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Using a Software Tool in Forecasting: a Case Study of Sales Forecasting Taking into Account Data Uncertainty

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Abstract: Forecasting is one of the logistics activities and a sales forecast is the starting point for the elaboration of business plans. Forecast accuracy affects the business outcomes and ultimately may significantly affect the economic stability of the company. The accuracy of the prediction depends on the suitability of the use of forecasting methods, experience, quality of input data, time period and other factors. The input data are usually not deterministic but they are often of random nature. They are affected by uncertainties of the market environment, and many other factors. Taking into account the input data uncertainty, the forecast error can by reduced. This article deals with the use of the software tool for incorporating data uncertainty into forecasting. Proposals are presented of a forecasting approach and simulation of the impact of uncertain input parameters to the target forecasted value by this case study model. The statistical analysis and risk analysis of the forecast results is carried out including sensitivity analysis and variables impact analysis.

Keywords: Forecasting, ARIMA, multiple linear regression, Monte Carlo simulation

1 Introduction

Sales forecasting is one of the crucial issues for enterprise logistics and supply chain management. Forecast accuracy affects the efficiency of the company planning process, the degree of goal achievement, total costs and the level of customer needs fulfilment. Strong competitive environment creates a constant pressure to reduce costs and increase customer service levels. The dynamics of the business environment and the uncertainty of market behaviour are the sources of many business risks and opportunities. Therefore, the reliability of forecasts under conditions of uncertainty is important but problematic. Various quantitative and qualitative forecasting techniques have been developed and each one has its advantages and drawbacks. A lot of research has been carried out in this area and different forecasting approaches are described in case studies. A systematic development of the forecasting expressions for exponential weighted moving averages was provided by Holt [1]. Holt examined methods for series with no trend, or additive or multiplicative trend. Taylor [2] constructed interval forecasts from quantile predictions generated using exponentially weighted quantile regression. Autoregressive integrated moving average (ARIMA) is one of the most popular linear models in time series forecasting. The objective of the research by [3] was to find an appropriate ARIMA model for price forecasting by considering the minimum of mean absolute percentage error (MAPE). Wang et al. [4] proposed residual modification models to improve the precision of seasonal ARIMA for electricity demand forecasting. The forecasting based on hybrid methodology that combines both autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) models for predicting was presented in [5–8]. Kavasseri and Seetharaman [9] examined the use of fractional-ARIMA or f-ARIMA models to model, and forecast wind speeds. Neto and Fiorelli [10] made a comparison between a model based on artificial neural network and a model based on physical principles as an auditing and predicting tool in order to forecast building energy consumption. Doganis et al. [11] presented a method which is a combination of two artificial intelligence technologies, namely the radial basis function (RBF) neural network architecture and a genetic algorithm (GA). Sun et al. [12] applied a novel neural network technique called ex-

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treme learning machine (ELM) to investigate the relationship between sales amount and some significant factors. Some other methods in the field of sales forecasting were presented in case studies [13–16]. Another significant issue dealt with in several studies is the possibility of incorporating risk and uncertainties into the forecasting process. Germain et al. [17] investigated the links among organizational structure, supply chain process variability, and performance as moderated by environmental uncertainty. Different software tools are used to analyse risk factors and provide simulations. The most widely used simulation is Monte Carlo. Klaas et al. [18] proposed a forecast of system parameters in order to maintain constantly high performance. The forecasting was used in context of a simulation based approach. A comparison of different estimation procedures by Monte Carlo simulation technique was carried out by [19]. A combination of a spatial interaction model and simulation approaches for the reliable estimation of retail interactions was proposed in [20]. Use of simulation methods was presented also in [21–28].

There are many described research and case studies within the area of forecasting but few of them deal with further analysis of the forecasted outcomes in terms of risk. This case study presents the possibilities of forecasting and forecast analysis when considering uncertainty or variability of inputs using the software for risk analysis.

2 Methods of forecasting and simulation

Forecasting of a demand and hence future sale earnings depends not only on the development of sales in the past but is influenced by several variable factors. Some of these factors are under control of a vendor or manufacturer more, others less or not at all. The most adjustable variable is usually the price of a product, but it is indirectly dependent on the price of competing products, the cost of inputs, as well as on macroeconomic variables such as inflation and the purchasing power of customers. This dependence is very strong in the case of consumption products. This paper brings proposals on how to solve a forecasting problem via computer simulation. The forecasting model consists of multi-regression forecast, and uses different approaches to solve a forecasting problem. A software tool for risk analysis working as an additional module to MS Excel is used.

