Zaitun Time Series

User Manual

Content

Zaitun Time Series

User Manual

Zaitun Software Developer Team
www.zaitunsoftware.com

Introduction

Chapter 1

Zaitun Time Series

Zaitun Time Series is designed for ease of use for statistical analysis, series modeling and forecasting of time series data. It provides several statistics and neural networks models, and graphical tools that will make your work on time series analysis easier.

- Statistics and Neural Networks Analysis
    - Trend Analysis
    - Decomposition
    - Moving Average
    - Exponential Smoothing
    - Correlogram
    - Neural Networks
- Graphical Tools
    - Time Series Plot
    - Actual and Predicted Plot
    - Actual and Forecasted Plot
    - Actual vs Predicted Plot
    - Residual Plot
    - Residual vs Actual Plot
    - Residual vs Predicted Plot

Zaitun Time Series was originally developed by the "Time Series" team as the final project of their four year diploma degrees in Sekolah Tinggi Ilmu Statistik Jakarta, Indonesia. Members of the team are Rizal Zaini Ahmad Fathony, Suryono Hadi Wibowo, Wawan Kurniawan, Muhamad Fuad Hasan, Al Maratul Sholihah, and Rismawaty. Now, the developer team in zaitunsoftware.com is continuing the development of **Zaitun Time Series**, the members of the team now are Rizal Zaini Ahmad Fathony, Aris Wijayanto, Dewi Andriyanti, and Lia Amelia.

Installation Guide

Chapter 2

System Requirements

Minimum Requirements

- Windows XP (SP2 or later), Windows Vista, Windows 2000 (SP4 or later), or Windows Server 2003 (SP1 or later)
- .NET Framework 2.0
- 600 MHz processor (Recommended: 1 GHz or faster)
- 192 MB of RAM (Recommended: 256 MB or more)
- 1024 x 768 screen resolution
- 10 MB hard drive space

Zaitun Time Series Installation

Zaitun Time Series installation is very simple and only takes a few minutes. To install **Zaitun Time Series**:

1. Please ensure that .NET Framework 2.0 is installed in your system.
2. Start “zaitun.msi”. It will install **Zaitun Time Series** into your computer. The welcome screen appears. Click **Next**.

FIGURE 1 **Welcome Screen**

3. Read the license agreement, and then click **I accept the terms in the License Agreement** to continue installing **Zaitun Time Series**.

FIGURE 2 **End-User License Agreement Screen**

4. Choose Destination Location Screen appears. You can choose to install **Zaitun Time Series** into the default directory "C:\Program Files\Zaitun Time Series" or choose another directory. If you want to change the destination location of **Zaitun Time Series**, click **Browse** button. Click **Next** button to install into default directory.

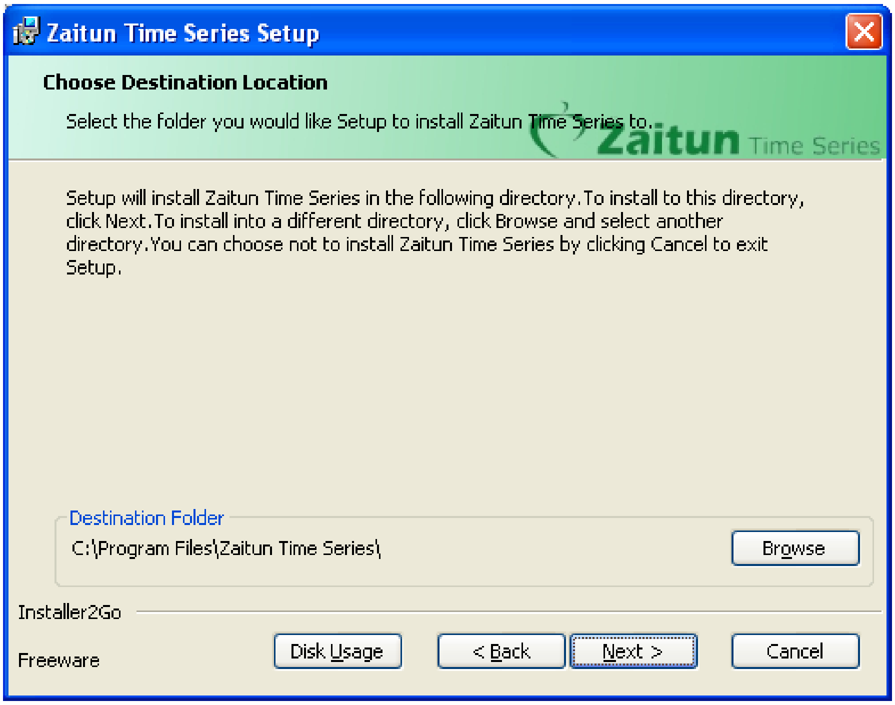


FIGURE 3 **Choose Destination Location Screen**

5. Ready to Install Screen appears. Click **Install** to begin the installation.

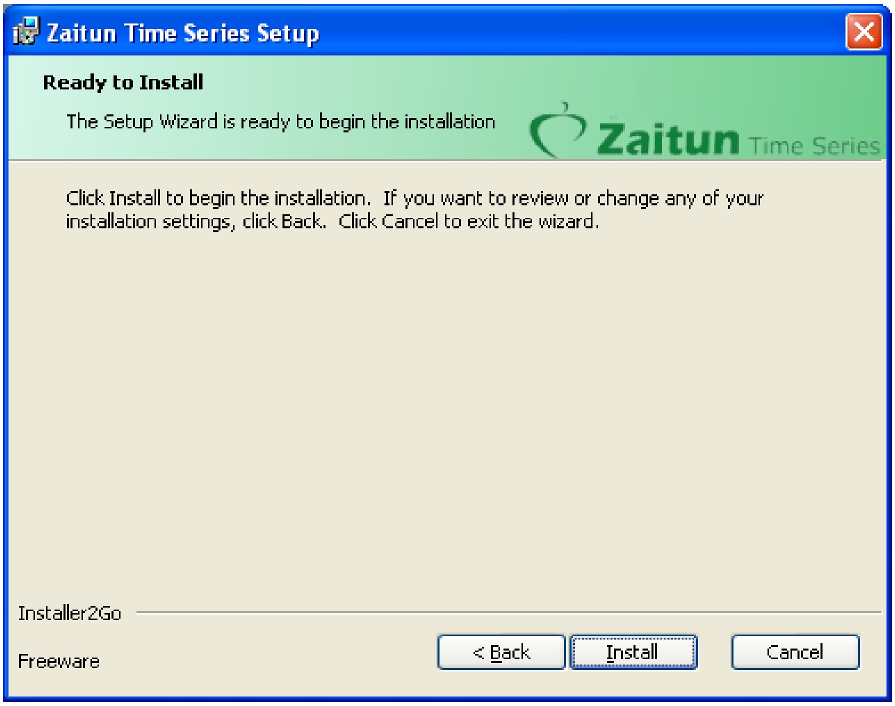


FIGURE 4 **Ready to Install Screen**

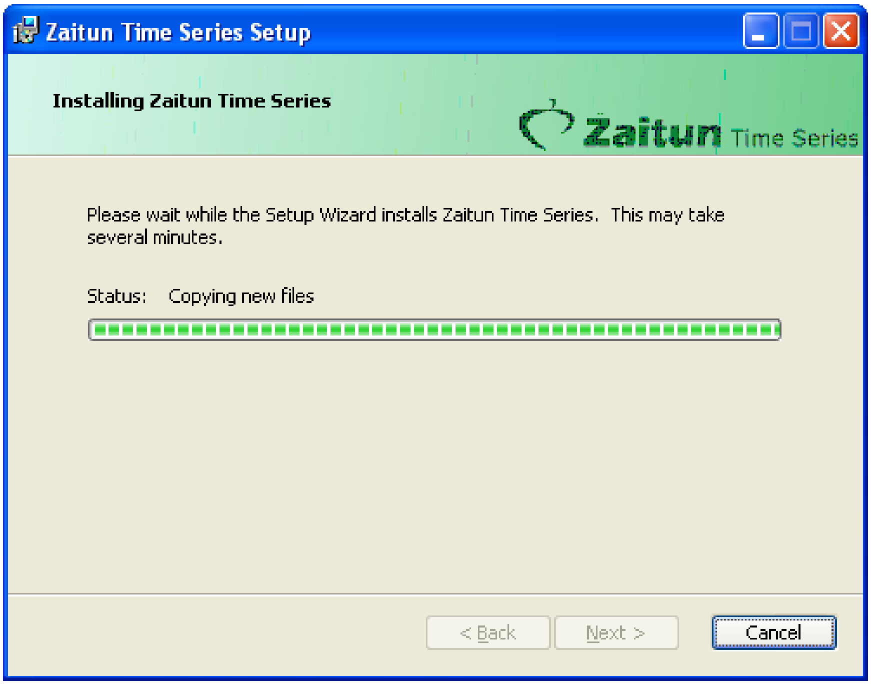


FIGURE 5 **Installing Zaitun Time Series Screen**

6. After the installation is complete, setup will inform you that the installation is successful. You may then launch **Zaitun Time Series** by clicking on "Launch Zaitun Time Series" checkbox. Click **Next** to continue and finish the setup.

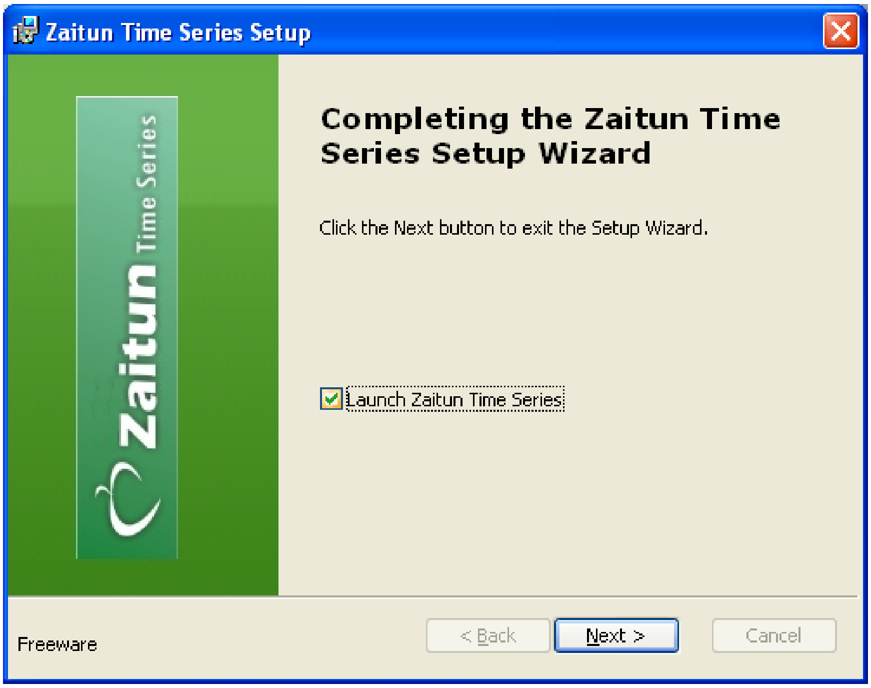


FIGURE 6 **Installation Completed Screen**

7. You can start using **Zaitun Time Series** by clicking the shortcut on start menu items.

Working with Data

Chapter 3

Creating A New Project

Zaitun Time Series represents time series data with the data point frequency (annual, monthly, weekly, daily, etc) ranging from start date to end date.

To create a new time series data project:

1. Click **File → New** to open the Create New Project dialog box.

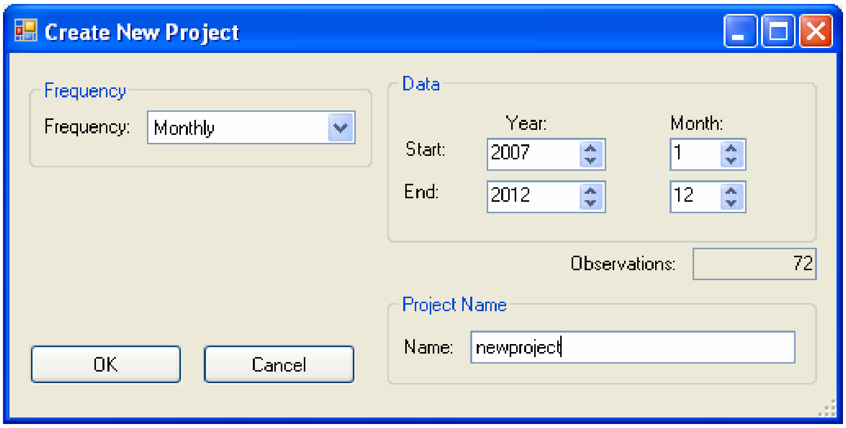


FIGURE 7 **Create New Project Dialog**

2. Specify the frequency of time series data.
3. Set the start date and end date.
4. Set the new project name.
5. Click the **OK** button. **Zaitun Time Series** will create a new empty project.

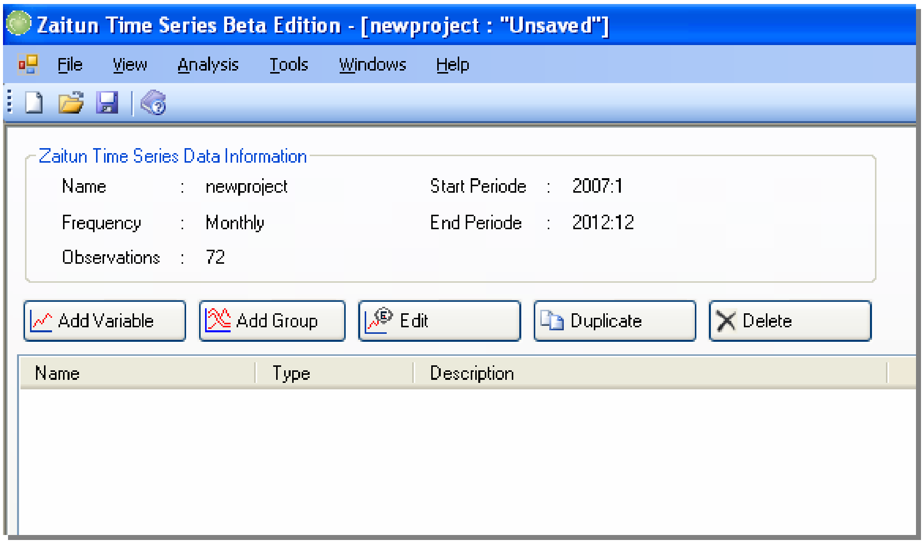


FIGURE 8 **New Empty Project**

Opening A Saved Project

You can also open a project file saved in your media disk.

To open a saved project:

1. Click **File → Open** to show Open Project dialog.

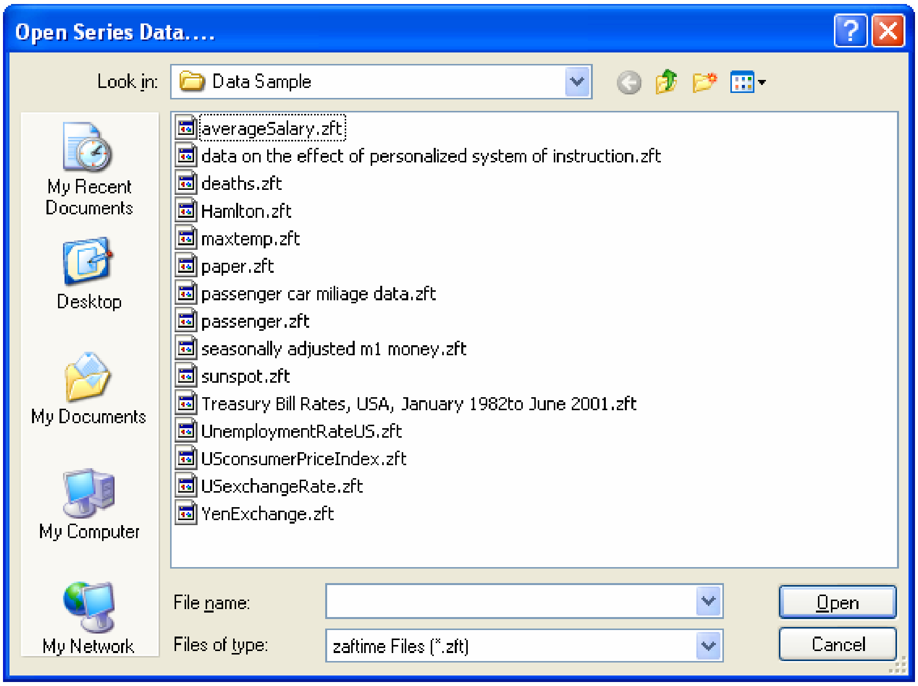


FIGURE 9 **Open File Dialog**

2. Specify your project file location (.zft file)
3. Click the **Open** button. **Zaitun Time Series** will open the selected project file.

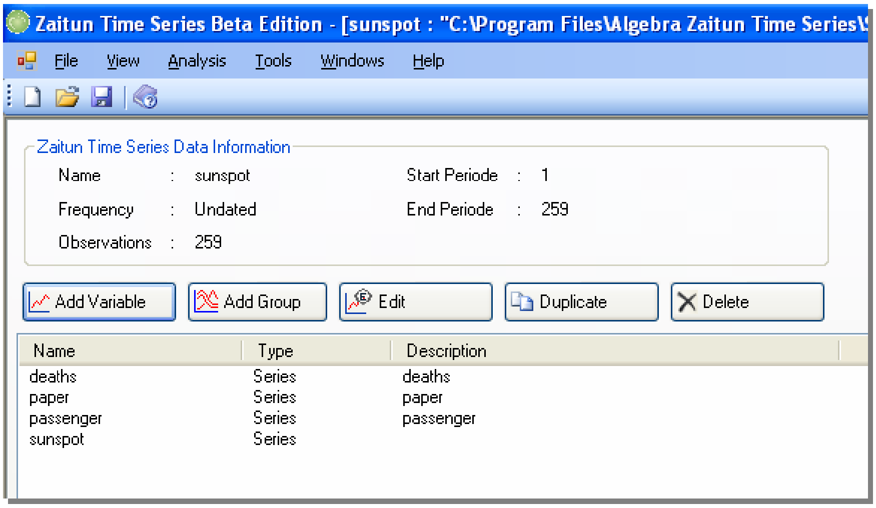


FIGURE 10 **Opened Project File**

Adding A Variable

A **Zaitun Time Series** variable is a series of data points constituting one time series data collection. For example, the recorded (annual, monthly, weekly, daily) time series values of the Indonesian Exchange Rate. A time series data project can contain more than one variable.

To add a new variable into current project:

1. Click the **Add Variable** button on top left side of current project view to open Create New Variable dialog.

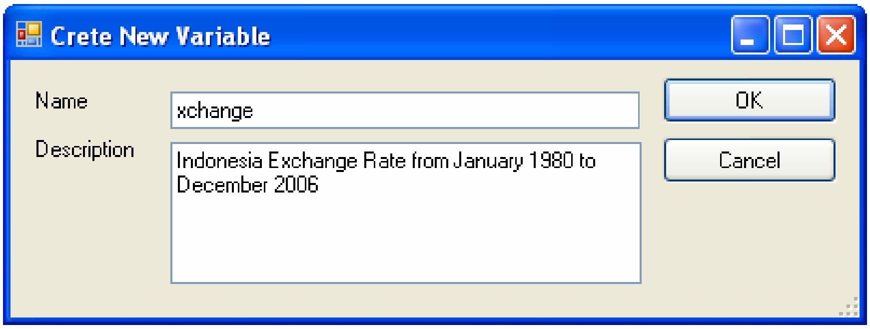


FIGURE 11 **Create New Variable Dialog**

2. Determine the new variable's name and its description.
3. Click the **OK** button. **Zaitun Time Series** will add this variable into current project.

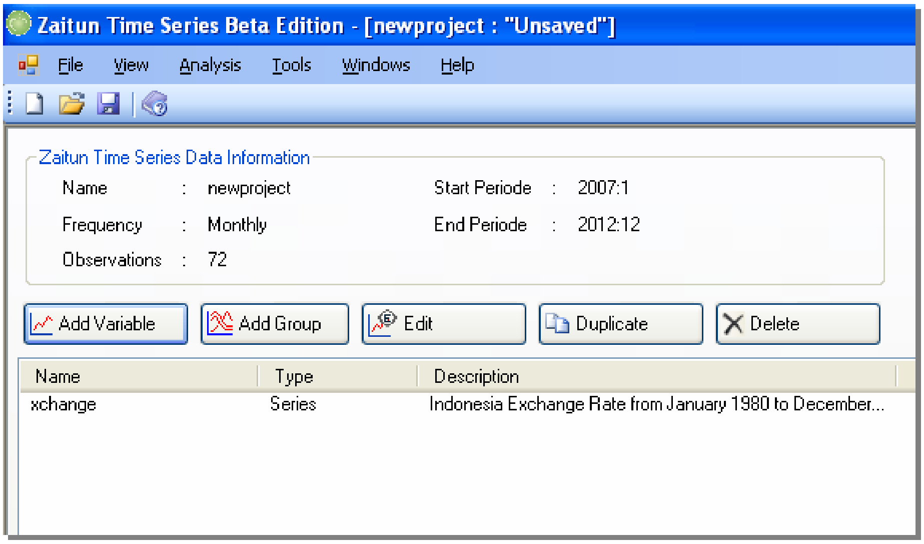


FIGURE 12 **Added Variable**

Adding A Group

The **Zaitun Time Series** group represents a collection of several time series variables. A group can contain two or more series variables. A time series data project can contain more than one group.

To add a new group into current project:

1. Click the **Add Group** button to open Create New Group dialog.

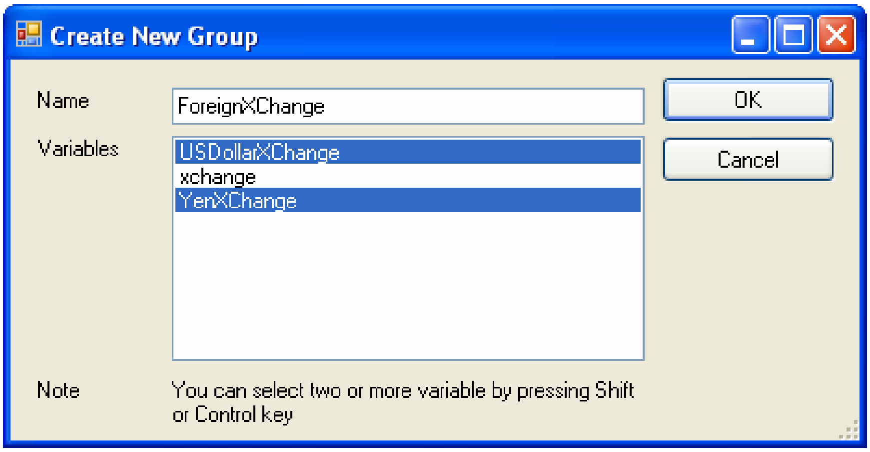


FIGURE 13 **Add Group Dialog**

2. Determine the new group's name.
3. Select variables belonging to this group. You can select two or more variables by pressing the Shift or Control key.
4. Click the **OK** button. **Zaitun Time Series** will add this group into current project.

