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Chapter

Seeking Accuracy in Forecasting Demand and Selling Prices: Comparison of Various Methods

Zineb Aman, Latifa Ezzine, Yassine Erraoui, Younes Fakhradine El Bahi and Haj El Moussami

Abstract

The need for a good forecast estimate is imperative for managing flows in a supply chain. For this, it is necessary to make forecasts and integrate them into the flow control models, in particular in contexts where demand is very variable. However, forecasts are never reliable, hence the need to give a measure of the quality of these forecasts, by giving a measure of the forecast uncertainty linked to the estimate made. Different forecasting models have been developed in the past, particularly in the statistical area. Before going to our application on real industrial cases which highlights a prospective study of demand forecasting and a comparative study of sales price forecasts, we begin, in the first section of this chapter, by presenting the forecasting models, as well as their validation and monitoring.

Keywords: forecasts, accuracy, quality of forecasts, demand forecasting, selling price forecasting

1. Introduction

For most companies, forecasting is a prerequisite for effective supply chain management. As explained by Lai et al. [1], forecasting is the basis of all production management systems. The entire supply chain is based on the data from forecast models.

In Ref. [2], the authors show the usefulness of forecasting and planning as a decision-making tool for organizing the supply chain across all horizons of time and at all levels.

In the academic field, forecasting occupies an important place. Given the primordial role of forecasting, we understand why many models have been developed since the beginning of the twentieth century. Research mainly developed from the 1950s onward with the use of mathematical models. A review of the literature was carried out by Stadtler [3]. We find there the interest of forecasting for the global supply chain in order to integrate the different organizations and coordinate their flows in order to satisfy the end consumer.

The various sources for making these forecasts are located throughout the supply chain, including the commercial part of the business. It is the analysis of this source that will help build the basis for future forecasting. In the end, the sources used to build the forecasts are therefore multiple.

2. Application to prospective approach: modeling and forecasting demand using the ARIMA models

In the manufacturing sector, forecasting demand is one of the most crucial problems in inventory management [4]; it can be used in various operational planning activities during the production process: capacity planning and management of used product acquisitions [5].

For both types of push/pull supply chain processes, demand forecasting forms the basis of all CS planning. The "pull" processes in the SC are performed in response to the client's request, while all the "push" processes are performed in anticipation of the client's request [6]. A business needs to know many factors related to forecasting demand. Some of these factors are listed below:

- past requests;
- product delivery time;
- planned advertising or marketing efforts;
- state of the economy;
- price reduction planned; and
- actions undertaken by competitors.

Businesses need to understand these factors before they can choose an appropriate forecasting method as it can be difficult to decide which method is the most suitable for forecasting. Forecasting methods are classified into the following types: time series, causal, qualitative, and simulation [6].

A time series is considered to be a set of observations cited in chronological order [7]. To forecast demand, time series forecasting models are based on historical data. These mathematical models used are based on the assumption that the future is an expansion of the past [8].

Numerous studies on demand forecasting by time series analysis have been carried out in several fields. They include demand forecasts for food sales [9], tourism [10], spare parts [4, 11], electricity [12, 13], automobiles [14], and some other goods and services [15–17].

In this section, we forecast the demand for a product in a food manufacturing operation based on real data, as well as the precision and characteristics of these forecasts.

Our study will be carried out according to the three stages of the Box-Jenkins approach: identification, estimation, and verification. We present the model relating to product demand from January 2010 to December 2015 as shown in **Figure 1**.

2.1 Identification of model

This refers to the initial preprocessing of the data to make it stationary and to the choice of p and q values that can be adjusted during model fitting.

We present the ACF and PACF diagrams of the series in **Figures 2** and **3**, respectively. We find that this series oscillates, respectively, around an average value, and its autocorrelation function decreases to zero point rapidly, which proves the stationarity of the time series studied.

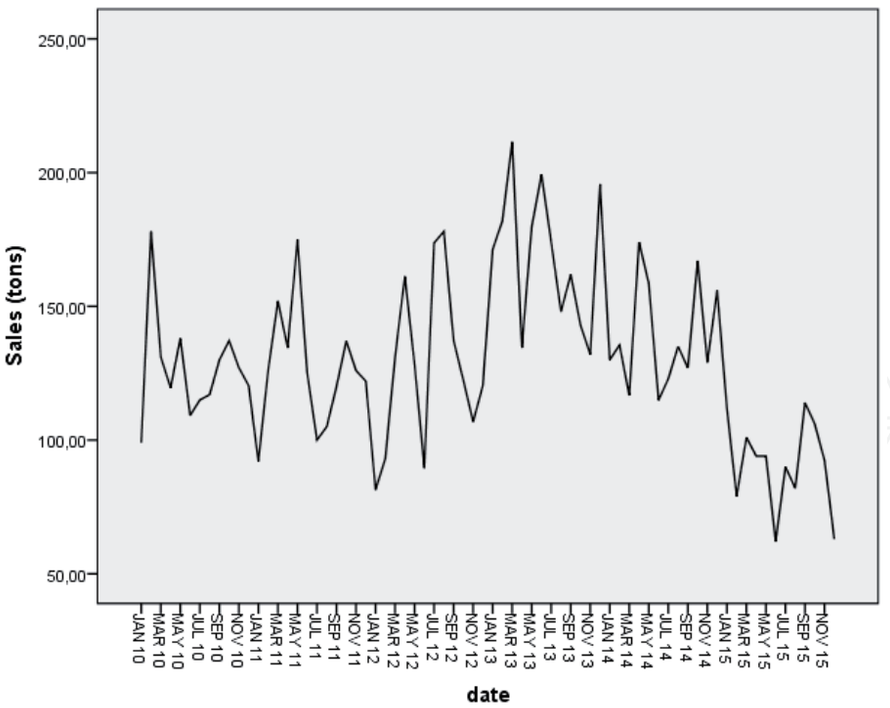


Figure 1.
Evolution of the final product's sales.

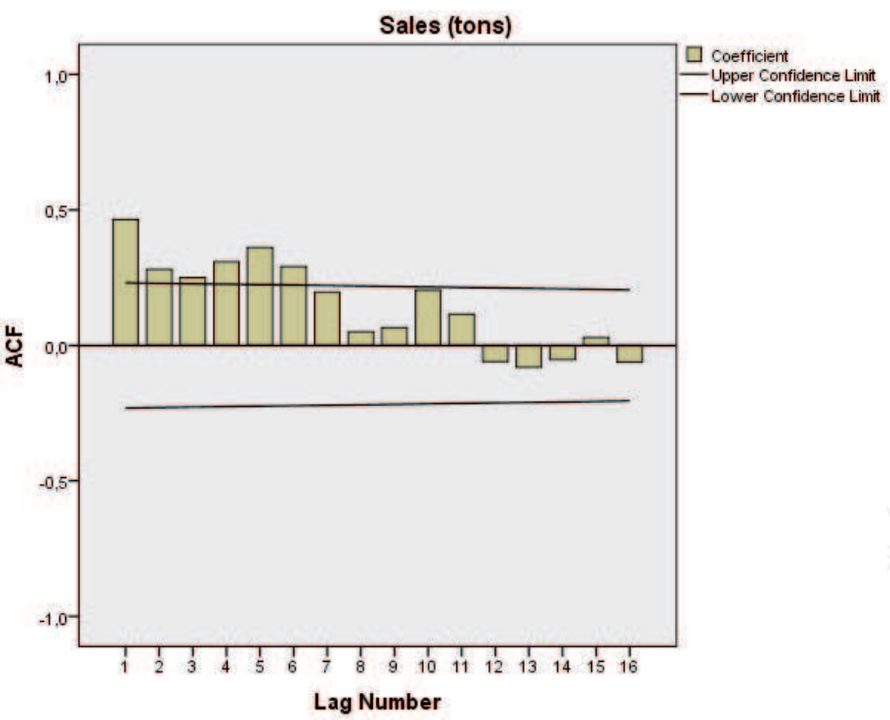


Figure 2.
ACF correlograms of the demand series.

