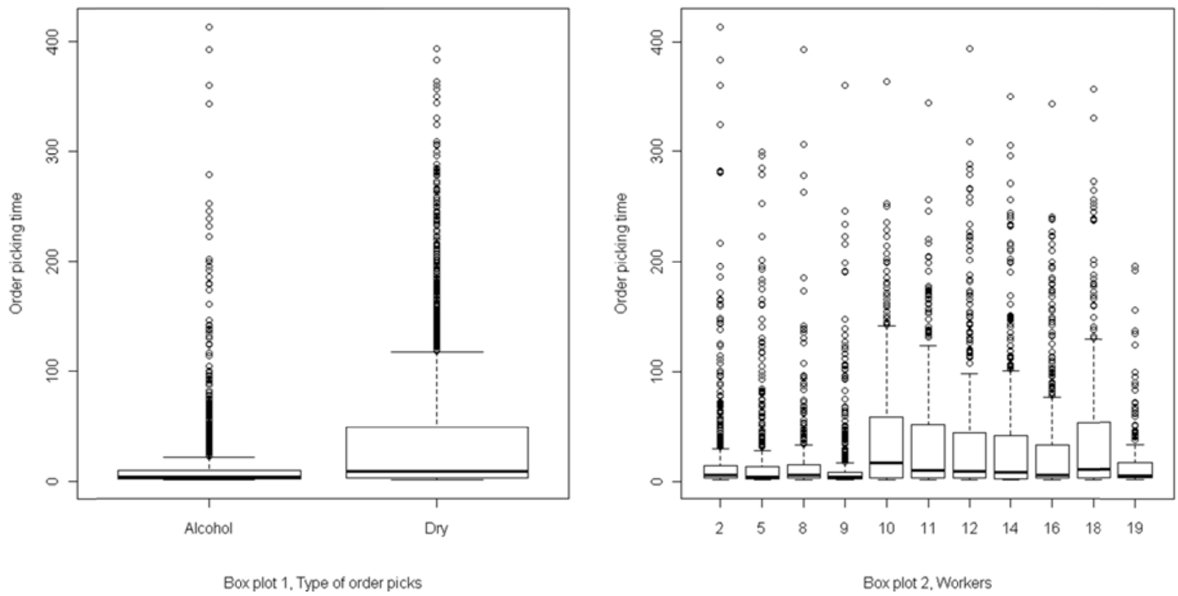

Figure 11: Box plot 1 and 2: Box plot 1, shows average processing time and its variance of order type alcohol and dry food. Box plot 2, shows average processing time and variance of workers.

1. Regression and forecasting models

Multivariable regression is used to build up a forecasting model to estimate how long time it will take each worker to perform the order picking tasks. Model 1 is based on number of pallets picked in an hour which is a widely used industrial standard for measuring performance in warehouses. Model 2 is based on our case study foreman's recommendations on how to improve model 1.

Regression and forecasting model 1:

Dependent variable:

$\boldsymbol{P} = Number\ of\ minutes\ it\ takes\ worker\ to\ complete\ order\ picking$

Independent variables:

$\boldsymbol{R}^w\ = dummy\ variable\ for\ workers$

$\boldsymbol{x}_1 = Number\ of\ boxes\ in\ order$

Coefficients:

$\boldsymbol{\beta}^w\ = Coefficents\ for\ workers$

$\alpha_1 = Coefficents\ for\ number\ of\ boxes$

$\alpha_0 = Intersection\ with\ Y\ axis$

Regression model 1:

$$\log \boldsymbol{P} = \boldsymbol{\beta}^w \cdot \boldsymbol{R}^w\ + \boldsymbol{\alpha}_1 * \log \boldsymbol{x}_1 + \alpha_0 \quad (6)$$

Forecasting model 1:

$$\widehat{\boldsymbol{P}} = e^{\boldsymbol{\beta}^w \cdot \boldsymbol{R}^w + \boldsymbol{\alpha}_0} * \boldsymbol{x}_1^{\boldsymbol{\alpha}_1} \quad (7)$$

Forecasting model in (7) is derivation from (6).

Regression and forecasting model 2:

Dependent variable:

$\boldsymbol{P}_i = Number\ of\ minutes\ it\ takes\ worker\ to\ compleat\ order\ picking$

Independent variables:

$\boldsymbol{R}^w\ = dummy\ variable\ for\ workers$

$\boldsymbol{R}^t\ \ = dummy\ variable\ for\ order\ type$

$\boldsymbol{x}_1 = Number\ of\ boxes$

$\boldsymbol{x}_2 = Number\ of\ pallets$

$\boldsymbol{x}_3 = Number\ of\ SKUs$

Coefficients:

$\boldsymbol{\beta}^w\ = Coefficents\ for\ workers$

$\boldsymbol{\beta}^t\ \ = Coefficents\ for\ order\ type$

$\alpha_1 = Coefficents\ for\ number\ of\ boxes$

$\alpha_2 = Coefficents\ for\ number\ of\ pallets$

$\alpha_3 = Coefficents\ for\ number\ SKUs$

$\alpha_0 = Intersection\ with\ Y\ axis$

Regression model 2:

$$log(\boldsymbol{P}) = \boldsymbol{\beta}^w \cdot \boldsymbol{R}^w\ + \boldsymbol{\beta}^t\ \cdot \boldsymbol{R}^t\ \ + \alpha_0 + \sum_{k=1}^{3} \log \boldsymbol{x_k} * \alpha_{\boldsymbol{k}} \quad (8)$$

Forecasting model 2:

$$\widehat{\boldsymbol{P}} = e^{\boldsymbol{\beta}^{w} \cdot \boldsymbol{R}^{w} + \boldsymbol{\beta}^{t} \cdot \boldsymbol{R}^{t} + \alpha_0 *} \prod_{k=1}^{3} \boldsymbol{x}_k^{\alpha_k} \qquad (9)$$

Forecasting model (9) is derivation from (8).

4.2.4 Data and outliers

To measure the time it takes a worker to complete an order picking task we have to examine what timestamps are available in the WMS database. As shown in Figure 6, the first action that a worker performs after he has selected an order picking task is to create a pallet in the WMS. The last action that a worker performs and we have information about is to put the last SKU on the pallet. The first and the last actions are used to measure the time it takes a worker to complete the order picking task. The measurement is in number of minutes from the beginning to the end. Workers can take lunch and coffee breaks during the order picking. Consequently, the risk of creating excessively long order picking time in the data these outliers have to be located and thrown out of the dataset before coefficients are estimated.

It is not obvious how to detect outliers without having any estimation about how long the processing time of each order picking should be. We propose the method of looking at the residuals and finding all data point that have residuals greater than three standard deviations from the mean. If this order picking tasks start time and end time have greater concentration around workers lunch and coffee breaks then the whole sample, it is likely that we have captured some outliers.

4.2.5 Implementation

For statistical computing we use the R software[1] [17]. R automatically creates dummy variables for non numeric variables or factors and estimates the coefficients in our regression model. It can also handle Poisson regression.

4.2.6 Comparison of forecasting models

We use coefficient of determination R^2 to compare the two models. This method is widely used in determining how well regression models perform [14].

$$SS_{tot} = \sum_{j} \left(P_j - \bar{P}\right)^2 \quad (10)$$

$$SS_{err} = \sum_{j} \left(P_j - \hat{P}_j\right)^2 \quad (11)$$

$$R^2 = 1 - \frac{SS_{err}}{ss_{tot}} \quad (12)$$

[1] R can be considered a different implementation of the S language which is developed at Bell laboratories by John Chambers. R is available as Free Software under the terms of the Free Software Foundation's GNU General Public License . The R software environment is widely used to implement statistical techniques via packages that are publicly available by CRAN family of internet sites.

R^2 takes value between 0 and 1 and the model that has the higher value is considered better. We plot the predicted order processing time against actual order processing time and use simple linear regression to draw a line through the data points. The slope of the line should be as close to 1 as possible. Plots of normalized residuals against processing time (Residual plot) are also visually inspected to see if there are any unwanted trends. Residual plot should be normally distributed along the zero line and not show any distinct patterns [14]. We also use simple linear regression to draw a line to compare the regression models. Slope of the line should follow the zero line or be as close to it as possible.

There are two types of errors that occur when we estimate processing time of workers. First error and less serious is when processing time is overestimated, this will just effect the potential utilization of workforce but not the scheduling itself. Second error is the underestimate of processing time which can render any scheduling plan useless unless if there is enough slack built into it to deal with longer processing times. The better forecasting model is used as an input for our optimization model. The forecasting model can also be used for other projects like creating a better bonus system that rewards the most productive worker. In addition, maximum and minimum order picking times of all available orders can be estimated.

Over-fitting occurs when regressing model describes random error instead of underlying relationship between dependent variable and independent variable. Over-fitting means that some of the relationships that appear statistically significant are actually just noise. Over-fitting can occur when we use many independent variables in regression models and can cause the regression model to have poor predicted performance since it can over exaggerate minor fluctuations in the data. To look for over-fitting we split our dataset in two, training and testing section. We perform regression on the training sett and use coefficients from the regression to forecast processing times in the test set. If coefficient of determination for the training set is much lower than for the whole dataset we suspect that we are over-fitting

3.3 Scheduling optimization model

3.3.1 Online rolling horizon scheduling

The most common objective of order-picking systems is to maximize the service level subject to resource constrains such as labor, machine and capital [7]. The service level is usually composed of factors such as average and variation of order delivery time, order integrity and accuracy. Constraints because of workers shifts schedule, order arrival and delivering also have to be met.

3.3.2 Mathematical programming

In this thesis we propose a Mixed Integer Linear Programming (MILP) optimization model to solve the order picking scheduling problem. The model is based on a discrete time representation and it assigns order picking task j to worker i to work on in time slot~~s~~ t with the objective of finishing the task before the defined delivering time. The optimization model is intended to help the foreman to make decisions on how to allocate order picking tasks to workers based on data from the WMS.

3.3.3 Implementation

For implementing our MILP we use Mathematical Programming Language (MPL) [2] [18] together with the Gurobi [3] [19] solver to make all the calculations. All of our data is stored in SQL Server 2008 [20] from Microsoft.