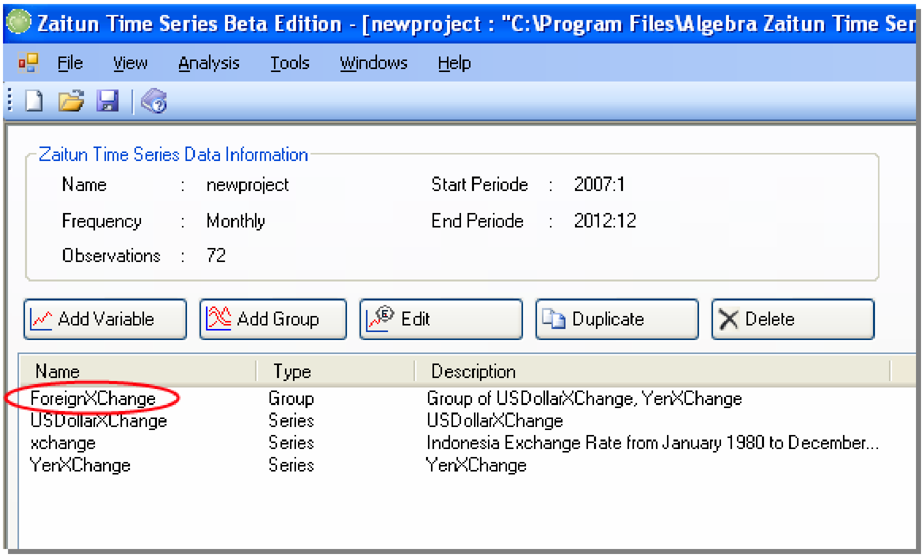


FIGURE 14 **Added Group**

Editing A Variable/Group

You can edit the name or description of a variable/group. To edit a variable/group:

1. Select the variable/group to be edited.

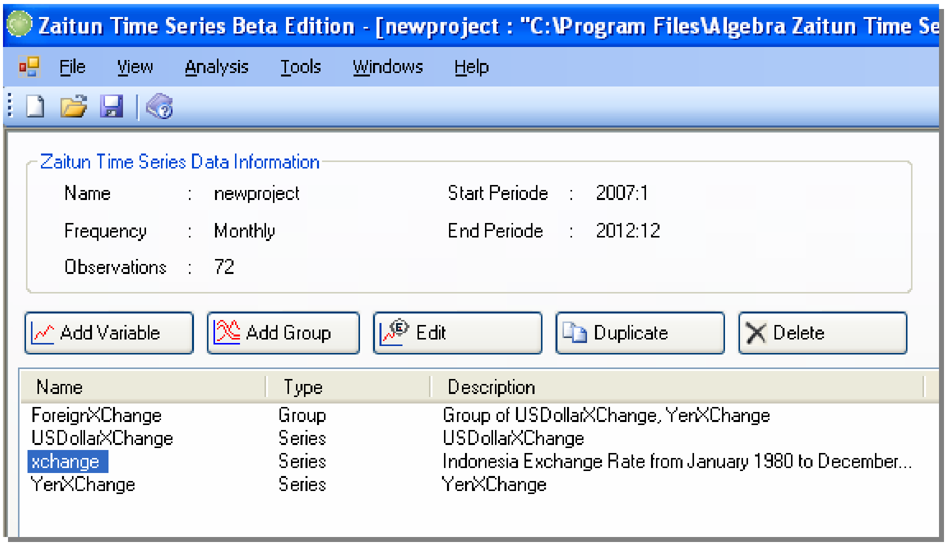


FIGURE 15 **Selected Variable**

2. Click the **Edit** button to show the Edit dialog.

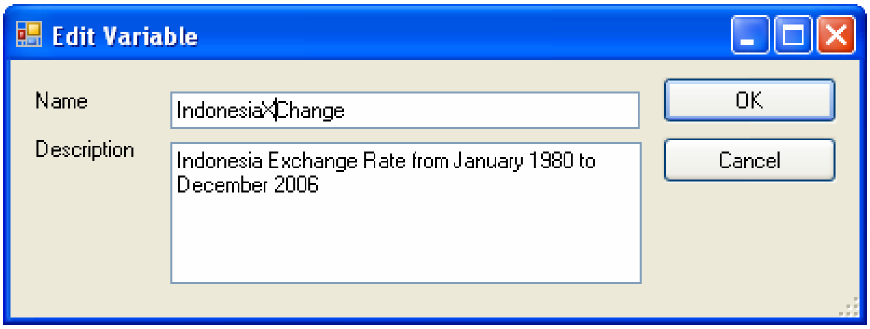


FIGURE 16 **Edit Variable Dialog**

3. Edit the name or description of this variable, and then click the **OK** button.

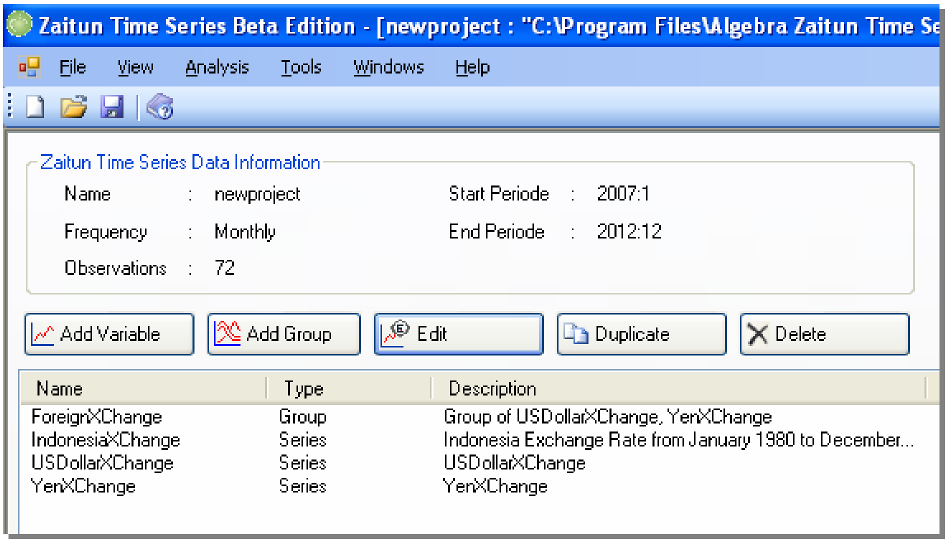


FIGURE 17 **Edited Variable**

Duplicating A Variable/Group

You can duplicate a variable/group. A duplicated variable/group has the same value as its source. To duplicate a variable/group:

1. Select the variable/group you want to duplicate.

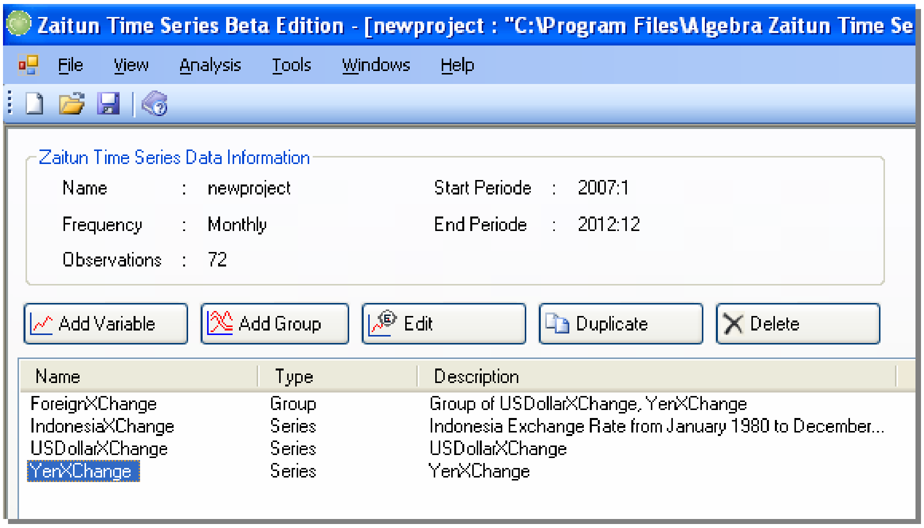


FIGURE 18 **Selected Variable**

2. Click the **Duplicate** button to show the Duplicate dialog.

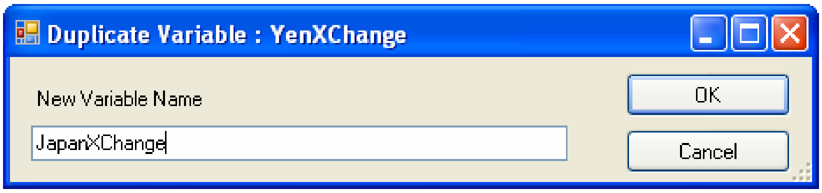


FIGURE 19 **Duplicate Variable Dialog**

3. Enter the new variable/group's name and then click the **OK** button. **Zaitun Time Series** will create a new variable/group that has same value as the source variable/group.

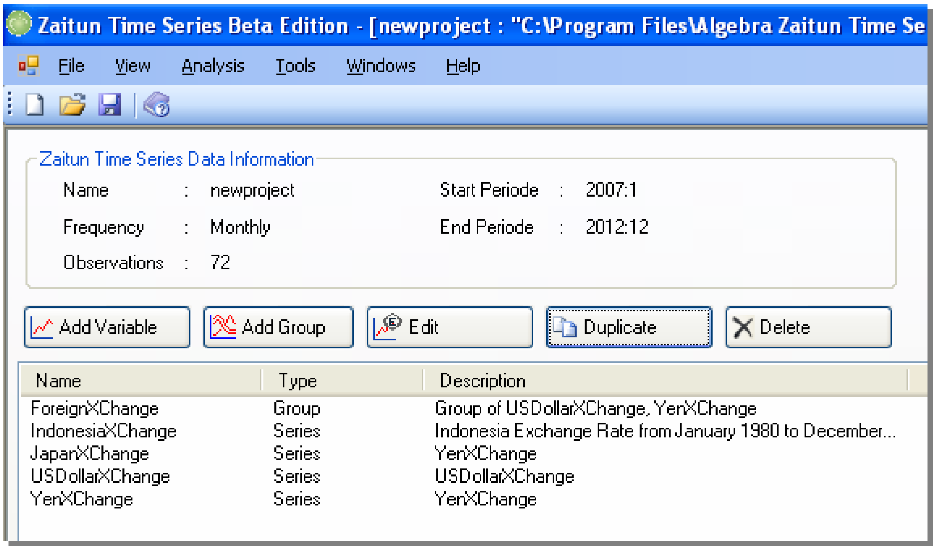


FIGURE 20 **Data View Screen after Duplicating the Variable**

Deleting A Variable/Group

You can also delete a variable/group you have created. To delete a variable/group:

1. Select the variable/group you want to delete.

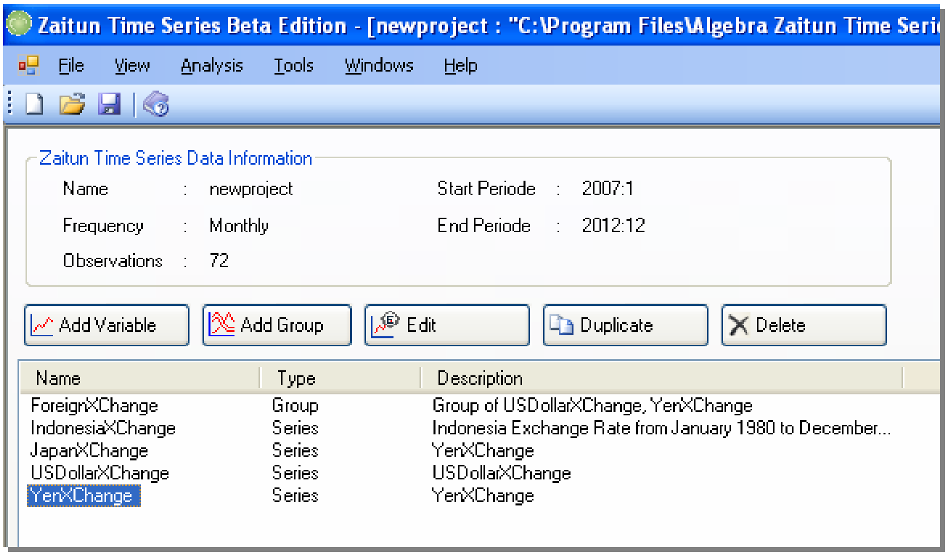


FIGURE 21 **Selected Variable**

2. Click the **Delete** button. A confirmation dialog appears. Click **Yes** if you are sure you wish to delete the selected variable/group.

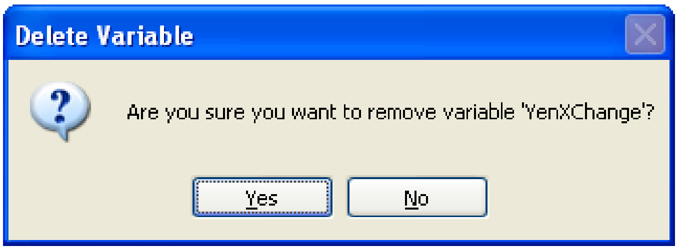


FIGURE 22 **Confirmation Dialog**

3. If you click **Yes** on the confirmation dialog, then the selected variable/group will be deleted from the current project.

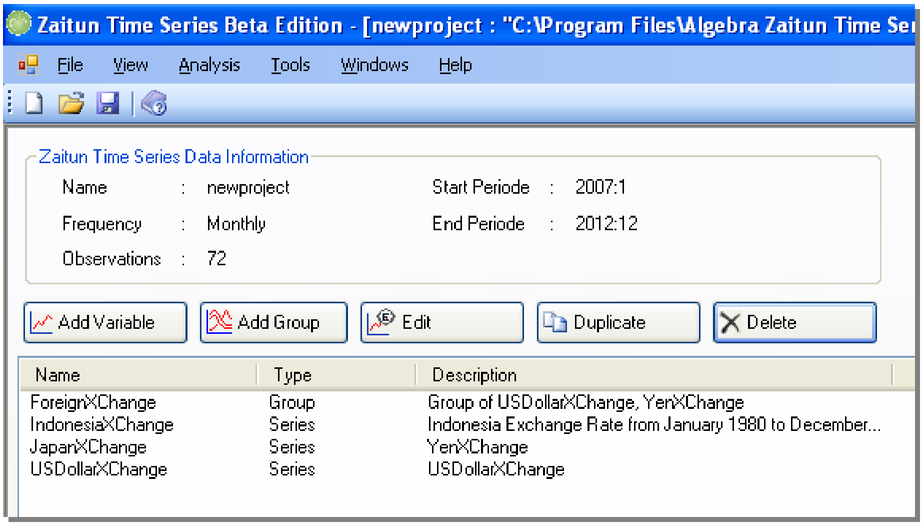


FIGURE 23 **Data View Screen after Deleting a Variable**

Viewing A Variable

Zaitun Time Series provides three ways to view a variable, spreadsheet view, graphic view, and statistics view. Viewing a variable is very simple. Double click the variable you wish to view. **Zaitun Time Series** will switch the main pane to the **Variable View** and view the selected variable.

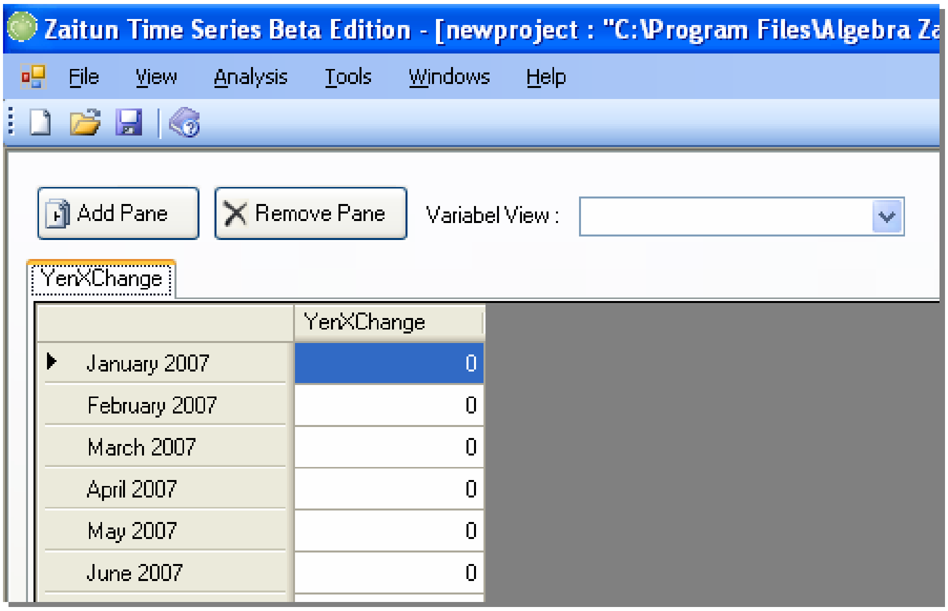


FIGURE 24 **Variable View**

You can also view a variable by manually switching the main pane to the **Variable View** Pane and clicking **Add Pane** button on the top left side of the **Variable Pane**.

Select Variable dialog appears. Select the variable you want to view and then click **OK**. **Zaitun Time Series** will add a new pane on the **Variable Pane** to view the variable.

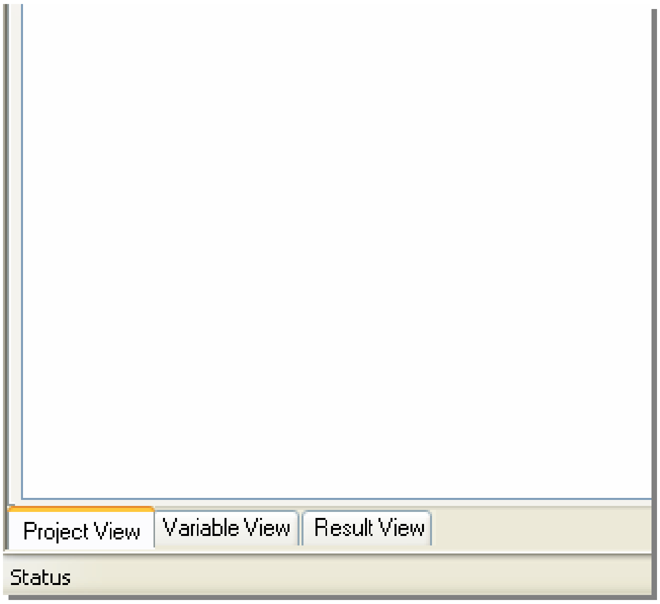


FIGURE 25 **Variable View Pane**

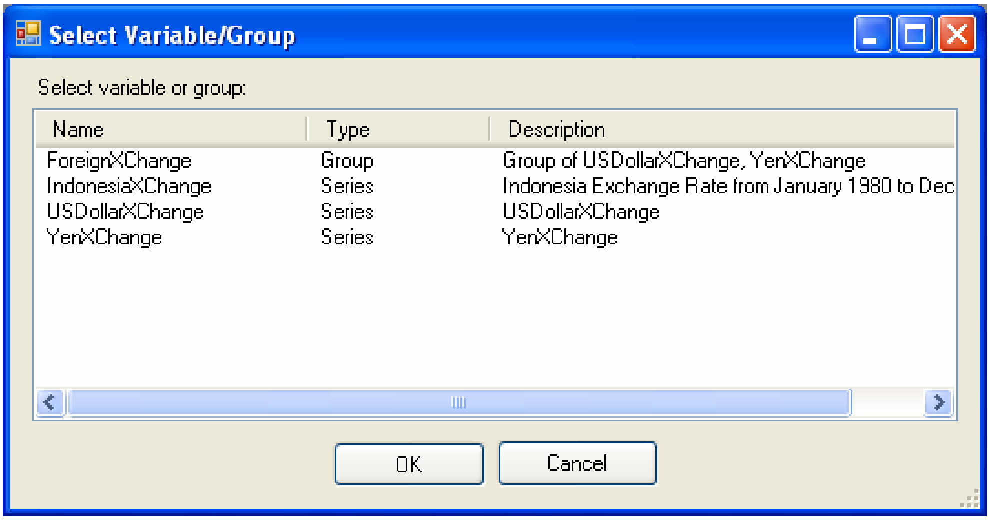


FIGURE 26 **Select Variable Dialog**

The default view is the spreadsheet view. To change the current view of a variable click on the Variable View Combo Box on the top of the **Variable View** pane. You can switch to graphic view or statistics view.

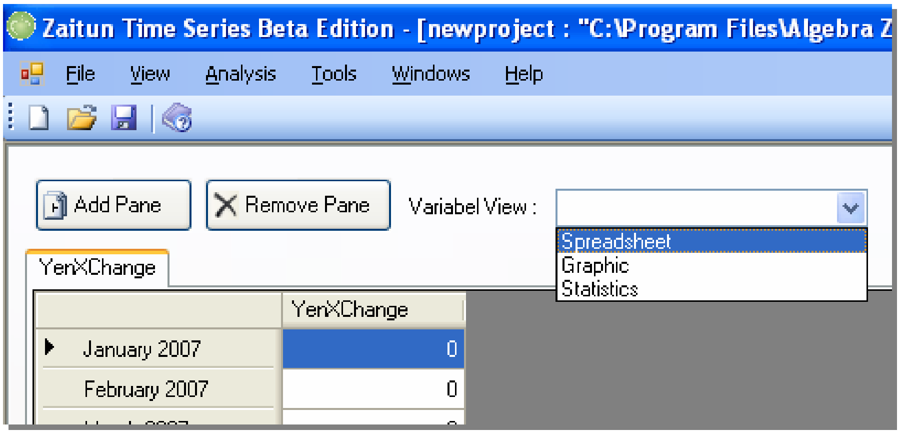


FIGURE 27 **Spreadsheet View**

Spreadsheet View shows variable values on a grid, it makes it easy for you to input or edit variable values by pressing numeric keys directly from keyboard. You can also paste values from an external program like Excel by right clicking the grid and selecting **Paste** menu.

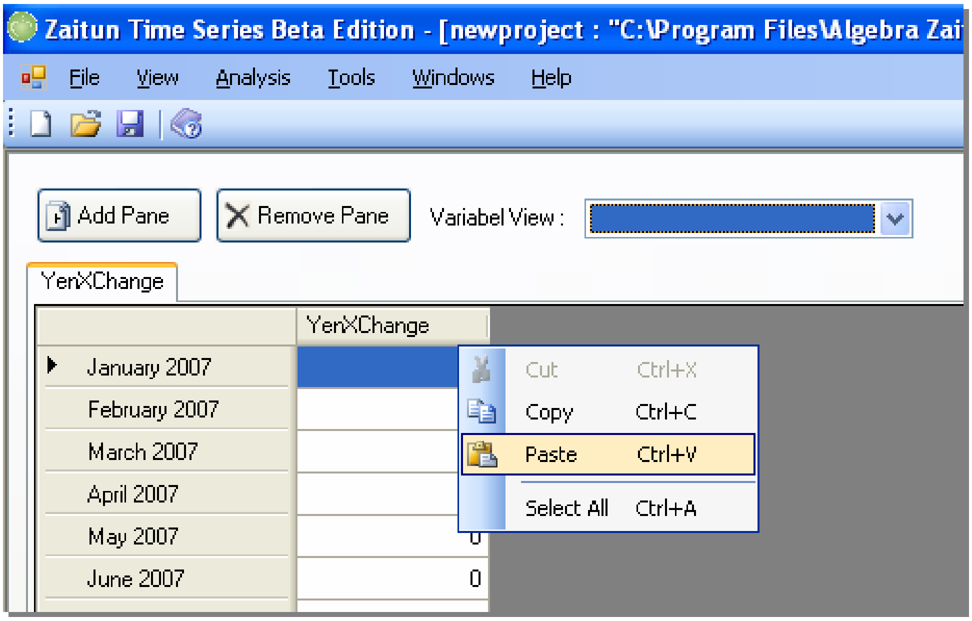


FIGURE 28 **Pasting Data into Spreadsheet View**

Graphic View shows variable values on a line chart. It makes it easy for you to analyze graphically the components of time series data of a variable. You will soon know whether the variable contains trend, cyclic, seasonal and irregular component.

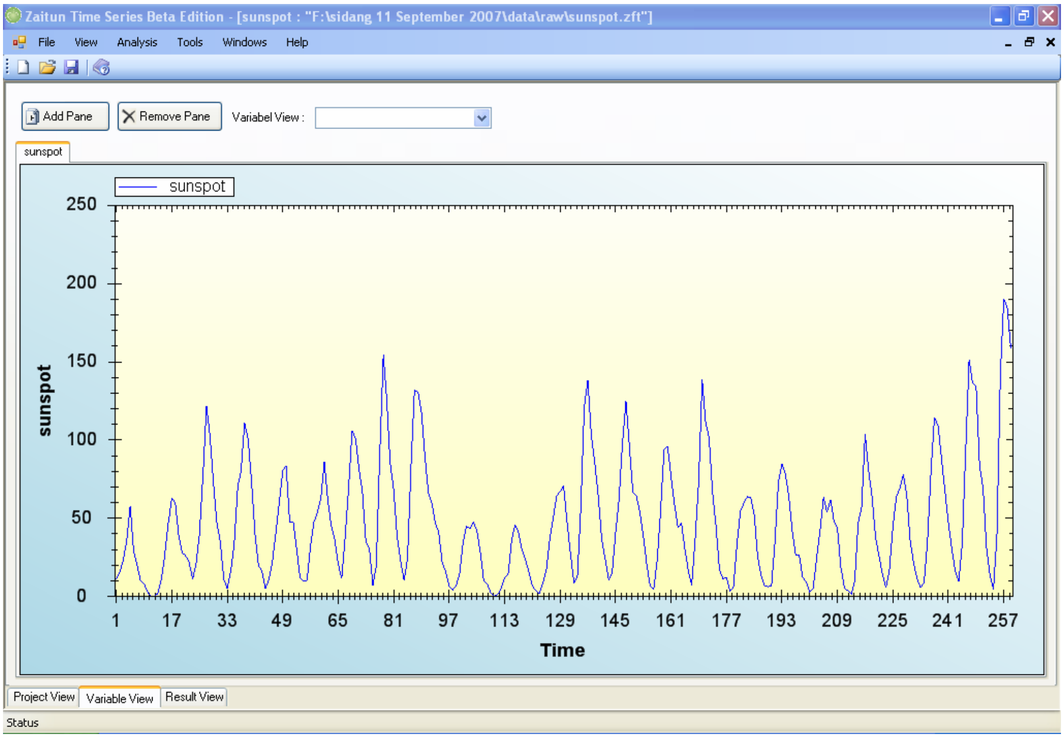


FIGURE 29 **Graphic View**

Statistics View shows simple descriptive statistics of a variable making it easy for you to analyze statistical properties of a variable.