Moreover, to assess whether the data come from a stationary process, we can perform the unit root test: Dickey-Fuller test for stationarity. After carrying out the test on the Xlstat software, the results are grouped in **Table 1**.

H_0: The series has a unit root.

H_1: The series does not have a unit root. The series is stationary.

The null hypothesis H_0 cannot be rejected since the calculated p value is greater than the significance level α set at 0.05. We calculated the risk of rejecting the null hypothesis H_0, while it is true. The risk is 84.38%.

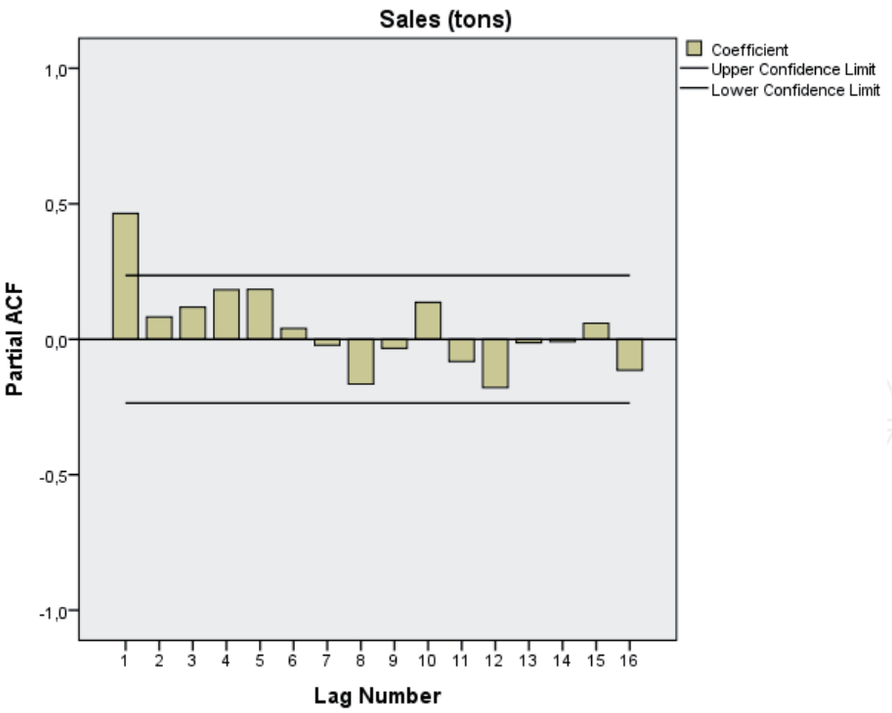


Figure 3.
PACF correlograms of the demand series.

Tau (observed value)	−1.350
Tau (critical value)	−0.717
p (unilateral)	0.844
α	0.05

Table 1.
Test results.

In our study, we checked the stationarity of the series, and we noted from the ACF and PACF correlograms that our model cannot be pure RA or pure MA. Therefore, we tested several models to identify the most suitable for our series.

2.2 Estimation of model coefficients

Using the ARIMA procedure of the SPSS time series module [18], we can estimate the coefficients of our model by providing the parameters p, q, and d [19–22].

The best model is as simple as possible and minimizes certain criteria, namely AIC criteria (Akaike criterion), SBC (Bayesian criterion of Schwarz), variance, and maximum likelihood [23–25]. The chosen model is that of ARIMA (0, 1, 1). For other models, either the Student "T-RATIO" test values are found in the range of ±1.96, or one of the values of the minimization criteria is higher than that found for the ARIMA model (1, 0, 1) with the constant value.

Table 2 presents the values of the different models. From this table, we choose the appropriate model on which we will base ourselves to make our forecasts.

It is clear from **Table 2** that the ARIMA model (1,0,1) is selected because all the coefficients are significantly different from 0 according to the Student test ($|\text{T-RATIO}| \geq 1.96$) with an acceptable level of adjustment.

The model residue is stationary and follows a white noise process in the range of ±40. The residue histogram shows whether the distribution of residues approximates a normal distribution. In our case, we have residues that distribute relatively normal around zero and with a relatively low dispersion at a 5% risk.

Characteristics		Models					
		ARIMA (1,0,2)	**ARIMA (2,0,2)**	**ARIMA (1,0,1)**	**ARIMA (1,0,0)**	**ARIMA (0,0,1)**	**ARIMA (1,0,1) without constant**
AR (1)	α_1	0.92913	0.71371	0.90792	0.49434	−0.41704	0.99755623
	SEB	0.104616	0.761758	0.094852	0.1074471	0.1119989	0.00444769
	T value	8.8813204	0.9369292	9.571955	4.600820	−3.723567	224.28617
	p value	0.00000000	0.35216008	0.000000	0.00001823	0.00039384	0.0000000
MA (1)	θ_1	0.52269	0.31779	0.63880			0.71392452
	SEB	0.167073	0.741595	0.161531			0.08579173
	T value	3.1284995	0.4285186	3,954655			8.32160
	p value	0.00258711	0.66964815	0.00018319			0.0000000
AR (2)	α_2		0.19759				
	SEB		0.659442				
	T value		0.2996279				
	p value		0.76538859				
MA (2)	θ_2	0.17062	0.30202				
	SEB	0.142258	0.409353				
	T value	1.1993429	0.7377864				
	p value	0.23455708	0.46322050				
Constant	Cte	124.42969	124.52640	125.53260	128.53887	129.22650	
	SEB	12.608189	12.601296	11.785537	6.5715235	4.8971088	
	T value	9.8689581	9.8820312	10.651411	19.559981	26.388326	
	p value	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	
AIC		688.86593	690.82312	688.77347	689.37103	693.59055	692.04831

Characteristics	Models					
	ARIMA (1,0,2)	**ARIMA (2,0,2)**	**ARIMA (1,0,1)**	**ARIMA (1,0,0)**	**ARIMA (0,0,1)**	**ARIMA (1,0,1) without constant**
SBC	697.9726	702.20645	695.60347	693.92437	698.14388	696.60164
Log likelihood	−340.43297	−340.41156	−341.38674	−342.68552	−344.79527	−344.02415
Error	28.034898	28.221721	28.214812	28.576249	29.443759	28.461048

Table 2.
Coefficients of different models.

