11 Demand Forecasting

Learning Objectives for This Chapter

- Understand the role of demand forecasting in SCOM
- Understand the forecasting process and methods in SCOM
- Understand the role of expert methods in forecasting
- Apply statistical methods to forecasting
- Calculate forecasts based on statistical methods
- Understand and apply measures for forecast quality assessments.

11.1 Introductory Case Study

Good forecasting is vital for all business planning. If estimates are too high, a company overproduces goods that cannot be sold. On the one hand, this is unnecessary production and increases costs for resources such as raw materials, workforce, or storage space. On the other hand, underproduction can result in shortages and lost business opportunities and a potential loss of customers who cannot be served.

Good forecasting can be a competitive advantage. For example, Walt Disney Entertainment Parks put extremely high emphasis on predicting the next hours', days' and weeks' demand. Since they have been managing to almost always accurately predict future demand, revenue has been increasing immensely. Moreover, forecasting can be useful for analyzing areas for improvement.

Predictions about demand need to be made. However, forecasts are almost always wrong, as operations to calculate them are rather complex. Demand sometimes changes without prior warning and usually the effects set in later, making it difficult for operations managers to react.

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D. Ivanov et al., *Global Supply Chain and Operations Management*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-319-94313-8_11

However, some demand swings can be taken into consideration with relative reliability, such as seasonal changes. These include weather or particular holidays. For example, a city hotel, a supermarket, a metal producer, and a knitwear shop are all differently dependent on these external factors. A city hotel has the most customers during the holiday season, whereas a knitwear shop sells primarily in autumn and winter. The supermarket may face peak times, for example during lunch and after work hours. The factory producing metals is the most likely to be independent of seasonal swings and to have a steady demand throughout the year. However, many businesses have realized the correlation between weather and sales, which is why demand for meteorological forecasting services has increased rapidly.

Forecasts are generally expressed in terms that are also useful for capacity management, production, and SC planning. The aim is not only to be as accurate as possible, but also to know the difference between the plan and actual data. This range can help to improve forecasts in the future and to estimate which forecasting techniques perform better. Moreover, forecasts are made for the close and long-term future. Generally, short-term forecasts tend to be more accurate.

There are various tools to generate a demand forecast:

- expert estimates,
- time series analysis,
- regression analysis.

An expert estimate is a qualitative analysis tool that is drawn from historic demand and expert opinions on future development. In one case, Sport Obermeyer, a sports clothing retailer, applied this method. Initially, the whole team was involved in a decision about the next forecast. However, management noticed that some people would always dominate the decision process, so they decided that decisions would be made independently and the results would be compared and clustered. If most team members had forecast a similar result the product was categorized as easy to forecast. Otherwise, it was labeled "hard to forecast." For these "hard to forecast" products, the sports retailer delayed forecasting in order to reduce errors. In the case of Sport Obermeyer, using expert opinions worked extremely well with the new method.

Time series analysis, for instance exponential smoothing, takes sales data from the past to estimate new demand in the future. The restaurant chain "Red Lobster" uses this analysis tool with demand forecasting software. Each evening the software creates a new forecast for the next day listing exactly which meals need to be prepared. Managers then adjust these forecasts based solely on local specialties.

Regression analysis can be applied to estimate the dependence between two factors. For example, in a telecommunication company, monthly repair efforts can be analyzed to estimate the numbers of service employees needed. There are various other options for predicting future demand. These include simple probability, neutral networks, and fuzzy logic, to name a few.

Demand forecasting in medical care has an extraordinary role. Unlike for production companies, an insufficient supply of resources does not mean an unhappy customer, but affects the condition of a patient's health. Even though hospitals serve the public, they also need to make a profit. Hence, the sector faces the same dilemma in forecasting demand to match supply and resources: lost sales opportunities equal lost treatment opportunities. On the other hand, the aim is to minimize excess capacities and to minimize costs.

Forecasts in hospitals can be useful when applied to human resources such as nurses and doctors, customers (patients needing treatment), and operational goods such as beds and medicines. For staffing beds, queuing models can be applied. These methods help to analyze the capacity utilization of beds. This can be relevant for long term planning to determine how many rooms and beds are needed. These are then fixed costs, which are difficult to reduce in the future. Average methods are not an appropriate measurement here. If the mean of all flu patients is taken over the year, there would be empty beds in summer and not nearly enough beds in winter.