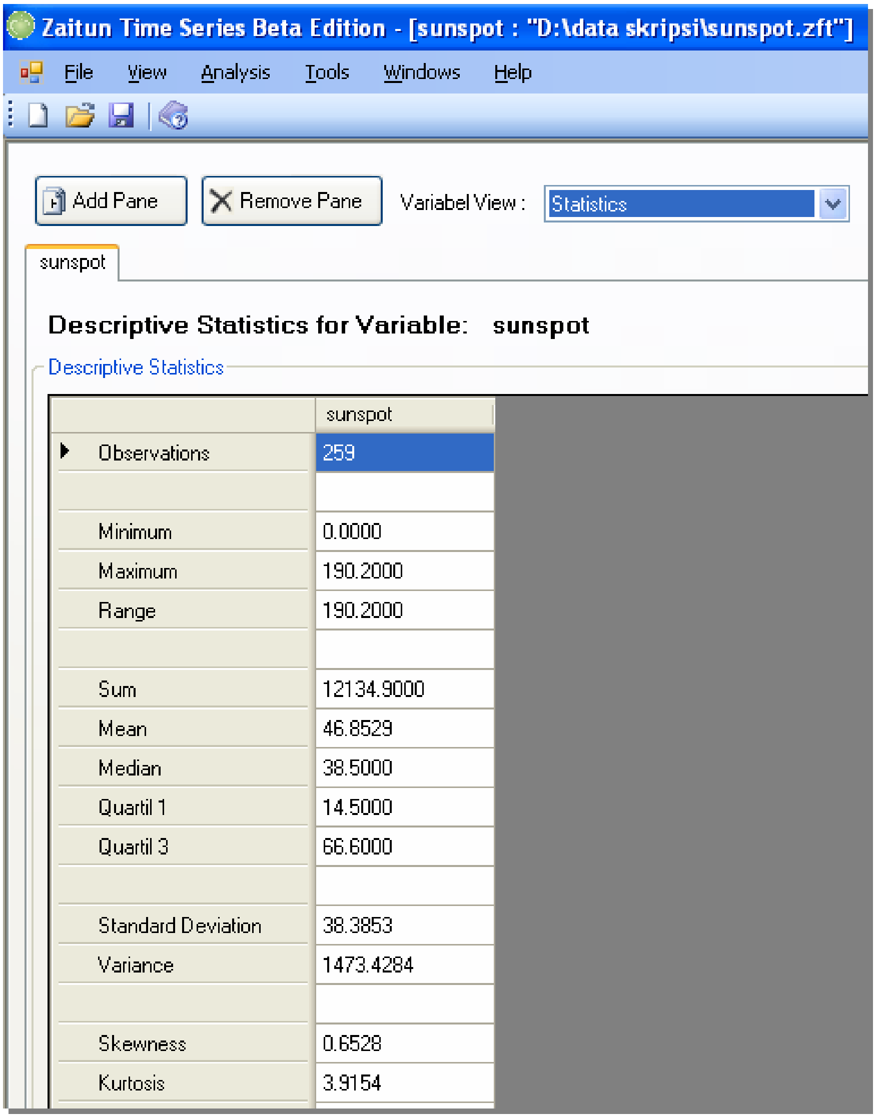


FIGURE 30 **Statistics View**

Viewing A Group

Zaitun Time Series provides two ways to view a group, spreadsheet view and graphic view. Viewing a group is not so different from viewing a variable. Just by double clicking the group you want to view, **Zaitun Time Series** will switch the main pane to **Variable View** and the selected group.

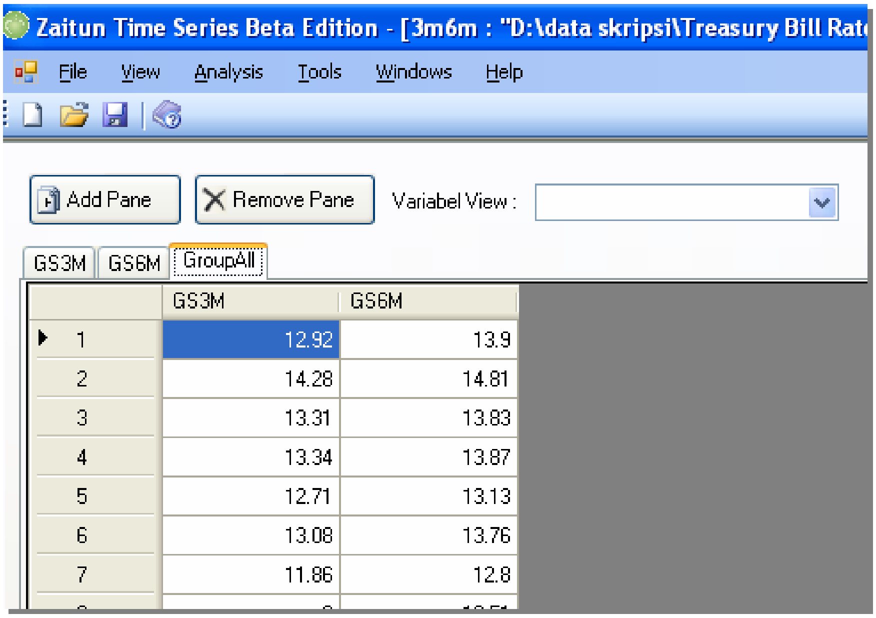


FIGURE 31 **Spreadsheet View of a Group**

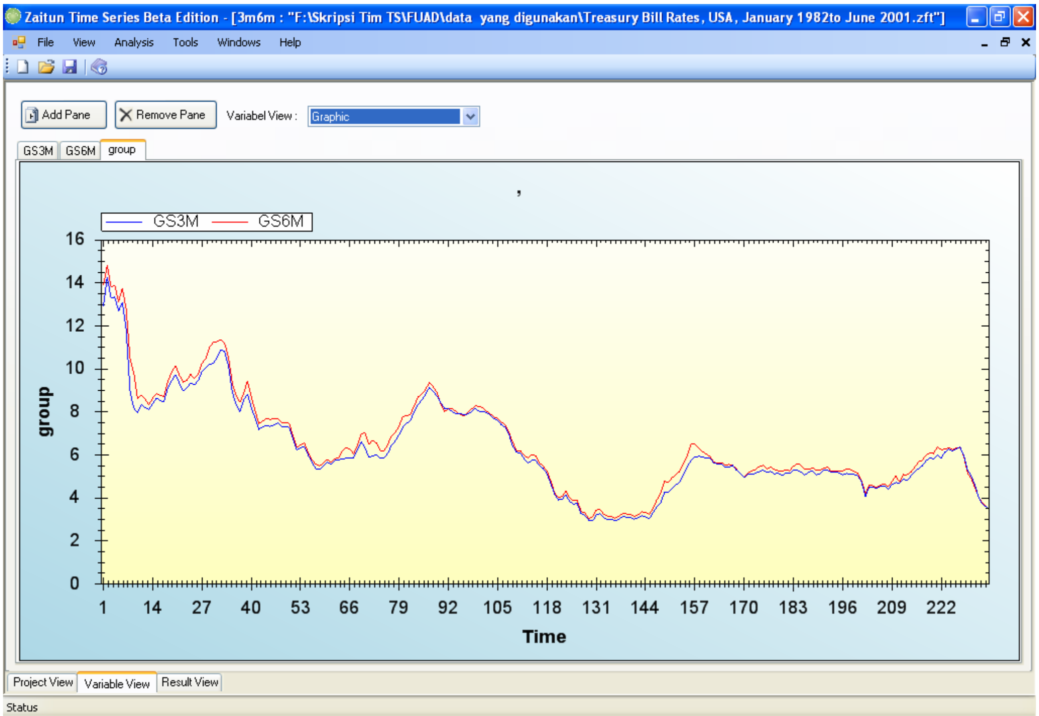


FIGURE 32 **Graphic View of A Group**

Transforming A Variable

Zaitun Time Series provides several transformation types that can be applied to a variable. They are differencing, seasonal differencing, logarithm, and square root. To transform a variable:

1. Click **Tools → Transform Variable** to show Transform Variable dialog.

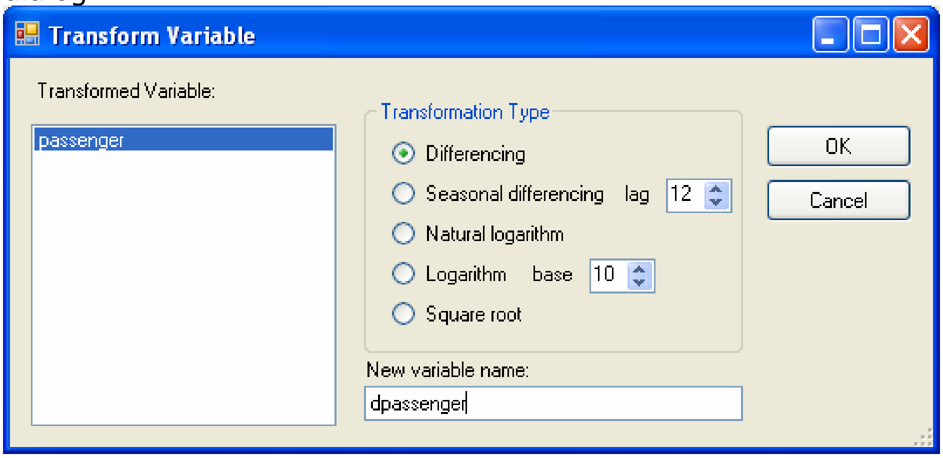


FIGURE 33 **Transform Variable Dialog**

2. Select a variable you want to transform and select the transformation type.
3. Determine the new variable's name and then click the **OK** button. **Zaitun Time Series** will create a transformed variable and add it into the current project.

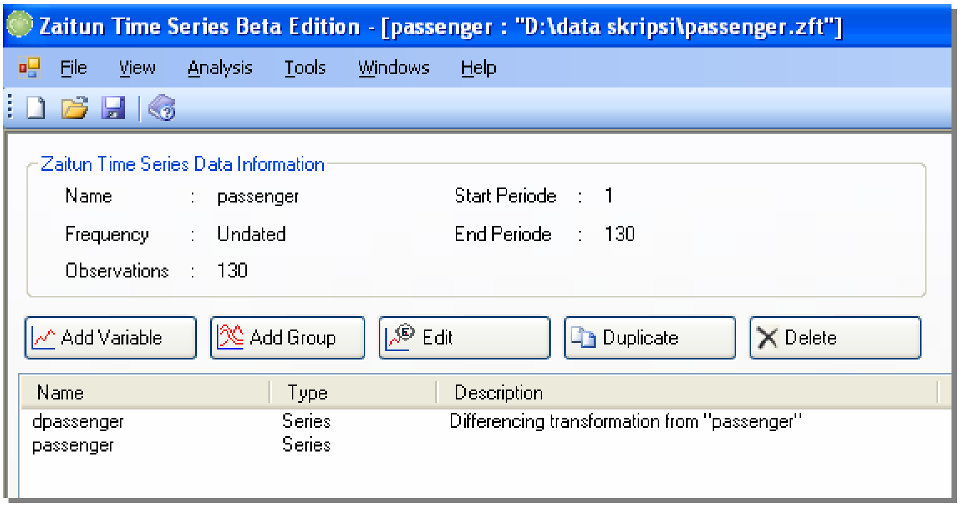


FIGURE 34 **Project View after Transforming a Variable**

Exporting The Data

Zaitun Time Series provides a facility to export the data created by **Zaitun Time Series** to another format. There are 2 formats available, CSV file and Excel File. **Zaitun Time Series** will export all of variables in the current project into a new CSV or Excel File, but it will not export the group data and the result data.

To export the current **Zaitun Time Series** project into a CSV file:

1. Click **File → Export → Export to CSV**.

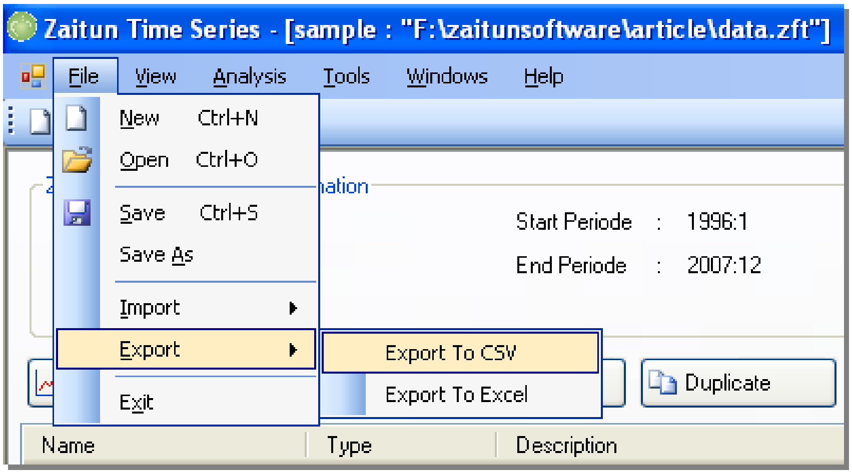


FIGURE 35 **Export to CSV** menu

2. **Export to CSV** dialog appear. Save the CSV file into the directory as you want.

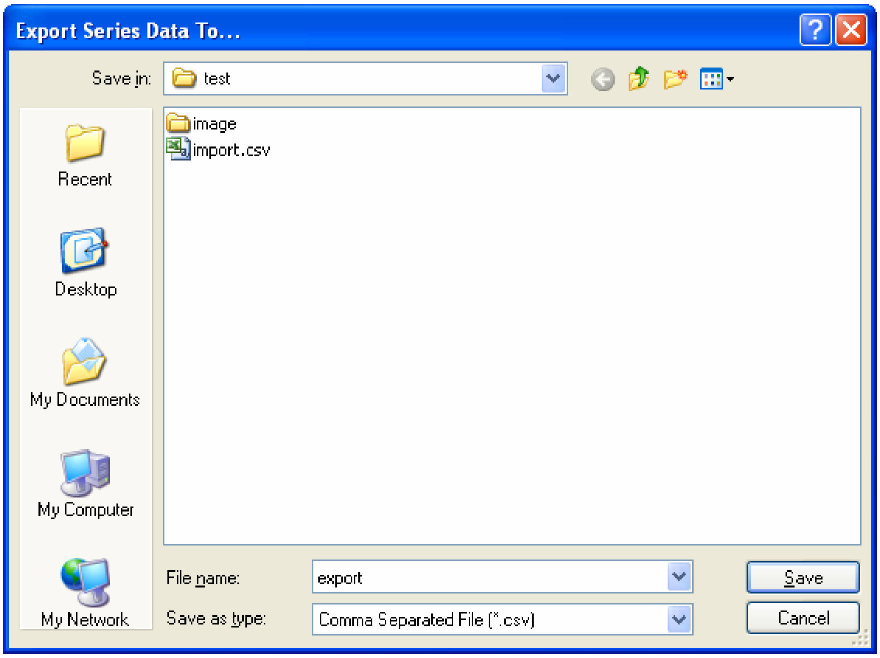


FIGURE 36 **Export to CSV** dialog

To export the current **Zaitun Time Series** project into an Excel file:

1. Click **File → Export → Export to Excel**.

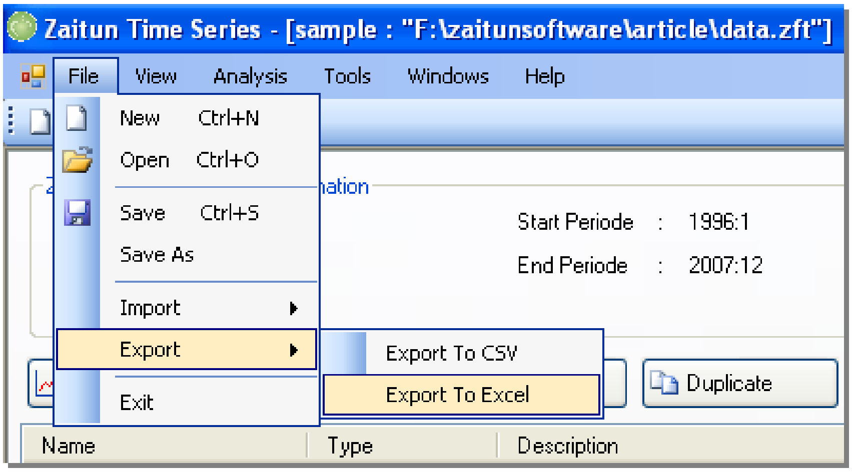


FIGURE 37 **Export to Excel** menu

2. **Export to Excel** dialog appear. Save the excel file into the directory as you want.

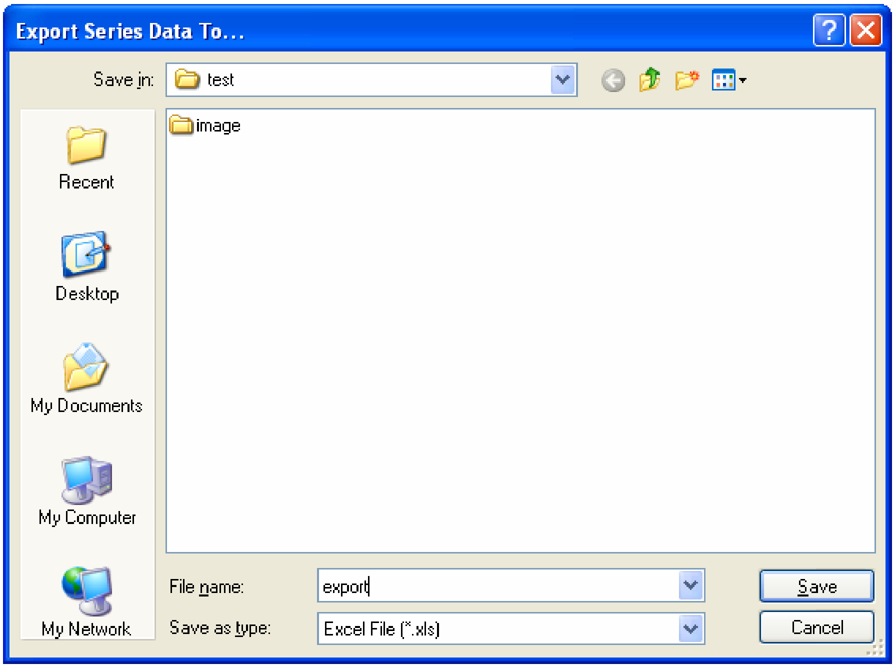


FIGURE 38 **Export to Excel** dialog

Importing Data

Zaitun Time Series provides a facility to import the data created by another software in a specified format. Zaitun Time Series provides a tool to import the data from CSV file (.csv) and Excel file (.xls).

Zaitun Time Series only accept numeric fields, both in the Excel format and the CSV format. Please do not include non numeric fields (e.g. "Nov 2007") in your CSV and Excel file which will be imported to **Zaitun Time Series**, except the first line/row which will be the list of variable name of the data.

To import a CSV file into the current **Zaitun Time Series** project:

1. Click **File → Import → Import to CSV**.

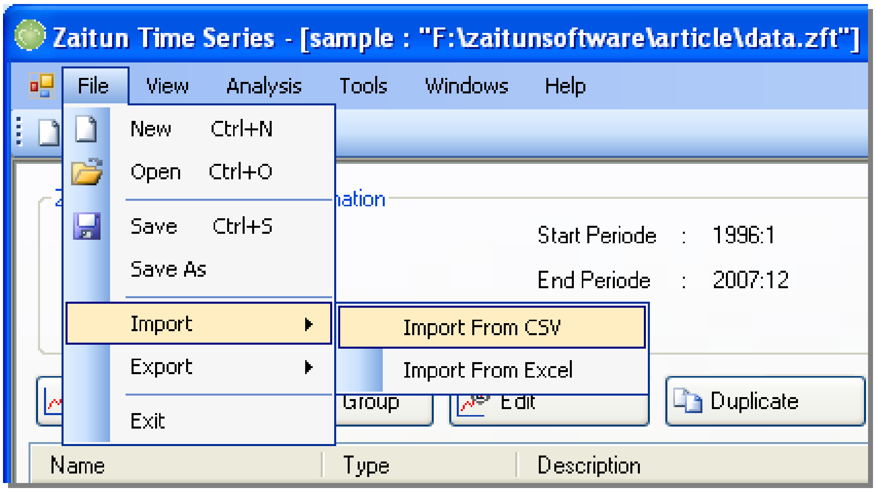


FIGURE 39 **Import from CSV** menu

2. The **Open CSV** dialog appear. Select the CSV file you want to import.

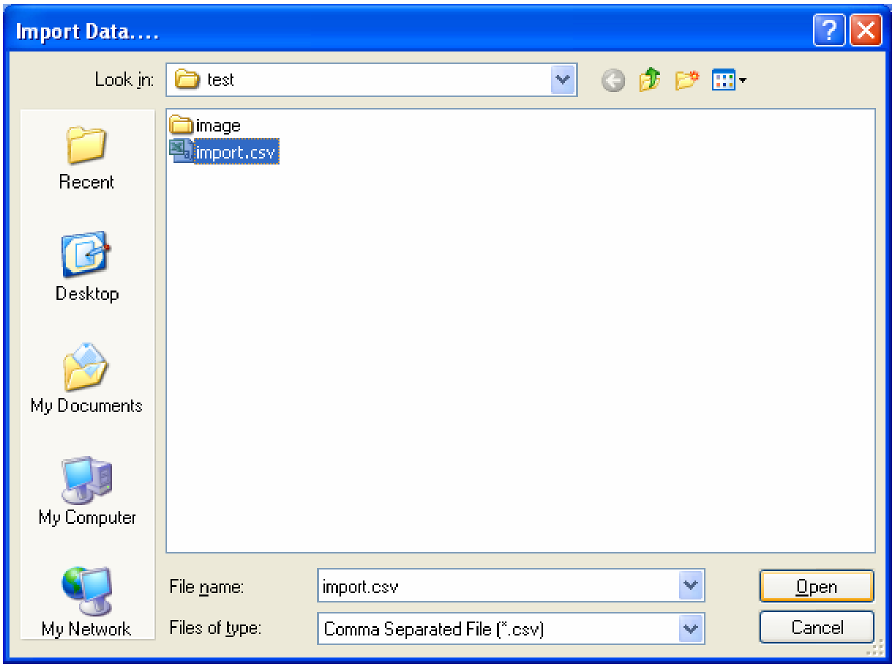


FIGURE 40 **Open CSV File** dialog

3. The **Import CSV** dialog appear. The CSV file can't contain non numeric fields except in the first line, which will be the variable name. Make sure the "Use First Row as Variable Name" option is checked if

your CSV File contains variable name information. Then, select variables you want to import by making a mark on some check boxes in the variable grid.

Click the OK button to import the selected variable in the CSV file into the current **Zaitun Time Series** project

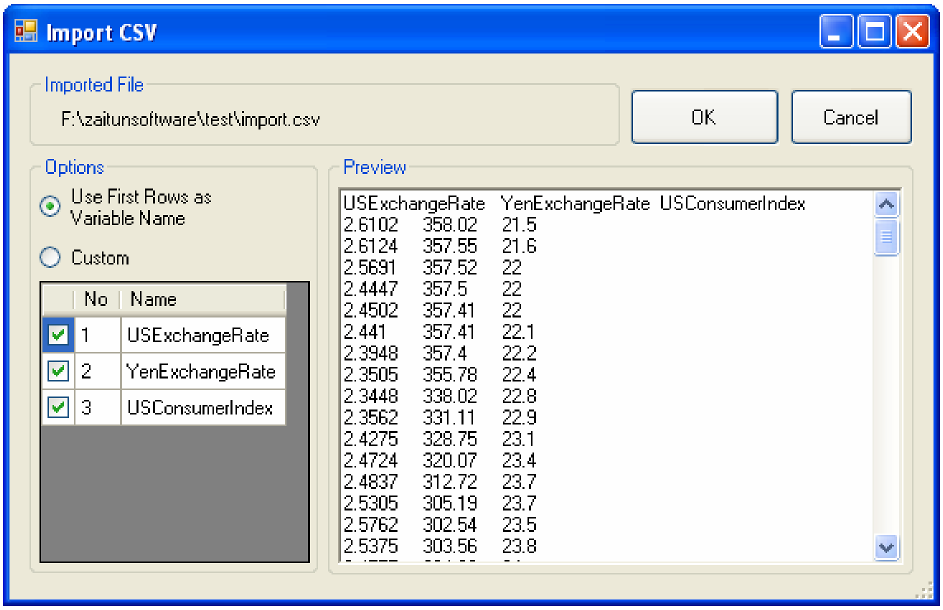


FIGURE 41 **Import CSV** dialog

To import an Excel file into the current **Zaitun Time Series** project:

1. Click **File → Import → Import to CSV**.

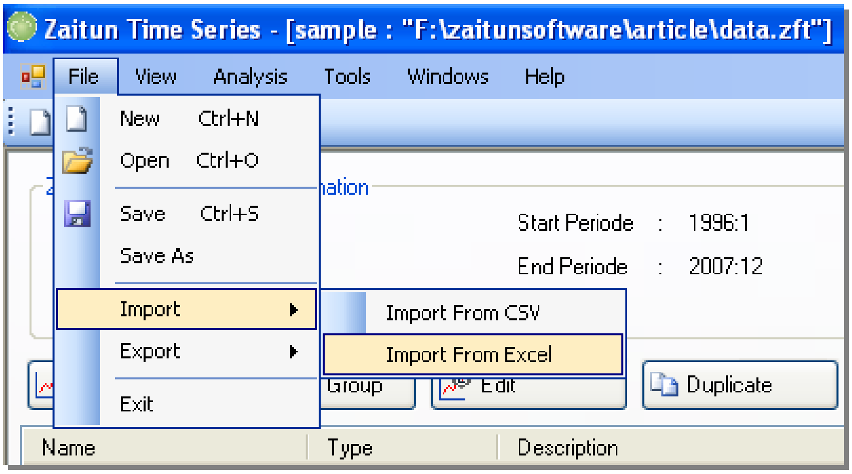


FIGURE 42 **Import from Excel** menu

2. **Open Excel** dialog appear. Select the Excel file you want to import.

