DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

PERFORMANCE OF TIME SERIES DECOMPOSITION FOR DIFFERENT TYPE OF TIME SERIES

by
Tuğçe ERDOĞAN

October, 2017
İZMİR

PERFORMANCE OF TIME SERIES DECOMPOSITION FOR DIFFERENT TYPE OF TIME SERIES

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science in Statistics

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October, 2017
İZMİR

M.Sc. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"PERFORMANCE OF TIME SERIES DECOMPOSITION FOR DIFFERENT TYPE OF TIME SERIES"** completed by **TUĞÇE ERDOĞAN** under supervision of **ASSOC. PROF. DR. SEDAT ÇAPAR** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science

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ACKNOWLEDGMENTS

First, I would like to express my sincere gratitude and thanks to my supervisor, Assoc. Prof. Dr. Sedat ÇAPAR for his support, sincerity, direction and information throughout my thesis.

I am also grateful to Ufuk BEYAZTAŞ for all his special help in computer programming with R. I also wish to thank to all of academic staff in Dokuz Eylül University Statistics Department especially, Assoc. Prof. Dr. Esin FİRUZAN, Assoc. Prof. Dr. Engin YILDIZTEPE and Beste BEYAZTAŞ for their support and helps.

Finally, special thanks to my mother Cemile ERDOĞAN, my father Hasan ERDOĞAN and my love Nuri Kaan SEVER for their endless love, patience and support during my studies and thanks to my best friend Ayhan YAĞCI for her moral, motivation and supporting me every day since started my master.

Tuğçe ERDOĞAN

PERFORMANCE OF TIME SERIES DECOMPOSITION FOR DIFFERENT TYPE OF TIME SERIES

ABSTRACT

Course of the time series and estimates to be made with this series, will help to determine the behavior for the next series. Especially due to the uncertainties in the world of business and economics, to determine the future behavior of the series has become extremely important. In such cases, the main and the oldest method that is used to reveal the properties of the time series is time series decomposition. Decomposition method is the easiest method to understand and make in short-term predictions. This method can reveal the seasonality and trend of a time series and split a time series into its components. In this study, a program in R is written for additive and multiplicative models in order to measure the effect of the decomposition method. Time series included in M-Competition are used to test the written R code. The results obtained were consistent with the results suggested in previous studies.

Key Words: Time series, decomposition methods, M-Competition

FARKLI ZAMAN SERİSİ TÜRLERİ İÇİN ZAMAN SERİLERİ AYRIŞTIRMASININ PERFORMANSI

ÖZ

Zaman serilerinin seyri ve bu seriler ile yapılacak tahminler, serinin geleceğe ilişkin davranış biçiminin belirlenmesine yardım etmektedir. Özellikle ekonomi ve iş dünyasında olan belirsizlikler nedeni ile serilerin geleceğe ilişkin davranış biçimini belirlemek son derece önem kazanmıştır. Bu gibi durumlarda zaman serisinin özelliklerini ortaya koymak için kullanılan yöntemlerden başlıca ve en eski olanı serinin bileşenlerine ayrıştırılmasıdır. Ayrıştırma yöntemi, kısa dönemli öngörülerde anlaşılması ve yapılması en kolay yöntemdir. Bu yöntem, bir serinin mevsimselliğini ve trendini ortaya çıkartabilmek ya da istenildiği takdirde bu hareketleri seriden arındırabilmek amaçlı da kullanabilen bir yöntemdir. Bu çalışmada bileşenlerine ayırma yönteminin etkisini ölçmek amacıyla toplamsal ve çarpımsal modeller için R programı kodları yazılmıştır. Yazılan kodlar M-Competition zaman serisi veri setine uygulanmıştır. Elde edilen sonuçların daha önceki çalışmalarda önerilen sonuçlarla tutarlı olduğu görülmüştür.

Anahtar Kelimeler: Zaman serileri, ayrıştırma yöntemleri, M-Competition

CONTENTS

Page

LIST OF FIGURES

Page

CHAPTER ONE
INTRODUCTION

1.1 Time Series

Time series modeling is a dynamic area of research that has attracted attentions of researchers in recent years. The main aim of time series modeling is to collect and study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series, i.e. to make forecasts. Time series forecasting thus can be termed as the act of predicting the future by understanding the past. Because of the indispensable importance of time series forecasting in numerous practical fields such as business, economics, finance, science and engineering, etc., proper care should be taken to fit an adequate model to the underlying time series (Adhikari & Agrawal, 2013).

The course of the time series and the predictions to be made with these series are useful in determining the behavior of the series in the future. It is especially important to determine the behavior of the uncertainties in the economic and business world and the future. In such a case, the methods used to elucidate the properties of the time series are to be decomposed into the main series components, and the oldest methods for decomposing series have been used in various fields since the beginning of the 20th century (Emeç, 2015).

Decomposition method seems to be used in two different ways, firstly in the analysis of trend removal and conjuncture movements. In 1880, the main purpose of the method used to purge the trend effect from the data was to remove the "false correlation" that emerged with the trend reason and to average it for a few years to purify it from the trend. Subsequently, the method of strictly eliminating the trend effect was developed, and in 1914 Anderson generalized the method of removing the trend from the center, including polynomials in the higher order. It is seen that the method which is mentioned afterwards on the wishes of economists to see the effects of the depressions experienced and to anticipate the possible future crises.

The method has allowed the analysis of the changes in conjuncture fluctuations by separating the effects of economic activities. A committee established in France in 1911 prepared a report on the causes and consequences of the economic crisis of 1907 and tried to make a distinction between trend and conjuncture effect for this purpose. The method was later applied in the United States to separate seasonal fluctuations from other components.

Decomposition method is the easiest method to understand and to make short turnaround predictions. In particular, this method is a method that can be used to reveal the seasonality of a season or, if desired, to make seasonal movements possible.

Time series forecasting is the process of using a model to generate predictions for future events based on known past events. If a time series can be predicted exactly, it is said to be deterministic. But most time series are stochastic in that future is only partly determined by past values, so that exact predictions are impossible and must be replaced by the idea that future values have a probability distribution which is conditioned by knowledge of past values.

A common assumption, time series is said to be stationary if there is no systematic trend, no systematic change in variance, and if strictly periodic variations or seasonality do not exist. Most processes in the world appear to be non-stationary. Even so much of the theory in time series literature is only applicable to stationary processes.

1.2 Time Series Components

A time series is supposed to be affected by four main components. There are Trend, Cyclical, Seasonal and Irregular components.

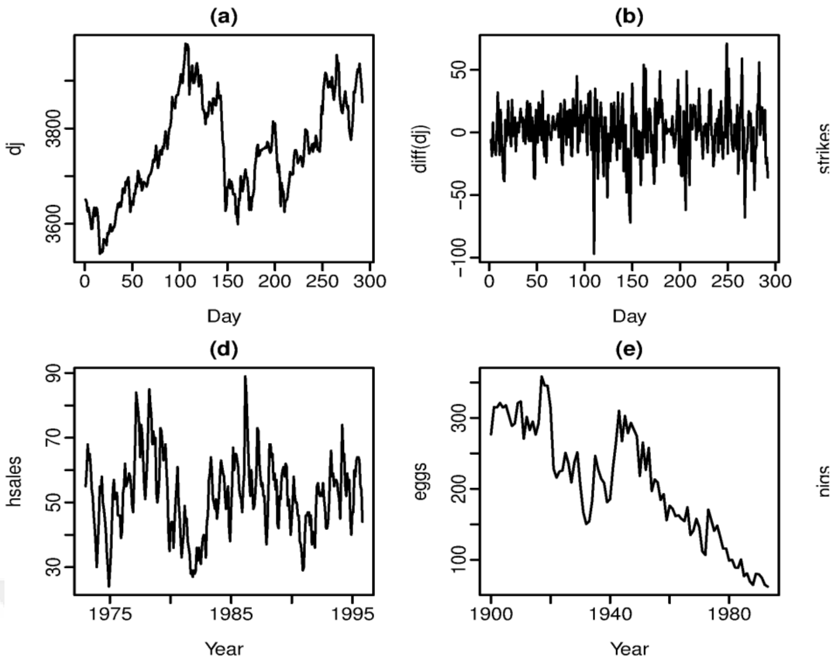


Figure 1.1 Time Series Components

Figure 1.1 (a)-(d) displays the components of a time series which are cyclic, irregular, seasonal, trend respectively.

1.2.1 Trend Component

Trend is the long-term movement in a time series without time or irregular effects and is a reflection of the underlying level. The trend can be increasing or decreasing as well as linear or nonlinear.

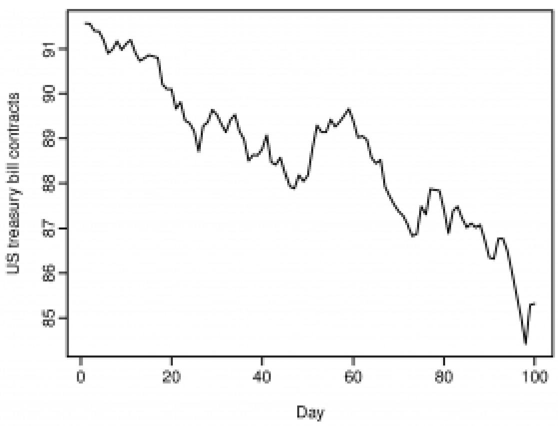


Figure 1.2 Trend Component

Figure 1.2 is the US treasury bill contracts show results from the Chicago market for 100 consecutive trading days in 1981. Here there is no seasonality, but an obvious downward trend **(**Athanasopoulos & Hyndman, 2012).

1.2.2 Seasonal Component

Seasonality is a component of a time series in which the data experiences regular and predictable changes that occur in regular calendar intervals such as months or fiscal year.

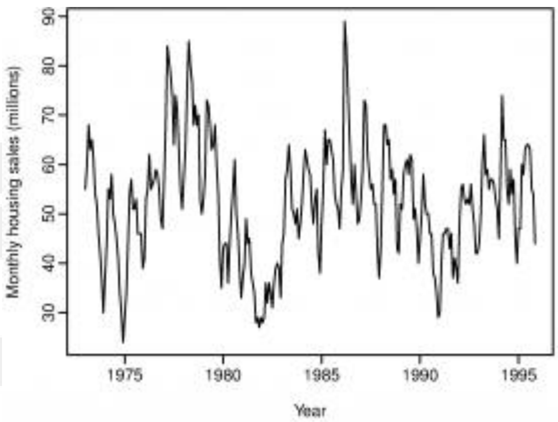


Figure 1.3 Seasonal Component

Figure 1.3 is the monthly housing sales show strong seasonality within each year, as well as some strong cyclic behavior with period about 6–10 years. There is no apparent trend in the data over this period **(**Athanasopoulos & Hyndman, 2012).

1.2.3 Irregular Component

The irregular component is results from short-term fluctuations in a series which are not systematic and in some instances not predictable.

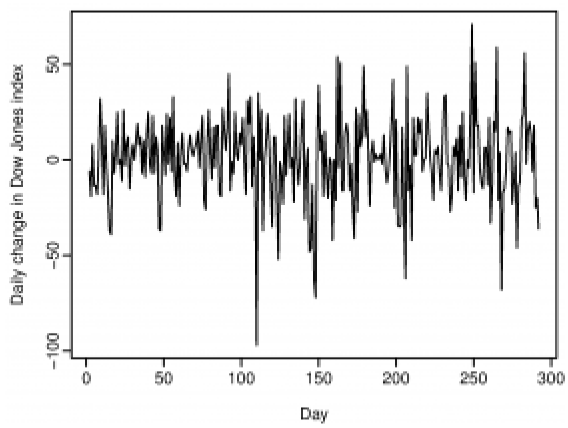


Figure 1.4 Irregular Component

Figure 1.4 is the daily change in the Dow Jones index has no trend, seasonality or cyclic behavior. There are random fluctuations which do not appear to be very predictable, and no strong patterns that would help with developing a forecasting model **(**Athanasopoulos & Hyndman, 2012).

1.2.4 Cyclical Component

Cyclical variations are long term movements that represent consistently recurring rises and declines in activity. That variation usually last longer than a year.

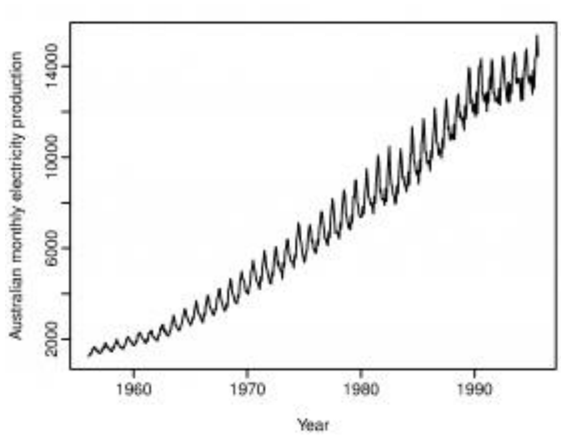


Figure 1.5 Cyclical Component

Figure 1.5 is the Australian monthly electricity production shows a strong increasing trend, with strong seasonality. There is no evidence of any cyclic behavior here **(**Athanasopoulos & Hyndman, 2012).

1.3 Basic Structures

There are two types of model which are called additive and multiplicative models.

The multiplicative decomposition model is

$$y_t = TR_t \times SN_t \times CL_t \times IR_t + \varepsilon_t \tag{1.1}$$

The additive decomposition model is

$$y_t = TR_t + SN_t + CL_t + IR_t + \varepsilon_t \tag{1.2}$$

$y_t =$ The observed value of the time series in time period t

$TR_t =$ The trend component in time period t

$SN_t =$ The seasonal component in time period t

$CL_t =$ The cyclical component in time period t

$IR_t =$ The irregular component in time period t

$\varepsilon_t =$ Residual term in time period t

1.4 Time Series Decomposition

Time series decomposition method is the easiest method to understand and make in short-term forecasting predictions. This method can reveal especially the seasonality and trend of a time series and split a time series into its components. In this thesis, a program in R is written for additive and multiplicative models in order to measure the effect of the decomposition method. Time series included in M-competition are used to test the written R program.