In medical care, emergency departments face the most extreme situation. Patients arrive randomly at any time of the day. This means the workload is highly variable. The severity of sicknesses also varies. To manage patient arrivals, hospitals apply systems which categorize patients as seriously ill, non-urgent, and routine. The latter are likely to be turned away from the emergency department and asked to arrange a doctor's appointment. For the first two categories a schedule is developed. Crowding in emergency departments endangers healthcare provision. Hence, forecasting plays an important role, and analytical models are used to ensure patients' needs are met more efficiently. Researchers have spent much effort in finding the best forecasting methods for this field.

In a sample emergency department, researchers came to the conclusion that time series analysis can provide a good method for indicating future needs. Daily patient attendances can be computed. For estimates, the autoregressive integrated moving average (ARIMA) method can be used, including such variables as holidays, air pollution, temperature, and humidity. The variables are then correlated to arrivals in the emergency department. The application of the ARIMA method can improve resource availability, especially staff planning.

Questions

In which fields is (demand) forecasting used?

Why is demand forecasting in medical care particularly challenging?

Why are means or averages not sensible measures for planning bed capacities?

Which analysis methods can be used to evaluate crowding problems in emergency departments?

11.2 Forecasting Process and Methods

Forecasting future demand is one of the major decisions in SCOM. Forecast sales data represent the input for further production, transportation, sourcing, and inventory planning. Moreover, many strategic decisions, such as facility location planning, revenue management, and process design, interact with demand forecasts (see Fig. 11.1).

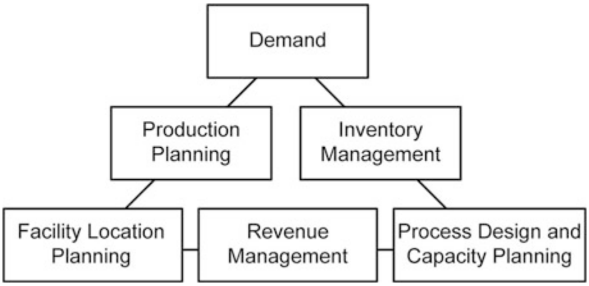


Fig. 11.1 Role of demand forecasting in SCOM

Forecasts can be made for operative or strategic issues. Similarly, different methods can be applied to forecast demand. In this section, we consider the process of forecasting, different time horizons, and basic forecasting methods.

11.2.1 The Forecasting Process and Time Horizons

The forecasting process begins with the definition of the objective. The second step is to determine the time horizon over which the forecasts should be performed. For example, for an airline, the objective might be to define how many airplanes should be purchased over the next 10 years. The next step is to select the method of forecasting. This depends on both the defined horizon and the available data. After data acquisition, forecasting is performed, typically using software.

The results should be controlled continuously since any SCOM system and its environment is highly dynamic and subject to many external and internal changes.

The forecasting process is presented in Fig. 11.2 using an example for forecasting the number of printed materials for a university lecture based on the prediction of student attendance.

A professor must define every week how many handouts should be printed for the next lecture. In this case, the time horizon is a week. For such short term issues, time series analysis is the preferred method. Based on the attendance list from the last lectures, exponential smoothing can be performed to predict demand.

Other time horizons may include anything from 3 months to 3 years. Examples of decisions for this medium-range horizon are sales and operations planning or budgeting. *Long term forecasting* typically refers to a period of over 3 years, e.g., new product planning, facility location planning, and research and development (R&D). *Medium-range* forecasts are used to deal with more comprehensive issues and support management decisions regarding planning and products, plants, and processes. *Short term forecasts* tend to be more accurate than longer term forecasts.

Fig. 11.2 Forecasting process

11.2.2 Forecasting Methods

Forecasting methods can be divided into qualitative and quantitative methods (see Fig. 11.3).

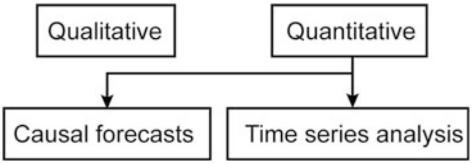
Qualitative methods are used when the situation is vague and little data exists. Typically, such situations have a long term nature or include decisions are to be taken about new technology or product. Forecasting for such cases involves intuition and experience. In many cases, the forecasting process relies on historical data such as demand numbers or turnovers. This works well as long as a company has reliable data which is available for the required forecasting. But how does this work if a company wants to launch a new technology? In this case, they must rely on expert views and customers' opinions.