The chosen model parameters are presented in **Table 3**.
The developed model is given by Eq. 1.

$$y_t = \delta + \alpha_1 y_{t-1} - \theta_1 \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

With:

- y_t , y_{t-1} : sales of periods t and t–1, respectively.
- $\varepsilon_t, \varepsilon_{t-1}$: residuals of periods t and t–1, and constitute a white nose.
- α_1, θ_1: coefficients of autoregressive and moving average processes, respectively.

We can easily extract from **Table 3** the coefficients of the autoregressive processes and moving averages and inject them into Eq. (1), which becomes:

$$y_t = 125{,}524 + 0{,}90792\, y_{t-1} - 0.6388\, \varepsilon_{t-1} \quad (2)$$

2.3 Accuracy of ARIMA (1, 0, 1) model

In order to assess the accuracy of the developed model, we compare the experimental and simulated sales during the same period. This comparison is drawn up in **Table 4** and reveals that the model selected has great precision and an ability to simulate dynamic sales behavior. Therefore, this model can be used to analyze and model the demand in this food manufacturing.

Figure 4 shows that the model is validated since the predicted demand fluctuates around the adjustment and the forecast demand, which remained between the upper limit and the lower limit.

The error varies, but it is within the tolerance range. In order to minimize this error, we are opting for other approaches in our future work.

2.4 Forecast

Once the appropriate model is defined and validated, we must do the forecasting, using the IBM SPSS forecasting. **Table 4** and **Figure 5** present the results of the

AR (1)	α_1	0.90792
	SEB	0.094852
	T value	9.571955
	p value	0.00000000
MA (1)	θ_1	0.63880
	SEB	0.161531
	T value	3.954655
	p value	0.00018319
Constant	Δ	125.53260

Table 3.
ARIMA model parameters.

Model		73	74	75	76	77	78	79	80	81	82
Sales-Model_1	Prévision	95.12	97.92	100.46	102.77	104.86	106.77	108.49	110.06	111.49	112.78
	UCL	151.41	156.21	160.35	163.95	167.08	169.83	172.25	174.38	176.26	177.93
	LCL	38.83	39.63	40.57	41.59	42.64	43.70	44.74	45.75	46.71	47.63

Table 4.
Forecast sales from January 2016 to October 2016.

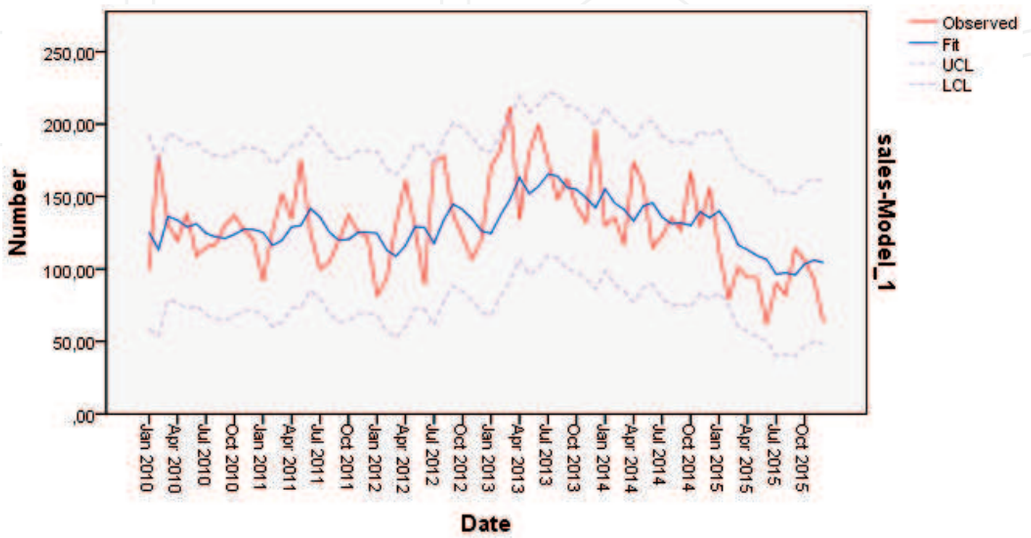


Figure 4.
Sales, fit, LCL, and UCL.

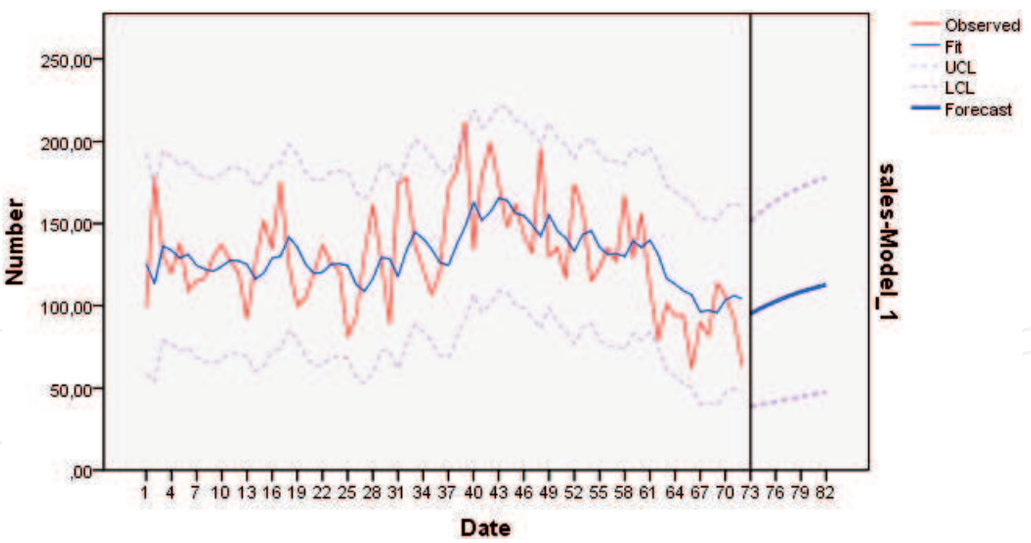


Figure 5.
Sales, fit, LCL, UCL, and forecasting.

sales forecasts that we obtained by applying our ARIMA model (1, 0, 1) for the next 10 months from January 2016 to October 2016.

The chosen model can therefore be used to model and forecast future demand in this food manufacturing. However, each time we have to feed historical data with new data to enrich it and thus improve the new model and forecasts.

The accrue forecasts presented facilitated the production decision in this business. Indeed, the model allowed us to forecast demand and make precise forecasts. Once we have a forecast of demand, it will be much easier to clearly plan the production and thus eliminate the heavy cost losses.

3. Application to comparative approach: comparison of the quality of forecasts obtained in the context of forecasting selling prices

Our second industrial application is devoted to a modeling study and comparative forecast of sales prices using ARIMA models, artificial neural networks, and support vector machines.

In this section, we will model the actual fuel price data named "SSP" in order to make important predictions to determine future selling prices. The model shown in **Figure 6** is based on the price of "SSP" fuel in a petroleum production from January 2012 to December 2016.

3.1 Forecasting using ARIMA models

3.1.1 Determination of the differentiation parameter

Under SPSS, we have drawn the autocorrelation function (ACF) and the partial autocorrelation function (PACF), the results found are presented in **Figures 7** and **8**.

The series has a large number of positive shifts for the autocorrelation function, so it must be differentiated.