For controlling the time series decomposition; mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), mean absolute error (MAE) and mean square error (MSE) estimation methods were investigated for the time series. Formulas of error measurements are given below;

$$MAPE = \frac{100}{N}.\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{1.3}$$

$$SMAPE = \frac{200}{N}.\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i + \hat{y}_i}\right| \tag{1.4}$$

$$MAE = \frac{1}{N}.\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{1.5}$$

$$MSE = \frac{1}{N}.\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{1.6}$$

CHAPTER TWO
DECOMPOSITION METHOD

2.1 Introduction

Sequentially occurring on the time axis and non-random measurements are called time series. The series obtained by observations made at consecutive regular intervals such as days, weeks, months, three months, six months, years for a certain period are called time series. Time series forecasting uses information regarding historical values and associated patterns to predict future activity.

One approach to the analysis of time series data is based on forecasting past data in order to decompose the underlying pattern in the data series from randomness. After the underlying pattern can be projected into the future and used as the forecast. This method is called decomposition. Decomposition methods include four components, trend factor, seasonal factor, irregular factor and cyclical factor. In this chapter, we will focus on modeling and forecasting the time series with these components.

Time series decomposition models are generally divided into two sections. These are additive models and multiplicative models.

2.2 Additive Model

The additive model assumes that the time series is the sum of the components. If any of the components are not in the series, the effect of component is assumed to be 0. The additive model formulas are given below.

1. Calculate a moving average equal to the length of the season (quarterly, monthly, yearly or etc.)

$$\sum_{i=1}^{Sl} \frac{x_i}{Sl} \tag{2.3}$$

2. Calculate the M-period central moving average. The central moving average equal to

$$CMA_t = tr_t + cl_t \tag{2.4}$$

3. Subtract the central moving average to obtain the seasonal error.

$$sn_t - ir_t = y_t - (tr_t + cl_t) = y_t - CMA_t \tag{2.5}$$

4. Adjust the total seasonal indexes to equal the number of periods. These seasonal factors are then normalized.

$$sn_t = \overline{sn_t} - \left(\frac{\sum_{t=1}^{L} \overline{sn_t}}{L}\right) \tag{2.6}$$

5. Normalized values are written in succession until the length of the season.

6. Deseasonalize the time series by subtracting it by seasonal index

$$d_t = y_t - sn_t \tag{2.7}$$

7. Compute the trend cyclical equation using deseasonalized data.

$$tr_t = b_0 + b_1 t \tag{2.8}$$

$$b_1 = \frac{n\sum_{t=1}^{n} td_t - \left(\sum_{t=1}^{n} t\right)\left(\sum_{t=1}^{n} d_t\right)}{n\sum_{t=1}^{n} t^2 - \left(\sum_{t=1}^{n} t\right)^2} \tag{2.9}$$

$$b_0 = \frac{\sum_{t=1}^{n} d_t}{n} - b_1 \left(\frac{\sum_{t=1}^{n} t}{n} \right) \tag{2.10}$$

8. Add the fitted trend values and the seasonal indexes to estimate the fitted values.

$$tr_t + sn_t = (b_0 + b_1 t) + sn_t \tag{2.11}$$

$$\hat{y}_t = tr_t + sn_t \tag{2.12}$$

9. Calculate the error squares.

$$(y_t - \hat{y}_t)^2 \tag{2.13}$$

2.3 Multiplicative Model

The multiplicative model assumes that the time series is the multiply of the components. If any of the components are not in the series, the effect of component is assumed to be 1. The multiplicative model formulas are given below.

1. Calculate a moving average equal to the length of the season (quarterly, monthly, yearly or etc.)

$$\sum_{i=1}^{Sl} \frac{x_i}{Sl} \tag{2.14}$$

2. Calculate the M-period central moving average. The central moving average equal to

$$CMA_t = tr_t \times cl_t \tag{2.15}$$

3. Divide the central moving average to obtain the seasonal error.

$$sn_t \times ir_t = \frac{y_t}{(tr_t \times cl_t)} = \frac{y_t}{CMA_t} \tag{2.16}$$

4. Adjust the total of the seasonal indexes to equal the number of periods. These seasonal factors are then normalized.

$$sn_t = \overline{sn_t} - \left(\frac{\sum_{t=1}^{L} \overline{sn_t}}{L}\right) \tag{2.17}$$

5. Normalized values are written in succession until the length of the season

6. Deseasonalize the time series by dividing it by seasonal index.

$$d_t = \frac{y_t}{sn_t} \tag{2.18}$$

7. Estimate the trend cyclical equation using deseasonalized data.

$$tr_t = b_0 + b_1 t \tag{2.19}$$

$$b_1 = \frac{n\sum_{t=1}^{n} td_t - \left(\sum_{t=1}^{n} t\right)\left(\sum_{t=1}^{n} d_t\right)}{n\sum_{t=1}^{n} t^2 - \left(\sum_{t=1}^{n} t\right)^2} \quad (2.20)$$

$$b_0 = \frac{\sum_{t=1}^{n} d_t}{n} - b_1\left(\frac{\sum_{t=1}^{n} t}{n}\right) \quad (2.21)$$

8. Multiply the fitted trend values and the seasonal indexes to estimate the fitted values.

$$tr_t \times sn_t = (b_0 + b_1 t) \times sn_t \quad (2.22)$$

$$\hat{y}_t = tr_t \times sn_t \quad (2.23)$$

9. Calculate the error squares.

$$(y_t - \hat{y}_t)^2 \quad (2.24)$$

CHAPTER THREE

APPLICATION

As mentioned earlier, a time series consists of components with trend, seasonal fluctuation, cyclic motion and irregular random motion. In this section, we will focus on modeling time series with these components and obtaining predictions.

The breakpoint is important in the decomposition method. For this reason, MAE, MSE, MAPE, SMAPE are calculated for different cut position and investigated which starting point is better. There are some examples given below.

	A	B	C	D	E	F
1						
2		1	2	3		
3	MAE	80,08366	79,9688	80,43593		2
4	MSE	6413,393	6395,009	6469,939		2
5	MAPE	100,2299	100,0861	100,6708		2
6	sMAPE	200,9216	200,3447	202,7011		2

Figure 3.1 Excel Application 1

In this example, the series QN10 is used and since this series is a quarterly, cuts were made starting from the first, second and third values. It is observed that it is better to start cutting from the second value for all error measures (Figure 3.1).

The breakpoint is important in the decomposition method. For this reason, MAE, MSE, MAPE, SMAPE are calculated for different cut position and investigated which starting point is better. There are some examples given below.

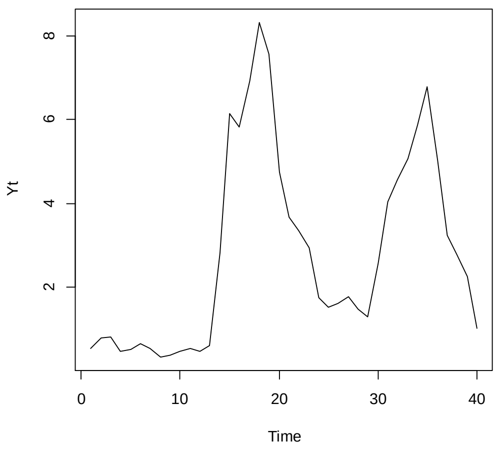
	A	B	C	D	E	F
1						
2		1	2	3		
3	MAE	14,34831	14,38275	14,42648		1
4	MSE	276,5372	276,1459	275,9732		3
5	MAPE	11,75955	11,78163	11,8096		1
6	sMAPE	11,54504	11,5741	11,61108		1

Figure 3.2 Excel Application 2

In this example, the series QNG16 is used and since this series is a quarterly, cuts were made starting from the first, second and third values. It is observed that it is better to start cutting from the first value MAE, MAPE, SMAPE error measures. But MSE is show that third value is better (Figure 3.2).

Then a R program is written and run for all time series in the M-Competition data set. M-Competition data is often used for comparing forecasting methods therefore we also prefer to use these time series. 1001 series first used in the 1982 M-Competition. The M-competition data set is 1001 time series collected from a variety of sources and covering micro, macro, and demographic data. These 1001 series were made up of 181 yearly, 203 quarterly and 617 monthly series.

The R code is run for the M-Competition data set. Seasonal and trend graphs were examined and it was observed that the estimations were appropriate. In the application of the R program, if we cut from middle values the results are same with the M-competition data.



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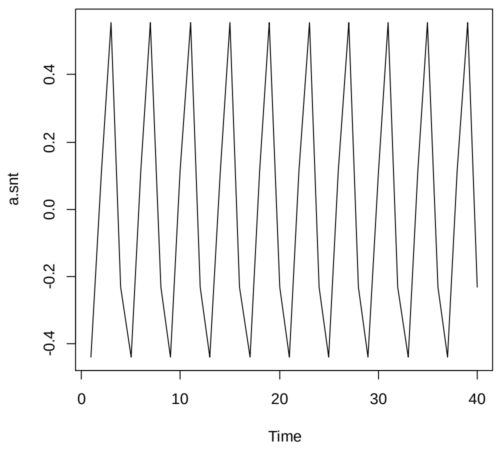

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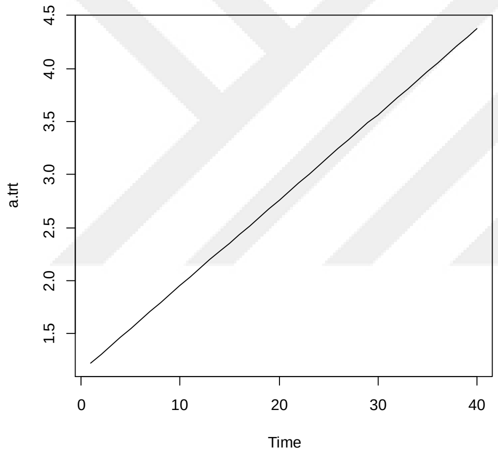

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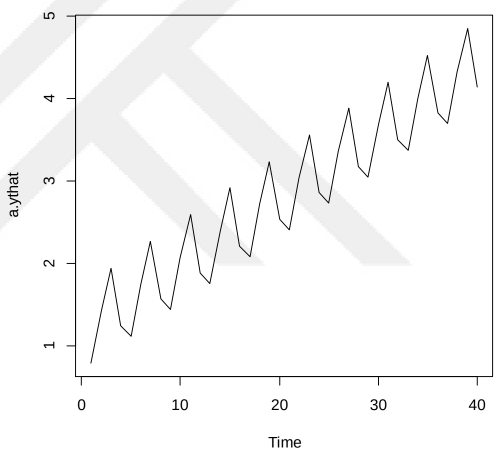
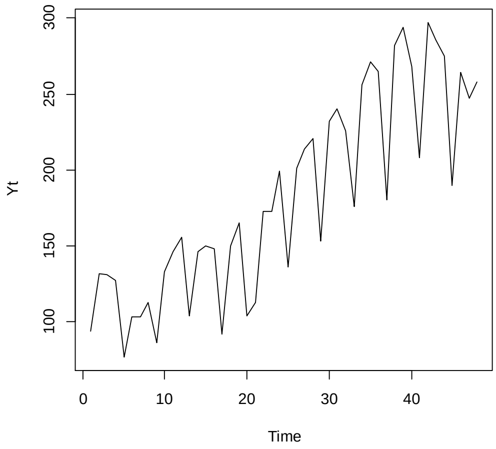


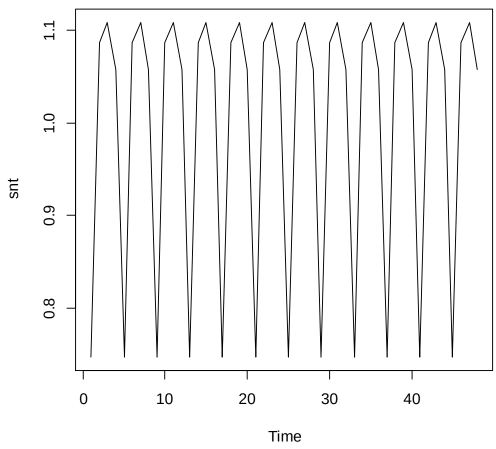
(d)

Figure 3.3 QRF1

Figure 3.3 (a) shows the QRF1 data set. The data set is quarterly. Figure 3.3 (b) gives time versus seasonal values separated from the trend. Figure 3.3 (c) shows the values only includes increasing trend. In the last figure 3.3 (d), there is an estimated data set figure made up of seasonality and trend figure. The seasonal indexes obtained from written R program were compared to those included in M-Competition data set and they were seen to be similar.