This expert type of forecasting is normally based on professional knowledge and experience. A company uses input from different experts to develop forecasting for the next period. The problem with the expert methods is that they are based on opinions, experiences, and knowledge of human beings, and are therefore subjective.

There are different methods for qualitative forecasting. One of the methods is *sales estimation*. For this method, a company asks their sales expert about the latest turnover figures and aggregates the data for overall turnover, using the data to develop a forecast. The next qualitative method is the *customer survey*. This is a good tool to use when a company launches a new product and there is no historical data or expert experiences. A company can ask their customers directly what they think of the new product and try to develop forecasting for the product launch.

The third method is the basic idea of qualitative forecasting—the *expert view*. A company asks proven experts about new technologies or their experiences with similar products in the past. These experts normally work in different departments of the same company.

Fig. 11.3 Forecasting methods



The best known qualitative forecasting method is the *Delphi Method*. It is an extension of the expert view and the feature is a structured multiple expert survey using specialists from different companies and institutions. The Delphi Method runs in two or more rounds. A moderator develops a questionnaire and all the experts reply anonymously. After the first round the moderator creates a new questionnaire based on the information he got. Answers to the first round are published to all other experts so everybody can rethink their view. Next, they fill out the new questionnaire and so on until it leads to a consensus.

Quantitative methods are used when historical data exists, e.g., existing products, existing technology or existing markets. These methods are based on statistics. Statistical methods can be classified in two different forecasting methods:

- causal forecast
- time series analysis.

In *causal forecasting*, the demand (y) for a product depends on a known factor (x) and because of this it can be forecast (see Fig. 11.4). For example: Demand for axis (y) depends on the number of citizens in a district (x). Linear trends can be found using the least squares technique that results in Eq. (11.1):

$$\widehat{y} = a + bx \tag{11.1}$$

where $\hat{y}$ is the computed value of the variable to be predicted (dependent variable); a is y-axis intercept; b is the slope of the regression line; and x is the independent variable.

Non-linear regression is more complicated, but also more realistic. For a causal forecasting method, it is important to have reliable historical data for the known factor (the independent variable).

On the other hand, there is *time series analysis*. It is based on historical sales data. Sets of evenly spaced numerical data can be obtained by observing response variables at regular time periods. This method actually forecasts on the basis of the past values and assumes that factors influencing past and present will continue to influence in future.

There are different methods to forecast demand depending on the temporal progress of demand (see Fig. 11.5):

If there is a constant demand for a product we can use the *Moving Average* or the *Simple Exponential Smoothing*. For products with a demand which is based on trends, we can use *Regression Analysis* or *Double Exponential Smoothing*. Products with seasonal demand can be forecast using *Triple Exponential Smoothing*.

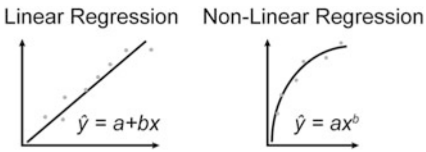


Fig. 11.4 Regression analysis

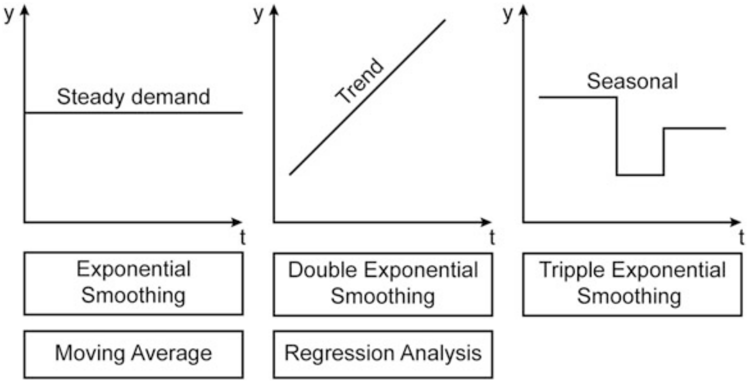


Fig. 11.5 Time series analysis

11.2.3 Forecasting Quality

Different forecasting methods can provide a different *forecast quality*. In order to estimate the quality of a forecast, some measures are used in practice, including

- mean absolute deviation (MAD),
- mean squared error (MSE),
- mean absolute percentage error (MAPE).

