

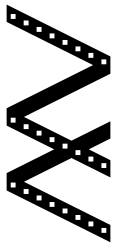
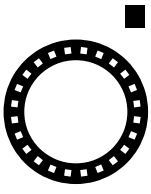
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Prof. Dr.-Ing. Dipl.-Wirt.-Ing Carsten Deckert

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Forecasting Game

Teaching Prospective Engineers Quantitative
Forecasting Techniques with a Simulation Game

Carsten Deckert, Julia Keszler, Helen Schmitz & Ahmed Mohya



Fachbereich Maschinenbau
und Verfahrenstechnik
Faculty of Mechanical
and Process Engineering



Hochschule Düsseldorf
University of Applied Sciences



Carsten Deckert 

Fachbereich Maschinenbau und Verfahrenstechnik
Hochschule Düsseldorf - University of Applied Sciences

Julia Keszler

Studierende des Masterstudiengangs Internationales
Wirtschaftsingenieurwesen (M. Sc.)
Hochschule Düsseldorf - University of Applied Sciences

Helen Schmitz

Studierende des Masterstudiengangs Internationales
Wirtschaftsingenieurwesen (M. Sc.)
Hochschule Düsseldorf - University of Applied Sciences

Ahmed Mohya

Fachbereich Maschinenbau und Verfahrenstechnik
Hochschule Düsseldorf - University of Applied Sciences

AUTHORS

Hochschule Düsseldorf
University of Applied Sciences



Fachbereich Maschinenbau & Verfahrenstechnik
Faculty of Mechanical and Process Engineering



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Abstract

In order to determine demand as precisely as possible, many businesses use several forecasting methods. The aim of forecasting is to determine future demand based on data from the past. The use of a specific method is not always easy and depends on a number of factors. To help prospective engineers find the most suitable forecasting method for a specific problem, a forecasting game was developed and then evaluated.

The paper describes the design and the evaluation of the forecasting game. In order to provide an overview of existing forecasting methods, the first part of the paper examined the mathematical fundamentals of eight different forecasting methods and outlined the requirements for their application.

The second part of the paper describes the creation of a forecasting game in which prospective engineers can learn how to determine the appropriate forecasting method for specific scenarios. In total, five scenarios covering the three different demand patterns (linear/stationary, trend and seasonal) as well as the forecast quality methods were developed and can be played through. For each scenario, the player has to choose the most appropriate forecasting method for a specific problem based on a self-created task description. To make the game as realistic as possible, a fictional company with a background story was designed.

The last part was about the evaluation of the forecasting game. For the evaluation, a student survey to gather the opinions of the students was conducted. The results of the student survey show an overall positive evaluation of the simulation game by the students. However, the test also showed that the game takes a certain amount of time. Since only 15 of the approximately 30 students who tested the game participated in the evaluation, the results are not significant.

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1 Introduction

“If you want to know the future, look at the past” is a famous quote typically attributed to Albert Einstein. Even though the context is different, the saying still applies to the forecasting methodology in which predictions of the future are tried to be foreseen on the basis of past data. Forecasting has a great significance on the economy as well as to the overall society. Predictions provide the opportunity to make informed business and societal decisions and develop a data-driven strategy. It allows businesses to be proactive instead of reactive (Bizer et al., 2013, p.7). Forecasting is a skill that is highly sought in the economy and taught at universities.

To achieve a successful learning outcome regarding the forecasting methodology, it is important to find and deploy a suitable learning strategy. Teaching strategies vary in their effectiveness to transmit knowledge, “Tell me and I forget, teach me and I may remember, involve me and I learn” is a quote attributed to Benjamin Franklin that describes the different effectiveness of teaching methods. Universities in the past only focused on teaching in which exercises often include the description of what method should be applied to solve these tasks. Modern university education is diving more into a practical teaching aspect, involving students in different projects to improve their practical understanding and make them learn by doing the tasks. However, nowadays, it is still typical that students practice and learn about forecasting methods based on given scenarios including the provision of the method which should be used. Nonetheless, in real life, no one will tell the student which method will be the correct one to use but rather the student needs to figure it out by himself. That is where the significance of simulation games comes into play, as they offer a learning opportunity.

Simulation games place the participants in a game scenario where previous perceived knowledge can be applied with low risk of failure consequences as well as further skills beyond the theoretical information can be acquired. Therefore, in the course of the paper, a Microsoft (MS) Excel-based forecasting simulation game is presented which provides learning and application opportunities on several forecasting methods in different settings.

Furthermore, the game is constructed to train the distinction of the right forecasting method to a given data set.

In this paper, the theoretical aspects of forecasting methods including forecasting quality techniques as well as the method on how to find the right forecasting model are discussed at first. Following, the different kinds of simulation games are explored and compared with each other, before the realization and structure of the forecasting game are explained and shown. After that, the first trial of the game in a bachelor course is described and the game is evaluated. Finally, a conclusion about the process and game is drawn in the last part of the paper.

2 Forecasting Basics

Forecasting is crucial for any kind of business or institution. It is important since many factors can be affected by the wrong choice of variables, such as the production size. For example, in the case of overproduction, many of the surplus products become unnecessary and costs increase e.g. for raw material and storage. However, in the case of underproduction, business opportunities can be lost as well as profit and potential customers. Therefore, forecasting can be found in every department and is very multifunctional in its use (Ivanov et al., 2019, pp. 319–321). In this paper, the focus is exclusively on demand forecasting.

In general, forecasting is a proactive, structured approach that predicts future events aiming to estimate as accurately as possible (Chase, 2009, p. 24; Hyndman & Athanasopoulos, 2018, pp. 14–15). This approach either uses subjective predictions like mathematical models, intuitive estimations by experts, or a combination of them involving historical data and knowledge of any future impacts that might influence the forecast (Heizer & Render, 2011, p. 136). Therefore, it is important to know that forecasts cannot predict the future demand perfectly and are always wrong to a certain extent (Ivanov et al., 2019, p. 319).

An important aspect of the forecast methodology is the consideration of forecast horizons in which the forecast techniques are categorized. The horizons are divided into short-range, medium-range, and long-range forecast horizons as shown below in figure 1.

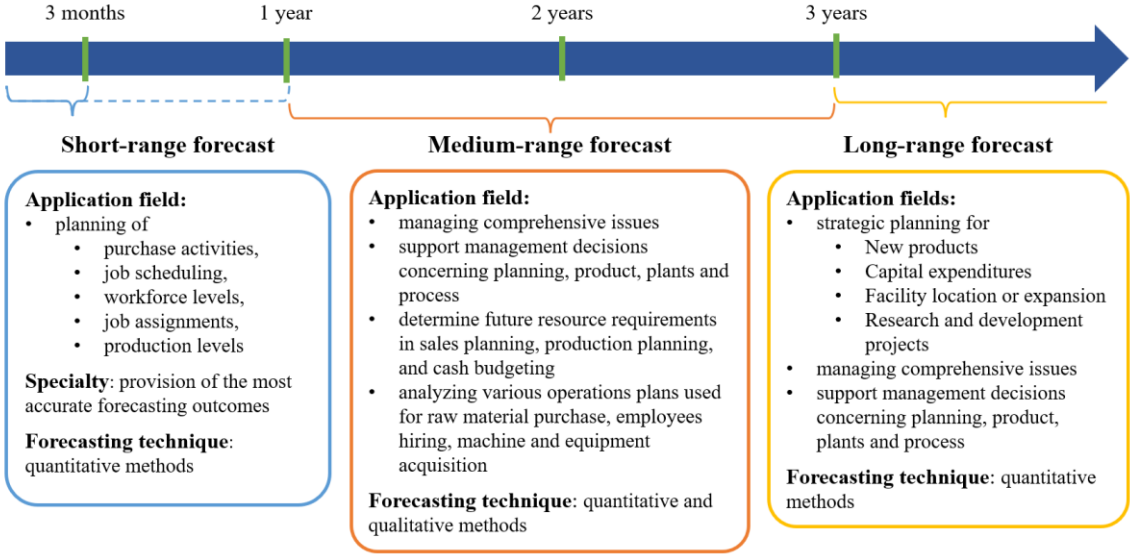


Figure 1: Forecasting horizons

Source: Own illustration based on Heizer & Render, 2011, pp. 136–137; Hyndman & Athanasopoulos, 2018, pp. 14–15; Ivanov et al., 2019, p. 322

For every forecast horizon, different forecasting techniques can be applied to estimate prognoses to the individual problem statements. These techniques are separated into qualitative and quantitative methods. *Qualitative methods*, also known as judgmental methods, are utilized while handling long-term forecasts and make use of professional knowledge, intuition, and experience (Ivanov et al., 2019, p. 323). The methods are especially useful when no or only little sufficient data is available and is currently the widely used forecasting method (Chase, 2009, p. 56; Hyndman & Athanasopoulos, 2018, pp. 16–19). *Quantitative methods* involve mathematical equations to forecast demand which rely on historical data and/or associate variables (Heizer & Render, 2011, pp. 139–140). Furthermore, the methods identify and consider demand patterns or interrelationships with other factors (Chase, 2009, p. 52). The statistic-based methods are further divided into two

subcategories: *time-series* and *causal methods* (Ivanov et al., 2019, p. 324). Time-series methods assume that the future demand will imitate the patterns of past demand observations (Heizer & Render, 2011, pp. 139–140), whereas causal methods estimate demand based on the dependence between associated factors and its changes in demand (Ivanov et al., 2019, p. 324). Commonly, a combination of qualitative and quantitative techniques produces the most accurate and effective forecast estimations (Armstrong & Green, 2005, p. 10). Figure 2 below depicts the forecasting techniques including their application advantages and disadvantages.