(a)



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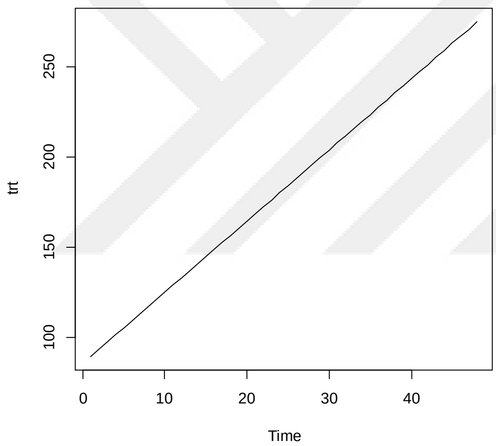

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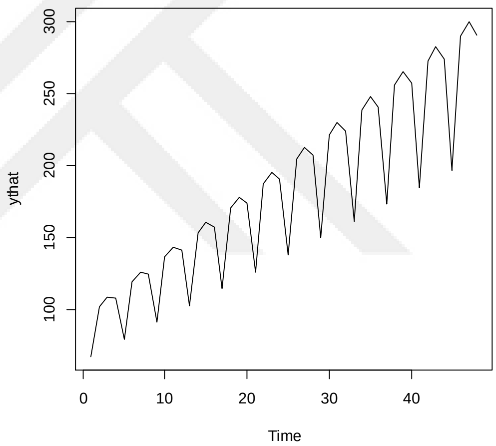
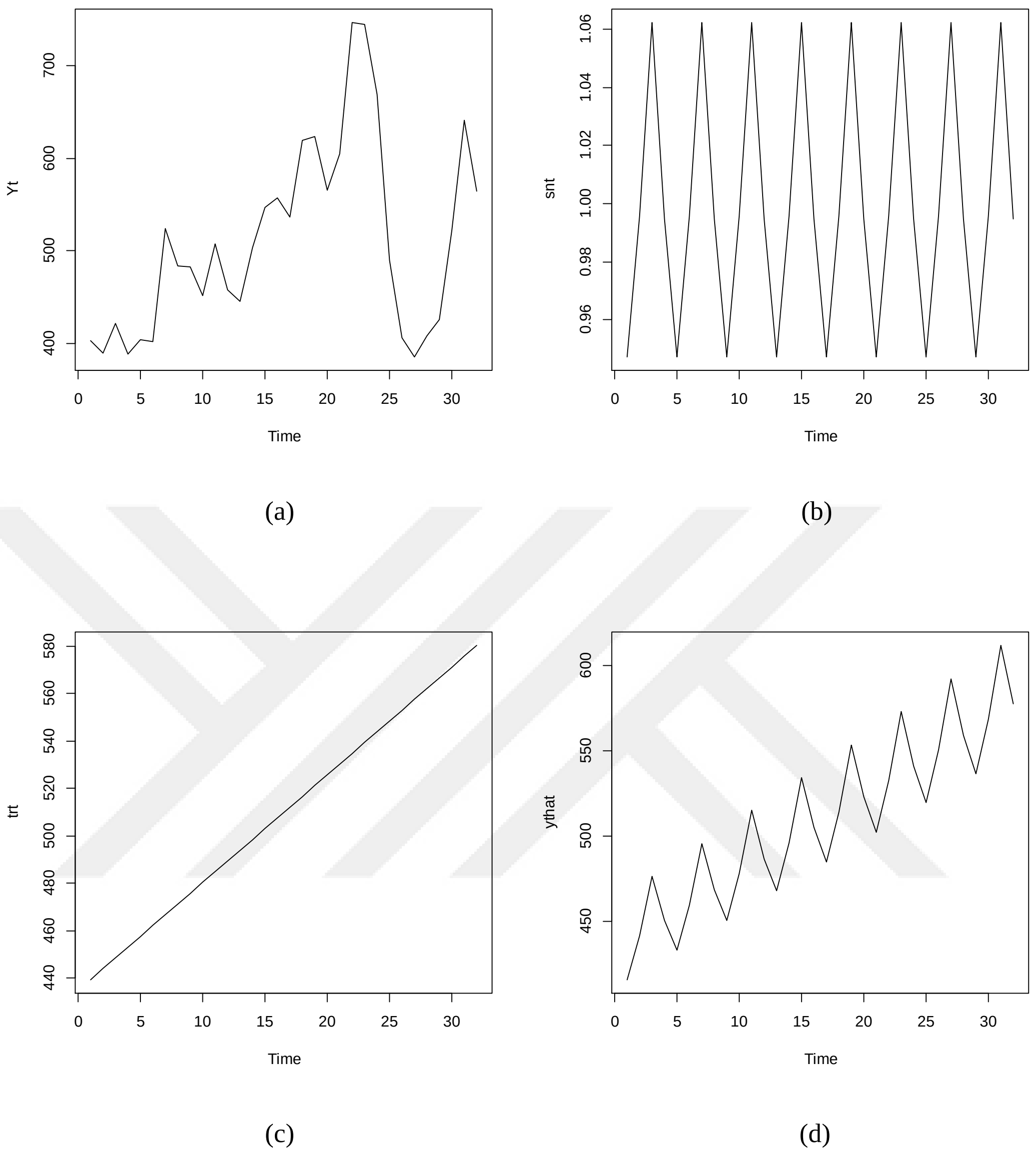


(d)

Figure 3.4 QRM1

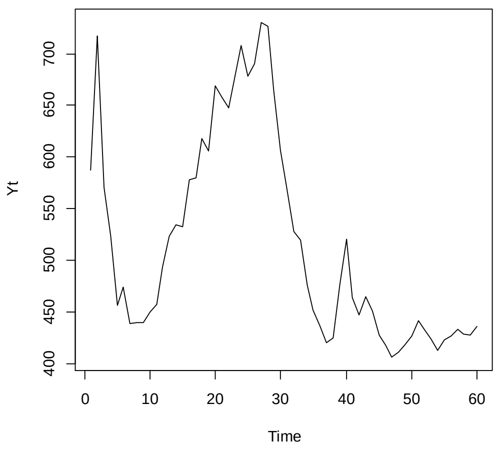
Figure 3.4 (a) shows the QRM1 data set. The data set is quarterly. Figure 3.4 (b) gives time versus seasonal values separated from the trend. Figure 3.4 (c) shows the values only includes increasing trend. In the last figure 3.4 (d), there is an estimated data set figure made up of seasonality and trend figure.



(a) (b) (c) (d)

Figure 3.5 QNF3

Figure 3.5 (a) shows the QNF3 data set. The data set is quarterly. Figure 3.5 (b) gives time versus seasonal values separated from the trend. Figure 3.5 (c) shows the values only includes increasing trend. In the last figure 3.5 (d), there is an estimated data set figure made up of seasonality and trend figure.



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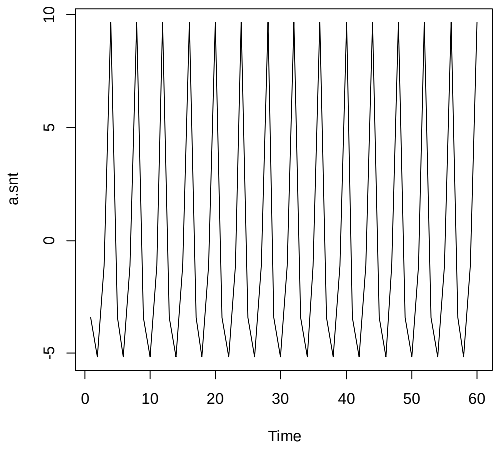

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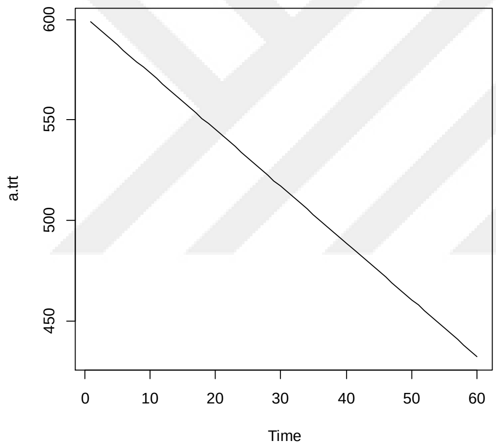

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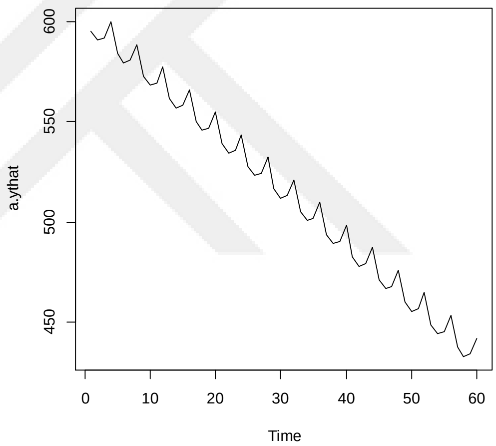
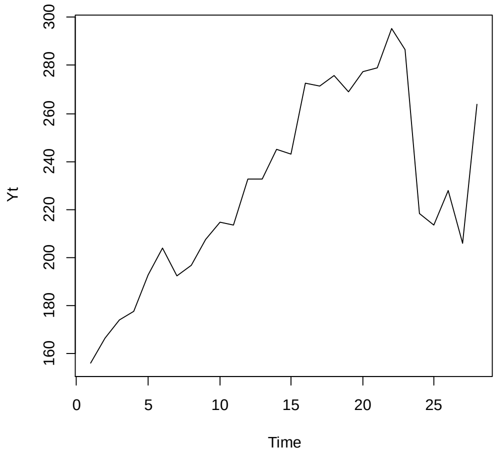


(d)

Figure 3.6 QNM7

Figure 3.6 (a) shows the QNM7 data set. The data set is quarterly. Figure 3.6 (b) gives time versus seasonal values separated from the trend. Figure 3.6 (c) shows the values only includes increasing trend. In the last figure 3.6 (d), there is an estimated data set figure made up of seasonality and trend figure.



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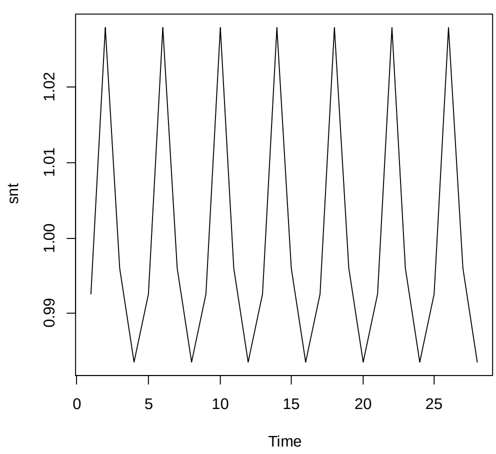

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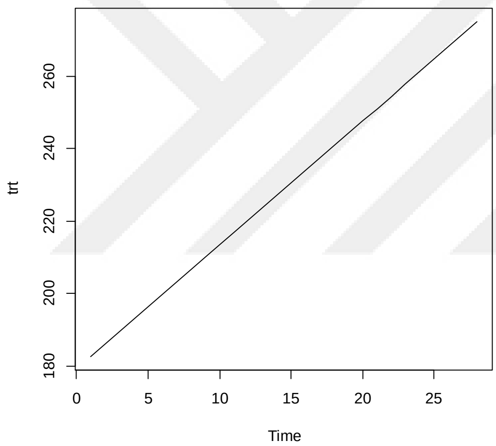

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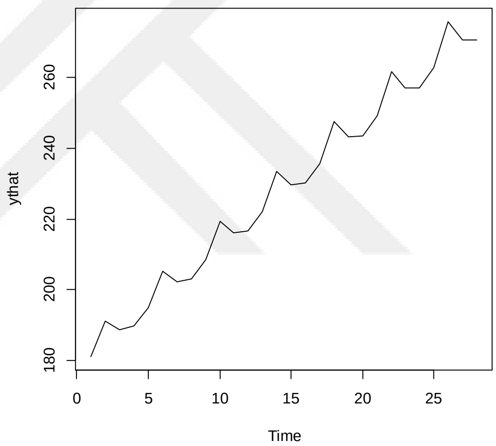
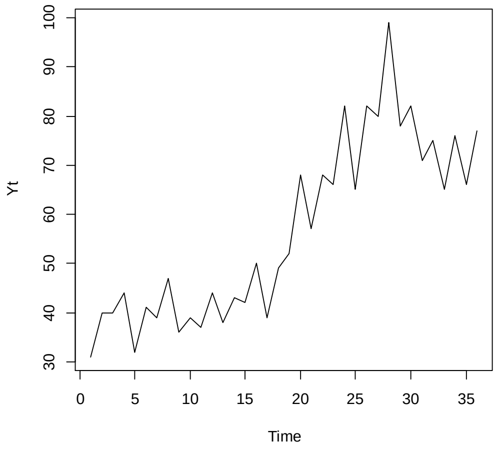


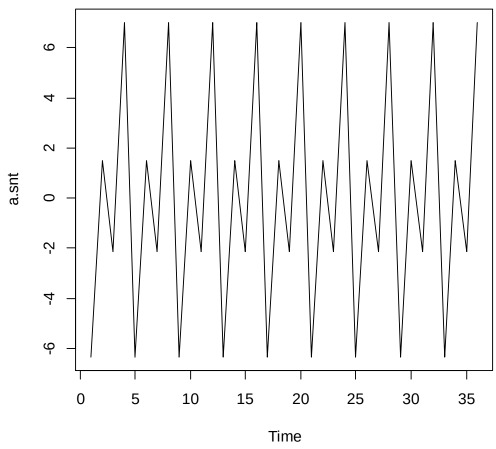
(d)

Figure 3.7 QNB1

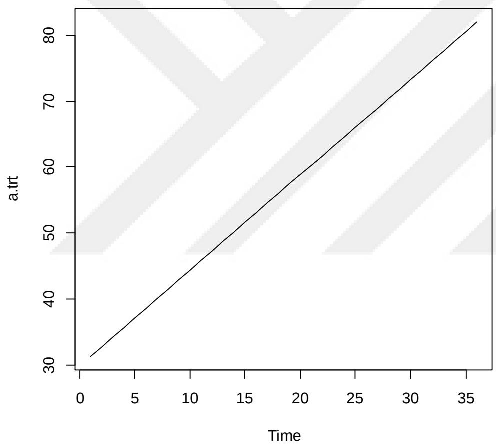
Figure 3.7 (a) shows the QNB1 data set. The data set is quarterly. Figure 3.7 (b) gives time versus seasonal values separated from the trend. Figure 3.7 (c) shows the values only includes increasing trend. In the last figure 3.7 (d), there is an estimated data set figure made up of seasonality and trend figure.