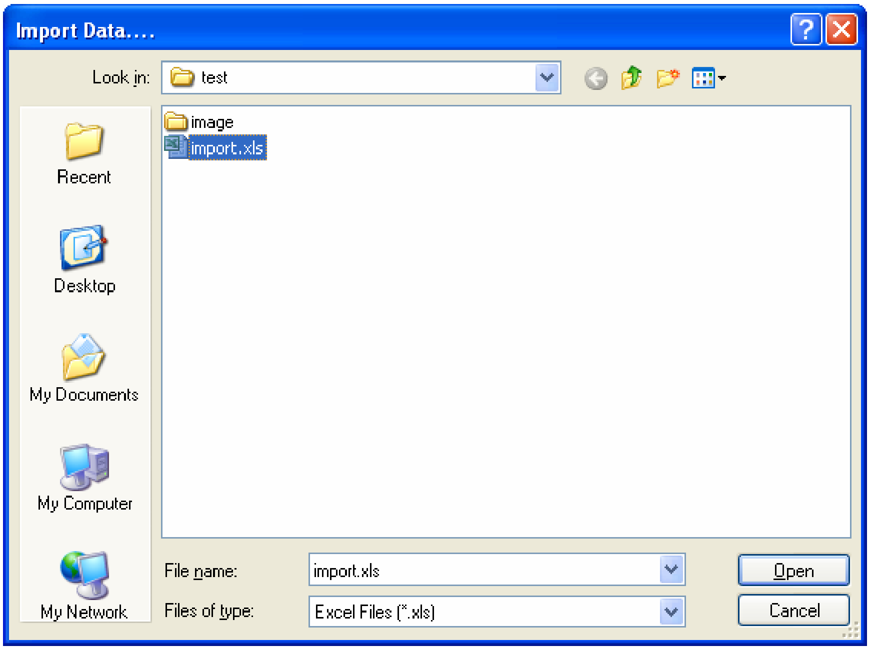


FIGURE 43 **Open Excel File** dialog

3. **Import Excel File** dialog appear. The Excel file can't contains non numeric field except the first row, which will be the variable name. Make sure the "Use First Row as Variable Name" option is checked if your Excel File contains variable name information. Then, select variables you want to import by making a mark on some check boxes in the variable grid. You can switch between sheets by selecting the sheet combo box in the Preview Pane.

   Click **OK** button to import the selected variable in Excel file into the current **Zaitun Time Series** project.

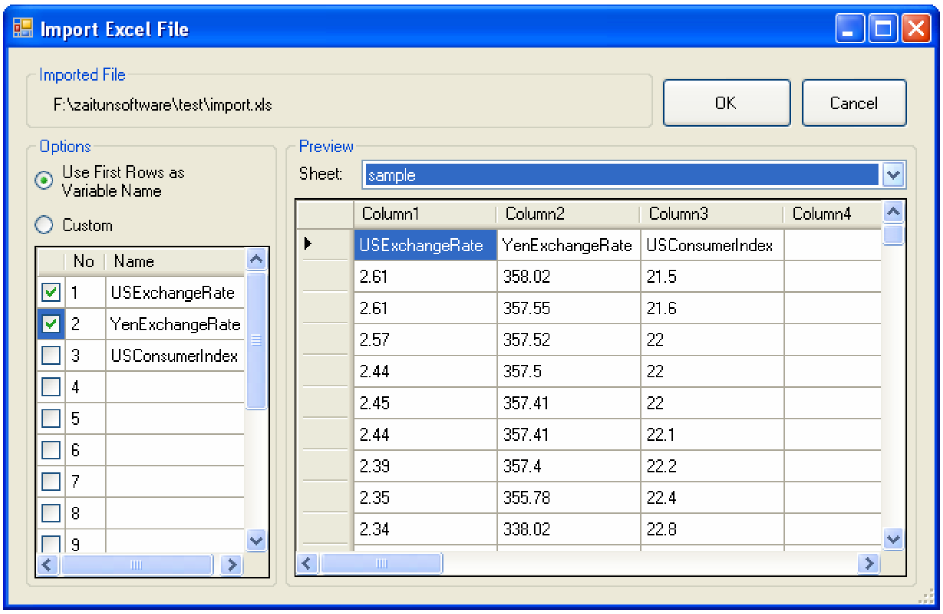


FIGURE 44 **Import Excel File** dialog

Trend Analysis

Chapter

4

Trend Analysis Overview

Linear Trend

Linear trend is a simple function described as a straight line along several points of time series value in time series graph. Linear trend has a common pattern:

$$T_t = a + b.Y_t$$

Where T_t = Trend value of period t

a = Constant of trend value at base period

b = Coefficient of trend line direction

Yt = an independent variable, represents time variable, usually assumed to have integer value 1, 2, 3,... as in the sequence of time series data.

There are several methods that can be used to find the linear trend equation of a time series. Most commonly used is least squares method. This method finds the coefficient values of the trend equation (a and b) by minimizing mean of squared error (MSE). The formula is:

$$b = \frac{n\sum Y_t T_t - \sum Y_t \sum T_t}{n\sum Y_t^2 - \sum (Y_t)^2}$$

$$a = \overline{Y}_t - b\overline{T}_t$$

Nonlinear Trend

In several cases, linear trend is not suitable for time series data. These cases occur when a time series has a different gradient between the beginning phase of the data and the next phase. For these cases, it is better to use nonlinear trend than linear trend.

There are several nonlinear trends, they are:

- Exponential

$$T_t = ab^Y$$

- Quadratic

$$T_t = a + bY_t + cY_t^2$$

- Cubic

$$T_t = a + bY_t + cY_t^2 + dY_t^3$$

The most suitable trend is a one with the smallest error, that is the smallest difference between actual data and estimated data from trend value. The common rule used to find the best trend is by choosing a trend with the smallest standard error value and having the biggest R-square value.

Trend Analysis with Zaitun Time Series

Zaitun Time Series provides a feature to analyze trend component of a time series. There are several trend types available e.g. linear, quadratic, cubic , and exponential. To make a trend analysis of a time series variable:

1. Click **Analysis → Trend Analysis** menu.

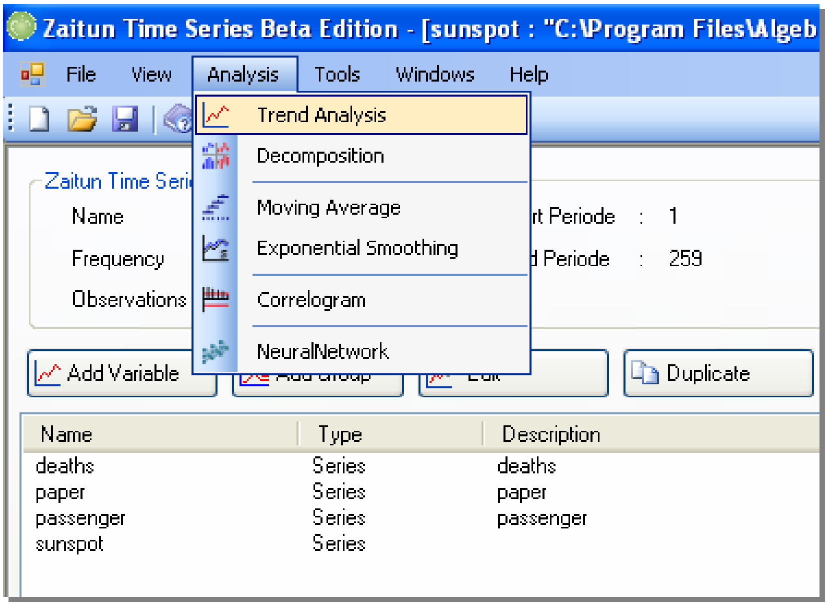


FIGURE 45 **Trend Analysis Menu**

2. The **Select Analyzed Variable Dialog** appears. Choose a variable you want to analyze with trend analysis, and then click **OK**.

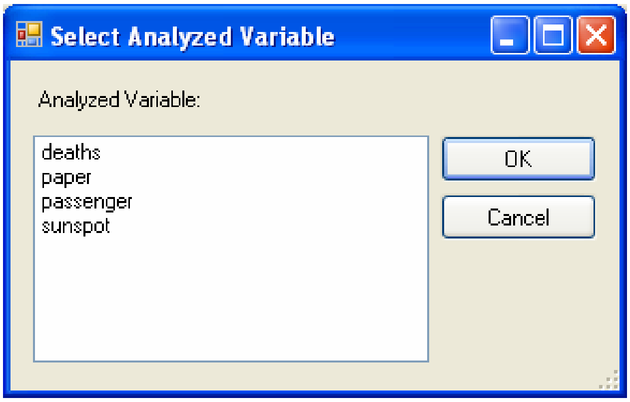


FIGURE 46 **Select Analyzed Variable Dialog**

3. The **Trend Analysis** form will appear. Choose the most suitable trend type for the selected variable.

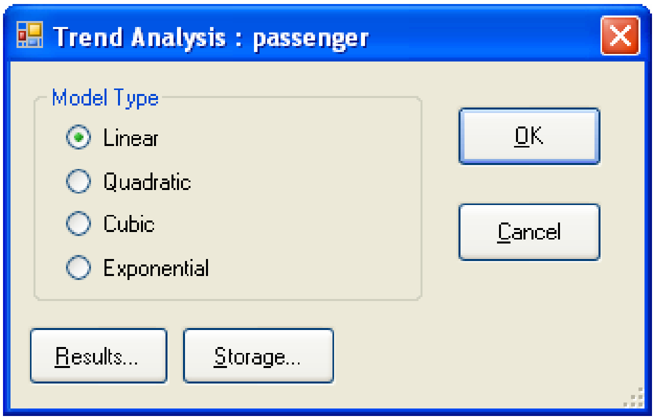


FIGURE 47 **Trend Analysis Form**

4. To select the analysis result to be viewed on **Result View**, click the **Results** button. Select the result views required by clicking the appropriate checkbox. For **Forecasted** selection, enter the data step you wish to forecast.

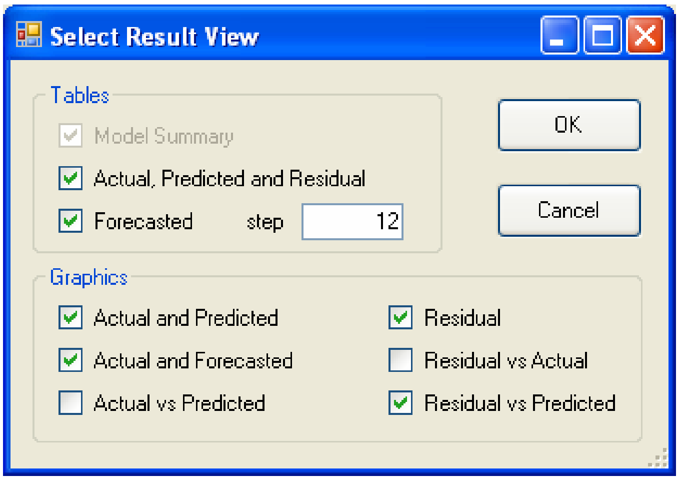


FIGURE 48 **Select Result View Dialog**

5. To save the residual and predicted data of the trend model as a new variable, you can click **Storage** button. Check on the item you want to save as a new variable, and then type the new variable name.

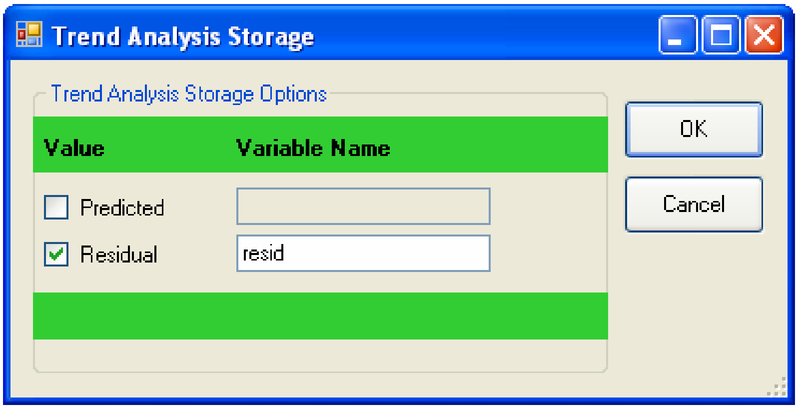


FIGURE 49 **Trend Analysis Storage Form**

6. After selecting the result views and determining whether you want to save the new variable or not, the software will show the **Trend Analysis** form again. Click the **OK** button to finish your analysis and show the result views.
7. The result views selected in previous step will be viewed as several panels on **Result View** tab page.

Trend Analysis Result

The result views of trend analysis in **Zaitun Time Series** are grouped into two categories, tables and graphics. See the details below:

1. Tables
   a. Model Summary

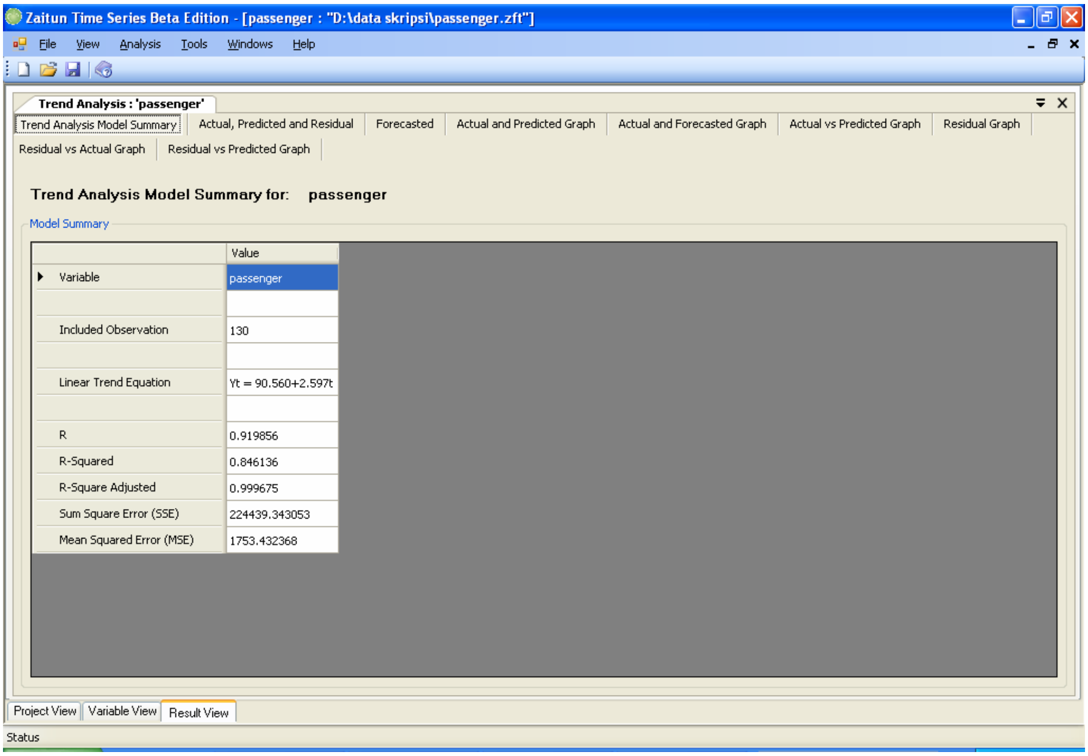
      Shows the summary of trend model.

   b. Actual, Predicted and Residual

      Show actual, predicted and residual values of trend model.

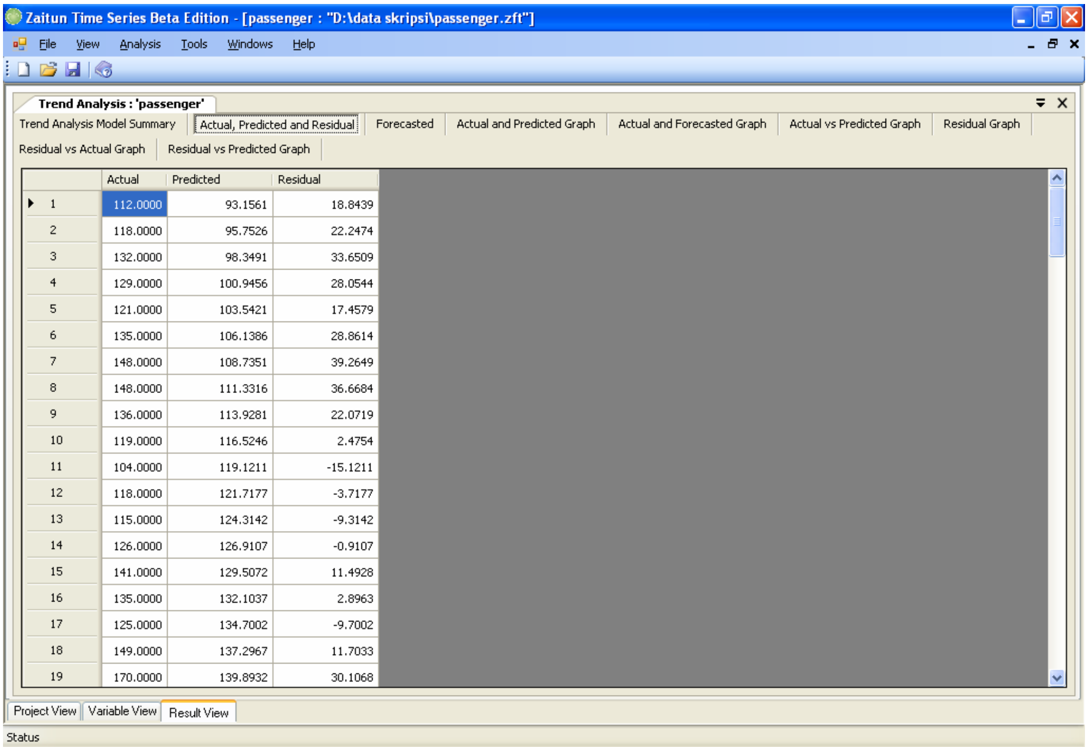
   c. Forecasted

      Shows forecasted values from trend model, as many steps of data you want to forecast.



	Value
Variable	passenger
Included Observation	130
Linear Trend Equation	Yt = 90.560+2.597t
R	0.919856
R-Squared	0.846136
R-Square Adjusted	0.999675
Sum Square Error (SSE)	224439.343053
Mean Squared Error (MSE)	1753.432368

FIGURE 50 **Table of Trend Analysis Model Summary**



	Actual	Predicted	Residual
1	112.0000	93.1561	18.8439
2	118.0000	95.7526	22.2474
3	132.0000	98.3491	33.6509
4	129.0000	100.9456	28.0544
5	121.0000	103.5421	17.4579
6	135.0000	106.1386	28.8614
7	148.0000	108.7351	39.2649
8	148.0000	111.3316	36.6684
9	136.0000	113.9281	22.0719
10	119.0000	116.5246	2.4754
11	104.0000	119.1211	-15.1211
12	118.0000	121.7177	-3.7177
13	115.0000	124.3142	-9.3142
14	126.0000	126.9107	-0.9107
15	141.0000	129.5072	11.4928
16	135.0000	132.1037	2.8963
17	125.0000	134.7002	-9.7002
18	149.0000	137.2967	11.7033
19	170.0000	139.8932	30.1068

FIGURE 51 **Table of Actual, Predicted and Residual Value**

2. Graphic

a. Actual and Predicted

Shows the line plot for actual and predicted values of trend model.

b. Actual and Forecasted

Shows the line plot for actual and forecasted values of trend model.

c. Actual vs. Predicted

Shows the scatter plot between actual and predicted values.

d. Residual

Shows the line plot for residual values of trend model.

e. Residual vs. Actual

Shows the scatter plot between residual and actual values.

f. Residual vs. Predicted

Shows the scatter plot between residual and predicted values.

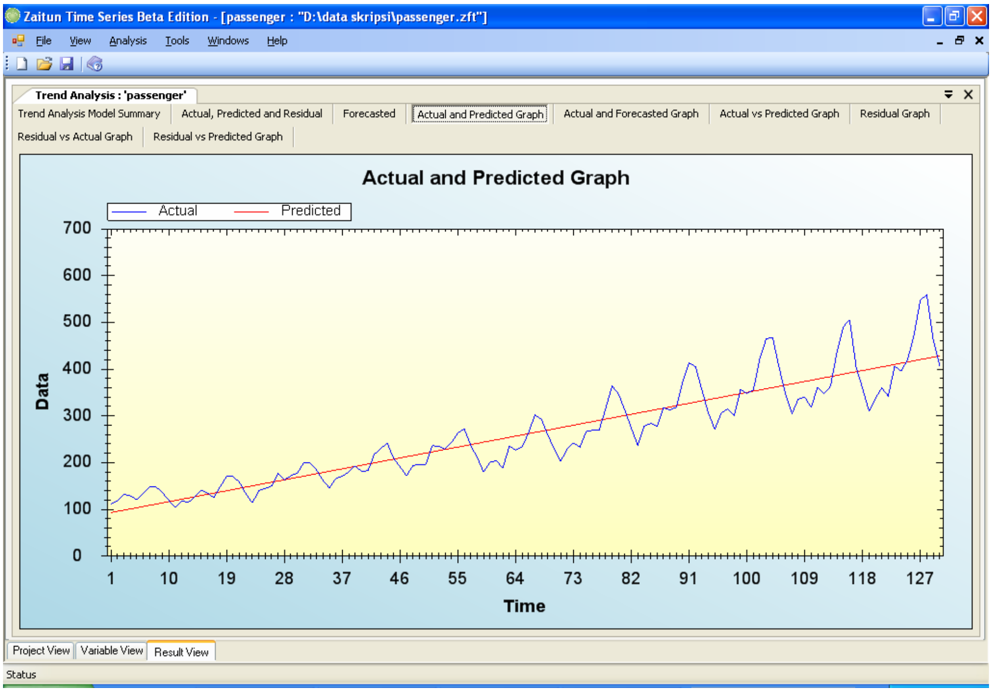


FIGURE 52 **Actual and Predicted Graph**

Moving Average Analysis

Chapter 5

Moving Average Overview

There are several methods which can be used to smooth time series data by moving averages. They are the Single Moving Average and the Double Moving Average methods. Both of them use several past data points to forecast the future.

Single Moving Average

The Single Moving Average method uses the last t periods to create a forecast. The new average value is calculated by removing the oldest value and replacing it with the newest value. This method is suitable for stationary data and for data which does not contain trend or seasonal components.

Let us have N points of data and use T observations to calculate the average value, notated as MA(T). It is described as:

Y_1 Y_2 .... Y_T	Y_{T+1} .... Y_N
Initialization group	Testing group

Time	Moving Average	Forecast
T	$Y = \dfrac{y_1 + y_2 + \ldots + y_t}{T}$	$F_{T+1} = \sum_{i=1}^{T} y_i / T$
T+1	$Y = \dfrac{y_2 + y_3 + \ldots + y_{t+1}}{T}$	$F_{T+2} = \sum_{i=2}^{T+1} y_i / T$
T+2	$Y = \dfrac{y_3 + y_4 + \ldots + y_{t+2}}{T}$	$F_{T+3} = \sum_{i=3}^{T+2} y_i / T$
	…..	

Double Moving Average

This method is based on the calculation of the second moving average. The Second moving average is calculated from the average of first moving average, notated by MA (T x T), means MA (T) period from MA

(T) period. This method can be used to forecast data with a linear trend component.

The procedure to calculate double moving average is:

1. Calculate single moving average $S_t^{'} = \frac{Y_t + \ldots + Y_{n-T+1}}{T}$

2. Calculate adjustment, which is the difference between single-MA and double-MA $\left(S_n^{'} - S_n^{''}\right)$, where $S_t^{''} = \frac{S_t^{'} + \ldots + S_{n-T+1}^{'}}{T}$

3. Adjust trend from period *n* to *n*+*m*, if you want to forecast *m* period ahead.

The forecasting value for *m* period ahead is a_n – where it is the adjusted average value for period *n* – added by the value of multiplication between *m* and trend component b_n.

Moving Average Analysis with Zaitun Time Series

Zaitun Time Series provides a feature to perform moving average analysis of a time series. Single moving average and double moving average are available. To perform the moving average analysis on a time series variable:

1. Click **Analysis → Moving Average**.

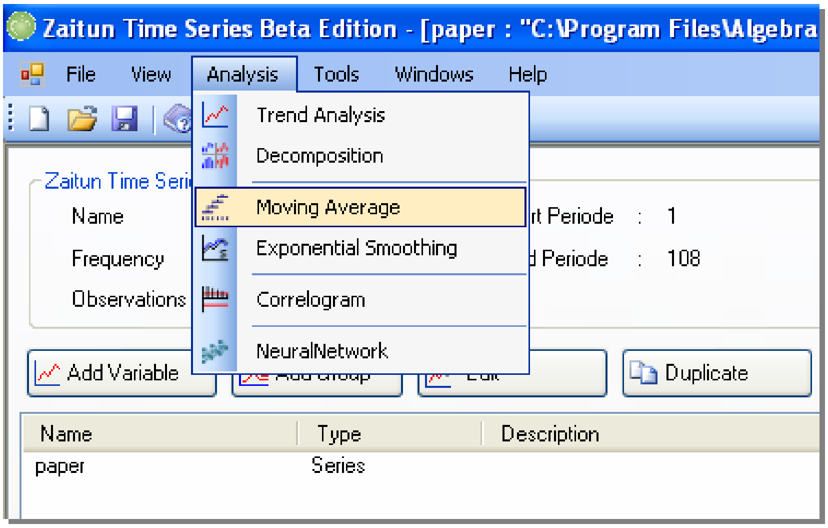


FIGURE 53 **Moving Average Menu**

2. **Select Variable Dialog** appears. Choose a variable you want to analyze with moving average analysis, and then click **OK**.

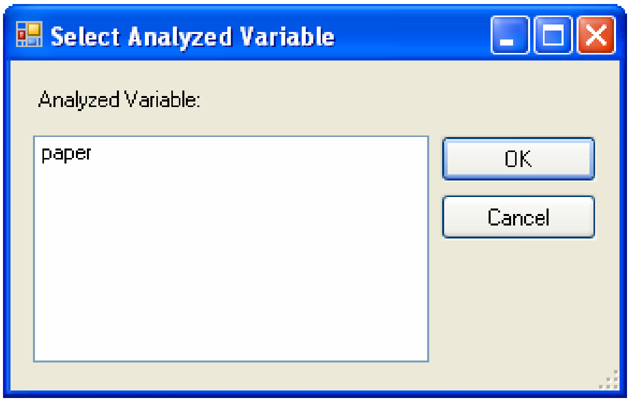


FIGURE 54 **Select Analyzed Variable Dialog**

3. The **Moving Average** form will appear. Choose the moving average method you wish to apply to your variable, and set the moving average order.