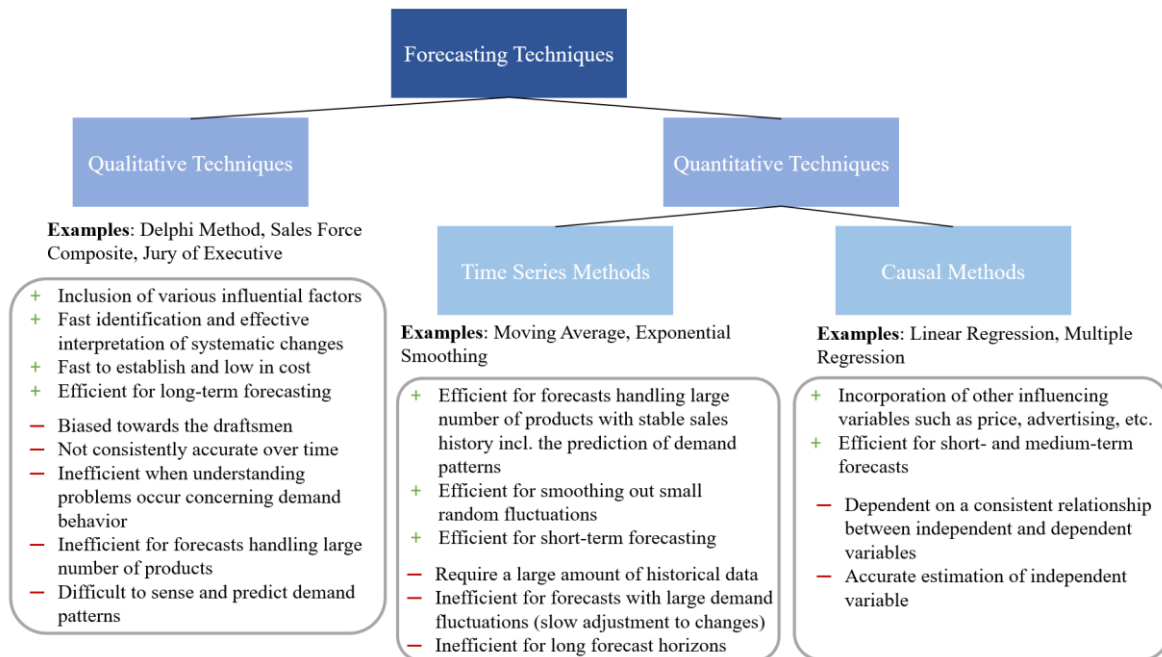


Figure 2: Forecasting techniques and their advantages and disadvantages

Source: Own illustration based on Chase, 2009, pp. 51-61

Another important aspect while forecasting demand is to consider demand patterns such as trend, seasonality, cycle, and randomness (unexplained variance) to ensure an accurate estimation (Chase, 2009, p. 53). Trend arises when a long-term increase or decrease in the data exists which does not need to be necessarily linear, whereas seasonality occurs when the data series is affected by a fixed and known frequency also called seasonal factors. A cycle exists when the data fluctuates in an unfixed frequency mostly due to economics.

While clustering the forecasting techniques according to the different demand patterns, the pattern trend and cycle are normally grouped (Hyndman & Athanasopoulos, 2018, pp. 31–32).

The act of planning a forecast has many advantages. On the one hand, demand forecasting enables effective downstream planning resulting in cost savings and for example reductions in customer backorders, out-of-stock situations, and finished goods inventory as well as the provision of high levels of customer service. On the other hand, the examination of forecast predictions helps to gain a better understanding of the market behavior resulting in possible improvements in the supply chain. Furthermore, a competitive advantage can be established by increasing a company's market share for products and services (Chase, 2009, p. 48). Generally, demand forecasting is especially effective in the areas of capacity management, production, supply chain planning, and helps to determine decisions about production scheduling, transportation, and personnel (Hyndman & Athanasopoulos, 2018, pp. 14–15; Ivanov et al., 2019, p. 320).

In contrast, forecasts are seldom perfect since some demand changes are unpredictable resulting in forecast errors. Furthermore, forecast techniques generally assume an underlying stability in the data series (Heizer & Render, 2011, p. 138). Hence, three laws should be kept in mind while establishing and dealing with demand forecasts (Heizer & Render, 2011, p. 138; Ivanov et al., 2019, p. 322):

1. Forecasts are always wrong.
2. Detailed forecasts are worse than aggregate forecasts.
3. The further into the future, the less reliable the forecast will be.

After the provision of a fundamental overview of the forecasting methodology, a selected variety of forecast techniques are closely discussed. Additionally, forecasting quality techniques are reviewed as well as a strategy about how to find an appropriate forecasting method is established.

2.1 Forecasting Methods

The following forecasting methods are typically used in operations management and, thus, will be part of the forecasting game which is elaborated in section 4. In total, seven time-series methods and one casual method will be discussed.

2.1.1 *Naïve Approach*

The *naïve approach* is the most cost-effective forecasting model considering that no sophisticated software or statistical modeler is required to calculate the forecasting values (Heizer & Render, 2011, pp. 140–141). The technique receives its name due to the naïve assumption that the forecast value of the next period is equal to the last observed value (Chase, 2009, p. 114). The naïve approach is written as:

$$F_t = F_{t-1}$$

where F_t = new forecast (1)

However, the model should not be underestimated. In some cases, the naïve approach estimates more accurate forecasting values than sophisticated models especially concerning economic and financial time-series. Nonetheless, the naïve approach should function more as a benchmark while comparing other quantitative models with each other and be continuously improved (Chase, 2009, p. 114; Hyndman & Athanasopoulos, 2018, pp. 47–50). Generally, the method provides a good starting point to determine the best-fitting forecasting method (Heizer & Render, 2011, p. 141).

Additionally, an alternative form of the naïve approach can be used when the time-series incorporates seasonality. This form is called the seasonal naïve approach where the forecast values are equal to the observed values from the last season (Hyndman & Athanasopoulos, 2018, pp. 47–50).

2.1.2 (Simple) Moving Average

The *moving average* originated in the 1920s and forms the basis of almost all following time-series models. The method was extensively applied in the 1950s and used to estimate the trend-cycle and irregular components of data models (Hyndman & Athanasopoulos, 2018, pp. 161–167). In general, the technique smooths out historical values to generate a forecast by extracting the forecast value out of the average demand from the previous periods. The method assumes that the values of the neighboring historical periods are likely to be similar to the expected values of the following period since these observations happened nearby in time. Thus, these nearby historical observations provide a good estimation for this next period. For every new period, the nearest historical periods are used to determine the forecast value by calculating the average value. The average value then moves onwards to the next period leaving the farthest historical period behind which provides the methods its name (Chase, 2009, pp. 110–115). The moving average is written as:

$$F_{t+1} = \frac{1}{n} \sum_{i=t-n+1}^t A_t$$

where A_t = is the demand in period t (2)
 n = number of prior periods

The principle behind this method is that the average eliminates some of the randomness in the time series and smooths out short-term irregularities as well as sudden fluctuations in the demand pattern to provide stable forecast estimates (Heizer & Render, 2011, pp. 141–143; Hyndman & Athanasopoulos, 2018, pp. 161–167). Therefore, it is important to determine the optimal length of data to include in the moving average. The larger the number of historical observations is included in the moving average the more randomness is removed from the time-series but also the more information may be lost in the process of averaging leaving the model less sensitive to data changes in the time-series (Chase, 2009, pp. 110–115; Heizer & Render, 2011, pp. 141–143).

In general, this forecasting technique faces hardships to react accordingly to data changes in a timely fashion and is only able to forecast accurately one period ahead. The model further requires extensive historical data records and storage capacities to work properly (Heizer & Render, 2011, pp. 141–143). Additionally, the model has difficulties picking up trend-cycles due to its averaged nature, and therefore, moving average becomes especially handy when the market demands can be assumed to stay steady over time (Heizer & Render, 2011, pp. 141–143; Hyndman & Athanasopoulos, 2018, pp. 161–167).

