Research Journal of Recent Sciences ISSN 2277-2502
Vol. **2(10),** 22-32, October **(2013)** *Res.J.Recent Sci.*

Presenting a Method for a Robust Prediction of Time Series Used in Financial Issues in an Automotive Manufacturing Company

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Available online at: www.isca.in, www.isca.me
Received 21st April 2013, revised 1st June 2013, accepted 30th July 2013

Abstract

For modeling and proper and reliable parametric estimating of self-correlated data and time series, robust methods are used; because of the fact that existence of contaminated data and outliers, has an undesirable effect on estimation of parameters in these models. Since in most financial data past data is effective on recent data, these problems can be implemented by models of time series. In this paper, autoregressive models are considered as a model for the time series. A new robust method is presented based on filtered S optimization approach to estimate the parameters of autoregressive model. Resulted robust model can be used for robust prediction of the future values. Finally, as a numerical example, resulted profit of an intermediate product in 148 months is presented and suggested robust method is applied on it. Robust method, compared to classical methods, shows higher efficiency in predicting future values.

Keywords: Time series, autoregressive model, outliers, robust estimation, financial data.

Introduction

Major categories of data in experimental analysis are time series. Time series, are orders of data collected discretely at equal time intervals. Time series have applications in many fields such as economy, trade and business, engineering sciences, natural sciences and social sciences. Dependence of contiguous observations is one of the most important innate features of time series, so finding this dependence and its description is of a great importance. Time series have many different models. These models are divided into two general categories: The category of static models and the category of non-static models. Static models are models in which the mean and the dispersion are consistent over time; otherwise they are non-static models. A common and important class of static models is the class of autoregressive models. In these models, the present data is defined based on the past data, plus a random error factor. In other words, the dependent data can be modeled based on prior independent data.

Many series such as industrial and commercial dependent data and especially financial issues display non-stationary behavior. This means that the data do not fluctuate around a constant mean. The series have trends in their data and the data fluctuates over time around them. These models can be converted to static models by differentiation of d. One of the common types of non-stationary models of time series is Autoregressive integrated moving average (ARIMA). The models consist of three main parameters, autoregressive parameter p, moving average parameter q and the differentiation parameter d. These models can be converted to autoregressive models by taking two parameters of d and q equal to zero. Time series models and other proposed models have been reviewed[1].

In many cases, particularly in time series analysis, some data are wrong and should be considered as outliers. These spots can have adverse effects on final analysis of results. For predicting the behavior of data we can use estimation of regression model based on the same approach. Prospective conclusions and analyses will be made based on this regression model, so having a model with a high accuracy will be very effective. The regression model is often estimated based on the method of Ordinary Least Squares. What is due to mention in this respect is that the method of Ordinary Least Squares is so sensitive about outliers and the existence of these kinds of data has an undesirable effect on the final conclusion. Therefore, to reduce the improper impact of the data, Modified Ordinary Least Squares method or Robust Methods should be applied. The outliers in time series are much more complex than the data, in terms of the independence of observations. This is because of different kinds of outliers in time series which is made due to the structure and properties of dependence of data. Different kinds of outliers in time series are divided into three categories: Additive Outliers (AOs), Replacement Outliers (ROs), and Innovation Outliers (IOs).

In the topic of time series, outliers and contaminated data have undesirable effects on estimation of regression model parameters and will vary according to the type of pollution. The some authors examined different types of the outliers and their effects on time series models[2,3,4]. Studied outliers, surface modifications and dispersion changes in time series[5]. Different approaches have risen in identifying outliers in the subject of time series[6].

In the subject of time series, identifying the kind of data model and identifying and estimating parameters of chosen model are raised. Outliers have undesirable effects on identification of model and estimation of its parameters. In the phase of identifying suitable models, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are used. Correlated functions regardless of model parameters can be used for describing the model. Partial Autocorrelation Function can be used in identifying the type of model[7]. The outliers adversely affect the correct estimation of Autocorrelation Function and Partial Autocorrelation Function. Therefore, for robust estimation we need Autocorrelation Function and Partial Autocorrelation Function. Therefore, the first step for robust estimation of regression models of time series is robust identification of model of problem.

Next step in robust estimation is robust assessment of model parameters suitable for time series. Robust regression methods can be used for robust estimation by adding appropriate filters for time series and structural changes. Proposed different techniques of robust estimation of regression models[8]. Presented robust estimation of parameters of first-order autoregressive model[9]. Examined the discussion of robust estimation of model parameters of time series in hybrid autoregressive moving average model (ARMA)[10]. Introduced the method for robust estimation of S for regression of conventional data[11]. Presented a fast algorithm for computing the proposed method of ***S*** assessment[12]. Suggested that the proposed method for estimating ***S*** for conventional data can be used for time series and it has an optimal performance for this class of data.