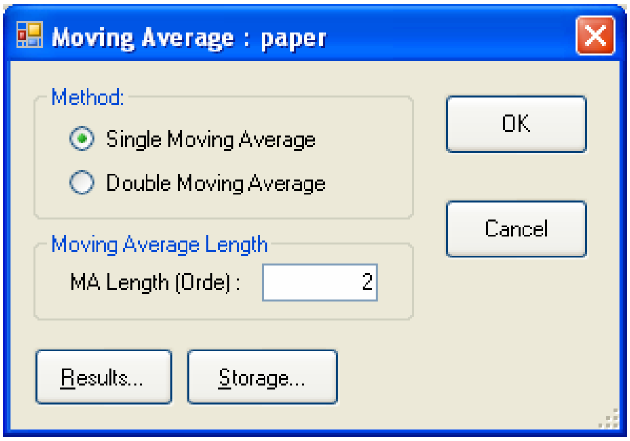


FIGURE 55 **Moving Average form**

4. To select the analysis result that will be shown on **Result View**, click the **Results** button. Check the boxes of any number of Result Views you wish to see. For the **Forecasted** selection, you have to enter the data step you wish to forecast.

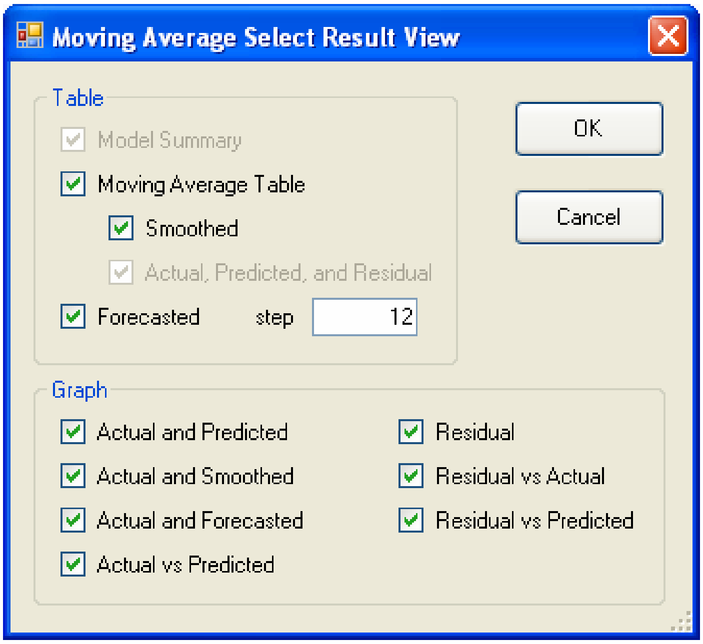


FIGURE 56 **Moving Average Select Result View Dialog**

5. To save residual, predicted or smoothed data from the model as a new variable, click the **Storage** button. Check the item you wish to save as a new variable, and then type in the new variable name.

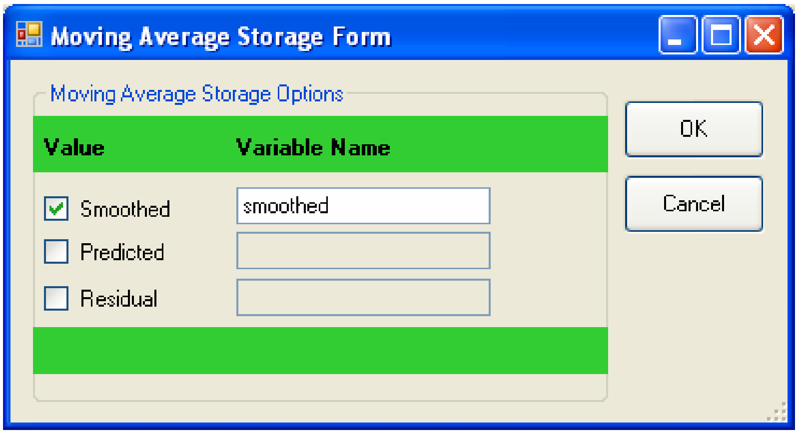


FIGURE 57 **Moving Average Storage Form**

6. After selecting result views and determining whether you want to save the new variable or not, the software will show the **Moving Average** form again. Click the **OK** button to finish your analysis and to show the result views.

7. The result views selected on the previous step will be viewed as several tabs on the **Result View** panel.

Moving Average Analysis Result

The result views of moving average analysis in **Zaitun Time Series** are grouped into two categories, they are tables and graphics. The details of them are described here:

1. Tables

   a. Model Summary

      Shows the summary of moving average model.

   b. Moving Average Table

      Shows actual, MA, predicted and residual values of moving average model.

   c. Forecasted

      Shows forecasted values from moving average model, as many steps of data you want to forecast.

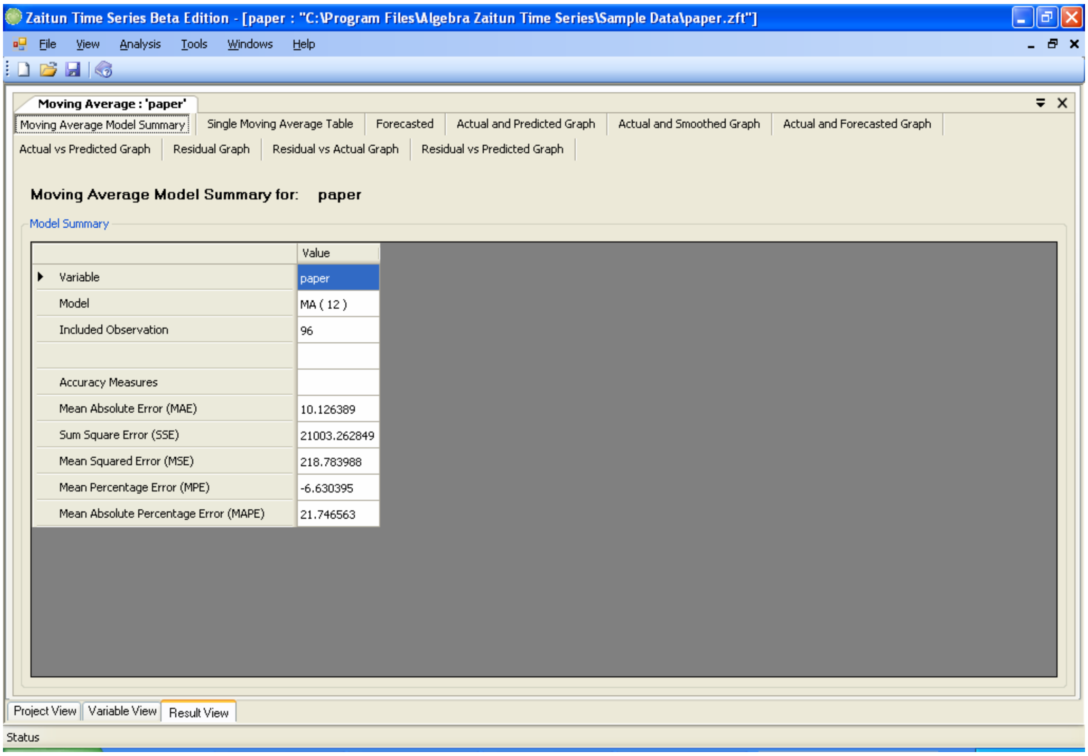


FIGURE 58 **Table of Moving Average Model Summary**

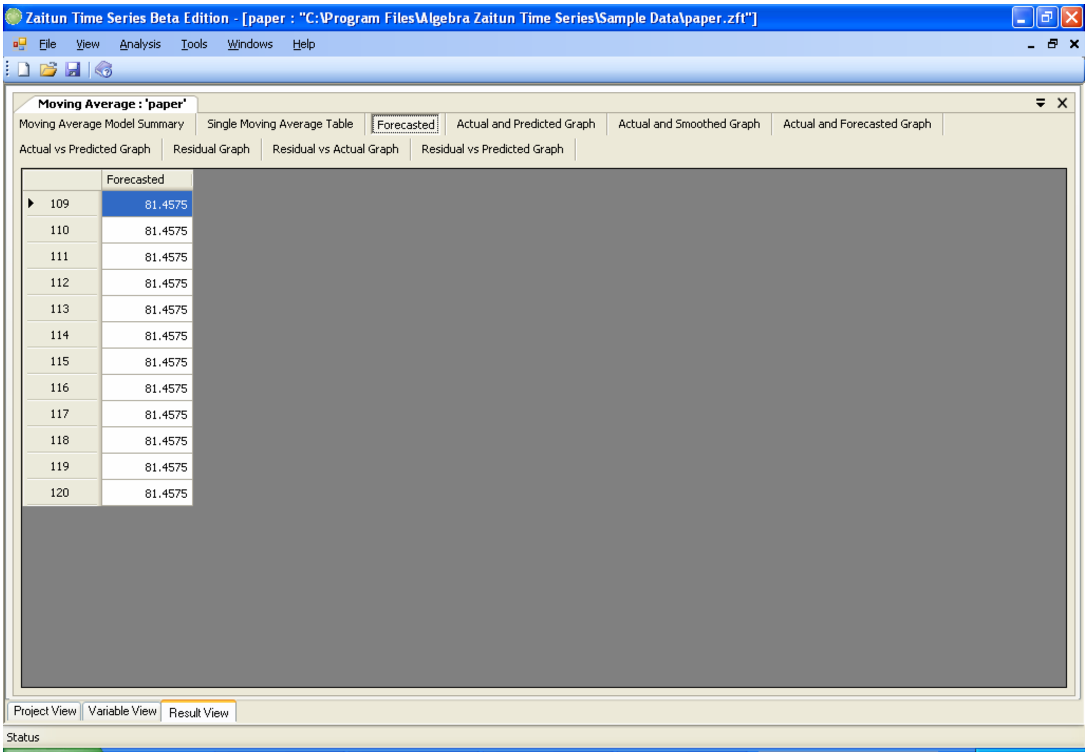


FIGURE 59 **Table of Forecasted Value**

2. Graphics
   a. Actual and Predicted

      Shows a line plot for actual and predicted values of moving average model.
   b. Actual and Smoothed

      Shows a line plot for actual and smoothed values of moving average model.
   c. Actual and Forecasted

      Shows a line plot for actual and forecasted values of moving average model.
   d. Actual vs Predicted

      Shows a scatter plot between actual and predicted values.
   e. Residual

      Shows a line plot for residual values of moving average model.
   f. Residual vs Actual

      Shows a scatter plot between residual and actual values.
   g. Residual vs Predicted

      Shows a scatter plot between residual and predicted values.

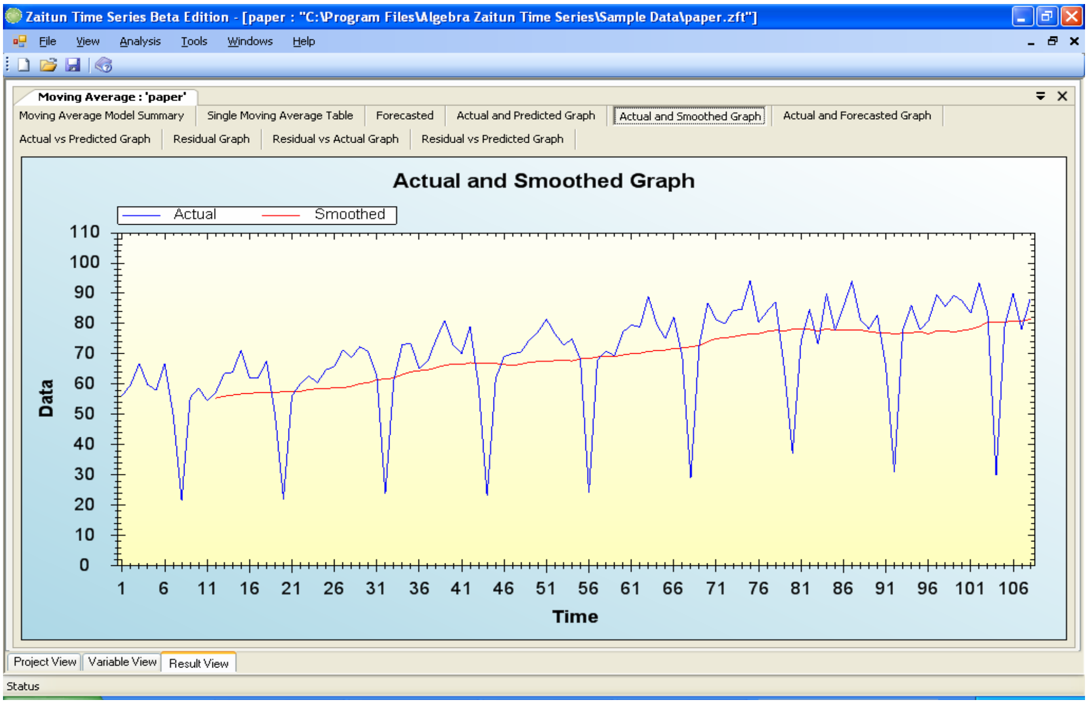


FIGURE 60 **Actual and Smoothed Graph**

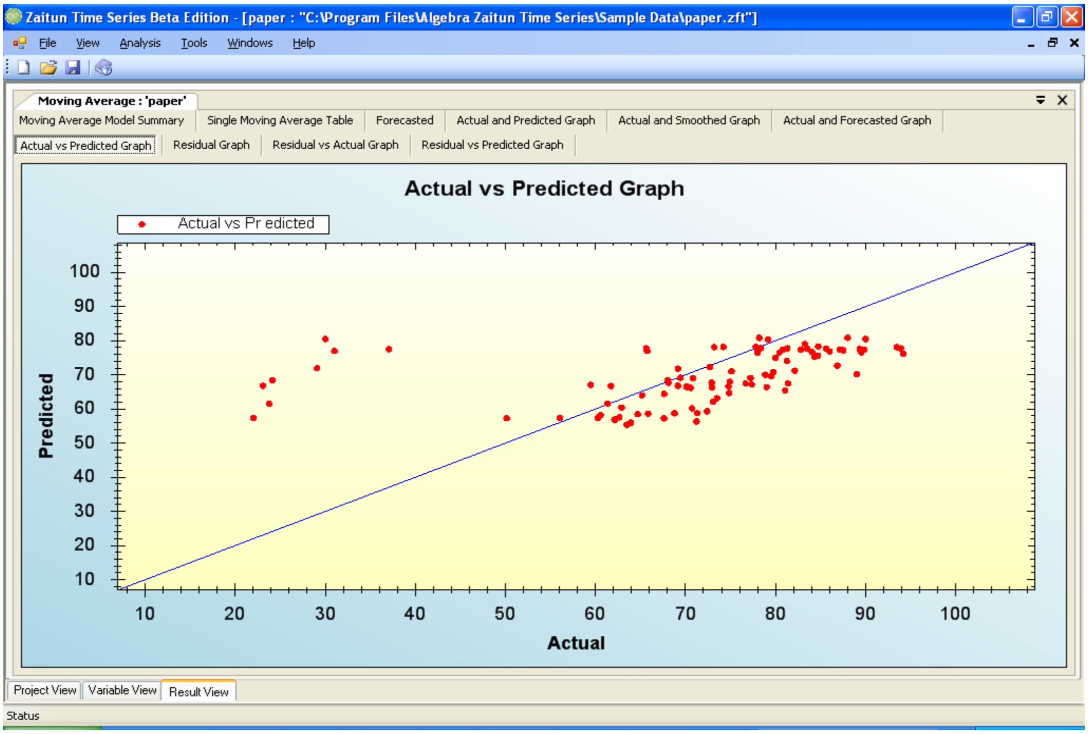


FIGURE 61 **Actual vs Predicted Graph**

Exponential Smoothing Analysis

Chapter

6

Exponential Smoothing Overview

Exponential smoothing is particular type of moving average technique applied to time series data, used to produce smoothed data for presentation, or to make forecasts. The Exponential smoothing method weights past observations by exponentially decreasing weights to forecast future values.

There are some categories of this method:

1) Single exponential smoothing;
2) Browns Double exponential smoothing method;
3) Holts Double exponential smoothing method; and
4) Winters Triple exponential smoothing method.

Single Exponential Smoothing

Single Exponential Smoothing is a procedure that repeats enumeration continually by using the newest data. This method can be used if the data is not significantly influenced by trend and seasonal factor.

To smooth the data with single exponential smoothing requires a parameter called the *smoothing constant* (α). Each data point is given a certain weighting, α for the newest data, α(1-α) for older data etc. The value of α must be between 0 and 1. The following is the equation of *smoothed value*:

$$S_n = \alpha[Y_n + (1-\alpha)Y_{n-1} + (1-\alpha)^2 Y_{n-2} + \ldots]$$

By doing a simple substitution, the equation above can be written as:

$$S_n = \alpha Y_n + (1-\alpha)S_{n-1}$$

Forecasting value $\hat{Y}_{n+1}$

Forecasting with single exponential smoothing can be done by substituting this equation:

$$\hat{Y}_{n+1} = \alpha Y_n + (1-\alpha)\hat{Y}_n$$

The equation above also can be written in the following way:

$$\hat{Y}_{n-1} = \hat{Y}_n + \alpha(e_n)$$

where $e_n = (Y_n - \hat{Y}_n)$ is the forecasting error for n period. From this equation, we can see that the forecasting resulted with this method is the last forecasted value added with an adjustment for error in the last forecasted value.

Starting value S_0

Practically, to calculate the smoothing statistic at the first observation Y_1, we can use the equation $S_1 = \alpha Y_1 + (1-\alpha)S_0$. Then it is substituted into the smoothing statistic equation to calculate $S_2 = \alpha Y_2 + (1-\alpha)S_1$, and the smoothing process is continued until we get S_n value. To calculate the equation above, a starting value S_0 is needed. S_0 can be calculated from the average of several observations. The first several observations can be chosen to determine S_0.

Double Exponential Smoothing (Browns)

This smoothing method can be used for data which contains a linear trend. This method is often called as Brown's one-parameter linear method.

The following equations are used in double exponential smoothing with Browns method:

Single smoothing statistic equation:

$$S^{`}_n = \alpha Y_n + (1-\alpha)S^{`}_{n-1}$$

Double smoothing statistic equation:

$$S^{``}_n = \alpha S^{`}_n + (1-\alpha)S^{``}_{n-1}$$

Forecasting value $\hat{Y}_{n+m}$

The procedure to calculate forecasting *m* forward period with double exponential smoothing with Brown method can be calculated from this equation:

$$\hat{Y}_{n+m} = \beta_{0,n} + \beta_{1,n}m$$

This equation is similar to linear trend method, where:

$$\beta_{0,n} = 2S^{`}_n - S^{``}_n$$

$$\beta_{1,n} = \frac{\alpha}{1-\alpha}\left(S_n^{`} - S_n^{``}\right)$$

Starting value S_0

The smoothing statistic equation above can be solved if the estimation value for S_0 is defined. Starting value S_0 is defined as:

$$S_0^{`} = \hat{\beta}_{0,0} - \frac{\alpha}{1-\alpha}\hat{\beta}_{1,0}$$

$$S_0^{``} = \hat{\beta}_{0,0} - 2\frac{\alpha}{1-\alpha}\hat{\beta}_{1,0}$$

We can use linear trend model constant calculated with the least square estimation method to estimate the coefficient of S_0, $\hat{\beta}_{0,0}$ and $\hat{\beta}_{1,0}$.

Double Exponential Smoothing (Holts)

This method is similar to Browns method, but Holts Method uses different parameters than the one used in original series to smooth the trend value.

The prediction of exponential smoothing can be obtained by using two smoothing constants (with values between 0 and 1) and three equations as follows:

$$S_n = \alpha Y_n + (1-\alpha)(S_{n-1} + T_{n-1}) \quad (1)$$

$$T_n = \gamma(S_n - S_{n-1}) + (1-\gamma)T_{n-1} \quad (2)$$

$$\hat{Y}_{n+m} = S_n + T_n m \quad (3)$$

Equation (1) calculates smoothing value S_n from the trend of the previous period T_{n-1} added by the last smoothing value S_{n-1}. Equation (2) calculates trend value T_n from S_n, S_{n-1}, and T_{n-1}. Finally, equation (3) (forward prediction) is obtained from trend, T_n, multiplied with the amount of next period forecasted, *m*, and added to basic value S_n.

Starting Value S_0 and T_0

There are two parameters needed to estimate exponential smoothing with Holts method, the smoothing value S_0 and the trend T_0. To find these parameters, the least squares method is used. The estimation value for S_0 is the intercept value of linear estimation, while T_0 is the slope value.

Triple Exponential Smoothing (Winters)

If a time series is stationary, the moving average method or single exponential smoothing can be used to analyze it. If a time series data has a trend component, then double exponential smoothing with Holts method can be used. However, if the time series data contains a seasonal component, then the Triple Exponential Smoothing (Winters) method can be used to handle it.

This method is based on three smoothing equations, Stationary Component, Trend and Seasonal. Both Seasonal component and Trend can be additive or multiplicative.

Additive

The whole smoothing equation

$$\mu_n = \alpha(y_n - S_{n-l}) + (1-\alpha)(\mu_{n-1} + T_n)$$

Trend smoothing

$$T_n = \gamma(\mu_n - \mu_{n-1}) + (1-\gamma)T_{n-1}$$

Seasonal smoothing

$$S_n = \beta(Y_n - \mu_n) + (1-\beta)S_{n-l}$$

Forecasted value

$$\hat{Y}_{n+m} = \mu_n + T_n m + S_{n-l+m}$$

Multiplicative

The whole smoothing equation

$$\mu_n = \alpha \frac{y_n}{S_{n-l}} + (1-\alpha)(\mu_{n-1} + T_n)$$

Trend smoothing

$$T_n = \gamma(\mu_n - \mu_{n-1}) + (1-\gamma)T_{n-1}$$

Seasonal smoothing

$$S_n = \beta \frac{Y_n}{\mu_n} + (1-\beta)S_{n-l}$$

Forecasted value

$$\hat{Y}_{n+m} = (\mu_n + T_n m)S_{n-l+m}$$

Where *l* is seasonal length (for example, amount of month, or quartile in a year), *T* is trend component, *S* is seasonal adjustment factor, and $\hat{Y}_{n+m}$ is forecasted value for m next period.

Starting value μ_0, T_0 and S_{j-l}

The starting values for μ_0 and T_0 can be obtained from regression equations which have actual variables as dependent variables and time variables as independent variables. This equation constant is a starting value estimation for μ_0 and *slope* of regression coefficient is a starting value estimation for the trend component T_0. Whereas the starting value for the seasonal component S_{j-l} is calculated by using *dummy-variable regression* on detrended data (without trend).

Exponential Smoothing Analysis with Zaitun Time Series

Zaitun Time Series performs exponential smoothing analysis of time series data, including single exponential smoothing, double exponential smoothing (Browns), double exponential smoothing (Holts), and triple exponential smoothing (Winters). To perform exponential smoothing analysis on a time series variable:

1. Click **Analysis → Exponential Smoothing**.

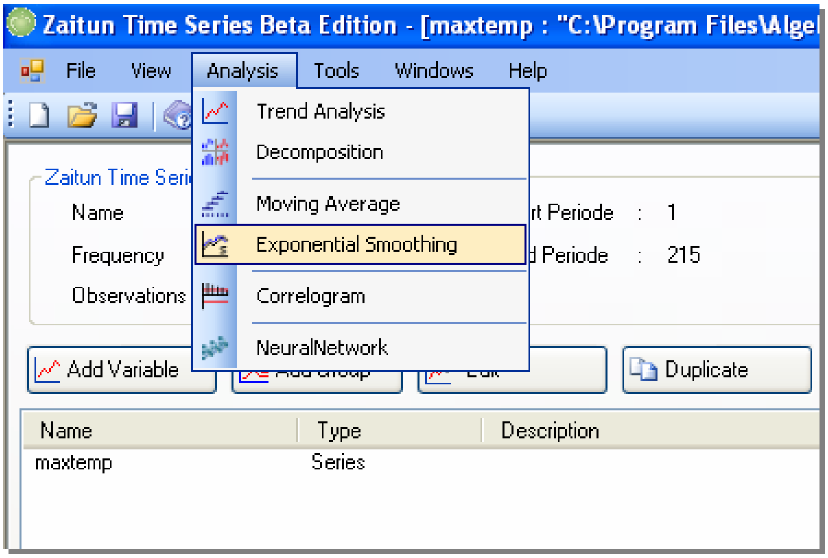


FIGURE 62 **Exponential Smoothing Menu**

2. Select Variable Dialog appears. Choose a variable you want to analyze with exponential smoothing analysis, and then click **OK**.

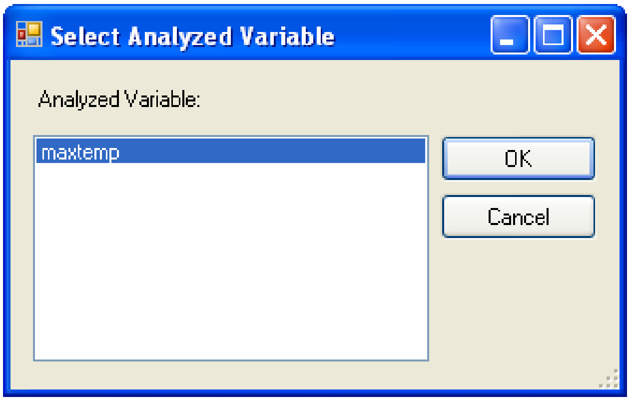


FIGURE 63 **Select Analyzed Variable Dialog**

3. The **Exponential Smoothing** form will appear. Choose the **Exponential Smoothing** method you want to apply to your variable, and determine the smoothing constant (alpha, beta, and gamma). For Triple Exponential Smoothing, determine its type, multiplicative or additive, and seasonal length.