2.1.3 *Weighted Moving Average*

The *weighted moving average* is an extended form of the (simple) moving average that incorporates weights to provide higher importance to the most recent observations in time-series. Essentially, the model predicts that the most recent observations provide a more accurate estimation for the next forecasting value. Thus, the weights are given in a descending order leaving the most recent observation with the highest weight (Chase, 2009, p. 116). The weighted moving average is written as:

$$F_{t+1} = \frac{\sum_{i=t-n+1}^t A_t \times W_t}{\sum_{i=t-n+1}^t W_t}$$

where W_t = is the weight in period t (3)

The assignment of the weights is difficult and happens through experience and intuition (Ivanov et al., 2019, p. 329). The right weight is important since if the observation is too heavily weighted, the model might react too quickly to large, unusual demand patterns resulting in bad forecasting predictions. However, an advantage over the simple moving average is that the weighted moving average is more responsive to data changes due to its weighting scheme (Heizer & Render, 2011, pp. 142–143).

2.1.4 *(Simple) Exponential Smoothing*

In the late 1950s, Robert Condell Brown developed the exponential smoothing technique which was then extended by Charles C. Holt and Peter R. Winters (Hyndman &

Athanasopoulos, 2018, p. 185) and is considered as one of the most sophisticated and widely applied forecasting models (Chase, 2009, p. 115). The forecasting technique is an enhancement of the weighted moving average which uses an exponential function consisting of weighted averages from historical observations to decrease the weighting power exponentially as the observations get older. Hence, the more recent observations are weighted higher (Hyndman & Athanasopoulos, 2018, p. 185). Primarily, there are three variants of the exponential smoothing technique depending on if the time-series experiences stationary, trend-cycle, or seasonal effects (Chase, 2009, p. 115).

The first variant is the *simple exponential smoothing* which is also called under various names such as single exponential smoothing or first-order exponential smoothing. This method is especially useful when the time-series is stationary and a short history with random data is available (Chase, 2009, pp. 116–120; Ivanov et al., 2019, pp. 329–330). Generally, the method adjusts the previous period’s forecast value by using the forecast error from that period to calculate the forecasting value of the next period (Chase, 2009, pp. 116–120). The model is written as:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where α = smoothing constant ($0 \leq \alpha \leq 1$) (4)

A_{t-1} = previous period’s actual demand

The weighting factor and the data’s average are determined through the smoothing constant α which is a value between 0 and 1. A high value of α (close to 1) weighs the more recent observations stronger, and the model is more sensitive to changes in the time-series. In comparison, a low value of α (close to 0) weighs the past observations stronger and stabilizes the observations ignoring possible changes in data. In case α equals 1, the model ignores all historical observations and functions as the naïve approach (Chase, 2009, pp. 116–120; Heizer & Render, 2011, pp. 144–145; Hyndman & Athanasopoulos, 2018, pp. 186–193). However, it is recommended to use a smoothing constant ranging between 0.05 to 0.5 for business applications (Heizer & Render, 2011, p. 145). The determination of the smoothing

constant is based on experience or, if possible, can be estimated from the observed data set by using forecasting quality methods which are described in 2.3 (Hyndman & Athanasopoulos, 2018, pp. 186–193).

A huge advantage of simple exponential smoothing is that it uses only a limited amount of data storage capacity in comparison to the moving average techniques and thus, is low in costs. The historical observations do not need to be stored in a database and hence, this method is more popular when large numbers of products need to be forecasted. Nonetheless, it is difficult to determine the optimal value for the smoothing constants and the method can only predict one period ahead with a higher degree of accuracy since it tends to over-forecast for a long forecast horizon. These advantages and disadvantages are also accountable to the following two exponential smoothing variants (Chase, 2009, pp. 116–120).

2.1.5 *Exponential Smoothing with Trend Adjustment (Holt's Model)*

The second variant of the exponential smoothing method is the *exponential smoothing with trend adjustment* or also named Holt's model, Holt's two-parameter method, double exponential smoothing, or second-order exponential smoothing. This variant was created by Charles C. Holt in 1957 which enables forecasting time-series that feature constant linear trends. As an extension to the simple exponential smoothing technique, the model exists out of three equations and uses two smoothing constants, α and β ranging between 0 and 1 (Chase, 2009, pp. 120–121; Hyndman & Athanasopoulos, 2018, pp. 193–198).

The first equation computes the exponential smoothed forecast by modifying the trend of the previous period with the addition of the last demand observation which brings the linear trend up to the current data's level. The second equation updates the trend with the result of the difference between the forecasting values of this period and the last period and thus, computes for the exponential smoothed trend. Lastly, the results of both equations are calculated together (Chase, 2009, pp. 120–121). The method is written as:

$$F_t = \alpha A_{t-1} + (1 - \alpha)(F_{t-1} + T_{t-1})$$
$$T_t = \beta (F_t - F_{t-1}) + (1 - \beta)T_{t-1}$$

$$FIT_{t+1} = F_t + T_t$$

where T_t = exponentially smoothed trend in period t (5)

β = smoothing constant ($0 \leq \beta \leq 1$)

FIT_{t+1} = forecast for the next period (forecast including trend)

Concerning the smoothing constants α and β , α is responsible for the smoothing of the data's average, like in the simple exponential smoothing method, whereas β accounts for the smoothing of the trend-cycle. If β is high (close to 1), the model weights the recent trend stronger and thus, it is more reactive towards changes in the trend. If β is low (close to 0), the model empathizes more on past trends and is likely to smooth out a current trend. The determination of β is difficult and happens through sophisticated forecast software which uses forecasting quality techniques or by the trial-and-error approach (Heizer & Render, 2011, pp. 148–151).

2.1.6 *Winters' Model*

The third and last variant is the *Winters' model* from Peter R. Winters, which is built upon Holt's model, and is suitable to handle seasonality in data. The model established in 1960 is further known as Holt's-Winters' model, triple exponential smoothing, Winters' three-parameter exponential smoothing, and Winters' method of seasonality. Generally, the model consists of four equations and three smoothing constants α , β , and γ ranging from 0 to 1. Furthermore, this variant is the most widely used forecasting method among the other sophisticated methods (Chase, 2009, pp. 121–123; Hyndman & Athanasopoulos, 2018, pp. 198–204).

The first two equations are very similar to the exponential smoothing with trend adjustment variant whereas the third equation handles the seasonality. Hence, the model accounts for the best when the time-series features stationary, trend-cycle, and seasonal effects. Moreover, Winters' model is composed out of two further versions: the multiplicative and additive method depending on whether the seasonality is calculated in a multiplicative or

additive fashion. Normally, the multiplicative method is applied when the seasonal variations change proportionally throughout the time-series, whereas the additive method is used when the seasonal variations stay mostly constant (Hyndman & Athanasopoulos, 2018, pp. 198–204). The multiplicative method is written as:

$$\begin{aligned}
 F_t &= \alpha \frac{A_t}{c_{t-N}} + (1 - \alpha)(F_{t-1} + T_{t-1}) \\
 T_t &= \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1} \\
 c_t &= \gamma \frac{A_t}{F_t} + (1 - \gamma)c_{t-N} \\
 FW_{t+1} &= (F_t + T_t)c_{t-N}
 \end{aligned}$$

where c_t = exponentially smoothed seasonality in period t (6.1)

γ = smoothing constant ($0 \leq \gamma \leq 1$)

FW_{t+1} = forecast for the next period

N = length of seasonality

Originally, the additive method was not used as frequently as the multiplicative method by forecasters but gained more popularity recently (Chase, 2009, p. 123). The additive method is written as:

$$\begin{aligned}
 F_t &= \alpha(A_t - c_{t-N}) + (1 - \alpha)(F_{t-1} + T_{t-1}) \\
 T_t &= \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1} \\
 c_t &= \gamma(A_t - F_t) + (1 - \gamma)c_{t-N} \\
 FW_{t+1} &= F_t + T_t + c_{t-N}
 \end{aligned}$$

(6.2)

Regarding the smoothing constants α , β , and γ , α is responsible for the smoothing of the data's average, whereas β accounts for the smoothing of the trend-cycle, and γ handles the smoothing of the seasonality. A high value of γ (close to 1) weighs the recent seasonality stronger and adapts to seasonal changes. In comparison, a low value of γ (close to 0) considers the past seasonality stronger and tends to stay steady regarding seasonal changes

(Hyndman & Athanasopoulos, 2018, pp. 198–204). The decision of the optimal γ value is difficult and happens like the previous two variants through the usage of forecasting quality techniques (Chase, 2009, p. 127). In this paper and in the game, only the multiplicative method will be used to reduce complexity in the game as well as because of its more frequent application.