The next step is to differentiate the series. You have to differentiate it enough to make it immobile but not drag with an excessive differentiation, which will cause a loss of information and therefore unstable models. In our case, we just had to take $d = 1$ because of the linearity of the trend.

Besides, to decide if the data come from a stationary process or not, we can carry out the unit root test: Dickey-Fuller test for stationarity. After performing the test on the Xlstat software, we grouped the results in **Table 5**.

H_0: The series has a unit root.

H_1: The series does not have a unit root. The series is stationary.

The null hypothesis H_0 must be rejected, and the alternative hypothesis H_1 must be accepted since the calculated p value is less than the significance level α set at 0.05. We calculated the risk of rejecting the null hypothesis H_0, while it is true. The risk is less than 0.92%.

We conclude that our model will have an order of differentiation $d = 1$. We also note that the T-RATIO for the constant of model μ is less than 2 in absolute value. We must therefore deduct it from the model before determining the parameters p and q.



Figure 6.
Selling price of "SSP."

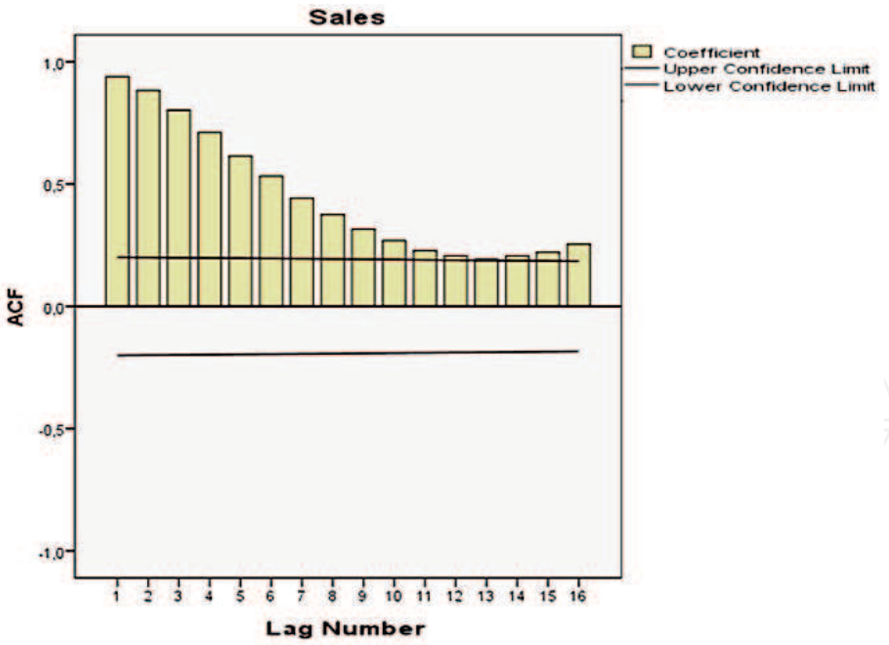


Figure 7.
ACF correlogram for the sales price series.

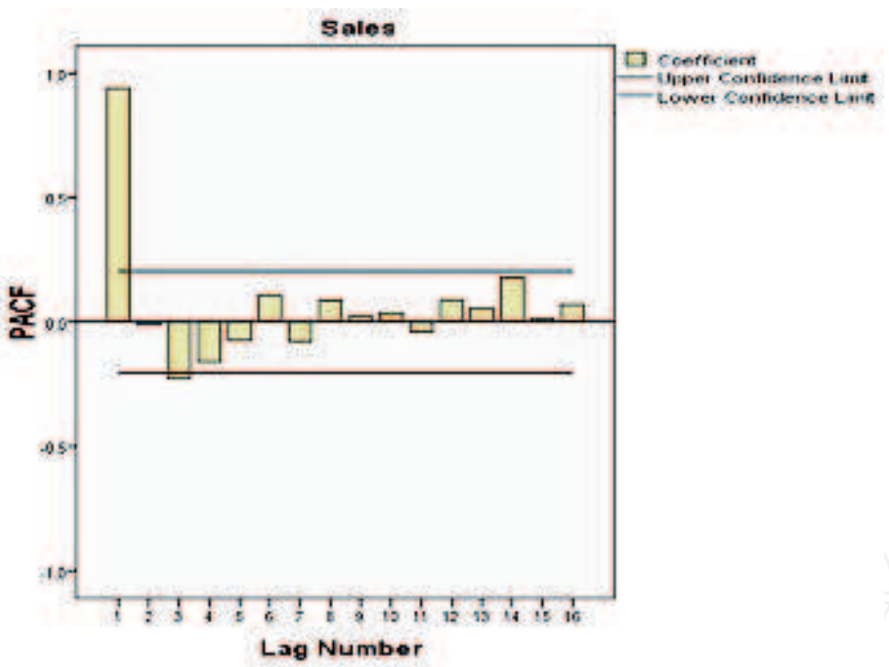


Figure 8.
PACF correlogram for the sales price series.

3.1.2 Determination of the autoregressive parameter

Figures 9 and **10** show the residue curve and the ACF and PACF diagrams of the residues of the ARIMA model (0, 1, 0), respectively.

We can clearly see from **Figures 9** and **10** that the partial autocorrelation has a significant peak at offset 2, and we can then deduce that the differentiated series comprises an autoregressive signature. The parameter p is therefore equal to 1.

However, the T-RATIO for the autoregressive parameter φ_1 is lower in absolute value than 2. So, we cannot retain this model. Similarly, the ARIMA model (2, 1, 0) presents the autoregressive parameters whose T-RATIO is less than 2 in absolute value.

Tau (observed value)	−4.0325
Tau (critical value)	−0.7648
***p* (unilateral)**	0.0092
α	0.05

Table 5.
Test results.

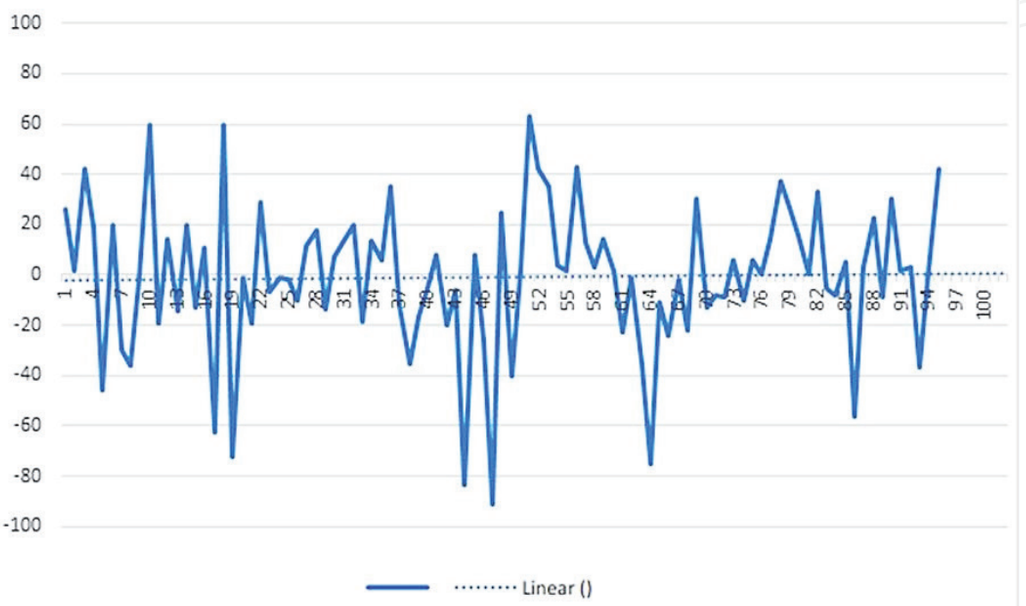


Figure 9.
Residue curve.

