Forecast deviations' impact on simulation-based decision-support

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Abstract

Title	Forecast deviations' impact on simulation-based decision-support.
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Background	Capacity decisions, both short- and long term, tend to have a high strategic value for manufacturing companies. A simulation model can be used to evaluate different capacity options. However, the simulation results can be difficult to interpret.
Purpose	The aim of this study is to provide further understanding of how to work with simulation-based decisions-making. In particular, further knowledge of the simulated output data's sensitivity to uncertainties in the input data is to be gained.
Delimitations	The scope of this study is limited to simulation models of one production site and two years of historic data. Neither alternative forecasting methods nor structural changes of the models will be investigated and/or evaluated.
Methodology	This is a field study of an exploratory and explanatory nature, with the project process following the U-model.
Experiments	The robustness and accuracy of a discrete event simulation model, relating to the existing deviations in the input data, was analysed. Furthermore, the accuracy's time dependency relating to the forecasted time frame of the input data was evaluated.
Key findings:	The discrete event simulation model gave robust results as early as a year ahead of time, with an accuracy deviation of ±2-3 percentage units, for the operational KPI EE. Operational losses seem to be more beneficial to model with distributions rather than averages. The discrete event simulation model allows more complex modelling of the laminators to reflect their individual behaviour. However, the current model behaviour ends up not accurately reflecting reality. As the uncertainty level in the different input datasets vary, an additional volume factor in the models could be adjusted to reflect this and increase the Throughput accuracy.

Keywords:	Discrete Event Simulation, Decision Support, Capacity Planning, Forecast deviations, Statistical Sensitivity Analysis

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Notations

AOS: Average Order Size

Block plan: The production scheduling method used at the case company's production site.

Bottleneck: The main operational capacity-constraint of the production process.

DES: Discrete Event Simulation

EE: Equipment Effectiveness (KPI)

KPI: Key Performance Indicator

Make-To-Order: The products are produced according to specific orders.

OEE: Overall Equipment Effectiveness (KPI)

Reel: A smaller board unit created by slitting a Roll.

Roll: The largest production board unit used at the case company.

TEE: Total Equipment Effectiveness (KPI)

QS: The product code used in the spreadsheet model, refers to only the Quality and Size characteristics of the product.

QSV: A product code, refers to the Quality, Size and Variant characteristics of the product.

VMR: Vendor Managed Replenishment

WIP: Work In Progress

1 Introduction

1.1 Background

Capacity decisions tend to have a high strategic value for manufacturing companies. To remain competitive it is necessary to be able to meet the future demand. As capacity changes can be both costly and time-consuming, it is often required to plan ahead. Since capacity planning is on top of the production planning hierarchy, it will then set the requirements for all other planning decisions, such as shop floor control and production scheduling. The time horizons for the capacity decisions can be both short- and long-term. A short-term decision could be to meet demand changes by applying overtime policies. Long-term decisions are often more permanent in their nature and could include major changes such as investing in new facilities or expensive equipment. (Hopp & Spearman, 2000, pp. 626 – 645)

To be able to analyse different capacity options it is necessary to have some form of model of the system at hand. In practice, as it is rarely possible to apply an exact mathematical model, a simulation model can be a useful tool. Simulation can be described as "the imitation of the operation of a real-world process or system over time". It gives the opportunity to construct complex structures and evaluate different options before investing the time and finances an actual implementation would require. However, using simulation is not without issues; the simulated results can be difficult to interpret and the model can be costly and time consuming to create and use. According to Banks, Carson & Nelson, manufacturing and materials handling systems are some of the areas best suited for simulation. (Banks, Carson & Nelson, 1996, pp. 3-5, 153) A promising future direction of simulation studies, as stated by Negahban & Smith, is the development of robust simulation-based tools to be used as decision-support at an operational level. (Negahban & Smith, 2014)

This study is conducted in collaboration with an international packaging solution provider based in Sweden. The company has several factories and currently each site uses an Excel spreadsheet model to plan the capacity needs for their respective production. For the purpose of gaining further and more accurate understanding of the future expected behaviour of the factories' capacity need, the company has invested in a more advanced discrete event simulation model. This model uses several datasets as input data, one being forecasted sales data. Several capacity decisions, such as comparing expected capacity needs with available capacity or comparing alternative capacity solutions, are then investigated and evaluated using this simulation model.

1.2 Problem discussion

According to Hopp & Spearman, the first law of forecasting states that forecasts will never be able to exactly predict the future outcome. This is due to the fact that all variables influencing the future outcome cannot possibly be included in a model. (Hopp & Spearman, 2000, pp. 414 – 430) This leads to the question of how to practically work with forecasted information in order to make well-informed capacity decisions.

The first task of this study is to investigate how the input data accuracy, in this case forecasted sales data, affects the factory simulation results. From this follows the problem of which input data uncertainty the simulation models are capable to handle while still providing robust results.

The second task is to compare and evaluate the performance of the discrete event simulation model to the static spreadsheet model currently used at the sites. The possible additional value gained of being able to perform more complex analyses by using the discrete event simulation model, is to be investigated.

These analyses aims at providing increased understanding of the input and output relationship of a discrete event simulation model, thus provide further insight into how to work with simulation results in the context of capacity decision-making.

1.3 Purpose & Goal

The purpose of this study is to further evaluate and create understanding of, by using a practical case, how to work with simulation-based decision-support. In particular, further knowledge of the cause and effect relationship between uncertainties in the input data and the simulated output is to be gained.

The goal of this study is to determine the credibility of the simulation model's results, relating to forecast deviations, and to provide a structured framework on how to advantageously utilize the gained knowledge as support in the capacity decision-making process.

1.4 Delimitations

Due to data volumes and time restrictions, certain limitations for the scope of this study have been made. Only a single, representative production site will be simulated. Furthermore, only two years of historic data are to be analysed. Neither alternative forecasting methods, nor other methods used for collecting input data for the models, will be evaluated. It is further assumed that all the provided models work as they are intended to. Therefore no structural changes in the model configurations will be investigated.

1.5 Report structure

Below a short summary of the structure of the report is presented.

Introduction	The background of the study is introduced. The problem is formulated and the purpose and goal are set.
Methodology	Explanations of the methodology used throughout the study are presented.
Theoretical framework	The theoretical foundation that makes up the basis of the study are introduced and explained.
Empirical framework	Description of material used in the study, such as the simulation models, datasets etc. are presented.
Initial experiments	The initial investigations needed in order to conduct the main experiments are given.
Main experiments and results	The main experiments of this study as well as their results are presented.
Discussion	The results of the main experiments are discussed.

Conclusion and recommendations	The findings of the study are summarized and a recommended framework is provided. Further study-areas that can complement this study are presented and the project process is evaluated.
References	The sources providing the information are listed.
Appendix	Back up material.

2 Methodology

In this section the methodology used throughout the study will be introduced. The methodology used has been of a flexible nature, i.e. it has been adapted during the course of the study to match changing circumstances. (Höst, Regnell & Runeson, 2006, pp. 31) The first part explains the overall approach of the study, the second introduces the data collection techniques used and the final part clarifies how the quality of the results was verified.

2.1 Approach

2.1.1 Study characteristics

According to McGrath, a compilation of research strategies can be done as shown below in Figure 2.1.

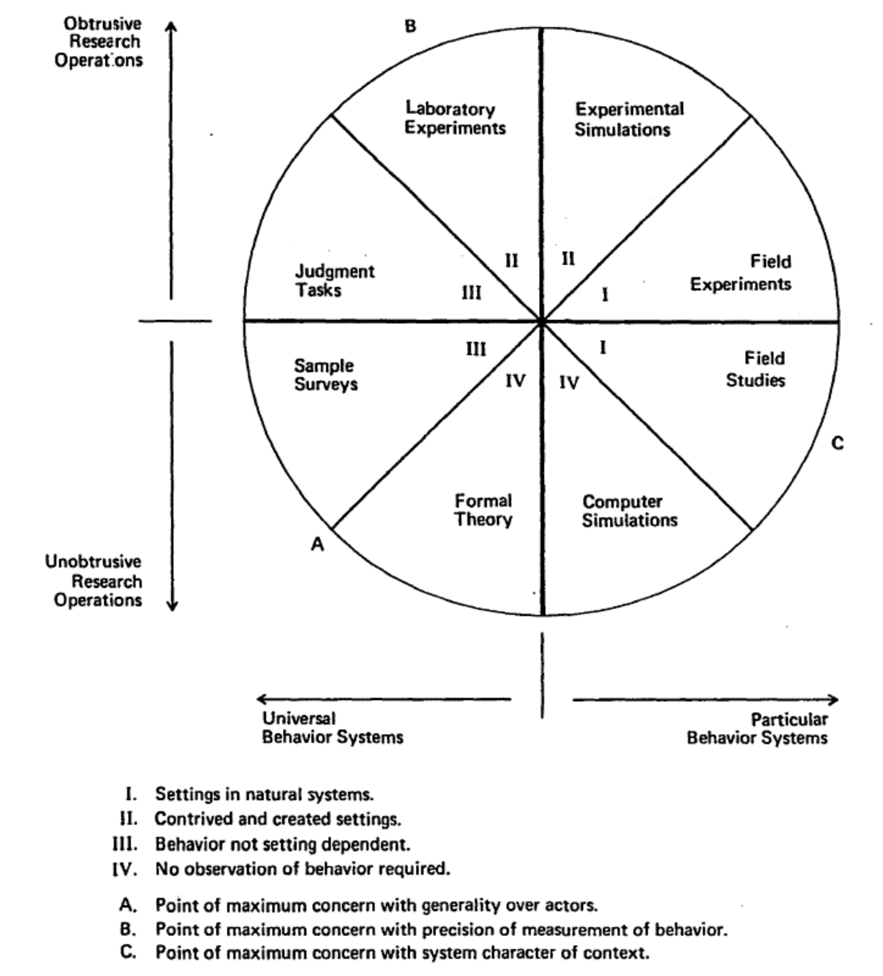

Figure 2.1 Research strategies. (McGrath, 1981, pp. 183)

Figure 2.1 divides different study approaches by categorizing them in two different ways; if they are obtrusive or not and if they are particular or universal in nature. By classifying a study in this way, it is easier to identify the main concern of the study and thereby maintaining the accurate focus throughout the project process.

This study is classified as an Experimental Simulations study since it is an obtrusive research operation, meaning a more hands-on approach was used rather than merely observing the system, and it concerns a case study which can be categorized as a study of a particular behaviour system. Therefore the focus should lean towards the behaviour of the system, i.e. letter B in Figure 2.1. (McGrath, 1981, pp. 183)

The purpose of a study can be divided into four categories; descriptive, exploratory, explanatory and problem solving. The overall purpose depends on the study characteristics, and the methodology should be chosen accordingly. (Höst et. al., 2006, pp. 29) This study is of an exploratory and explanatory nature.

2.1.2 Scientific approach

Depending on the nature of the study, different scientific approaches are suitable.

An inductive approach means that the research begins with data collection, which should be made without preconditions, from which conclusions are made. Conclusions based on an inductive approach are often of a more generic nature.

In a hypothetic-deductive approach the theory is given a more central role than in the inductive approach. Based on the existing theory, a hypothesis is derived and then tried empirically. A test is ideally conducted as an experiment where the influencing factors systematically are altered while observing the effects. A precondition for such an approach is that the researcher possesses some underlying knowledge of the matter at hand.

An abductive approach is when the study tries to identify the causes of a given result. This means working backwards, trying to eliminate and isolate the variables affecting the final result. The conclusions of such a study need to be practically tested in order to be validated.

(Wallén, 1996, pp. 47-48)

The approach of this study is similar to that of a hypothetic-deductive approach, where statistic hypotheses relating to the simulated results are tried in order to understand the model's behaviour.

2.1.3 Data characteristics

Quantitative and qualitative data

The data collected can be of either quantitative or qualitative nature. Quantitative data refers to data which can be enumerated and classified, such as size, weight and colour, which is practical for statistical analyses. Qualitative data consist of more detailed descriptions and requires analyzing-methods of a more categorizing nature. (Höst et. al., 2006, pp. 30)

Quantitative data, in form of historic forecasts, simulation output and historic order and production data, was used in this study to perform statistical analyses. This was combined with qualitative data, from literature and interviews, in order to gain a more detailed understanding of the processes and model configurations.

Primary and secondary data

Data can be divided into primary and secondary data, which relates to the source of the data. Primary data is data that have been created or collected for use in the study specifically, while secondary data is data which already existed independent to the study. (Bell, 2000, pp. 94)

In this study both kinds of data were used. Primary data was collected from the interviews with key figures at the company as well as from simulation analyses performed. Secondary data was gained both from the literature study and in form of historic data from e.g. forecasts used.

2.2 Data collection techniques

2.2.1 Literature review

A literature review's contribution to a project depends on the stage of the project process. As an initial step it gives the necessary background to the topic of interest. Further along the project the literature review can be used more specifically to answer more detailed questions that have arisen. (Höst et. al., 2006, pp. 59 - 66)

A literature review was conducted early on in the project process in order to form a theoretical base and gain further understanding of the problem at hand. The sources used were predominantly a combination of printed books and e-books, selected partially upon recommendation. Scientific articles were used as a complement to further deepening the knowledge in areas of interest. These materials were retrieved from Lund University's library portal LUBsearch using combinations of key words such as: discrete event simulation, forecast, uncertain*, capacity planning, decision making, manufacturing etc.

2.2.2 Interviews

Interviews are a flexible data gathering method. It gives the interviewer the opportunity to e.g. follow up questions so that the topic discussed will be fully covered. However, it is a time consuming data gathering technique and there is a risk of bias involved. (Bell, 2000, pp. 120-123)

An interview can be classified as structured, semi-structured or non-restricted. A structured interview can be compared to a questionnaire where a fixed set of questions is asked in a specific order. During a non-restricted interview it is the interviewee that leads the conversation and the interviewer's task is to makes sure that the conversation stays on topic. A semi-structured interview is a combination of the two previously mentioned interview methods, questions have been prepared in advance but depending on the development of the conversation questions can be added and reordered. (Höst et. al., 2006, pp. 34)

In this study, semi-structured interviews have been performed in order to gain knowledge about and understanding of the relevant processes and simulation models used at the company. While being semi-structured, the initial interviews leaned towards a more non-restricted nature as the processes first were introduced. As the study proceeded, the interviews became more structured as more detailed information was sought.

2.2.3 Modelling

Simulation modelling can be applied as a data collecting method by generating output data to be used for analyses of specific scenarios. In this study, simulation results were generated, using a range of historic data as input, in order to perform analyses.

2.3 Quality verification of results

In order to not draw conclusions on misleading information, it is important to continuously assess the quality of the results. The following validation aspects will be addressed in this study:

Reliability

Reliability refers to how dependable the research design and data gathering methods used are in terms of stochastic variances. To achieve a high reliability it is important to keep a detailed documentation of all stages throughout the study, thus enabling a third party to take part and provide insights. (Höst et. al., 2006, pp. 41 - 42) One of the measures taken to increase the reliability of the data used, was allowing the interviewees to read through a compilation of the collected data afterwards for eventual misunderstandings.

Validity

The validity of the research is to determine to what extent the intended object of the research really is measured. Triangulation, i.e. measuring the same object using different methods, is an example of an approach to increase the validity of the results. (Höst et. al., 2006, pp. 41-42) To achieve a high validity, several different analyses were done on the same datasets. Three Key Performance Indicators (KPIs) were used to provide various insights to the results.

Representativeness

Representativeness, sometimes referred to as external validity, refers to how general the results are, i.e. to what extent the obtained results can be applied on other situations. As this to a large part is determined by the used choice of samples, methods, restrictions etc., a detailed documentation can increase the external validation. However, case studies generally tend to have a low representativeness. (Höst et. al., pp. 41-42) To be able to use the historic data as input data for the simulation models, a few modifications were necessary. All changes were discussed with involved personnel and carefully documented in order to increase the representativeness of the study.

2.4 Project process

During the course of the study, the U-model has been used to keep track of the project progress, and continuously reconnect the work flow and results with the aim of the study. The path of the U-model is illustrated Figure 2.2.

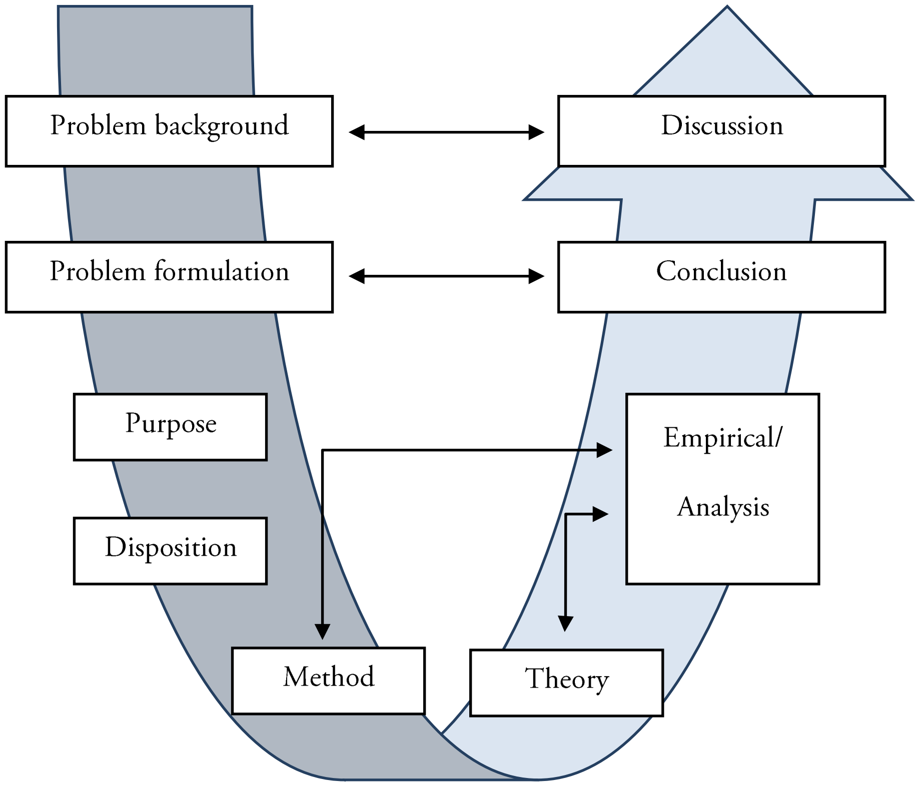

Figure 2.2 The U-model description of the different stages of a study and how they should reconnect. (Alvehus, 2013, pp. 38)

3 Theoretical framework

This section will provide the theoretical foundation of the study, i.e. give the background knowledge necessary to understand the experiments later conducted. It is divided into four main categories; Capacity planning, Forecasting, Simulation and Statistical framework.

3.1 Capacity planning

Capacity planning can involve many different types of capacity decisions of varying size. It can include everything from whether to invest in an additional manufacturing plant to how the everyday production should be run in order to reach the production volume targets. Capacity planning is listed high in the planning hierarchy of a factory. A high hierarchy position indicates a long term strategic value and a lower position indicates short term control issues. The company has to have a capacity strategy which should be closely connected with the core business plan, in order to know the size and what type of capacity that is needed. (Hopp & Spearman, 2000, pp. 432-433)

Capacity adjustments are sometimes needed in order to cope with changing conditions in the production such as fluctuation in demand. These adjustments can be short term or long term. Short term changes can involve overtime or changes in the number of working shifts used. Long term adjustments can for example be installing new machines or building a new production site. Depending on the characteristics of the decision, e.g. the magnitude of the decision or the expected time horizon of the decision's effect, more or less planning is required. For example, if a new production plant is prospected a possible implementation would increase the capacity for a long time to come. Thus long-term forecasting needs to be taken into consideration previous to making a decision and the planning process needs to be more rigorous than the one for smaller, more basic decisions. (Hopp & Spearman, 2000, pp. 410, 626-627)

In order to at a practical level be able to do any analysis of the capacity requirements at all, models are needed. (Hopp & Spearman, 2000, pp. 631) It is common that companies use spreadsheet based capacity modelling in their everyday operations. Even though more dynamic models exist, the need of a simple capacity model that can give quick answers still exists. (Ozturk, Coburn & Kitterman, 2003)

3.2 Forecasting

In order to plan and schedule production one must estimate the production quantities that will be demanded the upcoming time periods. To do this forecasting is used. Axsäter defines demand forecasting as "an estimated average of the demand size over some future period". Thus, when trying to predict the future outcome, it is important to consider the probable errors in these demand estimates as well. (Axsäter, 2006, pp. 7)

According to Hopp & Spearman there are three laws that should be taken into consideration when dealing with forecasting:

"*First law of forecasting*: Forecasts are always wrong!

Second law of forecasting: Detailed forecasts are worse than aggregate forecasts!

Third law of forecasting: The further into the future, the less reliable the forecast will be!"

(Hopp & Spearman, 2000, pp. 415)

3.2.1 Quantitative and qualitative forecasting

Forecasting methods can be categorized as either qualitative or quantitative. A qualitative forecast is based on the knowledge of experts or other experienced people in the field of interest. Quantitative forecasting methods are on the other hand based on quantifiable factors and parameters, such as e.g. historic demand data. There are two general types of quantitative forecasting methods; forecasting based on historic data and forecasting based on other factors, also referred to as time series models and causal models. (Axsäter, 2006, pp. 7-8) (Hopp & Spearman, 2000, pp. 414-415)

For computerized systems, forecasting based on historic data could be applied and developed to cover a wide spectrum of products. However, historical data might not in all situations be the best parameter to base a forecast on. Examples of these kinds of situations can be if the company is planning a promotion on one or more items of a competitor introduces a new competing product to the market. Here previous demand data might not be sufficient to give an accurate forecast and other parameters might have to be included manually. Another case where forecasting based on other factors can be used is when forecasting the demand for a sub-component product to another final product. In this case the demand forecast of this product could be derived from the final product's scheduled production plan. (Axsäter, 2006, pp. 7-8)

3.2.2 Time series model forecasting

There are different ways of predicting the upcoming need when dealing with time series models depending on the nature of the demand. Axsäter gives three demand models that could be used to describe the demand behaviour of a product and thus used to forecast the future demand; the constant model, the trend model and the trend-seasonal model. The constant model is used, as the name implies, when the demand over time can be assumed to be fairly constant except relatively small deviations with a mean of zero. This model is useful for products with stable demand, e.g. products that have reached the mature stage of the product life cycle. The trend model is suited for products with a predicted increasing or decreasing demand. In this case a linear development factor (positive or negative) is introduced to the model. The trend-seasonal model includes seasonal demand variations. This model is more or less the same as the trend model with the exception that a season-factor is introduced, which represent the seasonal increase or decrease in demand. This demand model is useful when dealing with products of seasonal demand variations, e.g. ice cream. (Axsäter, 2006, pp. 9-10)

There are products with demand patterns that are difficult to match to any of the above discussed models. One example is products with sporadic demand. In that case an alternative forecasting method is to only update the forecast in the time periods when the demand is positive. When this occurs both the size of the demand and the time between the time periods with positive demand is recorded and updated. (Axsäter, 2006, pp. 26)

In order to keep the forecasts up to date and incorporate new information obtained by recent events, the forecasts need to be updated. The updating method will vary depending on the choice of demand model. (Axsäter, 2006, pp. 11-20)

There are a few important points of forecast models worth mentioning. One limitation that applies for all of the above mentioned methods is that they all assume independence in the demand variation. As the complexity of the trend models increases, i.e. more parameter needs to be estimated, the uncertainty aspects of the model will also increase. Therefore the wisest choice might not always be the most complex, general model. Furthermore, it is important to note that the independent deviation included in the models cannot be forecasted, meaning that if the demand is volatile then the forecasted prognosis will include a higher uncertainty. Sales data is often used instead of demand data, as it is a more easily measured parameter. However, there can be a distinct difference between the actual demand and the items sold, e.g. due to stock-out. This also needs to be taken into consideration when making analysis of this kind. (Axsäter, 2006, pp. 10-11, 27, 34)

3.2.3 Evaluating forecasts

When doing forecasts it is of great importance to follow up the outcome and evaluate how well the predictions reflected the actual turn out. Two ways of measuring the performance of the forecasts are by either checking the probability that the difference between the forecasted demand and the actual turn out is within a certain number of standard deviations, or by checking that the forecasted demand in an acceptable way mirror the actual mean. (Axsäter, 2006, pp. 35-36)

3.3 Simulation

In order to grasp the concept and use of simulation, some definitions are first introduced. A *system* is defined as a group of objects that act and interact together in order to accomplish a logical purpose. With the *state* of a system it is referred to the collection of variables necessary to describe the system at a certain time, relative to the objectives of the study. Systems can be categorized into *continuous* respectively *discrete systems*. In a continuous system the state variables changes continuously over time, while in a discrete system the state variables will change instantaneously at discrete points in time. In practice, however, few systems are wholly one or the other. (Law & Kelton, 2000, pp. 3)(Banks, Carson & Nelson, 1996, pp. 9)

It is seldom possible to experiment on the actual system of interest due to several factors such as cost, time and feasibility. Therefore it is necessary to build a model to represent the system. Mathematical models, which can be either analytical or numerical, are commonly used for this purpose. If an analytic model exists then it usually is preferable as it will provide an exact answer. However, most often the systems are too complex for there to be an analytic solution and are instead studied using a numeric model, the most common one being *simulation*. (Law & Kelton, 2000, pp. 3-5)

An overview of the different ways to study a system can be seen in Figure 3.1.