In the topic of time series, the following observations and previous observations are of the same substance and a significant relationship is between them. Predicting future values of these series is of a great importance. The model estimated of the observations can be the base for predicting future observations. This modeling approach in prediction of future observations is used in mostly when we have little information about production of observations for prediction using other methods. Many studies in last years have been conducted to complete and improve time series models in order to predict future observations. One of the most important and widely used models in time series is integrated autoregressive moving average model. This category of models has the properties of the three categories of pure autoregressive model, pure moving average model and also hybrid autoregressive moving average model. But the most important limitation of this model is the condition of being linear in relationships. This condition can cause impossibility of using this method in examination of nonlinear equations. He suggested a prediction approach for finding an efficient model to improve the performance[13]. In his study which was based on neural network, the results of simulation indicated the point that neural network present robust predictions for a category of time series that show nonlinear behavior. In this study, the data of Taiwan's financial exchanges was examined to be compared to integrated autoregressive moving average model for a comparison of neural network's efficiency. Of course the neural network approach has limitations such as the need to large data for network education. He used an approach, based on a combination of neural network technique and integrated autoregressive moving average model in which the advantages of both approaches will be retained[14].

Many financial data can be modeled by time series models. Just like time series, the current values of financial data are also dependent on their previous data. Data related to financial issues are usually associated with the process over time and can be modeled by non-stationary models. If the data is homogenous, to analyze the models by differentiation of the data and changing them to autoregressive models or moving average and hybrid autoregressive model and moving average, we can study them more easily. Price, Gross Domestic Production (GDP) and Personal Disposal Income (PDI) are criteria which can be modeled based on time series. Gujarati, in his book titled as *Econometrics*, has pointed out the applications of time series as powerful and useful means in financial and economic data[15]. Due to the nature of time series data and the importance of the prediction in this topic, several researchers dealt with the prediction of future observations of the time series in financial issues.

Giordani and Villani have presented the dynamic non-Gaussian complex model for prediction in Econometrics[16].

Studied repeated and direct experimental prediction among single-variable and multivariable autoregressive models with time series data of the United States of America in 170 months from 1959 to 2002[17]. The idea of being robust, like modeling, can be analyzed in many predictions of time series. In prediction of time series desultory and contaminated data can have an undesirable effect on modeling and finally on prediction of observations and lead to have unreliable predictions. Presented a new robust approach based on a hybrid model to estimate the appropriate location of the warehouse stock[18]. Gagn´e and Duchesne offered a robust estimation for multivariable autoregressive model by exogenous variables[19]. A new approach was suggested by Hyndman and Ullah for predicting age of mortality and fertility rate over time[20]. This approach is robust for special years of war and epidemic diseases which work as outliers and it presents a flexible structure for regarding other limitations and information. Chao et al suggested a new recursive robust model for estimation of autoregressive model parameters for prediction of flood in which the model is constantly updated. In this model, harmonic least squares approach is used[21].

Croux et al. used *M* estimation method in robust estimation of exponential smoothing method and algorithm of Holt-winter which is considered in prediction[22]. Also, Gelper et al offered exponential smoothing method and robust algorithm of Holt-Winter for prediction[23]. Recently Kharin has provided new data and has used the average error of prediction risk as a base for analysis of his method[24]. Croux et al. presented a robust method for robust prediction of non-stationary time series[25]. The model used in this approach is the nonparametric regression model and is estimated robustly by *MM* estimation method. The presented method works well in the presence of outliers and data contaminations.

Robust predictions in financial data are extremely important; because the detailed predictions have effects on profitability. Araujo presented robust approach of self correction for robust prediction of financial data. The mentioned approach, eradicated the problems of random walk processes in financial time series[26]. For more specification of place of the conducted study among other researches in this field, table 1 shows a brief overview of the literature.

In this study, the ***S*** filtered robust estimation approach which is presented by Boente et al. is used for robust prediction of financial data[27]. The analyzed data follow autoregressive integrated moving average model with autoregressive parameter 1 and zero moving average that will be converted to a first-order autoregressive model (ARIMA (1,1, 0)). The mean squares error criterion has been used to determine the effectiveness of the proposed robust method in comparison to the classical least squares error approach.

Table-1
A brief review of the literature on the prediction of time series

Robust Regression for Time Series	**Prediction of Time Series**	**Robust Prediction of Time Series**	**Prediction of Financial Time Series**	**References Number**
Robust Autoregressive Model				**9**
S estimator				**11**
Fast calculation Algorithm of S estimator				**12**
	Prediction of Financial Data by Neural Network			**13**
	Combination of Neural Network and Hybrid Model of Autoregressive and Moving Average			**16**
Autoregressive Model	Repeated and Direct Prediction			**17**
Hybrid Model		Robust Prediction		**18**
		Multivariable Autoregressive Model with Exponential Variables		**19**
LC Model	Prediction of Mortality and Fertility Rate	Robust Prediction		**20**
Updatable Autoregressive Model	Prediction of Flood	Recursive Robust Prediction Approach		**21**
Using M estimator in Exponential Smoothing and Holt-Winter Algorithm				**22**
Exponential Smoothing Method and Holt-Winter Algorithm		Robust Prediction		**23**
		Data of Robust Prediction		**24**
MM Estimated Without Filter		Robust Prediction for Non-Stationary Series		**25**
			Prediction by Automatic Self-correction Approach	**26**
Filtered S Estimator		Robust Prediction of Time Series	Financial Data	**The Present Study**

This article includes the following sections: In section 2, the basic principles of autoregressive models and also integrated autoregressive moving average model and estimation of parameters of autoregressive models are described. In Section 3, ***S*** robust estimating approach is introduced to find a robust model in predictions of time series and the mode of filtering the autoregressive model. Numerical examples and case study on financial data will be examined in section 4; it indicates the high efficiency of the recommended robust method for prediction of future data in comparison to classic method. Ultimate conclusion is made in the final section.