3.1.3 Determination of the moving average parameter

Now, the T-RATIO for the moving average parameter θ_1 is lower in absolute value than 2. So we cannot retain this model. Similarly, the ARIMA model (0,1,2) presents moving average parameters whose T-RATIO is less than 2 in absolute value.

3.1.4 Mixed ARIMA model

After several iterations and tests, we concluded that only the ARIMA model (1,1,1) had higher T-RATIOS in absolute value than 2. This is the model we should use to make forecasts.

With the coefficients obtained now, we can write the equation of the model retained as follows:

$$y_t = y_{t-1} - 0.928\left(y_{t-1} - y_{t-2}\right) + 0.873\varepsilon_{t-1} + \varepsilon_t \tag{3}$$

Table 6 lists the forecasts obtained for the first quarter of 2017.

The graph in **Figure 11** proves the adequacy of the ARIMA model (1,1,1) developed, which is very close to the real model.

Table 2 allows us to admit that the chosen model can be used to model and forecast future sales in this petroleum production.

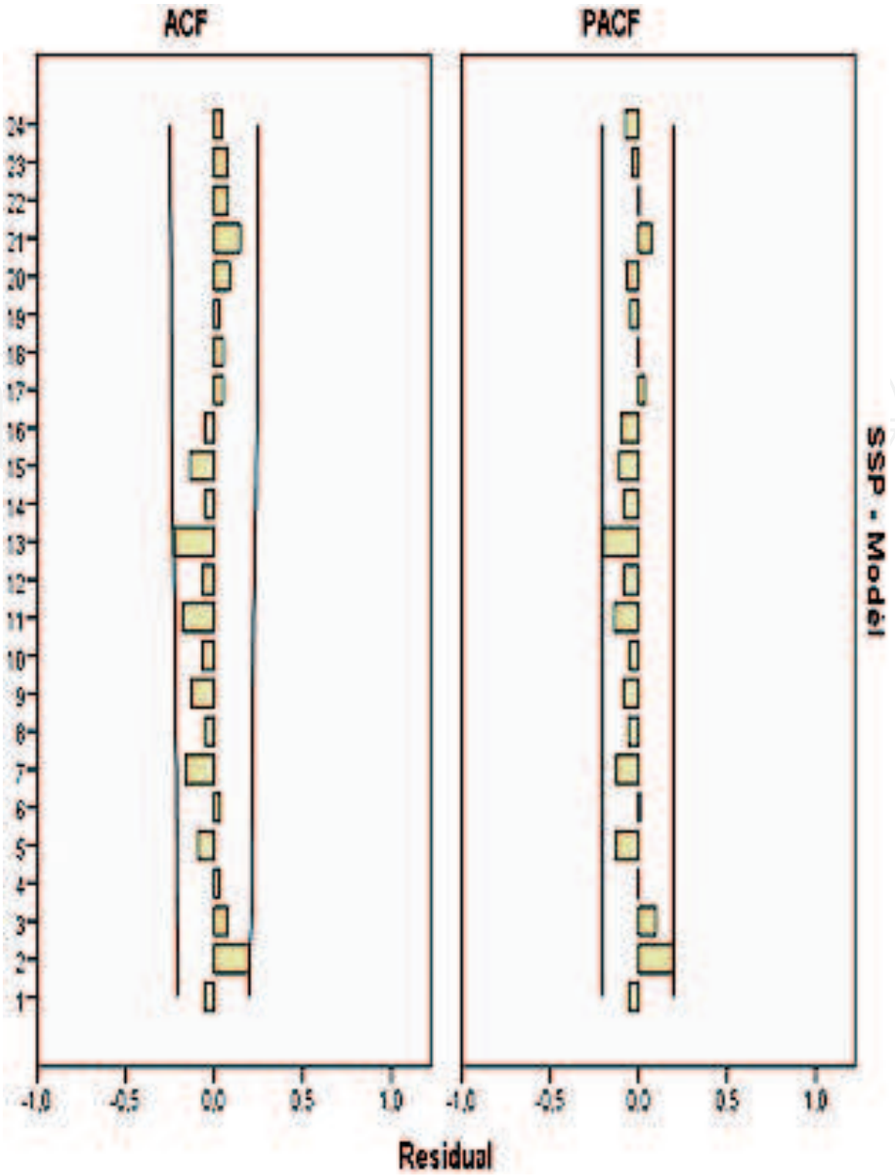


Figure 10.
ACF and PACF diagrams of the residues of the ARIMA model (0,1,0).

Fortnight	Real price	Model	% error
1Q January	1072	1042.49	−2.752798507
2Q January	1074	1043.05	−2.881750466
1Q February	1072	1043.59	−2.650186567
2Q February	1082	1044.21	−3.492606285
1Q March	1084	1044.81	−3.615313653
2Q March	1064	1045.48	−1.740601504

Table 6.
Forecast results for the ARIMA model (1,1,1) [26].

3.1.5 Forecasting using artificial neural networks

The goal here is to develop a relationship between experimental data collected from authentic sources to estimate the selling prices of fuel. We are trying to apply RBF radial-based neural networks, which are based on machine learning approaches

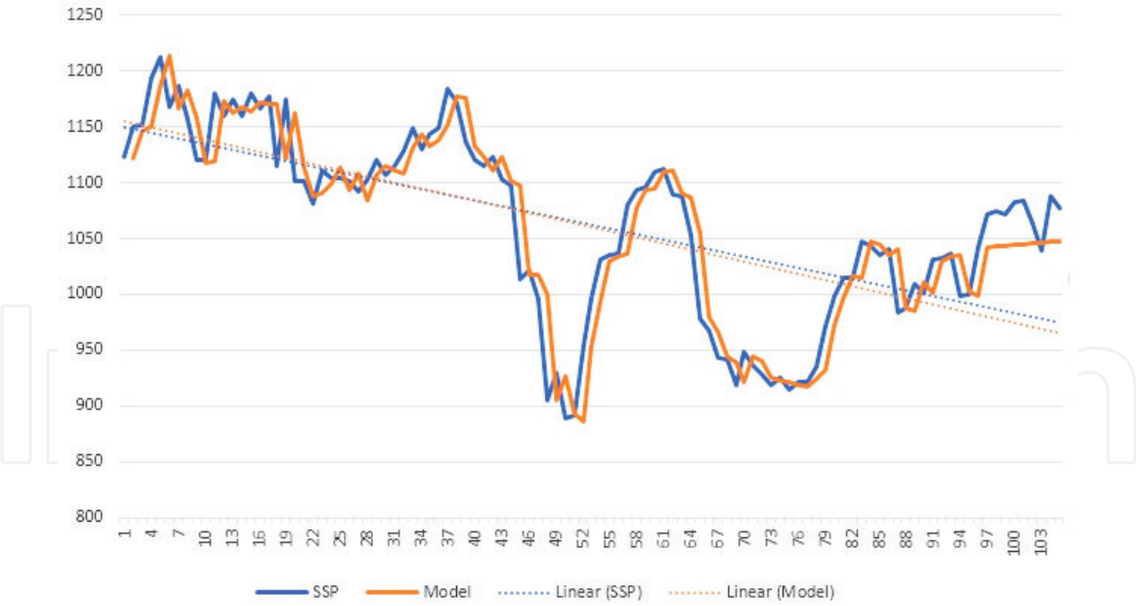


Figure 11.
Results of the ARIMA model (1,1,1) [26].

due to the complex relationships between the input parameter and the output parameter. In this section, we present the modeling approach using this technique to precisely compare it with the ARIMA model used in the previous section.