Time slots are chosen to be 15 minutes, it adds up to workers shifts that begin and end on half and whole hours. Average duration of order picking is 23 minutes so on average they should take up two timeslots to complete and have 7 minutes slack. On a normal working day there are 40 time slots available.

3.3.4 Optimization model

Indexes:

$$i = 1 \dots m \quad : Employees$$
$$j = 1 \dots n \quad : Tasks$$
$$t = 1 \dots T \quad : Time\ slots$$

Sets:

$$T_{shift_{i,t}} = \begin{Bmatrix} 1\ if\ emploee\ i\ is\ available\ for\ work\ during\ time\ period\ t \\ 0\ otherwise \end{Bmatrix}$$

Data:

$$d_j = Delivery\ time\ of\ task\ j$$
$$r_j = Order\ arival\ time$$
$$P_{i,j} = Processing\ time, time\ that\ emploee\ i\ takes\ to\ finish\ task\ j$$
$$\alpha = penalty\ for\ lateness$$
$$\beta = penalty\ for\ preemption$$

Binary Variables:

$$X_{i,j,t} = \begin{Bmatrix} 1\ if\ task\ j\ is\ assigned\ to\ emploee\ i\ at\ time\ t \\ 0\ otherwise \end{Bmatrix}$$
$$Setup_{i,j,t} = \begin{Bmatrix} 1\ if\ task\ j\ \ is\ not\ processed\ in\ timeslot\ t-1\ or\ not\ \ by\ the\ same\ worker \\ 0\ otherwise \end{Bmatrix}$$

Continuous variables:

$$L_j = Variable\ to\ calculate\ the\ lateness\ of\ job\ j$$
$$C_j = \ Work\ j\ ends$$

Objective function:

[2] MPL is a widely used integrated model development environment specially designed for modeling of optimization problems in a easy straight forward manner. It has interfaces to all major optimization solvers like gurobi and cplex. It generates all matrixes needed for the optimization solver to do its job and generates understandable solutions. MPL have the capability of getting input data from databases through ODBC connections. We use MPL version 4.2 for our modeling proposal.

[3] Gurobi[19] is a relatively new optimization solver. We use version 4.0.0.

The objective function includes the minimization of the total lateness and total setup weighted with the α and β parameters.

$$min\, Z = \alpha \sum_{j}^{n} L_j + \beta \sum_{i}^{I} \sum_{j}^{J} \sum_{t}^{T} Setup_{ijt} \qquad (13)$$

Constraints:

Equation (14) is used to calculate the end time of each order picking task.

$$X_{ijt} * t \leq C_j \; \forall\, i \in I, j \in J, t \in T \quad (14)$$

Equation (15) is used to calculate of the lateness of job j.

$$\sum_{j}^{n} C_j - d_j \; = \; L_j \; \forall\, j \in J \quad (15)$$

Order picking task j can't start until it has arrived which is ensured with equation (16).

$$X_{ijt} = 0 \;\; \forall\, t < \; r_j, i \in I, j \in J \quad (16)$$

All order picking tasks j must be assigned and finished. Note that this equation allows the orders to be processed by more than one worker if needed.

$$\sum_{i}^{m} \sum_{t}^{T} \frac{X_{ijt}}{P_{i,j}} \geq 1 \; \forall\, j \in J \quad (17)$$

Each order picking task j is not assigned to too many time slots t. If this is not done the optimize model will use up all available time slots making it hard for the foreman to make changes to the schedule.

$$\sum_{i}^{m} \sum_{t}^{T} \frac{X_{ijt}}{P_{i,j}} \leq 2 \; \forall\, j \in J \quad (18)$$

If the processing times were rounded upwards to the next whole multiply of a time slot duration (e.g. if job takes 25 minutes and the time slots are 15 minutes each then the processing time would be rounded upward to 30 minutes) then the right hand side of the equation could be 1 instead of 2. This would possible result in a tighter formulation.

For each time slot t only one worker i can work on each order picking task j.

$$\sum_{i}^{n} X_{ijt} \leq 1 \;\; , \forall\, j \in J, t \; \in T \quad (19)$$

Production capacity of each worker must be respected within each time period t.

$$\sum_{j}^{m} X_{ijt} \leq 1 \;\; , \forall\, i \in I, t \; \in T \quad (20)$$

Equation (22) activates the setup variable for three cases:

1) When order picking task starts for the first time
2) When order picking task starts after a break
3) When order picking task is moved between workers. As a result there is a penalty when the processing of a task is not continuous (preemption) and also when a task is moved from one worker to another.

$$X_{ijt} - X_{ijt-1} \leq Setup_{ijt}, \forall\ i \in I, j \in J, t\ \in T \quad (21)$$

Equation (23) is used to make the model respect the shifts, i.e. to ensure that worker i can only work during the shift.

$$X_{ijt} \leq 0, \forall\ t, i \in T_{shift_{i,t}} \quad (22)$$

$$X_{ijt}\ \epsilon\ \{0,1\}\ \forall\ i, j, t\ (23)$$

$$T_j \geq 0\ \forall\ j \in J \quad (24)$$

3.3.5 Experimental study

To test the optimization model we use real data from several working days where all order picking task were started and ended that same day. We compare actual schedules with optimized schedules obtained with different settings as described in the following three scenarios.

Scenario 1: The optimization model assumes the same number of workers and the same order picking tasks as the real working day. Penalty for lateness and penalty for preemption are kept equal.

Scenario 2: The optimization model uses as few of the best workers as possible and the same order picking tasks as the real working day. Penalty for lateness and penalty for preemption are kept equal.

Scenario 3: The optimization model uses as few of the best workers as possible. Same order picking tasks as the real working day are used. Penalty for preemption is much higher than for lateness.

It should be emphasized that the optimization model has more information than the foreman to schedule the working day. It has information on when orders arrive, when they should be delivered and how big they are before it starts to make the schedule for the day. By doing our testing like this we get an upper limit on best solution for our scenarios. When evaluating how well our scenarios do in comparison to the real day this has to be taken into account.

As criteria for comparison we use total lateness, $\sum_{j=1}^{n} L_j$, mean lateness $\frac{\sum_{j=1}^{n} L_j}{n}$, maximum lateness $\max(L_j)$, number of late orders, number of tasks switching between workers and number of times worker does another order picking task before finishing the order picking task that he has already started. We also compare the solution times for the different scenarios.

4. Results

We divide this chapter into two main sections. In the first section we talk about our results for the forecasting model and the comparisons of the two proposed models. In the second section we use the better forecasting model to forecast worker processing times and use this as an input for the proposed optimization model. We then compare the real world results to the three aforementioned scenarios for evaluating the results from the optimization model.

4.1 Forecasting

As explained previously we propose two forecasting models, a standard model (model 1) and an extended model that includes more independent variables (model 2).The performance of each model is evaluated by comparing the forecasting outcome with the real measurements of worker pick times. The data set used for testing consists of 5.672 picking tasks, performed by 11 workers over a four month period. The two regression models go through two steps: The first step is to use the residuals to find the outliers and the second step is to estimate regressions models coefficients without the outliers. Regression models solutions are then compared to decide which model is better. The model with lower coefficient of determination R^2 is the more suitable one. We plot the predicted order processing time against actual order processing time and use simple linear regression to draw a line through the data points. The slope of the line should be as near to 1 as possible. Plots of normalized residuals against processing time (Residual plot) are also visually inspected to see if there are any unwanted trends. Residual plot should be normally distributed along the zero line and not show any distinct patterns [14]. We also use simple linear regression to draw a line to compare the regression models. Slope of the line should follow the zero line or be as close to it as possible

4.1.1 Regression, model 1:

Model 1 has independent variables as workers and number of boxes (see equation 4 in Section X.X). In step 1 we do the regression on the whole dataset where in step 2 we do the regression again without outliers. We show that we get a better outcome without outliers.

4.1.1.1 Step 1:

As shown in Table 1 in Appendix A, all of the regression variables have low enough significant values (<0.05). R^2 value of 0.82 is also quite good. Plot 1 in figures 12 shows that predicted processing time corresponded well with actual values. The slope of the line is 0.84 which indicates that we are more likely to underestimate in our perdition. There are 182 outliers that are marked with red x in booth plots in Figure 12 and as we see, most of them have greater actual processing times than expected. However, some of the outliers have shorter predicted processing time than actual but they generally lie much further away so we throw them out. The residual plot in Figure 12 shows that there is some abnormality and the residuals are not normally distributed along the zero axes, this is however mainly due to outliers. The slope of the line in the residual plot in figure 10 is 0.0069.

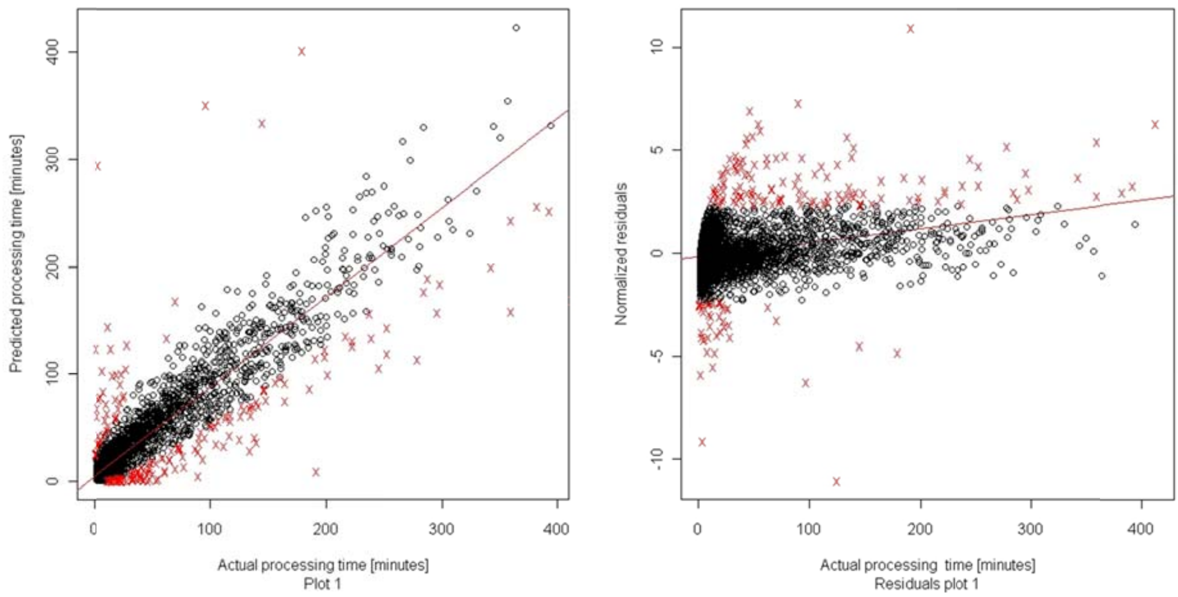

Figure 12: Plot 1 shows predicted processing times plotted against actual processing times. Residual plot 1 shows normalized residuals plotted actual processing times.

