A DECISION SUPPORT SYSTEM FOR COMBINING FORECASTING RESULTS

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ABSTRACT

A DECISION SUPPORT SYSTEM FOR COMBINING FORECASTING RESULTS

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The present study aims to develop an analysis package for combining forecasts that are obtained from different forecast methods. The package is composed of three modules, namely, the data input module, the data analysis module and the combination module.

In data input module, the data is entered and saved as an Excel file with the given name.

In data analysis module, the program computes the forecasts of the selected methods and displays the forecast results, the mean absolute errors, the mean square errors and the mean absolute percentage errors of these methods.

In combination module, the forecast results, computed in the data analysis module, are combined according to the selected combination methods.

All the detailed calculations of the forecasts and the values assigned by the program to minimize the mean absolute deviations, the mean square errors and the mean absolute percentage errors are displayed under the columns of the related method on the Excel spreadsheet of the file.

Keywords: Decision Support Systems, Forecasting, Combining Forecasts

ÖZ

TAHMİN SONUÇLARINI BİRLEŞTİRMEK İÇİN BİR KARAR DESTEK SİSTEMİ

BİLKAY, Tunç

Yüksek Lisans, Endüstri Mühendisliği Bölümü

Tez Yöneticisi: Doç. Dr. Tayyar ŞEN

Aralık 2003, 78 Sayfa

Bu çalışmada değişik tahmin yöntemlerinden elde edilen sonuçları birleştirmek için bir analiz paketi hazırlanmıştır. Geliştirilen paket, veri giriş modülü, veri analiz modülü ve birleştirme modülü olmak üzere toplam üç modülden oluşmaktadır.

Veri giriş modülünde, veri girişi ve Excel dosyası olarak verilen isim ile kaydı yapılmaktadır.

Veri analiz modülünde, program seçilen yöntemlerle tahminleri heasaplayıp, bu sonuçlarla bu yöntemlerin ortalama mutlak hatalarını, ortalama hata karelerini ve ortalama mutlak hata yüzdelerini göstermektedir.

Birleştirme modülünde, veri analiz modülünde hesaplanan tahminler seçilen birleştirme yöntemleri ile birleştirilmektedir.

Tahminlerin bütün detaylı hesaplamaları ve programın ortalama mutlak hataları, ortalama hata kareleri ve ortalama mutlak hata yüzdeleri azaltmak için belirlediği sabit değerler dosyanın Excel sayfasında ilgili yöntem kolonunun altında gösterilmektedir.

Anahtar Kelimeler: Karar Destek Sistemi, Tahmin, Tahmin Birleştirme

To My Family

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CHAPTER 1

INTRODUCTION

In management and administration, the need for planning and control is important because the lead time for managerial decision-making ranges from several years or more, as in the case of capital construction in the electric utility industry, to a few days or even hours, as in the example of meeting production or inventory levels. Information about the future events from forecasts are usually a critical input into a wide range of managerial and administrative decision-making, since today's plans are dependent on future expectations (Jarrett, 1987).

Forecasts are unavoidable in decision making. Every decision in inventory management and production planning requires an estimation of future demand. Forecasts are needed: to set up performance standards for customer service, to plan the allocation of total inventory investment, to place replenishment orders, to identify needs for additional production capacity and to choose between alternative operating strategies. Only one thing is certain after such decisions are made-*the forecasts will be in error*. What remains to be determined, is the exact size of the resulting errors and whether any past decisions need to be altered in response. Forecasts are at best imprecise, at worst misleading (Peterson and Silver, 1979).

Many of the forecasting techniques used today were developed in the nineteenth century. However, with the development of more sophisticated forecasting techniques, along with the arise of computers, forecasting has received more and more attention during recent years. This development is especially true since the proliferation of the small, personal computer.

New techniques for forecasting continue to be developed as management concern with the forecasting process continues to grow. A particular focus of this attention is on the errors that are inherent part of any forecasting procedure. Predictions as to future outcomes rarely are precisely on the mark; the forecaster can only endeavor to make the inevitable errors as small as possible.

Hundreds of statistical and forecasting packages have been developed for both mainframes and microcomputers (PCs). Managers with PCs on their desks and a knowledge of forecasting techniques are no longer dependent on staff for their forecasts. Modern managers are taking advantage of the ease and availability of sophisticated forecasting methods afforded by personal computers.

A developing branch of forecasting study involves the combination of two or more forecasting methods to produce the final forecasts. Research from over 200 studies demonstrates that combining forecasts produces consistent but modest gains in accuracy. However, this research does not define well the conditions under which combining is most effective or how methods should be combined in each situation (Hanke and Reitsch, 1995).

The primary conclusion of the paper written by Clemen (1990) is that forecast accuracy can be substantially improved through the combination of multiple individual forecasts and he stated that simple combination methods often work reasonably well relative to more complex combinations.

In their case study, Chan, Wong and Kingsman (1999) concluded that there appears to be no advantage in trying to find the best individual forecasting methods and the “Simple average” method (equal weights) is appropriate whenever combination of forecasts is not suggested by the method of optimal weights.

Due to the problems of selecting the methods or giving weights in combining forecast results that are obtained from different methods, suggested solution to the problem is an application of Decision Support System (DSS).

In this thesis, a software is developed for combining forecast results, on a personal computer using Visual Basic 6.0 Enterprise Edition. The software is mainly composed of three modules, namely the data input module, the data analysis module and the combination module.

In data input module, the user enters the historical data to the programme and saves the file. In the data analysis, the results of the individual forecast methods, that are selected by the user, and their mean absolute deviations (MAD), mean square errors (MSE) and mean absolute percentage errors (MAPE) are displayed and in the combination module these results are combined according to certain combination methods or according to the weights that are input by the user.

CHAPTER 2

AN OVERVIEW OF DECISION AND DECISION SUPPORT SYSTEMS

2.1. Decisions and Decision Making

A decision is a reasoned choice among alternatives. Making decisions is part of the broader subject of problem solving. Problem solving is the overall process of closing the gap between reality and a more desired situation. Each decision is characterized by a decision statement, a set of alternatives and a set of decision-making criteria. Managers' and other knowledge workers' decisions have a great impact on corporate success (Mallach, 2000).

Making decisions consists of several different activities that take place at different times. The decision maker has to perceive and understand problems. Once perceived, solutions must be designed; once solutions are designed, choices have to be made about a particular solution; finally, the solution has to be implemented (Laudon and Laudon, 2000).

Simon (1960) described four different stages in decision making that are intelligence, design, choice and implementation. These stages are as follows:

The intelligence stage consists of identifying the problems occurring in the organization. Intelligence indicates why, where and with what effects a situation occurs. This broad set of information-gathering activities is required to inform managers how well the organization is performing and to let them know where problems exist.

The design stage is the second stage of decision making and during this stage, the individual designs possible solutions to the problems. This activity may require more intelligence so that the manager can decide if a particular solution is appropriate. Smaller DSS are ideal in this stage of decision making because they operate on simple models, can be developed quickly and can be operated with limited data.

The choice stage consists of choosing among alternatives. Here a manager can use information tools that can calculate and keep track of the consequences, costs and opportunities provided by each alternative designed in the second stage. The decision maker might need a larger DSS to develop more extensive data on a variety of alternatives and to use complex analytic models needed to account for all the consequences.

The implementation stage is the last stage in decision making. Here, managers can use a reporting system that delivers routine reports on the progress of a specific solution. The system will also report some of the difficulties that arise, will indicate resource constraints and will suggest possible ameliorative actions.

It is important for the prospective developer of a DSS to understand these stages, because computers can support each decision stage in different ways, and the ideal computer support for a decision process depends on the stages that are important for that process.

Decision making remains one of the more challenging roles of a manager. Information systems have helped managers communicate and distribute information; however, they have provided only limited assistance for management decision making (Laudon and Laudon, 2000).

According to Mallach (1994), decisions can be organized along two dimensions: the nature of the decision to be made and the scope of the decision itself. Those categories are as follows:

A *structured decision* is one for which a well-defined decision-making procedure exists. More precisely, a structured decision is one for which the inputs, outputs and internal procedures of all decision phases can be specified. Each decision phase for which this is true is called a structured decision phase. Structured decisions can be left to a clerk or a computer.

An *unstructured decision* is one for which all three decision phases are unstructured. It is not known how to specify at least one aspect of each phase: its inputs, its outputs or its internal procedures. This may be because the decision is so new or so rare that it has not been studied carefully. Computers can still help the decision maker, but only with a lower level of support.

A *semistructured decision* has some structured aspects but cannot be completely structured. This usually means that some of its phases are structured but the other ones are not. Computers can provide a great deal of specific help with semistructured decisions. Conveniently, most organizational decisions are of this type.

The three levels of decision scope are as follows (Mallach, 1994):

A *strategic decision* is one that will affect the entire organization or a major part of it, for a long period of time. Strategic decisions affect organizational objectives and policies. Strategic decisions are generally, but not always, made at the upper levels of organizational management.

A *tactical decision*, also called a management control decision, will affect how a part of the organization does business for a limited time in the future. Tactical decisions are generally made by “middle managers”-those who are below the top executives who set strategic policies but are high enough to determine how an entire category of future actions will be taken.

An *operational decision* is one that affects activities taking place in the organization right now but either has little or no impact on the future or-if it does-is made within the confines of a controlling policy. Operational decisions relate to activities whose tasks, goals and resources have already been defined via prior strategic and tactical decisions. Operational decisions are generally made by lower level managers or by nonmanagerial personnel.

2.2. Decision Support Systems

Decision support systems (DSS) help managers make decisions that are semi-structured, unique or rapidly changing and not easily specified in advance. DSS have to be responsive enough to run several times a day in order to respond to changing conditions. DSS are designed so that users can work with them directly; these systems explicitly include user-friendly software. DSS are interactive; the user can change assumptions, ask new questions and include new data (Laudon and Laudon, 2000).

Major functions of DSS applications, provided by Kroenke (1989), are:

- Becoming familiar with a problem domain.
- Determining sensitivity of results to changes in decision variables.
- Identifying patterns.
- Predicting decision outcomes.
- Developing models of business processes.
- Computing optimum mixes.
- Facilitating group communication.

Sprague (1980) made a serious attempt to define DSS from a theoretical point of view and in terms of what it means in practice. His compromise, based on observations of many DSS of that era, includes these four characteristics:

1. They tend to be aimed at the less well structured, underspecified problems that upper level managers typically face.
2. They attempt to combine the use of models or analytic techniques with traditional data access and retrieval functions.
3. They specifically focus on features that make them easy to use by noncomputer people in an interactive mode.
4. They emphasize flexibility and adaptability to accommodate changes in the environment and the decision-making approach of the user.

2.2.1 Components of DSS

DSS is composed of four components (Sprague, 1980):

1. Data Management

The data management subsystem of a DSS relies, in general, on a variety of internal and external databases. It stores and manipulates the DSS database, as directed by either the model management or dialogue management components. Also it maintains an interface with external data sources such as TPS (Transaction Processing Systems) databases, data utilities and other DSS systems. Either the model management component or the dialogue management component can issue requests for data service. These requests are interpreted by the query processor, which may consult its own data directory; then the requests are executed by a DBMS (Database Management System) or by a program that is functionally equivalent to a DBMS.

2. Model Management

The power of DSS rests on the user's ability to apply quantitative, mathematical models to data. Models have different areas of application and come from a variety of sources. Software packages for developing DSS (so-called DSS generators) contain libraries of statistical models. These models include tools for the exploratory analysis of data-tools designed to obtain summarized measures such as mean and median values, variances, scatter plots and so forth. Other statistical models help analyze series of data and forecast future outcomes by approximating a set of data with a mathematical equation, by extending the trend of a curve by extrapolation techniques or by providing for seasonal adjustment.

3. Dialog Management

The notable feature of the dialog management subsystem is support of multiple forms of input and output. By combining various input and output capabilities of a DSS, users can engage in the individual dialog styles that best support their decision-making styles. The field of artificial intelligence has made some notable contributions to dialog management, such as the ability to specify what is wanted in a subset of natural language or to activate the system by voice. The window capability enables the user to maintain several activities at the same time, with the results displayed in screen windows.

4. User

For a successful DSS, the judgement and cognitive style of the user is very important. Each of the other three components of DSS interacts with each other and the user to support decision making. The user has a key role in the DSS, because of its support nature. So the user should be involved in the DSS building process.

2.2.2. Benefits of DSS

Measuring the benefits of decision support systems is difficult because of many of these benefits are qualitative. Some of these benefits, provided by Schultheis and Sumner (1998), are as follows:

- *The ability to examine more alternatives.* Spreadsheet tools make it possible to analyze alternative ways of allocating resources in a business and to visualize the impact of these options on cash flow.
- *The ability to achieve a better understanding of the business.* A decison support system can help managers analyze the long-range impact of a new marketing venture or a potential acquisition decision in a reasonable time, making it possible to foresee possible pitfalls and to avoid future problems.
- *The ability to respond quickly to unexpected situations.* With decision support systems, businesses can construct new models and quickly adapt them to changes in business policy and market share.

- *The ability to carry out ad hoc types of reporting and analysis.* Many managers want to ask questions of existing databases and to pull out data relevant to current business operations.
- *The ability to provide timely information for control of ongoing operations.* Information from a decision support system, for example, can provide a better picture of detailed expenses by company, by division and by department.
- *The ability to save time and costs.* A decision support system can handle an analysis much more quick than a calculator. Also the ability to perform what-if analyses improves the quality of a budget forecast or any other analysis.
- *The ability to make better decisions.* Decision support systems allow managers to consider issues and alternatives that they may not have explored before. Increased depth and sophistication of analysis are possible. Decision support systems help managers explore complex issues using relevant data analysis.

2.2.3. Risks of DSS

One of the major benefits of decision support systems is that users can analyze their own requirements, rather than rely on a systems analyst to understand and to specify these requirements for them. However, user development has risks. The following issues occur when users try to develop their own information systems (Schultheis and Sumner, 1998).

Lack of quality assurance. Quality assurance refers to procedures for data validation and testing, documentation and backup and recovery that are integral part of a good system. Without adequate validation of input data, output printed on reports may not be correct. When the developer suddenly left the firm, the application was lost because no documentation existed. Lack of backup and recovery may result in loss of critical data and time consuming manual rebuilding of these files.

Lack of data security. Password security for microcomputer based data management systems may be inadequate or nonexistent, leaving many users to resort to such procedures as key access to hardware or physically locking up diskettes.

Failure to specify correct requirements. Users can visualize their immediate, short term needs but find it more difficult to understand ongoing or long term requirements. In the design of decision support systems, outputs are constantly modified and the logic used in data analysis often changes. These changes introduce the chance of error, especially if the logic being used is not continually reviewed and documented.

Failure to understand design alternatives. One of the common problems in user development is a mismatch between software and design requirements. If a systems analyst had assessed the short and long term needs of the users in advance, the feasibility of various design options, including microcomputer, minicomputer and mainframe approaches, could have been considered.

CHAPTER 3

FORECASTING AND COMBINING FORECASTS

3.1. Forecasting

Forecasting is a systematic process of decisions and actions performed in an effort to predict the future by an analysis of the past. More precisely, forecasting attempts to predict change. If future events represented only a readily quantifiable change from historical events, future events or conditions could be predicted through quantitative projections of historical trends into the future. Methodologies that are used to describe historical events with mathematical equations (or a model) for the purpose of predicting future events are classified as quantitative projection techniques. However, there is much more to forecasting than projecting past trends.

Experience and intuitive reasoning quickly reveal that future events or conditions are not solely a function of historical trends. Even familiar abstractions such as trend, cycle and seasonality, while extremely useful to business forecasters, cannot be completely relied upon when it comes to predicting future events.