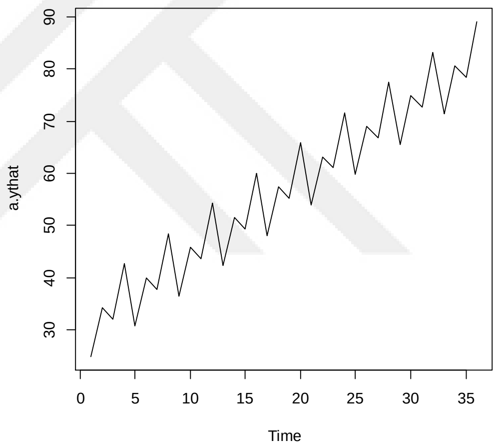
(a)



(b)



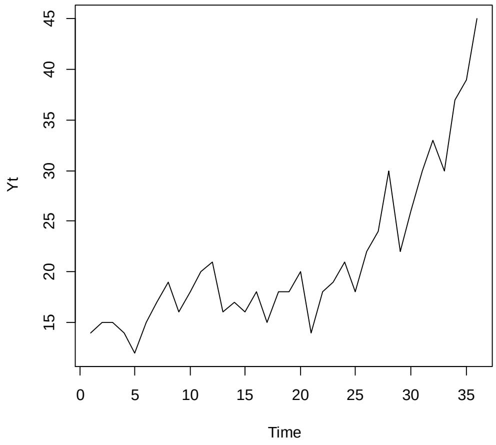
(c)



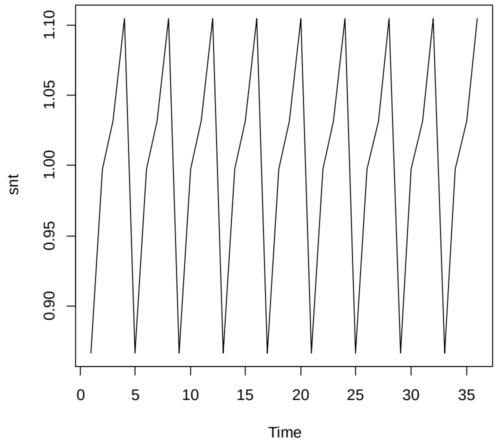
(d)

Figure 3.8 QRI3

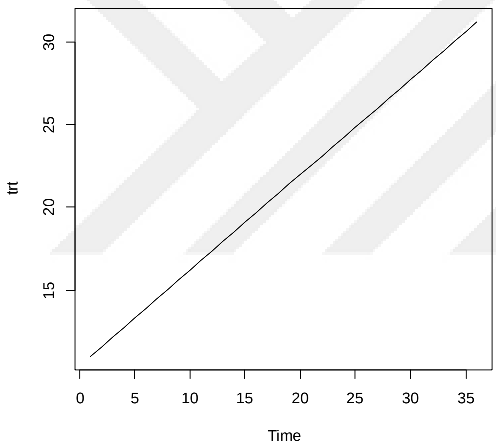
Figure 3.8 (a) shows the QRI3 data set. The data set is quarterly. Figure 3.8 (b) gives time versus seasonal values separated from the trend. Figure 3.8 (c) shows the values only includes increasing trend. In the last figure 3.8 (d), there is an estimated data set figure made up of seasonality and trend figure.



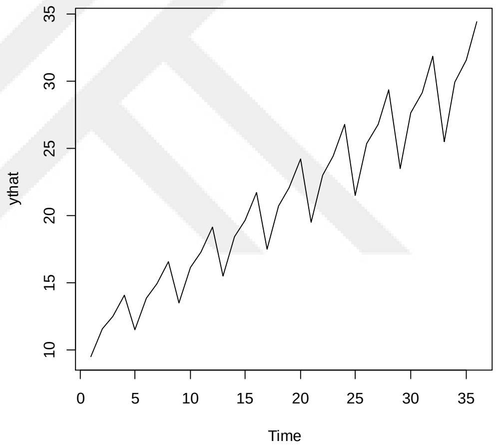
(a)



(b)



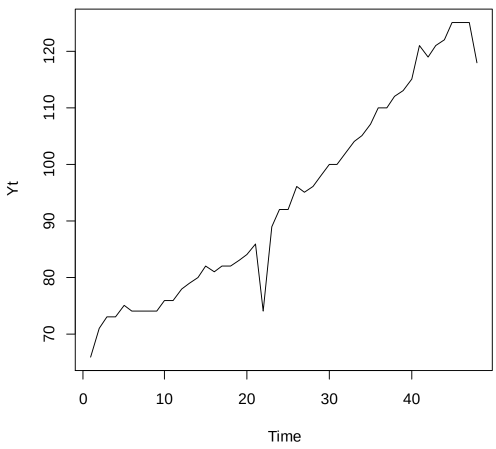
(c)



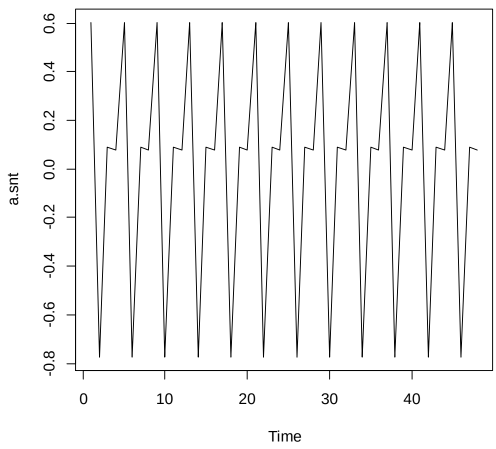
(d)

Figure 3.9 QNI6

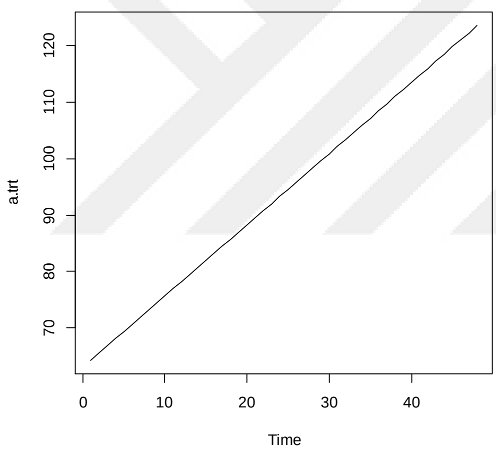
Figure 3.9 (a) shows the QNI6 data set. The data set is quarterly. Figure 3.9 (b) gives time versus seasonal values separated from the trend. Figure 3.9 (c) shows the values only includes increasing trend. In the last figure 3.9 (d), there is an estimated data set figure made up of seasonality and trend figure.



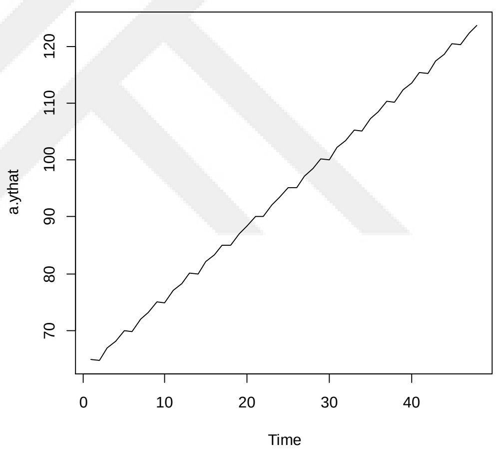
(a)



(b)



(c)



(d)

Figure 3.10 QNG5

Figure 3.10 (a) shows the QNG5 data set. The data set is quarterly. Figure 3.10 (b) gives time versus seasonal values separated from the trend. Figure 3.10 (c) shows the values only includes increasing trend. In the last figure 3.10 (d), there is an estimated data set figure made up of seasonality and trend figure.

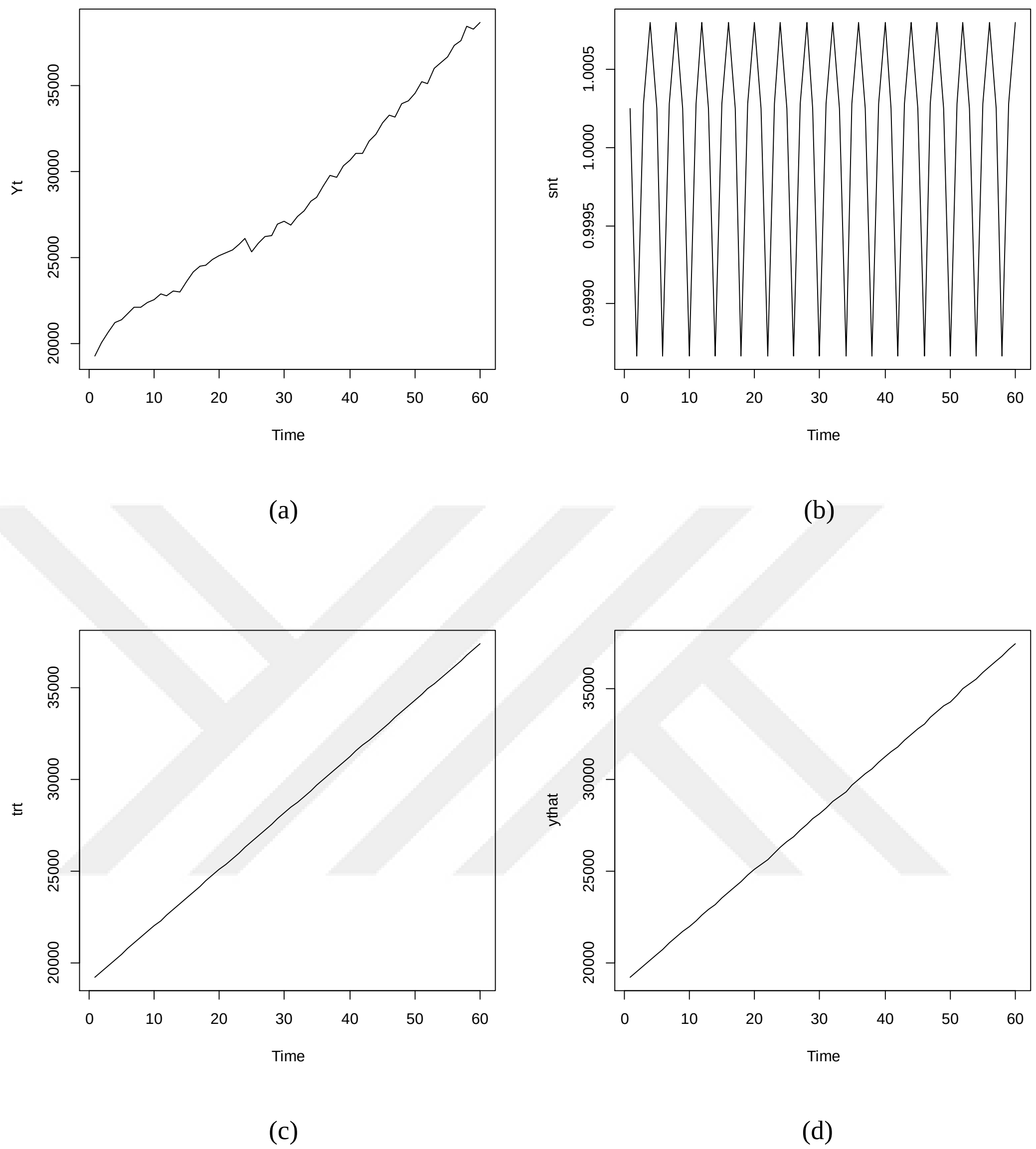
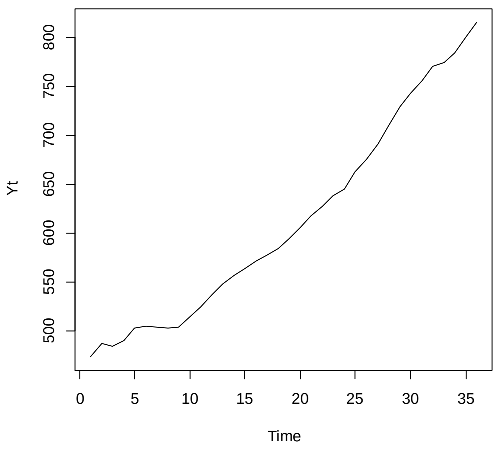
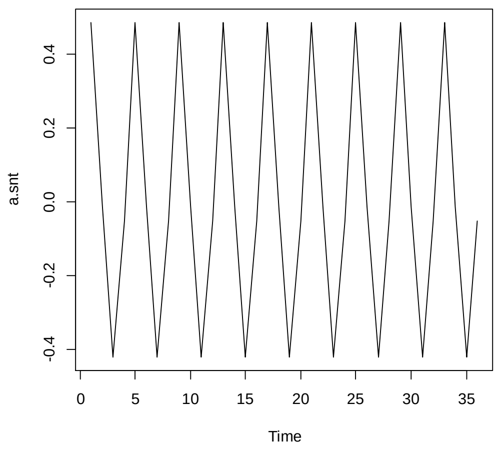


Figure 3.11 QNC1

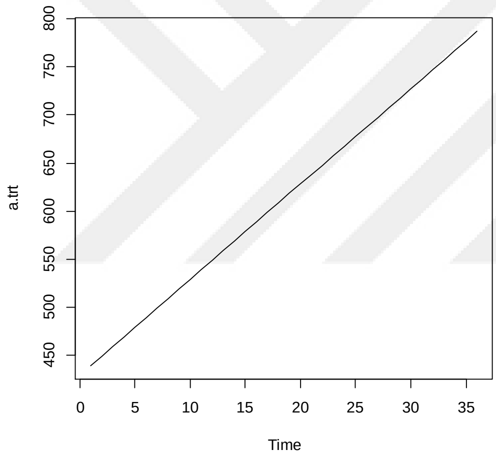
Figure 3.11 (a) shows the QNC1 data set. The data set is quarterly. Figure 3.11 (b) gives time versus seasonal values separated from the trend. Figure 3.11 (c) shows the values only includes increasing trend. In the last figure 3.11 (d), there is an estimated data set figure made up of seasonality and trend figure.