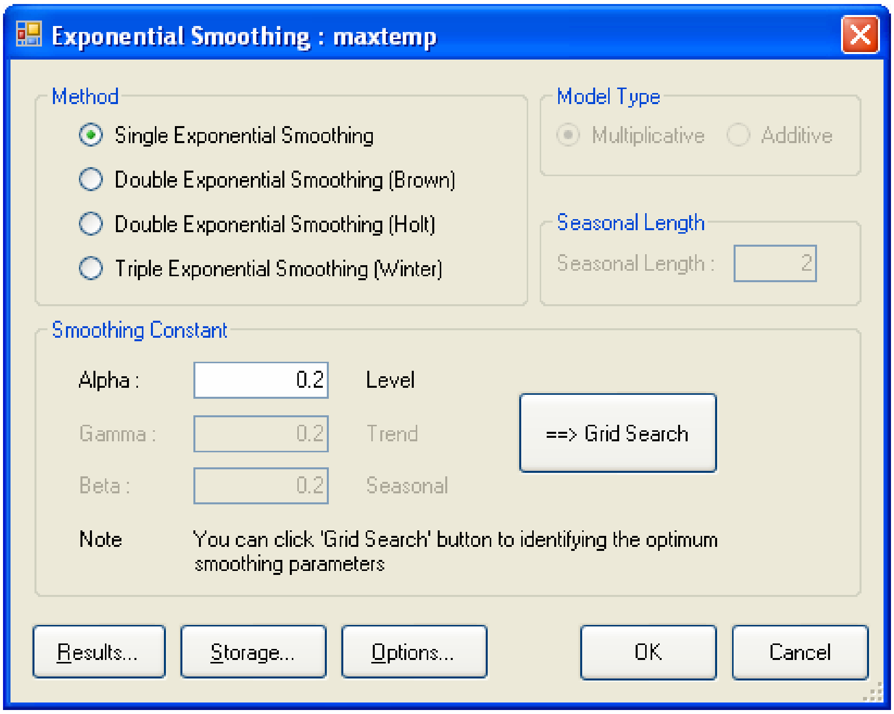


FIGURE 64 **Exponential Smoothing Form**

4. **Zaitun Time Series** also provides Grid Search facility to facilitate user in searching smoothing constant values in yielding the least MSE value. You can search smoothing constant value by determining minimum and maximum boundary and increment interval. Application will search the combination of smoothing constant value in interval above which has the least MSE. N combination (default =10) will be shown. To choose the best value

of smoothing constant click the value in list and click **Select This** button.

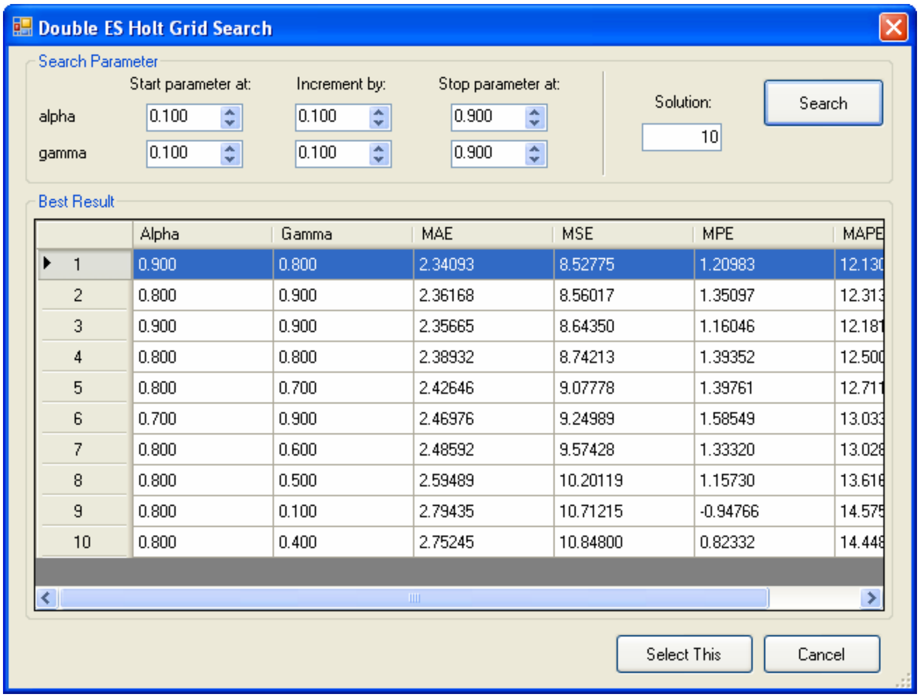


FIGURE 65 **Double ES Holt Grid Search**

5. To select analysis result that will be shown on **Result View**, click **Results** button. You can select some result views by clicking the checkbox of every selection. For **Forecasted** selection, you have to enter the data step you wish to forecast.

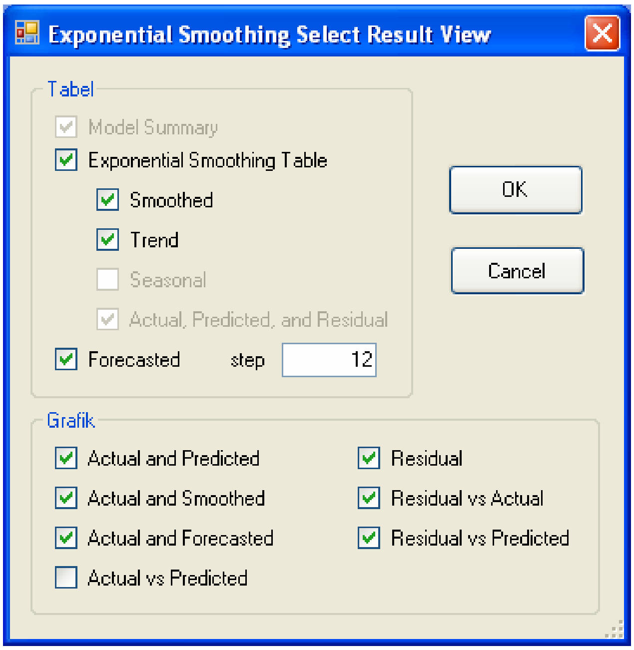


FIGURE 66 **Exponential Smoothing Select Result View**

6. To save the residual, predicted or smoothed data from the model as a new variable, click the **Storage** button. Check the items you want to save as new variables, and then type the new variable names.

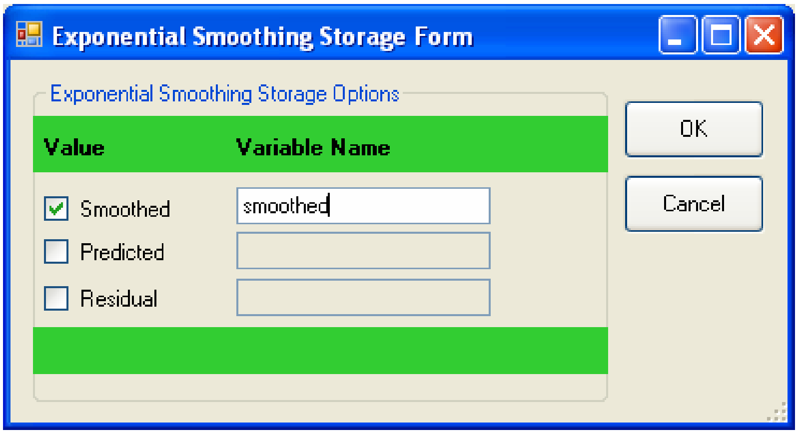


FIGURE 67 **Exponential Smoothing Storage Form**

7. After selecting the result views and determining whether you want to save the new variables or not, the software will show the **Exponential Smoothing** form again. Click the **OK** button to finish your analysis and to show the result views.
8. The selected result views on previous step will be viewed as several tabs on **Result View** panel.

Exponential Smoothing Analysis Result

The result views of exponential smoothing analysis in **Zaitun Time Series** are grouped into two categories, tables and graphics. The details of them are described here:

1. Tables
   a. Model Summary

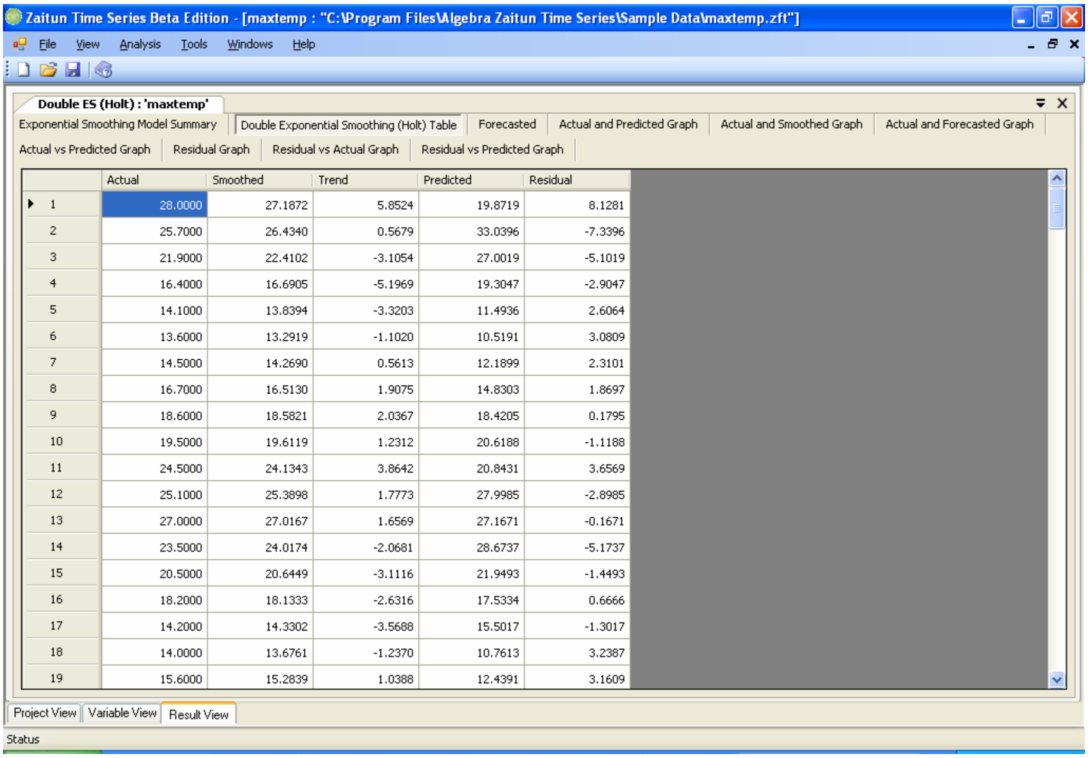
      Shows the summary of exponential smoothing model.

   b. Exponential Smoothing Table

      Shows actual, smoothed, trend, seasonal, predicted and residual values of exponential smoothing model.

   c. Forecasted

      Shows forecasted values from exponential smoothing model, as many steps of data you want to forecast.



	Actual	Smoothed	Trend	Predicted	Residual
1	28.0000	27.1872	5.8524	19.8719	8.1281
2	25.7000	26.4340	0.5679	33.0396	-7.3396
3	21.9000	22.4102	-3.1054	27.0019	-5.1019
4	16.4000	16.6905	-5.1969	19.3047	-2.9047
5	14.1000	13.8394	-3.3203	11.4936	2.6064
6	13.6000	13.2919	-1.1020	10.5191	3.0809
7	14.5000	14.2690	0.5613	12.1899	2.3101
8	16.7000	16.5130	1.9075	14.8303	1.8697
9	18.6000	18.5821	2.0367	18.4205	0.1795
10	19.5000	19.6119	1.2312	20.6188	-1.1188
11	24.5000	24.1343	3.8642	20.8431	3.6569
12	25.1000	25.3898	1.7773	27.9985	-2.8985
13	27.0000	27.0167	1.6569	27.1671	-0.1671
14	23.5000	24.0174	-2.0681	28.6737	-5.1737
15	20.5000	20.6449	-3.1116	21.9493	-1.4493
16	18.2000	18.1333	-2.6316	17.5334	0.6666
17	14.2000	14.3302	-3.5688	15.5017	-1.3017
18	14.0000	13.6761	-1.2370	10.7613	3.2387
19	15.6000	15.2839	1.0388	12.4391	3.1609

FIGURE 68 **Exponential Smoothing Holt Table**

2. Graphics

   a. Actual and Predicted

      Shows a line plot for actual and predicted values of exponential smoothing model.

   b. Actual and Smoothed

      Shows a line plot for actual and smoothed values of exponential smoothing model.

   c. Actual and Forecasted

      Shows a line plot for actual and forecasted values of exponential smoothing model.

   d. Actual vs Predicted

      Shows a scatter plot between actual and predicted values.

   e. Residual

      Shows a line plot for residual values of exponential smoothing model.

   f. Residual vs Actual

      Shows a scatter plot between residual and actual values.

   g. Residual vs Predicted

      Shows a scatter plot between residual and predicted values.

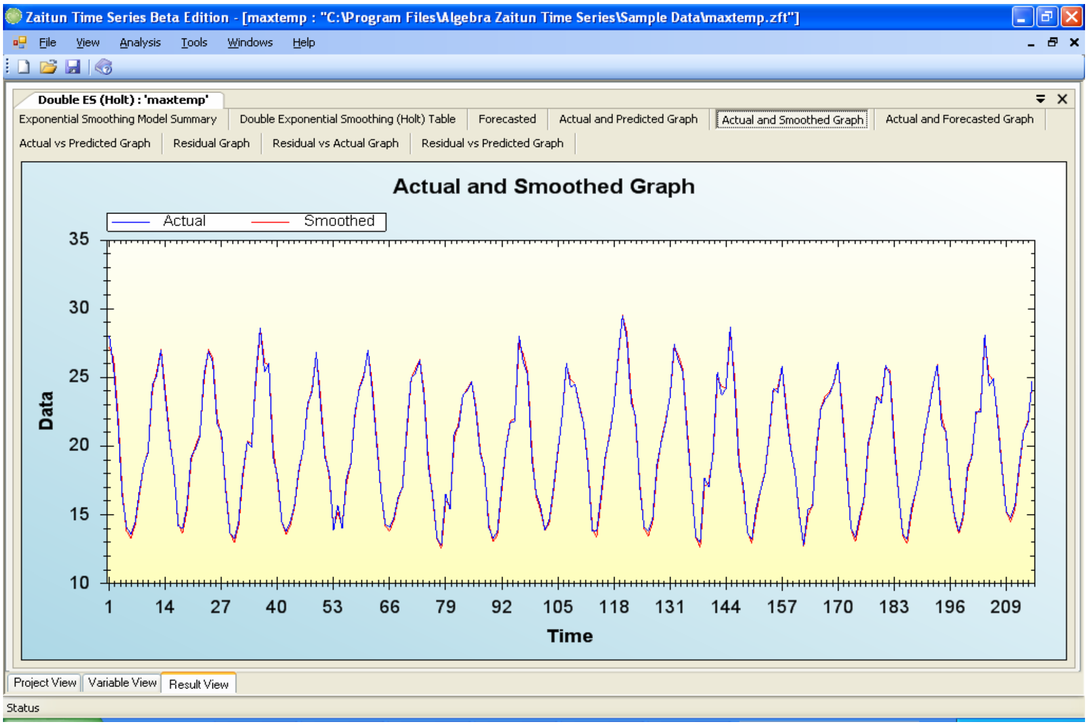


FIGURE 69 **Actual and Smoothed Graph**

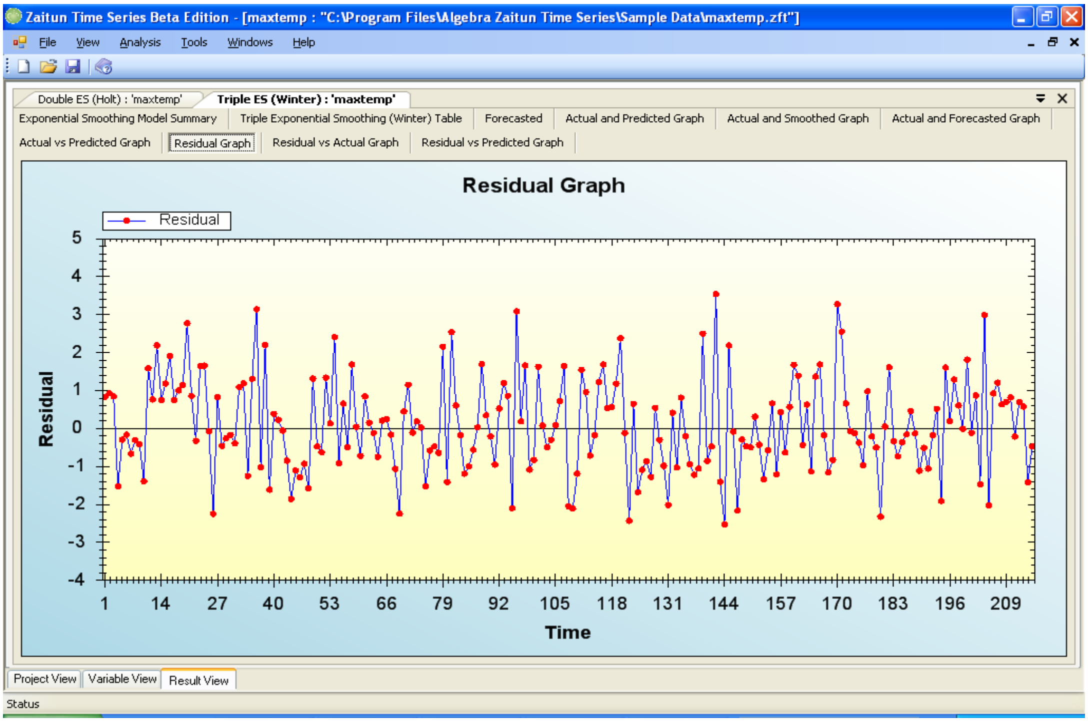


FIGURE 70 **Residual Graph**

Decomposition Analysis

Chapter 7

Decomposition Analysis Overview

Decomposition method tries to separate a time series data into several components. Decomposition method is often used not only in yielding forecast, but also in yielding information about time series component i.e. trend, cycle, seasonal, and irregular component. There are two relation types among those components, they are multiplicative and additive. Multiplicative type assumes if data value grows up then seasonal pattern will grow up too. While additive type assumes that data value resides in a constant wide at the middle of trend.

In the decomposition method, every cycle of data is assumed to be part of a trend. The decomposition method equations :

Multiplicative type:

$$Y_t = T_t \times S_t \times \varepsilon_t$$

Additive type:

$$Y_t = T_t + S_t + \varepsilon_t$$

The Seasonal Index value is calculated by using a ratio to moving average method

Decomposition Analysis with Zaitun Time Series

Zaitun Time Series performs decomposition analysis on time series data. To perform decomposition analysis on a time series variable:

1. Click **Analysis → Decomposition**.

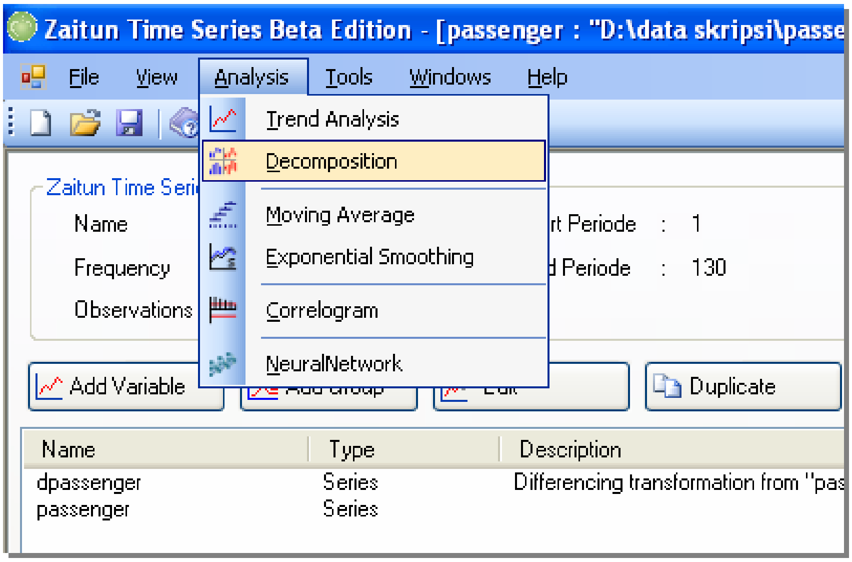


FIGURE 71 **Decomposition Menu**

2. Select Variable Dialog appears. Choose a variable you want to analyze with decomposition analysis, and then click **OK**.

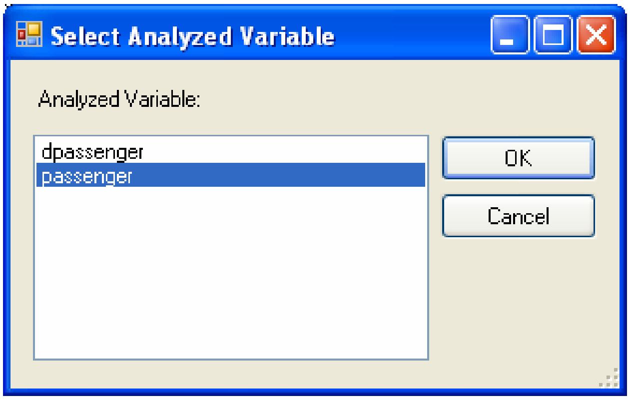


FIGURE 72 **Select Analyzed Variable Dialog**

3. The **Decomposition** form will appear. Determine the seasonal length, decomposition method (multiplicative or additive) and the used trend model. There are several trend models available, linear, quadratic, cubic, and exponential.

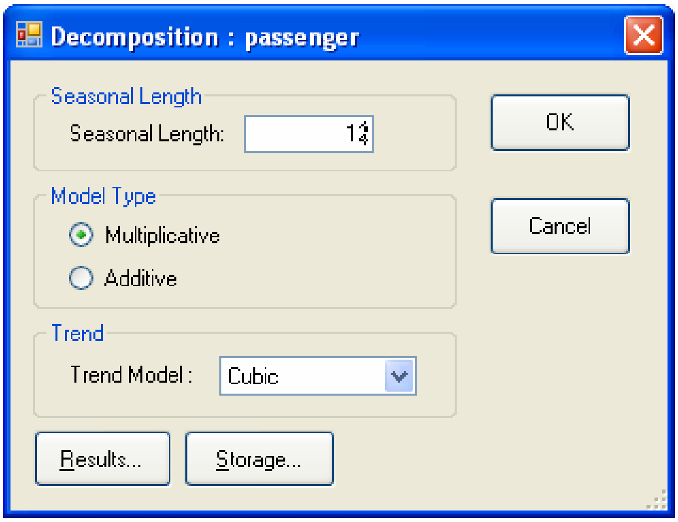


FIGURE 73 **Decomposition Form**

4. To select the analysis result that will be shown on **Result View**, click the **Results** button. Select the required result views by clicking the appropriate checkbox. For **Forecasted** selection, you have to enter the step of data you want to forecast.

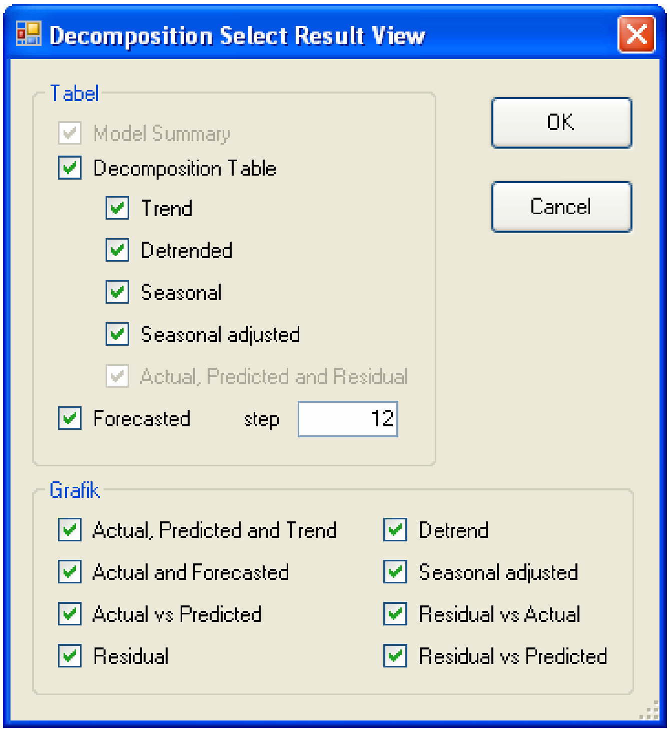


FIGURE 74 **Decomposition Select Result View**

5. To save trend, detrended, deseasonalized, residual, or predicted data from the model as new variables, click the **Storage** button. Check the item you want to save as a new variable, and then type the new variable name.

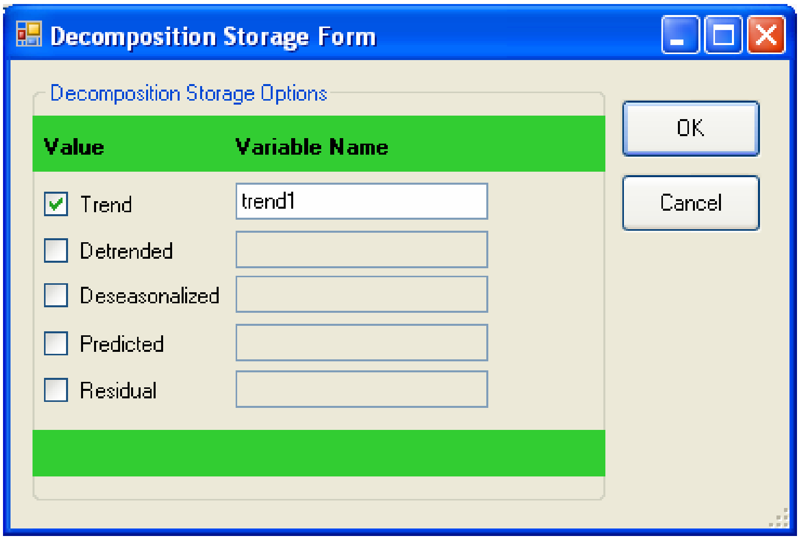


FIGURE 75 **Decomposition Storage Form**

6. After selecting result views and determining whether you want to save the new variables or not, the software will show the **Decomposition** form again. Click the **OK** button to finish the analysis and to show the result views.
7. The selected result views from the previous step will be viewed as several tabs on the **Result View** panel.