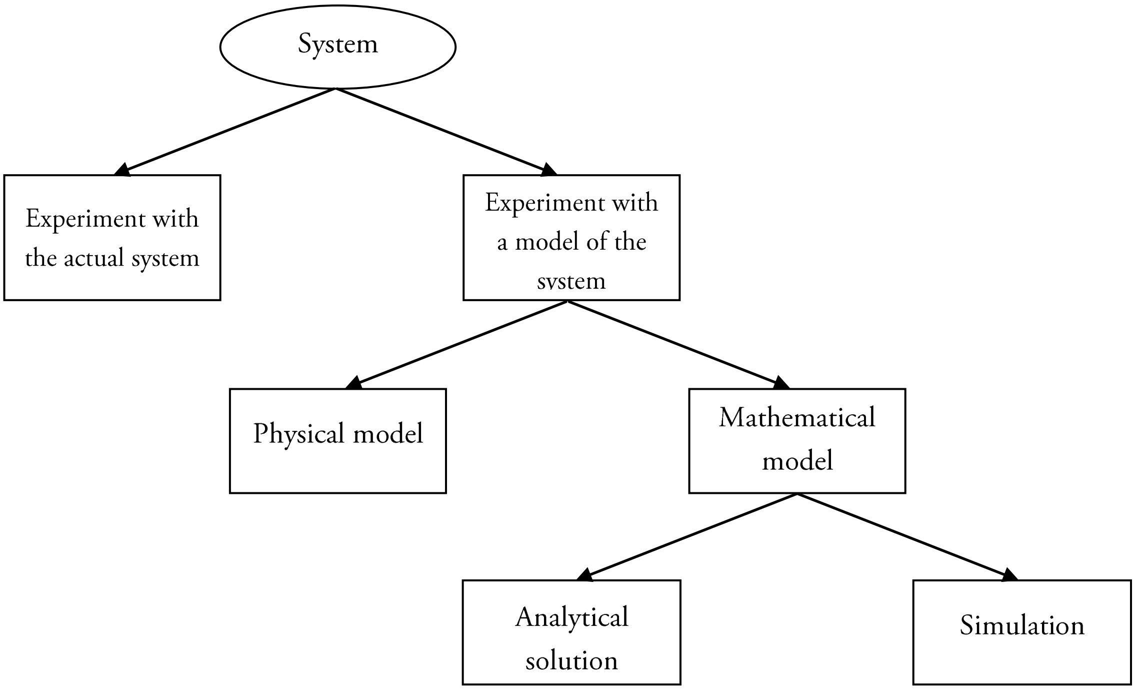

Figure 3.1 Ways to study a system. (Law & Kelton, 2000, pp.4)

3.3.1 Types of simulation models

Simulation models are often classified in accordance with the following three attribute-types:

Static or dynamic

A static model is a representation of a system at a particular point in time. A model that instead represents a system that changes over time is called a dynamic model.

Deterministic or stochastic

A deterministic model contains no random components. This gives that, once the relationships in the model have been specified, for each set of inputs there will be a unique set of outputs. On the other hand, if random components are included, it is classified as a stochastic model. As random input will in turn generate random output, the results of a stochastic simulation model can only be seen as an estimate of the reality.

Continuous or discrete

Continuous and discrete models are defined similarly to continuous and discrete systems respectively introduced above, i.e. the state variables are updated either continuously over time or instantaneous at discrete points in time. Note that a continuous model is not necessarily used to model a continuous system and vice versa. Nor does a simulation model have to be exclusively continuous or discrete; depending on the system characteristics and study's objective it could be beneficial to use a mixed model.

(Law & Kelton, 2000, pp. 5-6)

3.3.2 Discrete event simulation

Simulation models that are dynamic, stochastic and discrete are more commonly referred to as discrete-event simulation models and will be the main focus in this study. Basically, discrete-event simulation refers to the modelling of systems that evolve over time by state variables changing instantaneously at a discrete set of points in time. This set of points in times represents the moments at which an event, defined as an instantaneous occurrence that may change the state of the system, will occur. The dynamic nature of these models requires that the current value of the simulated time is kept track of during the simulation run. (Law & Kelton, 2000, pp. 6-7)

Discrete event simulation was found to be the most widely used simulation technique within manufacturing and business in published academic literature on simulation application between 1997 and 2006. According to Jahangirian et. al., the technique has shown to be appropriate to use for tactical and operational decision-making as well as convenient to use for e.g. detailed process analyses and resource utilization. (Jahangirian et. al., 2009) Its use has further increased in recent years as more computer power and memory have become available. Furthermore, as more manufacturing companies have been shown to successfully apply discrete event simulation the credibility of the technique has increased. Negahban & Smith, 2014)

3.3.3 Model output analysis

According to Law & Kelton, it is not uncommon that a lot of resources are spent on model development while little effort goes into appropriately analysing the simulation output (Law & Kelton, 2000, pp. 496).

If the simulation model generates random variables based on the input data values, i.e. the model is stochastic, the output data will exhibit random variability. Two simulations replications would thus produce two different streams of random numbers which in turn can be expected to produce two different sets of output data. A statistical output analysis on this data generated by the simulation model can then be conducted in order to predict the performance of the system that is modelled. If the system's performance is measured by the parameter θ, a simulation run will generate an estimator $\hat{\theta}$ of θ and the variance, or standard deviation, of $\hat{\theta}$ will give the preciseness of the estimation. An output variable X of a stochastic simulation can thus be considered a random variable with an unknown distribution. (Banks et. al., 1996, pp. 429) Note that a single replication would only give a particular realization of these random variables which might possess much larger variances in reality (Law & Kelton, 2000, pp. 496).

Thus, in order to estimate these distribution functions, or at least the parameters of various probability distributions, the output data is analysed. How the output analysis should be conducted depend on the behaviour of the stochastic process, which is either transient or steady-state. When properties of the process, e.g. the distributions, change over time the process is said to be in a transient state. If the properties instead remain unchanged over time the process has reached a steady-state. Systems may start out in a transient state and then reach a steady state as the time approaches infinity.

In order to study a steady-state behaviour of system a non-terminating simulation is used. As the object is to estimate parameters of stationary probability distributions, the interest lies in the system's behaviour as the time approaches infinity. There is thus no natural point at which to stop the simulation run in a non-terminating system. When the purpose instead is to study a system over a specific finite period of time, a terminating simulation is used. A specific event will naturally define the run length for a terminating simulation. (Cassandras & Lafortune, 2008, pp. 587-588)

3.3.4 Advantages & disadvantages of simulation

An overview of some advantages and disadvantages with using simulation are presented in the list below.

Advantages

- Due to the complexity of real-world systems, simulation is often the only possible investigation method. Even when applying an analytic model, it can be useful to use simulation to check the validity of the assumptions needed.
- With simulation the system performance can be estimated and evaluated under different conditions without disturbing the workings of the actual system.
- Furthermore, new or alternative system designs can be compared and evaluated via simulation. It also allows one to study scenarios which are not feasible in reality due to time constraints, costs etc.
- Simulation allows more control over the experimental conditions in comparison to experimenting with the actual system.
- In simulations the time can be compressed or expanded, i.e. the system workings can be speed-up or slow-down respectively. This allows one to both study systems of long time frames and systems on a more detailed level.

(Law & Kelton, 2000, pp. 91-92)

Disadvantages

- While optimization models are solved, simulation models are ”run” (Banks et. al.,1996, pp. 5). As each run of a stochastic simulation model only will generate an estimate, several independent runs are often required. Simulation models are thus more advantageous when comparing alternative system designs than optimization. If exact results are desired, an analytical model, if applicable, is still preferred. (Law & Kelton, 2000, pp. 92)
- Simulation models can be time-consuming and costly both to develop and analyze. It is also unlikely that two models of the same system, constructed by two independent individuals, will be the same. (Banks et. al., 1996, pp. 5)
- The large amount of data generated by simulation models can be difficult to interpret. If the model is stochastic then it is often challenging to determine if an observation is the effect of a systems interrelationships or just randomness. (Banks et. al., 1996, pp. 5) There is also a tendency to place too much confidence in the results than is justified. The most impressive simulation results are useless if the simulation model is not a valid representation of the system. (Law & Kelton, 2000, pp. 92)

3.3.5 FlexSim Simulation Software

FlexSim is a discrete-event simulation software program which uses 3-D models to provide visual aid. It is the analysis tool used, in this study, to model and simulate the factory. (FlexSim Software Product, Inc, 2010) Figure 3.2 illustrates an example of a FlexSim 3D model.

Figure 3.2 An example view of a FlexSim 3D model. (FlexSim Software Product, Inc, 2010)

(FlexSim Software Product, Inc, 2010)

3.4 Statistical framework

3.4.1 Normal distribution

The normal distribution is often used when describing variations of an event. To note that a stochastic variable, X, follows a normal distribution one uses the declaration $X \in N(\mu, \sigma)$, where μ is the mean and σ the standard deviation of the variable. The mathematical formula for the normal distributions density function is as follows:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

(Blom et. al., 2005, pp. 142-143)

A density function is a function that for continuous stochastic variables spreads out the probability mass 1 over the real axis. A criterion for a density function is thus that the integral of the function equals 1. The integral over the interval a to b thus states the probability mass of the value being between a and b, i.e.

$$P(a < X \leq b).$$

(Blom et. al., 2005, pp.55-56)

The shape of the graph given by the density function for the standardized normal distribution (μ=0 and σ=1) can be seen below in Figure 3.3.

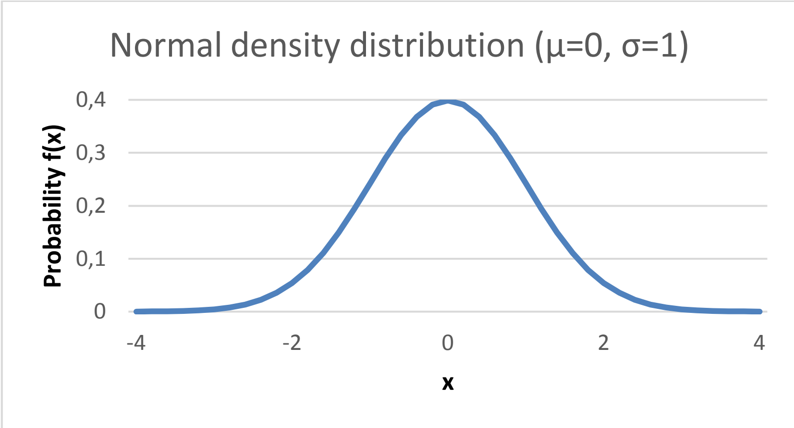

Figure 3.3 The density function for a standardized normal distribution.

The cumulative distribution function for the normal distribution is:

$$F_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt$$

(Blom et. al., 2005, pp. 143)

The cumulative distribution function is a function that states the probability of a value being less or equal to a chosen value x, i.e.

$$F_X(x) = P(X \leq x) = P(-\infty < X \leq x).$$

(Blom et. al., 2005, pp. 56)

This function for the standardized normal distribution can be seen below in Figure 3.4.

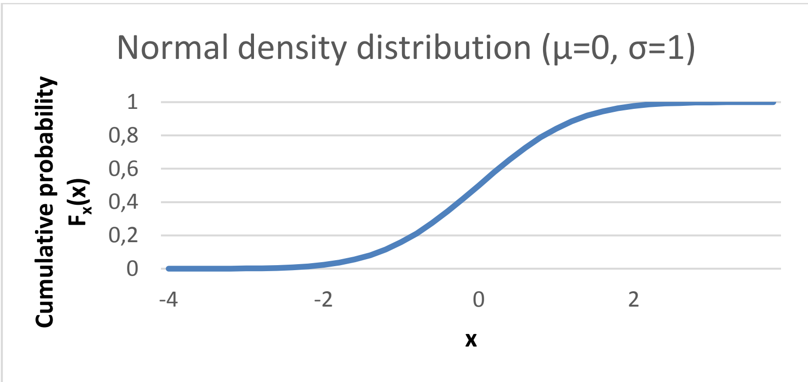

Figure 3.4 The cumulative distribution function for the standardized normal distribution.

When dealing with samples, the mean and standard deviation of the distribution are often unknown and are thus needed to be estimated. The arithmetic mean value is calculated as can be seen in the formula below:

$$\bar{x} = \frac{1}{n}\sum_{j=1}^{n} x_j = \frac{x_1 + x_2 + \cdots + x_n}{n}$$

where $x_1, \ldots, x_n$ are the observed values and n is the number of observations. (Blom et. al., 2005, pp. 228)

To calculate an estimation of the sample's standard deviation, the following formula is used:

$$s = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(x_j - \bar{x})^2}$$

where $x_1, \ldots, x_n$ are the observed values and n is the number of observations. (Blom et. al., 2005, pp. 228)

3.4.2 Properties of independent normal distributed stochastic variables

Below, three mathematical theorems that are used in this study will be given.

Theorem 1
If $X \in N(\mu_X, \sigma_X)$ and $Y \in N(\mu_Y, \sigma_Y)$, where X and Y are independent, then the following holds:

$$X - Y \in N\left(\mu_X - \mu_Y, \sqrt{\sigma_X^2 + \sigma_Y^2}\right),$$
$$X + Y \in N\left(\mu_X + \mu_Y, \sqrt{\sigma_X^2 + \sigma_Y^2}\right).$$

(Blom et al., 2005, pp. 151 (translated))

Theorem 2
If $X_1, X_2, \ldots, X_n$ are independent $N(\mu, \sigma)$ and $\sum_1^n X_i/n$ is their arithmetic mean, then the following holds:

$$\bar{X} \in N\left(\mu, \frac{\sigma}{\sqrt{n}}\right).$$

(Blom et al., 2005, pp. 152 (translated))

Theorem 3
If $X_1, X_2, \ldots, X_n$ are $N(\mu_1, \sigma_1)$ and if $Y_1, Y_2, \ldots, Y_n$ are $N(\mu_2, \sigma_2)$ and all variables are independent, then the following holds:

$$\overline{X} - \overline{Y} \in N\left(\mu_1 - \mu_2, \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_1^2}{n_1}}\right).$$

(Blom et al., 2005, pp. 152 (translated))

3.4.3 Confidence interval

When investigating an unknown parameter it is often preferable to use interval estimates, i.e. confidence interval, as opposed to single point estimates. A confidence interval for the unknown parameter θ with the confidence coefficient of $(1-\alpha)$ is defined as the interval I_θ that with the probability of $(1-\alpha)$ covers θ. For example, if the confidence coefficient is chosen to be 0.95, then the risk of the claim that the confidence interval covers the parameter θ being wrong, is 5 percent. Basically, the method will, with the probability of $(1-\alpha)$, result in a correct statement. Note that the confidence coefficient $(1-\alpha)$ should be chosen sufficiently large for there to be any practical value.

A confidence interval can be thought of as an "observation" of an interval with stochastic limits. If both limits are finite it is referred to as a two-tailed interval. If only one limit is finite is it instead a one-tailed interval. (Blom et al., 2005, pp. 287-290)

Application of the normal distribution

When it is desired to estimate an interval of an unknown parameter, based on random samples, the normal distribution is often applicable and convenient. (Blom et al., 2005, pp. 290) The confidence interval is acquired as seen below.

Let $x_1, \dots, x_n$ be random samples of $N(\mu, \sigma)$, i.e. $x_i,\ i = 1, \dots, n,$ are observations of the independent random variables $X_i \in N(\mu, \sigma)$. Then, according to Theorem 2, the arithmetic mean $\bar{X}$ is normal distributed with mean μ and standard deviation $\sigma/\sqrt{n}$. This gives that the difference

$$\mu - \lambda_{\alpha/2} * \left(\frac{\sigma}{\sqrt{n}}\right) < \bar{X} < \mu + \lambda_{\alpha/2} * \left(\frac{\sigma}{\sqrt{n}}\right)$$

is fulfilled with the probability $(1-\alpha)$. This can be converted into

$$\bar{X} - \lambda_{\alpha/2} * \left(\frac{\sigma}{\sqrt{n}}\right) < \mu < \bar{X} + \lambda_{\alpha/2} * \left(\frac{\sigma}{\sqrt{n}}\right),$$

thus giving the two-tailed confidence interval for μ with the confidence coefficient $(1-\alpha)$ as

$$I_\theta = (\bar{x} - \lambda_{\sigma/2} * (\frac{\sigma}{\sqrt{n}}), \bar{x} + \lambda_{\sigma/2} * (\frac{\sigma}{\sqrt{n}})).$$

(Blom et al., 2005, pp. 287-290)

If μ and σ are unknown they can be estimated with $\bar{x}$ and s respectively. In this case, the quantile table value of the normal distribution, $\lambda_{\sigma/2}$, is often replaced with the more cautious quantile table value of a t-distribution, $t_{\alpha/2}(f)$ where $f = (n-1)$. (Blom et. al., 2005, pp. 292, 397-398)

This is summarized in the following theorem.

Theorem 4
Let $x_1, \dots, x_n$ be random samples from $N(\mu, \sigma)$ where μ and σ are unknown. Then a two-tailed confidence interval for μ with the confidence coefficient $(1-\alpha)$ is:

$$I_\mu = \left(\bar{x} - t_{\alpha/2}(f) * \frac{s}{\sqrt{n}}, \bar{x} + t_{\alpha/2}(f) * \frac{s}{\sqrt{n}}\right) \ where\ f = (n-1)$$

(Blom et al., 2005, pp. 293 (translated))

3.4.4 Hypothesis test

The purpose of a hypothesis test is to determine whether or not to reject a proposed null hypothesis. A general method is as follows:

Given a random sample $\boldsymbol{x} = (x_1, \dots, x_n)$ from a distribution, a null hypothesis regarding some specification of the distribution is to be tried. First the null hypothesis, H_0, and the alternative hypothesis, H_1, which are to be mutually exclusive, are to be formulated. In order to try H_0, a suitable test statistic $t = t_{obs} = t(\boldsymbol{x})$ is then identified, where t_{obs} is an observation of the sample variable $t(X)$, as well as a critical area C, which is a part of the set that t can vary over. A significance test is then:

$$If \begin{cases} t_{obs} \in C => Discard\ H_0 \\ t_{obs} \,! \in C => Do\ not\ discard\ H_0 \end{cases}$$

With C attuned according to

$$P(t(\boldsymbol{X}) \in C) = \alpha \quad if\ H_0\ is\ true,$$

where α is the significance level, also called the test's risk of error, and chosen beforehand.

If the outcome is that $t_{obs} \in C$ then the result is said to be statistically significant on level α. Likewise, if the outcome is $t_{obs} \,! \in C$ then the results is *not* statistically significant on level α.

The critical area C is often an interval of the kind $t \leq a$ or $t \geq b$ where a and b are constants. If C consist of a single interval it is said to be one-tailed. If it instead consists of one of each kind and $a < b$, it is referred to as two-tailed. (Blom et. al., 2005, pp. 321-324) (Young & Smith, 2005, pp. 65-66)

Hypothesis tests are closely linked with confidence interval estimations. For example, hypothesis tests can be used to test if the hypothetical value θ lies within or outside of a specified confidence interval. (Blom et. al., 2005, pp. 329)

3.4.5 Statistical tools

When large amounts of data are involved, the use of graphical tools to aid the data analysis is often beneficial. (Bergman & Klefsjö, 2010, pp. 232) Below a histogram and scatter plot are briefly explained, followed by a description of the Kolmogorov-Smirnov Goodness-of-Fit test.

Histogram
A histogram is constructed by first creating intervals of the same size and then place the sorted data points of interest into the respective block were it fits. Based on this, a list of how many data point that exist in each of the respectively intervals is derived. By calculating how large part of the total number of data

points that is in each interval the relative frequency is found. A histogram is then the graphical plot in which the relative frequencies are plotted as bars. (Blom et. al., 2005, pp. 225-227)

An example of a histogram can be seen in Figure 3.5 below.

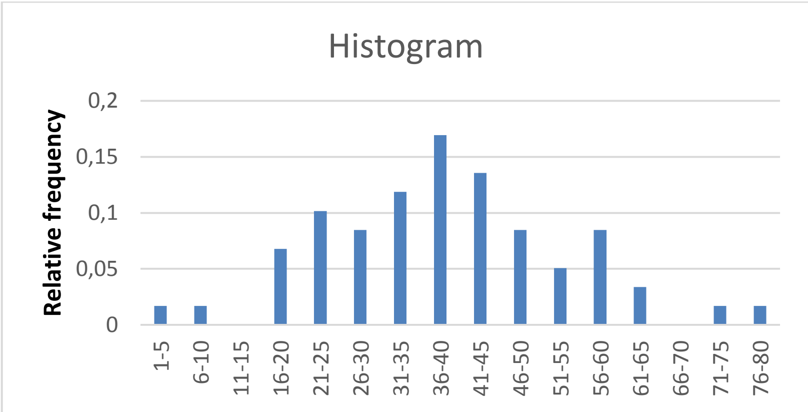

Figure 3.5 An example of a histogram.

As the histogram gives the relative frequency of the data, it can be a good graphical tool to use as a visual first test to guess the distribution of the observed data points.

Scatter plot

A scatter point is a graphical tool that can be used to investigate how one variable varies due to another explanatory variable. By varying the data points of the explanatory variables and observing the data points of the sought variable, a behavior pattern might be seen. (Bergman & Klefsjö, 2010, pp. 241-242)

Figure 3.6 gives an example of two scatter plots, one where the relationship between the variables is weak and one where the relationship between the variables is strong.

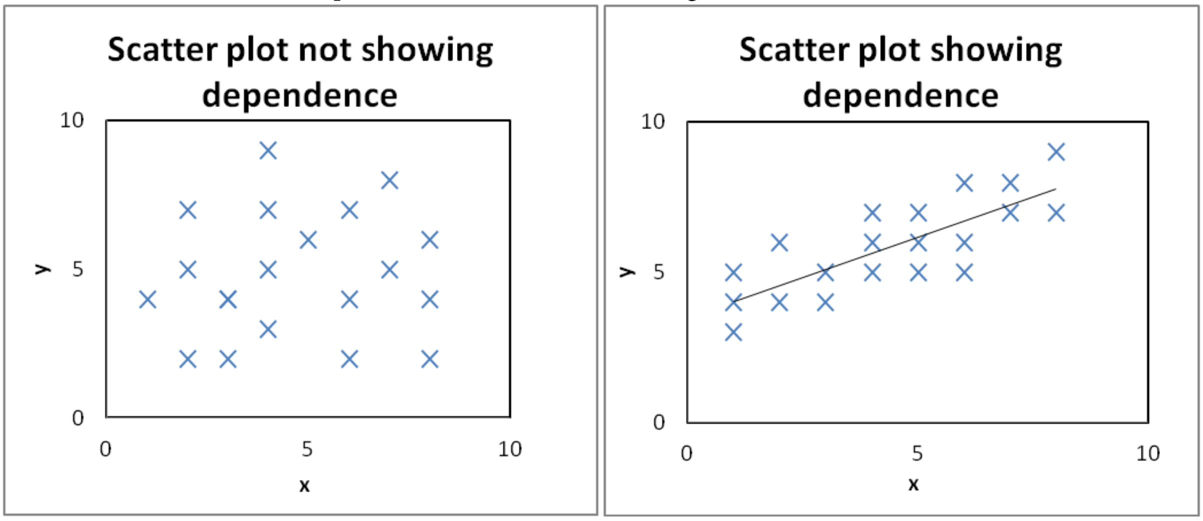

Figure 3.6 An example of two scatter plots, one where the variables are not showing any obvious dependence (left) and one where the variables are showing a linear dependence (right).

Kolmogorov-Smirnov Goodness-of-Fit test

The Kolmogorov-Smirnov Goodness-of-Fit test can be used as a hypothesis test when investigating if a data set distribution follows a certain general distribution, e.g the normal distribution. The absolute distances, between the cumulative distribution function of the sampled data and the cumulative general distribution of choice, are calculated. Denote the maximum absolute distance as D_{obsMAX}. The hypothesis that is to be tested is then:

H_0: The sampled distribution follows the general distribution that it is compared to.
H_1: The sampled distribution does not follow the general distribution that it is compared to.

The significance test is then formulated as:

$$If \begin{cases} D_{obsMAX} \geq D_{critical} => Discard\ H_0 \\ D_{obsMAX} < D_{critical} => \ H_0\ cannot\ be\ discarded \end{cases}$$

The test statistic $D_{critical}$ is calculated or taken from a table according to which significance level α that is desired to use.

(Massey, 1951)

4 Empirical framework

In this section the material and information needed in order to conduct the experiments in the following chapters will be described. First the production-, forecast-, and capacity decision-making process of the case company will be introduced. The simulation models and their differences will then be explained, followed by the data and the KPIs used in the study. Finally, the assumptions made will be listed

4.1 Production process description

The case company in this study produces packaging material used for food and beverages. The production process refines the material in three stages, printing, lamination and finishing; see illustration below in Figure 4.1.

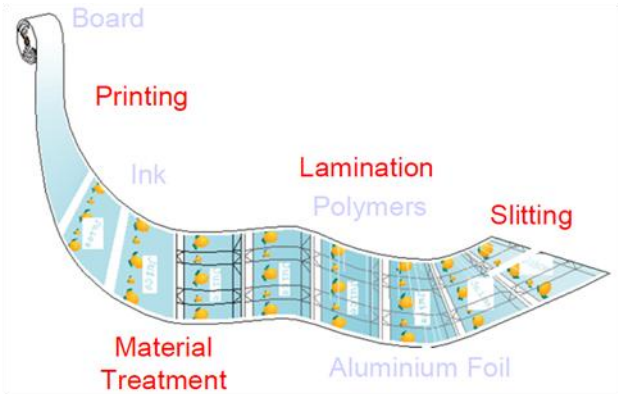

Figure 4.1 An illustrative picture of the production process of the packaging material.