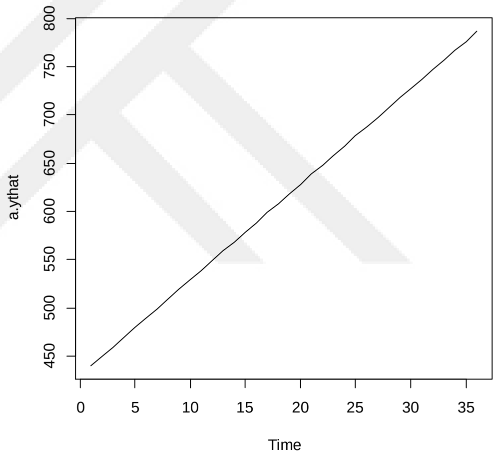
(a)



(b)



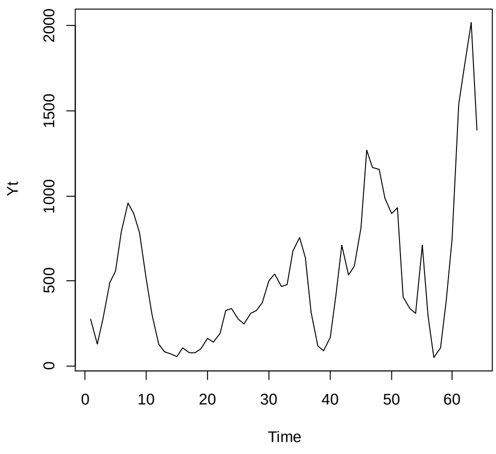
(c)



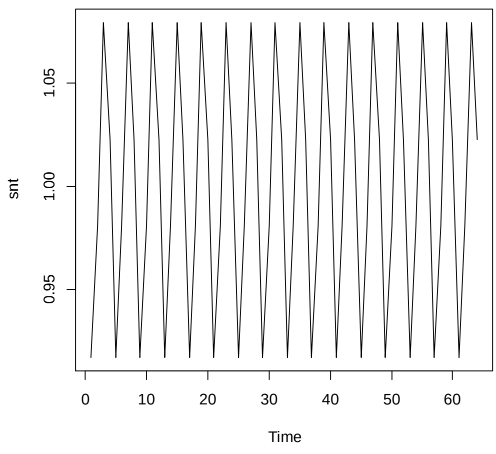
(d)

Figure 3.12 QRG7

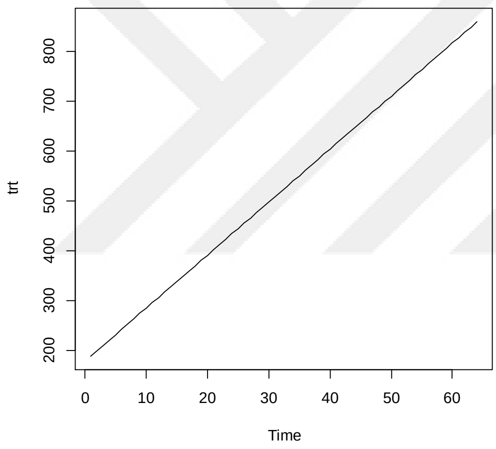
Figure 3.12 (a) shows the QRG7 data set. The data set is quarterly. Figure 3.12 (b) gives time versus seasonal values separated from the trend. Figure 3.12 (c) shows the values only includes increasing trend. In the last figure 3.12 (d), there is an estimated data set figure made up of seasonality and trend figure.



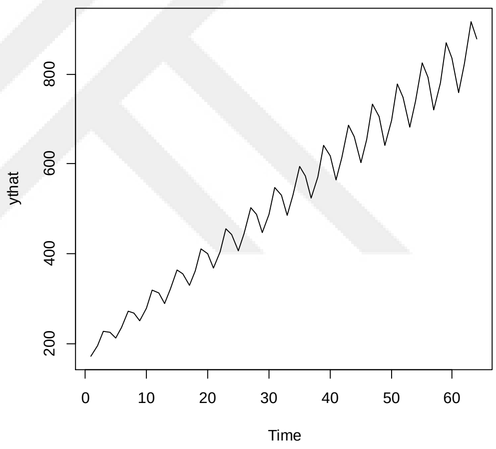
(a)



(b)



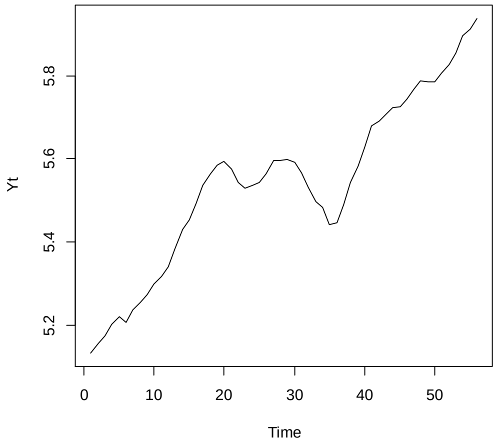
(c)



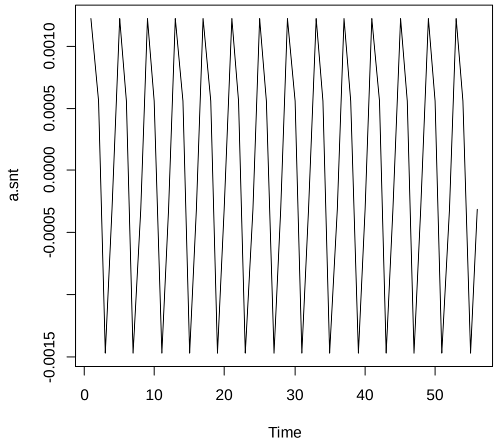
(d)

Figure 3.13 QRC1

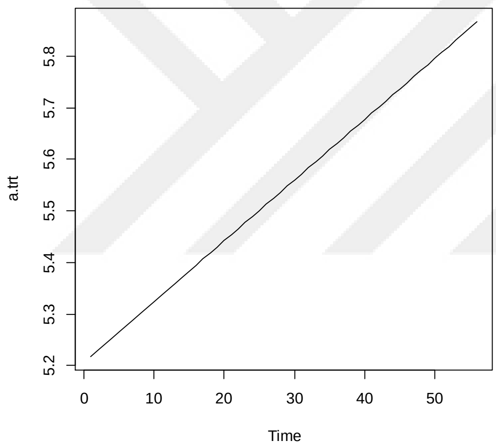
Figure 3.13 (a) shows the QRC1 data set. The data set is quarterly. Figure 3.13 (b) gives time versus seasonal values separated from the trend. Figure 3.13 (c) shows the values only includes increasing trend. In the last figure 3.13 (d), there is an estimated data set figure made up of seasonality and trend figure.



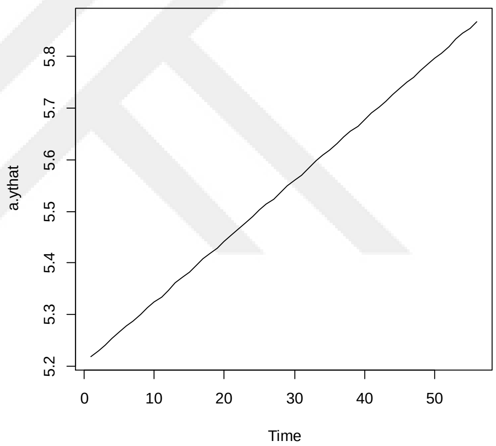
(a)



(b)



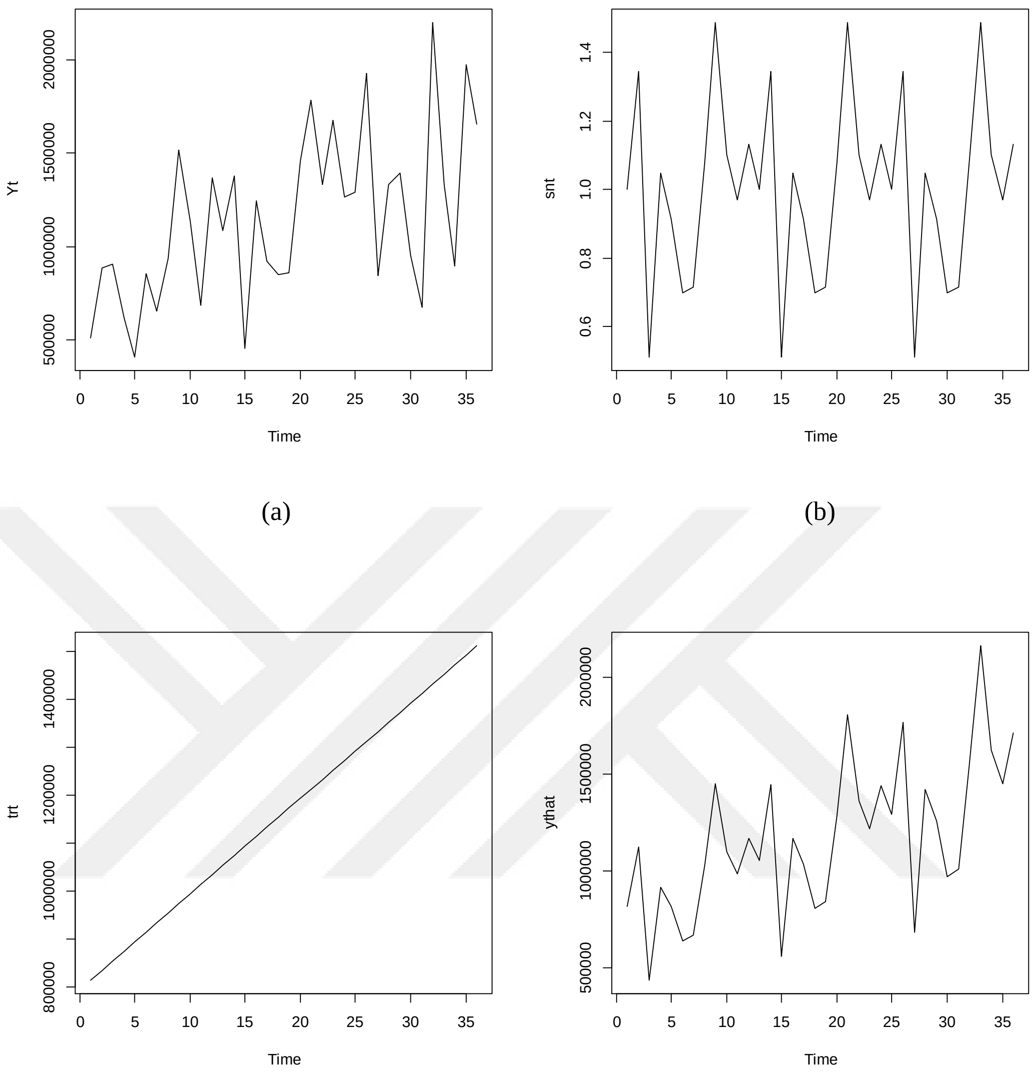
(c)



(d)

Figure 3.14 QND5

Figure 3.14 (a) shows the QND5 data set. The data set is quarterly. Figure 3.14 (b) gives time versus seasonal values separated from the trend. Figure 3.14 (c) shows the values only includes increasing trend. In the last figure 3.14 (d), there is an estimated data set figure made up of seasonality and trend figure.

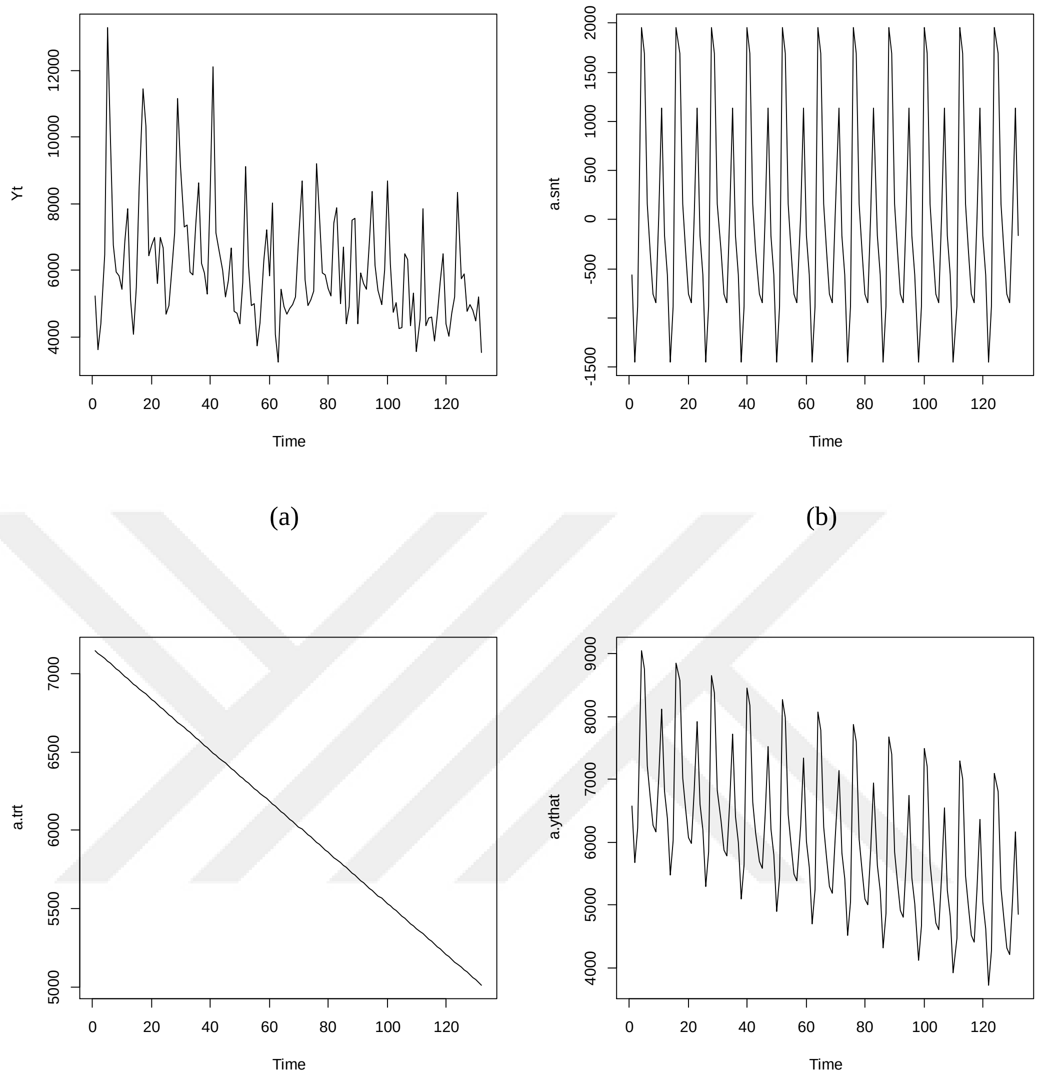


(a) (b)

(c) (d)

Figure 3.15 MRF1

Figure 3.15 (a) shows the MRF1 data set. The data set is monthly. Figure 3.15 (b) gives time versus seasonal values separated from the trend. Figure 3.15 (c) shows the values only includes increasing trend. In the last figure 3.15 (d), there is an estimated data set figure made up of seasonality and trend figure.