If worker goes for lunch or coffee break during the order picking time, the brake can lengthen measured order picking processing times and create outliers. Outliers can have dramatic effect on our estimation for regression model. Figure 14 shows us that outliers beginning time have higher concentration before lunch and coffee breaks than we would expect in all of the data. Outliers ending time also have higher concentration after lunch and coffee breaks than we would expect in all of the data. This indicates that our method of detecting outliers is good.

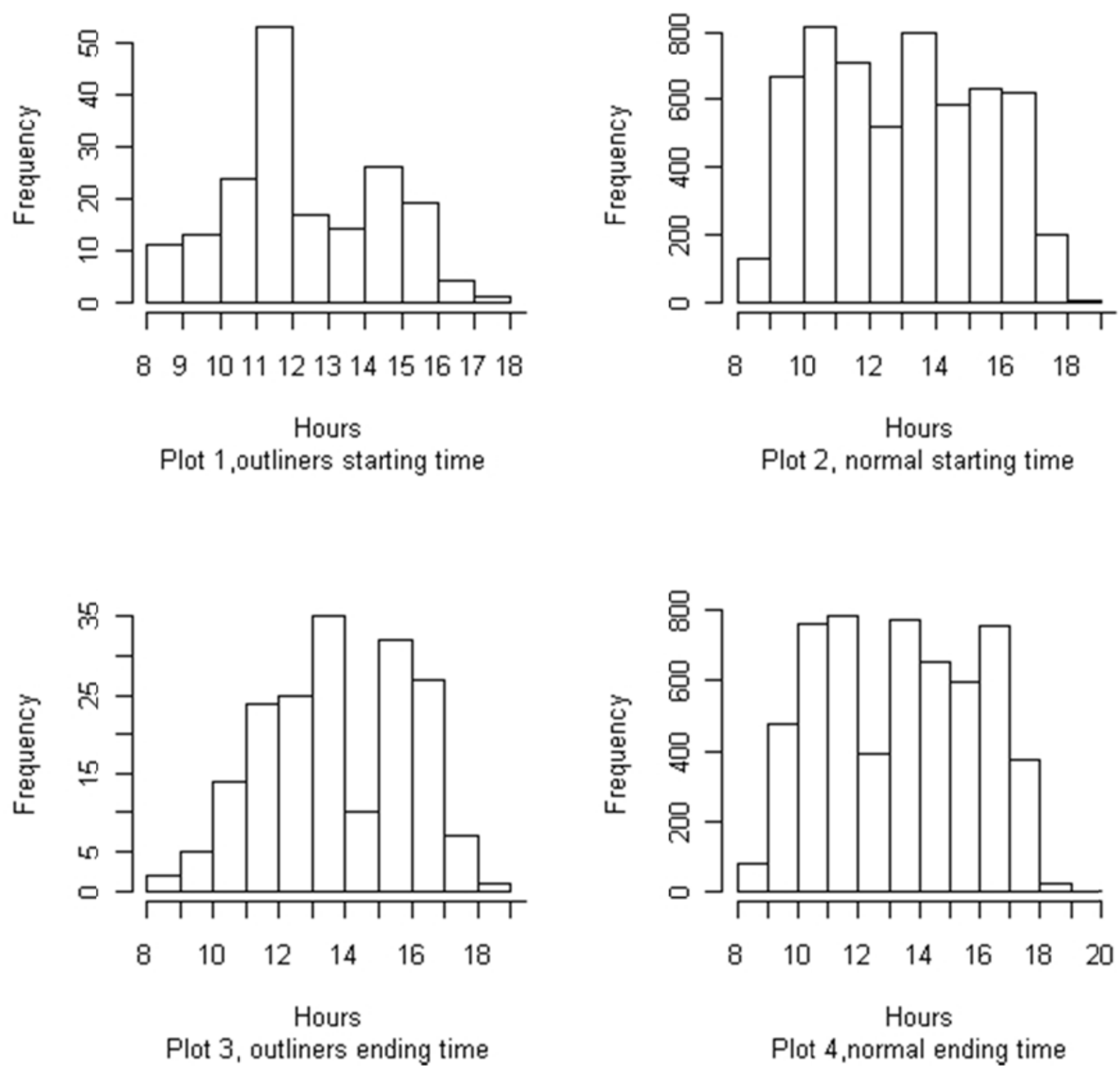

Figure 13: Plot 1 shows the concentration of outliers starting time. Plot 2 shows the concentration of normal starting time. Plot 3 shows the concentration of outliers ending time. Plot 4 shows the concentration of normal ending time.

4.1.1.2 Step 2:

In step 2 we perform regression with model 1 but without the outliers that we have found. As shown in Table 2 in Appendix A, all of the regression variables have high enough significant values. R2 value of 0.93 is much better because no outliers are now in the dataset. Plot 1 in Figure 15 shows us that predicted processing time corresponded also much better with predicted values. The slope is 0.91 which indicates fewer tendencies to underestimate the processing time. Residual plot in Figure 15 looks more evenly distributed than in Figure 10. The slope of the line is 0.0O49 which is a slight reduction from step 1.

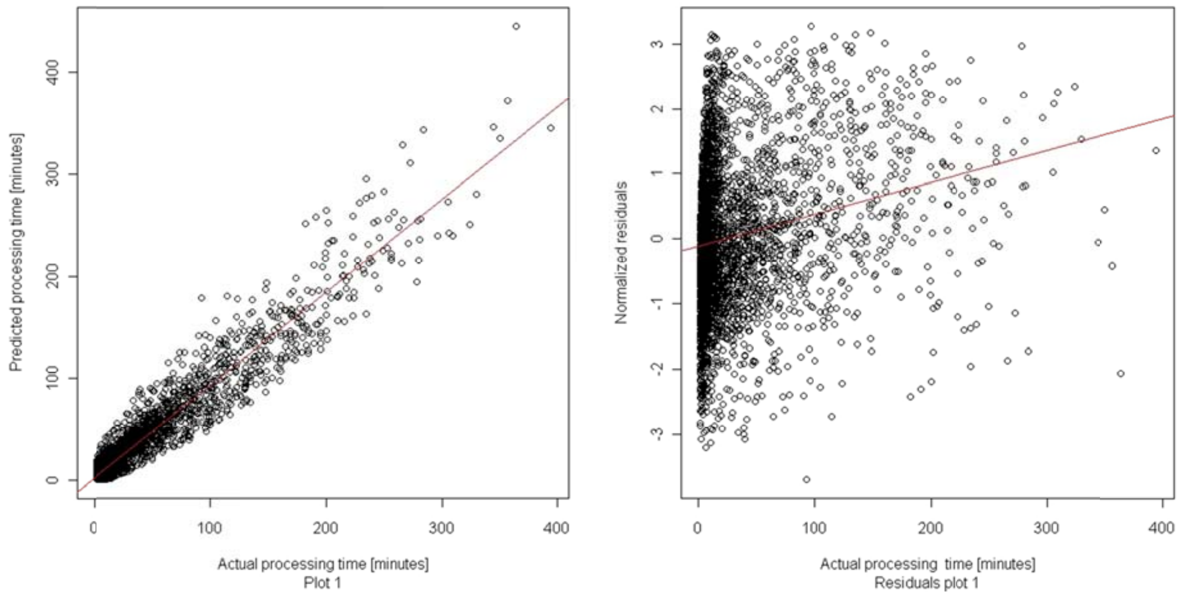

Figure 14: Plot 1 shows predicted processing times plotted against actual processing times. Residual plot 1 shows normalized residuals plotted actual processing times. Our independent variables are workers and # boxes.

4.1.2 Regression, model 2:

In model 2 we add independent variables to our model based on our case study foreman's recommendations'. Our original independent variables are: workers and number of boxes and we adder order type, number of pallets and number of SKUs to the model (see Equation 5 in Section 3.2). In step 1 we do the regression on the whole dataset, in step 2 we do the regression again without outliers. We show that we get a better outcome without outliers.

4.1.2.1 Step 1:

As shown in Table 3 in appendix A, all of the regression variables have high enough significant values. R2 value of 0.92 which is better than the regression in model 1, step 1 and not far from step 2. Plot 1 in Figure 16 shows us that predicted processing time correspond better actual values. The slope is 0.94. There are 188 outliers that are marked with red x in both plots in Figure 16 and we see most of them have greater actual processing time than expected. However some of the outliers have shorter predicted processing time than actual values but they generally lie much further away so we throw them out. The residual plot in Figure 16 shows that there is some abnormality and the residuals are not normally distributed along the zero axes, this is however mainly due to outliers. The slope of the line in the residual plot in figure 15 is 0.0052 which is lower than in regression model 1, step 1.