Preceding each production stage, there are buffer areas where the material can be stored until it can be passed on to the following stage. A more detailed description of each stage of the production process follows below.

Stage 1: Printing

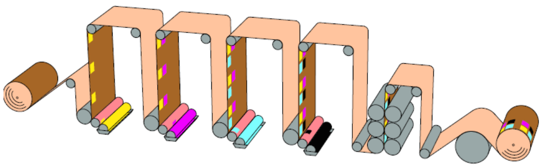

Figure 4.2 An illustration of the printing stage.

When an order arrives for production, the first stage is printing, see Figure 4.2. The printer is configured according to the orders specifications regarding, for example, the number of colours needed to print the customer's preferred design. The roll of base material is run through the printer where they are printed, creased and cut, after which the finished rolls are sent to the WIP-stock awaiting go-ahead for proceeding to the lamination stage.

Stage 2: Lamination

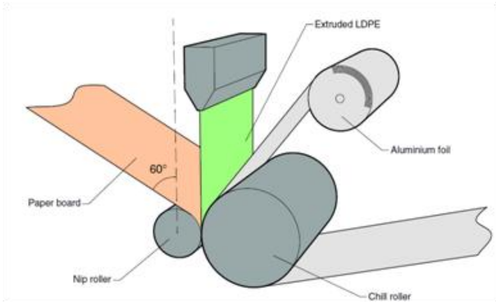

Figure 4.3 An illustration of the lamination stage.

The purpose of the lamination stage, seen in Figure 4.3, is to give the base paper boards certain functionalities which the product, that the specific package later should be filled with, requires. This is done by applying additional materials, such as plastic and aluminium foil, to the base boards. Once the rolls have been laminated, they are transported to a storage area in waiting of the finishing stage.

Stage 3: Finishing

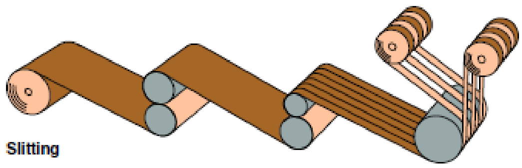

Figure 4.4 An illustration of the finishing sub-stage slitting.

Finishing consists of different machines; a slitter, a doctor, an oven, a wrapper and a palletizer. The slitter cuts the printed and laminated rolls into smaller reels, as can be seen in Figure 4.4. These smaller reels are the unit-size which are delivered to the customers. The purpose of the doctor machine is to unwind the rolls in order to perform different quality controls and remove defects. In some cases, the reels will then proceed to the oven stage where they are encased in shrink wrap for hygienic reasons. They are then palletized and wrapped. The reels are then ready to be shipped off to the corresponding customer.

4.1.1 Production characteristics

The bottleneck in this production process is considered to be the lamination stage, i.e. the laminators are the resource limiting the production capacity. The production flow can be described as a pull system preceding the laminator and a push system following it. As this production stage creates the strongest capacity constraint, it will be the main focus area in this study.

The factory production operates according to a Make-To-Order principal, i.e. the production can only start after an order is received. Each month, the production is divided into four planning cycles, basically a cycle consist of one week. Every cycle is then sequenced into different blocks, where each block represents one specific group of products that has similar lamination process to reduce the setup times. The incoming orders are then placed into the block that matches the order's QSV specifications, i.e. the products Quality Size Variant specifications, and the production schedule is formed. This schedule method is applied to the first two production stages. For the last stage, the First In – First Out (FIFO) principle is applied instead.

(Interview with Development Engineer, 2015-08-31)

4.1.2 The production site

To provide the reader with a basic comprehension of the size of the business conducted at the chosen production site, some general information and approximate figures will be presented.

The factory consists of three printers, two laminators and one finishing area. During the years of 2013 and 2014 the factory produced packaging material to approximately 50 different market countries. Key figures for understanding the scale of the factory can be seen in Table 4-1.

Table 4-1 Key factory figures.

	2013	**2014**
Number of different QSVs per year	94	139
Average number of different QSVs per month	66	78
Average number of orderlines per month	118	135
Average order size (packs/orderline)	4 500 000	4 200 000
Total ordered volume (packs)	6 300 000 000	6 800 000 000

(Case company's Database, 2015-10-26)

4.2 Forecasting at the case company

At the case company, the Market company is responsible for creating and providing sales forecasts as well as delivering the incoming customer orders to the factories, i.e. the Market company acts as the customer of the factories. The sales forecasts are made per customer and market. There are two types of forecasts, one yearly and one rolling.

Yearly sales forecast

Once a year the Market company makes a forecast over the upcoming three years. This forecast is based on customer input, market trend analysis and historical data, i.e. order pattern. The market trends are acquired from an independent third party and give an indication of the future sales trends for the products their packaging material are used for.

Rolling forecast

Once the annual forecast is set it is regularly updated every month in order to be as accurate as possible and follow the fluctuations. The updating process includes:

- Dialogue with customers
    - A request is sent to the customers for updates/feedback regarding the upcoming three months of demand. The response rate is about 40%.
- Utilization of the competence and experience of the personnel at the Market company
- Historic data
    - Statistical forecast calculations based on historic data (calculated by the software used).

To measure the forecasting performance KPIs, such as *sales forecast accuracy,* is used. This KPI is given as a direct feedback to the forecaster. The *sales forecast accuracy* measures how accurate the forecast was for the third forecasted month, i.e. in April the forecast figures for April made in January is evaluated. Direct contact between the Market company and the factories are only made when issues arise.

The forecast accuracy depends on many different factors which increase the uncertainty which can cause the forecast and the actual market demand to differ. One cause is market seasonality. An example of this is the summers that can be difficult to forecast due to product dependency of weather fluctuations. Another example is the difficulty to accurately predict the volume increase of certain products whose demand are known to peaks around holidays. Another reason for forecast deviation is that it is difficult to pin point exactly which month customers with more sporadic order pattern will place their orders. New customers or changes in current customer's specific product demand, also makes it more difficult to predict the future order sizes and patterns.

(Interview with Sales Forecast Driver, 2015-11-18)

4.3 Capacity decision-making process

A description of how capacity decisions are handled at the case company is provided below.

Once the Market company has provided the yearly forecast sales data for the following year, the planning group meet to discuss the expected capacity need. If there are any suggestions regarding allocation of volumes between factories, e.g. to reduce logistic costs, this is also taken into consideration during this meeting. Unless the rare case of questionable data figures, the Market company will then not be further involved in the process.

The expected capacity need is investigated by running the sales forecast data for each separate factory through a static spreadsheet model, which will be described further in 4.5 *Spreadsheet model*. The model output provides an indication as to how well the factory will be able to handle the volumes. A utilization of equipment not exceeding 95% is preferred.

In the case of the capacity model indicating lack of capacity, several options exist. If the capacity shortage size is expected to be relatively small and occur seldom, possible adjustments in the planned maintenance, stops etc. are investigated. It can also be handled at a factory level by preproducing volumes for Vendor Managed Replenishment (VMR) customers. If more frequent, larger capacity shortages are expected, then further adjustments, such as increasing the number of shifts or relocating volumes to other factories belonging to the same cluster, can be implemented.

During the year the capacity model is continuously updated by running the updated forecast as input data. In general, the forecasts for the following three months are used. Any capacity issues that arise during the course of the production can be handled with overtime. However, due to high costs it is preferable to avoid this.

If larger capacity investments are needed, such as a new machine, it is up to the factory to indicate this by composing a business case. Decisions regarding larger capacity investments are then made at a strategic level and approval by the board is required. However, the time, from such a request until a possible implementation is completed, is often long.

(Interview with Cluster Planning Analyst, 2015-09-18)

In Figure 4.5 below, a rough schematic of this capacity decision-making process can be seen.

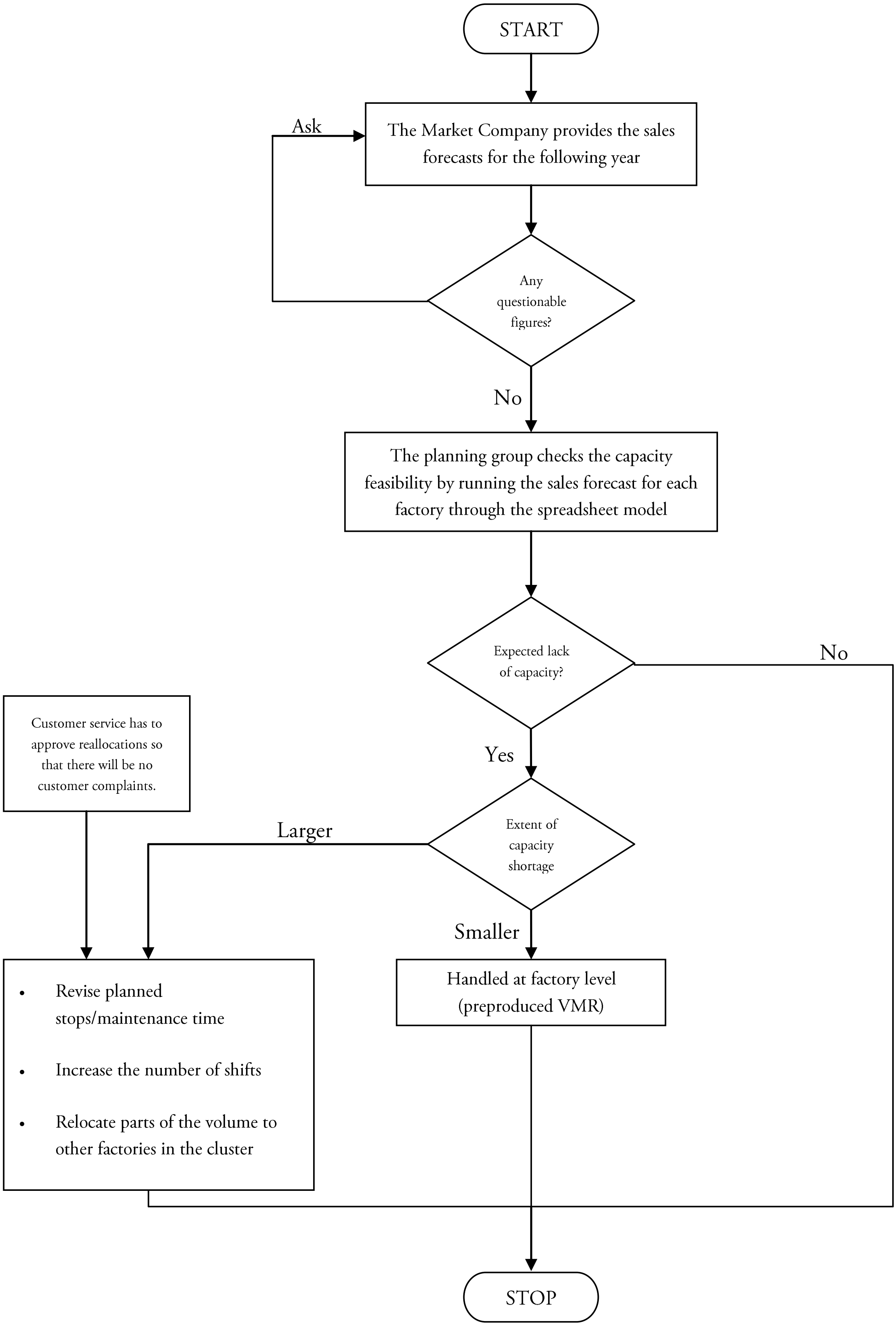

Figure 4.5 A flow chart over the capacity decision-making process at the case company.

4.4 Discrete event simulation model

In this study a premade discrete event simulation model of the selected production site was used. The mentioned model consists of three printers and two laminators, mirroring the set up in the actual factory. The third production stage, finishing, was not included in the model. As the second stage, lamination, is considered the bottleneck of the production and thus of main interest, the finishing stage could be considered outside the scope of this study and disregarded.

Originally the model was created in order to support development projects and later, as more strategic support was requested, developed further. (Correspondence with Virtual Engineering Manager, 2015-12-15) Currently, the model is still mainly used to provide support in development projects by testing conceptual solutions as well as to verify different layouts. The model has also been used for some capacity simulation but more potential in this area is expected. (Interview with Development Engineer, 2015-11-24)

The modelling of a selection of system characteristics is described below.

Production scheduling

To simulate the block structure of the production scheduling described above, a fictive block plan is inserted in the model, which is referred to as the ideal block plan. This ideal bock plan has been put together by using input from the factories and is supposed to provide an estimated behaviour of the scheduling.

Production cycles

In the discrete event simulation model, each month is similarly divided into four production cycles. These cycles are set up according to a calendar, which can also include the allocated timeslots of, for example, planned maintenance, weekends and national holidays. A cycle in the model always starts on a Monday morning and then continues until next Monday morning when the following cycle starts. At the beginning of a simulation run, the number of cycles for the run duration is calculated from the input data. Each cycle is then allocated a volume-share of the month's production target and planned according to the ideal block plan described above.

An example of a cycle is illustrated below, see Figure 4.6, where the blue days denotes regular working hours and red days denotes time outside of the regular working hours, in this case the weekend. If the allocated volume to be produced in a specific cycle is not reached during the simulated regular working hours it can be compensated with overtime during the weekends. Everything that is still not finished being produced at the end of the cycle is then discarded before the next cycle begins. Note that in the real production system, orders would clearly not simply be discarded in this way.

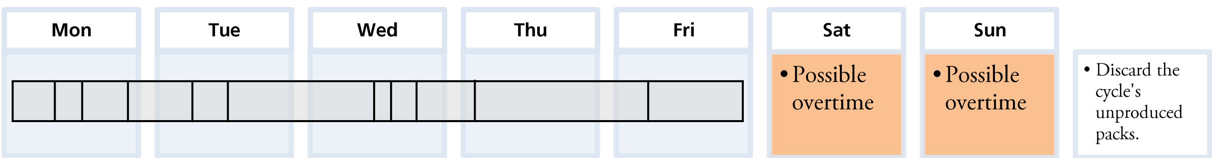

Figure 4.6 An illustration of a cycle's calendar in the simulation model, including an example setup of an ideal block plan. Blue denotes the regular working hours and red outside of regular working hours.

(Department of Virtual Engineering, 2015)

4.4.1 Model input

The discrete event simulation model requires two different databases to provide input data.

1. **Factory database** (factory DB)

   The factory DB contains information regarding the specific configurations of that particular factory, for example the site's ideal block plan.

2. **Order shape database** (OS DB)

   The OS DB contains order-specific information such as the forecasted demand. The order shapes contains, amongst other information, frequency information regarding the order characteristics. These frequencies describe the expected distribution of, for example, the number of colours for the orders and the Average Order Size (AOS) and are derived from the historic data of the previous year.

At the start of each run, the model then calculates suitable distributions regarding, for example, the number of colours used in printing from this frequency information.
(Interview with Data Analyst, 2015-09-01)

4.4.2 Model output

Once the simulation has completed a run, the output KPIs can be exported to an Excel template. Certain statistical numbers of interest, e.g. the mean and standard deviation for each KPI are calculated and provided. The KPI value for each individual replication is also displayed in the template. (Department of Virtual Engineering, 2015)

4.4.3 Model assumptions

In the simulation model the following inbuilt assumptions have been made:

- Infinite base material is available.
- There are no length limitations on the WIP-stock queues.

(Department of Virtual Engineering, 2015)

These assumptions should be kept in mind as possible error sources when comparing to the reality in the future experiments.

4.5 Spreadsheet model

To monitor the capacity need at the factory, a static spreadsheet model is currently being used at the company and at the production site. This spreadsheet model is used to calculate the factory's capacity for a particular upcoming time period, given the forecasted demand for this period. It is also used to estimate the material need required for the production period of interest. The spreadsheet model is developed in the Microsoft Office program Excel. The way the model is currently used in the capacity decision-making process can be seen in the flow chart in the previous section 4.3 *Capacity decision-making process.*

4.5.1 Model input

Before the model can be used, information regarding the specific characteristics of the factory to be simulated needs to be inserted into the pre-set tables of the model, as well as the forecasted sales volumes per QS for the time period of interest. The model then takes the inserted factory-, QS- and volume data and uses premade formulas in order to calculate the KPIs of interest.

4.5.2 Model output

Once the model is run, a result sheet shows how the factory will be able to handle the predicted production volumes each month given the inserted base data. As output data the model gives e.g. the expected utilization of the different machines in the factory and the main KPIs for the respective machine group. If the utilization of a machine group exceeds 100% the utilization the KPI will be marked red to indicate that that specific machine group will not be able to cope with the forecasted demand during that month. This indication can then be investigated and actions can be taken in order to prevent a production overload.

4.5.3 Model assumptions

The spreadsheet model is a deterministic model i.e. it does not take into consideration uncertainties and distributions in the inserted table values. This means that breakdowns and setup times are given as mean values based on historic measurements of these activities. The forecasted volumes are not modified by the model, i.e. the forecasted volumes that are inserted in the model as input data volumes will be the output volumes as well.

4.6 Comparison of models

A summary of the difference between the two models included in this study, in order to gain a better overview of their respective strengths and weaknesses, is shown in Table 4-2 below.

Table 4-2 A comparison of the discrete event simulation model and the spreadsheet model.

	Discrete event simulation model	**Spreadsheet model**
Model classification	Dynamic & Stochastic	Static & Deterministic
Input data	The input data is reworked and grouped into orders by using the order size frequency tables before it is run through the model.	The input data volumes becomes the model's output volumes.
Production scheduling	A block plan to better mimic the production scheduling of the real system is taken into consideration in the model.	No block plan for the production scheduling is included in the model.
Operational losses, e.g. stops and setup times	The stops, setup times and breakdowns etc. are stochastically modelled through distributions based on the input data.	The stops and setup times are statically calculated based on historic mean values.
The machines	Every machine is a separate unit. This gives that the settings can be configured and KPIs can be measured for each machine individually.	The machines in each machine group are considered identical and only the amount of machines in each machine group is noted. The result is then provided as an average per machine for each machine group.
Output data	The discrete event simulation model provides statistical means and standard deviations, etc., based on the replication data. (Stochastic model)	The results are given as exact numbers. (Deterministic model)
KPIs	KPIs for each separate activity are provided.	A limited selection of KPIs are provided.
Overview	The production process is visualized via 3D animations.	The production process is not visualized.
User-friendliness	The discrete event simulation model is more complex and therefore more difficult to get started with. It is, however, visually easy to understand the flow.	The spreadsheet model is very straight forward and easy to understand.
Main application of model	Provide support in development projects by testing conceptual solutions as well as to verify different layouts. KPI of main interest e.g. EE.	Investigate if the factories have the capacity to produce the upcoming year's forecasted volumes. KPI of main interest e.g. Utilization.

4.7 Key Performance Indicators

In order to measure their performance the company uses a number of Key Performance Indicators (KPIs) to follow up important parameters. The main KPIs used are:

Total Equipment Effectiveness (TEE) – Measures the total utilization of the equipment for manufacturing operations, considering Strategic, Planned and Operational Losses.

Overall Equipment Effectiveness (OEE) – Quantifies how well a manufacturing unit utilizes the equipment during the Manned Time, considering Planned and Operational Losses.

Equipment Effectiveness (EE) – Measures how effective a manufacturing unit utilizes the equipment during the Used Time, considering Operational Losses only. It is computed as follows:

$$EE = \frac{Effective\ time}{Used\ time}$$

In the picture below, Figure 4.7, more detailed information of which factors that are included in each of these main KPIs can be seen.

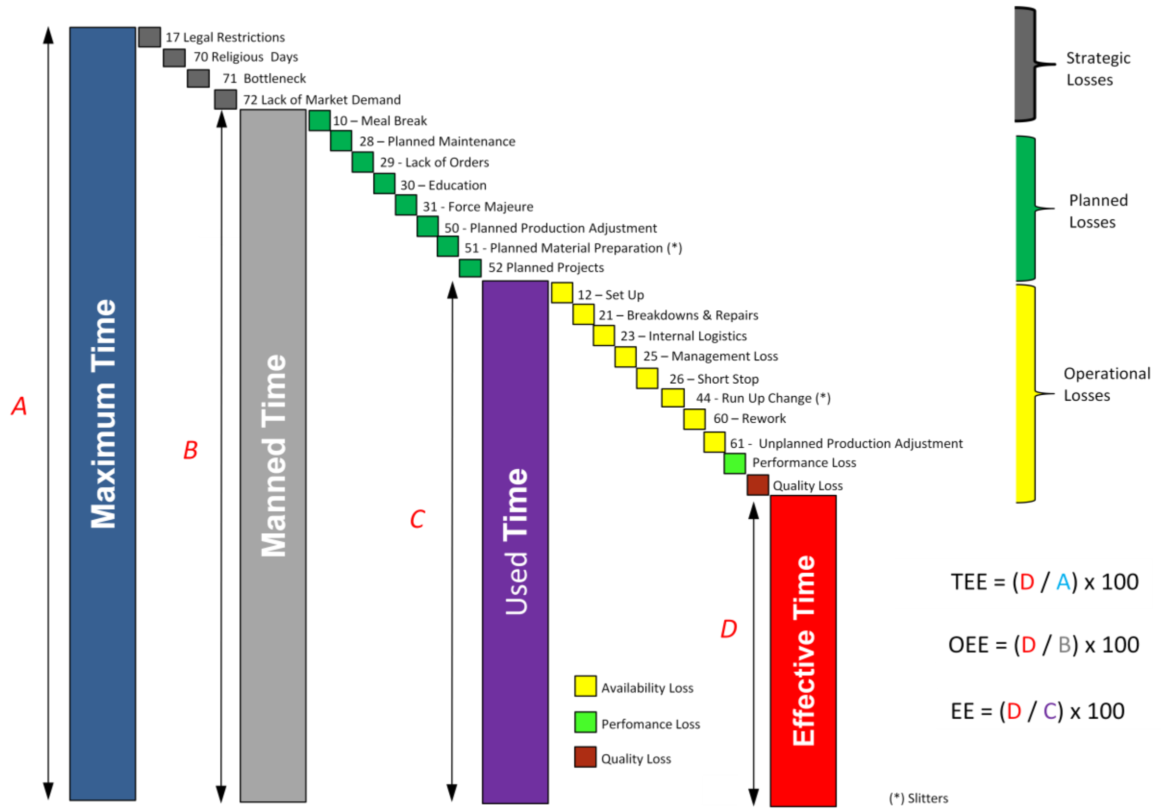

Figure 4.7 The building blocks of the KPIs: TEE, OEE and EE. (KPI guidelines, Case Company, 2015)

The choice and amount of KPIs to be taken into consideration for the investigations of this study are a trade-off between relevance, additional value gained and required analysis time. The result from too many KPIs can be difficult to process as well. Thus three KPIs, that were deemed suitable in order to achieve the goal of the study, were selected; Throughput, Utilization and the above mentioned EE. In other words, Throughput because it gives an intuitive understanding of the volume flow of the models, Utilization because it indicates the working time of the machines according to the planned production and finally EE since it indicates the actual time that the machines were producing.

Further definitions for the first two KPIs are provided below.

Throughput – The total number of packs that are produced during a specified period of time. It is measured in the unit Packs. This unit was chosen since the input volumes were given in this unit.

Utilization – The percentage of time that a machine is used in comparison with the total available time. It is computed as follows:

$$Utilization = \frac{Used\ time\ (effective)}{Manned\ time\ (planned)}$$

The total throughput will be investigated while Utilization and EE will be calculated as the average per laminator. Note that the simulation output will refer to the throughput of the lamination stage. For further elaboration regarding the effect of this see section 4.8 *Study assumptions*. When comparing the models, the averages were used due to the increased complexity looking at each machine separately would mean.

(KPI guidelines, Case Company, 2015)

4.8 Study assumptions

During the course of this study, certain assumptions had to be made. These assumptions and their impact on the study will be presented below:

No new frequency tables were made; the existing frequency distributions tables were used.
In the discrete event simulation model, distributions regarding order sizes, number of colours for printing, etc. is generated using the frequency input data. This frequency data is based on historical order information from the previous year's incoming orders. It is then assumed that e.g. the order sizes of the incoming orders per product and market more or less follows the same distribution as the previous year.

Since one of the delimitations of the study was that the model will not be modified, the current frequency table, based mainly on the historic data from 2014, was used for both years that were examined. It is assumed that the frequencies remained closely the same between these years. This delimitation was discussed with the involved personnel at the case company and was considered an acceptable assumption.

A pre-made ideal block plan was used and the QSVs not included were added.
Similar to the frequencies discussed above, the block plans at the production site changes over the years which reflects upon the discrete event simulation model's ideal block plan. This has also been disregarded in this study due to the increased complexity changing it would have provided. The current ideal block plan, from 2014, was thus chosen and considered constant between the years of interest.

In order to be able to make this assumption, block plans from 2013 and 2014, i.e. the years of interest, were compared. The comparison showed that all QSV-blocks that were included in the ideal block plan for 2013 were also included in the one for 2014, as well as additional blocks for newer QSVs. Therefore the block plan for 2014 was chosen and used. Likewise, personnel at the case company were consulted prior to this decision being made. As the discrete event simulation model is quite new, all the data configurations for the QSVs used the previous years were not included. Since the chosen ideal block plan did not include all the historic QSVs that were needed to run the simulation, these had to be added to the block plan, which was done by personnel at the case company.