Methodology

In this section, firstly the two most widely used models of time series that have been the subject of literature review, will be discussed briefly. These two kinds include autoregressive model, as a group of stationary models and integrated autoregressive moving average model as a class of non-stationary models. Estimation of parameters of autoregressive model is also a subject that will be discussed here. For estimation of its parameters, the approach of least squares error has been used which will be examined in this section.

Autoregressive Model as a Stationary Model in Time Series: This model is a stochastic model which is applied to show the behavior of time series in a mode that has a constant average model and variance. In this model, the current values of the observations are achieved from the product of coefficients in previous values plus a random error value. If the current value of observation is Z_t and the average value of process is μ and also if we show the current value of observations minus the average as $\tilde{Z}_t$, the autoregressive model is shown as follows:

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \phi_2 \tilde{Z}_{t-2} + ... + \phi_p \tilde{Z}_{t-p} + a_t \tag{1}$$

This equation is a regression model that connects the current observations to previous observations and models them. Therefore, this model is called autoregressive model. Defining ***B*** Recursive Function, the models will be rewritten as follows:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p \tag{2}$$

$$\phi(B)\, \tilde{Z}_t = a_t \tag{3}$$

Autoregressive Integrated Moving Average (ARIMA): The second category of models for time series is the category of non-stationary models which are often to be found in commerce and industry. In this category of models we are faced with a trend. A particular type of non-stationary models is Autoregressive integrated moving average model which can be converted to stationary models by appropriate differentiation. Regression equation of these models is as follows:

$$\varphi(B)\, \tilde{Z}_t = \phi(B)\, (1-B)^d\, \tilde{Z}_t = \theta(B)\, a_t \tag{4}$$

In this model $\varphi(B)$ is the performer of non-stationary autoregressive model which can be converted to stationary autoregressive model by ***d*** time differentiation. Also $\varphi(B)$ acts as the moving average part of the model.

Classical Approach Based on the Least Square Error for Estimation of Parameters in Autoregressive Model: After identifying the appropriate model for time series data, achieving the model parameters is essential. Autoregressive model of ***P*** order is defined as follows:

$$Z_t - \mu = \phi_1(Z_{t-1} - \mu) + \phi_2(Z_{t-2} - \mu) + ... + \phi_p(Z_{t-p} - \mu) + a_t \tag{5}$$

In this model a_t can be distributed independently and equally with zero average and σ_a^2 as variance. The constant value of the model is defined as follows:

$$\gamma = \mu(1 - \sum_{i=1}^{p} \phi_i) \tag{6}$$

Using least square error approach, Average Square of errors of observations should be minimized, thus the following minimizing equation for this purpose is defined as:

$$Minimize \sum_{t=1}^{p} \hat{a}_t^2(\phi, \mu) \tag{7}$$

While in this equation $\hat{a}_t$ is the estimated amount of residues which can be defined as follows:

$$\hat{a}_t = z_t - \gamma - \phi_1 z_{t-1} - \phi_2 z_{t-2} - ... - \phi_p z_{t-p} \tag{8}$$

So the parameters we want to estimate, such as coefficients of regression equation ϕ_i و μ, can be achieved by solving the equation (7).

Estimating Filtered Robust Approach of *S* for Time Series Models: Classical approach mentioned for estimating the parameters of the autoregressive model are sensitive to outliers. Therefore, in this part, a robust approach based on robust dispersion of estimation $\hat{\sigma}$ or dispersion of the residues has been presented. In this part we will consider ***P*** order autoregressive model. We will show contaminated data by y_t while $1 \le t \le T$. Vector of parameters that must be estimated is $\lambda = (\phi_1, \phi_2, ..., \phi_p, \mu)$. To estimate the parameters, the residual vector is defined to be $a(\lambda) = (\hat{u}_{p+1}(\lambda), ..., \hat{u}_T(\lambda))$ while:

$$\hat{a}_t(\lambda) = (y_t - \mu) - \phi_1(y_{t-1} - \mu) - \phi_2(y_{t-2} - \mu) - ... - \phi_p(y_{t-p} - \mu) \tag{9}$$