MAD measures the absolute deviation (ε) of forecast and actual data over T-periods according to formula (11.2):

$$\mathrm{MAD} = \frac{1}{T}\sum_{t=1}^{T} |\varepsilon_t| \tag{11.2}$$

MSE measures the quadratic deviation of forecast and actual data according to formula (11.3):

$$\mathrm{MSE} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_t^2 \tag{11.3}$$

MAPE measures the percentile deviation of forecast and actual data according to formula (11.4):

$$\mathrm{MAPE} = \frac{1}{\mathrm{T}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \left| \frac{\varepsilon_{\mathrm{t}}}{\mathrm{y}_{\mathrm{t}}} \right| \tag{11.4}$$

The practical problem with the MAD measure is that it expresses the absolute values and is therefore quantity-dependent. This makes it difficult to apply MAD for comparison of forecasts for different products. MSE is frequently used because of its good theoretical properties, but may be negatively affected by so-called outliers or freak values. MAPE is intuitively good and understandable and can be used for comparison of different forecasts where MAD/MSE values differ.

► **Practical Insight** In practice, statistically computed measures for forecast quality analysis need to be checked carefully. For example, consider actual sales data for five periods: 10–10–11–10–11 and two forecasts: (a) 8–8–9–8–9 and (b) 8–12–9–12–9. From a statistical point of view, both forecasts have the same MAD = 2. But from management point of view the first forecast (a) has a bias since we always produce less than demand. For managers it is more important to identify bias rather than strive for minimal forecast error.

11.3 Statistical Methods

In this section, we learn in more detail how to compute demand forecasts with the help of different statistical methods.

11.3.1 Linear Regression

Linear regression is normally used as a causal forecasting method. The procedure will be explained by taking sales in a newly established, small tea shop that depends on the number of customers as an example, as shown in Table 11.1.

The first step is to calculate the regression function $\widehat{y}(x) = \widehat{a} + \widehat{b}x$ with the parameter $\hat{a}$ and $\widehat{b}$. It is important to find the $\hat{a}$ and $\widehat{b}$ where the MSE has its minimum. To find the parameters we need to fill out the following Table 11.2.

In order to calculate the coefficient $\widehat{b}$, formula (11.5) can be used:

$$\widehat{b} = \frac{(6 \cdot 185{,}956) - (330 \cdot 3020)}{(6 \cdot 20{,}884) - (330)^2} = \frac{119{,}136}{16{,}404} \approx 7.263 \tag{11.5}$$

Table 11.1 Initial data for linear regression

Week n	Customer x_n	Sales (in €) y_n
1	26	269
2	35	389
3	43	432
4	67	536
5	78	685
6	81	709

Table 11.2 Results for calculating parameters

Week n	Customer x_n	Sales y_n (in €)	x_n^2	$x_n \cdot y_n$
1	26	269	676	6994
2	35	389	1225	13,615
3	43	432	1849	18,576
4	67	536	4489	35,912
5	78	685	6084	53,430
6	81	709	6561	57,429
$\sum$	330	3020	20,884	185,956

The computed value 7.263 means that when there is one more customer per week, sales income rises by approximately 7.26 €.

There are two options to calculate $\hat{a}$. The first option is the usage of Eq. (11.6):

$$\widehat{a} = \frac{\sum_{n=1}^{N} x_n^2 \sum_{n=1}^{N} y_n - \sum_{n=1}^{N} x_n \sum_{n=1}^{N} (x_n \cdot y_n)}{N \sum_{n=1}^{N} x_n^2 - \left(\sum_{n=1}^{N} x_n\right)^2} \tag{11.6}$$

The easier way is as follows (Eq. 11.7):

$$\widehat{a} = \bar{y} - \widehat{b}\bar{x} \tag{11.7}$$

When using formula (11.7) we have to calculate the average values: $\bar{y} = \frac{\sum_{n=1}^{N} y_n}{N}$ and $\bar{x} = \frac{\sum_{n=1}^{N} x_n}{N}$. For our example:

$$\widehat{a} = \frac{3020}{6} - \left(7263 \cdot \frac{330}{6}\right) \approx 103.868$$

The regression function now reads as follows: $\widehat{y}(x) = 103.868 + 7.263x$.