In both models standard weeks were used, and national holidays were excluded. The planned maintenance time of the laminators were changed to match the measured historic values.
In the discrete event simulation a calendar is used to plan the production cycles. In this calendar, time slots can be allocated to represent different events that effect the production such as planned maintenance or weekends or holidays during which the production will not be active. In this study a standard week is considered for each cycle. This means that a week consist of production five days a week with planned maintenance scheduled in the beginning of the first shift every Monday.

National holidays were excluded in the study due to complication with running certain months when they were introduced in the calendar. Another change made to the calendar was that the planned maintenance in the laminators was doubled compared to the original value used in the model. This was done after it was discovered that the time scheduled for maintenance in the simulation model did not match the time that was spent on this task according to the historic reports from the factory.

The assumptions mentioned above are described for the discrete event simulation model, but the same assumptions and values were also applied to the spreadsheet model in order to keep the models comparable.

The priority settings of the laminators were removed.
Since there are two laminators working in parallel at the factory, the jobs need to be divided and scheduled on the two machines. When the model first was received, there were some products that were prioritized in one of the laminators. However, the prioritized laminator was over-utilized when the other one had a low utilization status in comparison, a difference that did not mirror the reality according to historic reports from the case company database. This raised the discussion whether prioritizing of the products should be made or not. In consultancy with personnel at the case company it was concluded that this prioritization should be removed. This resulted in the assumption that, no prioritization between the laminators, i.e. the scheduling will operate according to the ideal block plan only, would give a better output.

In reality the two laminators differ somewhat when it comes to their capabilities and which products they can process. These restrictions are implemented in the model through the ideal block plan and have not been changed.

The throughput from the lamination stage is assumed to reflect the total production throughput.
As the discrete event simulation model includes only the first two stages, i.e. printing and lamination, the simulated throughput volumes will refer to the throughput from the laminators. To mirror this, the set up for the spreadsheet model was done likewise. However, the reports of the historically measured produced volumes refer to the final production throughput, i.e. after completing the finishing stage.

A possible explanation for a difference between the simulated throughput and the historic throughput is thus that not all products that passed the lamination stage managed to pass the finishing stage. However, as the lamination is the bottleneck stage and that, according to the personnel at the case company, the finishing stage is not expected to have any problems with managing the volumes, any difference was assumed to have little impact when comparing the results.

The basic QS data for the spreadsheet model were based on historic means.
The basic QS-data required by the spreadsheet model had to be added. This data was based on the historic information from the case company's database regarding the time period 1st of January 2012 to 30th of June 2015, this large time span was used to acquire information on as many QSs as possible. For the QSs that still lacked information, the same settings were given as those of another QS, whose characteristics were assumed to resembled the ones of the missing QS adequately.

Data alterations would not significantly alter the result.
The data used in this study had to be processed to some extent before used as input data in the simulation models. Due to lack of historic data as well as odd figures, a few products and orderliness were excluded from the investigations. It was deemed that the removal of these volumes would have little impact on the overall results.

5 Initial experiments

Prior to being able to conduct the main experiments, some initial investigations and calculations had to be done regarding the distribution of the output data and the KPIs used.

5.1 Output distribution

5.1.1 Discrete event simulation model

Prior to further experiments, it was investigated if the generated random variables of the discrete event simulation, given a certain number of replications, could be approximated as normally distributed. Note that the replications are assumed to be independent to each other.

Using, for instance, the yearly sales as input data in the discrete event simulation model, the run for January 2014 was replicated a total of 150 times. The result of each replication, using the KPI Throughput as an example, was sorted and plotted in a histogram in order to examine the distribution shape, see Figure 5.1 below.

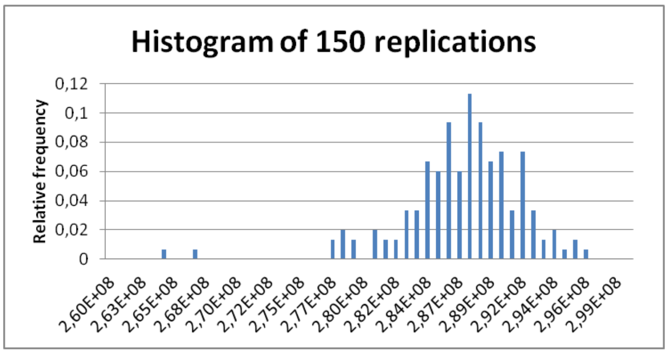

Figure 5.1 A histogram of 50 boxes of the KPI Throughput value from 150 replications.

Observing the histogram (Figure 5.1), the normal distribution seems to be a suitable distribution choice. To further support this claim, the Kolmogorov-Smirnov Goodness-of-Fit test was conducted, which gave:

$$D_{obsMAX} = 0{,}031 < D_{crit} = 0{,}328 \ (\alpha = 0{,}05) => \ H_0 \ cannot\ be\ discarded$$

I.e., on significance level $\alpha = 0{,}05$, the null hypothesis claim that the data follows a normal distribution could not be discarded.

As 150 replications for each run is rather time-consuming, the same tests were performed using only the data from the first 16 replications, see Figure 5.2 below.

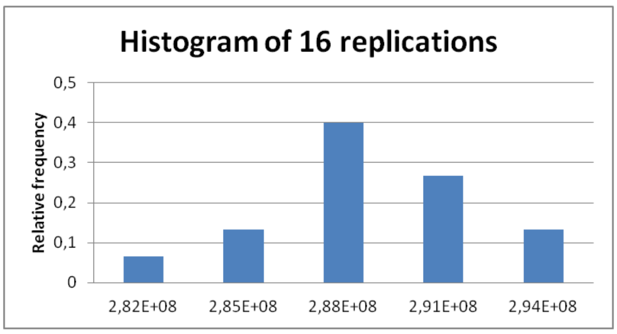

Figure 5.2 A histogram of 5 boxes from the first 16 replications of the KPI Throughput value.

Likewise, the Kolmogorov-Smirnov test gave:

$$D_{obsMAX} = 0{,}177 < D_{crit} = 0{,}328\ (\alpha = 0{,}05) => H_0\ cannot\ be\ discarded$$

Thus, for 16 replications the data also appears to follow a normal distribution.

5.1.2 Spreadsheet model

As the spreadsheet model is a deterministic model, the outputs will be deterministic values.

5.2 KPI calculations

As previously mentioned, the KPIs addressed were the total Throughput (packs) of the laminators, the average Utilization of the laminators (%) and the average EE of the laminators (%).

5.2.1 Discrete event simulation model

To achieve comparable KPIs, the ones mentioned above, the following adjustments to the generated KPI data of the discrete event simulations were made, using statistical mathematics.

Let the random variables X and Y denote the KPI outcome for LaminatorA and LaminatorB respectively. As shown in 5.1.1 *Discrete event simulation model*, the outcome could be considered to be normal distrusted, i.e. $X \in N(\mu_X, \sigma_X)$ and $Y \in N(\mu_Y, \sigma_Y)$. Furthermore, the laminators are assumed to be independent to each other but keep in mind that this is a rough assumption that will be addressed as a possible error source in the 7.2.5 *The independence of the laminators.*

According to Theorem 1, the sum of two independent normal distributions will be normal distributed as well. This gives that the total throughput for both laminators is distributed as follows:

$$X + Y \in N\left(\mu_X + \mu_Y, \sqrt{\sigma_X^2 + \sigma_Y^2}\right).$$

For the KPIs Utilization and EE, the average per laminator is sought and the distribution is as follows:

$$\frac{X + Y}{2} \in N\left(\frac{\mu_X + \mu_Y}{2}, \sqrt{\frac{\sigma_X^2 + \sigma_Y^2}{2}}\right).$$

5.2.2 Spreadsheet model

As the total Throughput as well as the average Utilization and EE per laminator were directly given, no adjustments were deemed necessary to the generated KPIs of the spreadsheet model.

6 Main experiments and results

This section will provide step-by-step explanations of the main investigations conducted. These investigations were made in order to achieve the purpose of gaining further understanding of the simulation results, as well as how to work with the results. First understanding of the volume's input-output relationship will be created. These are followed by the more in-depth investigations of the models' performance relating to the uncertainty factor, as well as time-frame, of the forecasted input data. Each investigation is followed by a compilation of the acquired results where the main findings will be highlighted and later addressed in the Discussion chapter.

To provide the reader with an overview of the investigations conducted in this chapter, a concept illustration of the possible data combinations to be used in the study is presented in Figure 6.1. The conceptual figure will reappear at the start of each experiment to indicate the data used and comparisons made.

		Results		
		Spreadsheet model	Discrete event simulation model	True historic KPI values
Input data	Yearly sales forecast			
	Rolling forecast			
	Historic order data			

Figure 6.1 A concept illustration of the data combinations used throughout the experiments. The highlighted boxes are the main focus in this study, i.e. the discrete event simulation runs.

The discrete event simulation model was used for terminating simulations. To assist the reader, a summary of all the data and how it has been used was compiled, and is presented below.

Data used as input data for the models:

- Yearly sales forecast from 2013 and 2014 were used, i.e. two reports. The reports concern all the 12 months of the year and were developed in 2012 and 2013 respectively.
- Rolling forecast from 2013 and 2014 were used, i.e. 24 reports. The reports were developed one for each month and concern the current month plus the upcoming 12 months. For example, the rolling forecast for March concern the months up to and including March the following year.
- Historical order data for 2013 and 2014 were retrieved from the case company's internal database.

The forecasted datasets contain all the expected orders for the production site during the time period that the forecast concerns. Each order contains the expected QSV volumes per sales market and per sales month.

Data used for comparison and evaluation purposes:

- Historic KPI data (Throughput, Utilization and EE) for each of the laminators were retrieved from the case company's internal database.

The same factory settings, e.g. planned maintenance time, were used for both models. This was in order to give the models, in as far as it was possible, the same preconditions.

6.1 Experiment 1: The relationship between the input and output volumes

The purpose of the first experiment was to create understanding of the basic volume flow both through the factory and through the models. The main interest lays in any volumes adjustments that are possibly made in the models, e.g. batching or waste compensation. The data used and the comparisons made are illustrated below, see Figure 6.2.

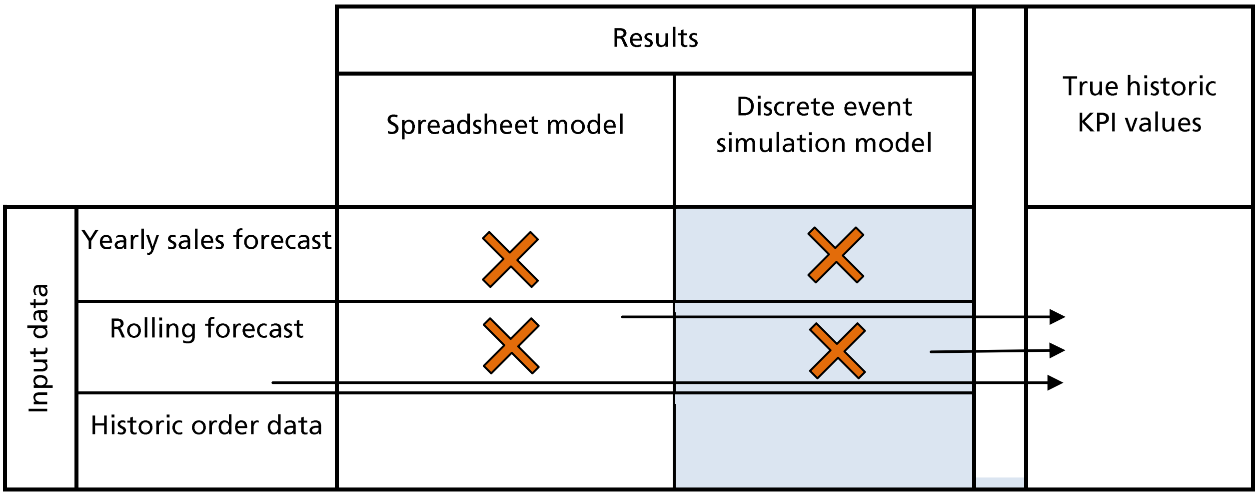

Figure 6.2 Description of data use and comparisons made in experiment 1. X denotes the simulations run, i.e. which input dataset used for which model. The arrows denote the data comparison made.

Note that this direct input-output relationship only applies for the production volume (the KPI Throughput), as the other KPIs are additional value generated when running the models, i.e. not available as input data.

To gain a basic understanding for the historic volume flow at the factory, the ordered and produced volumes each month are plotted in Figure 6.3 below.

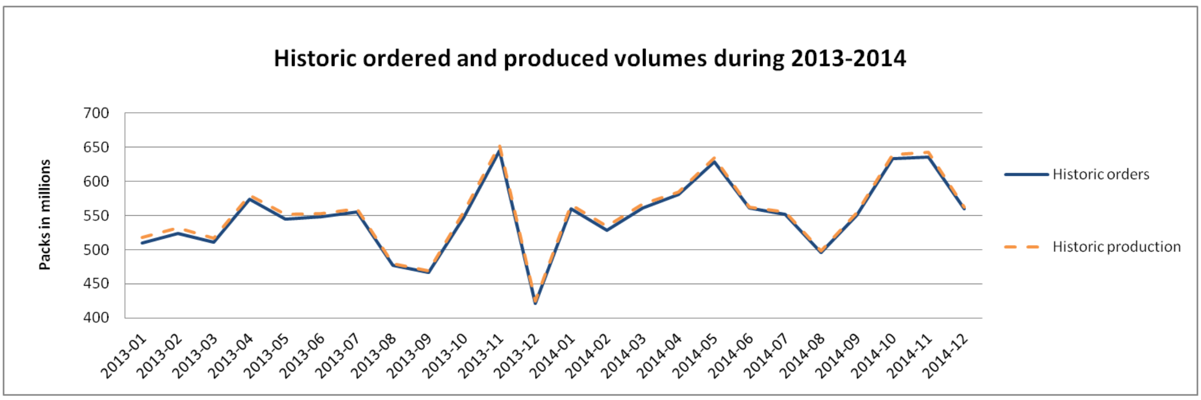

Figure 6.3 The historic ordered and produced volumes for each month of 2013 and 2014.

6.1.1 Discrete event simulation model

The input volumes and the generated output volumes for the discrete event simulation model, using the forecasted yearly sales data for 2013 and 2014, are plotted in Figure 6.4 below.

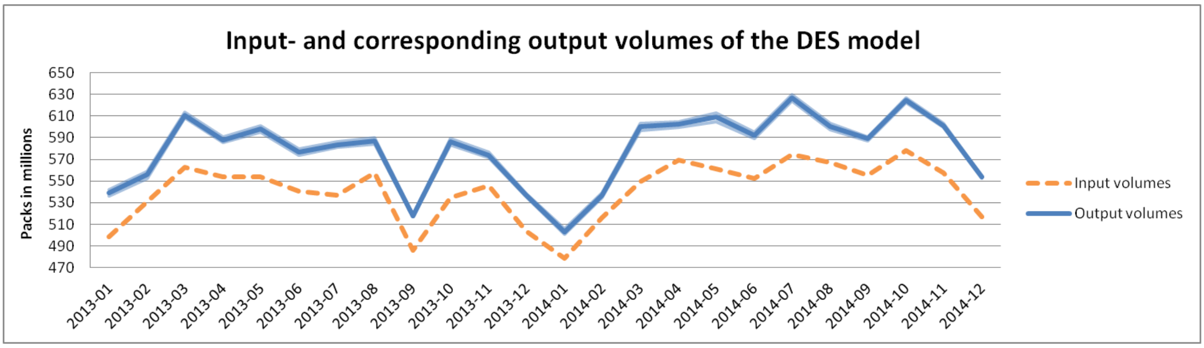

Figure 6.4 The input volumes and the corresponding output volumes of the discrete event simulation model for each month of 2013 and 2014, using yearly sales data the respective years.

The discrete event simulation model appears to produce additional volumes compared to the forecast volumes. It was indicated by personnel at the case company that this could be the results of a deliberate model configuration. In Figure 6.5, the forecast input volume has been increased by 5% in order to investigate the size of this additional volume factor. It appears that the production of the model was in fact roughly 5% larger.

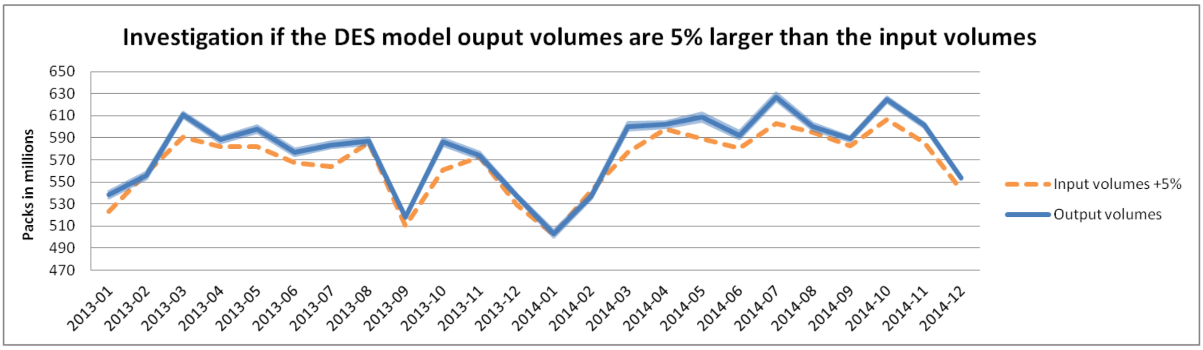

Figure 6.5 Input volumes from 2013 and 2014 using yearly sales data were increased by 5%. The output volumes were unchanged, i.e. they show the output volumes generated by the discrete event simulation model using the non-increased input volumes.

Next, any dependency between the input error and the output error of the volume was investigated, using the rolling report data that are forecasting 2014, as input data. The input error, i.e. the difference between the forecasted volumes and the true historical order data, and the output error, i.e. the difference between the model's expected production volumes and the true historical produced data, were plotted against each other in scatter plots, see Figure 6.6 for four selected months and Figure 6.7 for the yearly data complied. It appears that the input and output errors have a noticeable linear relationship.

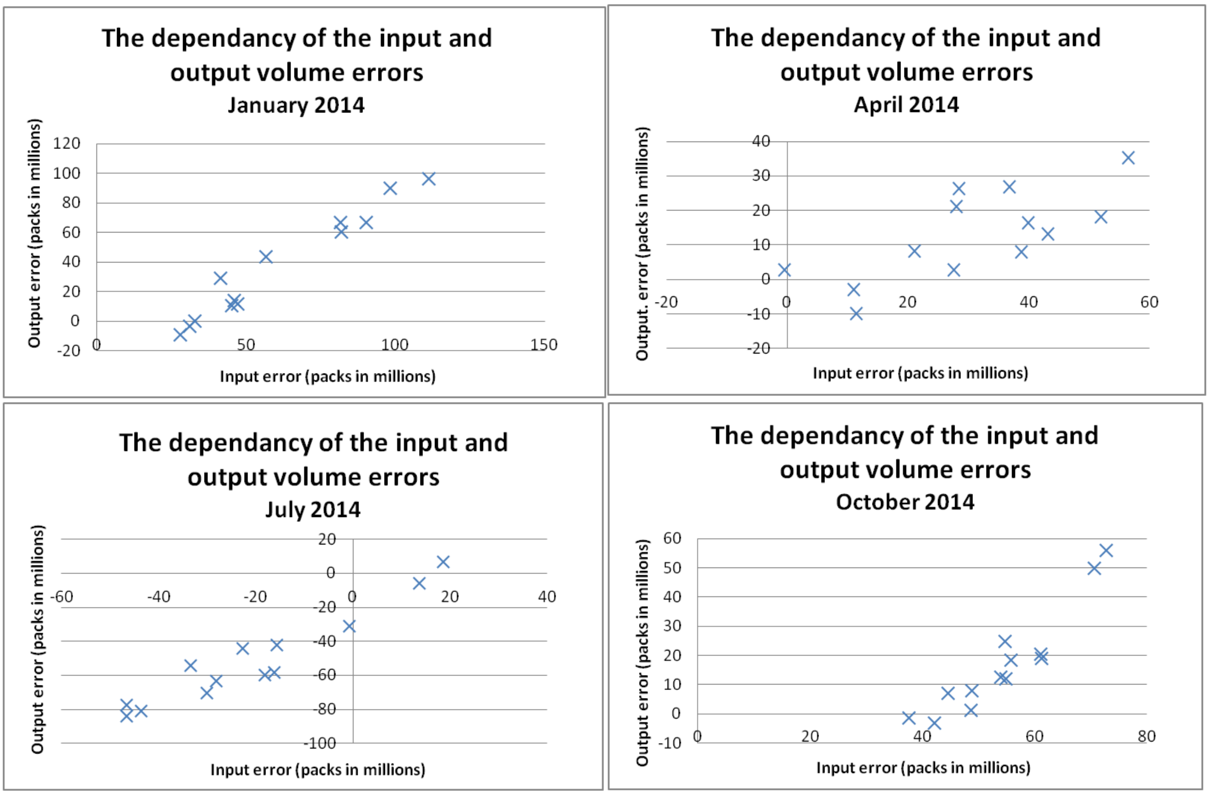

Figure 6.6 Scatter plots of the input volume errors in relation to the output volume errors for every fourth month of 2014, using the rolling forecasts from 2014 as input data in the discrete event simulation model.

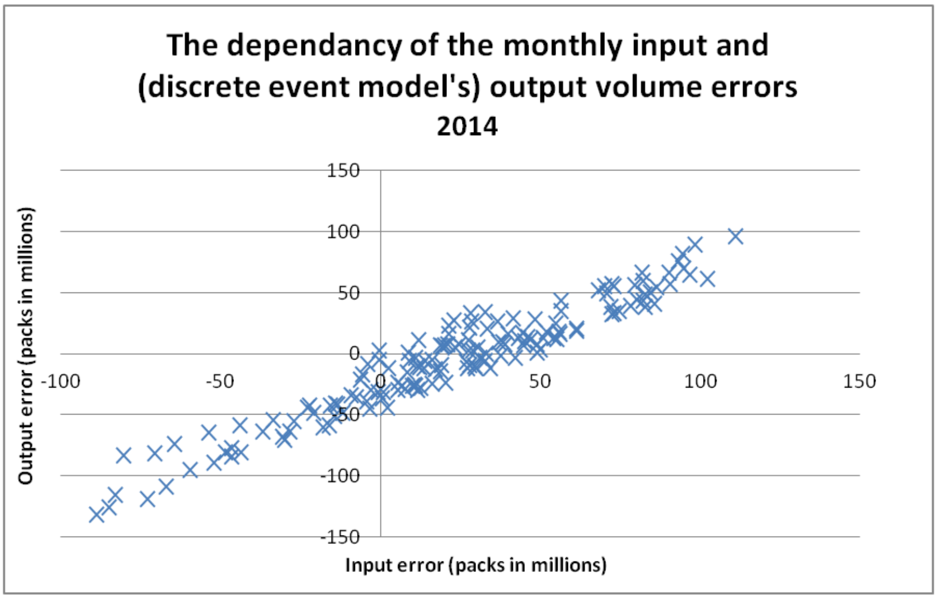

Figure 6.7 Scatter plot of the input volume errors in relation to the output volume errors for all months of 2014, using the rolling forecasts from 2014 as input data in the discrete event simulation model.

6.1.2 Spreadsheet model

The spreadsheet model is built on the premises that it is exactly the forecasted volumes for each month which is to be produced. Thus the input and output volumes are identical and the input and output errors are linear.

6.2 Results of experiment 1

It could be noted that the Throughput volumes closely followed the pattern of the input volumes. The production volumes generated by the discrete event simulation model are roughly 5% larger than the input data volumes. The error of the output volumes is linear dependant to the error of the input data volumes.

6.3 Experiment 2: Model's sensitivity to forecast deviations

Several sensitivity analyses were performed on the effect that the current deviations, caused by uncertainty, in the input data have on the output data of the discrete event simulation model. First the robustness of the output of the model, with respect to the currently existing forecast error, was investigated. Following this, the accuracy of the output data, both with and without an uncertainty factor in the input data, was evaluated. Finally, the performance of the discrete event simulation model, using the forecasted volumes, was compared to the one of the spreadsheet model using the same data.

For these purposes yearly sales forecasts for 2013 and 2014, as well as the historic order data for the same time periods, were used as input data. The KPIs of interest were the total Throughput (packs) of the laminators, the average Utilization of the laminators (%) and the average EE of the laminators (%).The data used and the comparisons made are illustrated below, see Figure 6.8.