Estimation of parameters can be achieved considering the scaled estimation $\hat{\sigma}$ from equation (10) as follows:

$$\hat{\lambda} = \arg\min_{\lambda} \hat{\sigma}(\hat{a}(\lambda)) \tag{10}$$

Estimation of ***S*** for regression equations can be calculated by putting a special mode of the scale used in *M* estimator of the special case of M, in the function $\hat{\sigma}$. Boente et al indicated suitability of this estimator for time series such as regression equations. Basic principles of S estimation, as mentioned by Rousseeuw and Yohai[11], are robust, considering dispersion of residues as maximum function of likelihood, and regression coefficients are calculated as follows:

$$\hat{\beta} = \arg\min_{\lambda} \hat{\sigma}(r(\beta)) \tag{11}$$

In the above equation, β is the regression coefficient that must be estimated and the amounts of residues is shown by $r(\beta)$. In the mode of robust estimation of time series, because of the effects of outliers on the process and in order to prevent the distribution of this effect to other residues, a robust prediction of residues should be calculated. Suppose that we show the filtered robust values by $\hat{x}_{t-i|t-1}$, $i = 1,2,3,..., p$.

The filtered robust residue value is calculated as follows:

$$\tilde{a}_t(\lambda) = (y_t - \mu) - \phi_1(\hat{x}_{t-1|t-1}) - \mu) - ... - \phi_p(\hat{x}_{t-p|t-p} - \mu) \tag{12}$$

A specific and common expression of observation value X_t is proposed by Brockwell and Davis[7] titled as State-space which will be used in the following parts.

$$X_t = \mu + \Phi(X_{t-1} - \mu) + d\, u_t \tag{13}$$

In this respect, we can consider that $X_t = (x_t, x_{t-1}, \ldots, x_{t-p-1})$, $d = (1,0,...,0)$ $\overline{\mu} = (\mu,...,\mu)$ and also $\Phi = \begin{bmatrix} \phi_1 & \phi_p \\ I & 0 \end{bmatrix}$. Thus, based on equation (13), the amount of $\hat{x}_{t|t-1}$ can be calculated as follows to obtain the robust prediction in time ***t***.

$$\hat{x}_{t|t-1} = \overline{\mu} + \Phi(\hat{x}_{t-1|t-1} - \overline{\mu}) \tag{14}$$

Finally, robust value of prediction of residues and value of observation in time ***t*** can be calculated by a recursive algorithm as follows:

$$\tilde{a}_t(\lambda) = (y_t - \mu) - \phi' \ (\hat{x}_{t-1|t-1}) - \mu) \tag{15}$$

$$\hat{X}_{t|t} = \hat{X}_{t|t-1} + \frac{1}{s_t} m_t \psi(\frac{\tilde{a}_t(\lambda)}{s_t}) \tag{16}$$

In the above equation, s_t is an estimation of the predictions of residues while $m_t = s_t^2$. Also, the function ψ is defined as:

$$\psi(a) = \begin{cases} a & if \quad |a| \le b \\ o & if \quad |a| > c \end{cases} \tag{17}$$

The robust value of an observation is $\hat{X}_{t|t} = \hat{X}_{t|t-1} + s_t \psi(\frac{\tilde{a}_t(\lambda)}{s_t})$ which can be summarized as follows:

$$\hat{X}_{t|t} = \hat{X}_{t|t-1} \quad if \quad |\tilde{a}_t| > c\, s_t \tag{18}$$

$$\hat{X}_{t|t} = y_t \quad if \quad |\tilde{a}_t| < b\, s_t \tag{19}$$

Equation (18) indicates that robust filtering of values, replaces the observations which their absolute value of robust prediction of residues is $\left|\tilde{a}_t / s_t\right| \ge c$ with filtered robust values of the past data; and also the equation (19) shows that if $\left|\tilde{a}_t / s_t\right| \le b$ is true, the observation value remains unchanged. This robust equation can be used for predictions of future observations.

Result and Discussion

We can conclude from the figure that the data have a trend over time and we can put them in the category of non-stationary series. In this research the data follow the model of $ARIMA(1,1,0)$. So the mention model becomes a pure autoregressive model by differentiation of the data of problem that its diagram is shown in figure 2.

Presenting the diagrams of self-correlation and partial self-correlation, supposing data which once are differentiated follow the mentioned model are endorsed. This is shown in figure 3. Adequacy of the model can be analyzed with the residues plot which is shown in figure 4.

Regarding the above diagrams, we can conclude that the data follow the model ARIMA (1, 1, 0). The model can be written as follows:

$$(1-B)(1-\phi B) Z_t = a_t \tag{20}$$

This model can be converted to a first order autoregressive model by one time differentiation. This is done by changing the following variable.

$$(1-B) Z_t = y_t \tag{21}$$

$$y_t(1-\phi B) = a_t \tag{22}$$

Differentiated observations from which average values are not subtracted are shown by y'_t. Thus, the final model is as follows:

$$y'_t = \mu_y(1-\phi) + \phi\, y'_{t-1} + a_t \tag{23}$$

Using the robust estimation approach of ***S***, proposed for time series in the last part, the two parameters ϕ and μ_y are estimated in the equation (23). The estimation is done in two robust and classic methods of least squares error for the data of first order autoregressive model and the results are reported in table 3. In robust method, parameters b and c are considered equal to 3.