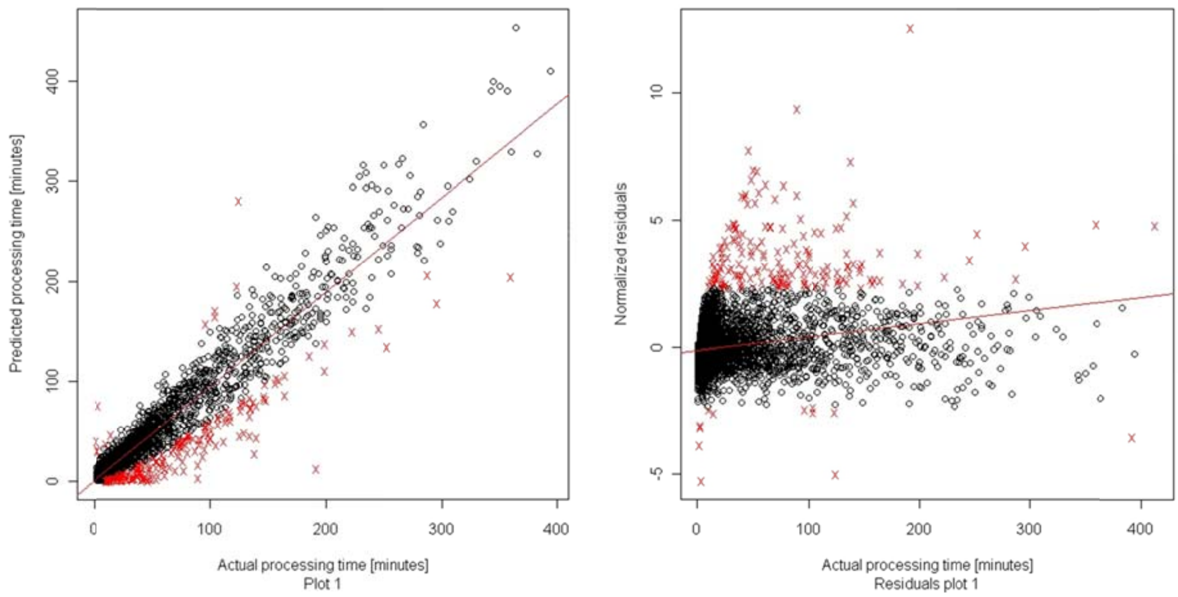

Figure 15: Plot 1 shows predicted processing times plotted against actual processing times. Residual plot 1 show normalized residuals plotted actual processing times.

Figure 16 shows us that outliers beginning time have higher concentration before lunch and coffee breaks than we would expect in all of the data. Outliers ending time also have higher concentration after lunch and coffee brakes than we would expect in all of the data. This difference is even higher than for regression model 1.

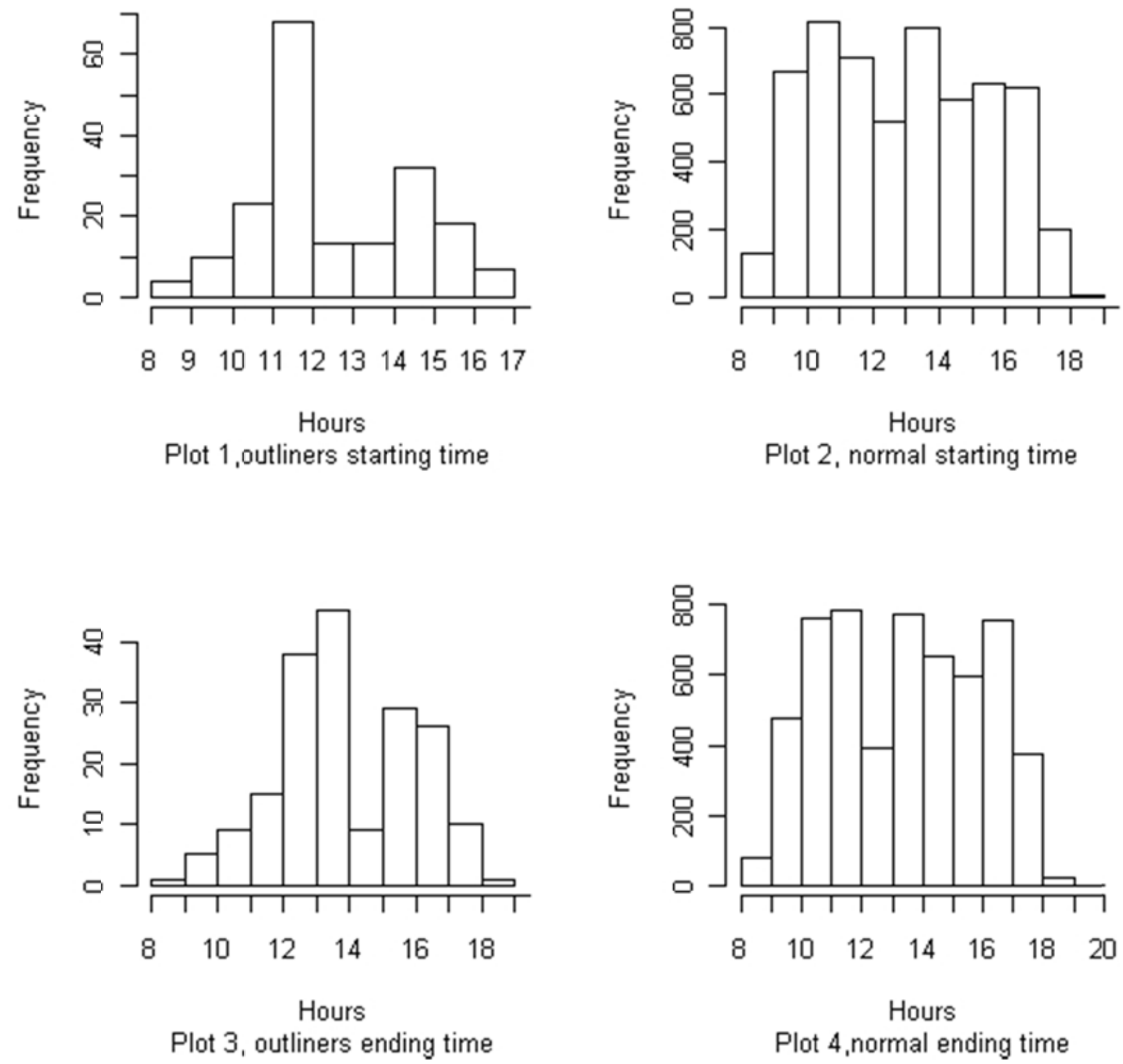

Figure 16: Plot 1 show the concentration of outliers starting time. Plot 2 shows the concentration of normal starting time. Plot 3 shows the concentration of outliers ending time. Plot 4 shows the concentration of normal ending time.

4.1.2.2 Step 2:

As shown in Table 4 in appendix A, all of the regression variables have high enough significant values. R^2 value of 0.96 is better than for regression model 1 step 2. Plot 1 in figures 17 shows us that predicted processing time corresponded also much better with predicted values. The slope is 0.97, which shows the regression model is performing very well. Residual plot in figure 17 looks more evenly distributed than in figure 14. The slope of the line is 0.0036 which is the best value so far.

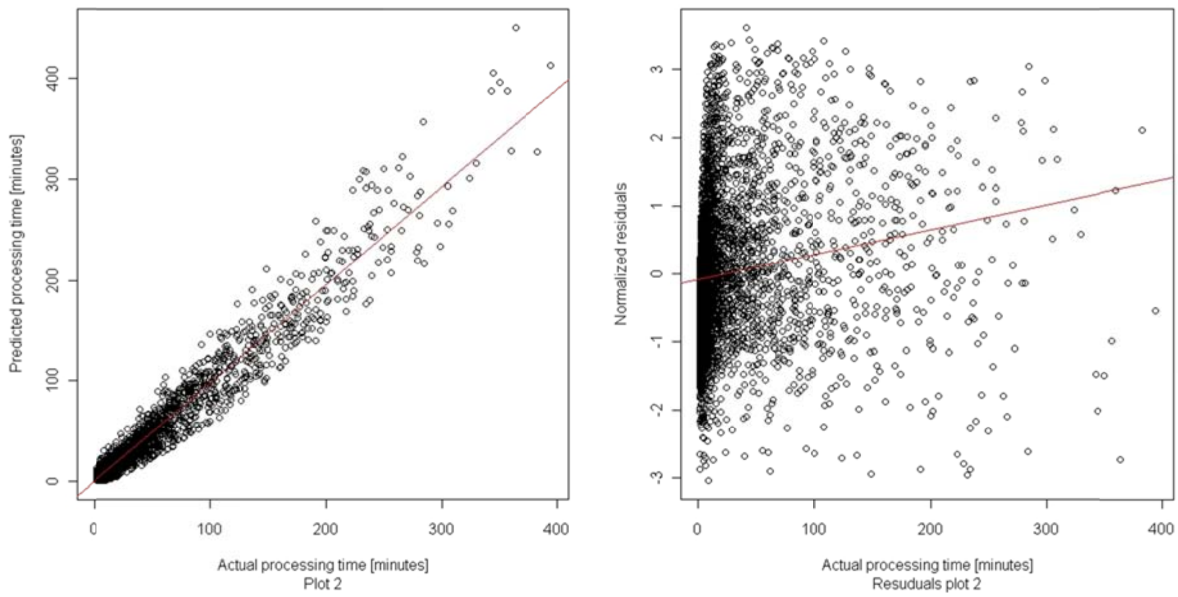

Figure 17: Plot 1 shows predicted processing times plotted against actual processing times. Residual plot 1 show normalized residuals plotted actual processing times. Our independent variables are workers, # boxes, # pallets, # SKUs, and type.

4.1.3 Comparison of regression models

As shown in Table 1, regression model 2 wins on all accounts. It has the highest score of R^2, the highest score of the predicted/actual plot slope and the best score of residual plot slope. We therefore determine that regression model 2 is better than model 1.

Regression steps	R^2	Predicted/Actual plot slope	Residual plot slope
Model 1, step 1	0.824	0.835	0.0069
Model 1, step 2	0.93	0.91	0.0049
Model 2, step 1	0.92	0.94	0.0052
Model 2, step 2	0.96	0.97	0.0036

Table 1: Comparisons on forecasting models.

Of the 182 outlier that we found with model 1 and 188 that we found with model 2, 119 of them were in both sets of outliers. There is a possibility that we are only getting better in fitting the data to the model when we remove outliers rather than the model getting better. An indication of this is when we fitted model 1 to the dataset without the outliers from model 2 and got R^2 0.90 which is lower than for model 1 in step 2. However if we remove the outliers that are found in both model 1 and model 2 we get $R^2_{\text{model 1}}$ is 0.90 and $R^2_{\text{model 2}}$ is 0.95 which shows that we are not just getting better in fitting the data to the model. We conclude that model 2 is better than model 1

To test our model 2 for over-fitting we do 1000 iterations where we first take a random sample of 2/3 of the data without the outliers from model 2 and use it for training, then we use the remaining 1/3 of the data to test the model. The average $R^2_{\text{Iteration}}$ is 0.97 which is remarkable since it is higher than when we use the whole dataset. Only one time out of the 1000 iterations does the $R^2_{Iteration}$ have smaller value than $R^2_{step2.2}$ .This indicates that we don't have a problem with over fitting. One worker gets significant value higher than 10% 18 times out of the 1000 iteration and another worker gets significant value higher than 10% 12 times out of 1000 iteration. This could suggest that we can't use our forecasting model to estimate worker number 5 and 12 order picking processing time. Since this happens rarely, we do not consider this a problem and this is most likely due to selection of data points for the training set.