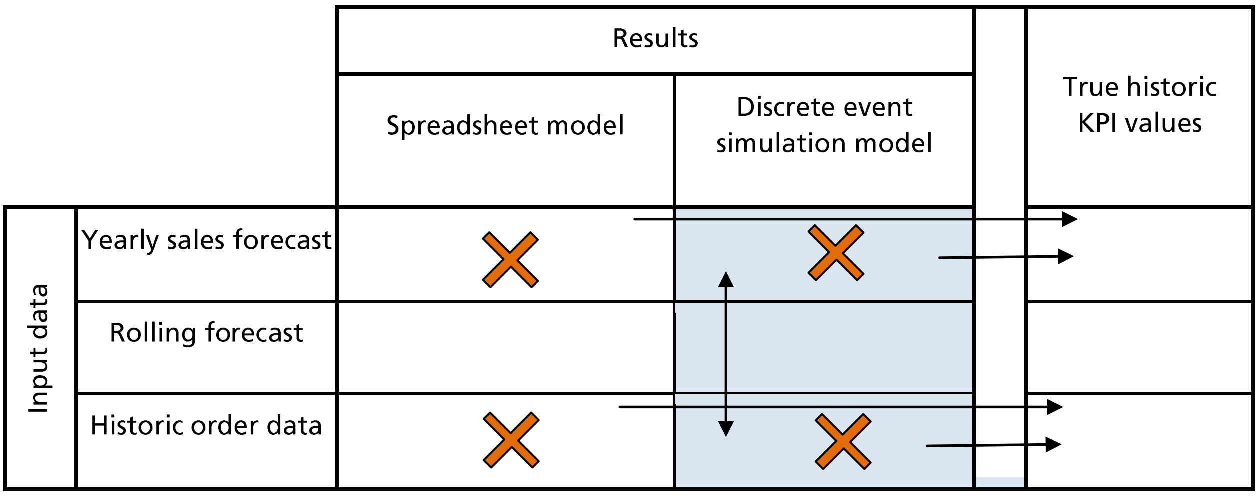

Figure 6.8 Description of data use and comparisons made in experiment 2. X denotes the simulations run, i.e. which input dataset used for which model. The arrows denote the data comparisons made.

6.3.1 Robustness of the output data

The robustness of the output data of the discrete event simulation model was investigated. The question to be answered was: Does the existing forecast error of the input data significantly affect the model's output? Figure 6.9 illustrates robustness for a model.

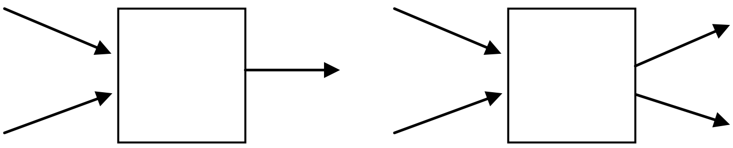

Figure 6.9 Schematic explanatory sketch of robustness. The left model illustrates a robust output behaviour, in relation to input deviations, whereas the right model does not.

The simulation was run twice for each year; once with the yearly sales forecast volumes as input data and once with the true historical order volumes for the same time period as input data. In other words, the simulation was run both with the regular level of uncertainty (the forecast) in the input data and with no uncertainty at all (the true historic) in the input data.

For each of the KPIs separately:

Denote X_i as the KPI value in the ith simulation replication using forecast input data and Y_i as the KPI value in the ith simulation replication using historic input data, with $i = 1, \dots, n$ where n is the number of simulation replications.

Let x_i and y_i denote the observed values, after running the simulation, of the independent random variables X_i and Y_i respectively, where $X_i \in N(\mu_1, \sigma_1)$ and $Y_i \in N(\mu_2, \sigma_2)$.

As the random variables across replications are considered normal distributed, see 5.1.1 *Discrete event simulation model* and independent, the arithmetic means $\bar{X}$ and $\bar{Y}$ will, according to Theorem 2, be normal distributed: $\bar{X} \in N\left(\mu_1, \frac{\sigma_1}{\sqrt{n}}\right)$ and $\bar{Y} \in N\left(\mu_2, \frac{\sigma_2}{\sqrt{n}}\right)$. As the means and standard deviations are unknown, they were approximated with $\bar{x}, s_1/\sqrt{n}$ and $\bar{y}, s_2/\sqrt{n}$ respectively.

It was now investigated if the mean from the output using forecast input data run and the mean from the output using historic input data run could be said to be significantly different. Denote the difference $\mu_1 - \mu_2$ as Δ as can be seen in Figure 6.10.

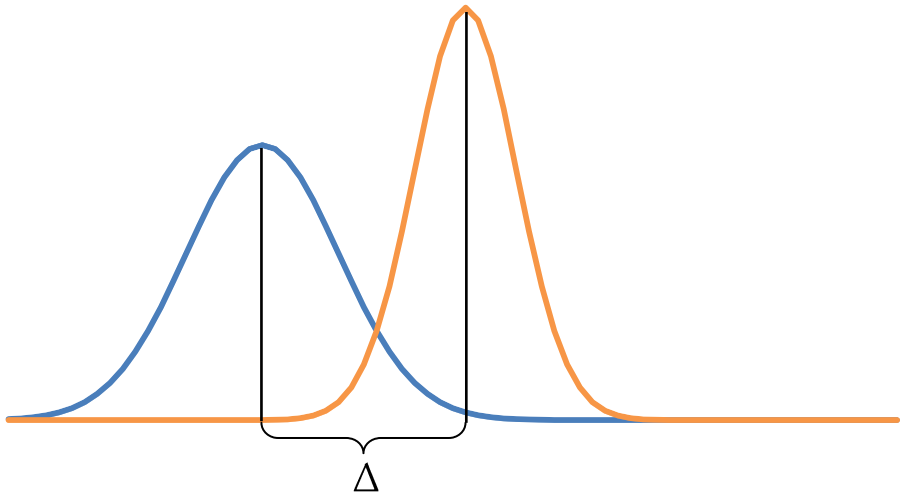

Figure 6.10 A schematic picture of the difference between the means of two normally distributed functions.

A two-tailed confidence interval for Δ was calculated, in accordance to Theorem 3, as:

$$I_\Delta = \left((\bar{x} - \bar{y}) - t_{\alpha/2}(f) * \left(\sqrt{\frac{s_1^2}{n} + \frac{s_2^2}{n}}\right), (\bar{x} - \bar{y}) + t_{\alpha/2}(f) * \left(\sqrt{\frac{s_1^2}{n} + \frac{s_2^2}{n}}\right)\right), \qquad with\ f = (n-1)$$

Here $n = 16$ and the confidence coefficient $(1 - \alpha)$ used was 0.9, 0.95 and 0.99, i.e. 90%, 95% and 99% confidence interval, which corresponds to using $t_{0,05}(15) = 1{,}75$, $t_{0,025}(15) = 2{,}13$ and $t_{0,005}(15) = 2{,}95$ respectively. (Table values found in (Blom et. al., 2005, pp. 398))

The following hypothesis test was conducted:

The null and alternative hypothesises:

$$\begin{cases} H_0: \Delta = 0 \\ H_1: \Delta \neq 0 \end{cases}$$

The significance test:

$$If \begin{cases} 0 \in I_\Delta => Do\ not\ discard\ H_0 \\ 0\ ! \in\ I_\Delta => Discard\ H_o \end{cases}$$

I.e. if the value 0 is included in the confidence interval of Δ, then the possibility that the simulation model will give the same results regardless of the current difference in the input datasets, cannot be discarded at significance level α.

A compilation of the results of the robustness test follows in 6.4 *Results of experiment 2*.

6.3.2 Model performance relating to uncertainties in the input data

The next question to be answered is: How accurate is the discrete event simulation with the current existing uncertainty of the input data, i.e. did it capture the true historic value of the KPI despite deviating input data? For these investigations the simulated output data, from using the yearly sales forecast volumes as input data, were used.

As before, let the independent random variable $X_i \in N(\mu, \sigma)$ denote the KPI value in the ith simulation replication and x_i its observed output value, $i = 1, \dots, n$. According to Theorem 2 the arithmetic mean is then $\bar{X} \in N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$. The unknown mean and standard deviations were once again approximated with $\bar{x}$ and $s/\sqrt{n}$.

Further denote θ as the true historic KPI value for the time period of interest.

A two-tailed confidence interval for the mean was calculated in accordance to Theorem 4:

$$I_\mu = (\bar{x} - t_{\alpha/2}(f) * \left(\frac{s}{\sqrt{n}}\right), \bar{x} + t_{\alpha/2}(f) * (\frac{s}{\sqrt{n}}))), \qquad with\ f = (n-1)$$

Here $n = 16$ and the confidence coefficient $(1-\alpha)$ used was 0.9, 0.95 and 0.99, which corresponds to using $t_{0,05}(15) = 1{,}75,\ t_{0,025}(15) = 2{,}13$ and $t_{0,005}(15) =\ 2{,}95$ respectively. (Table values found in (Blom et. al,. 2005, pp. 398))

The following hypothesis test was conducted:

The null and alternative hypothesis:

$$\begin{cases} H_0: \mu = \theta \\ H_1: \mu\ \neq \theta \end{cases}$$

The significance test:

$$If \begin{cases} \theta \in I_\mu => Do\ not\ discard\ H_0 \\ \theta\ ! \in\ I_\mu => Discard\ H_o \end{cases}$$

I.e. if θ is included in the confidence interval for the simulated KPI mean, then the possibility that the simulation will give the accurate value cannot be discarded at significance level α.

A compilation of the results of this uncertainty test follows in 6.4 *Results of experiment 2*.

6.3.3 Model performance relating to built-in uncertainties in the model itself

The same tests as in 6.3.2 *Model performance relating to uncertainties in the input data* above, was conducted once again, except that instead of using the sales forecast data, the historical order data for the same time periods were used as input data in the simulation models. In other words, when using accurate input data, i.e. the true historic order data, how good is the discrete event simulation model at capturing the true historical value of the KPIs? As the uncertainty factor in the input data now is removed, any deviations in the output data will be due to inbuilt uncertainties in the model itself.

A compilation of the results of this uncertainty test follows in 6.4 *Results of experiment 2*.

6.3.4 Model performance comparison

The performance of the discrete event simulation model and the spreadsheet model was compared. The absolute difference between each model's output and the true historical value were calculated in order to determine if any model predominately gave better estimations throughout the year.

Note that the spreadsheet model gives a deterministic output while the discrete event simulation model gives a stochastic output, which means that the absolute error will be deterministic and stochastic in turn.

Denote the true historic KPI value for the time period of interest as θ, the output of the spreadsheet model as γ and the stochastic output of the discrete event simulation as $X \in N(\mu, \sigma)$. The absolute error between θ and the spreadsheet model result is then $\varepsilon_1 = |\theta - \gamma|$ and the 95% confidence interval of the absolute error $\varepsilon_2 = |\theta - \mu|$ between θ and the discrete event simulation model is

$$I_{\varepsilon_2} = (|\theta - \bar{x}| - t_{\alpha/2}(f) * (\frac{s}{\sqrt{n}}), |\theta - \bar{x}| + t_{\alpha/2}(f) * (\frac{s}{\sqrt{n}})), \qquad with\ f = (n-1)$$

Here $n = 16$ and the confidence coefficent used is 95% which correspond to $t_{0,05}(15) = 2{,}13$.

Thus three scenarios present themselves:

$$\begin{cases} \varepsilon_1 > I_{\varepsilon_2} \\ \varepsilon_1 \in\ I_{\varepsilon_2} \\ \varepsilon_1 < I_{\varepsilon_2} \end{cases}$$

The first case is when the discrete event simulation model performs better, the second case occurs when both models perform equally well and the last case when the spreadsheet model performs better.

A compilation of the results of this comparison follows in 6.4 *Results of experiment 2*.

6.4 Results of experiment 2

In this section a compilation of notable results regarding the models' sensitivity relating to uncertainty is presented. The performance of the discrete event simulation model, relating to the robustness and the accuracy of the model when using input data with and without uncertainties, are compiled in Table 6-1. Following this, the comparison of the models performance is found in Table 6-2 and the average absolute errors of each model in Table 6-3.

Note that a higher confidence coefficient means a wider confidence interval. It is a trade-off between reducing the risk of error, i.e. that the method will not capture the true value, and the precision of the estimation, i.e. the confidence interval. However, that a higher confidence coefficient (0,90 0,95 0,99) will give a larger confidence interval might not be intuitive.

Recall, the general formula for a confidence interval for an unknown mean and standard deviation as

$$I_\mu = \left(\bar{x} - t_{\alpha/2}(f) * \frac{s}{\sqrt{n}}, \bar{x} + t_{\alpha/2}(f) * \frac{s}{\sqrt{n}}\right) \quad where\ f = (n-1)$$

The confidence coefficients 0,90, 0,95 and 0,99 uses the table values $t_{0,05}(15) = 1{,}75$, $t_{0,025}(15) = 2{,}13$ and $t_{0,005}(15) = 2{,}95$ respectively. Thus a 99% confidence interval will be approximately 38% wider than the 95% confidence interval, i.e. the probability that it cover the true value will increase but the precision is lowered. Likewise a 95% confidence interval is 22% wider than a 90% confidence interval.

Table 6-1 The robustness and the accuracy the discrete event simulation model, using yearly sales forecast and historic orders as input data. (*) The confidence interval width factor indicates the comparable increase in width relating to the confidence coefficient, i.e. the loss of precision in the estimation.

Throughput	% of time correct statement					
Year:	2013			2014		
% Confidence interval	90%	95%	99%	90%	95%	99%
Confidence interval width factor (*)	1,00	1,22	1,69	1,00	1,22	1,69
DES output is robust	8%	8%	17%	8%	8%	8%
DES (yearly sales forecast input data) incl. true	0%	0%	0%	0%	0%	8%
DES (historic order input data) incl. true	0%	0%	0%	0%	0%	0%

Utilization	% of time correct statement					
Year:	2013			2014		
% Confidence interval	90%	95%	99%	90%	95%	99%
Confidence interval width factor (*)	1,00	1,22	1,69	1,00	1,22	1,69
DES output is robust	25%	25%	25%	33%	33%	42%
DES (yearly sales forecast input data) incl. true	8%	8%	8%	0%	0%	8%
DES (historic order input data) incl. true	8%	8%	17%	0%	0%	0%

EE	% of time correct statement					
Year:	2013			2014		
% Confidence interval	90%	95%	99%	90%	95%	99%
Confidence interval width factor (*)	1,00	1,22	1,69	1,00	1,22	1,69
DES output is robust	75%	92%	100%	75%	83%	100%
DES (yearly sales forecast input data) incl. true	8%	8%	17%	25%	33%	33%
DES (historic order input data) incl. true	17%	17%	25%	8%	17%	33%

For a 95% confidence coefficient, the discrete event simulation model gave a robust value for the KPI EE in >80% of the cases. The cases in which the model generated robust results for the other KPIs are noticeable fewer.

From the individual monthly performance evaluation, graphical interpretations can be found in Appendix: *Experiment results for each month* (Table 1), the months of July and August tend to perform comparable poorer for the KPI EE than for the other months. No other clear pattern between the robustness of a KPI and specific months are prominent.

The output results seldom include the true historic KPI value even at a confidence coefficient of 99%. This result applies to the scenario where the uncertainty error in the input data is eliminated as well.

Table 6-2 A comparison between the performances of the models. The percentage shows how often each model, for each KPI, can be said to have a strict smaller absolute error to the true historic KPI value. DES denotes the discrete event simulation model, Sp denotes the spreadsheet model and Equal refers to when no model can be said to perform better, i.e. the absolute errors overlap.

(Yearly sales forecast input data)	% of the time closest		
Which model?	**DES**	**Equal**	**Sp**
Throughput	33%	13%	54%
Utilization	21%	8%	71%
EE	71%	4%	25%

(Historic order input data)	% of the time closest		
Which model?	**DES**	**Equal**	**Sp**
Throughput	0%	0%	100%
Utilization	17%	0%	83%
EE	75%	8%	17%

Table 6-3 The average absolute error per KPI and model, using forecast input data (upper table) and historic input data (lower table). Note that the absolute error is in the unit of the KPI, not as an error percentage of the KPI value. DES and Sp denotes the discrete event simulation model the spreadsheet model respectively.

(Yearly sales forecast input data)	Average absolute error	
Model:	**DES**	**Sp**
Throughput (packs in millions)	41,5-47,1	38,7
Utilization (percentage unit)	11,2-13,2%	5,7%
EE (percentage unit)	1,9-3,5%	7,0%

(Historic order input data)	Average absolute error	
Model:	**DES**	**Sp**
Throughput (packs in millions)	28,2-34,7	5,2
Utilization (percentage unit)	12,7-14,7%	6,7%
EE (percentage unit)	1,9-3,5%	7,4%

The discrete event simulation model predominately performs better, in >70% the cases, than the spreadsheet model for the KPI EE. This applies for both scenarios, i.e. with and without an uncertainty error in the input data.

The spreadsheet model predominately performs better, in >70% of the cases, than the discrete event simulation for the KPI Utilization. This applies for both scenarios, i.e. with and without an uncertainty error in the input data.

Note that as the difference between the historic order data and historic produced data is small (**Error! Reference source not found.**), and the output volumes equals the input volumes for the spreadsheet model, then the high performance, regarding the KPI Throughput of the spreadsheet model when using historic order as input data, is expected.

No clear patterns between a model's comparable performance and the individual months, see Appendix: *Experiment results for each month* (Table 2), are prominent.

6.5 Experiment 3: The time dependency of the output accuracy

The evolvement of both models' performance, as the time frame for the forecasts approaches, was looked into. The rolling sales data from each month of 2013 and 2014, i.e. a total of 24 datasets, were used for this purpose. Note that the months of 2013 will not be analysed as such, but the data is nonetheless required in order to conduct the experiments for the months of 2014.

The KPIs of interest were the total Throughput (packs) of the laminators, the average Utilization of the laminators (%) and the average EE of the laminators (%).The data used and the comparisons made are illustrated below, see Figure 6.11.

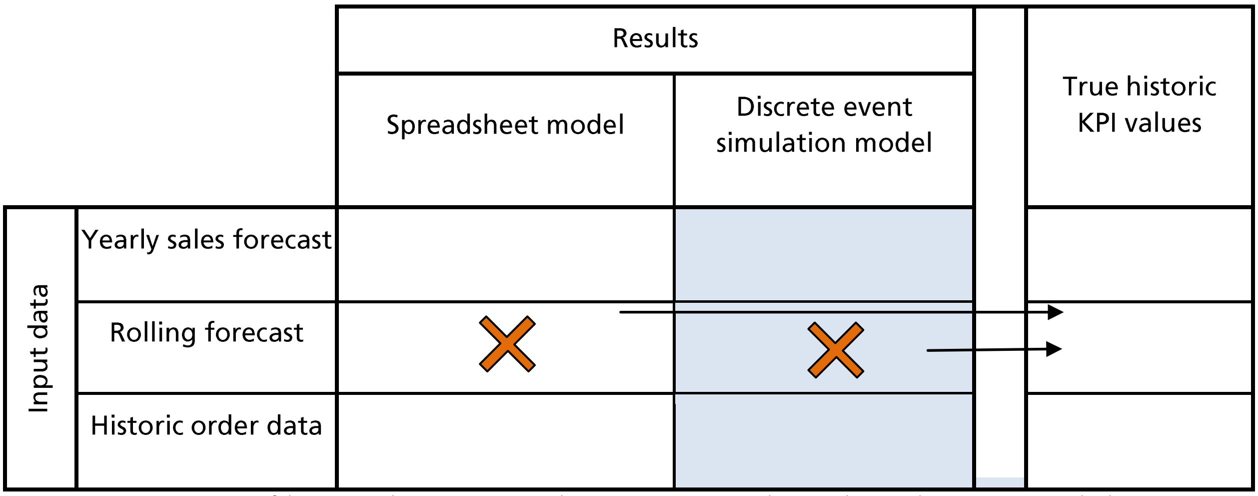

Figure 6.11 Description of data use and comparisons made in experiment 3. X denotes the simulations run, i.e. which input dataset used for which model. The arrows denote the data comparisons made.

6.5.1 Evolvement of output data as the forecasted time frame approaches

According to the third law of forecasting, which is rather intuitive, as the time frame for the forecast approaches, the forecast volumes can be expected to increase in accuracy. The objective of this investigation is to see if any pattern, regarding the performance of the output KPIs, can be identified when studying the evolvement of the forecast input data over time.

Let $T_j, j = 1, \dots, 12$, denote the month that is of interest to forecast, i.e.

T_1 = January 2014,
T_2 = February 2014,
…
T_{12} = December 2014.

Then $(T_j - k), k = 12, 11, \dots, 0$, refers to the time frame of the forecast for month T_j, i.e.

$(T_j - 12)$ = the forecast for month T_j that was provided 12 month previously,
$(T_j - 11)$ = the forecast for month T_j that was provided 11 month previously,
…
$(T_j - 0)$ = the forecast for month T_j that was provided month T_j.

Further denote θ_{T_j} as the true historic value for month T_j.

A schematic overview of the data points of interest is seen below in Figure 6.12.

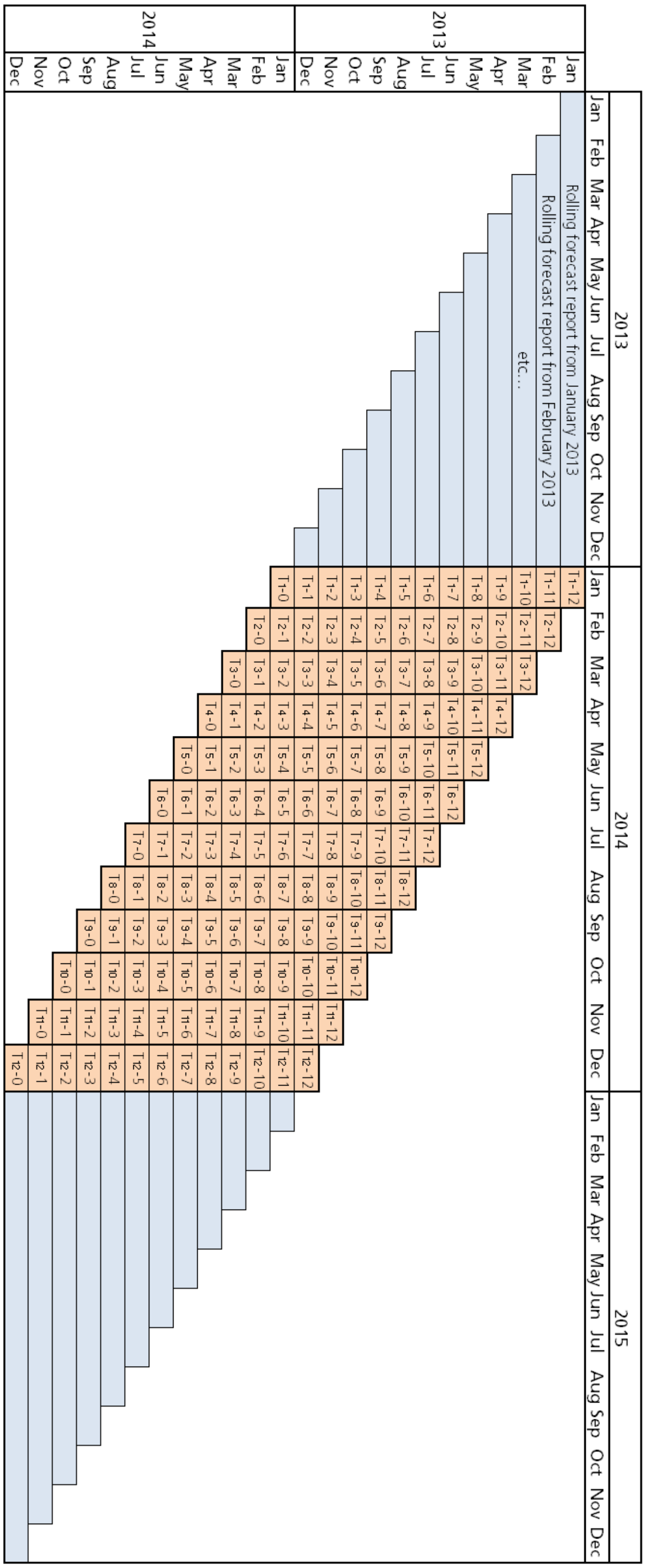

Figure 6.12 A schematic overview over which data points from the respective rolling forecast reports that were used for conducting the experiments for the months of 2014.

For each month T_j, both models' output KPI value at all time frames $(T_j - k)$, $k = 12, \dots, 0$, was plotted together with. θ_{T_j}.

As before, let the independent random variable $X_i \in N(\mu, \sigma)$ denote the KPI value in the ith simulation replication and x_i its observed output value, $i = 1, \dots, n$. According to Theorem 2 the arithmetic mean is $\bar{X} \in N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$ and the unknown mean and standard deviations were approximated with $\bar{x}$ and $s/\sqrt{n}$.

The confidence interval for the mean value for the time T_j , generated at the time frame $(j-k)$, by the discrete event simulation, was calculated according to Theorem 4 as:

$$I_{\mu,T_i-k} = (\bar{x}_{T_i-k} - t_{\frac{\alpha}{2}}(f) * \left(\frac{s_{T_i-k}}{\sqrt{n}}\right), \bar{x}_{T_i-k} + t_{\alpha/2}(f) * (\frac{s_{T_i-k}}{\sqrt{n}}))), \qquad with\ f = (n-1)$$

Here $n = 16$ and the confidence coefficent used is 95% which correspond to $t_{0,05}(15) = 2{,}13$.

The evolvement of the models' output data, as the forecasted time approaches, can be seen for the KPIs Throughput, Utilization and EE for May month in Figure 6.13, Figure 6.14 and Figure 6.15 respectively. For a complete collection of the monthly graphs for each KPI, refer to the Appendix: *Experiment results for each month* (Figure 1-9).