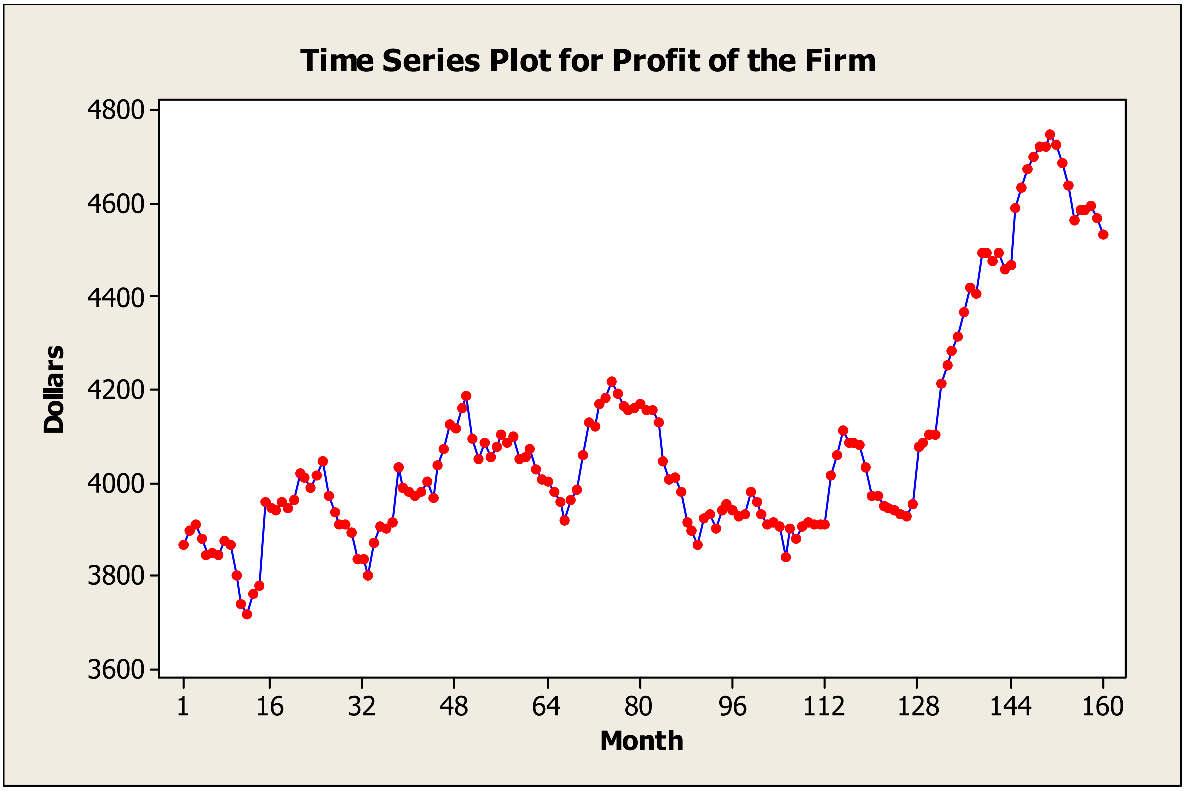

Figure-1
Time series plot for data of profit

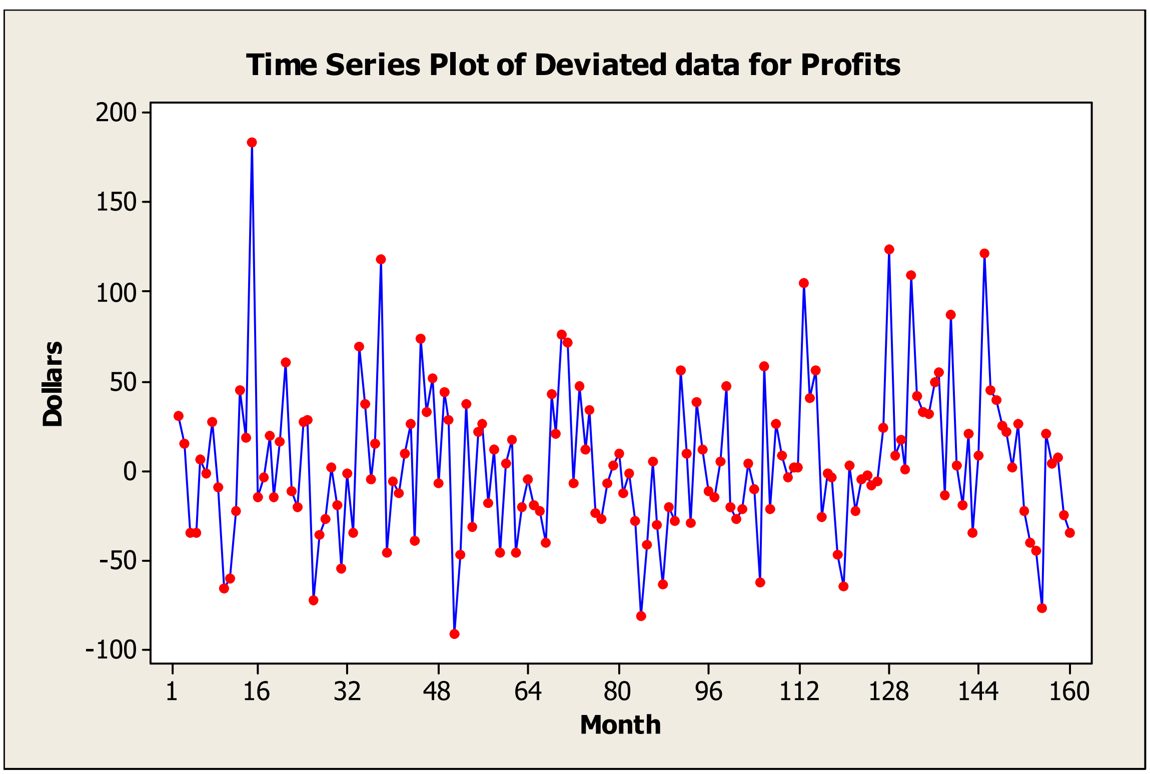

Figure-2
Time Series Plot of Deviated Data for Profits