A forecast is not an end product but rather an input to the decision-making process. A forecast is a prediction of what will happen under an assumed set of circumstances. Forecasts are also required for a variety of "what if" situations and for the formulation of business plans to alter base case projections that have proved unsatisfactory (Levenbach and Cleary, 1984).

According to McLeod (1998), there are three basic facts about forecasting that should be kept in mind as follows:

1. *All forecasts are projections of the past.* The best basis for predicting what will happen in the future is to look at the past. All types of forecasting follow this approach. This is the reason why accounting data is so important in forecasting; it provides historical base.
2. *All forecasts consist of semistructured decisions.* The decisions are based on some variables that can be easily measured and some that cannot.
3. *No forecasting technique is perfect.* Not even the most sophisticated mainframe forecasting package can be expected to predict the future with 100 percent accuracy.

Levenbach and Cleary (1982) described a forecasting process in terms of three phases:

1. Design phase: the premodeling activities associated with some problem and the evaluating of cost-benefit tradeoffs that must be considered when building statistical models. They recommend a five-stage procedure for the design phase of a forecasting process, with each stage consisting of a series of activities, actions and judgments as follows:

    - Defining the problem.
    - Listing alternative forecasting techniques.
    - Selecting among the alternatives for study.
    - Evaluating the alternatives.
    - Recommending the most appropriate technique(s).

2. Specification phase: the model-building activities. The specification phase deals with activities in the forecasting process that are necessary for:

    - Developing a theory of demand.
    - Dealing with data.
    - Selecting the appropriate forecasting techniques.

3. Evaluation phase: the forecasting and tracking activities that follow development of a model. The evaluation phase consists of the preparation, presentation and important tracking functions that must accompany a forecasting effort.

According to Sullivan and Claycombe (1977), the basic characteristics of forecasts are:

- Forecasts are usually incorrect.
- Forecasts should be two numbers (to indicate a range).
- Forecasts are more accurate for families of items (e.g. total annual sales of a company) than for individual items (e.g. annual sales of a product).
- Forecasts are less accurate far in the future.

Form the point of view of inventory management and production planning *an ideal forecast* defined by Peterson and Silver (1979) should:

- Estimate expected demand in physical units.
- Estimate probable range of actual demand around the expected value point (i.e., forecast error).
- Be timely-available sufficiently in advance of any decision that must be made.

- Be updated periodically so that revisions to decisions taken can be made promptly.
- Allow human judgment to override mechanical forecasts (whose primary advantage is the handling of massive amounts of historical data).

Since prediction of future sales is so closely linked with the judgment of forecasters, *an ideal forecaster* according to Peterson and Silver (1979) should:

- Be familiar with the economic, industry and product-specific contexts of his projections.
- Know the true value of his forecasting techniques.
- Be able to state clearly his objectives and assumptions.
- Be able to gather pertinent data and be able to validly expunge it of extraordinary observations.

Finally Peterson and Silver (1979) described an appropriate forecasting strategy for any organization that depends on:

- The availability of computer-based data processing facilities.
- The timing and accuracy of forecasts required.
- The availability and extent of historical and current data.

3.2. Combining Forecast Results

When building a forecasting model of the real world, one ought to use all the available data; one way of doing this would be to build a number of smaller models rather than one all-inclusive large model. The implication is that some method of combining the forecasts from the seperate small models will result in a better forecast than any one large all-inclusive model by itself.

The idea of combining business forecasting models was originally proposed by Bates and Granger (1969). Since the publication of their article, this strategy has received immense support in almost every empirical test of combined forecasts versus individual uncombined forecasts (Barry and Keating, 1990).

Instead of choosing the best model from among two or more alternatives, Barry and Keating combined the forecasts from these different models to obtain forecast improvement. It may actually be unwise to attempt to determine which of a number of forecasting methods yields the most accurate predictions. A more reasonable approach, according to the emprical evidence, is to combine the forecasts already made in order to obtain a combined forecast that is more accurate than any of the seperate predictions.

Any time that a particular forecast is ignored because it is not the "best" forecast produced, it is likely that valuable independent information contained in the discarded forecast has been lost. The information lost may be of two types:

1. Some variables included in the discarded forecast may not be included in the "best" forecast.
2. The discarded forecast may take use of a type of relationship ignored by the "best" forecast.

In the first case above, it is quite possible for several forecasts to be based upon different information; thus, ignoring any one of these forecasts would necessarily exclude the explanatory power unique to the information included in the discarded model. In the second situation, it is often the case that different assumptions are made in different models about the form of the relationship between the variables.

To be useful, forecasts that are combined must be unbiased. That is, each of the forecasts cannot consistently overestimate or underestimate the actual value. Combining forecasts is not a method for eliminating bias in a forecast.

It is expected that combinations of forecasts that use very different models are likely to be effective in reducing forecast error.

3.3. Studies about Combining Forecasts in Literature

This study is related with a decision support system for combining forecast results that are obtained from different forecasting methods so as to improve the forecast performance. The related studies in the literature are given to extend the scope of this study.

Ringuest and Tang (1987) presented a paper about simple rules for combining forecasts. This study is an empirical comparison of three rules for aggregating forecasts. The three combined forecasts evaluated are a simple average forecast, a median forecast and a focus forecast (an approach that develops forecasts by various techniques, then picks the forecast that was produced by the "best" of these techniques, where "best" is determined by some measure of forecast error). The results indicate that an average forecast will not perform as well as previous studies indicate if all or most of the individual forecasts tend to over- or under-predict simultaneously. The median forecast also seems to be suspect in this case. Focus forecasting, however, is found to perform well for all variables. The evidence indicates that focus forecasting is a reasonable alternative to simple averaging.

Holmen (1987) presented a paper that conducts an empirical analysis of the approaches to obtain linear combinations of forecasts. Simulated quarterly earnings were modeled using three ARIMA models. One-quarter ahead forecasts were then developed. These forecasts were combined using alternative approaches. The most accurate forecasts were obtained by adding a constant term and not constraining the weights to add up to one. The differences in the accuracy rankings were found to be statistically significant.

Reeves, Lawrence, Lawrence and Guerard (1988) made a study about combining earnings forecasts using multiple objective linear programming. In this study, exponential smoothing, univariate time series and (transfer function) bivariate time series models are combined to forecast annual corporate earnings for six major corporations. Consideration is given to combine forecasts generated by the same technique at different points in time as well as those generated by different techniques. Results indicate that combined forecasts outperform individual forecasts, that all three major categories of forecasting techniques are utilized in the construction of the efficient combined forecasts, that the techniques included in the combined forecasts and their relative weights can change over time and that the most recent forecasts do not always receive the most weight when combined with older forecasts.

Clemen (1990) presented a paper about the review and annotated bibliography of combining forecasts. He claimed that considerable literature has accumulated over the years regarding the combination of forecasts. The primary conclusion of this line of research is that forecast accuracy can be substantially improved through the combination of multiple individual forecasts. Furthermore, simple combination methods often work reasonably well relative to more complex combinations.

This paper provides a review and annotated bibliography of that literature, including contributions from the forecasting, psychology, statistics, and management science literatures. Finally, he concluded that combining forecasts should become part of the mainstream of forecasting practice.

Lobo (1991) presented a study that provides empirical evidence on the accuracy of alternative methods of combining security analysts' and statistical forecasts of annual corporate earnings. Linear cross-sectional least squares regression models with and without constant terms, and constrained and unconstrained forecast weights, are used to form combination forecasts in addition to equally weighted combinations. The empirical analysis indicates that combination forecasts formed using a linear model with no constant term and no constraints on the forecast weights are superior to forecasts generated using the other combination methods.

Arinze, Kim and Anandarajan (1997) proposed a paper about combining and selecting forecasting models using rule based induction. The purpose of this paper is to describe a machine learning approach and associated Expert System directed at improving forecasting accuracy by selecting the most appropriate single or hybrid forecasting method for any unique time series. By using training sets of time series (and their features), induced rules were created to predict the most appropriate forecasting method or combination of methods for new time series. Potential benefits include dramatic reductions in the effort and cost of forecasting; the provision of an expert 'assistant' for specialist forecasters and increases in forecasting accuracy.

Fischer and Harvey (1999) took action about what information do judges need to outperform the simple average in combining forecasts. They claimed that previous work has shown that combinations of seperate forecasts produced by judgment are inferior to those produced by simple averaging because judges were not informed of outcomes after producing each combined forecast. Results showed that when they are given this information and the information about errors made by the individual forecasters, judges combine their forecasts in a way that outperforms the simple average.

Chan, Wong and Kingsman (1999) presented a case study about the value of combining forecasts in inventory management in banking. The paper demonstrated that combining different forecasts could achieve significant improvements in demand forecasting performance and about 10% savings in the safety stocks to be maintained by the bank. They used four alternative weighting methods and concluded that i- there appears to be no advantage in trying to find the best individual forecasting methods for each item, ii- updating the weights every month is not useful and iii- whenever combination of forecasts is not suggested by the method of optimal weights, the “Simple average” method (equal weights) is appropriate.

Menezes, Bunn and Taylor (2000) proposed a paper about the review of guidelines for the use of combined forecasts. In this paper, they review evidence on the performance of different combining methods with the aim of providing practical guidelines based on three properties of the forecast errors: variance, asymmetry and serial correlation. The evidence indicates that using different criteria leads to distinct preferences and that the properties of the individual forecast errors can strongly influence the characteristics of the combination’s errors. They showed that a practical approach to combining also requires a degree of judgement on the attributes of error specification.

CHAPTER 4

SOFTWARE PACKAGE DEVELOPED

4.1. Introduction

The software package which has been developed in this study aims to help the user in combining the forecast results that are obtained from different forecasting methods. When combining forecasts, the forecaster should enter the past data, select the forecast methods that would be used, and select a combining method or give weights to the selected forecast methods to obtain a combined result. This package helps the user in making all these selections.

The package has three main modules. These are namely:

1. Data Input Module
2. Data Analysis Module
3. Combination Module

4.2. Program in General

This program requires Microsoft Windows as the operating system as it is developed in Microsoft Visual Basic programming language. The program also uses Microsoft Excel for storing the input data and the iteration results of the forecasting methods and MINITAB Release 13.20 for computing ARIMA.

When the program is executed it asks the user to select whether to input data or analyze data that is input and saved before. The main menu window is shown in Figure 4.1.

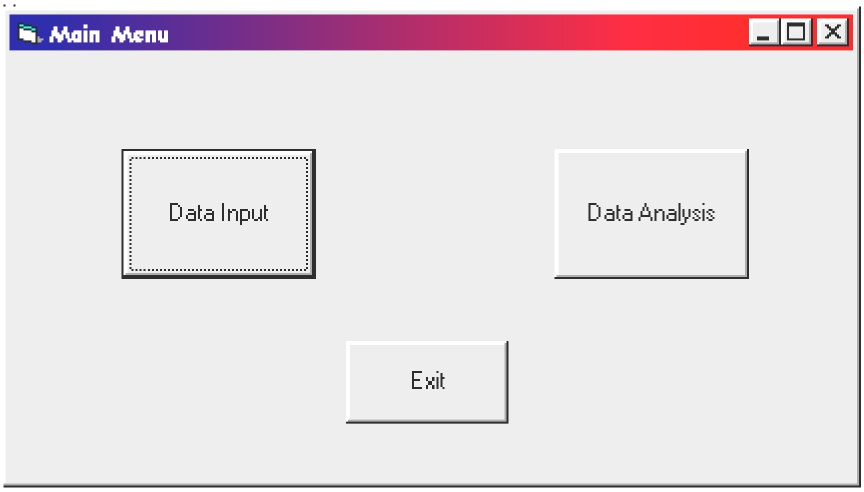


Figure 4.1 Main Menu Window

4.3. Data Input Module

When the user clicks the “Data Input” button, a new window is opened and asks the user the number of periods of data that is wanted to be input as shown in Figure 4.2.

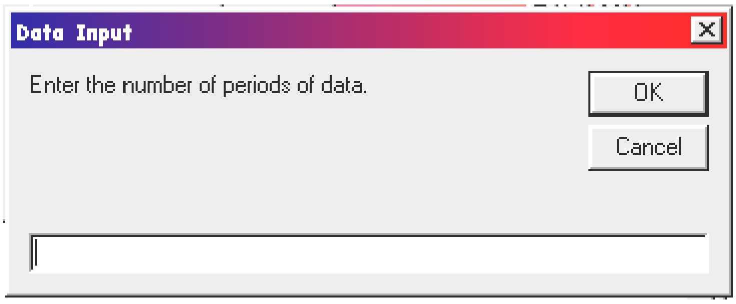


Figure 4.2 The number of Periods Window

After entering the number of periods, the program asks the numerical data of all the periods one by one as shown in Figure 4.3.

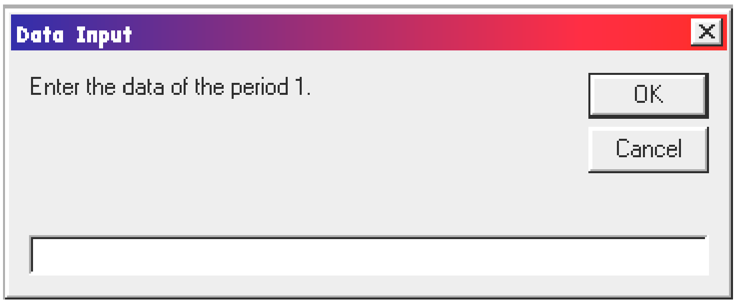


Figure 4.3 Data Entering Window

After entering the data of the last period, the name of the file is asked to save the data as a Microsoft Excel file as shown in Figure 4.4.

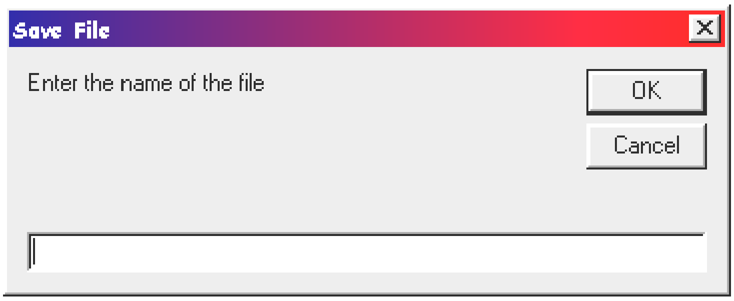


Figure 4.4 Entering the File Name Window

By saving the data with the given name as an Excel file, the data input module ends and the main menu window becomes active. By this window the user can enter another data, analyze the data that is saved or exit to the Windows.

The user can also prepare his database by entering the data to an Excel spreadsheet, but he should convert all the spreadsheet to "Number" category from the "Format Cells" menu of the Excel for the program to open the file.

4.4. Data Analysis Module

When the user clicks the "Data Analysis" button on the main menu window, the forecast and the error calculating methods window is opened and on this window the user can select the forecast methods and the error calculation method that he wants to use as shown in Figure 4.5.