2.1.7 *Seasonal Index*

When a time-series manifests seasonality, the *seasonal index* or also known as the multiplicative seasonal model can be applied. This model generates a seasonal index which is then multiplied by an estimate of average demand to forecast the demand for the next period. To apply this model, the trend-cycle needs to be removed from the data in case the observations show signs of a trend-cycle. Otherwise, the trend-cycle will distort the seasonal data and cannot estimate appropriate forecast values for the seasonality (Heizer & Render, 2011, pp. 153–154).

In detail, the model follows five steps. In the first step, the *average historical demand of each season unit* (i.e., hour, day, week, month, etc.) is calculated as well as the total average annual demand over all season units based on the output of the average historical demand. Secondly, the *average demand over all season units* is computed by dividing the total average annual demand by the number of seasons. The division of the average historical demand (step 1) by the average demand over all seasons (step 2) results in the *seasonal index* which is the third step. In the fourth step, the next year's *total annual demand* is estimated based on experience and assumptions. Lastly, the total annual demand (step 4) is divided by the number of seasons and then multiplied by the seasonal index for every season unit resulting in the *forecasting value* for the following periods (Heizer & Render, 2011, p. 154).

2.1.8 *Trend Projection*

A different approach as the previously discussed forecasting methods is the *trend projection* also known as linear regression or simple regression which belongs to the causal methods (Chase, 2009, p. 130; Heizer & Render, 2011, p. 149). This method forecasts future demand

based on the relationships with other influencing predictive demand variables while a linear trend is given. The model is further able to provide reliable estimations for medium and long-range forecasts. It is important for the model's application that the observations manifest a linear trend, otherwise, different mathematical equations for exponential or quadratic trends need to be used (Heizer & Render, 2011, pp. 151–153).

The main equation involves the dependent variable y (variable to be forecasted) and the independent variable x (explanatory variable) which are used to create a straight line through a scattered set of data points symbolizing the data observations. The line has the purpose to minimize the sum of squared differences (vertical deviations) from the data points to each of their corresponding estimates on the line. Thus, the minimization of the vertical deviations (also addressed as errors) decreases the distance among them (Chase, 2009, pp. 130–131). The trend projection is written as:

$$\hat{y} = a + bx$$

where \hat{y} = dependent variable (7.1)

a = y-axis intercept

b = slope of the regression line

x = independent variable

The optimal values for the y-axis intercept (7.2) and the slope of the regression line (7.3) are assessed through the following equations (Chase, 2009, pp. 130–131):

$$a = \bar{y} - b\bar{x}$$

where \bar{x} = average of the x-values (7.2)

\bar{y} = average of the y-values

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2}$$

where n = number of data points (7.3)

To apply the trend projection method successfully, the scattered data points must possess a linear relationship with each other so that the observations resemble a linear trend. Moreover, the deviations need to be random and normally distributed close around the line. Even though the model can be used for medium and long-range forecast horizons, it is not recommended to predict forecasting values far beyond the original database (Heizer & Render, 2011, pp. 151–143).

2.2 Forecasting Quality and Accuracy

The most important element in the forecasting process is to measure the forecast performance and its accuracy by using forecasting quality methods. These methods evaluate the overall accuracy of any forecasting model by comparing the forecasting values with the actual observed values from a time-series. The application of these models is important since it is impossible to improve the accuracy of a forecasting method when not measuring and benchmarking its current forecast performance (Chase, 2009, pp. 77–78).

In general, the evaluation of the forecasting quality has three intentions: (1) to examine the performance and effectiveness of a forecasting model on the accuracy of the predicted values, (2) to compare different quality models to determine the appropriate method and its variables to deploy, and (3) to monitor forecasts to ensure their good performance (Heizer & Render, 2011, p. 145). The aim of the determination of the right forecasting quality method is to create the most accurate demand forecast with the lowest error rate (Chase, 2009, p. 93). The error rate refers to the forecasting error which expresses the performance quality of a model by calculating the difference between an observed value and its forecast value (Hyndman & Athanasopoulos, 2018, pp. 62–71).

The application of forecast quality techniques has the greatest advantage while improving the demand forecasts for products at the lower levels of a company's product hierarchy or product mix since its enhancement will positively affect the entire supply chain. Even a small advance in the demand forecasting performance can already translate into significant improvements in supply chain activities such as inventory costs, backorders, and customer

services levels. However, the enhancement of demand forecasting is only successful when a company is willing to upgrade their forecasting skills including their expertise, have appropriate tools and applications available, and the employees are motivated to revise the overall forecasting process (Chase, 2009, pp. 78,49).

In the following, the three most known and applied forecast quality methods are discussed which will be a part of the forecasting game as well. Furthermore, it is important to note that other forecasting quality techniques besides the three exist and are practiced.

2.2.1 Mean Absolute Deviation (MAD)

The *mean absolute deviation* (MAD) measures the overall forecast error for a forecasting model implying the calculation of the absolute deviations of the forecast values and the actual observation over several periods (Heizer & Render, 2011, pp. 145–146; Ivanov et al., 2019, pp. 325–326). The MAD is written as:

$$MAD = \frac{1}{n} \sum_{t=1}^n |A_t - F_t|$$

where t = time period (8)

n = number of time periods

Since the result of the method expresses absolute values, MAD is dependent on the quantity of data being forecast meaning that the model needs different forecast alternatives for the same time-series to determine the best forecast method among these alternatives. Therefore, this method is difficult to adopt while comparing forecasts for different products with each other (Ivanov et al., 2019, pp. 325–326).

2.2.2 Mean Squared Error (MSE)

Another forecasting technique that measures the overall forecast error is the *mean squared error* (MSE). The model evaluates the quadratic deviation of the forecasted and observed

values exaggerating the forecasting errors (Heizer & Render, 2011, p. 147; Ivanov et al., 2019, pp. 325–326). MSE is written as:

$$MSE = \frac{1}{n} \sum_{t=1}^n [A_t - F_t]^2 \quad (9)$$

Like for the MAD method, MSE is dependent on the quantity of data being forecasted and best used to compare forecasting methods that are applied to the same time-series. Hence, this method is also difficult to apply for investigations of forecast methods from different time-series (Heizer & Render, 2011, p. 147).

2.2.3 Mean Absolute Percentage Error (MAPE)

The most preferred and widely used forecast quality method is the *mean absolute percentage error* (MAPE) which measures the deviation of the forecasted and observed values expressing the result as a percentage (Chase, 2009, pp. 86–87; Heizer & Render, 2011, pp. 147–148). MAPE is written as:

$$MAPE = \frac{1}{n} \sum_{t=1} \frac{|A_t - F_t|}{A_t} \times 100 \quad (10)$$

In comparison to MAD and MSE, MAPE is independent of the quantity of data being forecasted since the model's results are given in percentages and not absolute values. Hence, the model is applicable for analyzing forecast methods from the same and different time-series (Ivanov et al., 2019, pp. 325–326).

However, MAPE faces difficulties when the forecast values are below the actual values or when the actual demand is zero as well as when the demand is close to zero. In case the actual demand is zero, the model becomes undefined whereby when the demand is close to zero the model possesses extreme values distorting the magnitude of the forecasting errors

(Chase, 2009, pp. 86–87). Another disadvantage is that the method assumes that the data in the investigated time-series has a meaningful zero meaning that the zero point in the time series cannot be placed arbitrarily as it is in the case of temperature scales (Hyndman & Athanasopoulos, 2018, pp. 62–71). Moreover, MAPE is scale-dependent and can only work well while measuring the forecasting errors across time periods but not for different products for one certain period. For this case, the weighted absolute percentage error (WAPE) is the better fitting forecasting quality method which will not be discussed in this report (Chase, 2009, pp. 86–87).

2.3 The right forecasting method

Choosing the optimal forecasting method for a given situation is not an easy task to perform and, in some cases, more than one method may be suitable. Therefore, guidelines were established that help to initiate, design, and implement forecasting systems (Heizer & Render, 2011, p. 138). Generally, the guideline can be clustered into eight steps (Heizer & Render, 2011, p. 138; Hyndman & Athanasopoulos, 2018, pp. 21–23; Ivanov et al., 2019, pp. 322–323):

1. *Objective definition.* Determination of the forecast's application field and its stakeholders such as the people who require the forecast.
2. *Fundamental information gathering.* Selection of the products that need to be forecasted and collection of statistical data and accumulated expertise from the data collectors for these products.
3. *Primary analysis conduction.* Determination of the right time horizon and the inspection of demand patterns (trend-cycle, seasonality) including the existence of special outliers as well as the examination of data availability. Depending on the data availability, determination between the judgmental methods, time-series approaches, or the combination of those. Combined approaches tend to increase forecast accuracy and decrease the likelihood of large errors.
4. *Forecasting method(s) selection.* Choosing an/several appropriate forecasting method(s) based on the insights of the preliminary analysis.