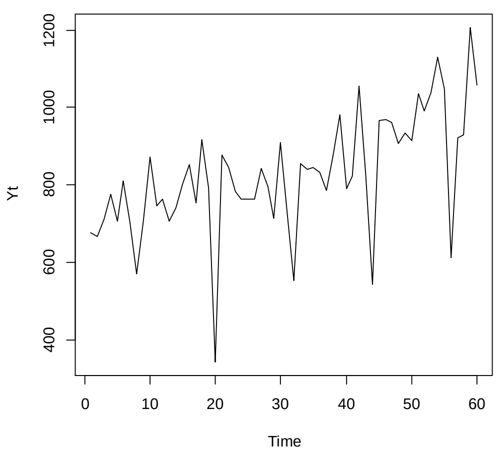


(a) (b)

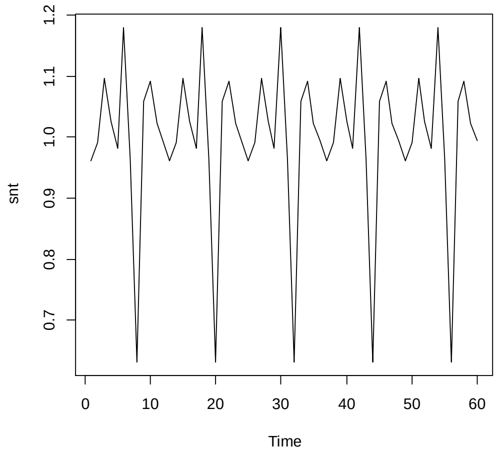
(c) (d)

Figure 3.16 MRM11

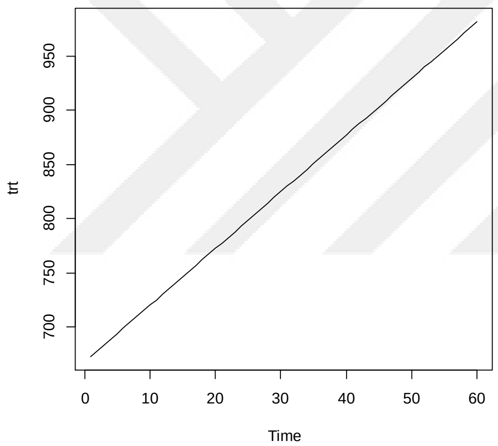
Figure 3.16 (a) shows the MRM11 data set. The data set is monthly. Figure 3.16 (b) gives time versus seasonal values separated from the trend. Figure 3.16 (c) shows the values only includes decreasing trend. In the last figure 3.16 (d), there is an estimated data set figure made up of seasonality and trend figure.



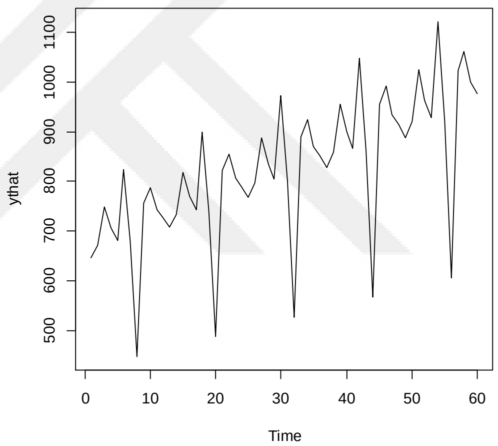
(a)



(b)



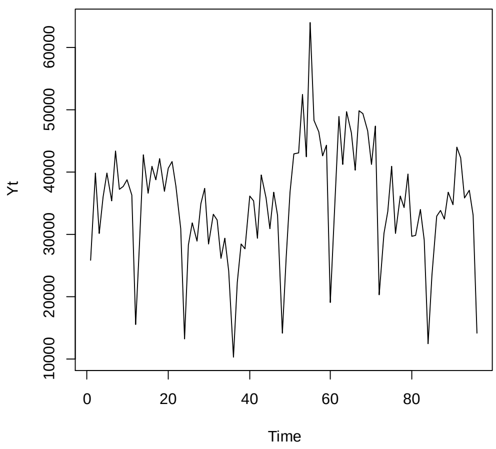
(c)



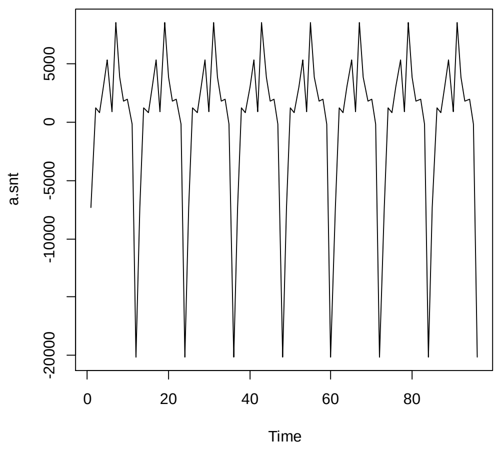
(d)

Figure 3.17 MRB21

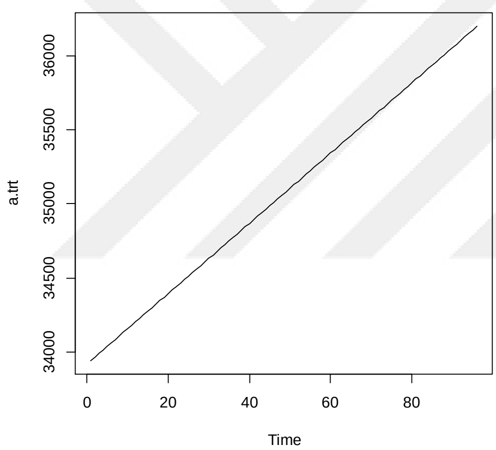
Figure 3.17 (a) shows the MRB21 data set. The data set is monthly. Figure 3.17 (b) gives time versus seasonal values separated from the trend. Figure 3.17 (c) shows the values only includes increasing trend. In the last figure 3.17 (d), there is an estimated data set figure made up of seasonality and trend figure.



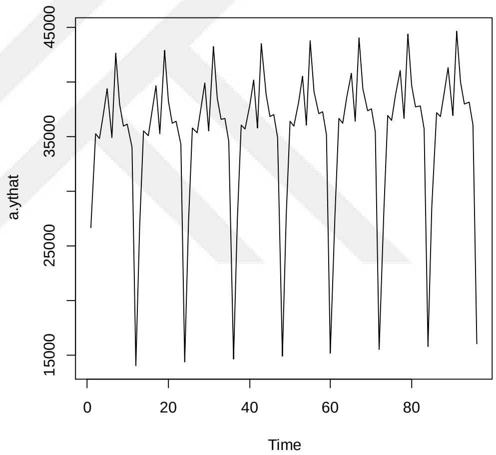
(a)



(b)



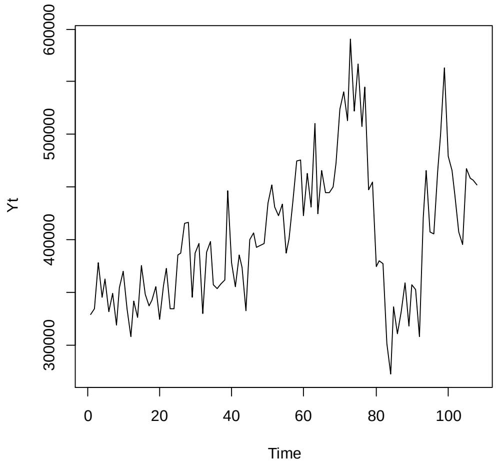
(c)



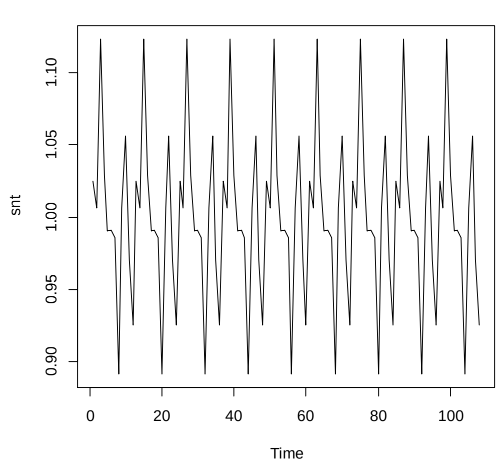
(d)

Figure 3.18 MNF1

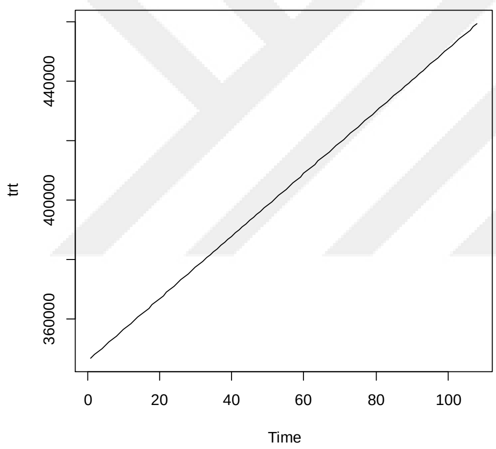
Figure 3.18 (a) shows the MNF1 data set. The data set is monthly. Figure 3.18 (b) gives time versus seasonal values separated from the trend. Figure 3.18 (c) shows the values only includes increasing trend. In the last figure 3.18 (d), there is an estimated data set figure made up of seasonality and trend figure.



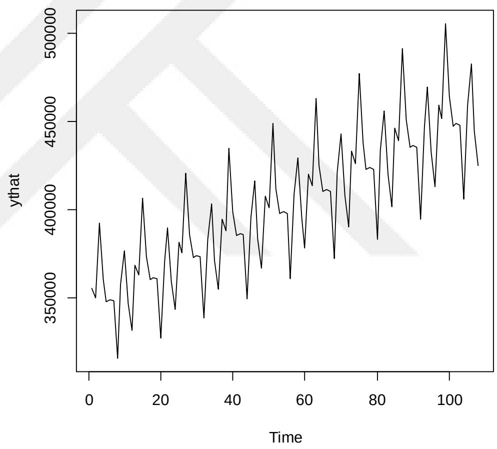
(a)



(b)



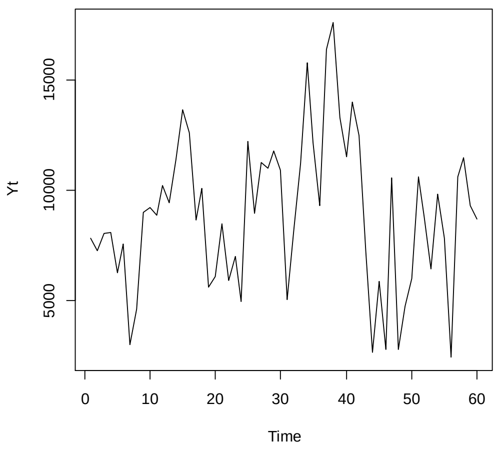
(c)



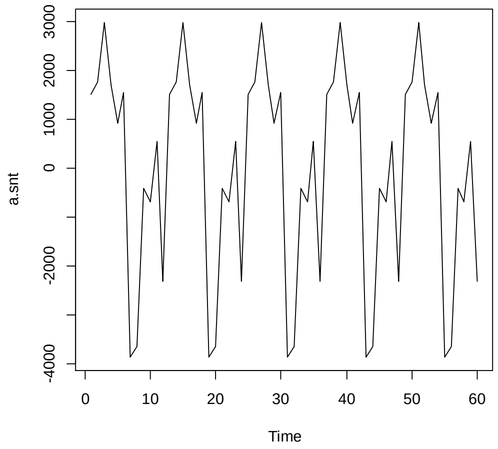
(d)

Figure 3.19 MNM57

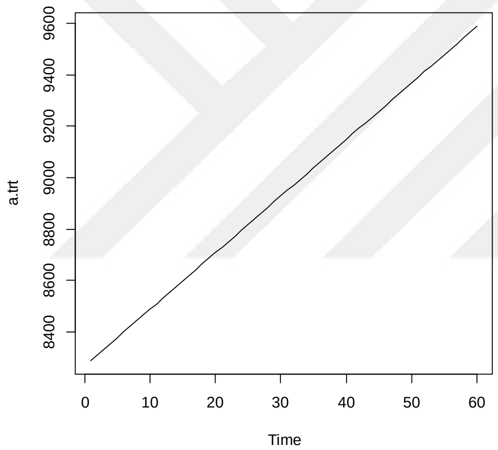
Figure 3.19 (a) shows the MNM57 data set. The data set is monthly. Figure 3.19 (b) gives time versus seasonal values separated from the trend. Figure 3.19 (c) shows the values only includes increasing trend. In the last figure 3.19 (d), there is an estimated data set figure made up of seasonality and trend figure.