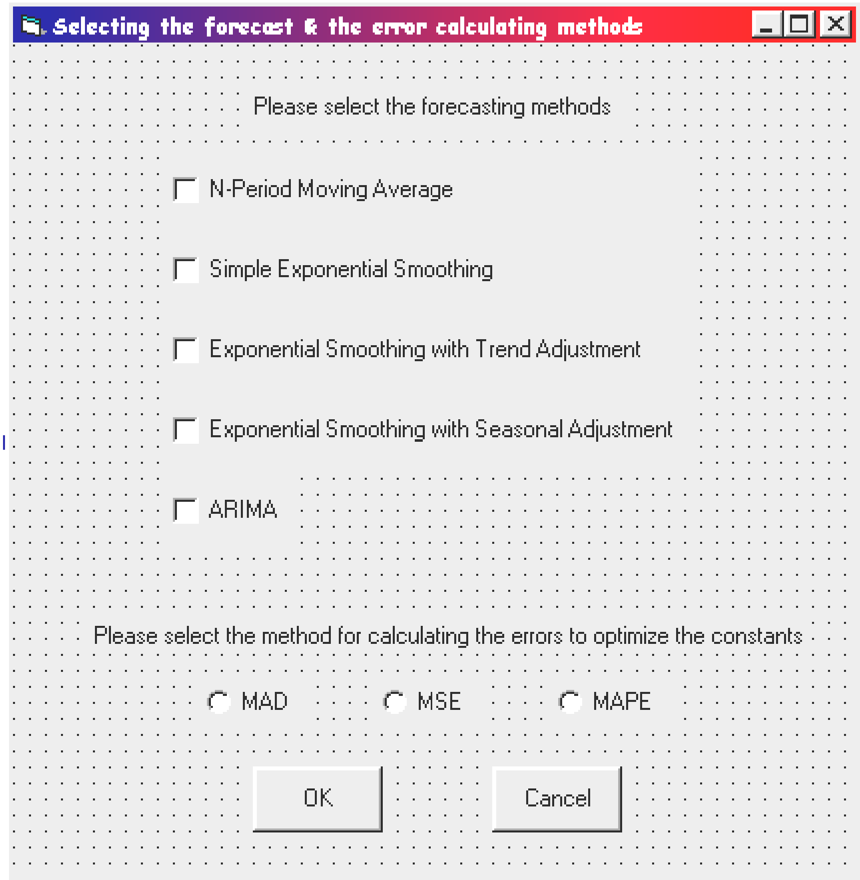


Figure 4.5 Forecast & Error Calculating Methods Window

There are some constants needed while making iterations of the methods shown in Figure 4.5, like N in the N-Period Moving Average Method or α, β and γ in the Exponential Smoothing Methods. In the program, these constants are calculated by incrementing them in their range (i.e. from 1 to the total number of periods for N by step size 1.0 and from 0.1 to 0.9 for α, β and γ by step size 0.1) and the values that minimize the value of the selected error calculation method are selected. But in the Exponential Smoothing with Seasonal Adjustment the cycle length, L and in ARIMA the order of the autoregressive (AR) component, the number of differences used to discount trends over time and the order of the moving average (MA) component are entered by the user. The error calculating methods are given as follows : (Hanke and Reitsch, 1995):

Mean Absolute Deviation:

$$\text{MAD} = \sum_{i=1}^{n} |A_t - F_t| \,/\, n \tag{4.1}$$

where:

A_t = Actual observed value for period t

F_t = Forecasted value for period t

n = Number of forecasted periods

Mean Square Error:

$$\text{MSE} = \sum_{i=1}^{n} (A_t - F_t)^2 \,/\, n \tag{4.2}$$

Mean Absolute Percentage Error:

$$\text{MAPE} = \sum_{i=1}^{n} [| A_t - F_t | / A_t] / n \qquad (4.3)$$

After selecting the forecast methods and the error calculating method, the program asks the user to enter the name of the file that is wanted to be opened and calculates the forecasts of the selected methods and displays the forecast results, the mean absolute deviations (MAD), the mean square errors (MSE) and the mean absolute percentage errors (MAPE) of the selected methods in a new window as shown in Figure 4.6.

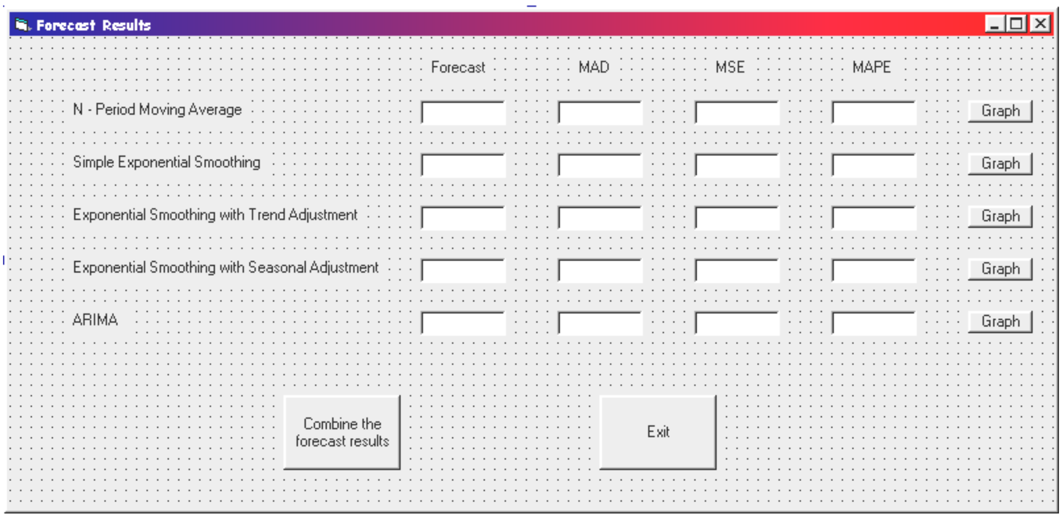
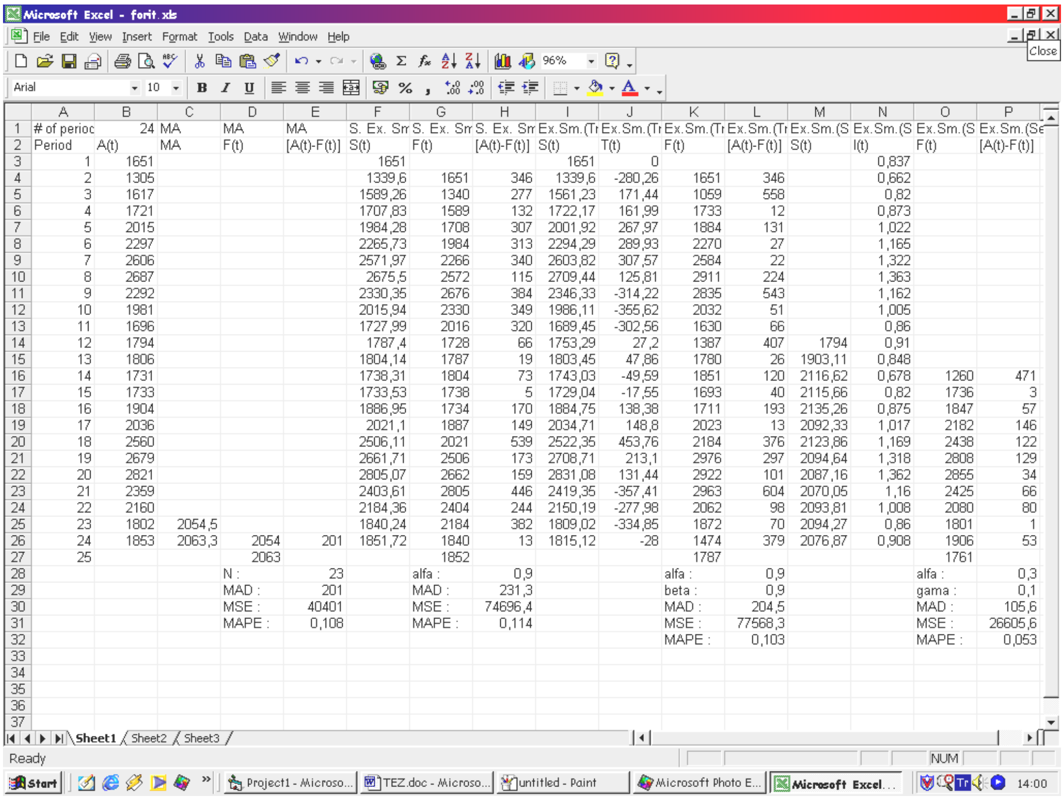


Figure 4.6 Forecast Results Window

The program also asks the user whether he wants to save the iterations of the forecast methods on the Excel spreadsheet or not. The user can open the file of the input data in Windows Excel and look at the iterations of the methods as shown in Figure 4.7.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(Se
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)]
3	1	1651				1651			1651	0				0,837		
4	2	1305				1339,6	1651	346	1339,6	-280,26	1651	346		0,662		
5	3	1617				1589,26	1340	277	1561,23	171,44	1059	558		0,82		
6	4	1721				1707,83	1589	132	1722,17	161,99	1733	12		0,873		
7	5	2015				1984,28	1708	307	2001,92	267,97	1884	131		1,022		
8	6	2297				2265,73	1984	313	2294,29	289,93	2270	27		1,165		
9	7	2606				2571,97	2266	340	2603,82	307,57	2584	22		1,322		
10	8	2687				2675,5	2572	115	2709,44	125,81	2911	224		1,363		
11	9	2292				2330,35	2676	384	2346,33	-314,22	2835	543		1,162		
12	10	1981				2015,94	2330	349	1986,11	-355,62	2032	51		1,005		
13	11	1696				1727,99	2016	320	1689,45	-302,56	1630	66		0,86		
14	12	1794				1787,4	1728	66	1753,29	27,2	1387	407	1794	0,91		
15	13	1806				1804,14	1787	19	1803,45	47,86	1780	26	1903,11	0,848		
16	14	1731				1738,31	1804	73	1743,03	-49,59	1851	120	2116,62	0,678	1260	471
17	15	1733				1733,53	1738	5	1729,04	-17,55	1693	40	2115,66	0,82	1736	3
18	16	1904				1886,95	1734	170	1884,75	138,38	1711	193	2135,26	0,875	1847	57
19	17	2036				2021,1	1887	149	2034,71	148,8	2023	13	2092,33	1,017	2182	146
20	18	2560				2506,11	2021	539	2522,35	453,76	2184	376	2123,86	1,169	2438	122
21	19	2679				2661,71	2506	173	2708,71	213,1	2976	297	2094,64	1,318	2808	129
22	20	2821				2805,07	2662	159	2831,08	131,44	2922	101	2087,16	1,362	2855	34
23	21	2359				2403,61	2805	446	2419,35	-357,41	2963	604	2070,05	1,16	2425	66
24	22	2160				2184,36	2404	244	2150,19	-277,98	2062	98	2093,81	1,008	2080	80
25	23	1802	2054,5			1840,24	2184	382	1809,02	-334,85	1872	70	2094,27	0,86	1801	1
26	24	1853	2063,3	2054	201	1851,72	1840	13	1815,12	-28	1474	379	2076,87	0,908	1906	53
27	25			2063			1852				1787				1761	
28				N :	23		alfa :	0,9			alfa :	0,9			alfa :	0,3
29				MAD :	201		MAD :	231,3			beta :	0,9			gama :	0,1
30				MSE :	40401		MSE :	74696,4			MAD :	204,5			MAD :	105,6
31				MAPE :	0,108		MAPE :	0,114			MSE :	77568,3			MSE :	26605,6
32											MAPE :	0,103			MAPE :	0,053
33																
34																
35																
36																
37																

Figure 4.7 Excel file showing the iterations

As it is shown in Figure 4.7, addition to the iteration results, the value of N in N-Period Moving Average Method, the value of α in Simple Exponential Smoothing, the values of α and β in Exponential Smoothing with Trend Adjustment and the values of α and γ in Exponential Smoothing with Seasonal

Adjustment that are found by the program are displayed below the columns of the related method.

The program also draws the graph of the actual and forecasted values of the forecast method when the "graph" buttons near the forecast methods on the "Forecast Results Window" are clicked as it is shown in Figure 4.8.

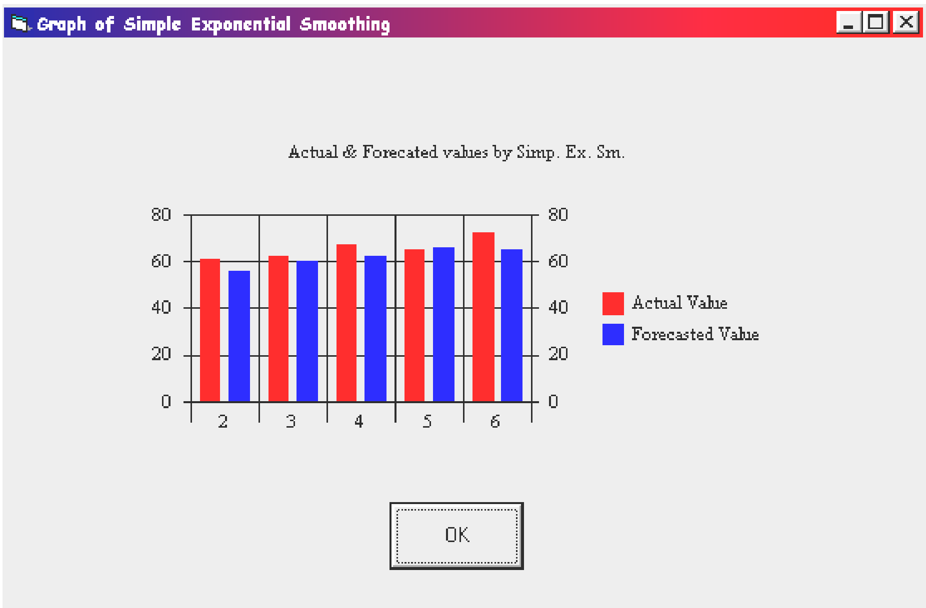


Figure 4.8 Graph Window

4.5. Combination Module

If the user clicks the "Combine the forecast results" button on the "Forecast Results Window" that is shown in Figure 4.6, a new window is opened to select the method for combining the forecast results as shown in Figure 4.9.

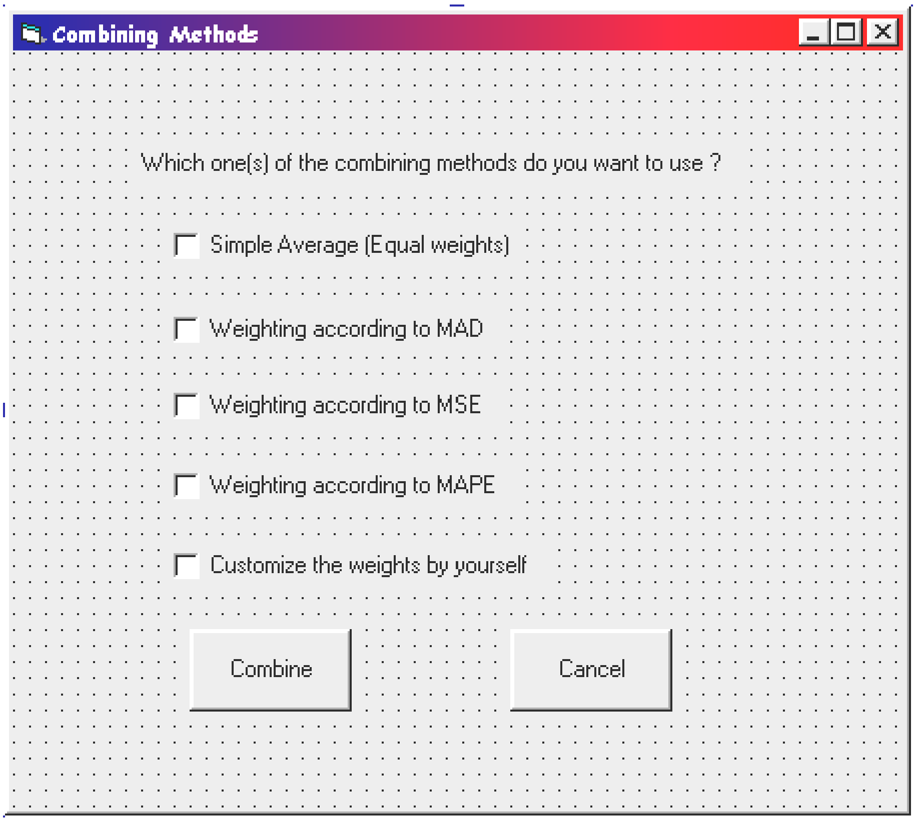


Figure 4.9 Combining Methods Window

While combining the forecast results the user can select five methods as shown in Figure 4.9. In simple average method (as it is mentioned on the window), the program directly takes the average of the results of the selected forecast methods.