5. *Data acquisition.* Acquisition of necessary data to conduct the forecast(s).
6. *Forecast execution.* Execution of the forecast(s) with the help of computer software and if applicable, comparing the different methods with each other as well as choosing the optimal forecast method.
7. *Result evaluation and correction implementation.* After the data availability of the actual observations for the forecasted periods, review of the method's accuracy level and if necessary, implementation of corrections to the method.
8. *Forecast control.* Continuous control and data collection of the forecast outcome to verify its accuracy. The product's demand can experience external and internal changes over time resulting in degradation of forecast accuracy.

While conducting the primary analysis, the forecasted product can be segmented further into one of the four categories of the product portfolio management matrix. The matrix is depicted in figure 3 below together with its forecasting methods below.

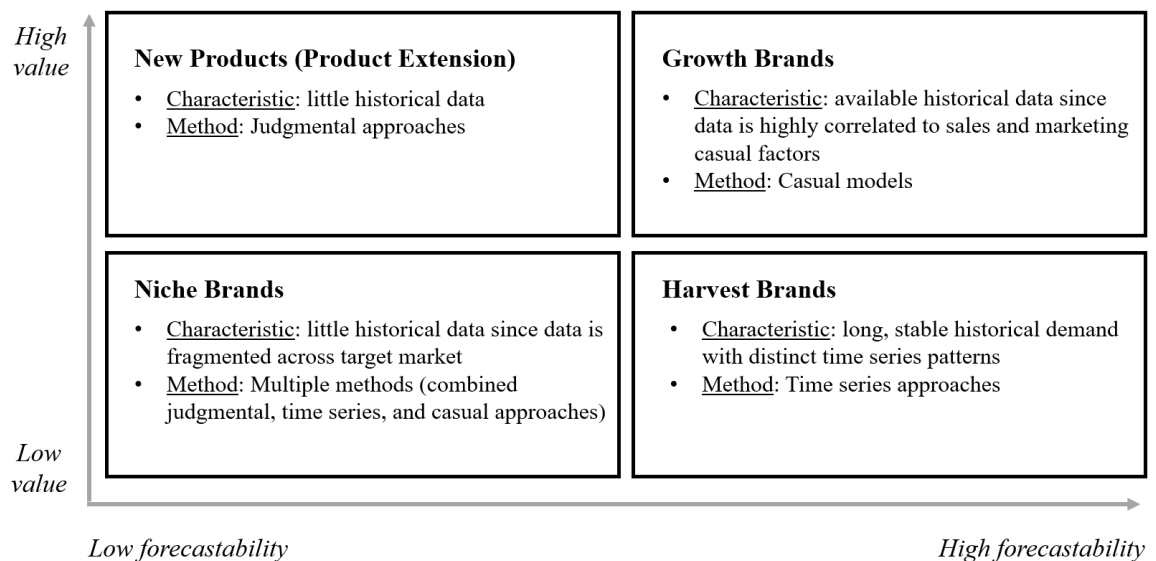


Figure 3: Product portfolio management matrix

Source: Own illustration based on Chase, 2009, pp. 69-74

The matrix clusters the product's value to the company and its forecastability. Furthermore, the matrix determines also the appropriate methods for each quadrant helping to choose the right forecasting method (Chase, 2009, pp. 69–74).

3 Simulation Games

Simulation games are games that imitate a real-life situation (Marchellatta, 2019). The effects of the participants' decisions are simulated, while the participants are taking on roles and representing interests in the scope of specific rules (Kühl et al., 2009, p. 125). The players have to make concrete decisions that have concrete consequences in the game which the players can experience and examine. The games consist of three dimensions: (1) the game and rules, (2) the roles and actors as well as (3) the used simulation and resources (Stanierowski & Schiffels, 2006, pp. 10).

The game and rules happen when the participants agree to reach a definite end goal within the means and the rules that are provided beforehand. In elemental psychology, a big emphasis is made on how important playing and games are for the cognitive development of children. Games and playing are seen as the basis for children's learning and even adults learn better while playing games. Like in simulation games, children assume roles and imitate reality. By doing this learners gain all abilities necessary for education and career, such as creativity, perseverance, and concentration (Hagermann, 2020). So the experience for the participants to emulate reality with limiting rules and taking the experience seriously is essential to the learning with the simulation game method.

The roles in the games are taken on by the participants of the game and each role has certain rules and functions. Each role implicitly has their own freedom within the rules of the game. Actors are not only single persons but can also be groups or organizations within the game. This leads to a more accurate simulation of the reality for the participants because they can interact with actors as they would interact in real-life situations during the simulation. The simulation and resources are essential for the imitation of reality. The simulation is a dynamic replication of reality and can be used for systematic analysis of scenarios that would

sometimes never be tested, due to money or security issues. For simulations, a model with the essential properties and factors of the processes and interaction is constructed. The simulation should be as close to reality as possible even though the players can lead the simulation game in directions that could never happen in real life (Stanierowski & Schiffels, 2006, p.12).

All these factors lead to simulation games being a very good method to teach and apply knowledge. Students could, for example, practice complex skills, abstract thinking, and decision-making under pressure and uncertainty. Moreover, the participants practice social skills due to the communicative nature of these games and it gives them through role-play the ability to see the scenarios from a new perspective which will enrich their horizon and help them in future decision making (Feldman, 1995).

3.1 Board Games and Role Play Simulation Games

Two possibilities of simulation games that can be played in person are board games and role-play simulation games. Board games often serve as a simplified structure of a company, a process, or an organization. One advantage of board games is that it is very illustrative and makes the flows of goods and values visible and comprehensible for the players (Stanierowski & Schiffels, 2006, p.10). The players interact via physical objects representing parts of the system and can see the results of their decision through these objects and the game design. Board games are a very illustrative way that helps the players understand the mechanism behind processes in a simplified way. Moreover, since board games are often played in groups, participants can practice social skills and improve their communication (Deckert et al., 2016, S. 12.).

During role-play simulation games several groups are usually in a competitive situation. Oftentimes a computer or the game leader simulates the reaction of a situation or system that is simulated. Usually conversational situations or company situations can be simulated well as role-plays. The main aim is to communicate with fellow participants and give the possibility of dynamic group processes. Moreover, subject-related behavior can be applied.

These games train practical competencies in using the learned methods for problem-solving and social skills (Deckert et al., 2016, p. 12.; Stanierowski & Schiffels, 2006, p. 12).

A good example of a role-play forecasting game is a stock market forecasting role-play simulation game that was played by the *Sonderforschungsgruppe Institutionenanalyse* (Collaborative Research Group on Institutional Analysis) in 2013. In three or twelve rounds the participants should forecast the value of the Volkswagen stock by evaluating newspaper articles from the same timeframe. After each round the participants filled in a form submitting their forecast suggestions and their confidence level regarding their answer. The aim of the study was to evaluate the forecasting abilities of experts compared to amateurs (Bizer et al., 2013, pp. 7). Even though the aim of the study was to measure the difference in forecasting abilities between professionals and amateurs, the study design was implemented into this forecasting game as well.

3.2 Computer-based Simulation Games

In computer-based simulation games, all decision variables related to the scenario are processed by the computer. The input that is created by the players can be immediately processed by the computer so that the result is immediately visible to the players. Afterward, the computer requires new responses from the players in the form of inputs (Deckert et al. 2016, p. 7). Oftentimes the group or the player is playing against the system itself and not against other players, which leads to a decreased effort in supervision. On the other hand, social competencies are not necessarily trained. A common form of computer-based simulation games is computer games (Deckert et al., 2016, p. 12.; Stanierowski & Schiffels, 2006, pp. 13; Kutergina, 2017).

A good example of a computer-based game is the beer inventory game by Cologne Business School (CBS). It is a business game for the simulation of selective warehousing strategies. The forecasting game is programmed in Excel and focuses on centralized and decentralized warehousing as well as safety stock. Furthermore, the game helps students apply their knowledge in operations management to get the best outcome possible and evidently

furthered the proficiency of the students in solution finding in this area. The game was designed in Excel as it allows the complex trade-offs between inventory, transport, and location costs, in particular the effects on the safety stock of inventory bundling. The participants can play out different strategies and can receive direct feedback on how their actions affect the distribution costs (Deckert et al., 2017 pp. 3).

3.3 Method Comparison

Each method of simulation games has its own advantages and disadvantages which have to be considered before deciding how to design a game. In the following table 1, the advantages and disadvantages of each simulation method are shown and evaluated.