The next step is to calculate the MSE using the regression function (see Table 11.3).

To calculate the forecast error ε_n we use formula (11.8):

Table 11.3 Results for calculating MSE

Week n	Customer x_n	Sales y_n (in €)	$y(x_n)$	ε_n	ε_n^2
1	26	269	292.706	23.706	561.974
2	35	389	358.073	−30.927	956.479
3	43	432	416.177	−15.823	250.367
4	67	536	590.489	54.489	2969.051
5	78	685	670.382	−14.618	213.686
6	81	709	692.171	−16.829	283.215
∑	330	3020			5234.773

$$\varepsilon_n = y(x_n) - y_n \tag{11.8}$$

To calculate the MSE we use formula (11.3):

$$\text{MSE} = \frac{5234.773}{6} = 872.462$$

11.3.2 Moving Average

The method of *moving average* is based on computing the average demand from the previous periods and using these values for forecasting. It is called "moving" because with every period the average value changes or moves onward.

Consider the following example and function to understand forecasting with the help of the moving average. Here, too, it is important to find the result with the lowest MSE. The demand for each subsequent period is computed subject to formula (11.9):

$$\hat{y}_{t+1} = \frac{1}{T} \sum_{\tau=t-T+1}^{t} y_t \tag{11.9}$$

where $\hat{y}_{t+1}$ is the forecast for the next period, y_τ is the demand in period *t,* and T is the number of periods. It is important to choose a T that is not too large and not too small. Normally you calculate with different T-values to find the one with the lowest MSE.

Consider this example. Lebon Ltd. wants to find its weekly average demand for Cupcakes. Table 11.4 illustrates the last weeks' demand.

Three different numbers of periods to be averaged are given:

$T_1 = 2$; $T_2 = 3$; and $T_3 = 4$. The calculation results are presented in Table 11.5.

For example, to compute the forecast for week #3: 31· = (26 + 35)/2 → we add demand from the previous two periods and divide it using T_1.

To check which T is the one with the smallest MSE we have to calculate the forecast error. It is important to start with a period where for all T-values the sales have been forecast in order to make the MSE values comparable. In this case it is week #5 (see Table 11.6).

Table 11.4 Initial data for moving average

Week t	1	2	3	4	5	6	7	8
Demand y_t	26	35	28	42	38	45	46	39

Table 11.5 Results calculating moving average with three different Ts

T	y_t	$\widehat{y}(T_1 = 2)$	$\widehat{y}(T_2 = 3)$	$\widehat{y}(T_3 = 4)$
1	26	–	–	–
2	35	–	–	–
3	28	31[a]	–	–
4	42	32	30	–
5	38	35	35	33
6	45	40	36	36
7	46	42	42	39
8	39	46	43	43

[a]Forecasted demand from this period onwards

Table 11.6 Results calculating MSE

t	y_t	$\widehat{y}(T_1 = 2)$	ε_t	ε_t^2	$\widehat{y}(T_2 = 3)$	ε_t	ε_t^2	$\widehat{y}(T_3 = 4)$	ε_t	ε_t^2
1	26	–	–	–	–	–	–	–	–	–
2	35	–	–	–	–	–	–	–	–	–
3	28	31	–	–	–	–	–	–	–	–
4	42	32	–	–	30	–	–	–	–	–
5	38	35	−3	9	35	−3	9	33	−5	25
6	45	40	−5	25	36	−9	81	36	−9	81
7	46	42	−4	16	42	−4	16	39	−7	49
8	39	46	7	49	43	4	16	43	4	16
$\sum$				99			122			171

Using the error calculation formula $\varepsilon_t = \widehat{y}(T) - y_t$ and Eq. (11.3), we get:

$$\text{MSE}(T_1) = \frac{99}{4} = 24.75 \quad \text{MSE}(T_2) = \frac{122}{4} = 30.5 \quad \text{MSE}(T_3) = \frac{171}{4} = 42.75$$

As we can see, the smallest T is the best one because there the MSE is at its minimum. For this reason the recommendation for forecasting the next periods will be using T = 2.