In the second combining method, the program combines the forecast results according to their mean absolute deviations (MAD), by giving the highest weight to the method that has the lowest MAD. The weights of the methods are calculated by equation (4.4).

$$w_j = \sum_{i=1}^{n} [MAD_i] / MAD_j \tag{4.4}$$

where:

w_j = The weight of the method j

n = The number of selected methods

MAD_i = The mean absolute deviation of the method i

In the third combining method, the program combines the forecast results according to their mean square errors (MSE), by giving the highest weight to the method that has the lowest MSE. The weights of the methods are calculated by the equation (4.4).

$$w_j = \sum_{i=1}^{n} [MSE_i] / MSE_j \tag{4.4}$$

where:

w_j = The weight of the method j

n = The number of selected methods

MSE_i = The mean square error of the method i

In the fourth combining method, the program combines the forecast results according to their mean absolute percentage error (MAPE), by giving the highest weight to the method that has the lowest MAPE. The weights of the methods are calculated by the equation (4.4).

$$w_j = \sum_{i=1}^{n} [MAPE_i] / MAPE_j \tag{4.4}$$

where:

w_j = The weight of the method j

n = The number of selected methods

$MAPE_i$= The mean absolute percentage error of the method i

The user has also an alternative to give weights to the methods by himself. By this alternative the user can use his judgement for combining the forecast results. If the "Customize the weights by yourself" option is checked, the program asks the weight of the selected forecast methods one by one as shown in Figure 4.10 and calculates the combined result according to these weights.

In all the combination methods by giving weights, the equation is divided by the sum of the weights after multiplying the weights with the forecast results to make the sum of the weights equal to one.

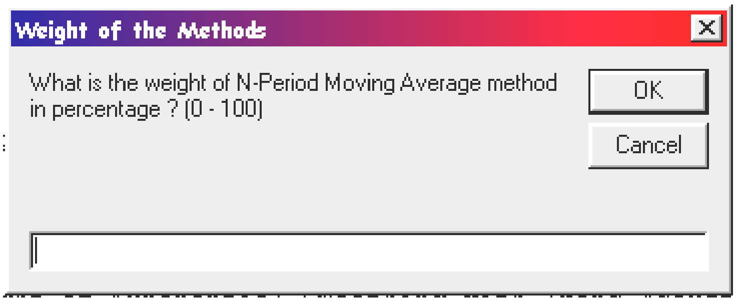


Figure 4.10 Weights of the Methods Window

When the user clicks the combine button on the "Combining Methods Window", the program combines the forecast results by the selected combining methods and displays another window that shows the results of the combinations and the MAD, MSE and MAPE of the combinations as shown in Figure 4.11.

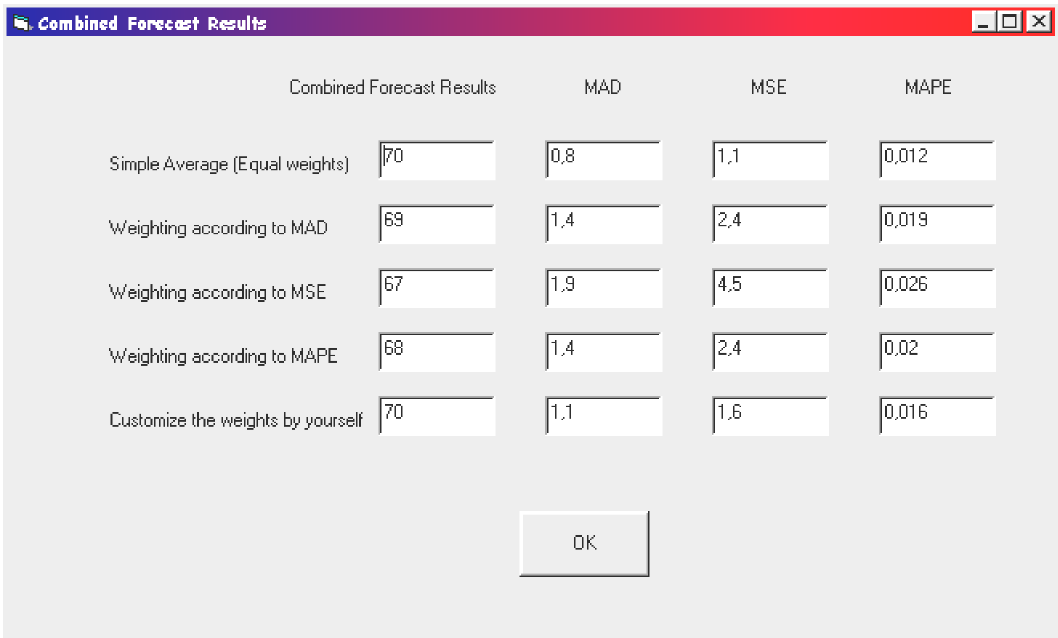


Figure 4.11 Combined Forecast Results Window

CHAPTER 5

SAMPLE RUNS

5.1. Sample Run 1

In this run the monthly price indices of Turkey for years 2001 and 2002 that are obtained from www.die.gov.tr are used and the price index of January 2003 (its actual value is 7662) is forecasted. The results obtained from the individual forecast methods are given at the table below (the constants are calculated to minimize MAD):

Table 5.1 Forecast Results (MAD) of Sample Run 1

Forecast Method	Forecast	MAD	MSE	MAPE
Moving Average	7469	172.5	38063.6	0.032
Simple Exponential Smoothing	7454	191	45687.3	0.036
Exponential Smoothing with Trend Adjustment	7641	88.8	11696.9	0.017
Exponential Smoothing with Seasonal Adjustment	4560	208.9	61323.9	0.032
ARIMA	7571	59.9	5454	0.011

After the results shown at Table 5.1 are combined, the results of the combination are given at Table 5.2:

Table 5.2 Combination Results (MAD) of Sample Run 1

Combination Method	Combined Forecast	MAD	MSE	MAPE
Simple Average	6939	55.3	3962.2	0.008
Weighting according to MAD	7232	54.5	3595.3	0.008
Weighting according to MSE	7427	55.9	4023.4	0.008
Weighting according to MAPE	7174	54.6	3591.1	0.008
Customized Weights	7104	53.9	3609.1	0.008

The results obtained from the individual forecast methods are given at Table 5.3 (the constants are calculated to minimize MSE & MAPE) (In this run all the constants are the same that minimize MSE and MAPE):

Table 5.3 Forecast Results (MSE & MAPE) of Sample Run 1

Forecast Method	Forecast	MAD	MSE	MAPE
Moving Average	7469	172.5	38063.6	0.032
Simple Exponential Smoothing	7454	191	45687.3	0.036
Exponential Smoothing with Trend Adjustment	7615	88.9	10606.7	0.017
Exponential Smoothing with Seasonal Adjustment	4560	208.9	61323.9	0.032
ARIMA	7571	59.9	5454	0.011

After the results shown at Table 5.3 are combined, the results of the combination are given at Table 5.4:

Table 5.4 Combination Results (MSE & MAPE) of Sample Run 1

Combination Method	Combined Forecast	MAD	MSE	MAPE
Simple Average	6934	51.8	3474.6	0.008
Weighting according to MAD	7225	50.7	3103.6	0.008
Weighting according to MSE	7425	52.2	3633.5	0.008
Weighting according to MAPE	7168	51	3113.2	0.008
Customized Weights	7098	50.2	3080.2	0.008

The customized weights of the methods are 0.15, 0.15, 0.25, 0.15 and 0.30 respectively and ARIMA (2, 2, 2) is used since it gives the smallest error.

The figure that shows the iteration results of the sample run is given in Appendix B.

5.2. Sample Run 2

In this run the data of foreigners arriving by month of arrival for years 1996 and 1997 that are obtained from www.die.gov.tr are used and the number of foreigners arrived in January 1998 (its actual value is 348164) is forecasted. The results obtained from the individual forecast methods are given at Table 5.5 (the constants are calculated to minimize MAD):

In the Sample Run 2 the ARIMA method can not estimate the model for the data (that is because the data is not stationary), so the combinations of the forecasts does not include ARIMA method.

Table 5.5 Forecast Results (MAD) of Sample Run 2

Forecast Method	Forecast	MAD	MSE	MAPE
Moving Average	419054	167672	4.5E+8	0.248
Simple Exponential Smoothing	435619	180717	5.0E+8	0.271
Exponential Smoothing with Trend Adjustment	262905	169537	5.1E+8	0.254
Exponential Smoothing with Seasonal Adjustment	309928	47656	3.2E+8	0.063

After the results shown at Table 5.5 are combined, the results of the combination are given at Table 5.6:

Table 5.6 Combination Results (MAD) of Sample Run 2

Combination Method	Combined Forecast	MAD	MSE	MAPE
Simple Average	356876	157815	3.5E10	0.211
Weighting according to MAD	337781	108805	1.6E10	0.142
Weighting according to MSE	320722	61825	5.5E9	0.075
Weighting according to MAPE	336032	103891	1.4E10	0.135
Customized Weights	338097	108362	1.6E10	0.141

The results obtained from the individual forecast methods are given at Table 5.7 (the constants are calculated to minimize MSE):

Table 5.7 Forecast Results (MSE) of Sample Run 2

Forecast Method	Forecast	MAD	MSE	MAPE
Moving Average	419054	167672	4.5E+8	0.248
Simple Exponential Smoothing	435619	180717	5.0E+8	0.271
Exponential Smoothing with Trend Adjustment	182363	176610	4.1E+8	0.282
Exponential Smoothing with Seasonal Adjustment	309928	47656	3.2E+8	0.063

After the results shown at Table 5.7 are combined, the results of the combination are given at Table 5.8:

Table 5.8 Combination Results (MSE) of Sample Run 2

Combination Method	Combined Forecast	MAD	MSE	MAPE
Simple Average	336741	134854	2.7E10	0.171
Weighting according to MAD	326289	93386	1.3E10	0.116
Weighting according to MSE	314786	56489	5.1E9	0.066
Weighting according to MAPE	326562	88959	1.1E10	0.11
Customized Weights	326016	93353	1.3E10	0.115

The results obtained from the individual forecast methods are given at Table 5.9 (the constants are calculated to minimize MAPE):

Table 5.9 Forecast Results (MAPE) of Sample Run 2

Forecast Method	Forecast	MAD	MSE	MAPE
Moving Average	419054	167672	4.53E+8	0.248
Simple Exponential Smoothing	435619	180717	5.03E+8	0.271
Exponential Smoothing with Trend Adjustment	262905	169537	5.14E+8	0.254
Exponential Smoothing with Seasonal Adjustment	314209	48770	3.33E+8	0.063

After the results shown at Table 5.9 are combined, the results of the combination are given at Table 5.10:

Table 5.10 Combination Results (MAPE) of Sample Run 2

Combination Method	Combined Forecast	MAD	MSE	MAPE
Simple Average	357947	158907	3.5E10	0.213
Weighting according to MAD	340449	112112	1.7E10	0.147
Weighting according to MSE	324542	65815	6.0E9	0.082
Weighting according to MAPE	338500	106410	1.5E10	0.139
Customized Weights	340452	110765	1.6E10	0.145

The customized weights of the methods are 0.15, 0.15, 0.15 and 0.55 respectively.

The figure that shows the iteration results of the sample run is given in Appendix B.

CHAPTER 6

DISCUSSION AND CONCLUSION

In this thesis, a specific decision support system is developed for combining forecasts to help the user in making decisions.

The program can compute the constant values of the methods (except ARIMA) to minimize the value of the error calculation method that is selected by the user (MAD, MSE or MAPE). But in the first sample run, the results of the methods do not change a lot with the error calculation method. Furthermore, the results computed according to MSE and MAPE are the same.

In the first sample run, the forecast computed by Exponential Smoothing with Trend Adjustment method is very near to the actual value of the index of January 2003 and its MAD, MSE and MAPE seems to be very small when they are compared with the other methods except ARIMA. The MAD, MSE and MAPE of ARIMA are the lowest but its forecast do not approach to the actual value as Exp. Sm. with Trend Adjustment. The forecasts of Moving Averages and

Simple Exponential Smoothing methods are acceptable but, the forecast of Exponential Smoothing with Seasonal Adjustment is very far from the actual value. However, the combination results show that combining forecasts takes the forecast results closer to the actual value. The combined forecast that is computed according to MSE gives a better result than the other combination methods, since the MSE method is more sensitive than the others.

In the first sample run Minitab can not estimate the model without differencing the data since the data is nonstationary. In the sample sample run ARIMA (2, 2, 2) is used, because its errors increase below and above these levels.

In the second sample run, Minitab can not estimate a model by differencing the data, but it is a good example showing the capability of combining forecasts. None of the forecast methods computes a forecast value that is close to the actual value by neither of the error calculation method (optimizing the constants to minimize MAD, MSE or MAPE). However, after combining the results, it is seen that the results of all combination methods are very close to the actual value. Also in this sample run combination of results according to MSE has the lowest error as it can be seen from Tables 5.6, 5.7 and 5.8, but its final result is not better than the other combination methods.

As it is seen at the sample runs, for every different data samples the method that gives the best forecast result differs according to the property of the data. If the mean of the data does not change a lot in time Moving Average, Simple Exponential Smoothing and ARIMA methods are expected to give more accurate results than the other methods. But if there is a trend in the data, Exponential Smoothing with Trend Adjustment method is expected to give the most reliable result since it is designed for the data that has a trend. And it is also true for Exponential Smoothing with Seasonal Adjustment method when there is seasonality in the data.

It is not easy for some data to find out whether it has a trend, seasonality or it follows a constant mean or not. So sometimes it is not very easy to select the forecasting method that would give the best result for the data.

Combining forecasts can be a solution for these problems. By combining forecasts, the errors of the unsuitable methods for that data can be pulled to an acceptable level. In some cases, combining forecasts could give worse results than the individual methods like in the first sample run, but in most of the cases the results of the combined forecasts are not out of the acceptable level.

In both of the sample runs it is also seen that the combined forecasts with customized weights could give better results than other combination methods. But the power of combining forecasts depends on the experience of the user, so it can be said that combining forecasts with customized weights is a combination of statistical methods with judgment.

For the future work on the same subject the following modifications can be made on the models and the program:

1. The optimal levels of the p, d and q values in ARIMA method can be computed by the program that would minimize the MAD, MSE or MAPE values.

2. The step size of the constants can be decreased to minimize the errors by using more powerful computers (In this program the step sizes are 0.1).

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APPENDIX A

FORECASTING METHODS

A.1. Moving Averages

The *N*-period moving-average method may be used to smooth out random variations and produce a reliable estimate of the underlying average occupancy. The method calculates a moving average MA_t for period *t* on the basis of selecting *N* of the most recent actual observations A_t, as shown in the following equation (Fitzsimmons and Fitzsimmons, 2001):

$$MA_t = (A_t + A_{t-1} + A_{t-2} + ... + A_{t-N+1}) / N \qquad (A.1)$$

N-period moving average deals only with the latest *T* periods of known data and the number of data points in each average does not change as time goes on. However, this method is slow to react because old data are given the same weight as new data in calculating the averages (Makridakis, Wheelwright and McGee, 1983).

A.2. Simple Exponential Smoothing

Simple exponential smoothing is the time series method most frequently used for demand forecasting. Simple exponential smoothing also "smooths out" blips in the data, but its power over the N-period moving average is threefold: (1) old data are never dropped or lost, (2) older data are given progressively less weight, and (3) the calculation is simple and requires only the most recent data (Fitzsimmons and Fitzsimmons, 2001).