3.1.6 Model development

The radial basis ANN model (comprising two layers) is trained for implementing the back propagation algorithm to minimize the mean squared error with one parameter (time) as the input and the desired output (fuel selling price). As presented on the visualization of the network shown in **Figure 12**, the first layer has radial basis transfer functions with the maximum number of 80 neurons, and the second layer has a linear transfer function, in order to build a consistent model for providing accurate forecasts [27].

Feature selection is one of the core concepts in machine learning, which hugely impacts the performance of our model. Irrelevant or partially relevant features can negatively impact model performance. Feature selection and data cleaning should be the first and most important step of our model designing. However, in our case, this step may be omitted as long as our point cloud is significant. Subsequently, the dataset was randomly divided into two disjoint subsets of training set (60% of total dataset), which help us train our dataset to find the adequate model and testing set (40% of total dataset) to validate the model found. The training set is applied in order to develop the network. After the training phase, the reliability and accuracy

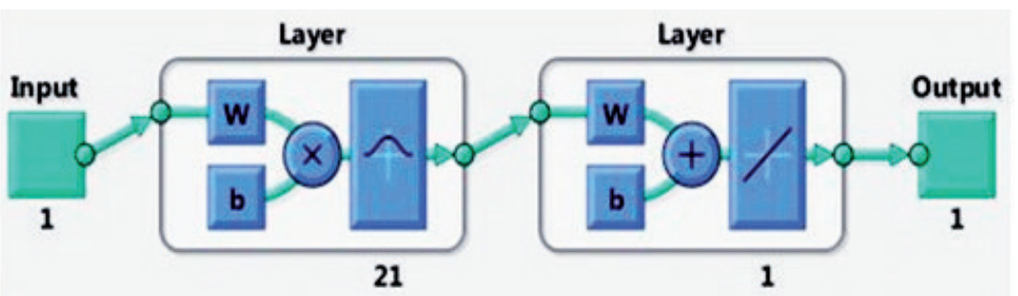


Figure 12.
Visualization of the RBF network.

of the network were perused with the test data. Besides, in our study, we implemented radial basis network of the MATLAB toolbox (i.e., "nwrb"). Furthermore, the Gaussian function is the main kernel function implemented here with the width parameter of 1 [27].

After executing the learning phase, we obtain **Figures 13** and **14** that represent the learning of our database. **Figure 15** represents the error in the training phase. During the test phase, we gave values to the input variable to visualize the results of the output and thus simulate our model.

3.1.7 Error optimization

Optimizing the error consists of a compromise to be made between the various parameters of the network, namely the speed, the objective, the number of neurons, and the number of neurons to be added to the hidden layer. This compromise is made on the basis of several tests of the different combinations carried out. Some of these combinations are presented in **Table 7**.

After making different combinations, we find that the error is considerable for all the compromises. Consequently, no model can adapt to the time series, especially in the long term. The reason behind this result is not only the large fluctuations in

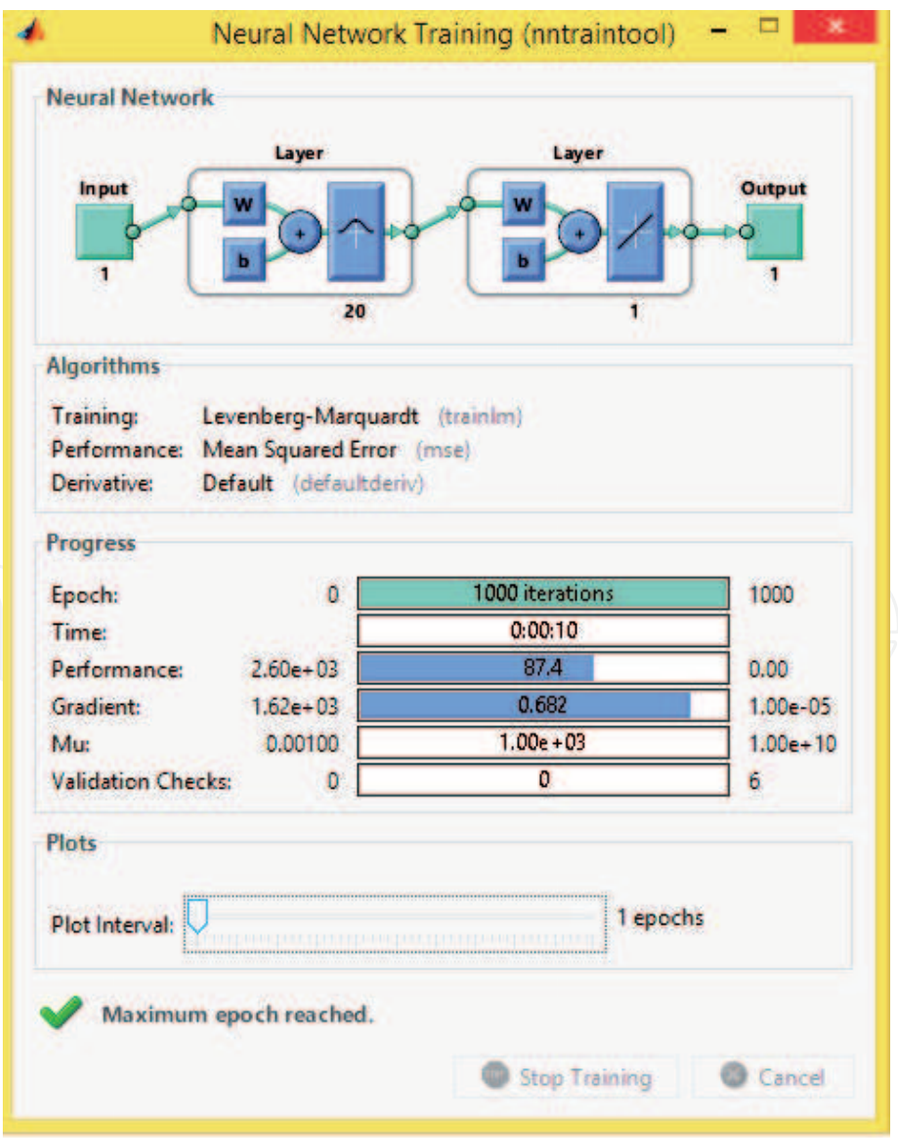


Figure 13.
Training of the RBF network.