To show how accurate model 2 is we take a random sample of 2/3 of the data without the outliers from model 2 and use it for training, then we use the remaining 1/3 of the data to test the model. Of the 2833 data points in 1800 instances the predicted value is greater and in 1033 instances it is less. The average overestimation is 4.37 minutes and the average underestimation is 6.13 minutes. The standard deviation of all the differences is 8.72 minutes.

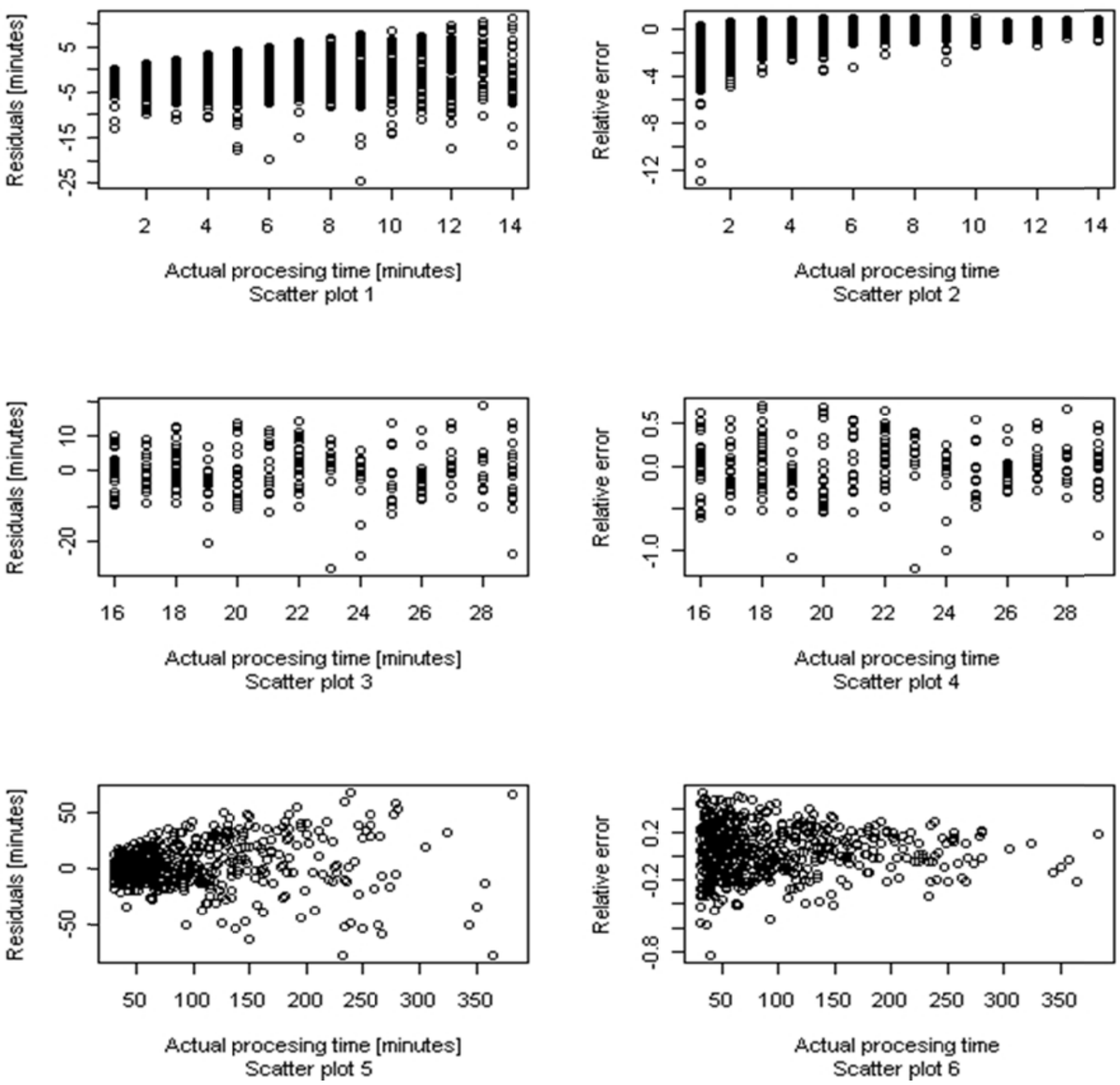

Figure 18: Scatter plot 1, 3 and 5 shows the difference in actual processing time and predicted value (residuals = actual time – predicted time) of model 2 and how it changes as processing time is longer. Scatter plot 2, 4 and 6 shows how relative errors changes of model 2 as processing time gets longer.

As shown in Figure 18 there is an increase in the error that the prediction of forecasting model 2 does as processing time increases but the relative error decreases. Relative error is quite high when processing time is from 0 to 15 minutes but it goes from 12 to about 2 rapidly. We are overestimating the processing time more often than underestimating which is a less harmful error to make when we intend to use the forecast for scheduling. Underestimating processing time can render our scheduling useless if we have not enough slack in our schedule to handle it. Overestimating the processing time will potentially reduce somewhat the efficiency of the order picking operations but the solution will still be valid.

4.1.4 Proposed regression model

Figure 19 shows a diagram of the chosen regression model out of the two proposed regression models, i.e. model 2. WMS database contains information about which worker picked which order, what type of order it was, how many boxes and SKUs where in the order and how many pallets. All this data is used in the forecasting model that predicts workers order processing time.

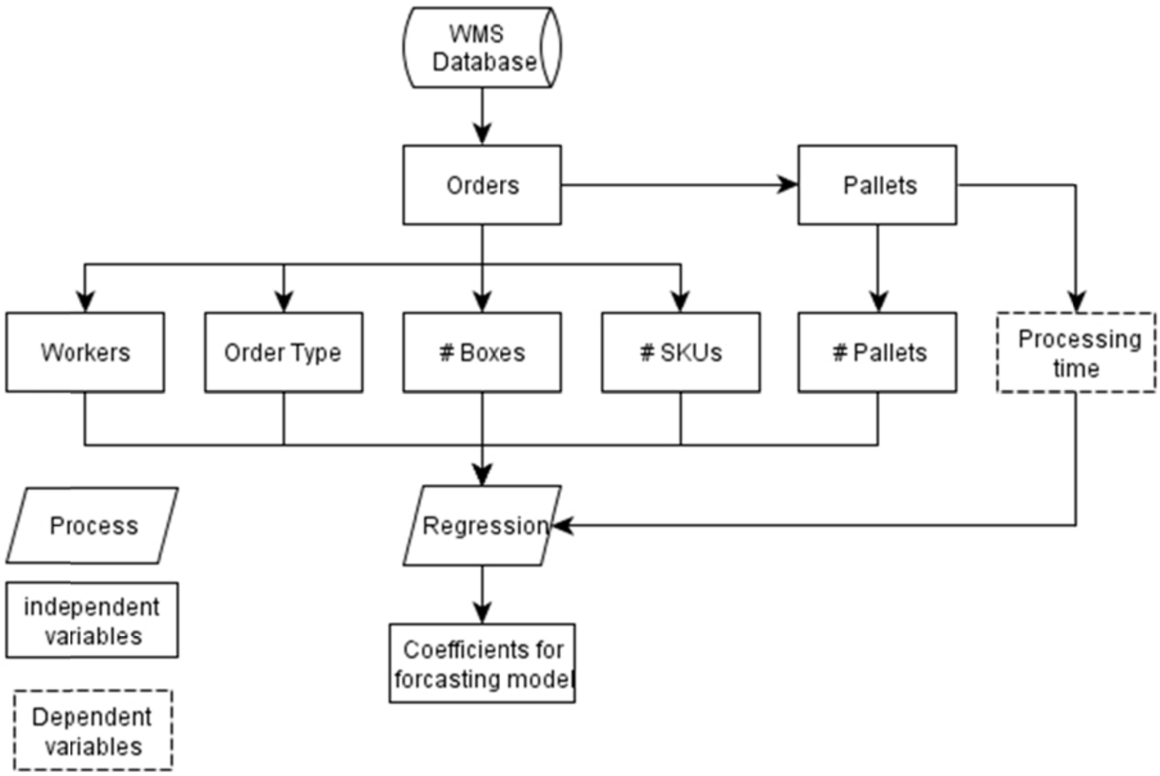

Figure 19: flowchart of data for regression model 2.

4.2 Optimization

We compare the results obtained with the optimization with 10 real working days where all order picking tasks were started and ended on the same day. We compare actual schedules of the real days to three different the scenarios specified in Section 3.3.4 and use the criteria for comparison as explained in Section 3.3.4.

Results for the 10 real work days are in Table 5 in Appendix A. Results for Scenario 1 is in Table 6 in Appendix A. Results for Scenario 2 is in Table 7 in Appendix A. Results for Scenario 3 is in Table 8 in Appendix A.

There are some days that have very high lateness for both the real day and the scenarios. This is because some customers have pre-set order picking days and delivery time. If the costumer sends in an order a day earlier than his order picking day, it can result in an error in our estimation of delivering time. The main rule of order delivery is that orders that come before noon have to be delivered the same day. Orders that come after noon have to be completed before noon the day after; however, this should not affect the comparison between scenarios lateness and the real day because in all cases everyone wants to finish the order as early as possible. If the correct delivering time is late during the day it can lead to bias against Real days lateness.

Tables 2 to 8 show us the testing parameter mean from the real world day and the scenarios along with the results of one sided paired t-test [14]. The t-test shows that if there is a statistical difference between real data and the scenarios. If the P-value is over 0.1 we say that the difference is inconclusive.

Table 2 shows that the solving time for Scenario 3 is the worst but that there is no conclusive difference between Scenario 1 and Scenario 2.