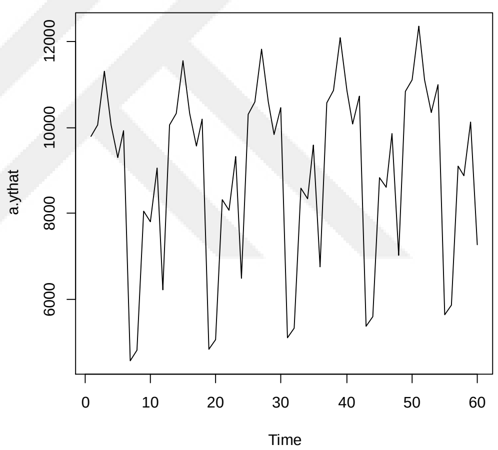
(a)



(b)



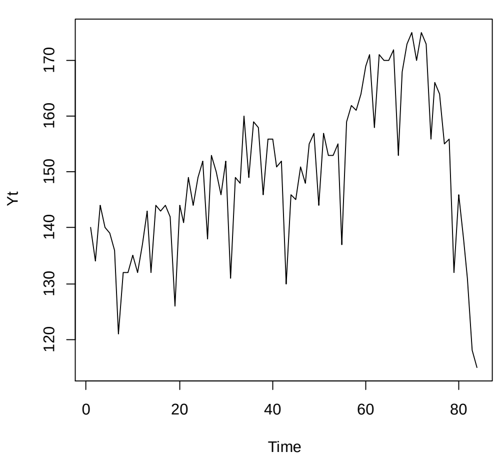
(c)



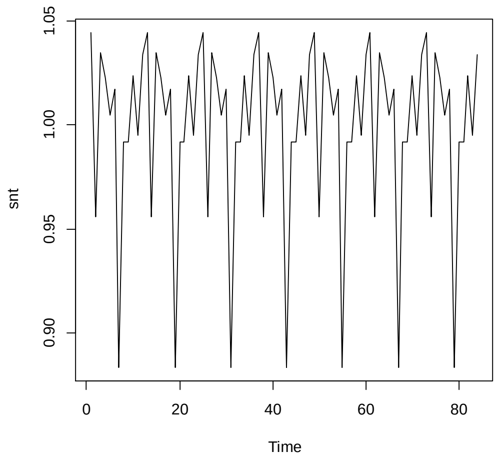
(d)

Figure 3.20 MNB66

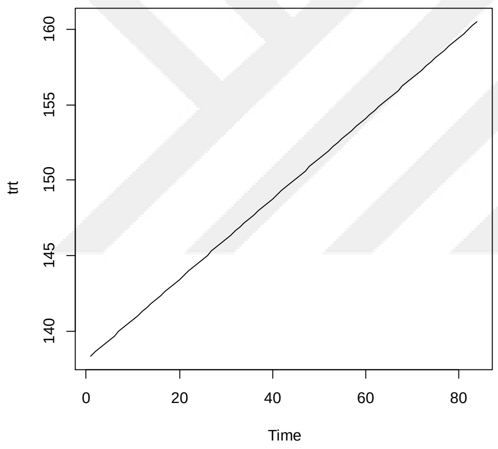
Figure 3.20 (a) shows the MNB66 data set. The data set is monthly. Figure 3.20 (b) gives time versus seasonal values separated from the trend. Figure 3.20 (c) shows the values only includes increasing trend. In the last figure 3.20 (d), there is an estimated data set figure made up of seasonality and trend figure.



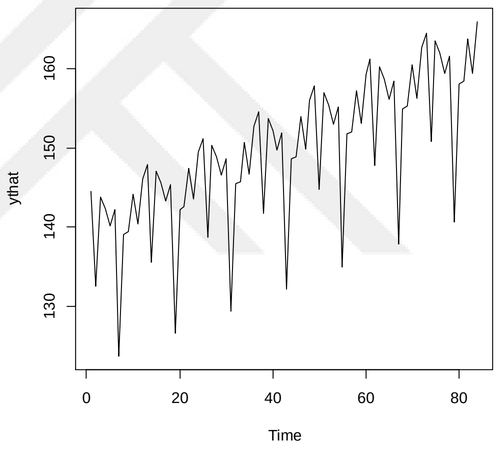
(a)



(b)



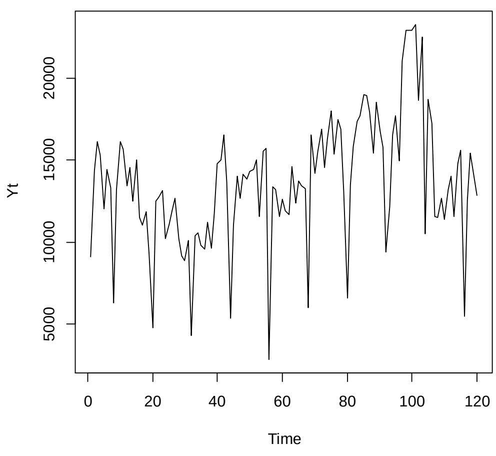
(c)



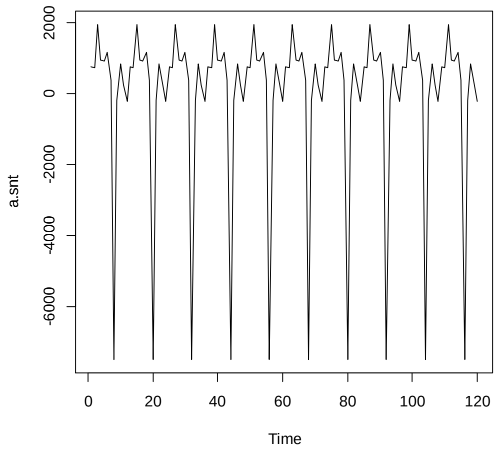
(d)

Figure 3.21 MRI11

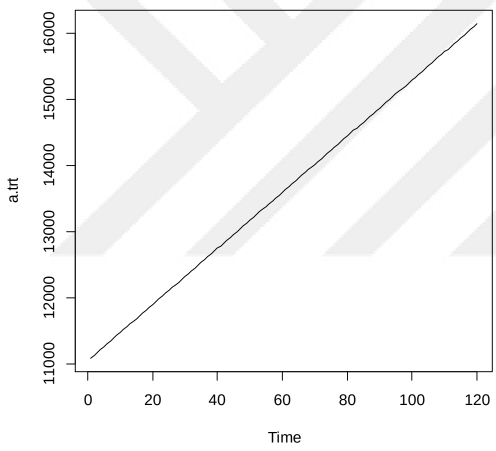
Figure 3.21 (a) shows the MRI11 data set. The data set is monthly. Figure 3.21 (b) gives time versus seasonal values separated from the trend. Figure 3.21 (c) shows the values only includes increasing trend. In the last figure 3.21 (d), there is an estimated data set figure made up of seasonality and trend figure.



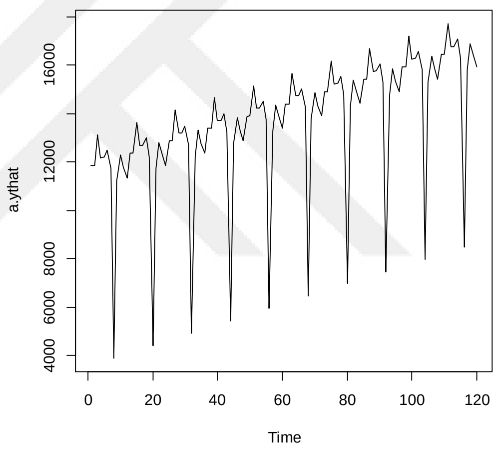
(a)



(b)



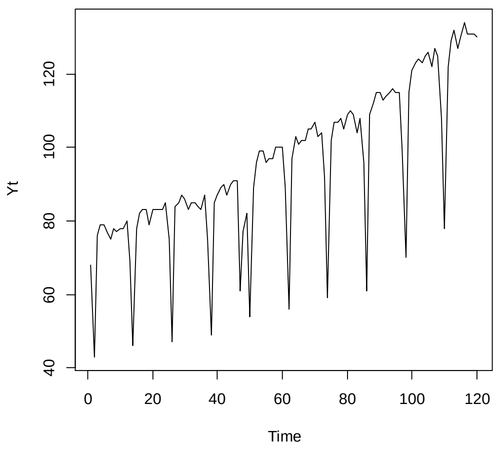
(c)



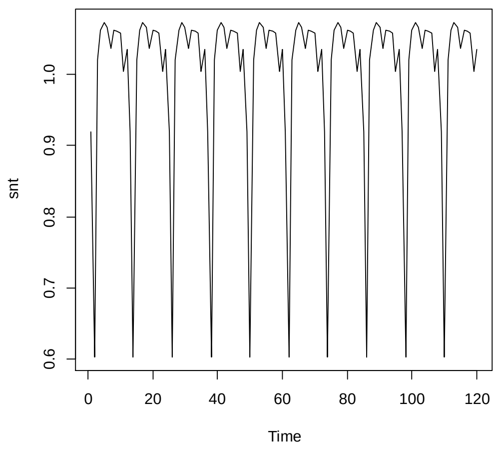
(d)

Figure 3.22 MNI19

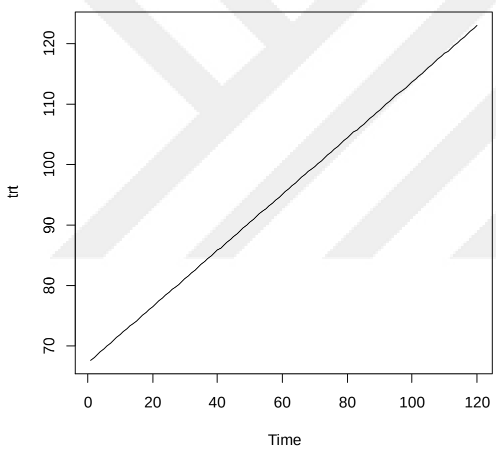
Figure 3.22 (a) shows the MNI19 data set. The data set is monthly. Figure 3.22 (b) gives time versus seasonal values separated from the trend. Figure 3.22 (c) shows the values only includes increasing trend. In the last figure 3.22 (d), there is an estimated data set figure made up of seasonality and trend figure.



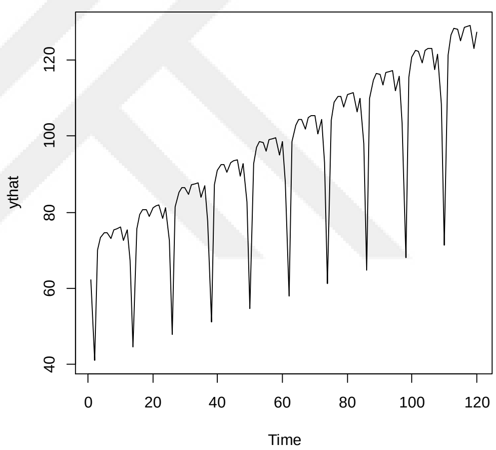
(a)



(b)



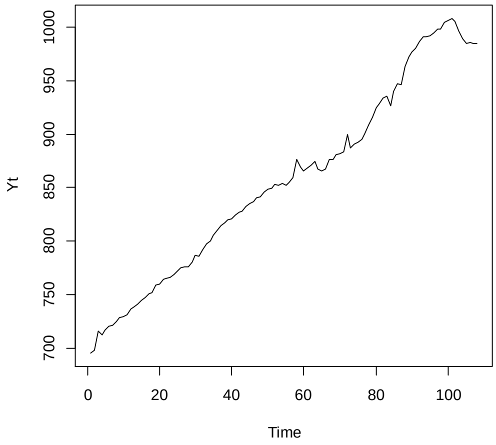
(c)



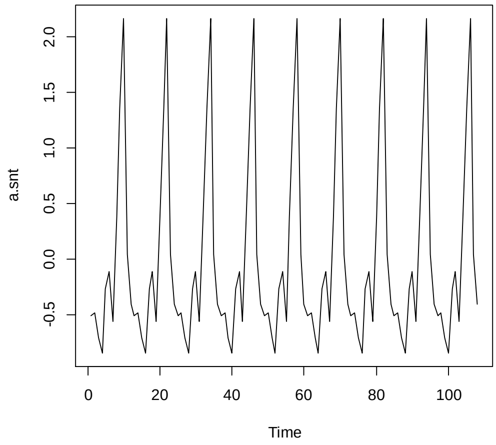
(d)

Figure 3.23 MRG1

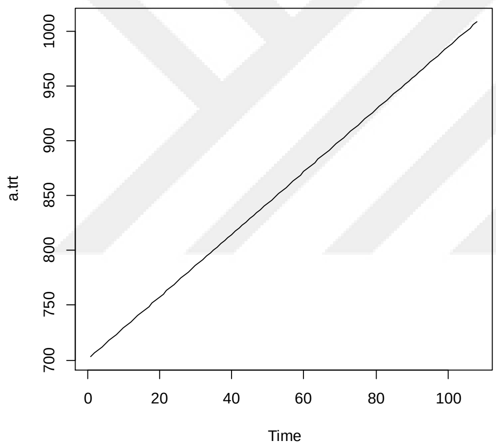
Figure 3.23 (a) shows the MRG1data set. The data set is monthly. Figure 3.23 (b) gives time versus seasonal values separated from the trend. Figure 3.23 (c) shows the values only includes increasing trend. In the last figure 3.23 (d), there is an estimated data set figure made up of seasonality and trend figure.