In some cases, a weighted moving average can be used. In this case, older data usually becomes less important and the weights are assigned to different periods based on experience and intuition.

11.3.3 Simple Exponential Smoothing

This method is close to that of the weighted moving average. The weightings decline exponentially and the most recent data are weighted higher. For sales forecasts, average demand/sales values of previous periods are exponentially weighted to forecast the next periods. The simple exponential average means working with a smoothing parameter α. The idea is to weight current demand higher and to assign lower weights to the previous demand.

In this method we use formula (11.10) to forecast the demand for the following periods:

$$\hat{y}_{t,t+1} = \alpha \cdot y_t + (1 - \alpha) \cdot \hat{y}_{t-1,t} \quad (11.10)$$

where $\hat{y}_{t,t+1}$ is the forecast that we are making in the current period for the following period, y_t is the current demand, and $\hat{y}_{t-1,t}$ is the forecast we made in the last period for the current period.

Consider the following example as an aid to understanding simple exponential smoothing. Demand for a product during the last six periods is provided (Table 11.7).

The smoothing parameters are $\alpha_1 = 0.3$ and $\alpha_2 = 0.5$. The idea is to choose the smoothing parameter which leads to a smaller MSE (see Table 11.8).

For example to compute the forecast sales for period #3: 54.5· = 0.3·44 + (1–0.3) · 59 → we multiply the demand in week #2 by α and the forecast demand for week #2 by (1 − α) to get the forecast for week #3. In this case, $MSE(\alpha_1) = \frac{338.75}{6} \approx 56.46$.

Consider the calculations for Table 11.9:

$MSE(\alpha_2) = 385.46/6 \approx 64.24$. As we can see, the second smoothing parameter leads to a higher MSE. For this reason it is advisable in this case to forecast demand for the following periods with the smoothing parameter of 0.3 instead of 0.5.

This method helps to forecast the call for products with a steady demand. But to forecast the sales for products which have a trend-shaped or seasonal demand we need other methods.

Table 11.7 Initial data for single exponential smoothing

Week t	1	2	3	4	5	6
Demand y_t	59	44	61	58	49	52

Table 11.8 Results for single exponential smoothing with $\alpha_1 = 0.3$

t	y_t	$\hat{y}_{t,t+1}$	ε_t	ε_t^2
0		59	–	–
1	59	59	0	0
2	44	59	15	225
3	61	54.5[a]	−6.5	42.25
4	58	56.45	−1.55	2.40
5	49	56.92	7.92	62.65
6	52	54.54	2.54	6.45
∑				338.75

[a]Forecasted demand from this period onwards

Table 11.9 Results for single exponential smoothing with $\alpha_2 = 0.5$

t	y_t	$\widehat{y}_{t,t+1}$	ε_t	ε_t^2
0		59	–	–
1	59	59	0	0
2	44	59	15	225
3	61	51.5	−9.5	90.25
4	58	56.3	−1.75	3.06
5	49	57.1	8.13	66.02
6	52	53.1	1.06	1.13
$\sum$				385.46

11.3.4 Double Exponential Smoothing

Double exponential smoothing is used for situations where a trend already exists. This method works with two smoothing factors, α and β. The basic idea is that demand is normally overrated when a trend is positive and underrated when the trend is negative. Consider the formula (11.11):

$$\widehat{y}_{t,t+\tau} = a_t + b_t \cdot \tau \tag{11.11}$$

Where $\widehat{y}_{t,t+\tau}$ is the forecast for the following period performed in the current period, a_t is the smoothed forecast, b_t is the smoothed trend parameter (slope), and τ is the parameter which describes the number of periods for which we are making the forecast. We calculate a_t and b_t as follows from Eqs. (11.12–11.13):

$$a_t = \alpha \cdot y_t + (1 - \alpha)c \cdot (a_{t-1} + b_{t-1}) \tag{11.12}$$

$$b_t = \beta \cdot (a_t - a_{t-1}) + (1 - \beta) \cdot b_{t-1} \tag{11.13}$$

Assume that we have the demand data of gluten-free bread in a small grocery shop for the last seven periods (Table 11.10).