2.1 Forecasting methods

Forecasting refers to the act of predicting the future. Many scientific approaches to forecasting exist. Each technique and method has advantages and disadvantages for particular types of data, so it is possible to forecast the data using several methods and then select the method that yields the best results. The methods used in this study are mentioned below.

2.1.1 Multiple linear regression

Multiple linear regression is used for data where one data series is a function of, or depends on, another data series. The goal of multiple linear regression is to find an equation that most closely matches the historical data.

Multiple linear regression finds the coefficients for the equation:

$$Y_t = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + e \tag{1}$$

where: b_1, b_2, and b_3, are the coefficients of the independent variables, b_0 is the y-intercept constant, and e is the error.

2.1.2 ARIMA model

As described in 2.1.1. where multiple regression model is explained, it has similar features to autoregressive model. ARIMA model integrates autoregressive (AR) and moving average (MA). If the independent variable “X” from multi regression model is replaced with dependent variable “Y” i.e. $x_1 = y_{t-1}$; $x_2 = y_{t-2}$ etc. then the autoregression model is defined:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \tag{2}$$

where: c – constant term, $\phi_{1,2,\ldots,p}$ – autoregression coefficients, ε_t – random part.

The moving average should not be considered as ordinary moving average because here it is defined as moving average of the error series “e_t”.

$$Y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \tag{3}$$

where: c – constant term, e_t – error term, $\theta_{1,\,2,\,\ldots\,q}$ – coefficients of MA.

Now the autoregressive model and moving average model can be joined together and the result is ARMA model but this model is suitable only for stationary data. This model can be extended to non-stationary series by allowing differencing of data series. This model is called autoregressive integrated moving average – ARIMA by Box and Jenkins [25].

There are numbers of variety of ARIMA models. The general non-seasonal ARIMA model is known as ARIMA (p, d, q): where: p – order of AR part, d – degree of first differencing involved, q – order of the MA part.

For example ARIMA (0,0,0) is a model where there is no AR aspect: y_t does not depend on y_{t-1}; there in no differencing involved and no MA part: y_t does not depend on e_{t-1}.

One final complexity to add to ARIMA models is seasonality. Then the ARIMA can be extended readily to handle seasonal aspect and the general shorthand notation ARIMA (p, d, q) (P, D, Q), where: p, d, q – non-seasonal part of model, P, D, Q – seasonal part of model.

General model of seasonal ARIMA (also known as SARIMA model) can be written as follows:

$$\begin{aligned} Y_t =& (1+\phi_1)Y_{t-1} - \phi_1 Y_{t-2} + (1+\Phi_1)Y_{t-4} \\ &- (1+\phi_1+\Phi_1+\phi_1\Phi_1)Y_{t-5} + (\phi_1+\phi_1\Phi_1)Y_{t-6} \\ &- \Phi_1 Y_{t-8} + (\Phi_1+\phi_1\Phi_1)Y_{t-9} \\ &- \phi_1\Phi_1 Y_{t-10} + e_t - \theta_1 e_{t-1} - \theta_1 e_{t-4} + \theta_1\Theta_1 e_{t-5} \end{aligned} \quad (4)$$

where: ϕ_1, Φ_1, θ_1, Θ_1 are coefficients calculated by the least square method, $e_t, e_{t-1}, \ldots, e_{t-5}$ – are forecast errors in periods t, t-1, . . ., t-5; $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-10}$ – past values of time series in periods t, t-1, ..., t-10.

When the coefficients ϕ_1, Φ_1, θ_1, Θ_1 are estimated from the data this equation can be used for forecasting [25].

2.1.3 Seasonal addition methods

It is a method of seasonal indexes, which, in some cases is called Seasonal addition. The method of seasonal indexes is based on the idea to assign some seasonal mark (index) to the particular period, and the forecast result is charged by this index according to the forecast period. For example if a case regards the annual seasonality, i.e. periodicity is 12 months, 12 indexes need to be calculated. When the data from several years then total (average) indexes are calculated (their number is also 12) [25].

$$SI^J_{JAN} = Y^J_{JAN}/Y^J_0; SI^J_{FEB} = Y^J_{FEB}/Y^J_0; \ldots SI^J_{DEC} = Y^J_{DEC}/Y^J_0 \quad (5)$$

where: SI^J_{JAN} – seasonal index of January in year J, etc., Y^J_{JAN} – observed value in January year J; Y^J_0 – average of observed values Y in year J.

$$TSI_{JAN} = \Sigma^m_{J=1} SI^J_{JAN}/m; TSI_{FEB} = \Sigma^m_{J=1} SI^J_{FEB}/m; \ldots TSI_{DEC} = \Sigma^m_{J=1} SI^J_{DEC}/m \quad (6)$$

where: TSI_{JAN} – total seasonal index of January, etc.; m – number of observed years.