Mean	Solving time	T- test	Solving time
Scenario 1	00:02:36	Sc. 1 vs. Sc. 2	26%
Scenario 2	00:03:12	Sc. 1 vs. Sc. 3	2%
Scenario 3	00:05:16	Sc. 2 vs. Sc. 3	1%

Table 2: Mean scenarios solving time and t-test.

Table 3 shows that total lateness is the lowest for Scenario 1 and second lowest for Scenario 2 but that there is no difference between Scenario 3 and the Real days.

Mean	Total lateness	T- test	Total lateness
Scenario 1	115,1	Real vs. Sc. 1	1%
Scenario 2	130,1	Real vs. Sc. 2	6%
Scenario 3	144,0	Real vs. Sc. 3	31%
Real days	155,0	Sc. 1 vs. Sc. 2	3%
		Sc. 1 vs. Sc. 3	5%
		Sc. 2 vs. Sc. 3	9%

Table 3: Mean total lateness and t-test

Table 4 shows that average lateness of the Real days is lower than Scenario 1 and 2, but there is inconclusive difference between the Real days and Scenario 3. There is however weak evidence to support that there is a difference between average lateness of Scenario 1 and 3 and Scenario 1 and Scenario 2.

Mean	Average lateness	T test	Mean lateness
Real days	16,9	Real vs. Sc. 1	5%
Scenario 3	28,9	Real vs. Sc. 2	8%
Scenario 2	31,5	Real vs. Sc. 3	11%
Scenario 1	44,2	Sc. 1 vs. Sc. 2	10%
		Sc. 1 vs. Sc. 3	9%
		Sc. 2 vs. Sc. 3	27%

Table 4: Mean average lateness and t-test

Table 5 shows that maximum lateness of the Real days is inconclusive from scenarios 1 to 3. On the other hand scenario 1 has lower maximum lateness from the other scenarios.

Mean	Maximum lateness	T- test	Max to late
Scenario 1	64,8	Real vs. Sc. 1	47%
Real days	66,2	Real vs. Sc. 2	46%
Scenario 2	68,1	Real vs. Sc. 3	45%
Scenario 3	68,8	Sc. 1 vs. Sc. 2	4%
		Sc. 1 vs. Sc. 3	7%
		Sc. 2 vs. Sc. 3	39%

Table 5: Mean maximum lateness and t-test

Table 6 shows that Scenario 1 has the lowest number of late orders and Scenario 2 has the second lowest number of late orders. Scenario 3 has the second most number of late orders and Real days have the most number of late orders.

Mean	# of late orders	T- test	# of late orders
Scenario 1	4,0	Real vs. Sc. 1	0%
Scenario 2	6,0	Real vs. Sc. 2	1%
Scenario 3	7,0	Real vs. Sc. 3	7%
Real days	8,9	Sc. 1 vs. Sc. 2	2%
		Sc. 1 vs. Sc. 3	1%
		Sc. 2 vs. Sc. 3	5%

Table 6: Mean number of late orders and t-test

Table 7 shows that Scenario 2 has the highest number of switching but there is inconclusive difference between the other means.

Mean	Switching	T test	Switching
Scenario 1	11,8	Real vs. Sc. 1	25%
Scenario 3	12,5	Real vs. Sc. 2	5%
Real days	15,6	Real vs. Sc. 3	24%
Scenario 2	25,7	Sc. 1 vs. Sc. 2	1%
		Sc. 1 vs. Sc. 3	44%
		Sc. 2 vs. Sc. 3	1%

Table 7: Mean number of switching and t-test

Table 8 shows that the Real days have the least preemption. There is inconclusive difference between Scenario 1 and 3 but Scenario 2 has most preemptions.

Mean	Preemption	T- test	Preemption
Real days	-	Real vs. Sc. 1	2%
Scenario 1	2,8	Real vs. Sc. 2	0%
Scenario 3	5,5	Real vs. Sc. 3	2%
Scenario 2	12,4	Sc. 1 vs. Sc. 2	0%
		Sc. 1 vs. Sc. 3	11%
		Sc. 2 vs. Sc. 3	0%

Table 8: Mean number of preemptions and t-test

Figure 20 to 23 shows us Gantt charts that illustrate which worker performed which order picking tasks and what time slots they were preformed. It is apparent from Figure 20 that the utilization of workers can be higher on a real day. Workers 2 and 18 have long stretches of time where they are not doing order picking. Even with this slackness worker 19 has to finish his last order picking time in overtime.

As shown in Figure 21 Scenario 1 has the same problem of low utilization. Figure 22 shows us that it is possible to use fewer workers to complete the order picking tasks within working hours and Figure 23 shows that it is possible to do so with lower number of preemptions and switching than in scenario 2.

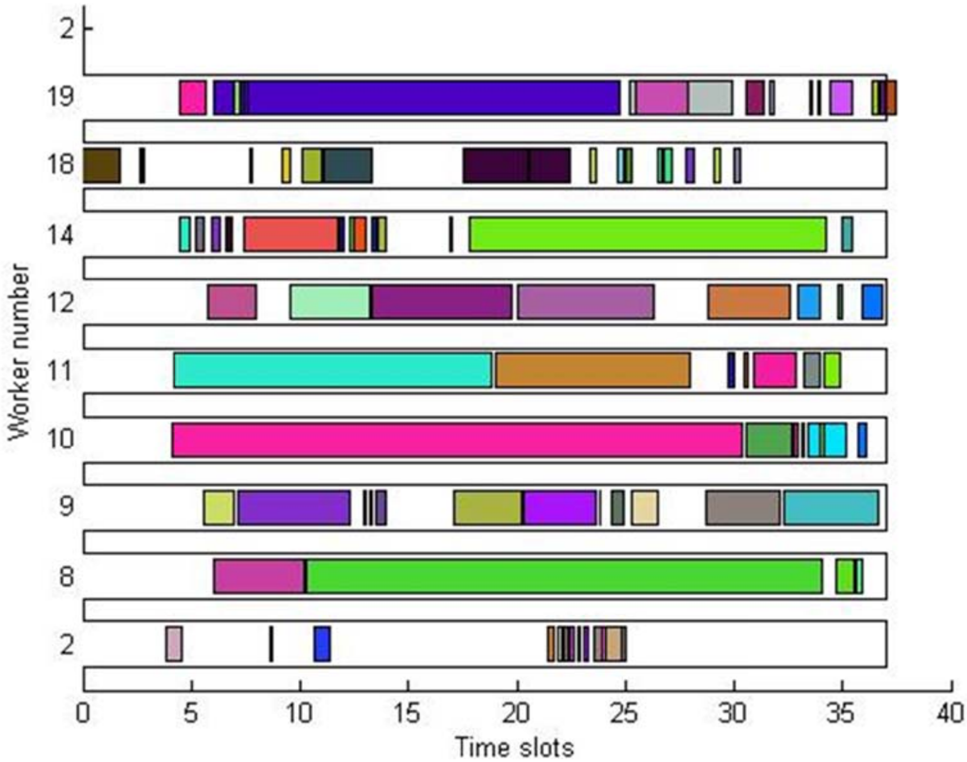

Figure 20: Gantt chart of real working day 06.01.2010. Worker 18 is on shift one that begins work at 08:00 and ends work at 16:30

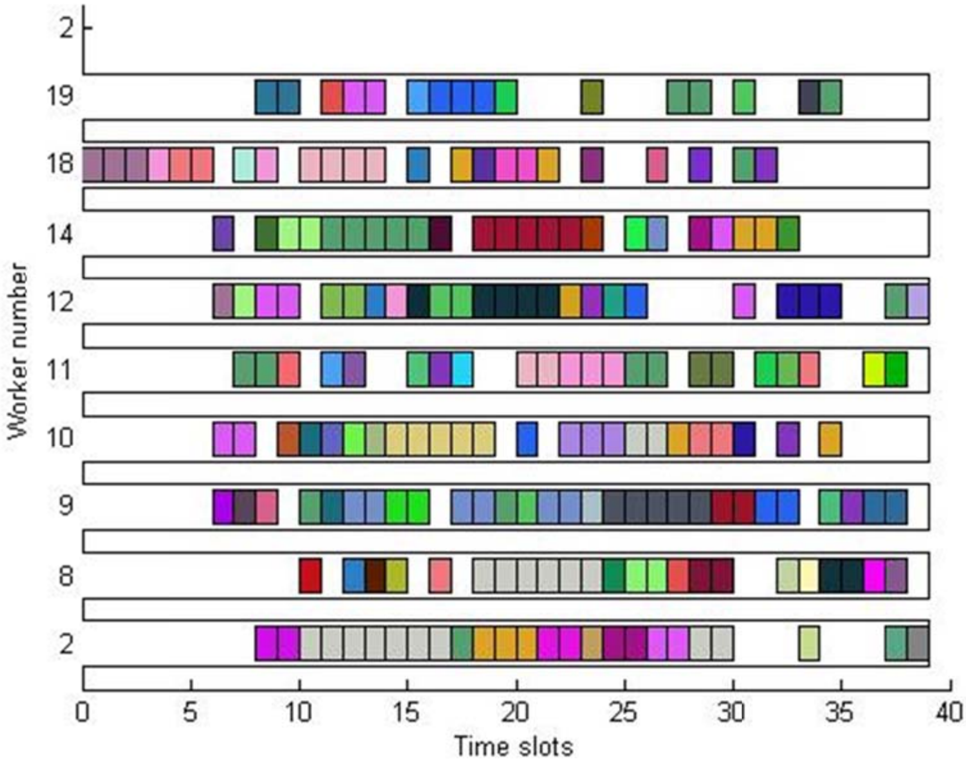

Figure 21: Gantt chart of scenario 1 day 06.01.2010. Worker 18 is on shift one that begins work at 08:00 and ends work at 16:30