To forecast the demand for 7 months in the following year we use the following parameters: $\alpha = 0.2$; $\beta = 0.35$; $\tau = 1$; $b_1 = 4$. The computational results are presented in Table 11.11:

By changing the smoothing factors we can obtain a more reliable forecast for the next periods where a trend exists.

To handle forecasts for seasonal products we can use *triple exponential smoothing*. In this case, the third parameter, for seasonal fluctuations, is added to double exponential smoothing.

Table 11.10 Initial data for double exponential smoothing

Months t	1	2	3	4	5	6	7
Demand y_t	249	257	269	285	298	302	312

Table 11.11 Results for double exponential smoothing

t	y_t	a_t	b_t	$\widehat{y}_{t,t+1}$
1	249	249	4	
2	257	253.80	4.28	253
3	269	260.26	5.04	258.08
4	285	269.25	6.42	265.31
5	298	280.14	7.99	275.67
6	302	290.90	8.96	288.12
7	312	302.28	9.81	299.85

11.4 Key Points and Outlook

In this chapter, we learned methods and practical tools for demand forecasting. Let us summarize the key points of this chapter as follows. For SCOM, it is important to understand the role, process, and methods of demand forecasting, since forecasts are used for both tactical and strategic decisions. Production planning, inventory management, facility location, and capacity planning rely on decisions that depend on demand forecasting.

The forecasting process consists of six steps: (1) define the objective; (2) determine the time horizon;(3) select the method of forecasting; (4) gather data; (5) perform the forecasting; (6) validate and control the results. Forecasting methods can be divided into qualitative and quantitative methods. Qualitative methods are used either for new product and technology or for long term decisions where data from the past cannot be considered a reliable source. Qualitative methods use expert knowledge and experience and include such techniques as *sales estimation, customer surveys*, *expert estimation*, and the *Delphi Method*.

We also learned several quantitative methods which are used when historical data exists and statistical tools can be applied. Regression analysis and time series analysis, including the moving average and exponential smoothing (simple, double, triple), belong to quantitative methods. We learned how to apply statistical methods for forecasting and to calculate the forecasts based on statistical methods.

For quantitative methods, it is important to understand the measures for forecasts' quality assessment, which are based on error estimation. The most popular measures are MSE, MAD, and MAPE.

Finally, it should be noted that a common problem with statistical methods are the reliability of historical data and future developments. If forecasting is only based on numeric data, it is not safe. Numeric data often does not consider external features such as ecological, economic, or political factors. Assume that demand for ice cream has increased over the few last years by 10% because of hot summers. The conclusion would be that the forecast for the following year would be high as well because the company assumes the weather will be hot again. If the company does not consider weather forecasts in its calculations or consider expert views, the forecast based only on historical data could be wrong. Another critical area is the forecasting of product returns in online retail industry. For this reason it is common practice to combine expert and statistical methods to get safer forecasts. Such methods are known as ARIMA (autoregressive integrated moving average model) and ANOVA (analysis of variance).

Bibliography

Chase CW (2013) Demand-driven forecasting: a structured approach to forecasting, 2nd edn. Wiley, Hoboken

Chopra S, Meindl P (2012) Supply chain management. Strategy, planning and operation, 5th edn. Pearson, Harlow

Günther H-O (2005) Supply chain management and advanced planning systems: a tutorial. In: Günther H-O, Mattfeld DC, Suhl L (eds) Supply chain management und logistik. Springer, Heidelberg, pp 3–40

Heizer J, Render B (2013) Operations management: sustainability and supply chain management, 11th edn. Pearson, Harlow

Render B, Stair RM, Hanna ME (2012) Quantitative analysis for management, 11th edn. Pearson, Harlow

Slack N, Chambers S, Johnston R (2010) Operations management, 6th edn. Pearson, Harlow

Stadtler H, Kilger C (2008) Supply chain management and advanced planning, 4th edn. Springer, Berlin

References for Sect. 11.1

Hoot NR et al (2008) Forecasting emergency department crowding: a direct event simulation. Ann Emerg Med 52(2):117–125

Sun Y, Heng BH, Seow YT, Seow E (2009) Forecasting daily attendances at an emergency department to aid resource planning. BMC Emerg Med 9:1

Thonemann U (2010) Operations management, 2nd edn. Pearson Studium, München