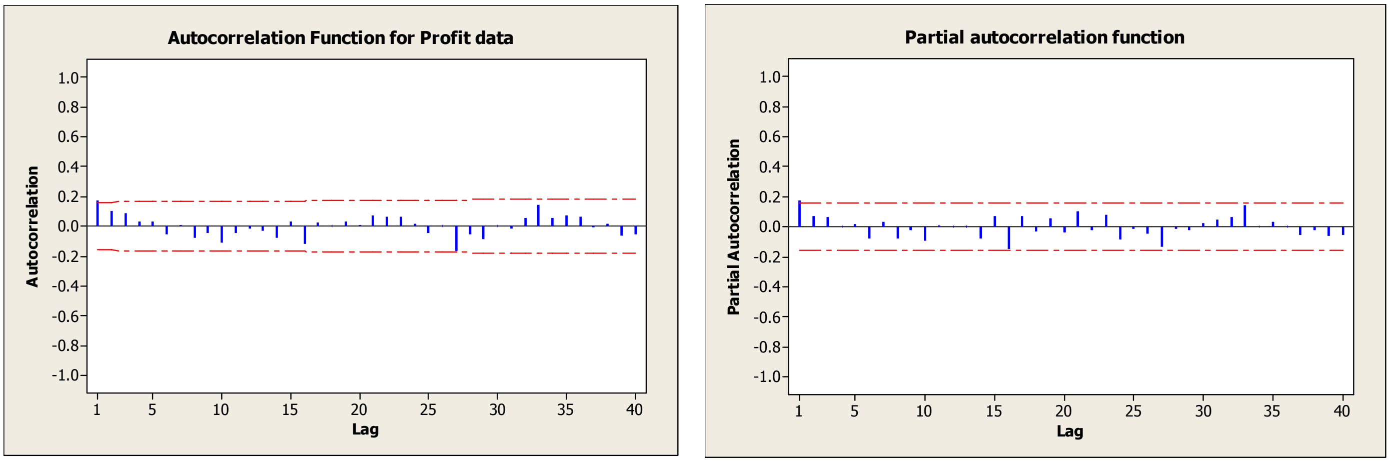

Figure-3
Presenting Diagrams of Autocorrelation Function and Partial Autocorrelation Function of the Differentiated Data