2.2 Methods of measuring forecast error

There are many ways to verify the reliability of calculated forecasts. One way is comparing the model accuracy with real values within the interval <1; n>, where n is a number of comparisons (Real value - Forecast value). Another way is comparison calculated (forecasted) values with the actual event which will occur in the future. This method has a disadvantage in taking a long time, because the error indicators of forecasting react to the incorrect forecasts after a certain amount of comparison (Real value - Forecast value) in the future. The third way is a comparison of the real and forecasted values again back in the past, however, unlike the first method, these data are not included in the calculation of the forecast.

There are widely known indicators for the calculation of the forecast errors, for our case Mean Absolute Percentage Error (MAPE) is the chosen indicator which indicates the error in percentage and is the clearest expression of forecasting errors.

$$MAPE = (1/n)\Sigma^n_{i=1}((\text{Real value}_i - \text{Forecast}_i)/\text{Real value}_i) \quad (7)$$

MAPE calculation in the presented model is done by the software according to the first mentioned case.

2.3 Simulation sampling method

The simulation is done by Monte Carlo methodology. Its principle is to generate randomly values in all assumptions that are previously defined in the forecasting model. There is also defined the number of random generations (the more generations, the more accurate the calculation is) which also mean the number of calculations. This is advisable to explore ranges of outcomes and also to graphically express the forecast.

3 Defining the forecasting problem

The described methods and procedures are used for forecasting sales of the chosen product. The sale of a refrigerator serves as a model case study. The real sales data was obtained from a retail store, which is a part of the big store network of electronics and home electrical appliances. Data of sales, prices and revenues over a period of 24 months is presented in Table 1. Revenues are calculated by multiplying the quantity sold and the average price. Total revenues are the sum of the monthly revenues.

The forecast is based on historical data - the quantities sold and the average monthly prices. The time series is 24 months. The basic unit of time for which forecasts are made (the forecasting period) is a month. The forecasting horizon is 12 months. On the basis of the time series analysis of two-year sales, it is clear that the different phases of raised and fallen sales are repeated. In our case it is the season of one year period (cycle) i.e. 12 months. The aim is to forecast sales in value terms (sales) to be the dependent variable on the independent variables, price and quantity. Although the law in terms of market price and the quantity sold are mutually influenced values for the purposes of this model, reliance between the price and quantity is neglected. It is due to the simplification of the model, but also on the basis of real market conditions. This is a product with many substitutes, and the demand is influenced by a number of other factors. Price is considered as partially controllable independent variable with the specified interval of variability (maximum and minimum price). Demand is expressed in numbers of sold units and it is the independent non-controllable variable. Forecasting method is selected based on the accuracy of forecasts. Input parameters for forecasting are in the Table 2.

Causal model is also based on the following estimates (or required) values of particular parameters:

Forecasting is performed to achieve the highest accuracy of forecasting. Inaccuracy is set to be not more than 10% according to the MAPE. The required sale growth rate is set to 2%. It is estimated according to the latest annual increase. The final forecast and expected value of sales is analysed according to the simulation results in terms of probability and risk. Monte Carlo simulations are performed with 1000 trials.

4 The procedure of forecast creation

The procedure of forecast creation, simulation and the result analysis consist of the following activities:

1. Forecasting:
   - time series analysis in term of seasonality;
   - definition of variable dependence;
   - "events" impact analysis to time series behaviour;
   - the choice of methods of forecasting, choice of forecast errors calculation method.
2. Simulation and risk analysis:
   - uncertainty definition for random variables (distribution, probable value, standard deviation etc.);
   - analysis of the probability of achieving the expected outcomes;
   - the sensitivity analysis of output to inputs variability.

The scheme of the procedure is shown on Figure 1.