Table 1: Evaluation of different kinds of simulation games

Method	Advantages	Disadvantages
Board Games	<ul style="list-style-type: none"> • Visual • Improve communication 	<ul style="list-style-type: none"> • Very simple • Costly equipment • Not scalable
Role Play	<ul style="list-style-type: none"> • Strong focus on communication • Close to reality 	<ul style="list-style-type: none"> • Need for other players • Dependent on the game leader
Computer based	<ul style="list-style-type: none"> • Scalable • Can be done remotely • Close to reality 	<ul style="list-style-type: none"> • No social interaction needed • Further explanation might be not available

For board games, the advantage is that it is very visual and needs a lot of communication among the participants which is positive for their communication skills. On the other hand, the scenario needs to be simplified quite a lot to be put into a visually appealing board game. Therefore, complicated mathematical problems are not possible. Also, board games are not easily scalable as the equipment is costly and needs to be manufactured for every set of the game.

Role-play games are similar to board games, as they focus a lot on communication and further social skills. They are close to reality as business decisions are often made in a group

setting. On the negative side, to play the game one needs to have several participants which are not always available, and often the game needs to be supervised by a game leader to know the impact of a decision.

Computer-based games have the upside of being easily scalable as one just needs the game and a computer. They can be played in remote settings which are very common nowadays and are close to reality. For example, in a business setting, the game trains the players to conduct analysis and make a final decision before presenting the results to the management board. On the other hand, the computer-based game does not necessarily motivate one to perform social interactions and therefore, does not improve social skills. If these games are played in a remote setting and there are difficulties in understanding, there might be no help or further explanation available which can frustrate the participants.

When the decision falls on one of the three types of simulation games, it is important to know what will be the focus of the game. If the focus is more on communication skills and group-based problem solving, a role-play or a board game might be suited for this. Especially, if the problem is very one-dimensional and easy to visualize or solve in a certain amount of time. Computer-based games, however, are very well suited for complex mathematical problems, as it is possible to program a mathematical background structure for the game. Moreover, computer-based games are scalable and therefore suitable for a growing group of participants like students as long as the focus is not on communication.

4 Creation and Realization of the Simulation Game

In the following part, the design process of the forecasting simulation game is elaborated as well as its concept and structure are discussed. At first, the type of the simulation game is determined before the game structure's content is illustrated as well as the layout and program structure of the Excel tool.

4.1 Type of Simulation Game

The forecasting simulation game was realized as a computer-based simulation game in MS Excel. The tool has several advantages. First, MS Excel is widely available and known among students. It is a very common tool used in the economy as well and therefore, provides the students learning opportunities for their work life. Moreover, the data structure and the possibility to use formulas and data columns are very helpful for forecasting as one often has data tables and repeat steps over a period of time to calculate the forecast based on past data. Lastly, Excel is a simple tool to design and program as it provides a base structure and available program components.

The developed forecasting game was designed as a computer-based simulation game because the participants should have the possibility to solve the game by themselves or in small groups in remote online and offline settings. In the work-life, forecasting tasks are also mainly made on the computer and this game is designed to be close to a real-life working scenario. Thus, the game is constructed around several scenarios that should give the participants a broad range of work situations. In the game, the participants should apply their knowledge and the provided information of the given scenario to find solutions for the presented problem. Moreover, the game is aimed to be entertaining as well as to provide learning opportunities on several different forecasting methods.

4.2 Game Structure

The forecasting game uses a fictional company as its initial game foundation on which the forecasting exercises are based. The fictional company Clothes&More is a clothing company that produces everyday clothing for every gender and age. In the game, the company faces problems to forecast accurate demand estimations due to changes in their production lines. Hereby, the user of the game should help the company to find the best-fitting forecasting model and the demand value for the next period in the data set.

In total, the game provides five different exercises or problems called scenarios that the user can solve. A list of potential fitting forecasting methods including their condition values such

as the value of alpha helps the user to find the right forecasting methods for the current scenario. To guide the user through the game and give them some application help, a set of rules were established which can be found on the first tab of the forecasting game.

In the first exercises, the company Clothes&More faces difficulties in their best-selling white basic T-shirt line. Since the demand of this line is quite stable and provides an extensive record regarding the previous sales, the first exercise focuses on linear and stationary demand models. Here, the user can apply the methods Moving Average, Weighted Moving Average, Exponential Smoothing, and Naive Approach. Since the data series incorporated two conditions, (1) recent data is more important than the past data, and (2) demand values change quickly but still fluctuate stable in a certain range, the best-fitting model to the condition is the third option of the Weighted Moving Average. The third option incorporates values of 4 months with weights of 0.4, 0.3, 0.2, and 0.1 using 0.4 for the most recent month.

The second exercise addresses that the popularity of the white basic T-shirt line increased steadily due to a new fashion trend. Thus, a trend is incorporated in the second scenario for which the methods Exponential Smoothing with Trend Adjustment, Trend Projection, and the Naive Approach can be used. The method Moving Average was given as well so that the user can compare the outputs and their effects on the demand of a stationary model with more trend-relevant models. The right forecasting model for this exercise is the third option of the Exponential Smoothing method with an alpha value of 0.5 since this model together with the trend projection are the only methods that consider a demand trend. The trend projection achieves also well-fitting forecasting values but considering that the recent data of the clothing line is more important. Furthermore, the clothing line should be more responsive to recent trend changes, thus, the Exponential Smoothing method is more suitable.

A seasonal effect is included in the third exercise. Some time has passed at Clothes&More and the previous fashion trend has changed to a trend that is only worn in the summer months. This effect can be calculated by the Seasonal Index, Winters' Model, and the Naive Approach. Like in the second exercise, the Simple Exponential Smoothing method was

chosen to illustrate the effects of stationary methods with more sophisticated models to the user. The Seasonal Index is the correct forecasting method for this exercise because it considers a seasonal effect and can act without an additional trend. In comparison, the Winters' Model is the only other model that considers seasonality but incorporates a trend in its functions. Since the data series does not show any trend signs, the Seasonal Index is the correct solution.

In the fourth exercise, Clothes&More introduced a new clothing line which has been introduced to the market recently. Hence, the user needs to figure out how to find the right forecasted method for a scenario in which almost non-existing data is given. Possible options for this exercise are Moving Average, Exponential Smoothing, Trend Projection, and Naive Approach to cover all demand patterns. The difficulty of this exercise is that no sufficient data is available to make an accurate assumption on which forecasting method to use. However, the Naive Approach provides a good starting point and acts mostly as a benchmark. Therefore, the Naive Approach is the most applicable method to use.

Lastly, the company wants to revise the demand forecast quality of three T-shirt lines and determine which line has the most accurate forecasted numbers. The methods MAD, MSE, and MAPE are used for this task. The only forecast quality method that can establish a useful result is MAPE since it is the only method that can compare different data sets due to its independent nature. In contrast, MSE and MAD are dependent on the data series and can only be used to compare different forecasting methods for the same data set.

If the indicated solution from the user is correct, this can be seen in the result tab at the end. This sheet provides the correct method solution including the forecasted demand value for the next period. Furthermore, it contains an explanation of why this solution is correct and illustrates how far the indicated value of the user might differ from the correct value. In the case the user wants to check if the other proposed but not the most optimal methods were calculated correctly, the mathematical solutions for those methods are also given. Additionally, an overview of all used forecasting methods including their formulas and application explanations is provided as well.

The overarching aim of this forecasting game is to enable its user to learn more about the application of the forecasting methods usually used in operations management without the provision of the right forecasting method to use as well as to practice the mathematical structure behind those methods. In detail, the user of the game will learn:

1. to distinguish the right forecasting method based on the task description and the demand data before calculating every possible method,
2. to decide which condition values (ex. weighting values; values for alpha, beta, gamma) are the best for the given scenario, and
3. to compare the different forecasts with the help of quality methods (MAD, MSE, MAPE) in case of uncertainty.

Thus, the main objective of this game is to learn the right application of various forecasting methods based on different given scenarios. It is further important to mention, that through the set of proposed forecasting methods including their condition values the user is constrained to those options and cannot choose freely. However, it would be impossible to revise if the initial solution of the user is correct due to the many possibilities the methods and their condition values enable. Therefore, it is further to note that other methods or different condition values could be more suitable for the scenario than those from the proposed list.

4.3 Structure of the Excel Tool

As explained before the forecasting game was designed in MS Excel. To prevent the participants from changing the game or revealing the programming of the game, the pages are blocked except for the areas where the participants can calculate and write in. The aim is to guide the participants to the solution of each page through the game and for them to work independently. The different scenarios are color-coded, for example, scenario one is yellow, scenario two is green, etc., to make it easier for the participants to track where they are and what scenario is referred to.

The MS Excel tool starts with an introduction page which can be seen in figure 4 on which the fictional company of the game and its rules are presented. The short story of Clothes&More includes the overall aim of the game, therefore the participants can start the game knowing what subject to expect from it. The rules draw clear boundaries and guidelines for the participants right from the start, hence, it is clear for them how to proceed throughout the game.