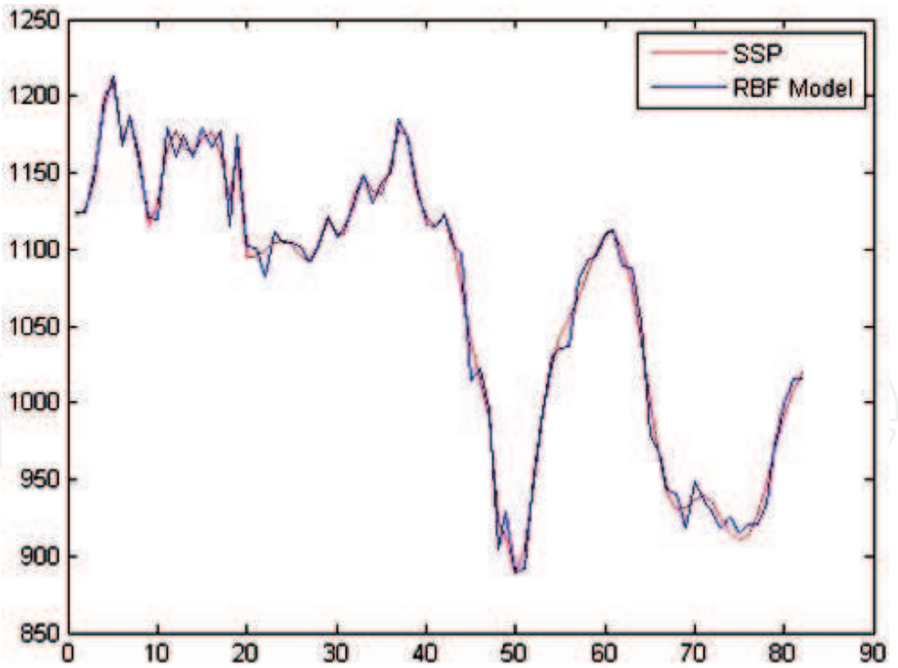


Figure 14.
Training graph of the RBF network.

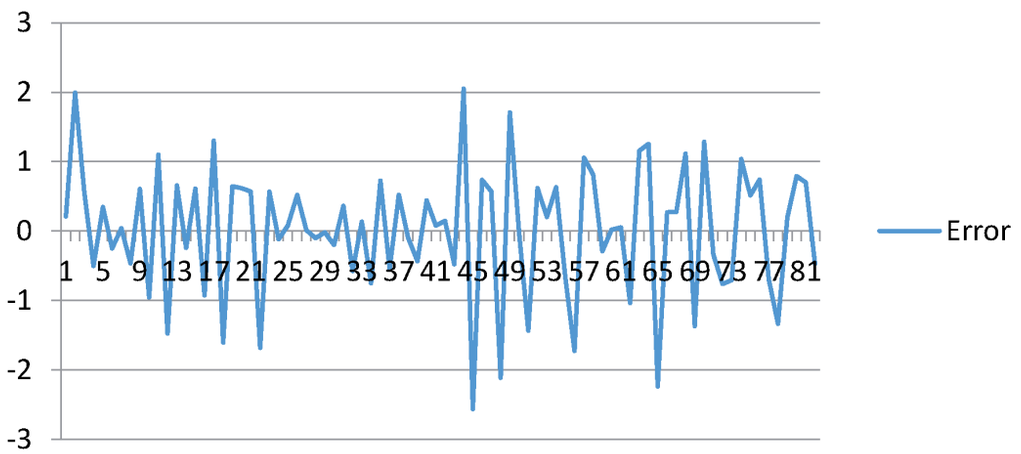


Figure 15.
The graph of error.

Parameters			
Goal	**Spread**	**MN**	**DF**
0 .01	1.5	25	25
0.01	1	25	30
0.01	2	30	30
0.01	0.8	12	30
0.01	1.57	10	30

Table 7.
Part of different combinations made.

the selling price of the fuel but also the percentage of the total dataset used in the training stage (60%). In fact, this percentage will not allow us to predict 40% of the total dataset. We will have to increase the percentage of training. In the next step,

we will consider 80% of the total dataset for the training phase and 20% for testing the model. **Table 8** summarizes the different combinations [27].

The combination that minimizes the error is therefore:

- goal = 0.01;
- spread = 1;
- MN = 20; and
- DF = 30.

We can conclude that learning with 80% of the database gives increased results in comparison with the other case (learning with 60%) since the error is minimized. The output is calculated and presented in **Table 9**.

From **Table 9**, we can clearly see that the selected model can be used to model and forecast future sales in this petroleum manufacturing. As a last part, we will use the methodology of support vector machines to see that this is going to give a result.

3.1.8 Forecasting using support vector machines (SVMs)

The aim of our current work is to develop a relationship between experimental data collected from authentic sources to estimate the selling price of fuel. We are trying to apply support vector machines based on machine learning approaches because of the complex relationships between the input parameter and the output.

We prepared our database and then developed the program in Python language, which will be compiled on Spyder software.

We imported our dataset, which is the actual price of our fuel studied, created, and indexed the location of values from the database. Then, we standardized the data so that it corresponds to the learning process that will be carried out using the SVR function. In fact, we have divided our database into a learning part and another for the test. We tried two main distributions: (1) 60% of our database used in the learning phase and 40% used in the testing phase and (2) 80% of our database used in the learning phase and 20% used in the testing phase. We have kept the second distributions based on the results obtained after compiling the program. After that, we learned "Train X" and "Train Y" and executed the test to finally calculate the average of the errors and obtained the values predicted in the test phase, which are grouped in **Figure 16**.

The average error is equal to 26.882361, which represents 2.53%. The error graph is shown in **Figure 17**.

Parameters				**Relative error (%)**
Goal	**Spread**	**MN**	**DF**	
0.01	1	10	30	9.37
0.01	0.25	25	25	7.61
0.01	0.5	30	20	5.29
0.01	0.8	30	20	3.21
0.01	1	20	30	**1.95**

Table 8.
Error comparison for several combinations of parameters.

It is clear that the model chosen can be used to model and forecast future sales for this petroleum industry since the error observed (2.53%) respects the allowable margin of error set by the company at 3%. In addition, the SVR function is a useful tool, which guarantees good precision and minimizes the error compared to the ARIMA model.

Input (time)	Real value of output	Predicted value of output	% error
83	1038	1027.2	1.04046243
84	1043	1044.8	−0.1725791
85	1035	1033.4	0.15458937
86	1040	1034.3	0.54807692
87	1016	1034.7	−1.84055118
88	1015	1034.8	−1.95073892
89	1010	1034.9	−2.46534653
90	1001	1034.9	−3.38661339
91	1031	1034.9	−0.37827352
92	1033	1034.9	−0.1839303
93	1036	1034.9	0.10617761
94	1030	1034.9	−0.47572816
95	1000	1034.9	−3.49
96	1042	1034.9	0.68138196
97	1072	1034.9	3.4608209
98	1074	1034.9	3.6405959
99	1072	1034.9	3.4608209
100	1082	1034.9	4.35304991
101	1084	1034.9	4.5295203
102	1064	1034.9	2.73496241

Table 9.
Predicted value of output after using the RBF model.