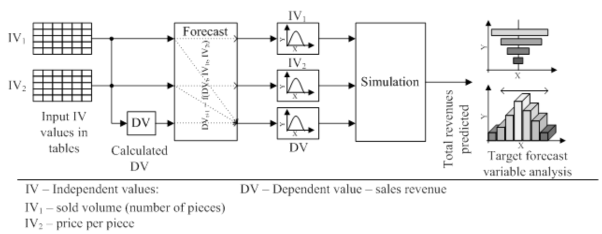

Figure 1: Scheme of forecast and simulation procedure.

4.1 Forecasting and simulation parameters definition

Forecasts are created for both independent and variables – sale and price. The forecasted value at sale is further considered as average value of the required amount. For the simulation, assumption for sale is defined by the normal distribution with standard deviation 5 (Table 3), which corresponds to the real potential deviations from the forecast demand (Figure 2). The price, as indicated above, is partly adjustable value and its variety partly reflects the impact of other non-controllable market variables. Forecasted values, in defining the assumption, are considered as the most probable value for the triangular distribution. Other distribution parameters are the minimum and maximum values. The minimum value of €200 is the lowest limit of price, the goods has been never sold below this price. The maximum value of €270 is the upper limit prices (Figure 2). Forecast and simulation settings are presented in the Table 3.

There are two models presented for forecasting of sales based on different assumptions:

Table 1: Input data about the sale, monthly average prices and revenues.

Period	Month	Sale [€]	Average price [€]	Sales revenue [€]	Total revenue [€]
1	January ´14	104	259	26936	
2	February ´14	81	265	21465	
3	March ´14	131	259	33929	
4	April ´14	146	250	36500	
5	May ´14	143	248	35464	
6	June ´14	204	230	46920	
7	July ´14	212	220	46640	441009
8	August ´14	211	220	46420	
9	September ´14	156	230	35880	
10	October ´14	145	235	34075	
11	November ´14	185	220	40700	
12	December ´14	164	220	36080	
13	January ´15	125	245	30625	
14	February ´15	115	259	29785	
15	March ´15	131	250	32750	
16	April ´15	144	256	36864	
17	May ´15	166	250	41500	
18	June ´15	195	220	42900	
19	July ´15	200	225	45000	457067
20	August ´15	195	225	43875	
21	September ´15	203	246	49938	
22	October ´15	131	230	30130	
23	November ´15	174	220	38280	
24	December ´15	161	220	35420	
	Growth rate				3.6%

Table 2: Input parameters for forecasting.

Forecast and simulation parameter	Value
Forecasting period	1 month
Forecasting horizon	12 months
Time series	24 months
Range of price	€200 – 270
Desired accuracy of forecast (MAPE)	<10 %
Desired revenue growth	>2 %
Number of trials in simulation	1000

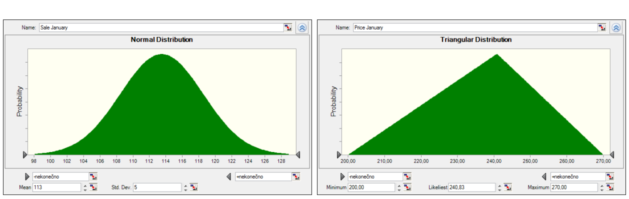

Figure 2: Example of normal and triangular distribution for January sale and price.

1. The first model presents a simple model for seasonal forecasting, which is determined based on the analysis of historical data. There are clearly identifiable fluctuations of sales in time series, where is the cycle repeated in 12 months. Forecasting method is selected on the basis of accuracy according the MAPE, while the most accurate method is chosen, by which the forecasted curves takes significant features of the historic behaviour.
2. The second model of forecasting uses the function event that allows to give more weight to data at certain periods to increase the forecast accuracy. The factors, that have a significant impact on the final forecasted value and are not the input variables, are possible to take into account in forecasting. These are, for example, hot summer time and associated higher demand of the sold product, respectively a higher failure rate in the case of the presented model. The second event is the pre-Christmas period and the end of the year when households and companies are buying more (Table 3).

4.2 Forecasting results

Based on the above specified parameters, settings and methods, the forecast is conducted. It is predicted price, sold quantity and revenue per month. Total revenue is counted as the sum of monthly revenues. There are forecasted value of revenue per year of €448,824 for the first model and €462,167 for the second model. Both forecasts are lower than expected total revenue €466,208, which is estimated by the growth rate of the last period to 2%. All predicted values of variables and target values are shown on Table 4. The diagrams of historical and forecasted values for sale and sales revenue are in Figures 3 - 6.