Decomposition Analysis Result

The result views of decomposition analysis in **Zaitun Time Series** are grouped into two categories, they are tables and graphics. The details of them are described here:

1. Tables
   a. Model Summary

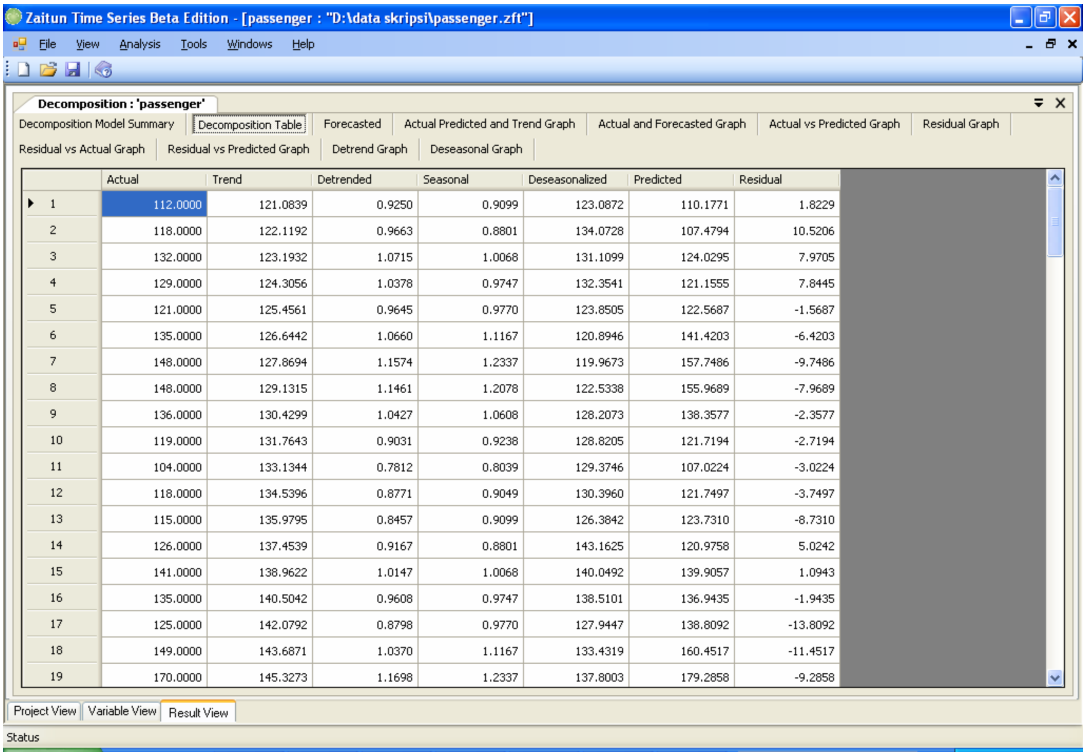
      Shows the summary of decomposition model.

   b. Decomposition Table

      Shows actual, smoothed, trend, seasonal, predicted and residual values of decomposition model.

   c. Forecasted

      Shows forecasted values from decomposition model, as many steps of data you want to forecast.



	Actual	Trend	Detrended	Seasonal	Deseasonalized	Predicted	Residual
1	112.0000	121.0839	0.9250	0.9099	123.0872	110.1771	1.8229
2	118.0000	122.1192	0.9663	0.8801	134.0728	107.4794	10.5206
3	132.0000	123.1932	1.0715	1.0068	131.1099	124.0295	7.9705
4	129.0000	124.3056	1.0378	0.9747	132.3541	121.1555	7.8445
5	121.0000	125.4561	0.9645	0.9770	123.8505	122.5687	-1.5687
6	135.0000	126.6442	1.0660	1.1167	120.8946	141.4203	-6.4203
7	148.0000	127.8694	1.1574	1.2337	119.9673	157.7486	-9.7486
8	148.0000	129.1315	1.1461	1.2078	122.5338	155.9689	-7.9689
9	136.0000	130.4299	1.0427	1.0608	128.2073	138.3577	-2.3577
10	119.0000	131.7643	0.9031	0.9238	128.8205	121.7194	-2.7194
11	104.0000	133.1344	0.7812	0.8039	129.3746	107.0224	-3.0224
12	118.0000	134.5396	0.8771	0.9049	130.3960	121.7497	-3.7497
13	115.0000	135.9795	0.8457	0.9099	126.3842	123.7310	-8.7310
14	126.0000	137.4539	0.9167	0.8801	143.1625	120.9758	5.0242
15	141.0000	138.9622	1.0147	1.0068	140.0492	139.9057	1.0943
16	135.0000	140.5042	0.9608	0.9747	138.5101	136.9435	-1.9435
17	125.0000	142.0792	0.8798	0.9770	127.9447	138.8092	-13.8092
18	149.0000	143.6871	1.0370	1.1167	133.4319	160.4517	-11.4517
19	170.0000	145.3273	1.1698	1.2337	137.8003	179.2858	-9.2858

FIGURE 76 **Decomposition Table**

2. Graphics
   a. Actual, Predicted and Trend

      Shows a line plot for actual, predicted and trend values of decomposition model.

   b. Actual and Forecasted

      Shows a line plot for actual and forecasted values of decomposition model.

   c. Actual vs Predicted

      Shows a scatter plot between actual and predicted values.

   d. Residual

      Shows a line plot for residual values of decomposition model.

   e. Residual vs Actual

      Shows a scatter plot between residual and actual values.

   f. Residual vs Predicted

      Shows a scatter plot between residual and predicted values.

g. Detrended Graph

Shows a line plot for detrended values of decomposition model.

h. Deseasonalized Graph

Shows a line plot for deseasonalized values of decomposition model.

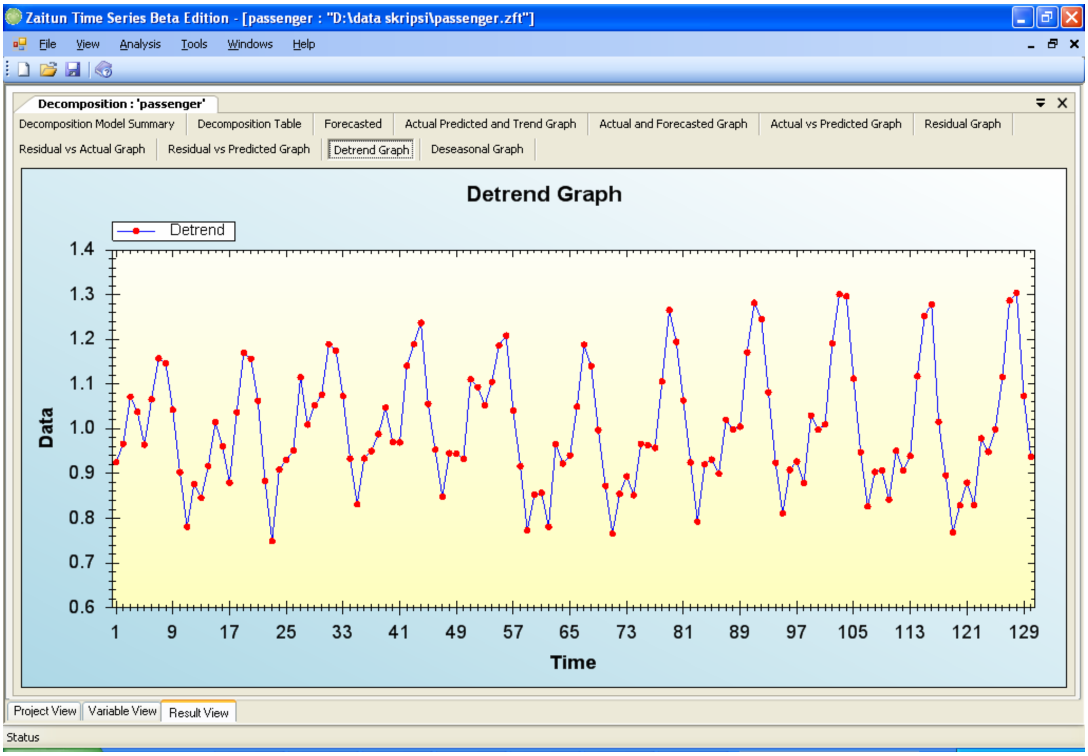


FIGURE 77 **Detrend Graph**

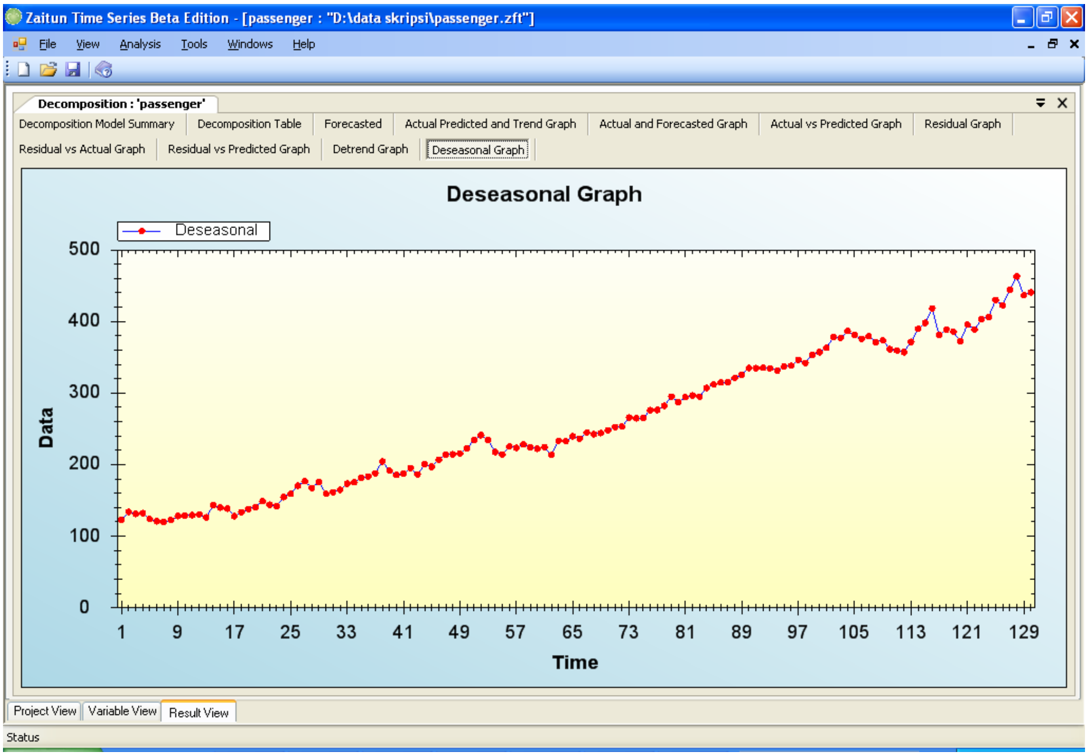


FIGURE 78 **Deseasonal Graph**

Correlogram

Chapter 8

Correlogram Overview

Correlogram or Autocorrelation Function (ACF) is a graphic of autocorrelation values from several time intervals in time series data. ACF explains how big the successive data correlation in a time series data. ACF can be used to determine whether a time series data is stationary or not.

ACF represents comparison between covariant on lag k and its variant. ACF formulated as follows:

$$\rho_k = \frac{\sum_{t=k+1}^{T} \left(Y_t - \overline{Y}\right)\left(Y_{t-k} - \overline{Y}\right)}{\sum_{t=1}^{T} \left(Y_t - \overline{Y}\right)^2}$$

Where :

ρ_k : ACF coefficient in *lag* k.

T : The number of observations (the amount of observed period).

Y_t : Observation in t period.

$\overline{Y}$: Mean.

Y_{t-k} : Observation in *t-k* period.

ACF (ρ_k) has value started from -1 to 1. If ACF value on every lag is 0, hence the data is stationary. As a rough rule, lag length needed to analyze is one third or a quarter of the number of observations of a time series data.

Also, to determine whether a time series data is stationary or not, you can use the statistical test based on standard error (se). By following the normal distribution standard, the interval with signification equal to 95 % for ρ_k with the sample number equal to T is

$$\rho_k = \pm 1.96 \times (se)$$ or

$$\rho_k = \pm 1.96 \times \sqrt{1/T}$$

If ACF coefficient value is in interval with signification equal to 95%, then null hypothetic (H_0) that shows ACF value (ρ_k) equal to 0 can not be rejected. It means that the data is stationary.

Besides that, to know whether time series data is stationary or not, Q statistical test which follows Chi Square distribution can be used. Q statistical value formulated below:

$$Q_m = n(n+2)\sum_{k=1}^{m}\left(\frac{\rho_k^{\ 2}}{n-k}\right)$$

Where:

m : Number of the tested lag.

Q_m : Q statistical value in lag m.

n : The number of samples.

ρ_k : ACF coefficient in lag k.

If the Q statistical value is smaller than Q value obtained from chi squares (χ^2) table in certain significant level, then null hypothetic (H_0) which shows that ACF value (ρ_k) equal to 0 can not be rejected. It shows that the data is stationary.

Corellogram with Zaitun Time Series

Zaitun Time Series displays the autocorrelation function (ACF) values and graphic of a time series. To display corellogram of a time series variable:

1. Click **Analysis → Corellogram**.

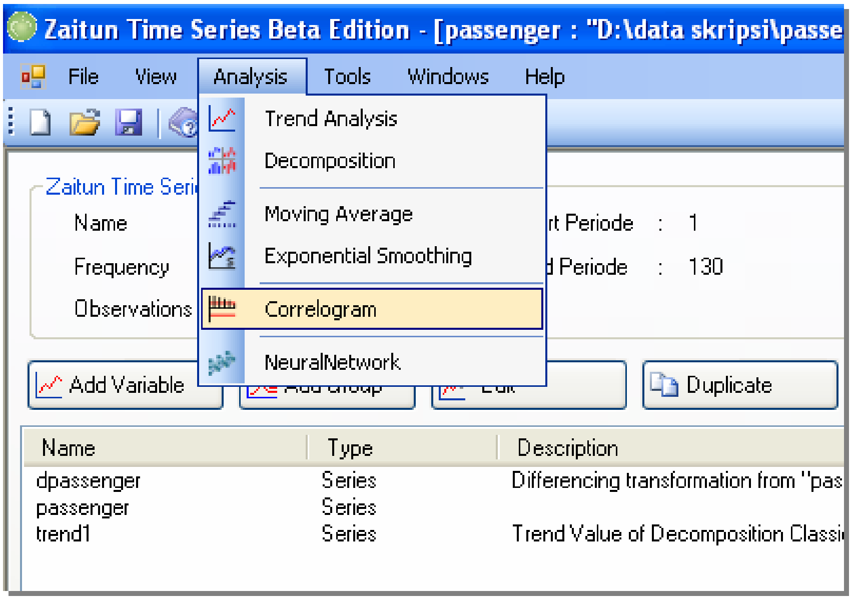


FIGURE 79 **Correlogram Menu**

2. Select Variable Dialog appears. Choose a variable for the corellogram which you wish to display and then click **OK**.

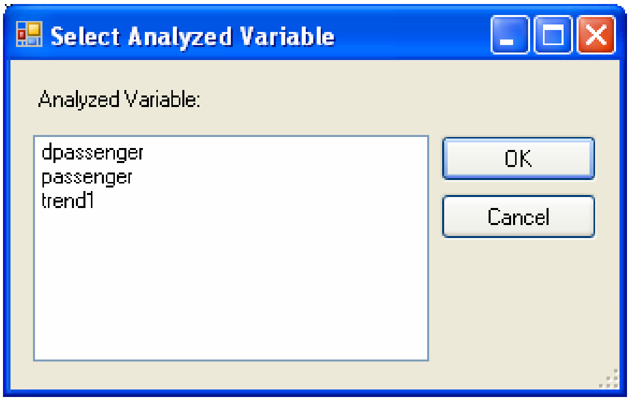


FIGURE 80 **Deseasonal Graph**

3. The **Correlogram** form will appear. Select the data you wish to display, original data (level), first differencing data, or second differencing data. Also determine the number of the included lag. Click **OK** to display the result.

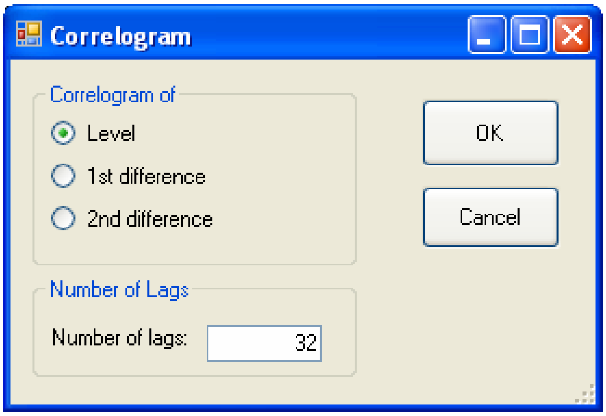


FIGURE 81 **Correlogram Form**

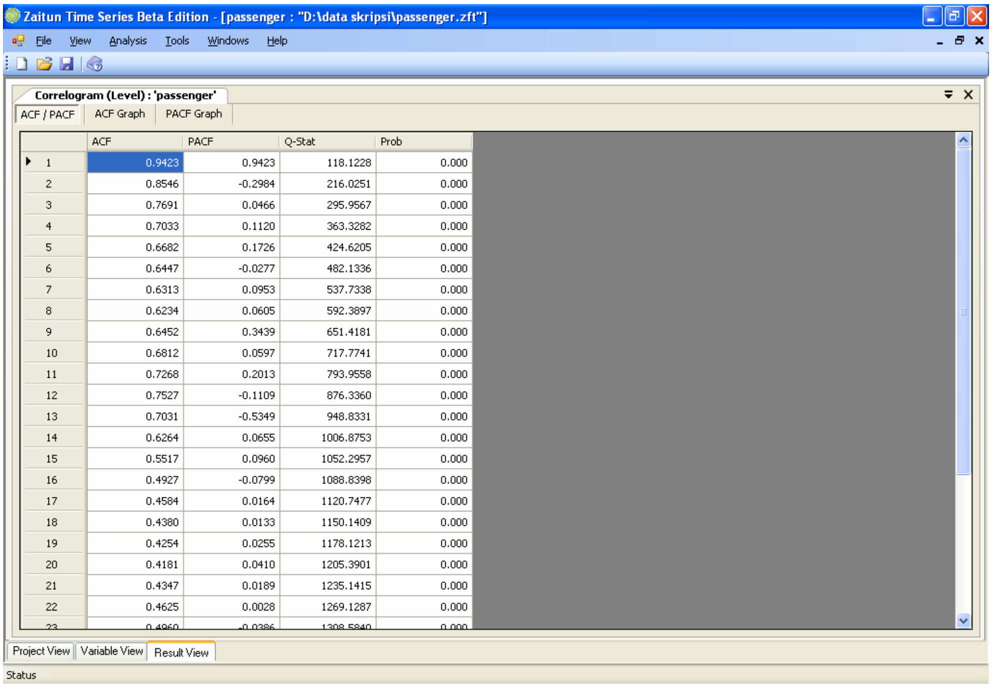
4. The Corellogram result will be viewed on the **Result View** panel in several tabs.

Corellogram Result View

The result views of correlogram in **Zaitun Time Series** are:

1. ACF/PACF Table

   Shows ACF, PACF, Q statistics, and probability values



	ACF	PACF	Q-Stat	Prob
1	0.9423	0.9423	118.1228	0.000
2	0.8546	-0.2984	216.0251	0.000
3	0.7691	0.0466	295.9567	0.000
4	0.7033	0.1120	363.3282	0.000
5	0.6682	0.1726	424.6205	0.000
6	0.6447	-0.0277	482.1336	0.000
7	0.6313	0.0953	537.7338	0.000
8	0.6234	0.0605	592.3897	0.000
9	0.6452	0.3439	651.4181	0.000
10	0.6812	0.0597	717.7741	0.000
11	0.7268	0.2013	793.9558	0.000
12	0.7527	-0.1109	876.3360	0.000
13	0.7031	-0.5349	948.8331	0.000
14	0.6264	0.0655	1006.8753	0.000
15	0.5517	0.0960	1052.2957	0.000
16	0.4927	-0.0799	1088.8398	0.000
17	0.4584	0.0164	1120.7477	0.000
18	0.4380	0.0133	1150.1409	0.000
19	0.4254	0.0255	1178.1213	0.000
20	0.4181	0.0410	1205.3901	0.000
21	0.4347	0.0189	1235.1415	0.000
22	0.4625	0.0028	1269.1287	0.000

FIGURE 82 **ACF/PACF Table**

2. ACF Graph

   Shows the bar chart of ACF values.

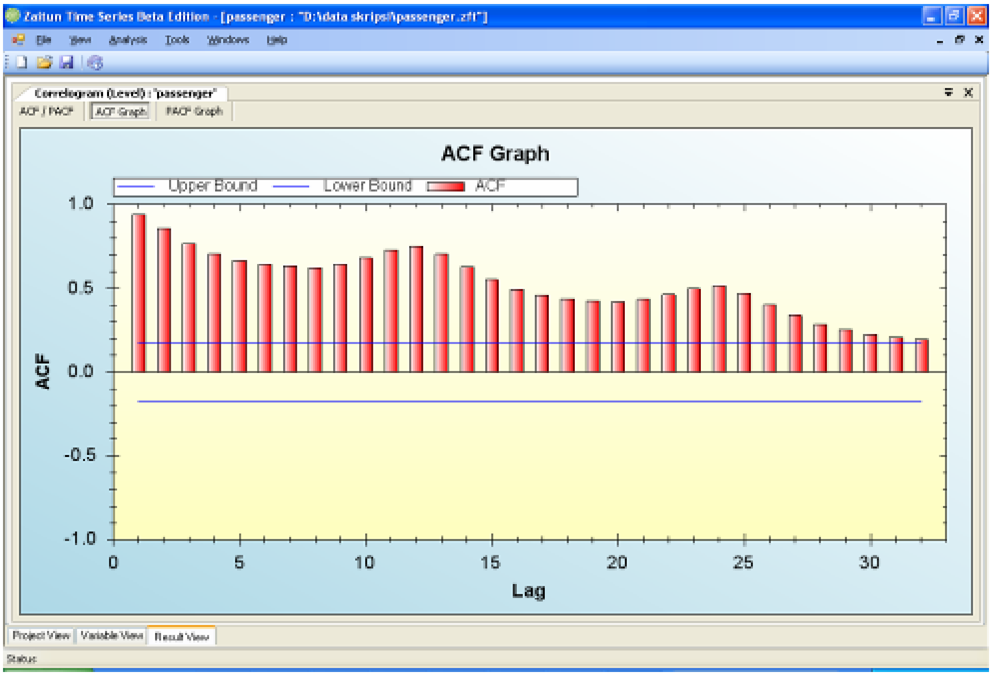


FIGURE 83 **ACF Graph**

3. PACF Graph

   Shows the bar chart of PACF values.

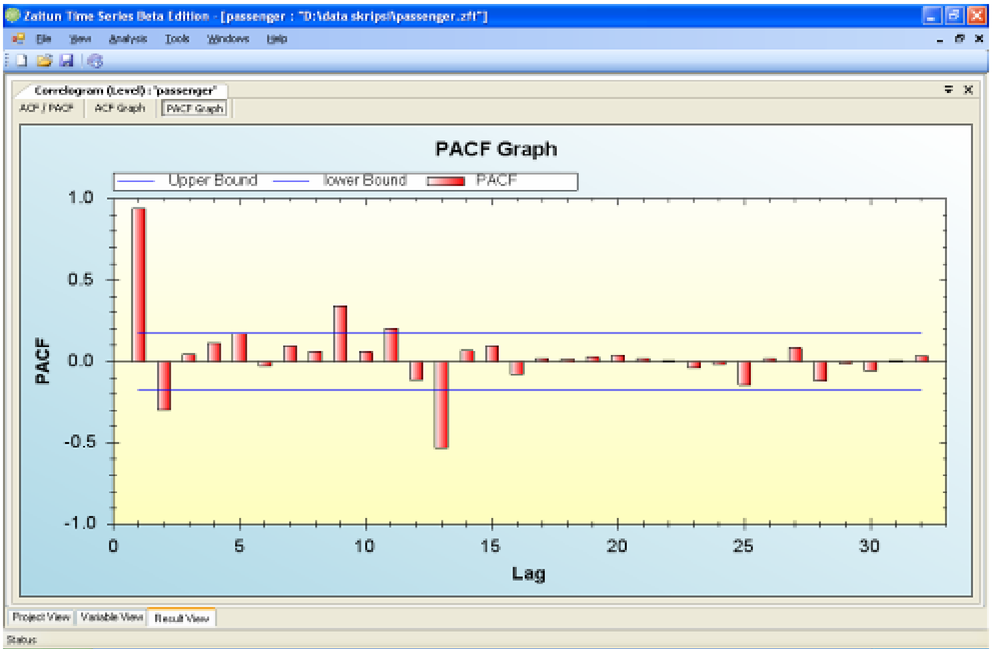


FIGURE 84 **PACF Graph**

Neural Network Analysis

Chapter 9

Neural Network Overview

Artificial Neural Networks or often called **Neural Networks** is a computation technique which has made significant progress in recent times. Neural networks have proven their capability of handling various problems in a number of scientific disciplines. Neural networks have a powerful ability called **universal approximation**, they can approximate all multivariate continue functions to every level of accuracy including for non-linear functions.