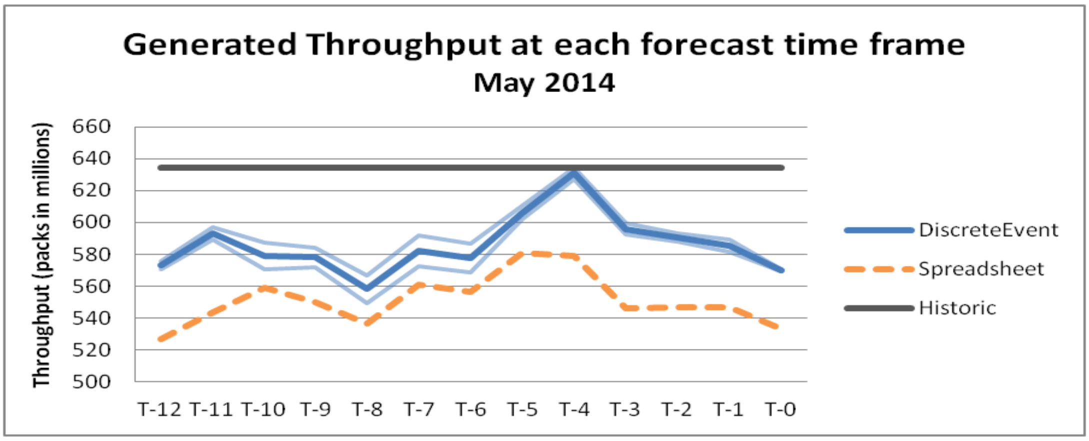

Figure 6.13 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Throughput in May 2014. The true historic KPI value for the month of May 2014 is also included.

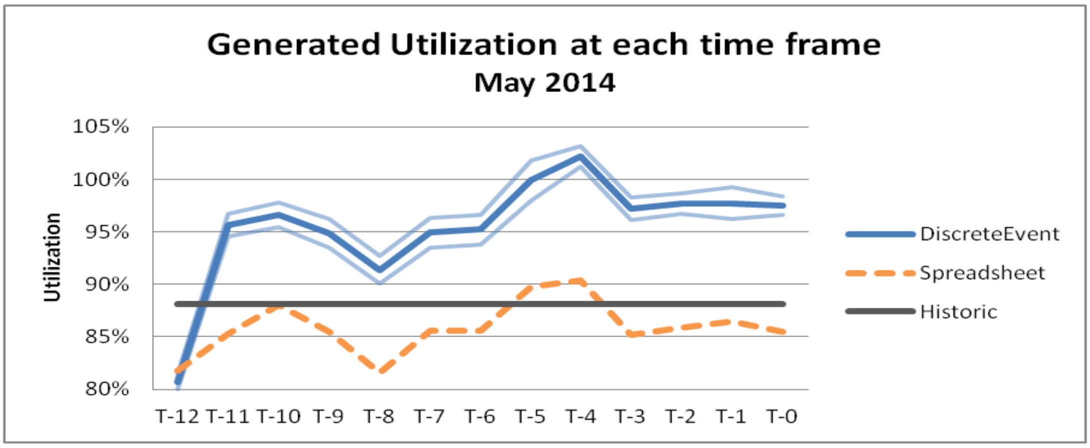

Figure 6.14 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Utilization in May 2014. The true historic KPI value for the month of May 2014 is also included.

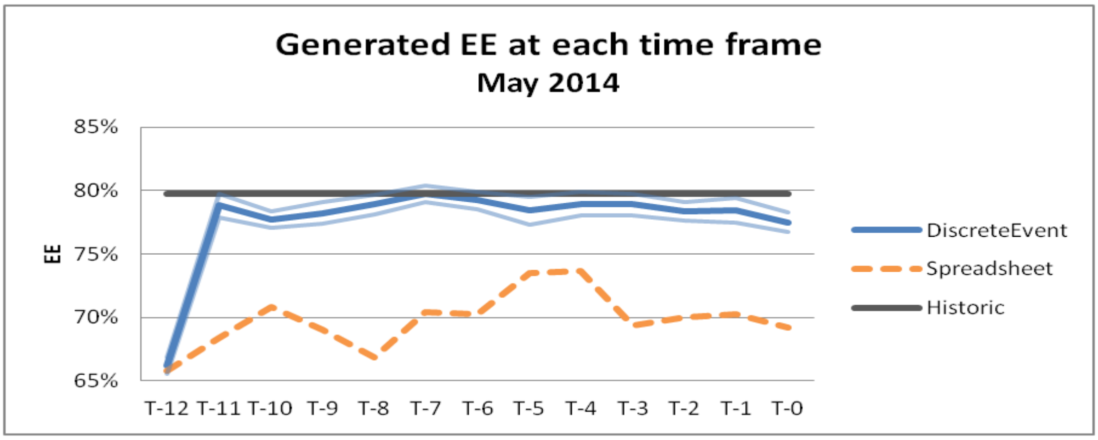

Figure 6.15 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI EEt in May 2014. The true historic KPI value for the month of May 2014 is also included.

Evaluating the performance of the discrete event simulation model

At each time frame $(T_j - k)$, $k = 12, \dots, 0$, the possibility that θ_{T_j} is included in the confidence interval for the mean μ at $(T_j - k)$, I_{μ,T_j-k}, was investigated. The following hypothesis test was conducted:

The null and alternative hypothesis:

$$\begin{cases} H_0: \mu = \theta \\ H_1: \mu \neq \theta \end{cases}$$

The significance test:

$$If \begin{cases} \theta_{T_j} \in I_{\mu,T_j-k} => Do\ not\ discard\ H_0 \\ \theta_{T_j}\ ! \in\ I_{\mu,T_j-k} => Discard\ H_o \end{cases}$$

I.e. if θ_j is included in the confidence interval for the simulated KPI mean, then the possibility that the simulation will give the accurate value cannot be discarded at significance level α.

6.5.2 Model performance comparison

At each forecasted time frame $(T_i - k)$, $k = 12, \dots, 0$, for each month T_i, $i = 1, \dots, 12$, the absolute difference between each model's output and the true historic value that month was calculated. This was done in order to determine if any model predominately, or in specific pattern, gave better estimations.

Note that, as stated before in 6.3.4 *Model performance comparison*, the absolute difference between a deterministic and stochastic variable will be stochastic, i.e. the absolute error will have a confidence interval. The possible outcomes are as previously stated: either of the models performs better than the other or both perform equally well. (For more information of the calculations conducted, refer to 6.3.4 *Model performance comparison*.)

6.6 Results of Experiment 3

In this section a compilation of notable result regarding the time dependency of the output accuracy is presented. The evolution of the absolute average error is seen if Figure 6.16, the performance evaluation of the discrete event simulation model in Table 6-4 and the compiled comparison of the models in Table 6-5.

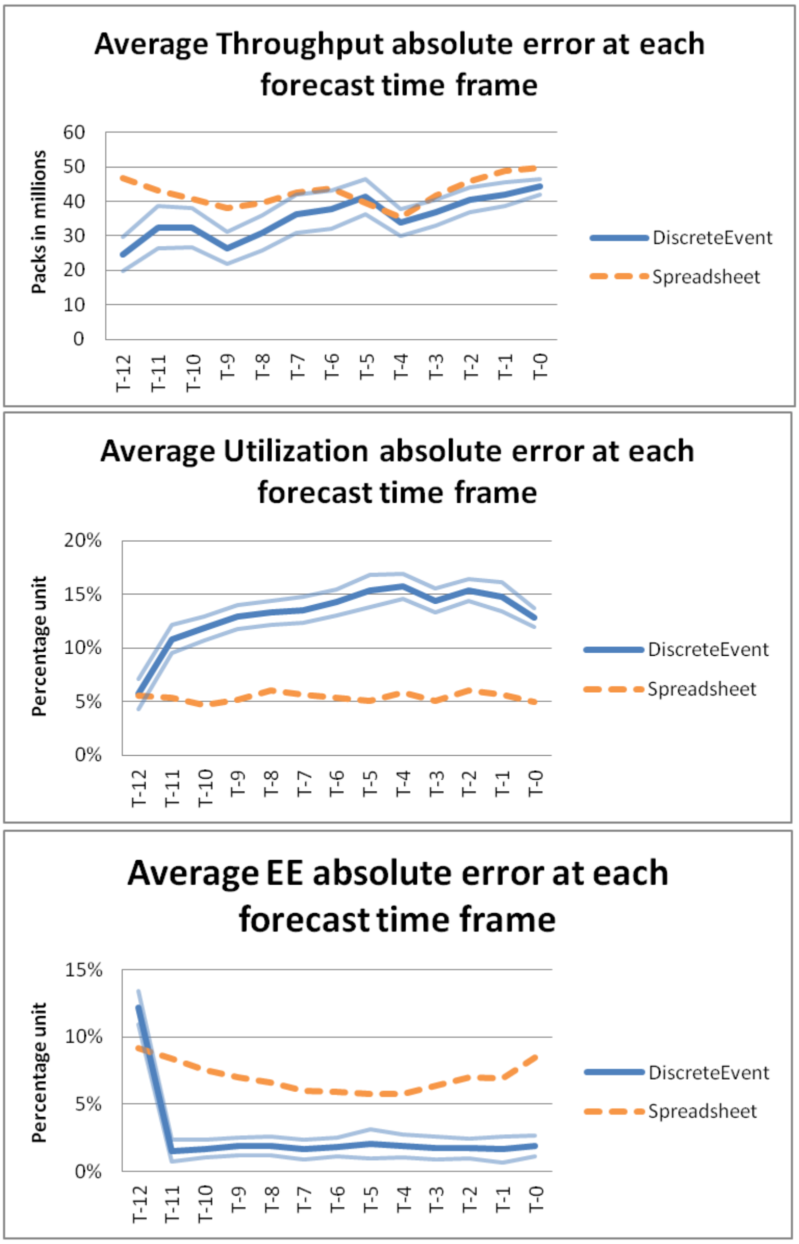

Figure 6.16 For each of the KPIs: Throughput, Utilization and EE: The average absolute error at each time frame T-k, k=12,...,0, for the KPI EE, using rolling forecast as input data for both models. Note that the y-axis is in the unit of the KPI.

The absolute average error for the KPI EE generated by the discrete event simulation model appears to reach a steady level at the time frame $T_j - 11$, i.e. the prediction given eleven months ahead of time is as accurate as it will be.

Likewise, the absolute average error for the KPI Utilization generated by the spreadsheet model appears to remain at a steady level regardless of the investigated time frame of the forecast.

For the other KPIs, the absolute average error does not appear stable.

Table 6-4 For the KPIs Throughput, Utilization and EE respectively: A compilation of the discrete event simulation model's performance at each time frame for all months of 2014, using rolling forecast as input data. When the true historic value is within the confidence interval of the output it is denoted as 1, otherwise as 0.

Throughput														
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	%OK
T-12	0	0	0	0	0	0	1	0	0	0	0	0	1	8%
T-11	0	0	0	0	0	0	1	0	1	0	0	0	2	17%
T-10	0	0	0	0	0	0	0	0	1	0	0	0	1	8%
T-9	0	0	0	0	0	0	0	0	1	0	0	0	1	8%
T-8	1	0	0	0	0	0	0	0	0	0	0	0	1	8%
T-7	0	0	1	0	0	0	0	0	0	1	0	0	2	17%
T-6	0	0	1	1	0	0	0	0	0	0	0	0	2	17%
T-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-4	0	0	0	1	0	0	0	0	0	0	0	0	1	8%
T-3	0	0	1	0	0	0	0	0	0	0	0	0	1	8%
T-2	0	0	0	1	0	0	0	0	0	0	0	0	1	8%
T-1	0	0	0	0	0	0	0	0	0	1	0	0	1	8%
T-0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
												Total:	14	9%

Utilization														
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	%OK
T-12	0	0	0	0	0	0	0	0	0	1	1	0	2	17%
T-11	1	0	0	0	0	0	0	0	0	0	0	0	1	8%
T-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-9	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-8	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-7	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-6	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-5	1	0	0	0	0	0	0	0	0	0	0	0	1	8%
T-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
												Total:	4	3%

EE														
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	%OK
T-12	0	0	0	0	0	0	0	0	0	0	0	0	0	0%
T-11	0	0	0	0	1	0	0	1	0	1	1	0	4	33%
T-10	0	0	0	0	0	0	0	1	0	1	0	1	3	25%
T-9	0	0	0	0	0	0	0	0	0	1	0	0	1	8%
T-8	0	0	0	0	0	0	0	0	0	1	1	0	2	17%
T-7	0	0	0	0	1	0	0	1	0	1	0	0	3	25%
T-6	0	0	0	0	1	0	0	1	0	1	0	0	3	25%
T-5	0	0	0	0	0	0	0	1	0	1	1	0	3	25%
T-4	0	0	0	0	1	0	0	1	0	1	0	0	3	25%
T-3	0	0	0	0	1	0	0	0	0	1	0	0	2	17%
T-2	0	0	0	0	0	0	0	0	0	1	1	0	2	17%
T-1	0	0	0	0	0	0	0	1	0	1	1	0	3	25%
T-0	0	0	0	0	0	0	0	0	0	1	0	1	2	17%
												Total:	31	20%

No pattern of increased accuracy in relation to the time frame $(T_j - k), k = 12, \ldots, 1,$ using a 95% confidence interval, were prominent.

Table 6-5 For the KPIs Throughput, Utilization and EE respectively: A comparison between the performance of the models in relation to the true historic KPI value at each time frame and for each month. DE=the discrete event simulation model, has the strict smaller absolute error, S=the spreadsheet model, has the strict smaller absolute error, Equal=no model can be said to perform better, i.e. the absolute errors overlap.

	Throughput												% of times closest		
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	DES	Equal	Sp
T-12	DES	DES	DES	DES	DES	DES	DES	Sp	DES	DES	DES	Equal	83%	8%	8%
T-11	DES	Sp	DES	DES	DES	DES	DES	Sp	Equal	DES	DES	Sp	67%	8%	25%
T-10	DES	Sp	DES	DES	DES	DES	Sp	Sp	DES	DES	DES	Sp	67%	0%	33%
T-9	DES	DES	Equal	DES	DES	DES	Sp	Sp	Equal	DES	DES	Sp	58%	17%	25%
T-8	DES	DES	DES	DES	DES	Equal	Sp	Equal	Sp	DES	DES	Sp	58%	17%	25%
T-7	DES	Equal	DES	DES	DES	DES	Sp	Sp	Sp	DES	DES	Sp	58%	8%	33%
T-6	DES	Equal	DES	DES	DES	Sp	Sp	Sp	Sp	DES	DES	DES	58%	8%	33%
T-5	DES	DES	Equal	DES	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	50%	8%	42%
T-4	DES	DES	Sp	Equal	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	42%	8%	50%
T-3	DES	Equal	DES	DES	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	50%	8%	42%
T-2	DES	DES	DES	DES	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	58%	0%	42%
T-1	DES	DES	DES	DES	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	58%	0%	42%
T-0	DES	DES	DES	DES	DES	Sp	Sp	Sp	Sp	DES	DES	Sp	58%	0%	42%
												Total:	59%	7%	34%

	Utilization												% of times closest		
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	DES	Equal	Sp
T-12	DES	Equal	Equal	DES	Sp	Equal	Equal	Sp	Sp	Equal	DES	Equal	25%	50%	25%
T-11	DES	Sp	Sp	DES	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	25%	0%	75%
T-10	DES	Sp	Sp	Equal	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	17%	8%	75%
T-9	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-8	DES	Sp	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	17%	0%	83%
T-7	DES	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	17%	0%	83%
T-6	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-5	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-4	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-3	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-2	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	0%	92%
T-1	DES	Sp	Sp	Equal	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	8%	8%	83%
T-0	DES	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	17%	0%	83%
												Total:	13%	5%	81%

	EE												% of times closest		
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	DE	Equal	S
T-12	DES	Sp	Sp	Equal	Equal	Sp	Equal	Sp	Sp	Sp	Sp	Sp	8%	25%	67%
T-11	DES	Sp	DES	DES	DES	DES	DES	DES	DES	DES	DES	DES	92%	0%	8%
T-10	DES	Sp	DES	DES	DES	DES	DES	DES	DES	DES	Equal	DES	83%	8%	8%
T-9	DES	Equal	DES	DES	DES	Equal	DES	DES	DES	DES	Equal	DES	75%	25%	0%
T-8	DES	Equal	DES	DES	DES	Sp	DES	DES	Equal	DES	Equal	DES	67%	25%	8%
T-7	DES	Equal	DES	DES	DES	Equal	DES	DES	Sp	DES	Equal	DES	67%	25%	8%
T-6	DES	Equal	DES	DES	DES	Equal	DES	DES	Sp	DES	Equal	DES	67%	25%	8%
T-5	DES	Equal	Equal	DES	DES	Equal	DES	DES	Equal	DES	Equal	DES	58%	42%	0%
T-4	DES	Sp	Equal	DES	DES	Sp	DES	DES	Equal	DES	DES	DES	67%	17%	17%
T-3	DES	Equal	DES	DES	DES	Sp	DES	DES	Sp	DES	Sp	DES	67%	8%	25%
T-2	DES	Equal	DES	DES	DES	Sp	DES	DES	Sp	DES	DES	DES	75%	8%	17%
T-1	DES	Equal	DES	DES	DES	Sp	DES	DES	Sp	DES	Equal	DES	67%	17%	17%
T-0	DES	DES	DES	DES	DES	DES	DES	DES	Sp	DES	DES	DES	92%	0%	8%
												Total:	68%	17%	15%

When using a 95% confidence coefficient, the discrete event simulation model predominately performs better that the spreadsheet model for the KPIs EE and Throughput in 68% and 59% of the cases respectively.

The spreadsheet model performs better that the discrete event simulation model for the KPI Utilization in 81% of the cases.

A few possible patterns can be noted. At the single time frame $(T_j - 12)$ the spreadsheet model predominately perform better for the KPI EE. For the KPI Throughput, the spreadsheet model performs better for the later time frames, i.e. approaching $(T_j - 0)$, for the succeeding cluster of months: June, July, August and September.

7 Discussion

In this section the results in general, as well as in the context of decision support, will be discussed. Furthermore, the potential effects of the assumptions made and other error sources will be elaborated on.

7.1 Discussion of results

7.1.1 KPI trade-off

No single model was found to predominately perform better for all the investigated KPIs. For example, the discrete event simulation model gave comparable better estimations for the KPI EE but comparable worse estimations of the KPI Utilization. A KPI trade-off is thus made when selecting one of the models.

Verifying a model for many separate KPIs is not a wholly uncomplicated matter, as adjustments made to increasing the accuracy of one KPI could end up affecting the accuracy of another. Recall the Utilization as the used time/manned time and EE as the effective time/used time (see Figure 4.7). Any adjustments made to increase the accuracy of the Utilization may thus end up affect the accuracy of EE. As both KPIs depend on the input volumes, they will be affected by any volume adjustments to increase the Throughput accuracy as well.

7.1.2 Relationship between the input-output volumes

As the production operates according to a Make-To-Order principal, it is not surprising that the simulated output volumes closely follow the input volumes. The interest lies instead in the difference between the models. The discrete event simulation model was noted to increases the volumes with roughly 5%. According to involved personnel, this may be due to a configuration made to make up for unaccounted waste etc. Comparing the model's Throughput performance, using the two different forecast datasets as input data, it is noted that when using the yearly sales forecast the spreadsheet model have a higher performance rate (in 54% compared to 33% of the times when using a 95% confidence coefficient) but when using the rolling production forecast the discrete event simulation model has a higher performance rate (in 59% compared to 34% of the times when using a 95% confidence coefficient). The 5% volume increase appears to work in favour of the discrete event simulation when the rolling forecast is used as input data. This also implies that the rolling forecast volumes tend to be lower than the yearly sales forecast's. From a small-scale comparison of the two forecasts, a slight difference in the total volume was found.

As the output volume error has a linear relationship with the input volumes there lies potential in obtaining more accurate Throughput values by adjusting an additional volume factor in the discrete event simulation model according to which input dataset that is used. However, adjusting the volumes will in turn affect other KPIs. In the case of EE, it was seen that it was very robust against the existing input volume deviations (in 83% of the time using a 95% confidence coefficient) and with a stable absolute error value throughout the forecasted time frames. Thus a more accurate Throughput could probably be reached without affecting the accuracy of EE. The KPI Utilization, on the other hand, would be more sensitive to volume changes. It is, as was previously discussed, a trade-off between the performances of the KPIs.

7.1.3 Accuracy, robustness and time dependency of the models

The deviations do not appear dependent on the time frame for the KPI Throughput for neither of the models. However, as it is logical to assume that the forecasts will deviate less from the true value when the forecasted time approaches, a possible explanation is that the factories might start to preproduce for the upcoming three months, thus making the actual production reported for the forecasted month differ from the forecast.

The results indicate that the spreadsheet model has a high comparable performance for calculating Utilization. The error also appears to stay at around ±6 percentage units regardless of the dataset or time frame of the forecast. As this is an established model which purpose is to perform mainly this calculation, and often to do so a year in advance, this is not surprising. The low performance for the discrete event simulation model for this KPI is rather more so. As mentioned, an average of the Utilization rate between the two laminators was calculated. This recalculation is certainty a potential error source. As the Utilization is calculated as used time/manned time, and the manned time for the models are equal and fixed, the difference has to be related to the planned losses (see Figure 4.7). It is rather likely that the additional volumes, the discrete event simulation model produces, discussed further above, is the main influence. This is further indicated by the simulated Utilization value exceeding the historic value in most cases (see Appendix: *Experiment results for each month*, Figure 4-6).

Stable values for the KPI EE were found as early as 11 months prior to the actual forecasted month for the discrete event simulation model, using rolling forecast input data. Similar robust results are given when using the yearly forecast data. However, the true value is still not included in the confidence interval more than in a few occurrences. If an error margin of ±2-3 percentage units is deemed acceptable, the EE result can be considered reliable at least a year in advance, possible longer. However, the result of the time dependency analysis of EE for T-12, i.e. the prediction made 12 months before, stands out and does not resemble the pattern for the remaining results. The same observation can be made for the KPI Utilization. Since the input volumes for this month are roughly of the same size as the other months, this event does not appear to be caused by lower production volumes going through the model. This occurrence unfortunately remains unexplained.

An interesting observation made was that, while the discrete event simulation model provides, using the yearly sales data, consistent robust result for most month of 2013 and 2014 for the KPI EE, the months of July and August were slightly worse off. As the summer months were said to be more difficult to forecast, due to e.g. product's weather dependency, this could be a reflection of this increased uncertainty. However, more years would be needed to be analysed in order to ascertain this.

7.1.4 Strengths and weaknesses of the models

After doing the experiments, it became clear that the models have different strengths and weaknesses. To start with, it is evident that the discrete event simulation model has an accurate and robust performance which is comparably higher than that of the spreadsheet model regarding predicting the KPI EE. One reason for this is most likely that it models certain stochastic variables through distributions rather than mean values, as is the case with the spreadsheet model. Operational losses, such as breakdowns, short stops and other uncertain events occurring during production, tend to be beneficial to model with distributions as they don't occur according to an average. The high accuracy of the EE can thus be related to the increased complexity of the discrete event simulation model's way of calculating these operational losses.

Another major difference between the models is how they model the machines. As previously described, the spreadsheet model handles all the machines of a machine groups as identical units, whereas the discrete event simulation model models them as individual units. This allows the discrete event simulation model to steer the settings of each machine as well as to provide results per individual machine. However, while conducting the experiments of this study, it was noted that the two laminators in the discrete event mode had a very unevenly distributed Utilization. One of the laminators had a Utilization significantly exceeding 100% and the other was underutilized. When comparing with the historically reported Utilization of the both laminators, this phenomenon was not detected, instead their KPI value were quite even. The removal of the priority setting in the laminator for some products did not in particular result in a more evenly distributed Utilization. The reason for this behaviour might possible lie in the ideal block plan. The ideal block plan might not with enough accuracy reflect the settings of the scheduled block plan at the factory, thus altering the workload for each of the laminators by not dividing the products between the laminators as it is done in reality. Alternatively, the opposite might hold true, the ideal block plan follows the scheduling too strictly while in reality exceptions are sometimes made. Thus production adjustments, which would have been done at the factory, instead of allowing overtime as is done in the model, are lost. As overtime is costly and is to be avoided at the factory if possible, it makes little sense that one laminator would be allowed to be over utilized while the other is underutilized. The spreadsheet model, which calculates according to each machine having exactly half the workload, ends up giving a more accurate estimation per laminator in this case. Thus, while the discrete event simulation model allows more complex modelling of the machines, complexity does not necessarily need to reflect accuracy. To reconnect with theory, the use of a static spreadsheet model to provide quick answers still exists. (Ozturk, Coburn & Kitterman, 2003)

7.2 Discussion of error sources

When working with simulation and any form of modelling, it is impossible to regard every detail of the real system, and hence assumptions have to be made. But every assumption and delimitation has a cost and the results will be affected. In this study all assumption made have been thoroughly discussed with involved personnel in order to limit the risk of making too drastic generalisations. A few possible error sources will be discussed further.

7.2.1 Model modifications

One thing that was altered in the discrete event simulation model was the ideal block plan in the factory DB. After running the simulation it was noted that the Utilization of the individual laminators differed extensively, one was over utilized (Utilization was over 100%) and the other did not reach its full capacity. When comparing with historic data, the laminators should be more similarly utilized. As previous mentioned, one possible reason for this difference can be how the products are scheduled in the ideal bock plan.

The assumption that only standard weeks were considered means that the modelled factory runs every day except weekends. This means that the KPIs for months in holiday season, such as Christmas in December and Easter in March/April will in reality be more constraint since the factory stands idle more days than is simulated and the real EE and Utilization can thus be expected to be higher in reality than for the simulations. However, such a pattern is not clear from the results.