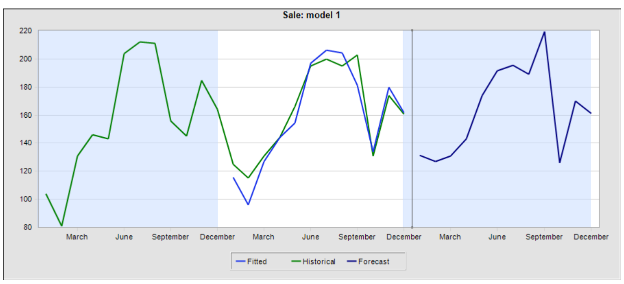

Figure 3: Forecast diagram of variable sale: model 1.

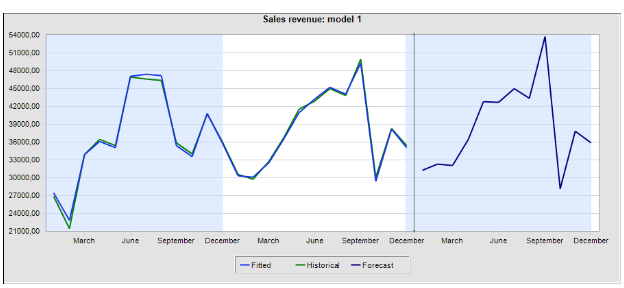

Figure 4: Forecast diagram of variable sales revenue: model 1.

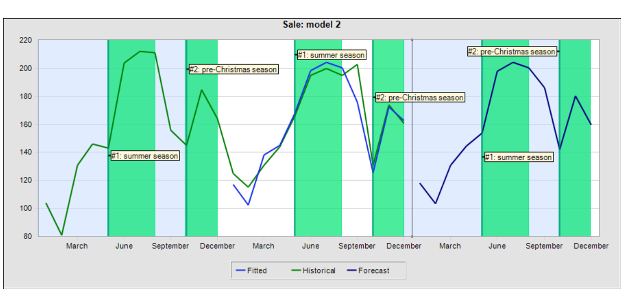

Figure 5: Forecast diagram of variable sale with marked events: model 2.

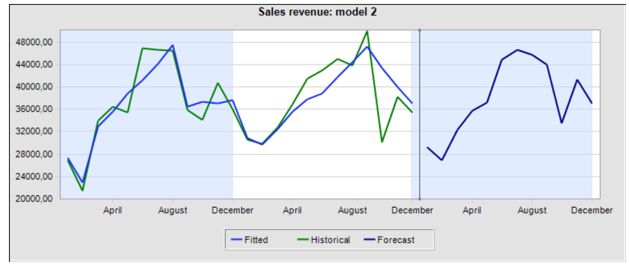

Figure 6: Forecast diagram of variable sale revenue: model 2.

4.3 Monte Carlo simulation process results

Monte Carlo simulation is done for the forecasted variable of total sale revenue. The simulation results are available in the form of diagrams and reports presenting the statistical characteristics of the simulation. In our case, according to the simulation (Figure 7 and 8), when considered the above defined uncertainty of sales and prices, there is low probability that sales next year will reach at least the forecasted level. The probability to achieve total revenue at forecasted level is about 33.27% according to model 1 and 41.32% according to model 2 (Figure 6 and 7). The probability of estimated increasing of total revenue about 2% (€466208) is only 0.83% for model 1 and 26.63% for the second model.

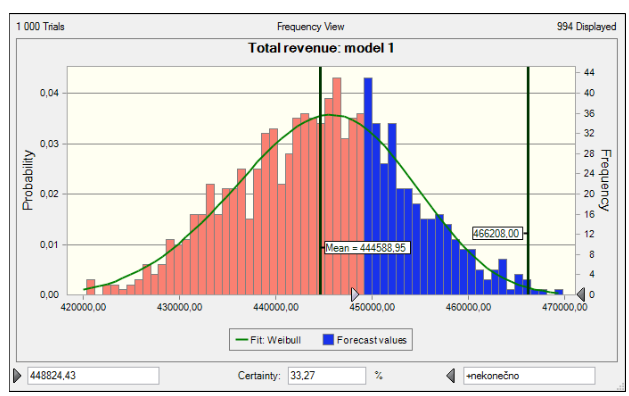

Figure 7: Forecast chart for total revenue per year: model 1.