Simple exponential smoothing is based on the concept of feeding back the forecast error to correct the previous smoothed value.

$$S_t = S_{t-1} + \alpha(A_t - S_{t-1}) \qquad \text{(A.2)}$$

or

$$S_t = \alpha(A_t) + (1 - \alpha)S_{t-1} \qquad \text{(A.3)}$$

where:

S_t = Smoothed value for period t

A_t = Actual observed value for period t

α = Smoothing constant (usually assigned a value between 0.1 and 0.9)

The term ($A_t – S_{t-1}$) represents the forecast error because it is the difference between the actual observation and the smoothed value that was calculated in the prior period. A fraction α of this forecast error is added to the previous smoothed value to obtain the new smoothed value S_t.

Simple exponential smoothing assumes that the pattern of data is distributed about a constant mean. Thus, the smoothed value calculated in period *t* is used as the forecast for period (*t+1*) rounded to an integer, as shown below:

$$F_{t+1} = S_t \tag{A.4}$$

Note that older observations never disappear entirely from the calculation of S_t as they would when the *N*–period moving average is used, but they do assume progressively decreasing importance.

A.3. Exponential Smoothing with Trend Adjustment

The trend in a set of data is the average rate at which the observed values change from one period to the next over time. The changes created by the trend can be treated using an extension of simple exponential smoothing (Fitzsimmons and Fitzsimmons, 2001).

The smoothed value is calculated using the following equation, which is equation (A.2) modified by the addition of a trend value to the previous smoothed value to account the rate of increase.

$$S_t = \alpha(A_t) + (1 - \alpha)(S_{t-1} + T_{t-1}) \tag{A.5}$$

where:

S_t = Smoothed value for period t

A_t = Actual observed value for period t

α = Smoothing constant (usually assigned a value between 0.1 and 0.9)

T_{t-1} = Trend value for period (t - 1)

To incorporate a trend adjustment in the calculation, β is used as a smoothing constant. This constant usually is assigned a value between 0.1 and 0.9 and may be the same as or different from α. The trend for a given period t is defined by the rate of change in the smoothed value from one period to the next. The smoothed trend is calculated at period t using the equation below, which is a modification of the basic exponential smoothing equation [Equation (A.3)]:

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1} \tag{A.6}$$

where:

Tt = The smoothed trend for period t

S_t = Smoothed value for period t

β = Smoothing constant for trend (usually assigned a value between 0.1 and 0.9)

Then the forecast for the next period is:

$$F_{t+1} = S_t + T_t \tag{A.7}$$

A.4. Exponential Smoothing with Seasonal Adjustment

To account for seasonal effects on a set of data, another extension of simple exponential smoothing can be used. First, the seasonality is removed from the data and then those data is smoothed; finally the seasonality is put back in to determine a forecast (Fitzsimmons and Fitzsimmons, 2001).

Note that there should be actual data for at least one full season before the smoothing and forecasting calculations begin.

A seasonality index is used to deseasonalize the data in a given cycle. It is calculated by the following equation:

$$I_t = A_t / \overline{A} \tag{A.8}$$

where:

$\overline{A}$ = $(A_1 + A_2 + ... + A_L) / L$

I_t = Seasonality index for period t

L = Cycle length

A_t = Actual observed value for period t

$\overline{A}$ = Average of actual observed values in cycle L

Then the data is deseasonalized by using the seasonality indices according to the equation below, which is a minor modification of the basic exponential smoothing equation [Equation (A.3)]:

$$S_t = \alpha(A_t / I_{t-L}) + (1 - \alpha)S_{t-1} \tag{A.9}$$

The forecast for the period (t + 1) then is made by seasonalizing the smoothed value for the period t according to the following formula:

$$F_{t+1} = (S_t)(I_{t-L+1}) \quad (A.10)$$

If the seasonality indices are stable, forecasts that are based on only one cycle, L, will be reliable. If, however, the indices are not stable, they can be adjusted, or smoothed, as new data become available. To apply the concept of exponential smoothing to the index, a new constant γ is used. The smoothed estimate of the seasonality index then is calculated from the following formula:

$$I_t = \gamma(A_t / S_t) + (1 - \gamma)I_{t-L} \quad (A.11)$$

where:

I_t = The smoothed estimate of the seasonality index for period t

γ = Smoothing constant for season (usually assigned a value between 0.1 and 0.9)

A_t = Actual observed value for period t

S_t = Smoothed value for period t

A.5. ARIMA

The abbreviation ARIMA is for “autoregressive integrated moving average” model. Integrated (I) refers to “differencing” of the data series. The autoregression (AR), differencing (I) and moving-average (MA) portion make up the three numbers following ARIMA.

ARIMA time series models are designed for stationary time series. A stationary time series is one whose basic statistical properties such as the mean or variance remain constant over time. Most time series encountered in some forecasting applications are not stationary series. If a nonstationary time series can be made stationary by taking d differences (usually d = 1 or 2), the result is a model for the *differenced* series.

For an ARIMA model, the order is given by the three letters p, d and q. The order of the autoregressive component is p, the order of differencing needed to achieve stationarity is d and the order of the moving-average part is q (Jarrett, 1991).

ARIMA (*p*, *d*, *q*) models use combinations of past values and past errors. The ARIMA model takes the form (Hanke and Reitsch, 1998):

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \epsilon_t - w_1\epsilon_{t-1} - w_2\epsilon_{t-2} - ... - w_q\epsilon_{t-q}$$

where

Y_t = Dependent variable

Y_{t-1}, Y_{t-2}, Y_{t-p} = Independent variables that are dependent variables lagged specific time periods

ϕ_0, ϕ_1, ϕ_2, ϕ_p = Regression coefficients

w_1, w_2, w_q = Weights

ϵ_t = Residual or error

ϵ_{t-1}, ϵ_{t-2}, ϵ_{t-q} = Previous values of residuals

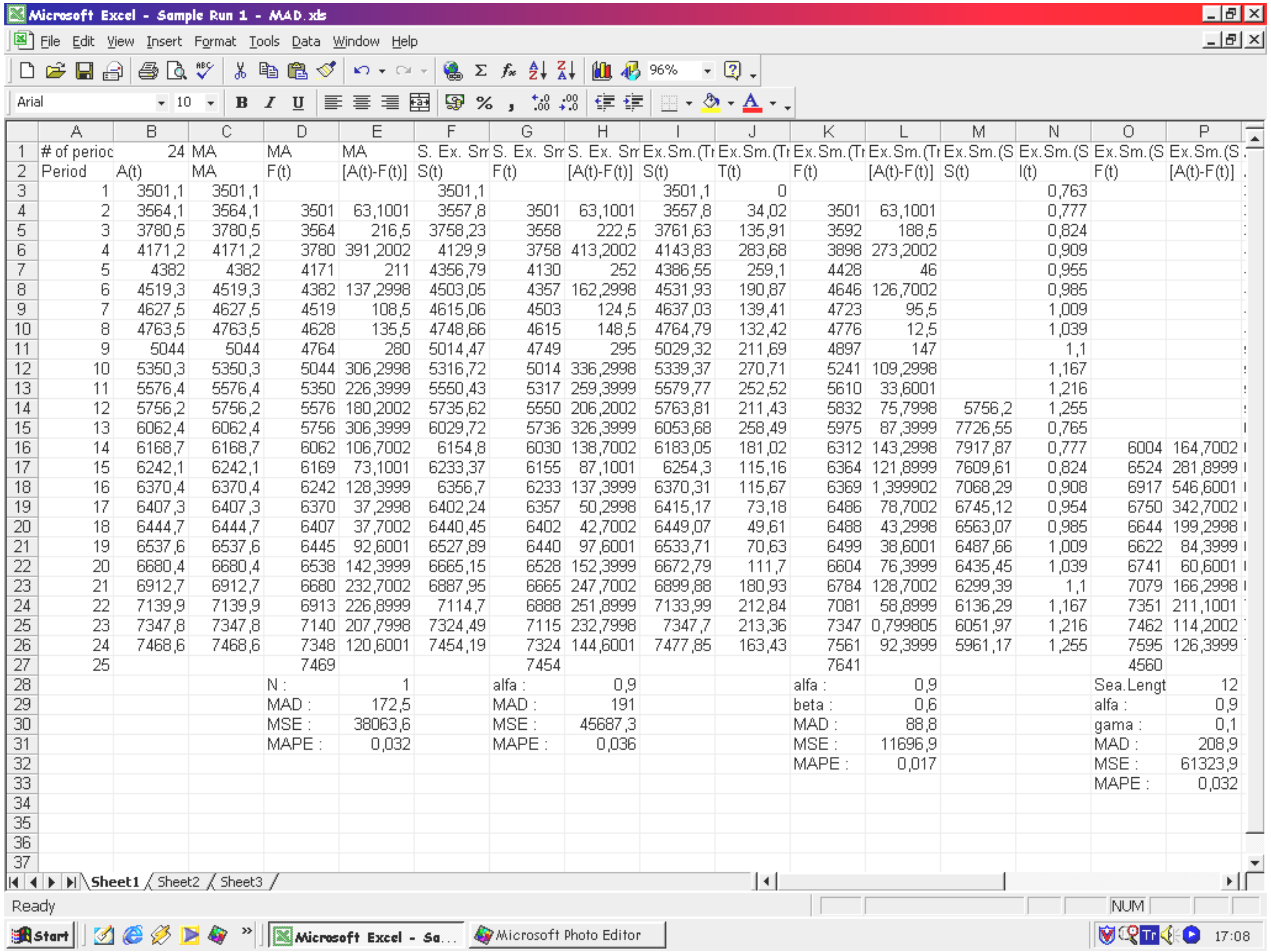
According to Levenbach and Cleary (1984), the ARIMA models have proved to be excellent short-term forecasting models for a wide variety of time series. A significant advantage of ARIMA is that, forecasts can be developed in a very short time. More time is spent obtaining and validating the data than in building the models. Therefore, a practitioner can often deliver significant results early in a project for which an ARIMA model is used.

APPENDIX B

DETAILED RESULTS OF SAMPLE RUNS

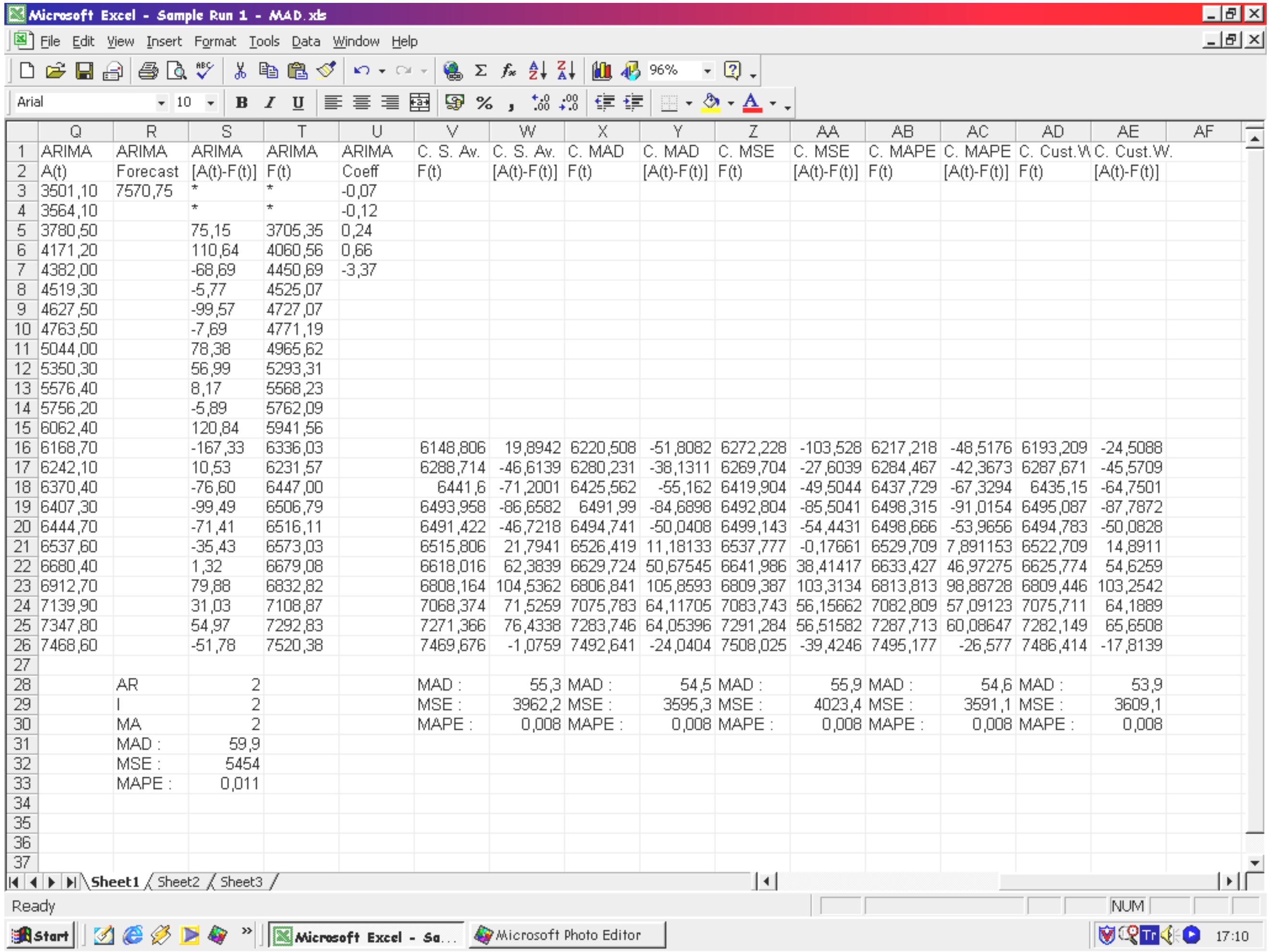
Sample Run 1

The results obtained from the individual forecast methods are given at Figure B.1 and Figure B.2 in which the constants are calculated to minimize MAD and MSE - MAPE respectively (In this sample run the results of MSE and MAPE are same).