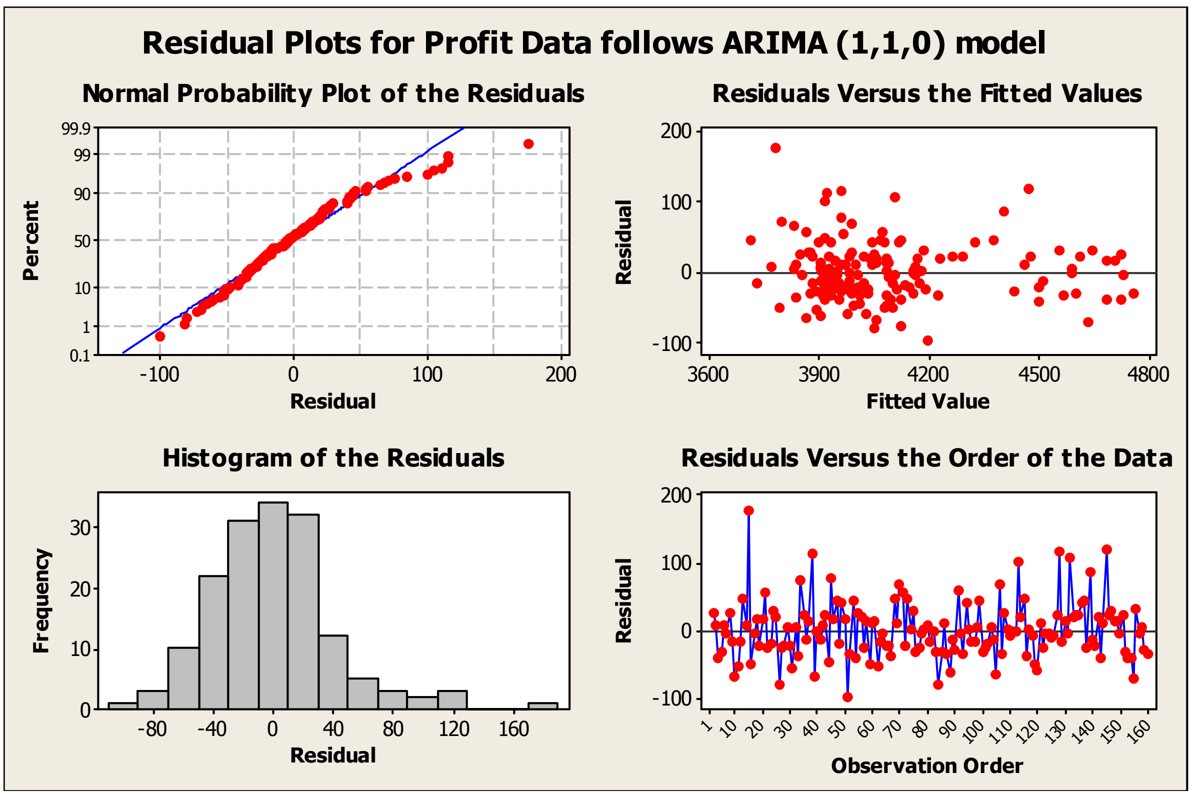

Figure-4
The Residues Diagrams of the Time Series Model of Data of Profits

Table-2
Estimated parameters of autoregressive method by two of classical and robust methods

Method / Parameters	Least Squares Error	Filtered Robust S Estimation
ϕ	0.1709	0.2103
μ_y	4.17	-0.511
σ_a	31.25	41.59

The next step is the prediction. In this step we have collected the data of 149 to 160 and we will use the first 148 data to predict the next 12 data; and then we will compare the results to the real data. The integrated autoregressive moving average model for the main data of problem and without average fraction can be achieved from the equations (21) and (23) and can be expressed as follows:

$$Z'_t = (1+\phi)\, Z'_{t-1} - \phi Z'_{t-2} + \mu_y \tag{24}$$

In this regard, Z'_t is the actual observed value of the subtracted average and μ_y is the average of stationary model that can be estimated. The predicted values are presented in table 4. In this table, the criterion of square error has been used for comparing the predicting methods; and finally, as it is clear, the sum of squares error of the robust method is less than the classical method and a better and more accurate prediction has been done.

In figure 5, the actual amounts of values and robust and classical predictions have been presented.

As indicated in figure 5, the robust prediction values are closer to actual values in comparison to the classical prediction values. Figure 6 shows the diagram of contaminated data model versus the robust model.

Table-3
Prediction values in two classical and robust modes and the amount of error in prediction

Number	Real	Least Squares Error	Robust	Estimation Error of the Least Squares Error Method	Estimation Error of Robust Method
149	4722.32	4709.00	4705.30	177.34	289.79
150	4723.60	4714.61	4705.77	80.90	317.92
151	4750.05	4719.74	4705.36	919.04	1997.25
152	4727.27	4724.7	4704.77	6.204	506.68
153	4686.84	4729.82	4704.13	1847.35	299.05
154	4641.70	4734.85	4703.48	8676.36	3817.30
155	4564.79	4739.88	4702.84	30656.33	19057.96
156	4585.23	4744.91	4702.19	25496.08	13679.52
157	4588.60	4749.94	4701.54	26030.47	12757.15
158	4596.13	4754.96	4700.90	25227.83	10975.50
159	4570.77	4759.99	4700.25	35804.06	16763.59
160	4535.37	4765.02	4699.60	52741.01	26972.20
Total Error				207663	107434