Risk analysis of the forecast results includes sensitivity analysis and variables impact analysis. The influence of assumptions on the target forecast variable (total revenue) is shown on the sensitivity chart. Sensitivity chart displays which assumptions are the most important or least important in the model. Tornado chart displays which input variables have the greatest impact on the result. It allows us to focus on those factors that drive outcome while ignoring irrelevant factors.

Table 3: Forecast and simulation settings.

Parameter	Independent variable		Dependent variable
	Sale	Price	Revenue
Forecast method: model 1	Seasonal Additive	SARIMA(2,0,2)(1,0,1)	Multiple linear regression
Forecast method: model 2	SARIMA(1,0,0)(0,1,1)	SARIMA(2,0,2)(1,0,1)	Multiple linear regression
Seasonality	Yes	Yes	Yes
Cycle	12 months	12 months	12 months
Error measure	MAPE	MAPE	MAPE
Distribution	Normal	Triangular	–
Distribution parameters	Std. Dev. 5 Mean (forecast)	Min. 200, Max.270 Likeliest (forecast)	–
Event	Summer season Pre-Christmas season	–	–

Table 4: Forecasted values.

Month	Sale [€]		Average price [€]		Sales revenue [€]		Total revenue [€]	
Model	1	2	1	2	1	2	1	2
January	113	118	240.83	237.88	26895	28270		
February	96	103	254.88	250.88	24937	25935		
March	131	131	246.74	242.54	32040	31882		
April	145	145	255.91	252.84	36861	36256		
May	153	154	249.25	247.30	37810	37876		
June	200	198	221.23	219.48	44698	45888		
July	207	204	229.55	228.76	47593	48289	448824	462167
August	204	201	229.12	228.88	46855	47433		
September	177	186	248.91	249.60	43489	46035		
October	139	142	229.45	240.90	31213	34375		
November	180	181	223.59	232.42	40269	42907		
December	163	160	224.14	224.25	36161	37021		
Error measure % (MAPE)	10.23	4.18	1.93	1.63	1.19	3.49		
Total sale revenue assumption (2% growth)							466208	

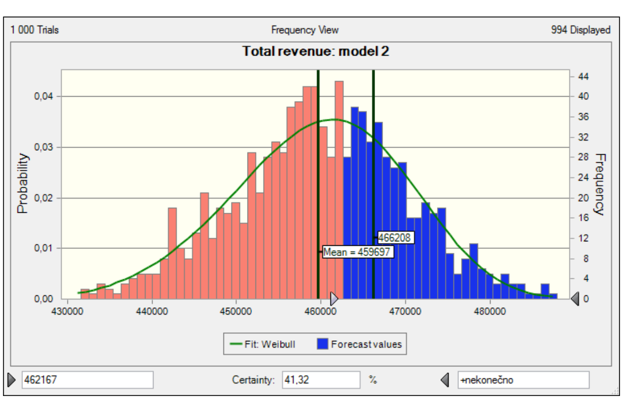

Figure 8: Forecast chart for total revenue per year: model 2.

The results of sensitivity analysis and tornado chart show that the variable with the greatest impact on total revenue in both models is sold volume in July, August and June (Figure 9 and 10). These are months with the largest quantity sold. But sensitive analysis for model 1 shows that price assumption in particular months, especially in March, August and April, has the strongest impact on the target forecast variable. In model 2, where sale in some seasons has significant impact on the final forecasted value, the most important variable is sale assumption (Figure 10).

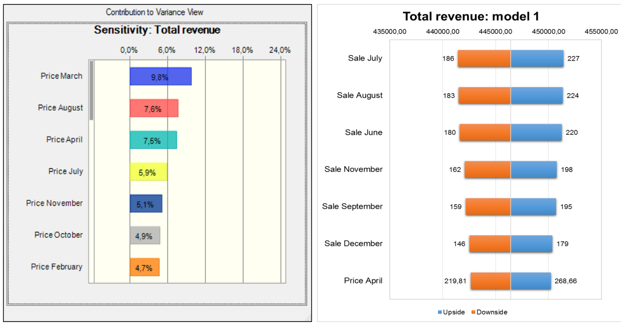

Figure 9: Sensitivity chart and tornado chart for total revenue per year: model 1.