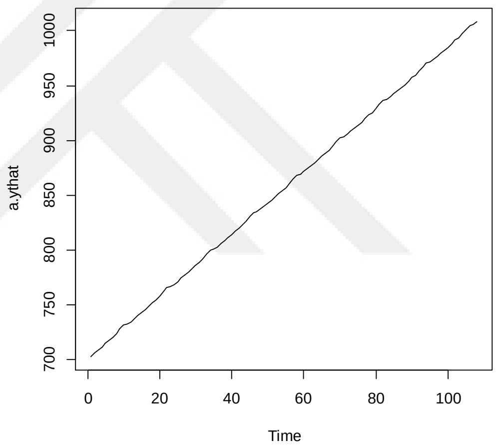
(a)



(b)



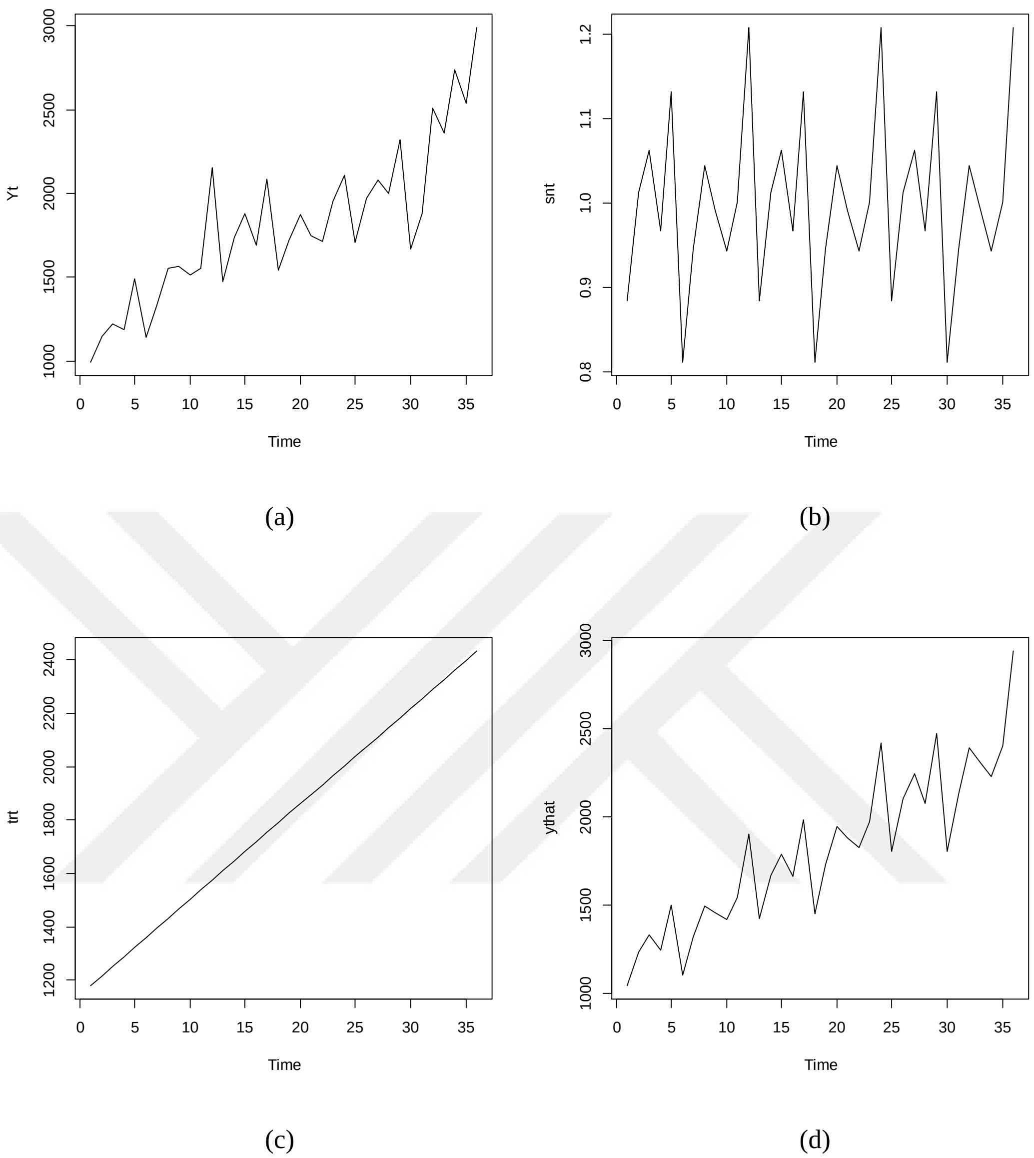
(c)



(d)

Figure 3.24 MRC1

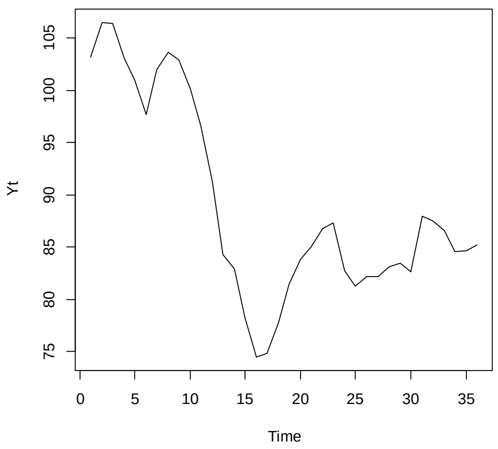
Figure 3.24 (a) shows the MRC1 data set. The data set is monthly. Figure 3.24 (b) gives time versus seasonal values separated from the trend. Figure 3.24 (c) shows the values only includes increasing trend. In the last figure 3.24 (d), there is an estimated data set figure made up of seasonality and trend figure.



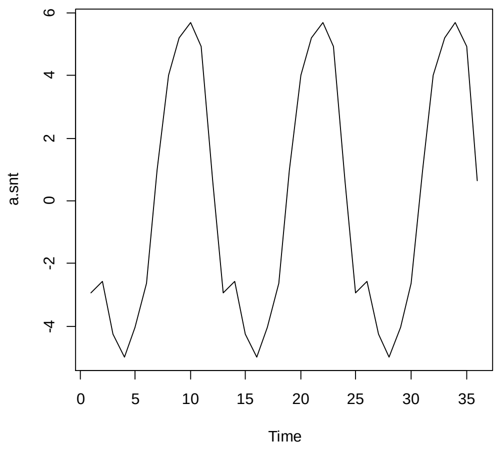
(a) (b) (c) (d)

Figure 3.25 MNG31

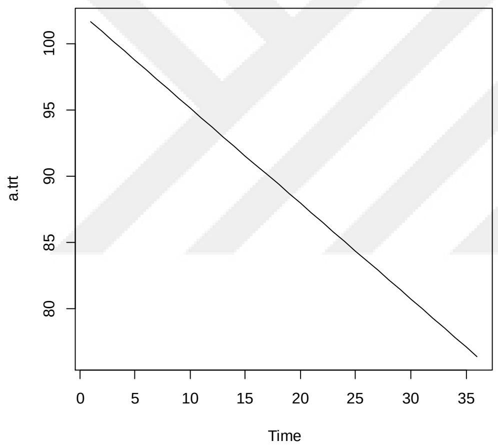
Figure 3.25 (a) shows the MNG31 data set. The data set is monthly. Figure 3.25 (b) gives time versus seasonal values separated from the trend. Figure 3.25 (c) shows the values only includes increasing trend. In the last figure 3.25 (d), there is an estimated data set figure made up of seasonality and trend figure.



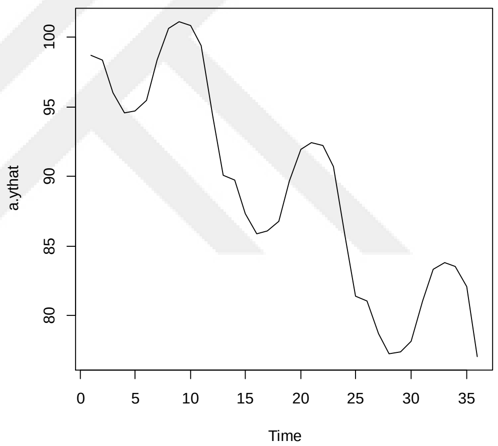
(a)



(b)



(c)



(d)

Figure 3.26 MNC3

Figure 3.26 (a) shows the MNC3 data set. The data set is monthly. Figure 3.26 (b) gives time versus seasonal values separated from the trend. Figure 3.26 (c) shows the values only includes decreasing trend. In the last figure 3.26 (d), there is an estimated data set figure made up of seasonality and trend figure.

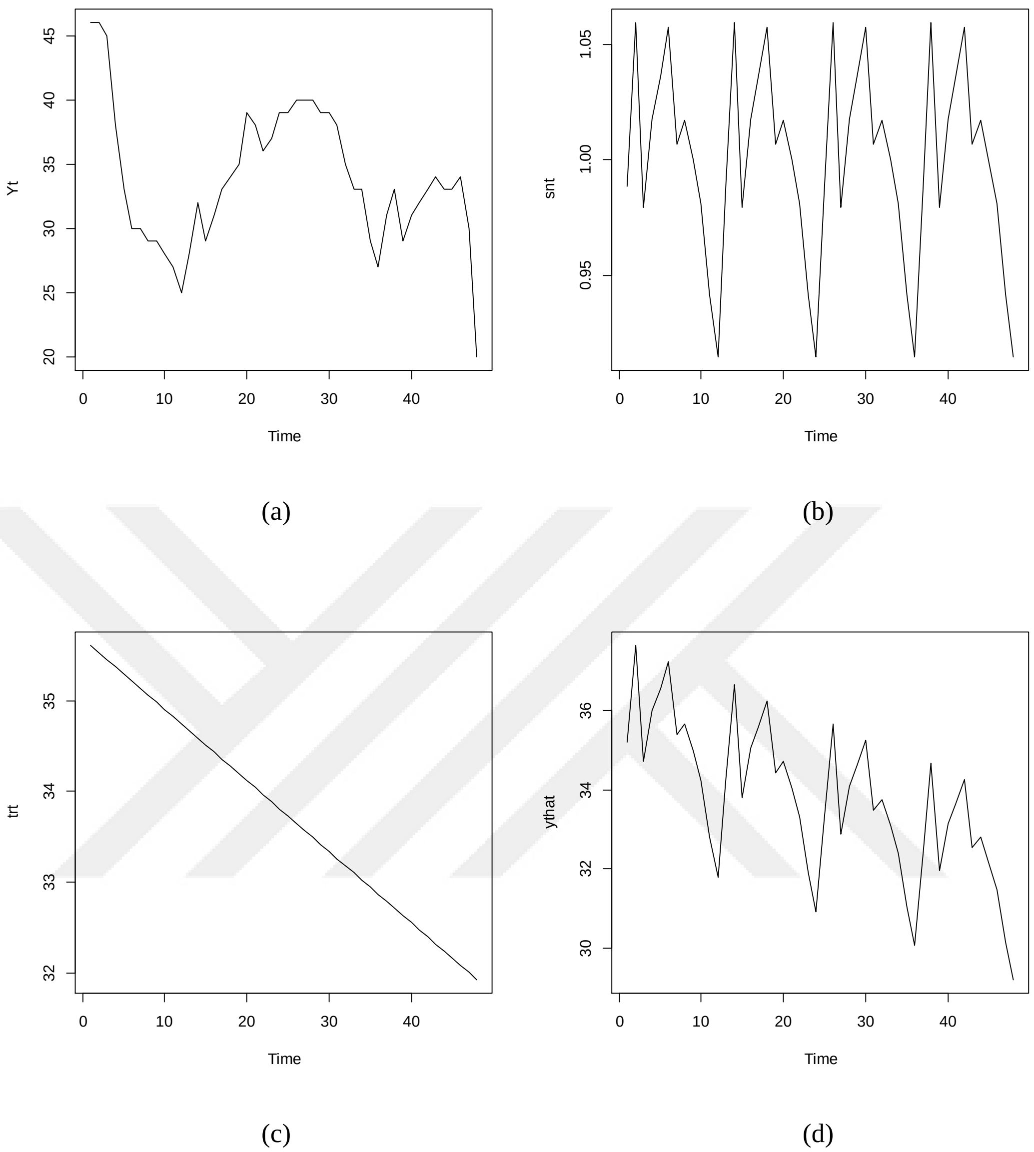


Figure 3.27 MND3

Figure 3.27 (a) shows the MND3 data set. The data set is monthly. Figure 3.27 (b) gives time versus seasonal values separated from the trend. Figure 3.27 (c) shows the values only includes decreasing trend. In the last figure 3.27 (d), there is an estimated data set figure made up of seasonality and trend figure.

CHAPTER FOUR
CONCLUSION

One approach of analysis of time series data is based on forecasting past data in order to decompose the underlying pattern in the data series from randomness. After that the underlying pattern can be projected into the future and used as the forecast. This method is called decomposition. Decomposition methods include four components, trend factor, seasonal factor, irregular factor and cyclical factor.

Time series decomposition method is the easiest method to understand and make in short-term forecasting predictions. This method can reveal especially the seasonality and trend of a time series and split a time series into its components.

In this thesis, the method of time series decomposition is examined in forecasting time series. There are two models of time series decomposition which are multiplicative and additive models. The method of multiplicative and additive decomposition is explained by formulas. These formulas were first applied in Excel. Then codes were written in R program by using these formulas. Time series included in M-competition are used to test the written R program. The seasonal indexes obtained from written R program were compared to those included in M-Competition data set and they were seen to be similar for all data set in M-Competition data.

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