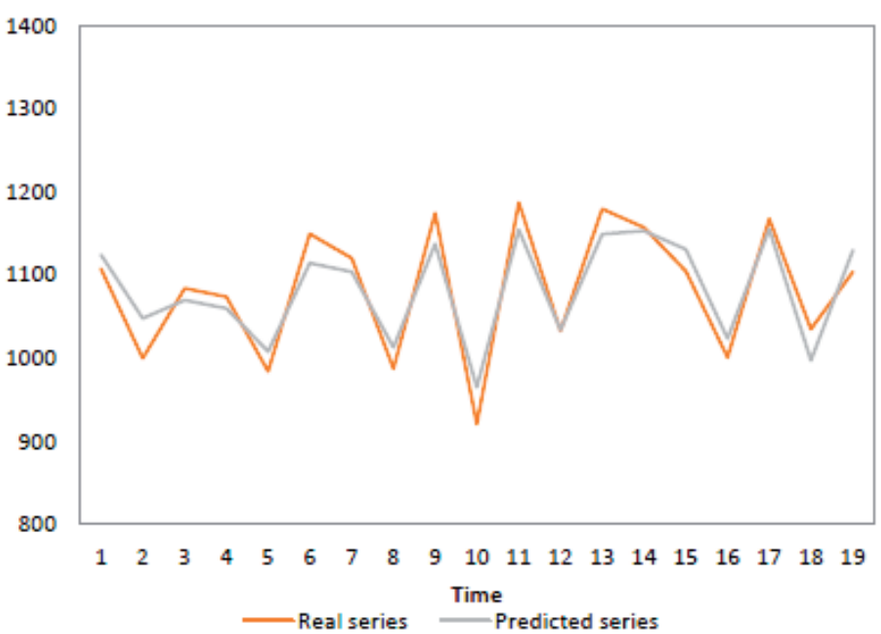


Figure 16.
Results of the SVR function.

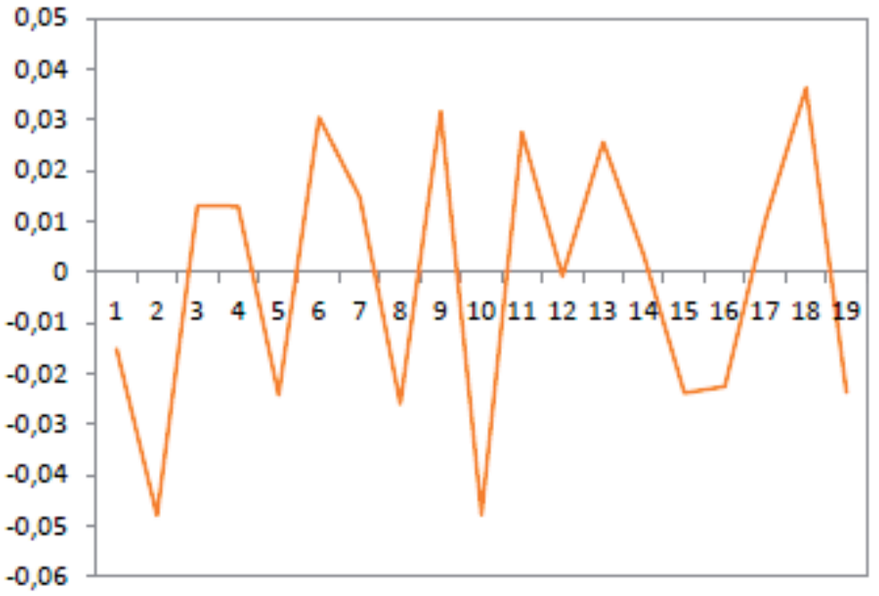


Figure 17.
Error graph.

3.2 Synthesis

In the first industrial application of this chapter, we modeled demand using ARIMA models. The model we have obtained will allow the company to forecast demand and make precise forecasts.

In the second application, we studied the selling prices of the SSP via three methodologies: ARIMA, RBF, and SVMs.

First, we developed an ARIMA model based on historical data. This study allowed us to determine the ARIMA model (1,1,1), which gives gasoline price forecasts close to the margin to reach for the first quarter of the current year with an average margin of error 2.855%. Second, we used the RBF technique to improve the modeling and forecasting of the selling price of fuel. It was found that this technique has proven its strength manifested in the error, which has been further minimized: 1.95% instead of 2.85% for the ARIMA model. Finally, we used the SVM function. The forecasts made are quite satisfactory because they respect the margin tolerated by the company. The error of the SVM function is around 2.53%.

As a summary, the SVM function has proven its strength manifesting itself in the error, which has been further minimized: 2.53% instead of 2.885% for the ARIMA model, but which remains higher than the error obtained using the RBF technique.

4. Conclusion

For most companies, forecasting is a prerequisite for effective supply chain management. Forecasting is the basis of all production management systems. The entire supply chain is based on data from forecast models.

In this chapter, we have presented the study of forecasting demand and selling prices in industrial companies. We also carried out a comparative study aimed at minimizing the error to guarantee increased forecasts.

In the first part, we modeled the future demand for a food company using ARIMA models based on the Box-Jenkins methodology. The model we have obtained will allow the company to forecast demand and make precise forecasts.

We can clearly see that the chosen model can be used to model and forecast future demand for this agribusiness, but each time we need to populate the historical data with the new data.

Second, we carried out a study, which consists in comparing the quality of the forecasts obtained in the context of forecasting selling prices. We presented the application of three different methodologies allowing us to make sales forecasts in a company operating in the petroleum sector.

We have developed an ARIMA model based on historical data. This study allowed us to determine the optimal autoregressive, moving average, and differentiation parameters in order to make predictions. We found that the ARIMA model (1,1,1) gives gasoline price forecasts close to the margin to reach for the first quarter of the current year with an average margin of error of 2.855% included within the margin of error tolerated by the company (plus or minus 3% as margin of error). In addition, the hypothesis that the residues are white Gaussian noise has always been verified.

Then, we tried forecasting selling prices via the RBF technique in order to improve the modeling and forecasting done before. To do this, we have developed an RBF network based on historical data to come up with conclusions in terms of superiority of forecast performance. Consequently, the use of this technique has proven itself and has allowed us to minimize the error, which is 1.95% versus 2.85% for the ARIMA model.

Finally, we studied the SSP selling prices via the SVM function. We prepared our database and then developed the program in Python language, which will be compiled on Spyder software. The forecasts made are quite satisfactory with regard to the constraint imposed by the company (plus or minus 3% margin of error). The error of the SVM function is around 2.53%. Consequently, the SVM function has proven its strength manifesting itself in the error, which has been further minimized: 2.53% instead of 2.855% for the ARIMA model, but which remains higher by comparing it with the error obtained if we had opted for neural networks.

Author details

Zineb Aman[1*], Latifa Ezzine[2], Yassine Erraoui[1], Younes Fakhradine El Bahi[3] and Haj El Moussami[1]

1 Mechanics and Integrated Engineering, ENSAM School, Moulay Ismail University, Meknes, Morocco

2 Modeling, Control Systems and Telecommunications, EST, Moulay Ismail University, Meknes, Morocco

3 Industrial Management and Innovation, Faculty of Science and Technology, Settat, Morocco

*Address all correspondence to: zineb.aman@gmail.com

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