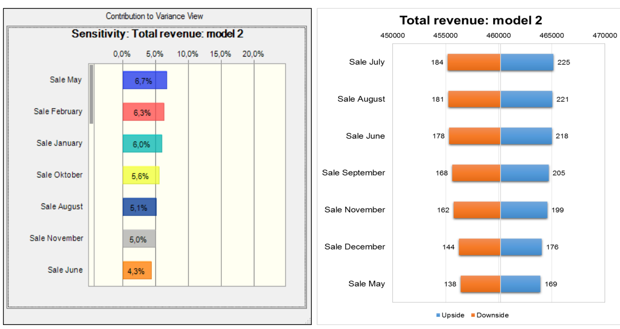

Figure 10: Sensitivity chart and tornado chart for total revenue per year: model 2.

5 Summary and discussion

Two models of approaches of forecasting have been demonstrated in this case study. According to model one, where the impact of other events is not considered, forecasting of sales and prices reached a lower accuracy than forecast by model 2 (Table 4). Forecast of dependent variables showed a slightly higher errors (MAPE 3.49%) in model 2 as in model 1 (MAPE 1.19%) which is, however, sufficient accuracy. After defining the uncertainty for the independent variables, the probability of achieving the forecasted values of total revenue per year was tested by the simulation Monte Carlo. The probability to achieve the level of total revenue at least of forecast level is lower in model 1 than in model 2 (Figure 7 and 8). This analysis, when considering the uncertainty of prices and sales, also confirms forecasts with lower errors in model 2. Risk analysis, in case of output sensitivity to the variability of input, identifies major risk of variability of prices in model 1, on the contrary, a major risk in model 2 is uncertainty of demand. Tornado chart, for both models, identifies the sales in each month as the factor with the most significant impact on the target variable, in descending order from "strongest" month.

An important factor affecting the accuracy of the forecast is to define uncertainty. There was uncertainty of sale defined by the normal distribution with a standard deviation of 5 pieces from predicted values in this case study. Uncertainty defined for price is defined with triangular distribution, interval considered from the lower to upper price limit. The likeliest value is according to the forecast (Table 3). When defining assumption by this way, in some months, the price was the most likely situated near the lower or upper price limit, which increased the risk of price movements to positive or to negative direction. This aspect is reflected in the sensitivity chart in model 1, when the price is a greater risk that revenues are deflected from the forecasted value. When creating model 2, events have been defined to emphasize selling. By this, the selling has been evaluated as dominant risk variable (Figure 10) by the software. Since, the price is a more controllable variable, model 2 is more accurate and better corresponds to the image of the real behaviour of the market.

6 Conclusion

Forecasting is a crucial process in terms of logistics, based on which many activities in a company and supply chain are planned and implemented. Forecast accuracy affects readiness of the enterprise to be flexible in responding to market demand, its future costs and benefits. The use of appropriate programs is a way how to make the forecasting process more effective.

In this article, a sale forecasting using the software tool for risk analysis has been presented. Based on time series analysis, forecasting, statistics analysis and risk analysis was conducted. Forecasting has been undertaken using two different approaches- when considering simple seasonality of sales (model 1) and when considering sale seasonality along with the impact of known events on demand (model 2). Subsequent analysis of forecast has been focused on the identification and analysis of risk factors. Defining input variables uncertainty and using Monte Carlo simulation the probability of achieving the forecast revenue and the likelihood of achieving the estimated revenue growth were analysed. Model 2 was considered to be more accurate. Using sensitivity analysis the variables which assumption most influenced the target were identified. These were the variables that the company should monitor in order not to miss the objective pursued. In model 2, sale uncertainty is the most serious factor and company's marketing activities should be aimed in this direction. In model 1, it is price. The most important variables in terms of the objective achievement are sales and they were presented in the tornado charts.

The presented case study describes only a model situation and greatly reduces the complexity of reality. It presents the possible approaches to creating simulation models in forecasting and risk analysis. But creation of a specific model must always be based on the particular situation and reflect the specific conditions. The use of software tools in forecasting can increase accuracy, or identify risks at a number of uncertain or variable inputs that affects the target. It is necessary to note, while the simulation software tools allow the ability to process large amounts of data numerically, they have their limitations. Computer simulation cannot fully replace comprehensive thinking ability of a human who uses heuristic methods and broader perception of reality.

The researched issue makes a wide space for further research in the area of using computer simulation, risk analysis and solution optimization in order to maximize or minimize the output (profit, costs, etc.). The topic is interesting also in terms of further development of software tools that would be able to create simulation models including complex set of variables.

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