7.2.2 Limiting the scope to the bottleneck

As the lamination is the second stage the input volumes depend on the output volumes of the first stage, printing. Thus the Throughput could be affected, not only by the capacity limit of the lamination machines, but due to lack of incoming orders from the printers. However, the production scheduling is planned according to the bottleneck, the lamination, meaning the printing machines should be scheduled to keep this bottleneck fed. Shortage from the printers due to machine breakdowns is not expected. That the lamination is the bottleneck should also allow the assumption that the total Throughput of the laminators adequately reflects the total Throughput of the production site.

7.2.3 Data limitations

To evaluate the models' performance a point of reference was needed. For this purpose the historically logged KPI values at the factory at the relevant time points were used. However, these values might not be exactly comparable to the models' generated KPIs. The factory might chose to preproduce volumes when they have spare capacity, making the monthly produced volumes differ from the forecasted volumes. This phenomenon is not included in the models and is therefore a possible error source that should be acknowledged. This can also be seen as the historic KPI points of reference having a variance.

When running the discrete event simulation model, 16 replications were made. This number of replications was chosen with consideration to the simulation run time required and the capacity-limit of the software when using as large input data sets as was used in this study. However, if a smaller confidence interval estimations from the output results are wanted, more replications would be needed. (When the model is used at the case company, around 8 replications are made. This will give a wider confidence interval and may therefore more frequently include the true value than the results of this study gave.)

In this study, two years of data has been used. For statistically stronger results regarding seasonal pattern, a longer time span than this would be necessary. However, due to a limited amount of data available as well as the time constraint of the study, this was not further investigated.

7.2.4 A standard deviation of zero

After running the simulation and analysing the results, it was found that the output KPI Packs (Throughput) for some runs in some replications gave a standard deviation of zero for a few months for one of the laminators. This was not a frequent event, but it was discussed with personnel at the case company and some model settings were investigated. In consultancy with personnel at the case company it was decided to continue with the simulation runs even though the problem had not been completely eliminated, but it should be noted as a possible error source. Note that no structural changes were made to the model.

7.2.5 The independence of the laminators

In the experiments the laminators were treated as independent in order to be able to apply certain statistical calculation. That would mean that the volume flow through one would not affect the volume flow through the other. This was not quite the case here, as the QSVs that are able to be processed in both laminators would be sent to the first one with spare capacity. The ideal block plan in the discrete event simulation model, however, would increase the independence as it restricts some QSVs to one or the other of the laminators.

8 Conclusion & recommendations

The conclusions of the study, as well as the recommended framework for how to use the findings as capacity related decision-support, will be presented. This is followed by a couple of proposals for future study areas to build upon and compliment the findings of this study. An evaluation of this study will then round up the chapter and report.

8.1 Conclusion

To conclude, when selecting either model a trade-off in the KPI performances is made. Depending of which KPI that is of most interest, the discrete event simulation model and the spreadsheet model have different strengths and weaknesses in their performance.

For an operational KPI, such as EE, the more complex discrete event simulation model has been shown to provide strong results for use as a decision-basis. This is possibly due to that operational losses, e.g. breakdowns and other stochastic events occurring during production, tend to be more beneficial to model with distributions rather than averages. The result of this KPI was not significantly affected by the measured input deviations during 2013 and 2014. If an error margin of $\pm$2-3 percentage units is acceptable, then the model provides a strong results at least a year ahead of time.

In the case of Utilization, more complex modelling does not necessarily mean more accurate results. The workload for the machines becomes more unevenly distributed in the discrete event simulation model than what is realistic based in historically reported values, possible due to the more complex scheduling configurations. Here the averages provided by the static spreadsheet model gives a better reflection of the reality.

For the KPI Throughput, the discrete event simulation was found to perform slightly different depending on if the yearly or rolling forecast dataset was used as input data. As the volume flow is linear in the model, this variation in input uncertainty could possibly be countered by adjusting a volume adding factor according to which input dataset is used, thus increasing the accuracy of the Throughput.

8.2 Recommended framework

Use the advantages of the different models accordingly while keeping in mind that a KPI trade-off is made when either model is selected.

- Use the discrete event simulation model as support for capacity decisions based on EE.
    - As the KPI can be considered stable with deviations of ± 2 percentage units, at least a year in advance, it can provide a strong basis for more long-term capacity decisions.
- Continue using the static spreadsheet as support for capacity decisions based on Utilization.
    - To avoid basing decisions on misleading data, keep in mind that the results still deviate around ± 6 percentage units.
    - If additional value, by viewing the laminators as individual units, is desired, further evaluation of the KPI per laminator for the discrete event simulation model is recommended.
- Continue evaluating the additional volume factor to increase the accuracy of the Throughput.
- Give the simulated results suitable credibility.
    - Keep in mind that the stochastic estimate seldom actually includes the true value with a 95% confidence interval based on 16 replications.
    - Depending on which error margins are deemed acceptable, keep verifying the discrete event simulation model.

8.3 Proposals of further studies

This study took into account the effect, on the discrete event simulation model's robustness, that the monthly forecast error of two recent years have had. Due to time constraint, the robustness of the model was not stress-tested further. As there is no guarantee that these years accurately represent the whole expected set of uncertainty in the input data, further sensitivity analysis against more extreme variations in the input data is proposed.

As discussed, the accuracy of the Throughput of the discrete event simulation model varies when using yearly sales forecasts or rolling production forecasts as input data. As the output volume error linearly depend on the input volume error, further investigations regarding the size of any volume adding factors, in order to reduce the output volume error, could be beneficial to conduct. An attempt to remove such a factor, by altering a variable in the discrete event simulation model, was tried in this study, but it reflected uneven on the individual Throughput of the laminators. Due to time constraints further tests were excluded from this study. If a new study is to be conducted relating to this matter, the first recommended step would be to identify all locations in the model setup where any such factor currently is nested. Closer collaborations with the Market company could also prove advantageous in order to better understand the input data used and accordingly adjust the models' production volumes. Closer collaborations with the Market company could also prove advantage in order to better understand the input data used and accordingly adjust the models production volumes.

8.4 Study evaluation

8.4.1 Purpose and goal

The purpose of this study was to further evaluate and create understanding of how to work with simulation-based decision-support. In particular, further knowledge of the cause and effect relationship between uncertainties in the input data and the simulated output data were to be gained.

Relating to this purpose, the goal was to determine the credibility of the simulation model's results, relating to forecast deviations, and to provide a structured framework on how to advantageously utilize the gained knowledge as support in the capacity decision-making process.

- The credibility of the simulation model's results, relating to forecast deviations, was concluded above.
- A framework for how to advantageous utilize the gained knowledge in the capacity decision-making process was presented above.

The goal of this study has thus been achieved.

8.4.2 Time management

As this thesis was to be conducted in the time span of 20 weeks, activity scheduling and time management were of importance. For this purpose, a time table including the different activity stages and their allocated time was composed the first week and has been followed throughout the project process. A few reflections made during the course of this study, perhaps useful for the reader expecting to undertake a similar study, are listed below.

After the literature review, a compilation of the expected data was made and requested according to schedule. However, collecting and managing the data turned out to be a more time consuming activity than expected. This is not uncommon for simulation studies (Banks et. al., 1996, pp. 5). Scheduling extra time for unexpected issues at this activity stage could thus be beneficial.

The interviews were scheduled as early as it was reasonable and possible. To increase the reliability of the collected material the interviewees were to be given enough time read through the complied interview afterward for any misunderstandings. As it could take a while to receive the approved material, it was thus necessary to start the process early.

A log of each day's activities was kept during the course of the study. This proved to be very useful in order to keep track of all communications and it is strongly recommended.

9 References

Alvehus, J. (2013) *Skriva uppsats med kvalitativ metod: en handbok.* Stockholm: Liber AB.

Axsäter, S. (2006) *Inventory Control*, 2nd ed., New York: Springer.

Banks, J., Carson, J. S., Nelson, B. L. (1996). *Discrete-Event System Simulation.* 2nd ed., New Jersey: Prentice-Hall, Inc.

Bell, J. (2000) *Introduktion till forskningsmetodik.* Lund: Studentlitteratur.

Bergman, B., Klefsjö, B. (2010) *Quality – From Customer Needs to Customer Satisfaction.* 3rd ed., Lund: Studentlitteratur.

Blom, G., Enger, J., Englund, G., Grandell, J., Holst, L. (2005) *Sannolikhetsteori och statistikteori med tillämpningar*, 5th ed., Lund: Studentlitteratur.

Cassandras, C. G., Lafortune, S. (2008) *Introduction to Discrete Event Systems.* Boston: Springer.

FlexSim Software Product, Inc, (2010) *Flexsim simulation software – Basic training: Training Course 1 Manual.* (Retrieved 2015-11-13)

Hopp J. W., Spearman, L. M. (2000) *Factory Physics: Foundations of Manufacturing.* 2nd ed., New York: The McGraw-Hill Companies, Inc.

Höst, M., Regnell, B., Runeson, P. (2006) *Att genomföra examensarbete.* Lund: Studentlitteratur AB.

Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., Young, T. (2009) Simulation in manufacturing and business: A review. *European Journal of Operational Research 203*(1) (2010), 1-13. (Retrieved: 2015-12-03)

Law, A. M., Kelton, W. D. (2000) *Simulation Modeling and Analysis*, 3rd ed., The McGraw-Hill Companies, Inc.

Massey, F. Jr J. (1951) The Kolmogorov-Smirnov Test for Goodness of Fit. *Journal of the American Statistical Association 46*(253), 68-78. (Retrieved 2015-11-29)

McGrath, J. E. (1981) Dilemmatics, "The Study of Research Choice and Dilemmas". *American Behavioral Scientist 25*(2), 179-210. (Retrieved 2015-08-11)

Negahban, A., Smith J. S. (2014) Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems 33*(1) (2014), 241-261. (Retrieved: 2015-12-03)

Ozturk, O., Coburn, M.B., and Kitterman, S., 2003. *Conceptualization, design and implementation of a static capacity model.* Proceedings of the 2003 winter simulation conference, New Orleans, LA, 1373–1376. (Retrieved 2015-11-12)

Wallén, G. (1996) *Vetenskapsteori och forskningsmetodik*. 2nd ed., Lund: Studentlitteratur.

Young, G. A., Smith R. L. (2005) *Essentials of Statistical Inference*. Cambridge: Cambridge University Press.

Interviews

Development Engineer, Department of Virtual Engineering, Interview, 2015-08-31.

Sales Forecast Driver, Market company, Interview, 2015-11-18.

Cluster Planning Analyst, Planning group, Interview, 2015-09-18.

Data Analyst, Department of Virtual Engineering, Interview, 2015-09-01.

Department of Virtual Engineering, Unstructured interviews 2015-09-01 – 2015-11-30.

Virtual Engineering Manager, Department of Virtual Engineering, Email correspondence 2015-12-15.

Appendix: Experiment results for each month

The following tables and graphs are found in this appendix:

- The result per each month from the investigations conducted in 6.3 *Experiment 2: Model's sensitivity to forecast deviations*, see Table 1 and Table 2.
- The graphical interpretation for each month of the investigations conducted in 6.5 *Experiment 3: The time dependency of the output accuracy*, see Figure 1-9.

Table 6 The robustness and the accuracy the discrete event model of each simulated month using yearly sales forecast and historic orders as input data.

Throughput																																										
2013	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust	x	x	x																											x							1	1	2	8%	8%	17%
DES (forecast data) incl. true																																					0	0	0	0%	0%	0%
DES (historic data) incl. true																																					0	0	0	0%	0%	0%
DES output is robust & incl. true																																					0	0	0	0%	0%	0%
2014	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust										x	x	x																									1	1	1	8%	8%	8%
DES (forecast data) incl. true						x																															0	0	1	0%	0%	8%
DES (historic data) incl. true																																					0	0	0	0%	0%	0%
DES output is robust & incl. true																																					0	0	0	0%	0%	0%

Utilization																																										
2013	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust	x	x	x										x	x	x	x	x	x																			3	3	3	25%	25%	25%
DES (forecast data) incl. true	x	x	x																																		1	1	1	8%	8%	8%
DES (historic data) incl. true	x	x	x																																	x	1	1	2	8%	8%	17%
DES output is robust & incl. true	x	x	x																																		1	1	1	8%	8%	8%
2014	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust				x	x	x	x	x	x	x	x	x						x	x	x	x																4	4	5	33%	33%	42%
DES (forecast data) incl. true			x																																		0	0	1	0%	0%	8%
DES (historic data) incl. true																																					0	0	0	0%	0%	0%
DES output is robust & incl. true																																					0	0	0	0%	0%	0%

EE																																										
2013	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x		x	x			x	x	x	x	x	x	x	x	x	x	x	x	x	9	11	12	75%	92%	100%
DES (forecast data) incl. true																														x				x	x	x	1	1	2	8%	8%	17%
DES (historic data) incl. true																						x	x	x						x				x	x	x	2	2	3	17%	17%	25%
DES output is robust & incl. true																														x				x	x	x	1	1	2	8%	8%	17%
2014	**Jan**			**Feb**			**Mar**			**Apr**			**May**			**Jun**			**Jul**			**Aug**			**Sep**			**Oct**			**Nov**			**Dec**			**Total**			**% OK**		
% Confidence interval	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%	90%	95%	99%
DES output is robust	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x			x	x	x	x	x	x	x		x	x	x	x	x	9	10	12	75%	83%	100%
DES (forecast data) incl. true													x	x	x							x	x	x				x	x	x					x	x	3	4	4	25%	33%	33%
DES (historic data) incl. true															x									x					x	x				x	x	x	1	2	4	8%	17%	33%
DES output is robust & incl. true															x									x					x	x					x	x	0	2	4	0%	17%	33%

Table 7 A comparison between the performances of the models in relation to the true historic KPI value for each month. DES=the discrete event model has the strict smaller absolute error, Sp=the spreadsheet model has the strict smaller absolute error, Equal=no model can be said to perform better, i.e. the absolute errors overlap.

Which model is closer (using yearly sales forecasts as input data) to the true historic value?																											
Year:	2013												2014												% of times closest		
Month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**Maj**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**DES**	**Equal**	**Sp**
Throuhgput	Equal	Sp	Sp	DES	Sp	Sp	Equal	Sp	Sp	Sp	DES	Sp	DES	DES	Sp	Equal	DES	Sp	Sp	Sp	Sp	DES	DES	DES	33%	13%	54%
Utilization	DES	Sp	Sp	Sp	Sp	Sp	DES	Equal	Sp	DES	Sp	Equal	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	DES	21%	8%	71%
EE	DES	Sp	Sp	Sp	DES	Sp	DES	DES	DES	DES	DES	DES	DES	Sp	DES	DES	DES	Sp	DES	DES	DES	DES	Equal	DES	71%	4%	25%

Which model is closer (using historic order data as input data) to the true historic value?																											
Year:	2013												2014												% of times closest		
Month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**Maj**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**DES**	**Equal**	**Sp**
Throuhgput	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	Sp	0%	0%	100%
Utilization	DES	Sp	Sp	Sp	Sp	Sp	Sp	DES	Sp	Sp	Sp	DES	Sp	Sp	Sp	Sp	Sp	Sp	Sp	DES	Sp	Sp	Sp	Sp	17%	0%	83%
EE	DES	Sp	DES	Sp	DES	Sp	DES	DES	DES	DES	DES	DES	DES	Equal	Equal	DES	DES	Sp	DES	DES	DES	DES	DES	DES	75%	8%	17%

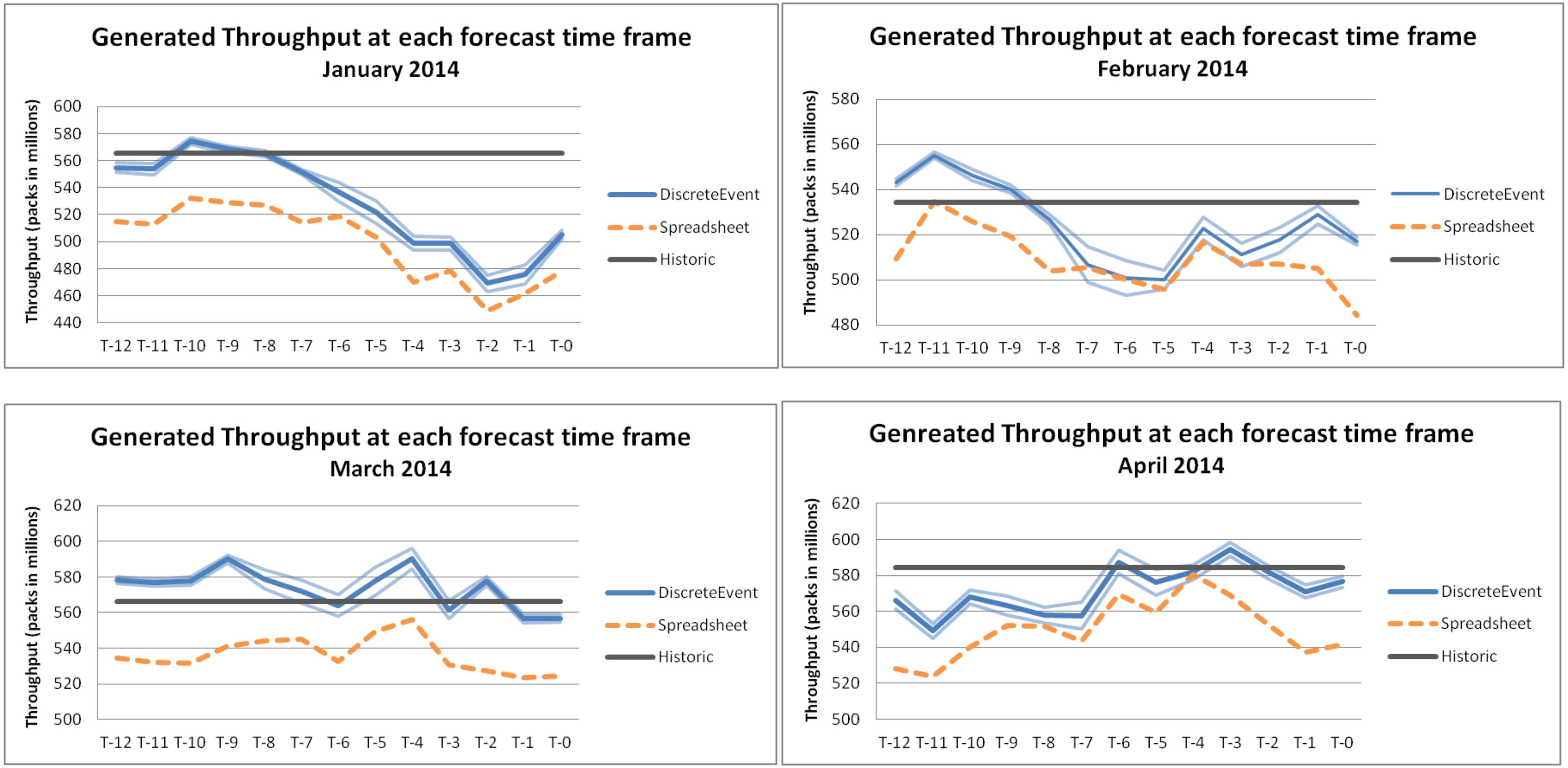

Figure 17 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Throughput and the months of (upper left to lower right) January, February, March and April 2014. The true historic KPI value for each month is also included.

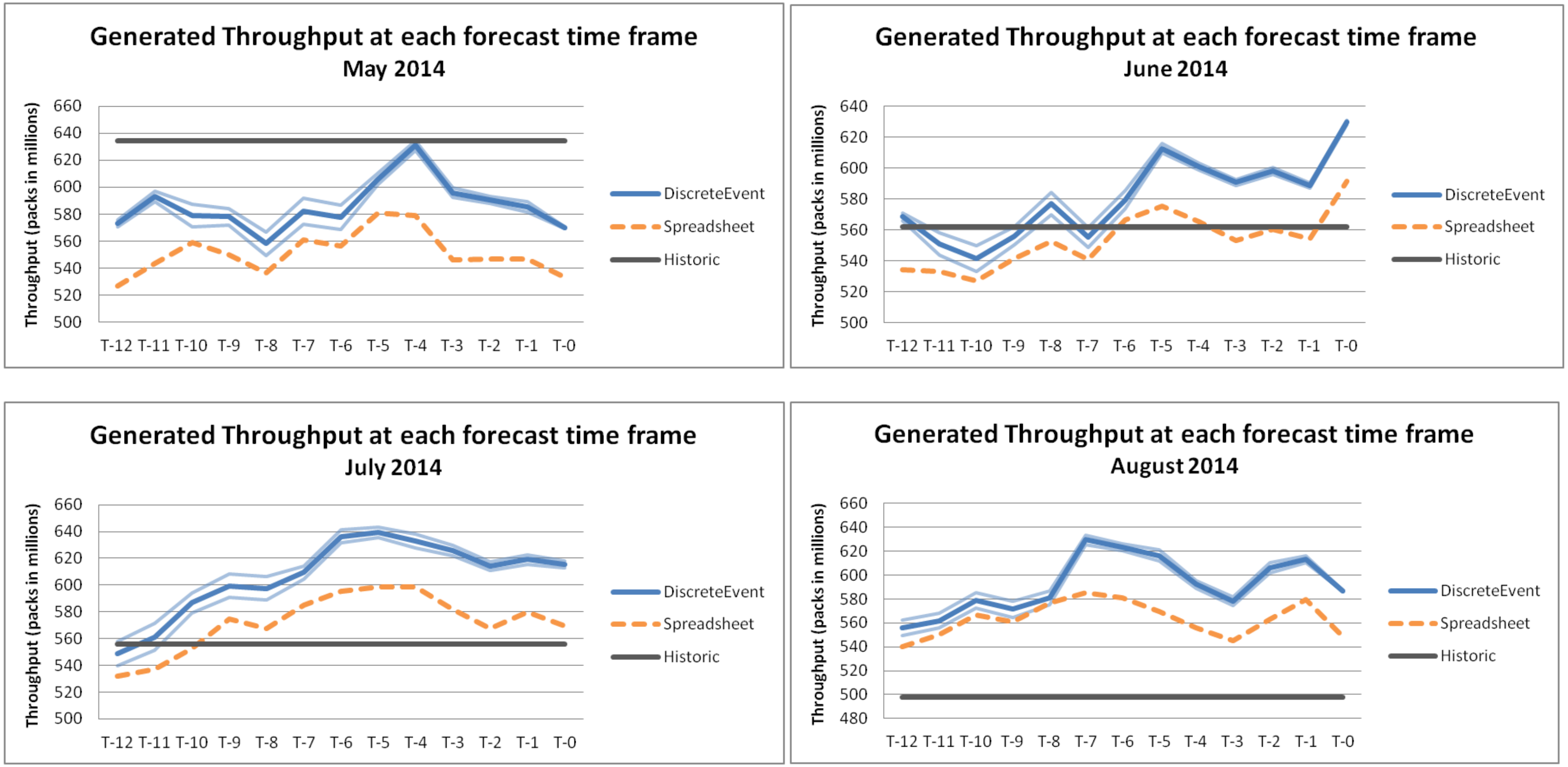

Figure 18 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Throughput and the months of (upper left to lower right) May, June, July and August 2014. The true historic KPI value for each month is also included.

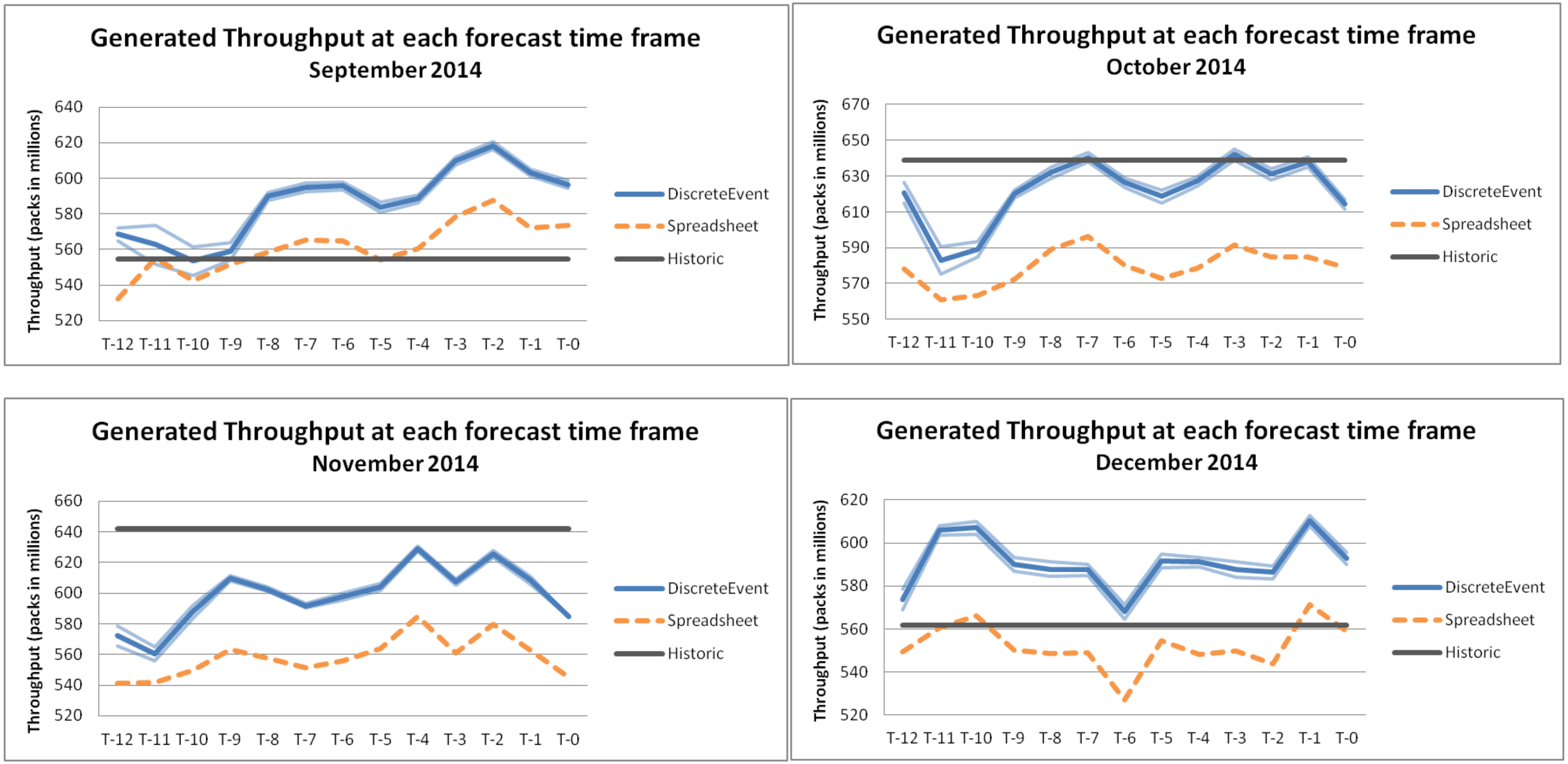

Figure 19 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Throughput and the months of (upper left to lower right) September, October, November and December 2014. The true historic KPI value for each month is also included.