The ability of neural networks in universal approximation has been used by some researchers to forecast time series data in various kinds of data. The researches show that Neural Networks have a satisfactory performance in forecasting time series data.

Neural networks mechanisms imitate biological neural network mechanisms. Like biological neural networks, neural networks consists of neurons which are connected to each other and operate in parallel. The information processing mechanism in every neuron is adopted from the biological neuron.

Neurons in a neural network are grouped into several layers. Every layer can have one or more neurons. There are three layers in neural network architecture; they are the input layer, the output layer, and the hidden layer.

The function of the input layer is for data entry, data processing takes place in the hidden middle layer and the output layer functions as the data output result. The following illustration shows the architecture of neural networks.

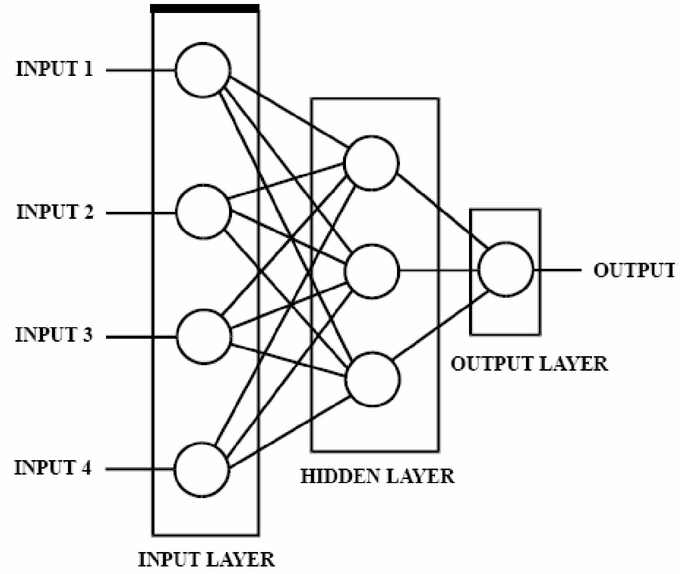


FIGURE 85 **Architecture of Neural Network**

Information processing in every neuron is done by summing the multiplication result of connection weights with input data. The result is transferred to the next neuron through the activation function. There are several kinds of activation functions, i.e. linear, semi linear, sigmoid, bipolar sigmoid and hyperbolic tangent.

In time series data forecasting, the input value for the input layer can be variable data of previous period (lagged variable) or the other variable used to help forecasting, can be qualitative or quantitative.

To forecast one variable (univariate), input data for the input layer and output data in the output layer is similar to the autoregressive model AR(p). On certain point of t , forecasted data $\hat{y}_{t+1}$ calculated by using $p = n$ observation $y_t, y_{t-1}, \ldots, y_{t-n+1}$ from n previous point $t, t-1, t-2, \ldots, t-n+1$, where n shows the number of neuron inputs in a neural network.

Neural Network Analysis with Zaitun Time Series

Zaitun Time Series provides neural network modeling of time series data. To perform neural network modeling on a time series variable:

1. Click **Analysis → Neural Network**.

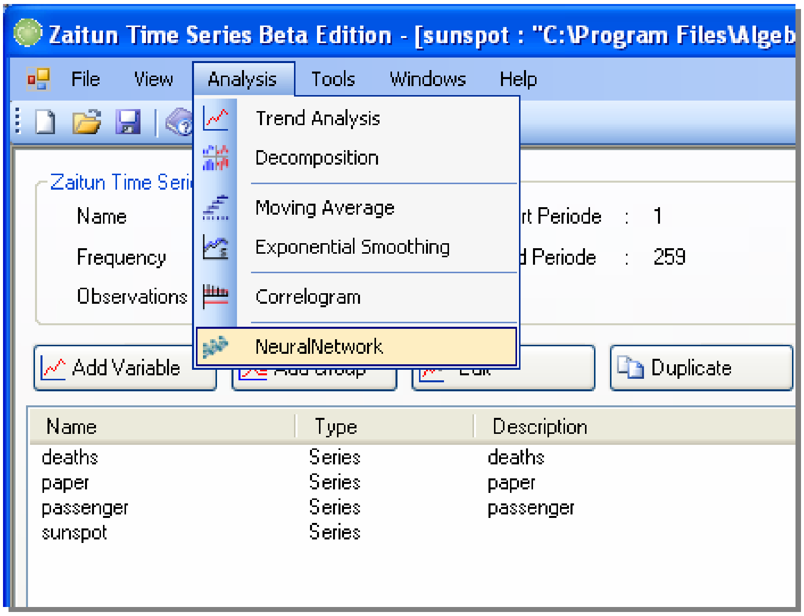


FIGURE 86 **Neural Network Menu**

2. Select Variable Dialog appears. Choose a variable you want to build its neural network model, and then click **OK**.

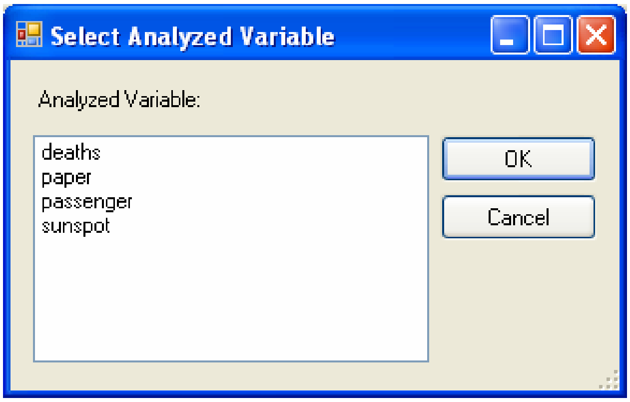


FIGURE 87 **Select Analyzed Variable Dialog**

3. The **Neural network** analysis form will appear. Determine the parameters of the neural network model you want to build. You can determine the parameters of the neural network architecture, activation function, and learning algorithm. You can also set up the stopping condition or use early stopping cross-validation method.

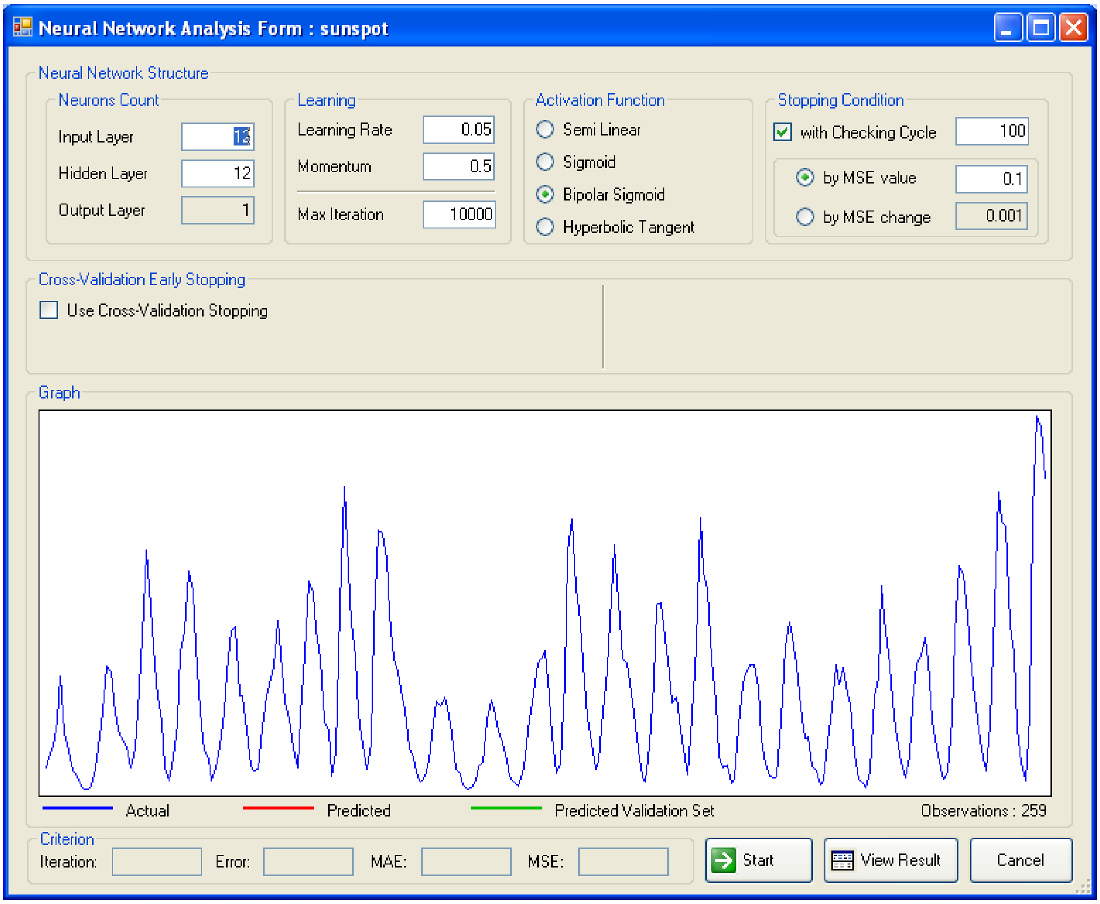


FIGURE 88 **Neural Network Analysis Form**

4. Click **Start**. The learning process will start and run until the stopping condition is fulfilled or the operation has reached the maximum number of iterations.
5. You can stop the learning process any time by clicking **Stop** while the learning process is running.

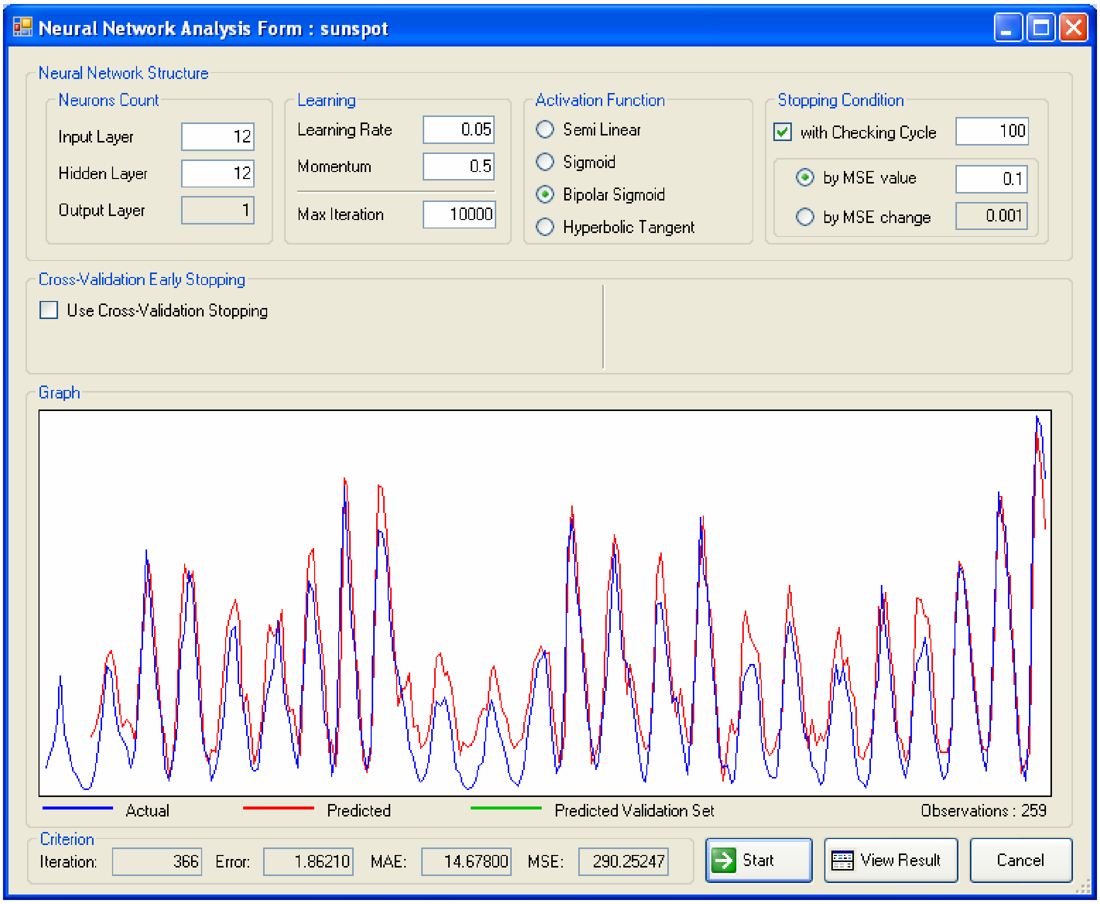


FIGURE 89 **The Result of Neural Network Analysis Form**

6. After the learning process is finished, click the **View Result** button to display the model result.

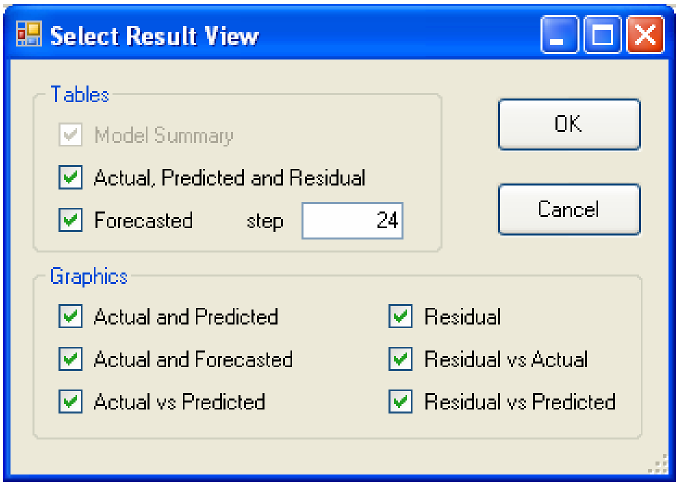


FIGURE 90 **Select Result View**

7. The **Select Result View** dialog will appear. Select the result views you want to display, and then click **OK**. You can forecast the data

by clicking the **Forecasted** item and determine the number of data you want to forecast.

8. The selected model result will be displayed on **Result View** panel in several tabs.

Neural Network Modeling Result

The result views of neural network modeling in **Zaitun Time Series** are grouped into two categories, tables and graphics. The details of them are described here:

1. Tables

    a. Model Summary

    Shows the summary of the neural network model.

    b. Actual, Predicted and Residual

    Shows actual, predicted and residual values of the neural network model.

    c. Forecasted

    Shows forecasted values from neural network model, as many steps of data you want to forecast.

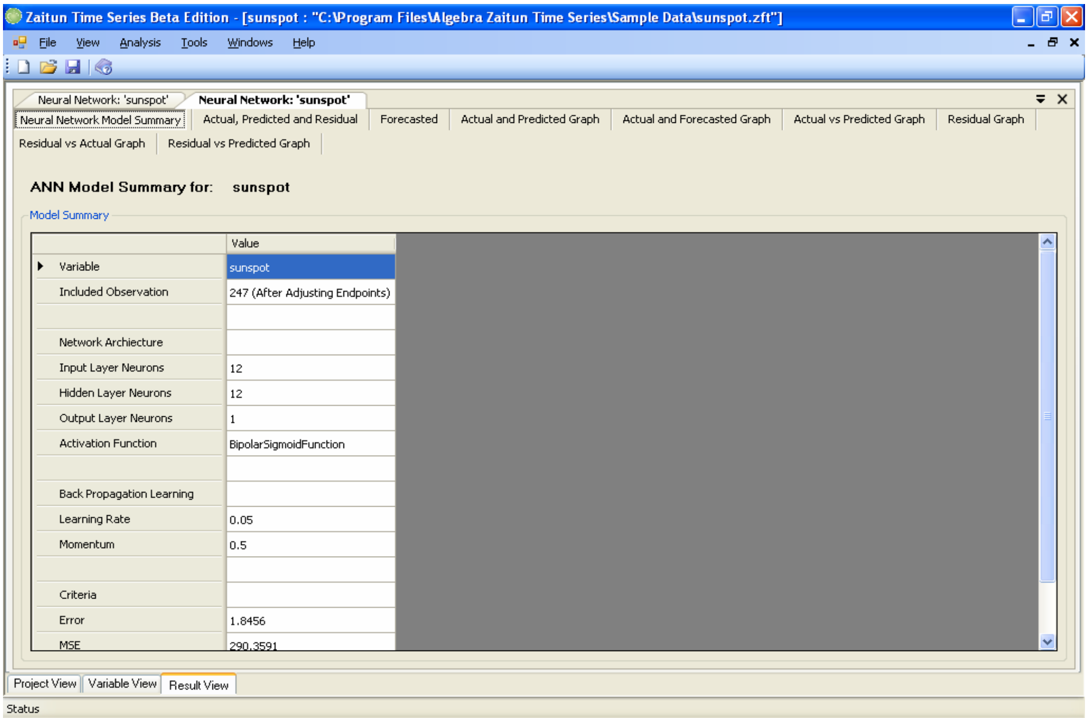


FIGURE 91 **Neural Network Model Summary**

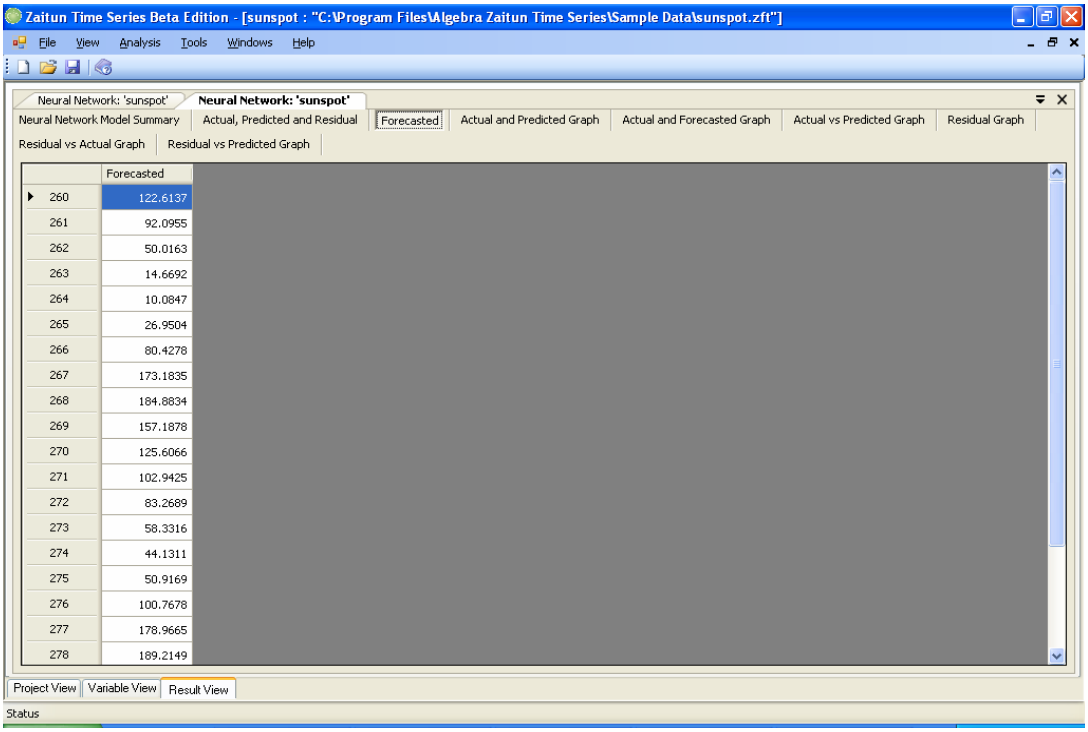


FIGURE 92 **Table of Forecasted**

2. Graphics
   a. Actual and Predicted

      Shows a line plot for actual and predicted values of neural network model.

   b. Actual and Forecasted

      Shows a line plot for actual and forecasted values of neural network model.

   c. Actual vs Predicted

      Shows a scatter plot between actual and predicted values.

   d. Residual

      Shows a line plot for residual values of neural network model.

   e. Residual vs Actual

      Shows a scatter plot between residual and actual values.

   f. Residual vs Predicted

      Shows a scatter plot between residual and predicted values.

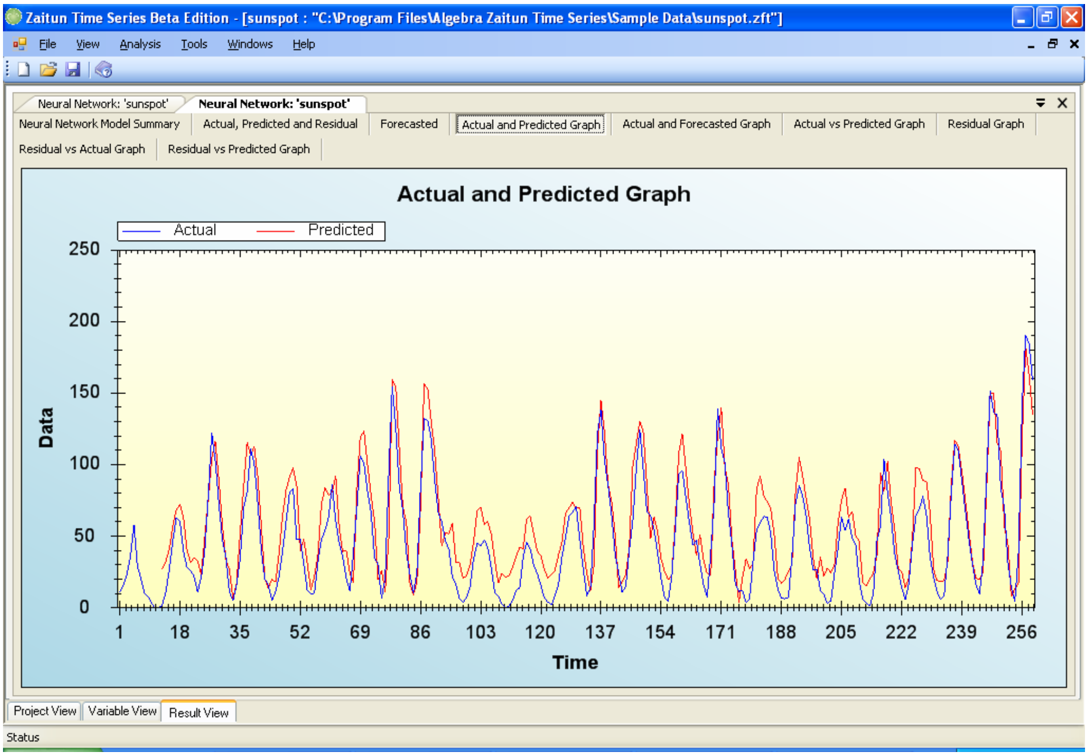


FIGURE 93 **Actual and Predicted Graph**

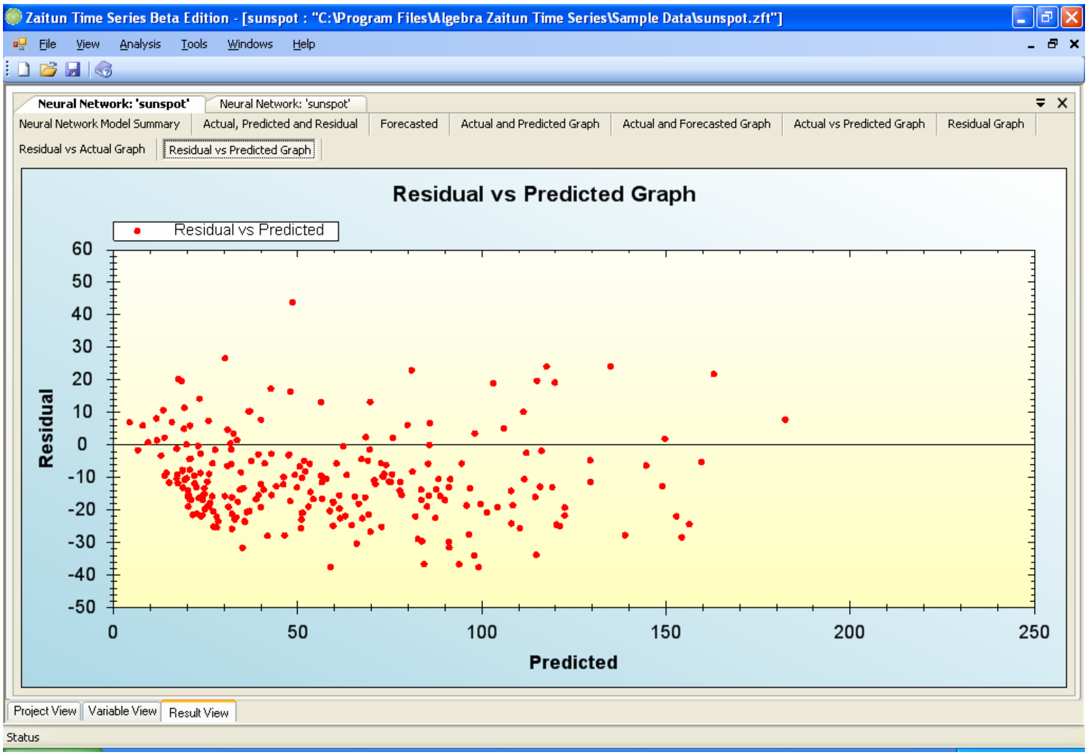


FIGURE 94 **Residual vs Predicted Graph**

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