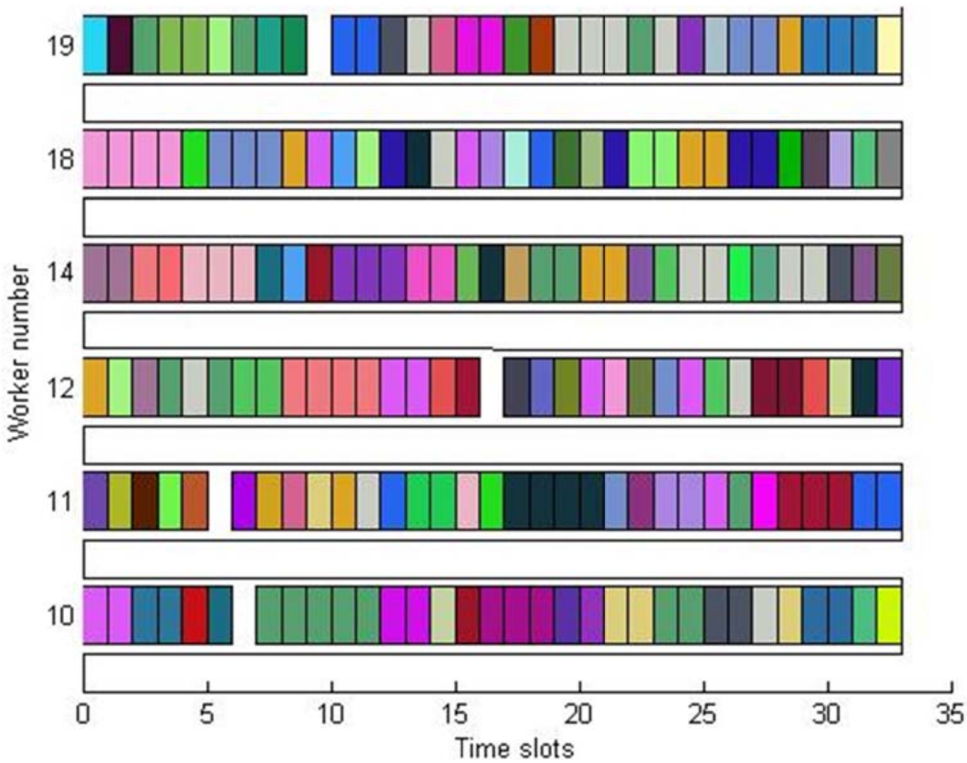

Figure 22: Gantt chart of scenario 2 day 06.01.2010.

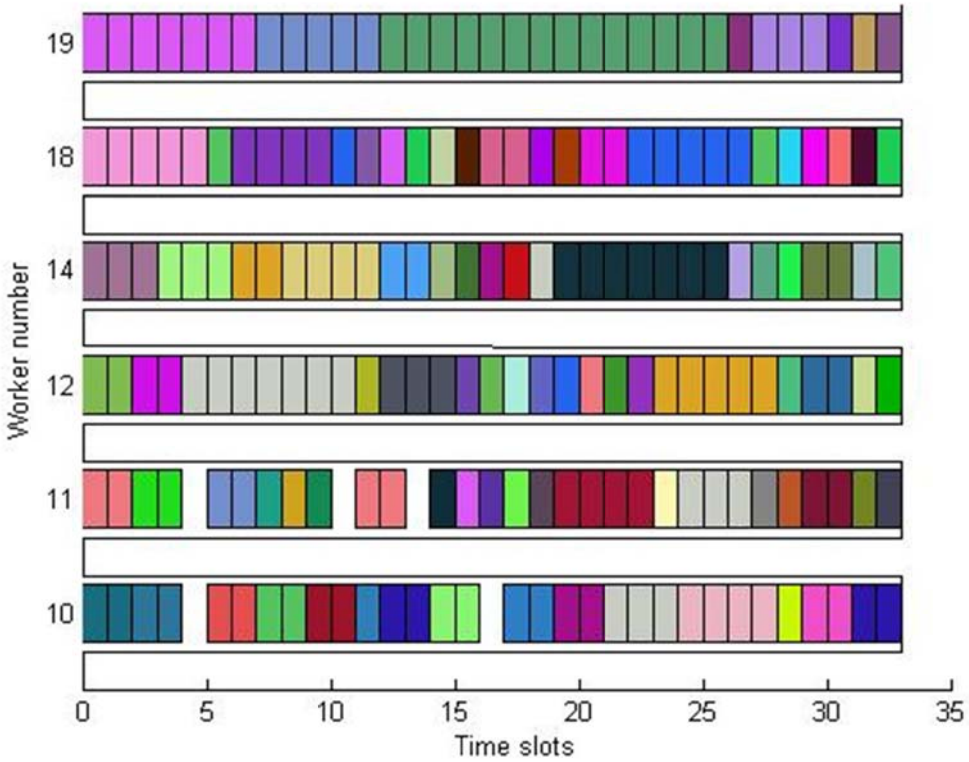

Figure 23: Gantt chart of scenario 3 day 06.01.2010

5. Discussions

As shown in Table 2 the average solution time for all of the scenarios is quite high. The warehouse foreman is working in a real time environment and has to be able to re-optimize his order picking schedule many times a day. He might even want to re-optimize his schedule every time a new order arrives. It takes 3 to 8 minutes for us to calculate the optimal scheduling solution; this can undermine the effectiveness of using our method in warehouses. Faster solving algorithms based on heuristics for example we may wish to stop branching when the gap between the upper and lower bounds becomes smaller than a certain threshold. Search algorithms could be advised but usually they do not find the best solution. In real world situation like the one we are studying a good solution is necessity that is not far from the best theoretical solution but we don't have to demand on having the best theoretical solution for it to work.

There is a great need for warehouses to service their costumers faster and better with less cost. Many warehouses have looked at capital intensive investments such as high level Automated Storage and Retrieval Systems (AS/RS) systems that are known to have output of 500 picks on average per order picker hour. Newly developed systems indicate that up to 1000 handling per picker hour are feasible [1]. Not all warehouses need such an output or their economic reality does not allow them to invest in an expensive AS/RS systems. It is estimated that only 20% of warehouses use some sort of AS/RS. The rest use low-level, picker-to-parts systems employing humans. These warehouses also need better utilization of their resources without going into expensive investments of AS/RS systems.

With our case study we have shown that the data that should be currently available in most modern WMS can be used to predict how long time it will take each worker to process order picking tasks.

Warehouse management can use the predicted processing times to manually schedule their picking for a small number of workers or orders. If the order number is high, an optimization model can give the foreman a proposed order picking schedule for his workers. Warehouse foreman has to be able to easily modify the proposed order picking schedule or verify that it is suitable.

To make this feasible some sort of software has to be used for all the data manipulations and calculations. The warehouse management has to have a general user interface (GUI) with a visual display of all available workers, shifts information and all available orders. The manager should be able to drag an order over workers shift plan where the length of the order is changed, showing how much of a worker's shift would be used if the manager decides that this worker should perform the order picking task. If the manager drags the same order over another worker the length of it changes according to the new worker's predicted processing time. We propose using some kind of Gantt type chart like shown in Figure 7 to show all the workers and the picking tasks that have been assigned. The management also has to be able to change order delivering times according to changes in distributions and carriers time plans.

Figure 25 shows a flowchart of information and how they should interface with different procedures of our proposed software for our case studies 3PL company's warehouse.

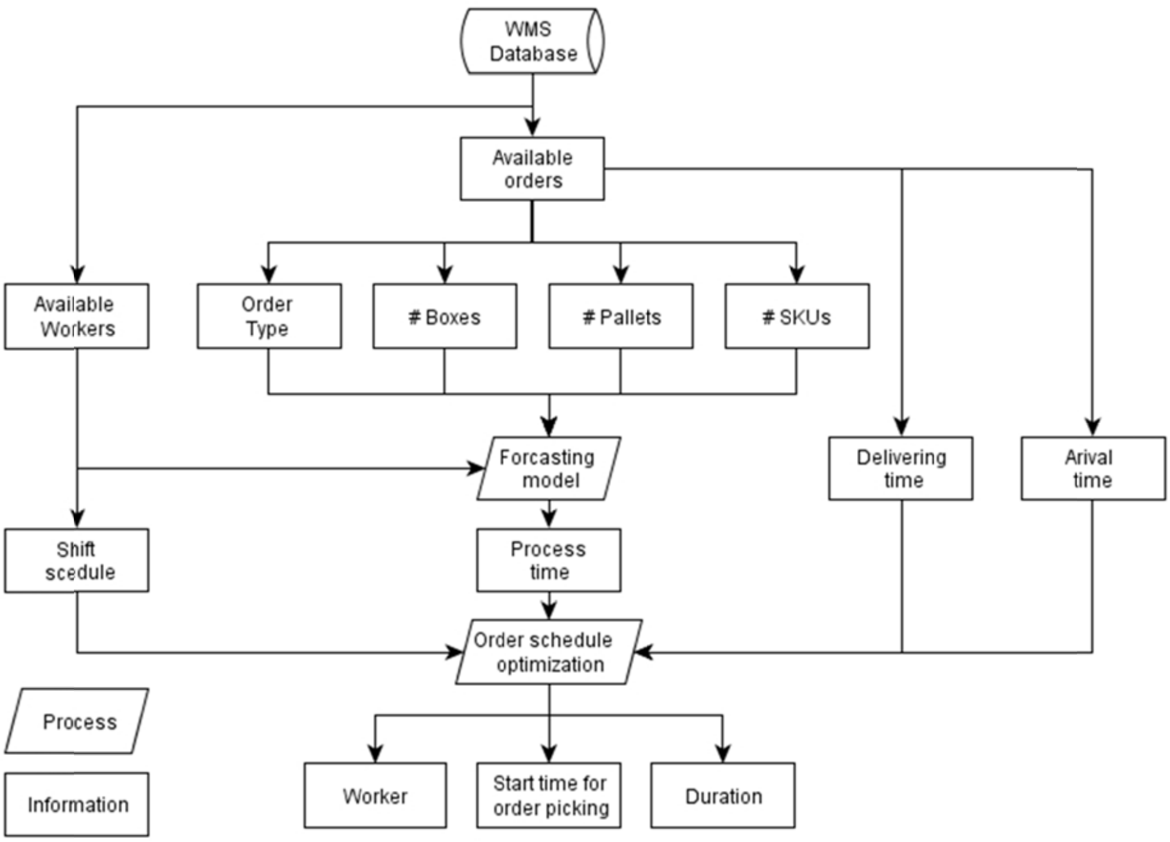

Figure 24: A flowchart of forecasting and optimization of order picking scheduling.