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)]
3	1	3501,1	3501,1			3501,1			3501,1	0				0,763		
4	2	3564,1	3564,1	3501	63,1001	3557,8	3501	63,1001	3557,8	34,02	3501	63,1001		0,777		
5	3	3780,5	3780,5	3564	216,5	3758,23	3558	222,5	3761,63	135,91	3592	188,5		0,824		
6	4	4171,2	4171,2	3780	391,2002	4129,9	3758	413,2002	4143,83	283,68	3898	273,2002		0,909		
7	5	4382	4382	4171	211	4356,79	4130	252	4386,55	259,1	4428	46		0,955		
8	6	4519,3	4519,3	4382	137,2998	4503,05	4357	162,2998	4531,93	190,87	4646	126,7002		0,985		
9	7	4627,5	4627,5	4519	108,5	4615,06	4503	124,5	4637,03	139,41	4723	95,5		1,009		
10	8	4763,5	4763,5	4628	135,5	4748,66	4615	148,5	4764,79	132,42	4776	12,5		1,039		
11	9	5044	5044	4764	280	5014,47	4749	295	5029,32	211,69	4897	147		1,1		
12	10	5350,3	5350,3	5044	306,2998	5316,72	5014	336,2998	5339,37	270,71	5241	109,2998		1,167		
13	11	5576,4	5576,4	5350	226,3999	5550,43	5317	259,3999	5579,77	252,52	5610	33,6001		1,216		
14	12	5756,2	5756,2	5576	180,2002	5735,62	5550	206,2002	5763,81	211,43	5832	75,7998	5756,2	1,255		
15	13	6062,4	6062,4	5756	306,3999	6029,72	5736	326,3999	6053,68	258,49	5975	87,3999	7726,55	0,765		
16	14	6168,7	6168,7	6062	106,7002	6154,8	6030	138,7002	6183,05	181,02	6312	143,2998	7917,87	0,777	6004	164,7002
17	15	6242,1	6242,1	6169	73,1001	6233,37	6155	87,1001	6254,3	115,16	6364	121,8999	7609,61	0,824	6524	281,8999
18	16	6370,4	6370,4	6242	128,3999	6356,7	6233	137,3999	6370,31	115,67	6369	1,399902	7068,29	0,908	6917	546,6001
19	17	6407,3	6407,3	6370	37,2998	6402,24	6357	50,2998	6415,17	73,18	6486	78,7002	6745,12	0,954	6750	342,7002
20	18	6444,7	6444,7	6407	37,7002	6440,45	6402	42,7002	6449,07	49,61	6488	43,2998	6563,07	0,985	6644	199,2998
21	19	6537,6	6537,6	6445	92,6001	6527,89	6440	97,6001	6533,71	70,63	6499	38,6001	6487,66	1,009	6622	84,3999
22	20	6680,4	6680,4	6538	142,3999	6665,15	6528	152,3999	6672,79	111,7	6604	76,3999	6435,45	1,039	6741	60,6001
23	21	6912,7	6912,7	6680	232,7002	6887,95	6665	247,7002	6899,88	180,93	6784	128,7002	6299,39	1,1	7079	166,2998
24	22	7139,9	7139,9	6913	226,8999	7114,7	6888	251,8999	7133,99	212,84	7081	58,8999	6136,29	1,167	7351	211,1001
25	23	7347,8	7347,8	7140	207,7998	7324,49	7115	232,7998	7347,7	213,36	7347	0,799805	6051,97	1,216	7462	114,2002
26	24	7468,6	7468,6	7348	120,6001	7454,19	7324	144,6001	7477,85	163,43	7561	92,3999	5961,17	1,255	7595	126,3999
27	25			7469			7454				7641				4560	
28				N :	1		alfa :	0,9			alfa :	0,9			Sea.Lengt	12
29				MAD :	172,5		MAD :	191			beta :	0,6			alfa :	0,9
30				MSE :	38063,6		MSE :	45687,3			MAD :	88,8			gama :	0,1
31				MAPE :	0,032		MAPE :	0,036			MSE :	11696,9			MAD :	208,9
32											MAPE :	0,017			MSE :	61323,9
33															MAPE :	0,032

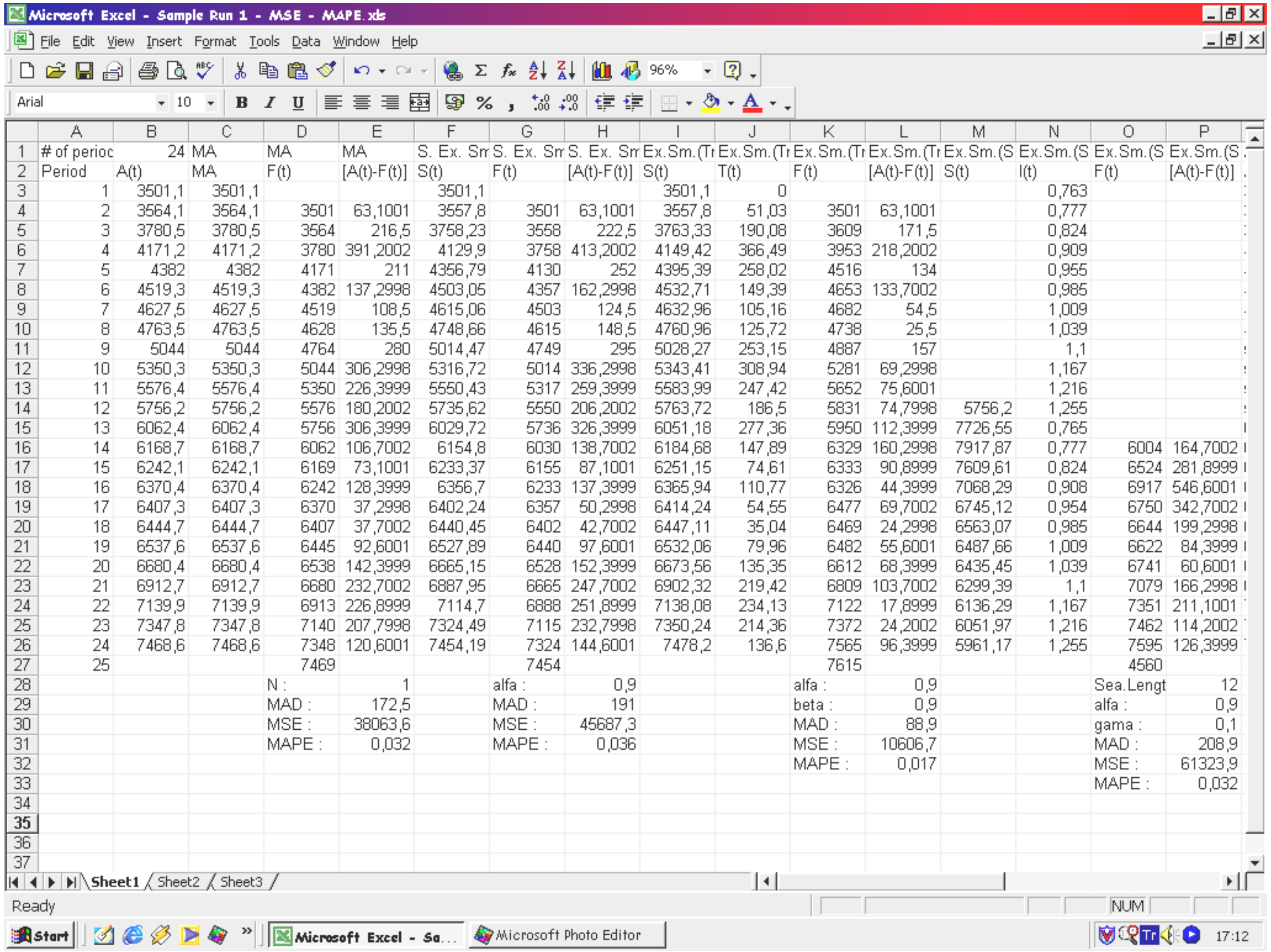
Figure B.1. The Iteration Results of Sample Run 1 (MAD)



Microsoft Excel - Sample Run 1 - MAD.xls

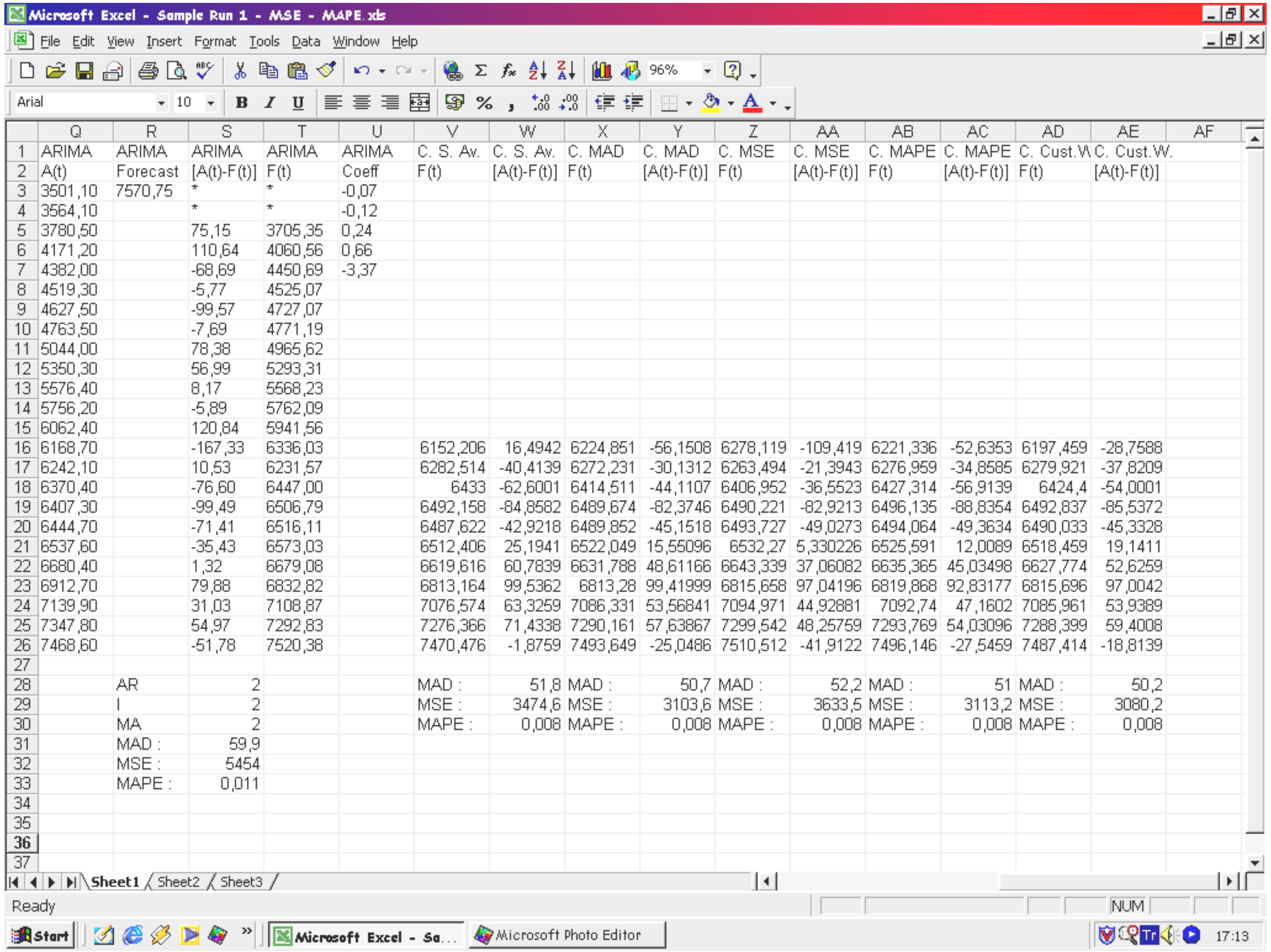
	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF
1	ARIMA	ARIMA	ARIMA	ARIMA	ARIMA	C. S. Av.	C. S. Av.	C. MAD	C. MAD	C. MSE	C. MSE	C. MAPE	C. MAPE	C. Cust.W	C. Cust.W.	
2	A(t)	Forecast	[A(t)-F(t)]	F(t)	Coeff	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	
3	3501,10	7570,75	*	*	-0,07											
4	3564,10		*	*	-0,12											
5	3780,50		75,15	3705,35	0,24											
6	4171,20		110,64	4060,56	0,66											
7	4382,00		-68,69	4450,69	-3,37											
8	4519,30		-5,77	4525,07												
9	4627,50		-99,57	4727,07												
10	4763,50		-7,69	4771,19												
11	5044,00		78,38	4965,62												
12	5350,30		56,99	5293,31												
13	5576,40		8,17	5568,23												
14	5756,20		-5,89	5762,09												
15	6062,40		120,84	5941,56												
16	6168,70		-167,33	6336,03		6148,806	19,8942	6220,508	-51,8082	6272,228	-103,528	6217,218	-48,5176	6193,209	-24,5088	
17	6242,10		10,53	6231,57		6288,714	-46,6139	6280,231	-38,1311	6269,704	-27,6039	6284,467	-42,3673	6287,671	-45,5709	
18	6370,40		-76,60	6447,00		6441,6	-71,2001	6425,562	-55,162	6419,904	-49,5044	6437,729	-67,3294	6435,15	-64,7501	
19	6407,30		-99,49	6506,79		6493,958	-86,6582	6491,99	-84,6898	6492,804	-85,5041	6498,315	-91,0154	6495,087	-87,7872	
20	6444,70		-71,41	6516,11		6491,422	-46,7218	6494,741	-50,0408	6499,143	-54,4431	6498,666	-53,9656	6494,783	-50,0828	
21	6537,60		-35,43	6573,03		6515,806	21,7941	6526,419	11,18133	6537,777	-0,17661	6529,709	7,891153	6522,709	14,8911	
22	6680,40		1,32	6679,08		6618,016	62,3839	6629,724	50,67545	6641,986	38,41417	6633,427	46,97275	6625,774	54,6259	
23	6912,70		79,88	6832,82		6808,164	104,5362	6806,841	105,8593	6809,387	103,3134	6813,813	98,88728	6809,446	103,2542	
24	7139,90		31,03	7108,87		7068,374	71,5259	7075,783	64,11705	7083,743	56,15662	7082,809	57,09123	7075,711	64,1889	
25	7347,80		54,97	7292,83		7271,366	76,4338	7283,746	64,05396	7291,284	56,51582	7287,713	60,08647	7282,149	65,6508	
26	7468,60		-51,78	7520,38		7469,676	-1,0759	7492,641	-24,0404	7508,025	-39,4246	7495,177	-26,577	7486,414	-17,8139	
27																
28		AR	2			MAD :	55,3	MAD :	54,5	MAD :	55,9	MAD :	54,6	MAD :	53,9	
29		I	2			MSE :	3962,2	MSE :	3595,3	MSE :	4023,4	MSE :	3591,1	MSE :	3609,1	
30		MA	2			MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	
31		MAD :	59,9													
32		MSE :	5454													
33		MAPE :	0,011													

Figure B.1. (continued)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)]
3	1	3501,1	3501,1			3501,1			3501,1	0				0,763		
4	2	3564,1	3564,1	3501	63,1001	3557,8	3501	63,1001	3557,8	51,03	3501	63,1001		0,777		
5	3	3780,5	3780,5	3564	216,5	3758,23	3558	222,5	3763,33	190,08	3609	171,5		0,824		
6	4	4171,2	4171,2	3780	391,2002	4129,9	3758	413,2002	4149,42	366,49	3953	218,2002		0,909		
7	5	4382	4382	4171	211	4356,79	4130	252	4395,39	258,02	4516	134		0,955		
8	6	4519,3	4519,3	4382	137,2998	4503,05	4357	162,2998	4532,71	149,39	4653	133,7002		0,985		
9	7	4627,5	4627,5	4519	108,5	4615,06	4503	124,5	4632,96	105,16	4682	54,5		1,009		
10	8	4763,5	4763,5	4628	135,5	4748,66	4615	148,5	4760,96	125,72	4738	25,5		1,039		
11	9	5044	5044	4764	280	5014,47	4749	295	5028,27	253,15	4887	157		1,1		
12	10	5350,3	5350,3	5044	306,2998	5316,72	5014	336,2998	5343,41	308,94	5281	69,2998		1,167		
13	11	5576,4	5576,4	5350	226,3999	5550,43	5317	259,3999	5583,99	247,42	5652	75,6001		1,216		
14	12	5756,2	5756,2	5576	180,2002	5735,62	5550	206,2002	5763,72	186,5	5831	74,7998	5756,2	1,255		
15	13	6062,4	6062,4	5756	306,3999	6029,72	5736	326,3999	6051,18	277,36	5950	112,3999	7726,55	0,765		
16	14	6168,7	6168,7	6062	106,7002	6154,8	6030	138,7002	6184,68	147,89	6329	160,2998	7917,87	0,777	6004	164,7002
17	15	6242,1	6242,1	6169	73,1001	6233,37	6155	87,1001	6251,15	74,61	6333	90,8999	7609,61	0,824	6524	281,8999
18	16	6370,4	6370,4	6242	128,3999	6356,7	6233	137,3999	6365,94	110,77	6326	44,3999	7068,29	0,908	6917	546,6001
19	17	6407,3	6407,3	6370	37,2998	6402,24	6357	50,2998	6414,24	54,55	6477	69,7002	6745,12	0,954	6750	342,7002
20	18	6444,7	6444,7	6407	37,7002	6440,45	6402	42,7002	6447,11	35,04	6469	24,2998	6563,07	0,985	6644	199,2998
21	19	6537,6	6537,6	6445	92,6001	6527,89	6440	97,6001	6532,06	79,96	6482	55,6001	6487,66	1,009	6622	84,3999
22	20	6680,4	6680,4	6538	142,3999	6665,15	6528	152,3999	6673,56	135,35	6612	68,3999	6435,45	1,039	6741	60,6001
23	21	6912,7	6912,7	6680	232,7002	6887,95	6665	247,7002	6902,32	219,42	6809	103,7002	6299,39	1,1	7079	166,2998
24	22	7139,9	7139,9	6913	226,8999	7114,7	6888	251,8999	7138,08	234,13	7122	17,8999	6136,29	1,167	7351	211,1001
25	23	7347,8	7347,8	7140	207,7998	7324,49	7115	232,7998	7350,24	214,36	7372	24,2002	6051,97	1,216	7462	114,2002
26	24	7468,6	7468,6	7348	120,6001	7454,19	7324	144,6001	7478,2	136,6	7565	96,3999	5961,17	1,255	7595	126,3999
27	25			7469			7454				7615				4560	
28				N :	1		alfa :	0,9			alfa :	0,9			Sea.Lengt	12
29				MAD :	172,5		MAD :	191			beta :	0,9			alfa :	0,9
30				MSE :	38063,6		MSE :	45687,3			MAD :	88,9			gama :	0,1
31				MAPE :	0,032		MAPE :	0,036			MSE :	10606,7			MAD :	208,9
32											MAPE :	0,017			MSE :	61323,9
33															MAPE :	0,032