Forecasting Game
A Game to Practice the Application and Selection of Quantitative Forecasting Techniques in the Case of a Fictional Company
by Helen Schmitz and Julia Keszler
Scenario
Clothes&More is a clothing company that produces clothes for every gender and age. Nowadays, the company is facing troubles while forecasting accurate demand estimations. It is your task to help the company to find the best-suited forecast method including the most accurate forecasted demand outcome for every given situation. In total, five scenarios need to be solved.
Rules
<ol style="list-style-type: none"> 1. Every scenario exercise is located on an individual excel sheet which can be accessed down below using the tabs buttons. Ideally the exercises are solved after each other. 2. On each sheet, a short scenario description for the exercise and calculation table(s) are given. Please, add your calculation directly into the demand file or into the extra provided calculation tables. 3. On the right side of every sheet, information regarding the possible forecasting method options, their formula, and additional information on those methods are provided. Please use only these given forecasting options to solve the given scenario. 4. After solving the exercise, please select your chosen method from a dropdown list and enter your result for the given situation in the solution box which is labeled "What are you deciding for?" and can be found on the right side of every sheet below the forecasting method options. Whether your method and result are correct will be displayed in the last tab called "Result". The solution will only be visible, after you enter your solution in the solutionbox. 5. In case you are unsure if your selected method is correct, you can use the comparison table at the bottom of the calculation table using the <u>Medium Average Deviation (MAD)</u> method to compare your results with each other. 6. The graphic at the bottom of the side shows you the graphs of the demand, the compared solutions from the comparison table and the solutions of different options of certain forecasting methods to help you visualize the demand and the forecast. 7. All exercise solutions as well as the examination of your results are displayed on the final tab called "Result". 8. Lastly, and most importantly, have fun!!

Figure 4: Introduction page of the forecasting game

The first four scenario pages are generally following the same structure that can be seen in figure 5 below. The figure shows the page of scenario one as an example of how the game is structured in the first four scenarios.

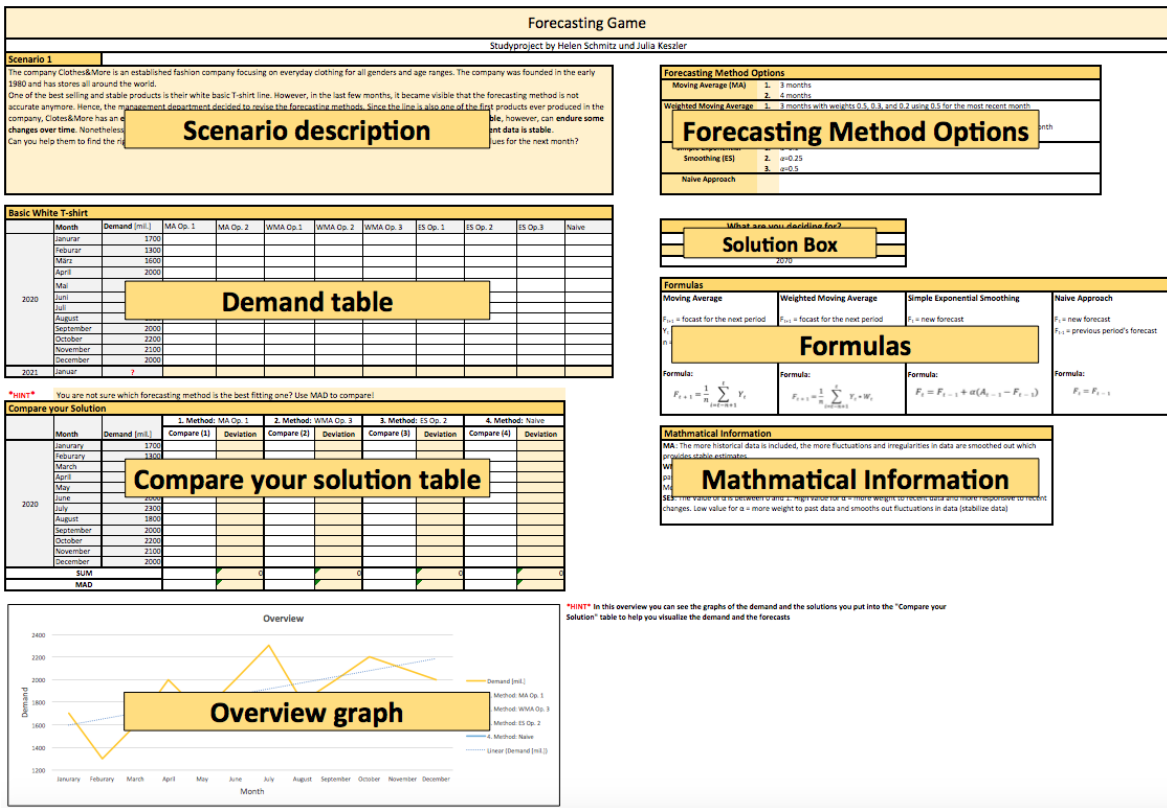


Figure 5: Scenario one page of the forecasting game

On the upper left side, the participants can read a short text which introduces them to the first scenario. The text contains all the information necessary to decide on the right method and presents the goal of the exercise. On the right side, at about the same height as the scenario description, different *forecasting method options* are shown that are optional for this game. The participant should choose either one of these methods to solve the scenario.

In the first table underneath the scenario description, the table with the past demand is visible to the participant. This table can also be used to do the calculations of the proposed models to solve the exercise. For more complicated calculations in later scenarios, separate calculation tables are given below the demand table as they provide more guidance and space for the calculations. On the scenario three page, a hint was added as well to give more mathematical guidance to the participants if help is needed.

If the participant is unsure of how to solve the calculations, formulas of the possible methods and mathematical information are provided on the right side of the page. Underneath the solution box, which is located underneath the solution box. In the *compare your solution* table, the participants can fill in their forecasting solution for each month into the compare column. Then the table calculates the deviation between the demand and the compare solution automatically and shows the mean average deviation. In the overview graph, the solutions from the *compare your solution* table are visualized as well as the demand and a trend line for the demand. The visualization of the demand should help the participant visualize the data and make their decision which method and which option they should choose as the correct method.

In the end, the participant should fill in the solution box. Under *what are you deciding for* the participants can choose either one of the options provided in the dropdown menu, which only contains the optional methods for this exercise. Afterward, the user can enter their solution in the field of *your solution*. Scenario five has a slightly different structure due to its different task. This can be seen in figure 6 below.

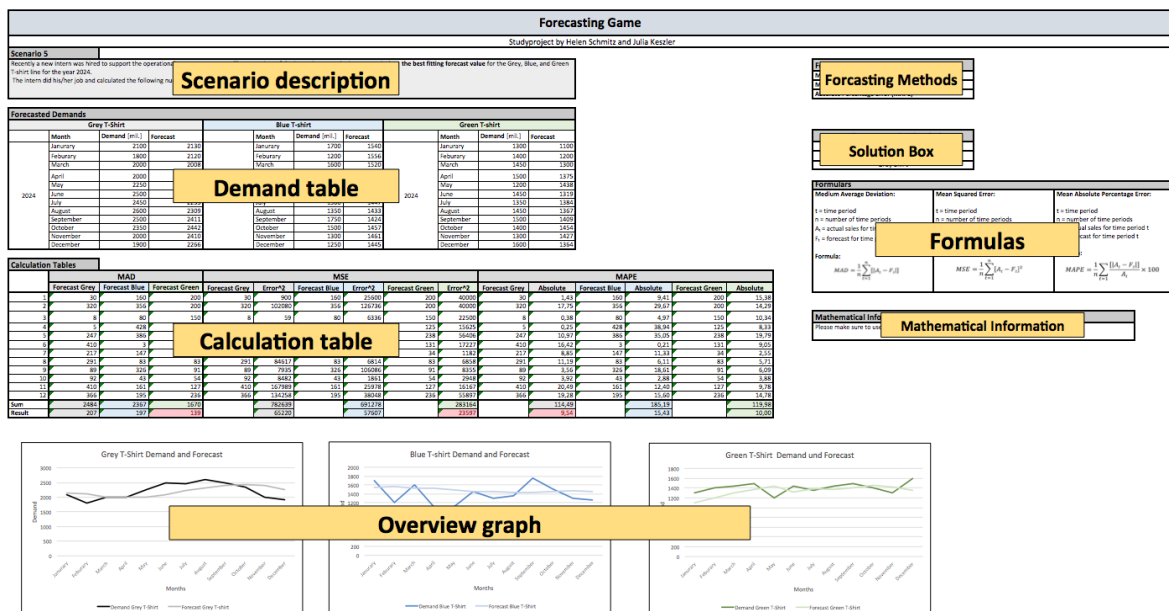


Figure 6: Scenario five page of the forecasting game

The goal of scenario five is to determine which forecast is the most accurate. This page has a forecast and demand table with three different columns for three different T-shirt lines, which shows the demand and the forecast below the scenario description. Because the goal is to compare the forecasts of the three clothing lines with each other, the page is designed to be able to compare the three clothing lines easily. Therefore, in the upper table, the data of each clothing line appears next to each other in the calculation tables for the possible forecasting quality models. For additional support, the demand and the forecasts for the three clothing lines are visualized in the three graphs at the bottom.