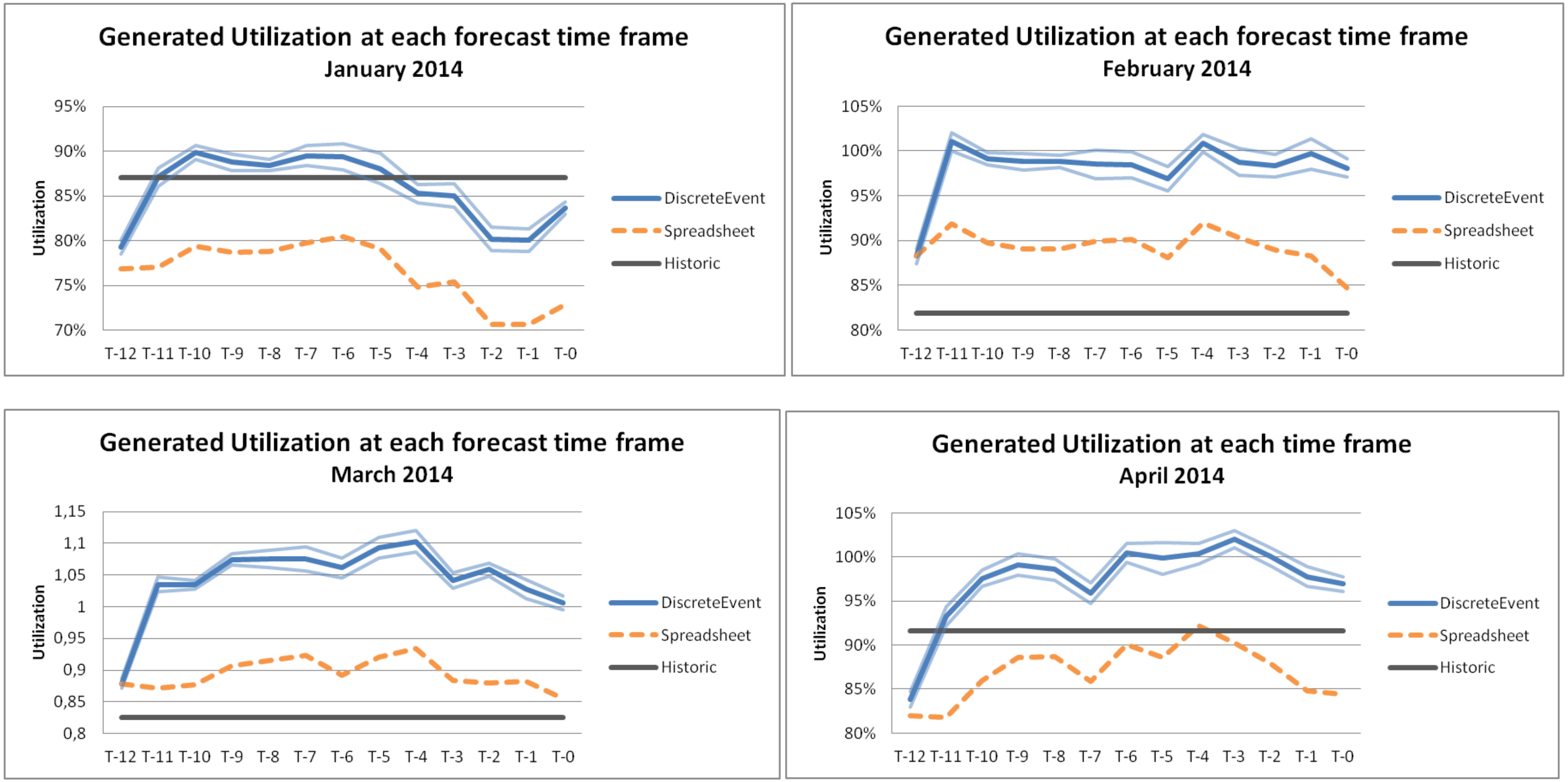

Figure 20 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Utilization and the months of (upper left to lower right) January, February, March and April 2014. The true historic KPI value for each month is also included.

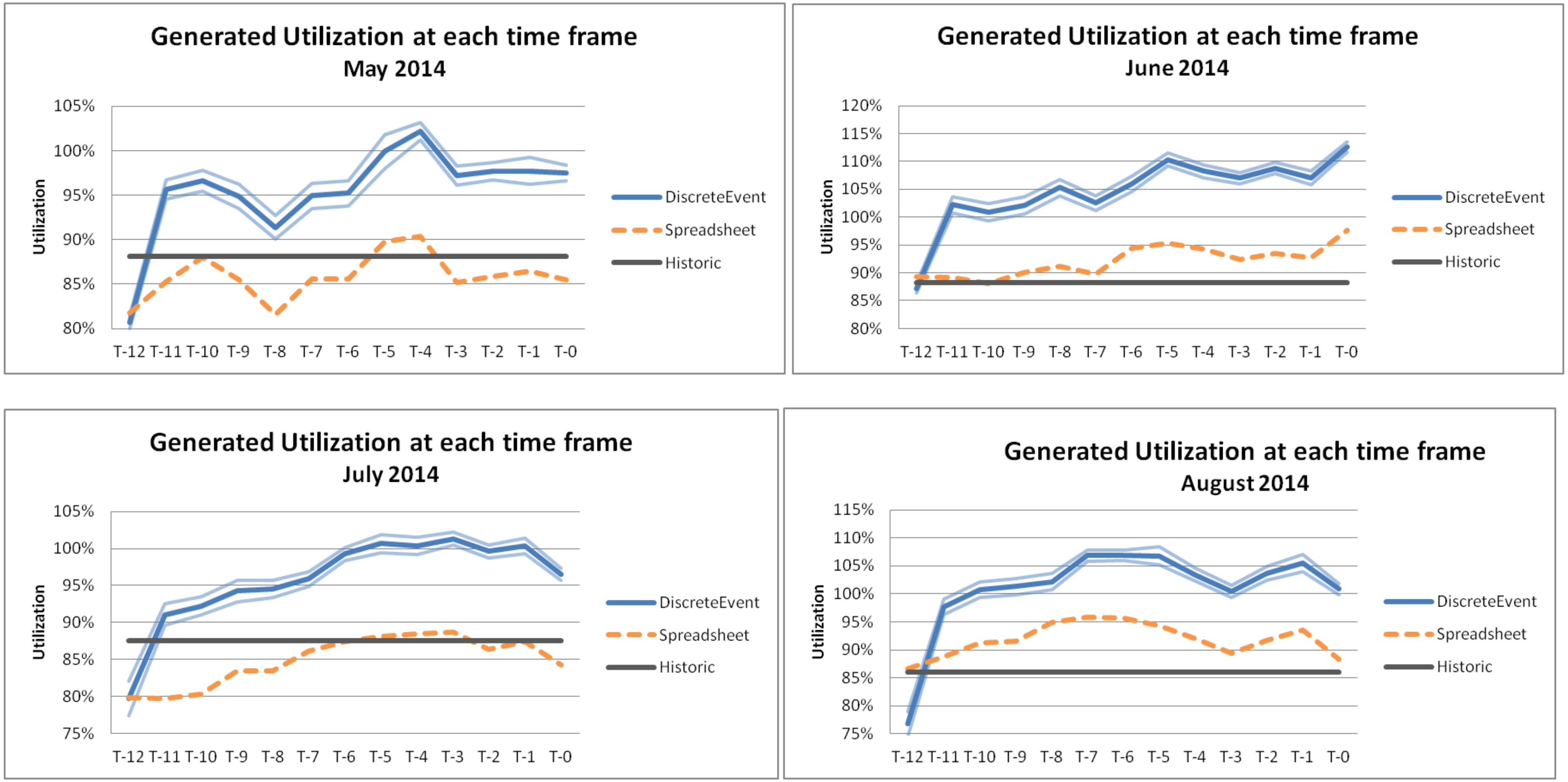

Figure 21 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Utilization and the months of (upper left to lower right) May, June, July, August 2014. The true historic KPI value for each month is also included.

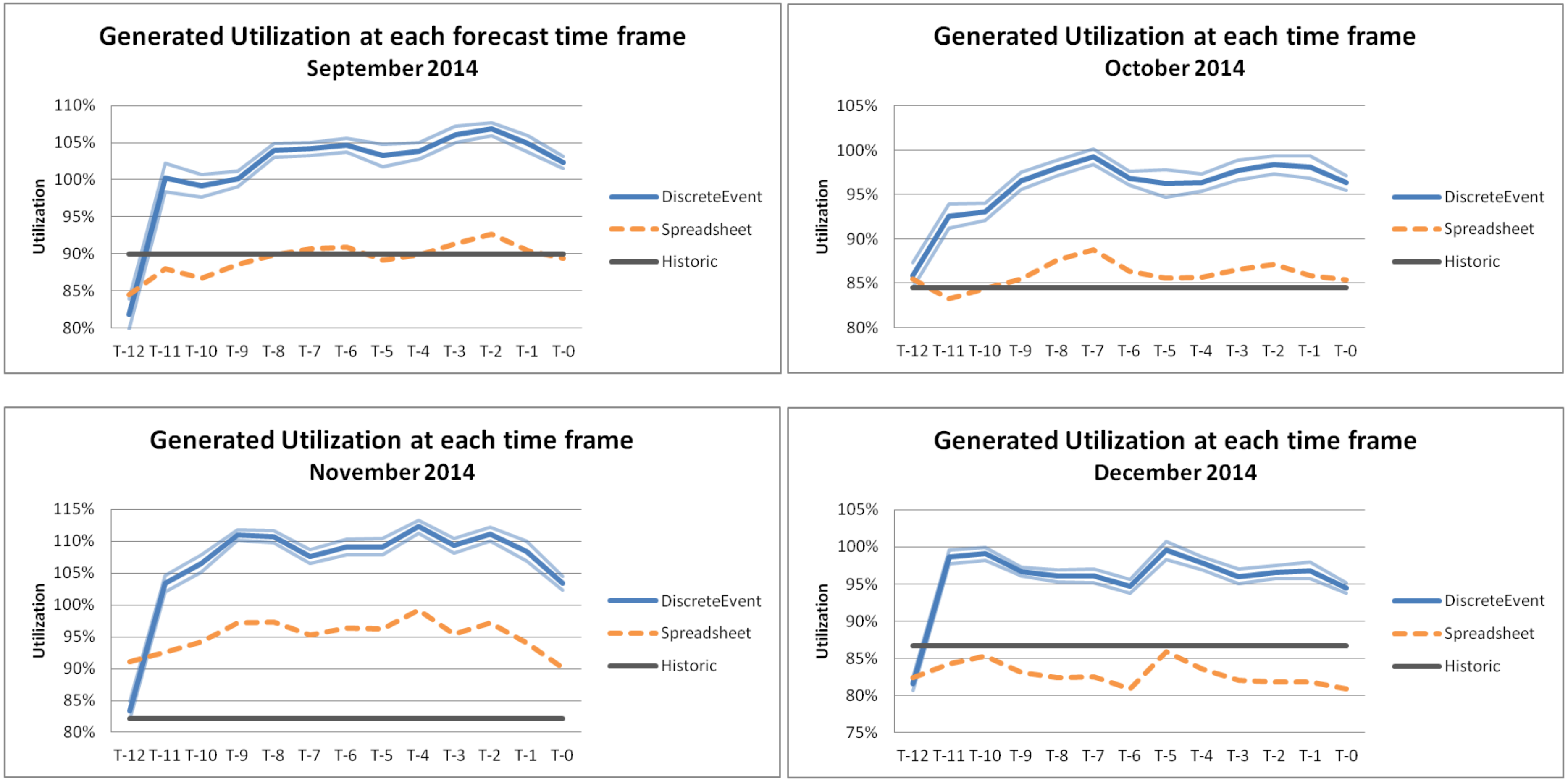

Figure 22 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Utilization and the months of (upper left to lower right) September, October, November and December. The true historic KPI value for each month is also included.

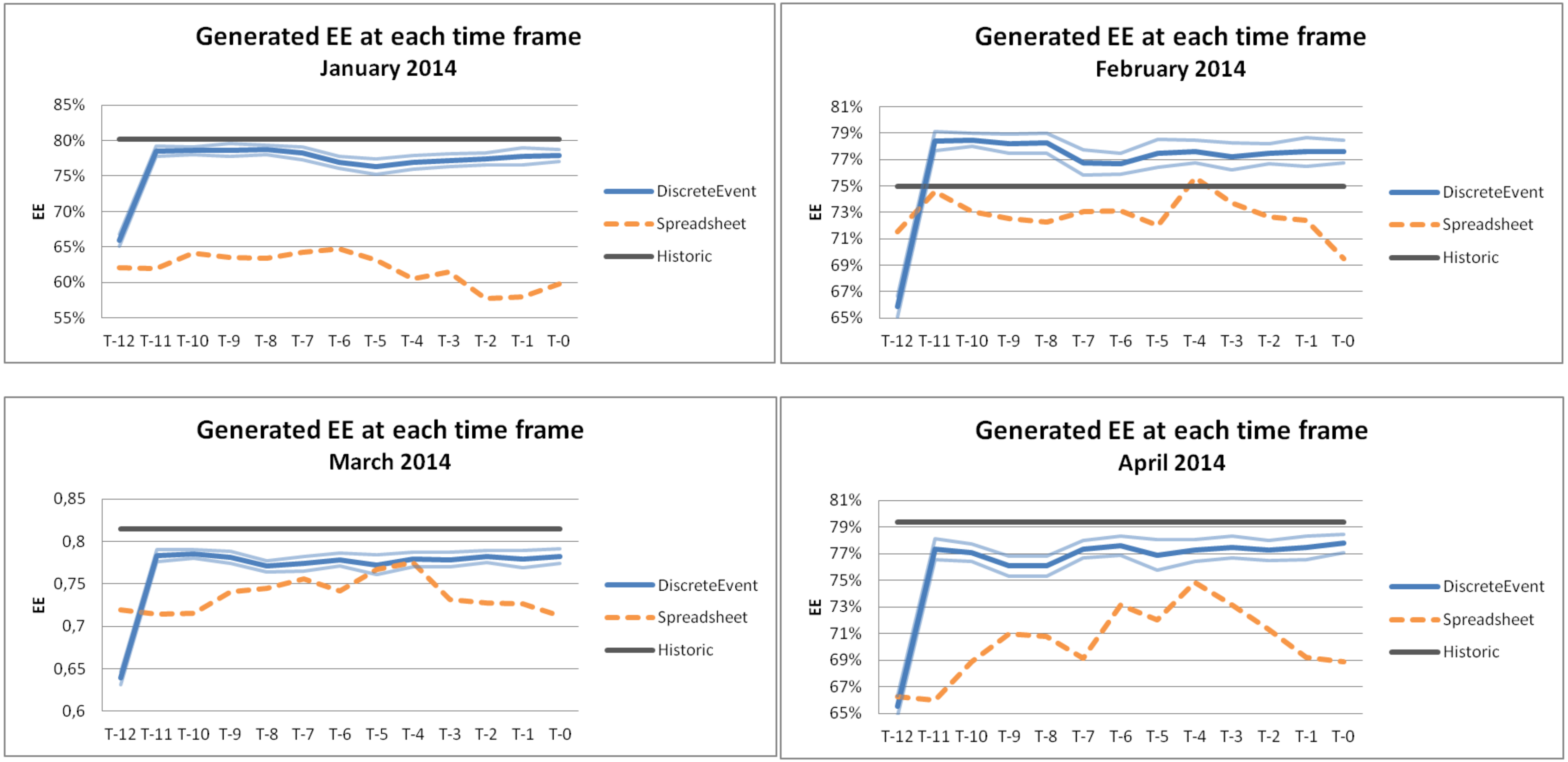

Figure 23 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI EE and the months of (upper left to lower right) January, February, March and April 2014. The true historic KPI value for each month is also included.

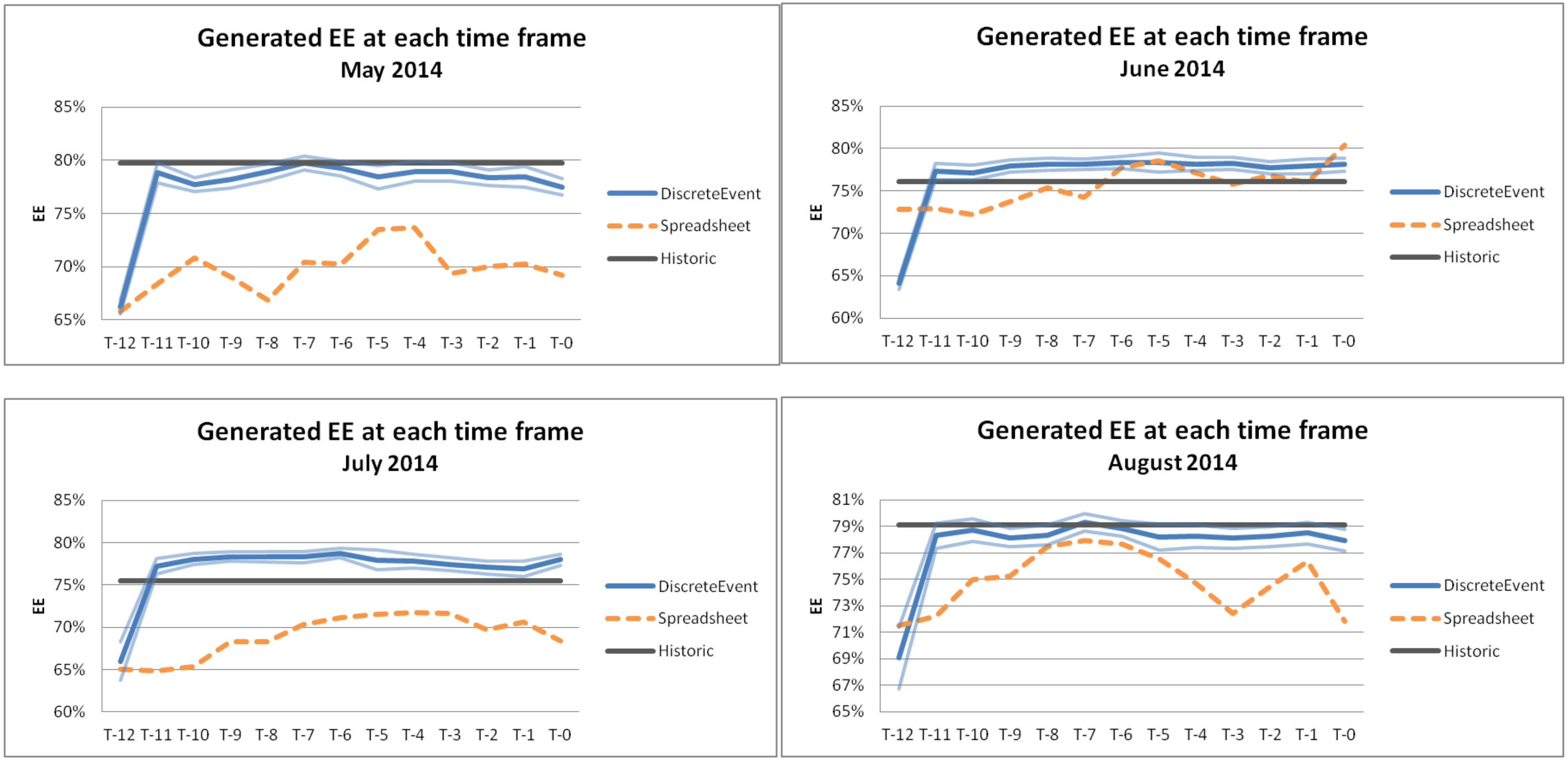

Figure 24 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI EE and the months of (upper left to lower right) May, June, July and August 2014. The true historic KPI value for each month is also included.

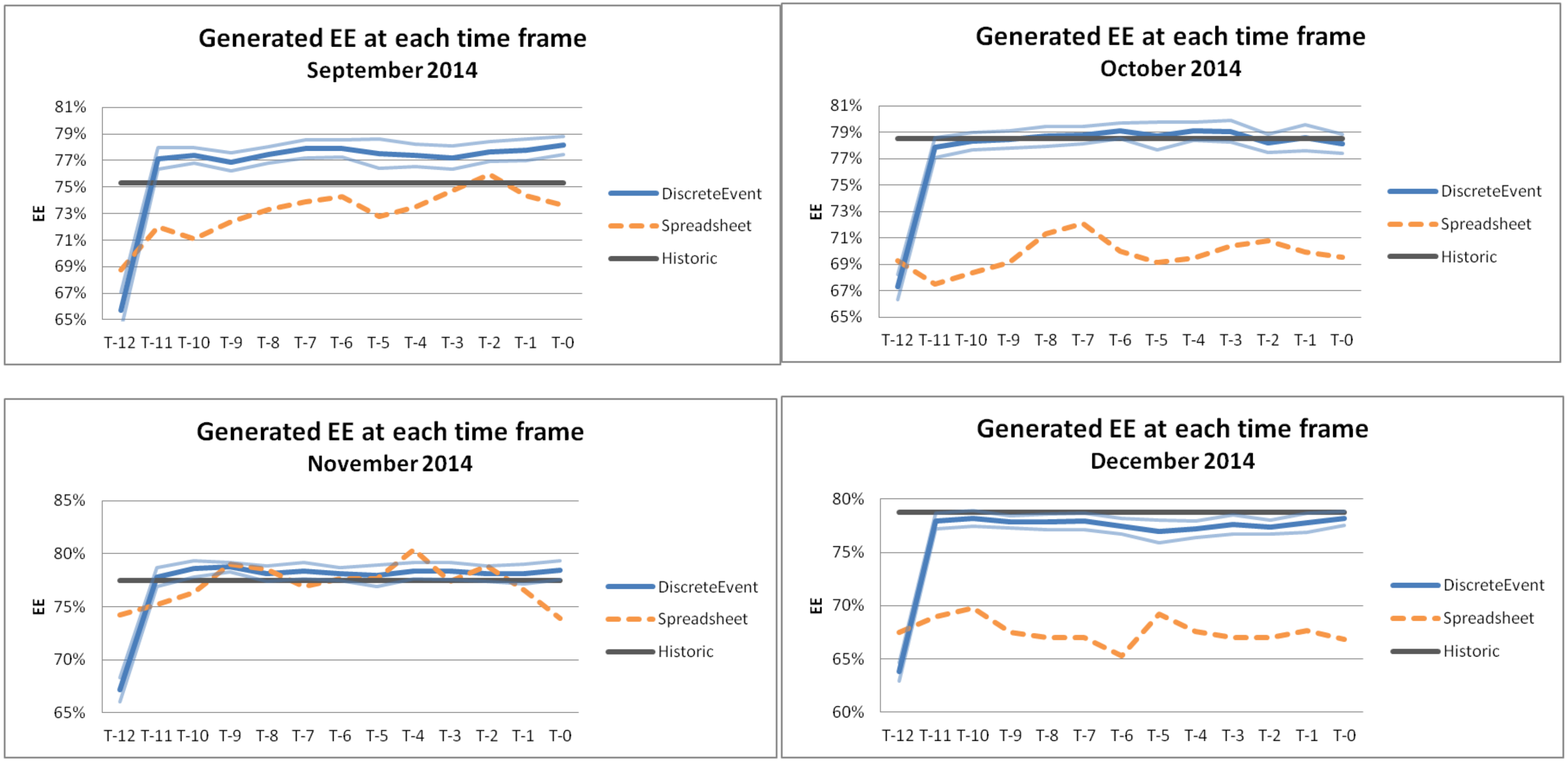

Figure 25 The generated output of both models at each forecast time, using rolling forecasts as input data, for the KPI Et and the months of (upper left to lower right) September, October, November and December 2014. The true historic KPI value for each month is also included.