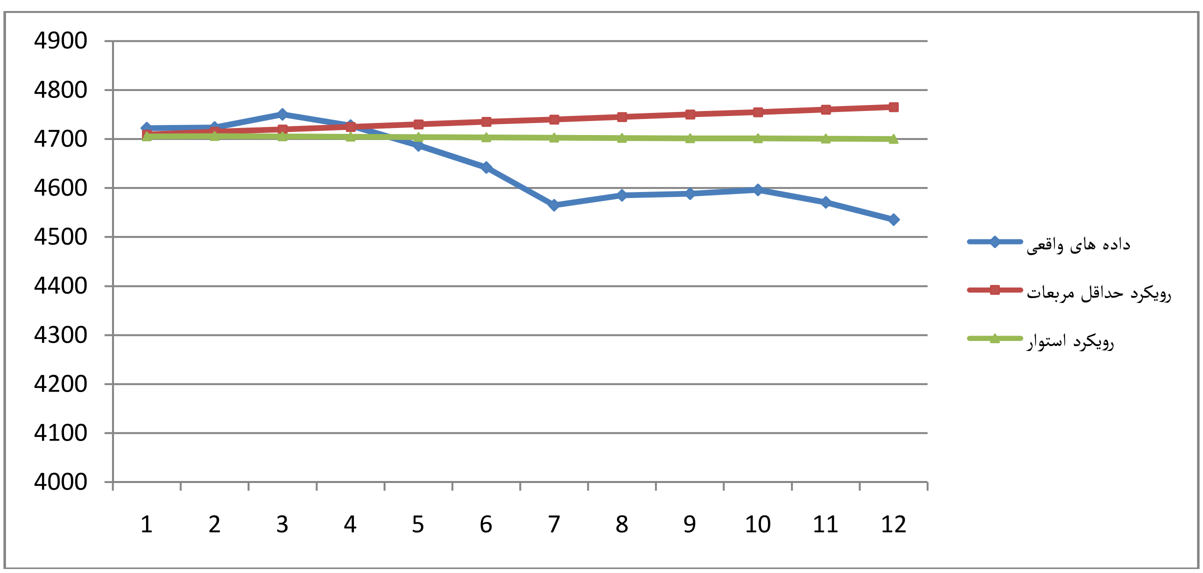

Figure-5
Comparison of robust and classical values of predictions

Also figure 7 shows the diagram of the residues of robust method and non robust method.

Thus, the robust method in the presence of pollution works better than the least squares error method and leads to a better prediction for future observations.

Conclusion

This research examines the use of robust estimation algorithm ***S*** in the prediction of time series. This approach has been used in predicting future values of financial data. To investigate this approach, the data collected from the profit amount of a production company in 148 months has been studied, in which the integrated autoregressive moving average model is followed. After the differentiation of the data, the model becomes a first order autoregressive model. Calculations that have been done show the efficiency of robust prediction approach in comparison to classical prediction method, considering the actual observation square error from the amount of prediction. To continue the researches in this subject area, considering the analysis of other models of time series and other robust approaches is recommended.

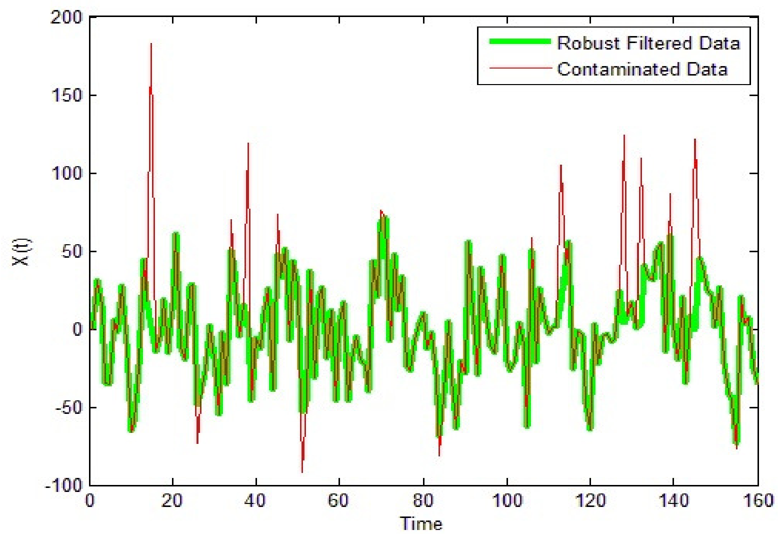

Figure-6
The diagram of contaminated data and robust predictions of them

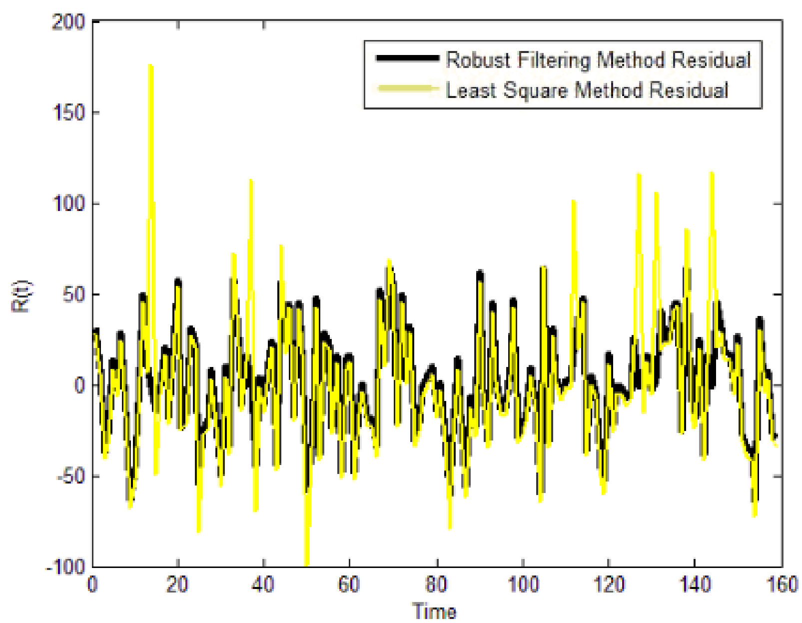

Figure-7
The diagram of prediction of two methods of least squares error method and robust method

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