Figure B.2. The Iteration Results of Sample Run 1 (MSE & MAPE)

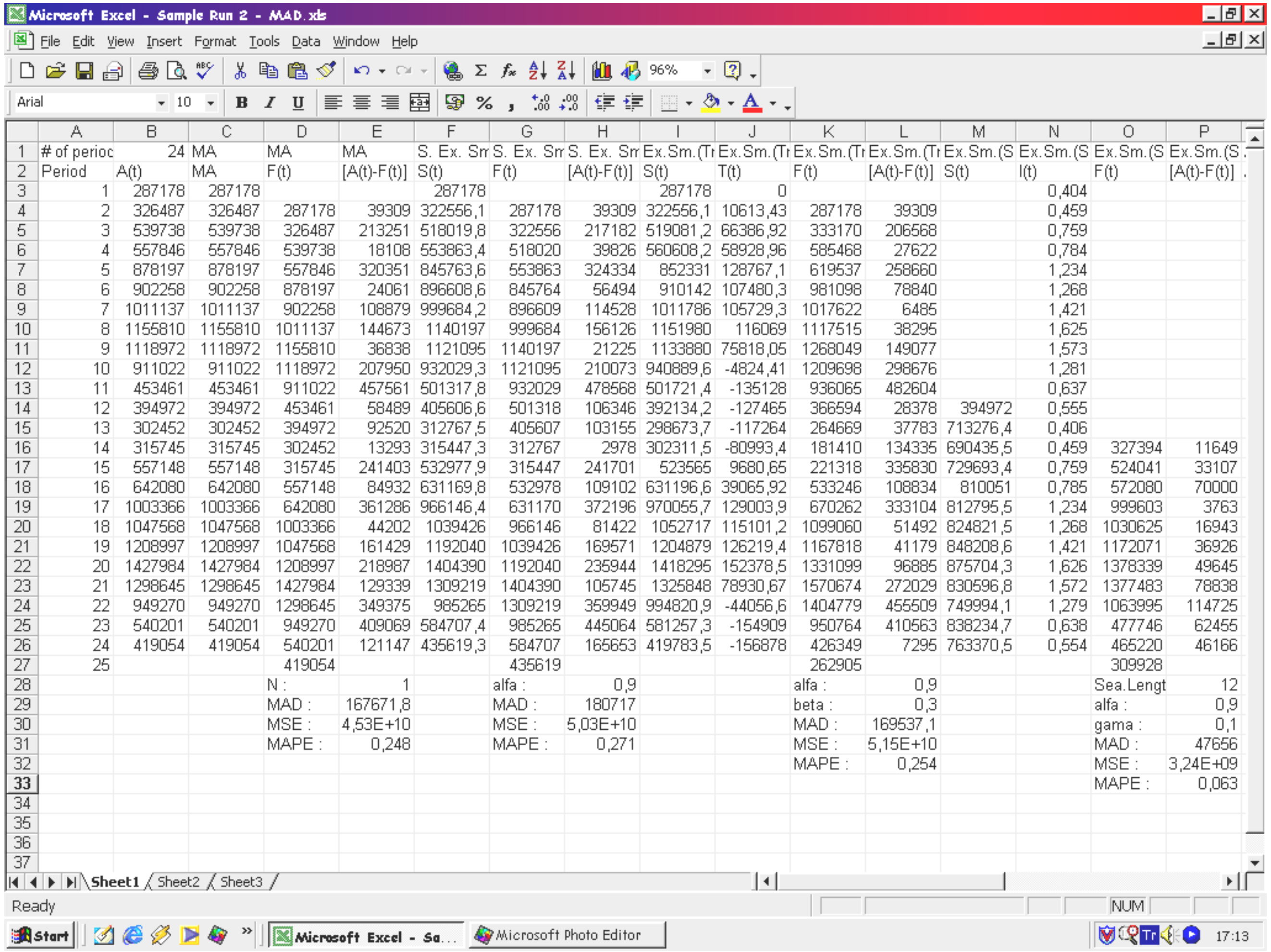


	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF
1	ARIMA	ARIMA	ARIMA	ARIMA	ARIMA	C. S. Av.	C. S. Av.	C. MAD	C. MAD	C. MSE	C. MSE	C. MAPE	C. MAPE	C. Cust.W	C. Cust.W.	
2	A(t)	Forecast	[A(t)-F(t)]	F(t)	Coeff	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	
3	3501,10	7570,75	*	*	-0,07											
4	3564,10		*	*	-0,12											
5	3780,50		75,15	3705,35	0,24											
6	4171,20		110,64	4060,56	0,66											
7	4382,00		-68,69	4450,69	-3,37											
8	4519,30		-5,77	4525,07												
9	4627,50		-99,57	4727,07												
10	4763,50		-7,69	4771,19												
11	5044,00		78,38	4965,62												
12	5350,30		56,99	5293,31												
13	5576,40		8,17	5568,23												
14	5756,20		-5,89	5762,09												
15	6062,40		120,84	5941,56												
16	6168,70		-167,33	6336,03		6152,206	16,4942	6224,851	-56,1508	6278,119	-109,419	6221,336	-52,6353	6197,459	-28,7588	
17	6242,10		10,53	6231,57		6282,514	-40,4139	6272,231	-30,1312	6263,494	-21,3943	6276,959	-34,8585	6279,921	-37,8209	
18	6370,40		-76,60	6447,00		6433	-62,6001	6414,511	-44,1107	6406,952	-36,5523	6427,314	-56,9139	6424,4	-54,0001	
19	6407,30		-99,49	6506,79		6492,158	-84,8582	6489,674	-82,3746	6490,221	-82,9213	6496,135	-88,8354	6492,837	-85,5372	
20	6444,70		-71,41	6516,11		6487,622	-42,9218	6489,852	-45,1518	6493,727	-49,0273	6494,064	-49,3634	6490,033	-45,3328	
21	6537,60		-35,43	6573,03		6512,406	25,1941	6522,049	15,55096	6532,27	5,330226	6525,591	12,0089	6518,459	19,1411	
22	6680,40		1,32	6679,08		6619,616	60,7839	6631,788	48,61166	6643,339	37,06082	6635,365	45,03498	6627,774	52,6259	
23	6912,70		79,88	6832,82		6813,164	99,5362	6813,28	99,41999	6815,658	97,04196	6819,868	92,83177	6815,696	97,0042	
24	7139,90		31,03	7108,87		7076,574	63,3259	7086,331	53,56841	7094,971	44,92881	7092,74	47,1602	7085,961	53,9389	
25	7347,80		54,97	7292,83		7276,366	71,4338	7290,161	57,63867	7299,542	48,25759	7293,769	54,03096	7288,399	59,4008	
26	7468,60		-51,78	7520,38		7470,476	-1,8759	7493,649	-25,0486	7510,512	-41,9122	7496,146	-27,5459	7487,414	-18,8139	
27																
28		AR	2			MAD :	51,8	MAD :	50,7	MAD :	52,2	MAD :	51	MAD :	50,2	
29		I	2			MSE :	3474,6	MSE :	3103,6	MSE :	3633,5	MSE :	3113,2	MSE :	3080,2	
30		MA	2			MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	MAPE :	0,008	
31		MAD :	59,9													
32		MSE :	5454													
33		MAPE :	0,011													
34																
35																
36																
37																

Figure B.2. (continued)

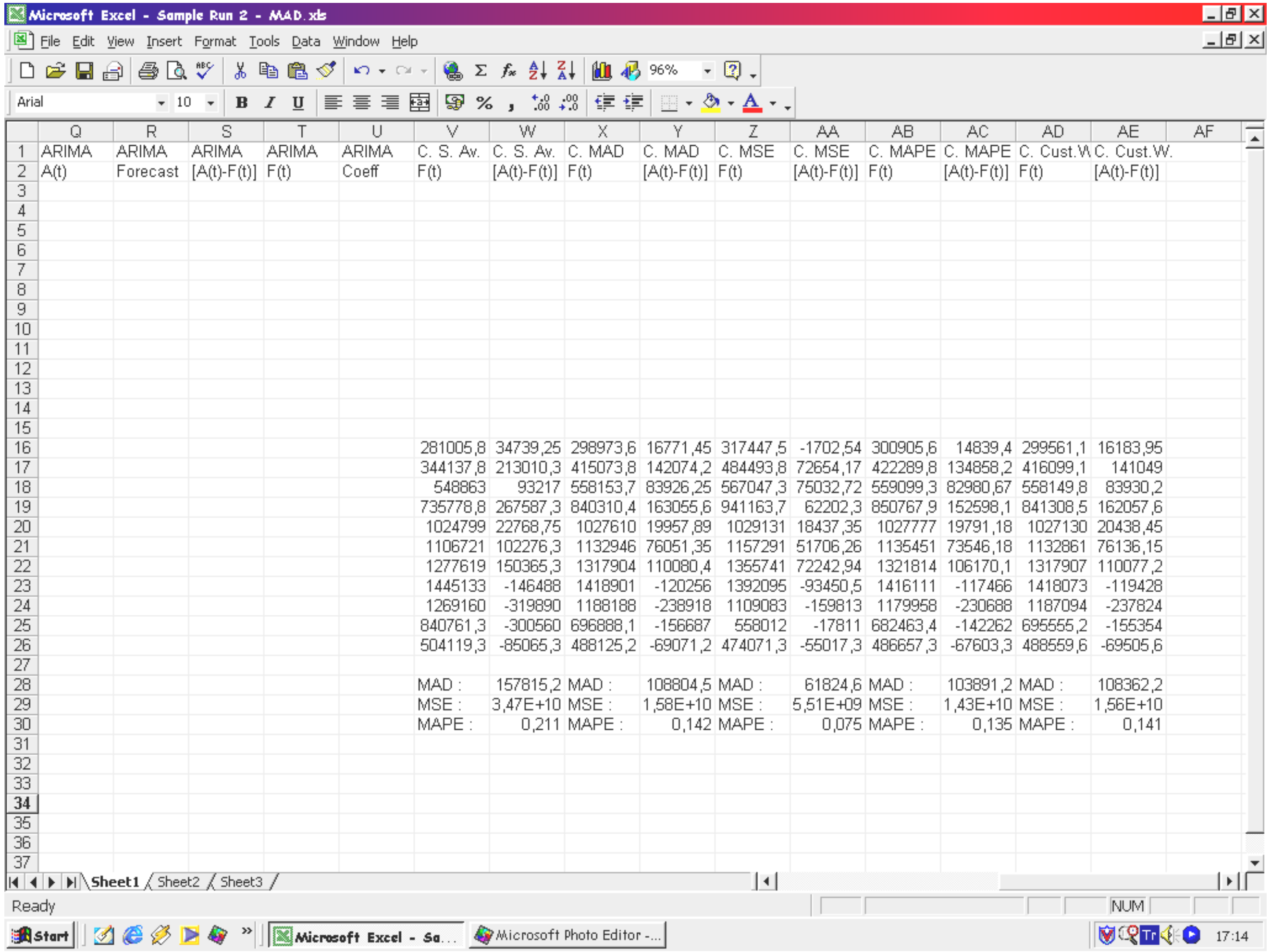
Sample Run 2

The results obtained from the individual forecast methods are given at Figure B.3 Figure B.4 and Figure B.5 in which the constants are calculated to minimize MAD, MSE and MAPE respectively