Further work has to be done regarding the implementation for the online rolling horizon environment. That requires data manipulation in order to ensure that data and work status is always up to date when a new optimization is started. By not directly addressing or testing the functionality in the online rolling horizon environment we believe our results only indicate the upper limit of the benefit of using the proposed optimization procedure to schedule order picking tasks.

6. Conclusions

In this thesis we have proposed a method for forecasting the length of time it will take an individual worker in a warehouse to pick orders. We first use a forecasting model based on a standard measurement of order picking speed in the warehouse and compare it with a model that is proposed in collaboration with our case study warehouse foremen. We show that our collaboration with the foremen paid off with a better model. We propose a method to deal with outlier in our dataset because of work pauses during the order picking and how we are able to get rid of most of the influence of such pauses.

We also propose an optimization method for scheduling the order picking tasks to workers. We compared ten real days of order picking with results obtained for three different scenarios with the optimization model. The optimized results gave schedules that were able to perform no worse than real day scenarios with reduction of 30% to 60% of the workforce. As expected we have more preemption and switching than in the real days results but we can reduce this effect by selecting higher penalties for preemption in the objective function of the optimization model.

We propose the development of a software solution that helps the warehouse foreman to schedule the order picking tasks either manually or with the help of optimization.

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Appendix A

A.1Tables

Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
factor(Worker)2	-0,1075710	0,0127360	-8,45	<2e-16	***
factor(Worker)5	-0,2383160	0,0144520	-16,49	<2e-16	***
factor(Worker)8	0,1258700	0,0144400	8,72	<2e-16	***
factor(Worker)9	-0,4269010	0,0130160	-32,80	<2e-16	***
factor(Worker)10	-0,4730610	0,0148690	-31,82	<2e-16	***
factor(Worker)11	-0,3830390	0,0145770	-26,28	<2e-16	***
factor(Worker)12	-0,3529010	0,0145000	-24,34	<2e-16	***
factor(Worker)14	-0,4867960	0,0142810	-34,09	<2e-16	***
factor(Worker)16	-0,4371480	0,0143670	-30,43	<2e-16	***
factor(Worker)18	-0,4085210	0,0150330	-27,17	<2e-16	***
factor(Worker)19	-0,3236920	0,0189100	-17,12	<2e-16	***
factor(Type)Dry	0,3932530	0,0075860	51,84	<2e-16	***
log(Boxes)	0,8519740	0,0021170	402,46	<2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 (Dispersion parameter for poisson family taken to be 1) Null deviance: 935538 on 5672 degrees of freedom Residual deviance: 36877 on 5659 degrees of freedom AIC: 59121 Number of Fisher Scoring iterations: 5					

Table 1: Results from forecasting model 1 step 1

Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0,275966	0,013612	-20,27	<2e-16	***
factor(Worker)5	-0,164776	0,015574	-10,58	<2e-16	***
factor(Worker)8	0,163734	0,016144	10,14	<2e-16	***
factor(Worker)9	-0,362905	0,013716	-26,46	<2e-16	***
factor(Worker)10	-0,447459	0,013404	-33,38	<2e-16	***
factor(Worker)11	-0,344098	0,013321	-25,83	<2e-16	***
factor(Worker)12	-0,319239	0,013177	-24,23	<2e-16	***
factor(Worker)14	-0,452055	0,012908	-35,02	<2e-16	***
factor(Worker)16	-0,392094	0,013303	-29,48	<2e-16	***
factor(Worker)18	-0,372601	0,013784	-27,03	<2e-16	***
factor(Worker)19	-0,296335	0,019782	-14,98	<2e-16	***
factor(Type)Dry	0,355823	0,008698	40,91	<2e-16	***
log(Boxes)	0,899329	0,002462	365,28	<2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 (Dispersion parameter for poisson family taken to be 1) Null deviance: 260839 on 5489 degrees of freedom Residual deviance: 19842 on 5477 degrees of freedom AIC: 41053 Number of Fisher Scoring iterations: 5					

Table 2: Results from forecasting model 1 step 2

Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
factor(Type)Alcohol	0,664115	0,01415	46,94	<2e-16	***
factor(Type)Dry	0,559735	0,01599	35	<2e-16	***
factor(Worker)5	-0,174773	0,01349	-12,96	<2e-16	***
factor(Worker)8	0,214821	0,0142	15,13	<2e-16	***
factor(Worker)9	-0,358833	0,01262	-28,44	<2e-16	***
factor(Worker)10	-0,586126	0,01245	-47,09	<2e-16	***
factor(Worker)11	-0,410812	0,01246	-32,96	<2e-16	***
factor(Worker)12	-0,411157	0,01221	-33,67	<2e-16	***
factor(Worker)14	-0,605095	0,01207	-50,12	<2e-16	***
factor(Worker)16	-0,483658	0,01243	-38,91	<2e-16	***
factor(Worker)18	-0,433769	0,01276	-34	<2e-16	***
factor(Worker)19	-0,294107	0,01833	-16,05	<2e-16	***
log(Pallets)	0,24376	0,00656	37,13	<2e-16	***
log(Boxes)	0,415629	0,00469	88,63	<2e-16	***
log(SKUs)	0,386076	0,00457	84,51	<2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 (Dispersion parameter for poisson family taken to be 1) Null deviance: 935538 on 5672 degrees of freedom Residual deviance: 24327 on 5657 degrees of freedom AIC: 46575 Number of Fisher Scoring iterations: 5					

Table 3: Results from forecasting model 2 step 1

Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
factor(Type)Alcohol	0,39843	0,0162	24,59	<2e-16	***
factor(Type)Dry	0,34703	0,01886	18,4	<2e-16	***
factor(Worker)5	-0,2107	0,01552	-13,58	<2e-16	***
factor(Worker)8	0,17207	0,01616	10,65	<2e-16	***
factor(Worker)9	-0,3547	0,01373	-25,84	<2e-16	***
factor(Worker)10	-0,5745	0,01349	-42,57	<2e-16	***
factor(Worker)11	-0,4101	0,01342	-30,57	<2e-16	***
factor(Worker)12	-0,405	0,01324	-30,6	<2e-16	***
factor(Worker)14	-0,5835	0,01312	-44,49	<2e-16	***
factor(Worker)16	-0,4664	0,01338	-34,86	<2e-16	***
factor(Worker)18	-0,4348	0,01382	-31,46	<2e-16	***
factor(Worker)19	-0,3568	0,01978	-18,04	<2e-16	***
log(Pallets)	0,19138	0,00731	26,18	<2e-16	***
log(Boxes)	0,51478	0,00579	88,94	<2e-16	***
log(SKUs)	0,32967	0,00529	62,31	<2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 811537 on 5490 degrees of freedom
Residual deviance: 14169 on 5475 degrees of freedom
AIC: 35384

Number of Fisher Scoring iterations: 5

Table 4: Results from forecasting model 2 step 2

Date	total lateness'	Median lateness	maximum to late	# of late orders	Switching	Preemption
6.1.2010	65	9	28	7	13	0
7.1.2010	184	46	80	4	9	0
17.2.2010	178	14	123	12	17	0
26.2.2010	408	12	92	34	9	0
5.1.2010	42	11	29	4	21	0
24.2.2010	208	26	80	8	19	0
16.2.2010	14	7	10	4	18	0
3.3.2010	31	14	123	3	15	0
24.3.2010	98	10	14	5	13	0
17.3.2010	322	20	83	8	22	0

Table 5: Results from Real day

Date	# Orders	# Workers	Solving time	Total lateness	Median lateness	Maximum to late	# of late orders	Switching	Preemption
6.1.2010	82	9	00:03:24	57	14,3	34	4	41	10
7.1.2010	70	10	00:02:02	190	63,3	88	3	7	2
17.2.2010	110	11	00:01:39	91	91,0	91	1	0	0
26.2.2010	61	10	00:01:29	371	14,3	90	26	13	2
5.1.2010	87	10	00:01:16	0	0,0	0	0	0	0
24.2.2010	94	10	00:02:04	74	37,0	73	2	0	0
16.2.2010	84	11	00:01:34	1	1,0	1	1	0	0
3.3.2010	77	10	00:01:18	0	0,0	0	0	1	1
24.3.2010	96	10	00:03:56	75	75,0	75	1	30	9
17.3.2010	94	11	00:07:19	292	146,0	196	2	26	4

Table 6: Results from scenario 1

Date	# Orders	# Workers	Solving time	Total lateness	Median lateness	Maximum to late	# of late orders	Switching	Preemption
6.1.2010	82	6	00:04:00	67	13,4	29	5	42	18
7.1.2010	70	4	00:00:14	202	40,4	91	5	16	15
17.2.2010	111	7	00:07:09	97	97,0	97	1	1	0
26.2.2010	62	4	00:00:31	450	12,9	96	35	15	11
5.1.2010	88	6	00:00:45	7	2,3	4	3	39	17
24.2.2010	95	7	00:00:38	93	46,5	88	2	7	3
16.2.2010	86	6	00:01:56	5	2,5	3	2	7	2
3.3.2010	77	6	00:03:18	0	0,0	0	0	43	10
24.3.2010	96	7	00:00:54	80	40,0	78	2	36	20
17.3.2010	94	6	00:12:39	300	60,0	195	5	51	28

Table 7: Results from scenario 2

Date	# Orders	# Workers	Solving time	Total lateness	Median lateness	Maximum to late	# of late orders	Switching	Preemption
6.1.2010	82	6	00:04:49	80	8,9	28	9	11	5
7.1.2010	70	4	00:00:27	184	61,3	82	3	0	0
17.2.2010	111	7	00:12:04	97	97,0	97	1	0	0
26.2.2010	62	4	00:00:46	535	14,9	108	36	11	5
5.1.2010	88	6	00:02:47	6	1,5	2	4	34	13
24.2.2010	95	7	00:05:23	83	16,6	77	5	0	0
16.2.2010	86	6	00:02:19	20	10,0	16	2	2	0
3.3.2010	77	6	00:06:47	0	0,0	0	0	3	1
24.3.2010	96	7	00:05:11	87	29,0	82	3	30	11
17.3.2010	94	6	00:12:09	348	49,7	196	7	34	20

Table 8: Results from scenario 3