After entering the solution in the solution box, the participants can go to the result page. This is true for all the scenarios. The result page is depicted in figure 7. The figure shows the state of the result page when the initial solutions of the participants are not entered yet in the solution box of the previous pages. The correct answer and its explanation are only visible when a method is chosen and a solution of the user is entered on the scenario page.

This hurdle is designed to prevent students from looking at the solutions beforehand.

Forecasting Game
 Designed by: *[Name]*

Summary

Results of the scenarios

Results of the other methods

Forecasting Method	Model	Area	Forecast	Forecast	Forecast	Forecast	Forecast	Forecast
Simple Moving Average	$F_t = \frac{1}{n} \sum_{i=1}^n Y_{t-i}$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Weighted Moving Average	$F_t = \sum_{i=1}^n W_i Y_{t-i}$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Exponential Smoothing	$F_t = \alpha Y_t + (1-\alpha)F_{t-1}$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Linear Trend	$F_t = a + bT$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Seasonal	$F_t = \sum_{i=1}^n W_i Y_{t-i}$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Forecast Error	$F_t = \dots$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic
Forecast Error	$F_t = \dots$	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic	Arithmetic

Forecasting Method Overview

Figure 7: Structure of the result page

The page starts with explaining the overall aim of the game as well as its objectives and provides a short summary. Underneath the explanation, the result and its explanation are shown in color-coded tables representing the five different scenarios. Figure 8 illustrates an excerpt of the result page showing the solution of the first scenario when its solution has been entered.

Results								
Scenario 1								
Correct Solution	Method	Result	Your Solution	Method	Result	Overall Accuracy		Difference
	Weighted Moving Average Option 3	2070		Incorrect	2000	no		70
Goal	Find forecast value for January 2021							
Explanation	<p>In the exercise description, it is stated that the line reacts according to two conditions. Firstly, it is mentioned that the recent data is more important than the past data hinting to use the weighted moving average or exponential smoothing. Both of these models emphasize stronger the recent data due to the usage of weights or a high alpha value. The simple moving average focuses only a bit on recent data but does not empathize with them, and the naive model does not set a focus at all. Hence, the simple moving average and naive approach can be ruled out.</p> <p>Secondly, the description mentions that the demand values change quickly but still fluctuate stable in a certain range (1300-2200 million T-shirts). Hence, the method needs to be reactive to changes but also be able to smooth out fluctuations. The exponential smoothing model may be fitted to the first condition but not to the second condition. A high value of alpha not only sets a focus on recent data but also sets emphasis to change the average. In contrast, a low value of alpha would stabilize the average but weights past data more.</p> <p>Therefore, only the weighted moving average is left to be considered. The method matches the requirements to focus on recent changes and to contain a stable average. Now a decision between the three options needs to be made. Since the inclusion of more historical data (more months) smooths out stronger fluctuations in data, the weighting moving average for 4 months is the best fitting model.</p>							

Figure 8: Result table of scenario one filled in

For the depicted example, the method Naive Approach was selected and the result 2000 million T-shirts was entered. The result table shows the correct solution including its method and result as well as the solution the participants have entered. The initial solution of the participant is further highlighted whether it is correct or incorrect. Correct and incorrect are color-coded in green and red to make it more obvious to the participant whether their answer was right or wrong. The overall accuracy part of the table indicates whether the participant is correct in both the method and the mathematical solution. Under *difference*, the user can see how far off their mathematical results differ from the right answer, which may help them to find the error source. Moreover, the task of the scenario is mentioned again to highlight the content of the exercise. Under *explanation*, the finding of the solution is explained including reasons why the method is correct. The explanation furthers the understanding of the participant and helps them gain insight into the development of the solutions.

On the bottom of the result page, the participants can see the results of the other methods as well. The information is also only revealed after entering the information in the solution box. This second solution table should help the participants to compare their solutions even if a different method was chosen by them or if they want to know the solutions to other methods. or they want to know what the solution of a different method is.

In the table on the right side of the page, an overview of the used forecasting methods is given. The overview informs about the data pattern, forecasting horizons, and the methods'

constraints. The provided information should help the participants to further their mathematical understanding of the different methods and supports the understanding of the solution explanations.

5 First experiences with the simulation game

The simulation game was tested as part of a bachelor's degree course in industrial engineering at the Hochschule Düsseldorf University of Applied Sciences (HSD). The course, called Procurement and Supply Chain Management, took place in the summer semester of 2022 (SS2022). During the course, the prospective engineers learn the basics of procurement and supply chain management in 13 lectures. The simulation game was used in the third lecture "Stochastic Demand Calculation". Only the forecasting methods for constant processes were presented in the game, as these are the forecasting methods taught in the course. The forecasting methods were: Moving average, Weighted moving average, Simple exponential smoothing and the Naive approach.

In order to evaluate the effectiveness of the simulation game, a survey was conducted among the students. A questionnaire was developed in which the students could give their assessment after testing the simulation game. The questionnaire was then evaluated. Approximately 30 students participated in the third lecture and thus in the simulation game. Of the 30 students, 15 evaluable questionnaires were submitted.

Overall, the students give a positive evaluation of the simulation game. Most of them agree or strongly agree that the lessons had a clear structure (80%) and enhanced their understanding (93%) and that they enjoyed working on the lessons (73%). This is in line with the finding that most students would recommend the simulation game to fellow students (80%) and would like to have more lessons in this course (67%) as well as in other courses (93). The simulation game is seen as an add-on rather than a substitute for other learning materials. All students see the lessons as a good addition or variation to the learning materials they already have.

6 Conclusion

The main objective of this paper has been the documentation of the creation of a forecasting game in which its users can learn about the determination of the right forecasting method for a given scenario without specifying the used method and its best-fitting condition values. Specifically, the user needs to distinguish the right forecasting method to a certain problem based on a task description as well as to decide the best fitting condition values to the method. Additionally, the user can practice the mathematical approach behind the methods using the MS Excel tool.

The game was created based on the forecasting methods typically used in operations management. In advance, the paper investigated closely the mathematical background of seven time-series models and one causal model and the requirements for their proper application. Furthermore, the aspects and advantages of simulation games were discussed and the three types of simulation games (board games, roleplays, and computer-based games) were compared. Based on these research results it was decided to develop a computer-based game with the help of the MS Excel tool. In order to create a realistic game, a fictional company was included as the game's backstory. In the game, the user can play through five scenarios based on the three different demand patterns (linear/ stationary, trend, and seasonal) as well as the forecast quality methods.

As previously mentioned, the concept of the game is that the user should freely decide which forecasting method should be applied to the given scenario. However, the eight different forecasting models with their condition values enable many possibilities to calculate the problem which would be hard to revise on their correctness and the best outcome for the scenario. Therefore, for each scenario, a set of proposed forecasting methods including some options for their condition values are provided. Another restriction of the game is that through the predetermined set of proposed forecasting methods for each scenario, it is possible that other methods or different condition values could identify more fitting forecasting values as those from the proposed list.

First experiences with the simulation game were made at the Hochschule Düsseldorf University of Applied Sciences (HSD) among the bachelor students of industrial engineering. Here a German version of the game was tested, which only contains the first scenario, the prediction methods for constant processes. The results of the student survey show an overall positive evaluation of the simulation game by the students. The game is seen as a valuable addition to the existing learning material. However, the test also showed that processing the simulation game takes a certain amount of time. Unfortunately, only 15 of the approximately 30 students who tested the simulation game participated in the evaluation, which precludes the results from being significant.

Looking forward to the next steps, the game will be tested by the Master's degree students of the course *Operations Management* focusing on the more advanced scenarios two and three, which are based on a trend and seasonal problem. Once the game has been tested by the master's students, the perception of the game will be evaluated again and, if necessary, the game will be improved based on the feedback. If the game is well received by the students, it could be included in the curriculum.

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Editors

Prof. Dr.-Ing. Dipl.-Wirt.-Ing Jörg Niemann

Prof. Dr.-Ing. Carsten Deckert

**Fachbereich Maschinenbau und Verfahrenstechnik
Faculty of Mechanical and Process Engineering**

**Hochschule Düsseldorf
University of Applied Sciences
Münsterstraße 156
40476 Düsseldorf**

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