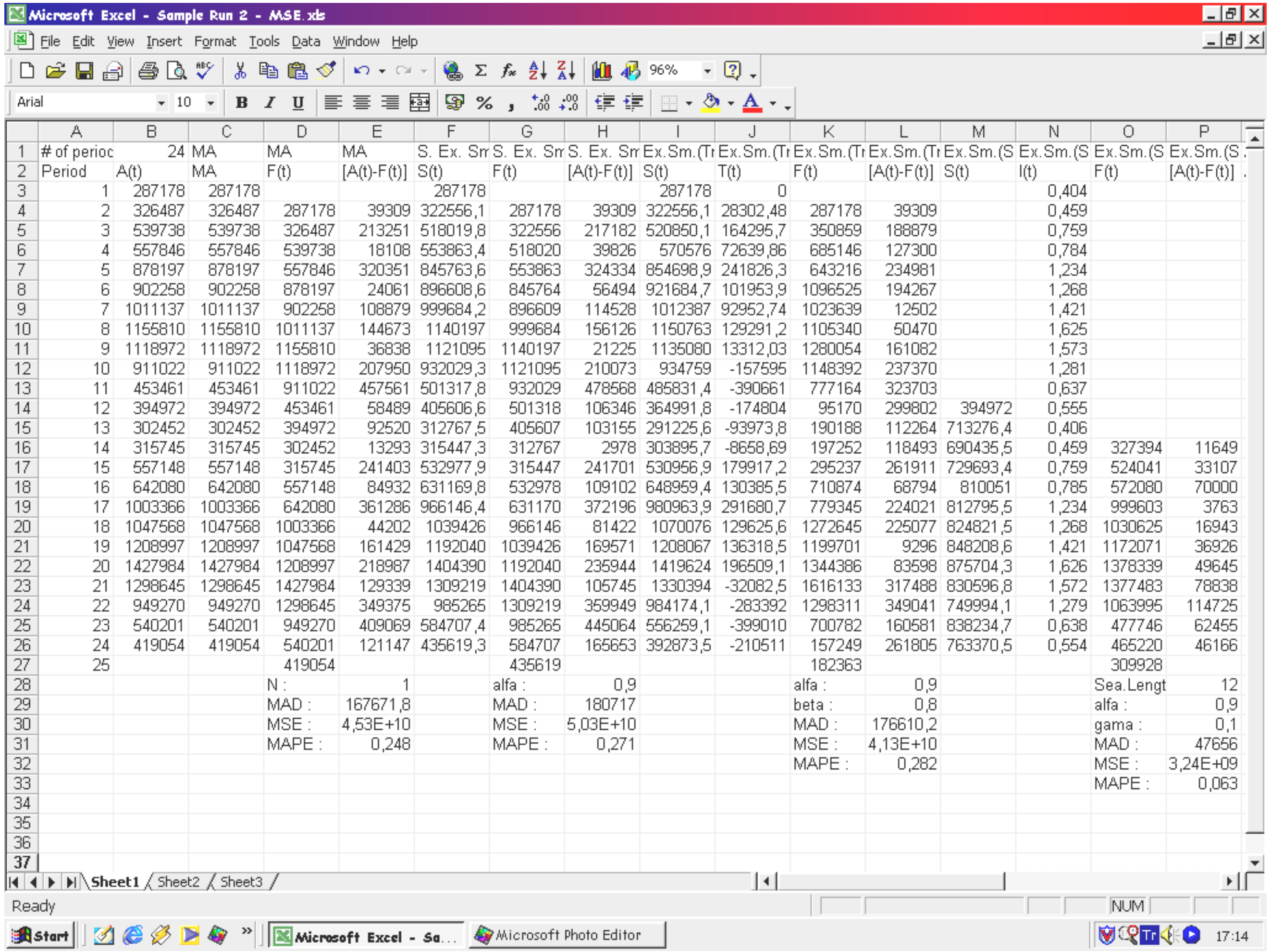
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)]
3	1	287178	287178			287178			287178	0				0,404		
4	2	326487	326487	287178	39309	322556,1	287178	39309	322556,1	10613,43	287178	39309		0,459		
5	3	539738	539738	326487	213251	518019,8	322556	217182	519081,2	66386,92	333170	206568		0,759		
6	4	557846	557846	539738	18108	553863,4	518020	39826	560608,2	58928,96	585468	27622		0,784		
7	5	878197	878197	557846	320351	845763,6	553863	324334	852331	128767,1	619537	258660		1,234		
8	6	902258	902258	878197	24061	896608,6	845764	56494	910142	107480,3	981098	78840		1,268		
9	7	1011137	1011137	902258	108879	999684,2	896609	114528	1011786	105729,3	1017622	6485		1,421		
10	8	1155810	1155810	1011137	144673	1140197	999684	156126	1151980	116069	1117515	38295		1,625		
11	9	1118972	1118972	1155810	36838	1121095	1140197	21225	1133880	75818,05	1268049	149077		1,573		
12	10	911022	911022	1118972	207950	932029,3	1121095	210073	940889,6	-4824,41	1209698	298676		1,281		
13	11	453461	453461	911022	457561	501317,8	932029	478568	501721,4	-135128	936065	482604		0,637		
14	12	394972	394972	453461	58489	405606,6	501318	106346	392134,2	-127465	366594	28378	394972	0,555		
15	13	302452	302452	394972	92520	312767,5	405607	103155	298673,7	-117264	264669	37783	713276,4	0,406		
16	14	315745	315745	302452	13293	315447,3	312767	2978	302311,5	-80993,4	181410	134335	690435,5	0,459	327394	11649
17	15	557148	557148	315745	241403	532977,9	315447	241701	523565	9680,65	221318	335830	729693,4	0,759	524041	33107
18	16	642080	642080	557148	84932	631169,8	532978	109102	631196,6	39065,92	533246	108834	810051	0,785	572080	70000
19	17	1003366	1003366	642080	361286	966146,4	631170	372196	970055,7	129003,9	670262	333104	812795,5	1,234	999603	3763
20	18	1047568	1047568	1003366	44202	1039426	966146	81422	1052717	115101,2	1099060	51492	824821,5	1,268	1030625	16943
21	19	1208997	1208997	1047568	161429	1192040	1039426	169571	1204879	126219,4	1167818	41179	848208,6	1,421	1172071	36926
22	20	1427984	1427984	1208997	218987	1404390	1192040	235944	1418295	152378,5	1331099	96885	875704,3	1,626	1378339	49645
23	21	1298645	1298645	1427984	129339	1309219	1404390	105745	1325848	78930,67	1570674	272029	830596,8	1,572	1377483	78838
24	22	949270	949270	1298645	349375	985265	1309219	359949	994820,9	-44056,6	1404779	455509	749994,1	1,279	1063995	114725
25	23	540201	540201	949270	409069	584707,4	985265	445064	581257,3	-154909	950764	410563	838234,7	0,638	477746	62455
26	24	419054	419054	540201	121147	435619,3	584707	165653	419783,5	-156878	426349	7295	763370,5	0,554	465220	46166
27	25			419054			435619				262905				309928	
28				N :	1		alfa :	0,9			alfa :	0,9			Sea.Lengt	12
29				MAD :	167671,8		MAD :	180717			beta :	0,3			alfa :	0,9
30				MSE :	4,53E+10		MSE :	5,03E+10			MAD :	169537,1			gama :	0,1
31				MAPE :	0,248		MAPE :	0,271			MSE :	5,15E+10			MAD :	47656
32											MAPE :	0,254			MSE :	3,24E+09
33															MAPE :	0,063

Figure B.3. The Iteration Results of Sample Run 2 (MAD)



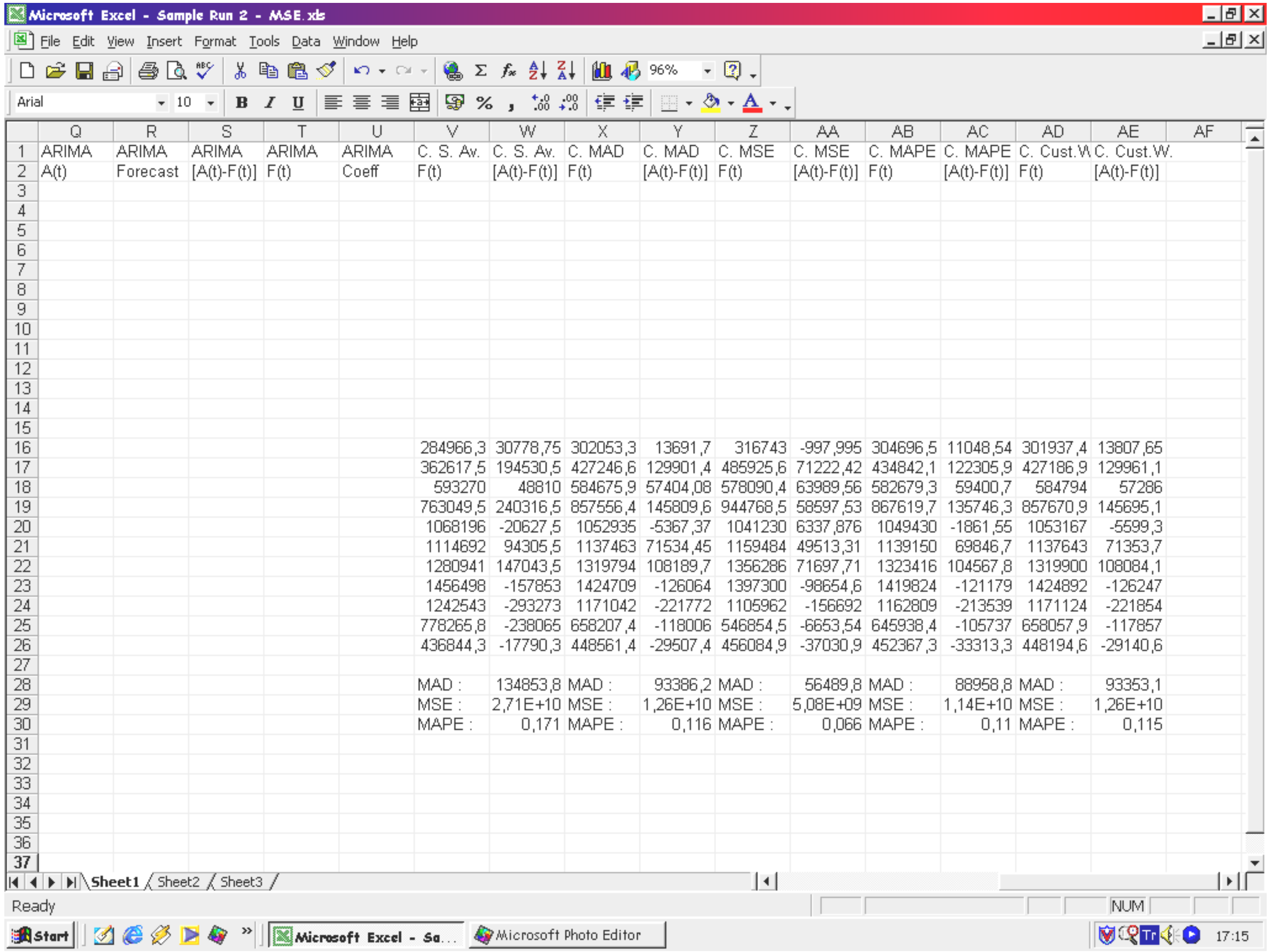
Row	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
1	ARIMA	ARIMA	ARIMA	ARIMA	ARIMA	C. S. Av.	C. S. Av.	C. MAD	C. MAD	C. MSE	C. MSE	C. MAPE	C. MAPE	C. Cust.W	C. Cust.W.
2	A(t)	Forecast	[A(t)-F(t)]	F(t)	Coeff	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]
16						281005,8	34739,25	298973,6	16771,45	317447,5	-1702,54	300905,6	14839,4	299561,1	16183,95
17						344137,8	213010,3	415073,8	142074,2	484493,8	72654,17	422289,8	134858,2	416099,1	141049
18						548863	93217	558153,7	83926,25	567047,3	75032,72	559099,3	82980,67	558149,8	83930,2
19						735778,8	267587,3	840310,4	163055,6	941163,7	62202,3	850767,9	152598,1	841308,5	162057,6
20						1024799	22768,75	1027610	19957,89	1029131	18437,35	1027777	19791,18	1027130	20438,45
21						1106721	102276,3	1132946	76051,35	1157291	51706,26	1135451	73546,18	1132861	76136,15
22						1277619	150365,3	1317904	110080,4	1355741	72242,94	1321814	106170,1	1317907	110077,2
23						1445133	-146488	1418901	-120256	1392095	-93450,5	1416111	-117466	1418073	-119428
24						1269160	-319890	1188188	-238918	1109083	-159813	1179958	-230688	1187094	-237824
25						840761,3	-300560	696888,1	-156687	558012	-17811	682463,4	-142262	695555,2	-155354
26						504119,3	-85065,3	488125,2	-69071,2	474071,3	-55017,3	486657,3	-67603,3	488559,6	-69505,6
28						MAD :	157815,2	MAD :	108804,5	MAD :	61824,6	MAD :	103891,2	MAD :	108362,2
29						MSE :	3,47E+10	MSE :	1,58E+10	MSE :	5,51E+09	MSE :	1,43E+10	MSE :	1,56E+10
30						MAPE :	0,211	MAPE :	0,142	MAPE :	0,075	MAPE :	0,135	MAPE :	0,141

Figure B.3. (continued)



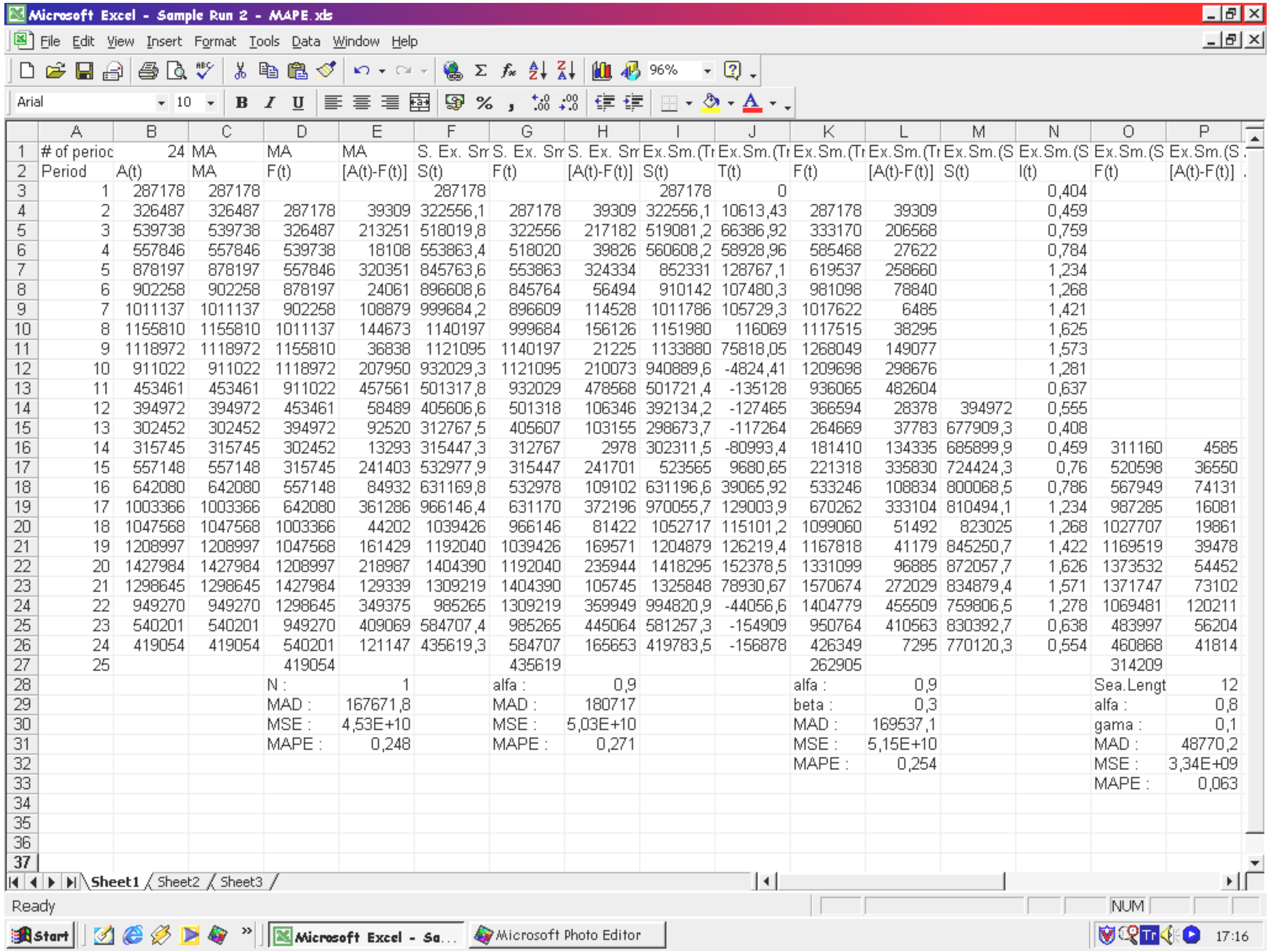
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)]
3	1	287178	287178			287178			287178	0				0,404		
4	2	326487	326487	287178	39309	322556,1	287178	39309	322556,1	28302,48	287178	39309		0,459		
5	3	539738	539738	326487	213251	518019,8	322556	217182	520850,1	164295,7	350859	188879		0,759		
6	4	557846	557846	539738	18108	553863,4	518020	39826	570576	72639,86	685146	127300		0,784		
7	5	878197	878197	557846	320351	845763,6	553863	324334	854698,9	241826,3	643216	234981		1,234		
8	6	902258	902258	878197	24061	896608,6	845764	56494	921684,7	101953,9	1096525	194267		1,268		
9	7	1011137	1011137	902258	108879	999684,2	896609	114528	1012387	92952,74	1023639	12502		1,421		
10	8	1155810	1155810	1011137	144673	1140197	999684	156126	1150763	129291,2	1105340	50470		1,625		
11	9	1118972	1118972	1155810	36838	1121095	1140197	21225	1135080	13312,03	1280054	161082		1,573		
12	10	911022	911022	1118972	207950	932029,3	1121095	210073	934759	-157595	1148392	237370		1,281		
13	11	453461	453461	911022	457561	501317,8	932029	478568	485831,4	-390661	777164	323703		0,637		
14	12	394972	394972	453461	58489	405606,6	501318	106346	364991,8	-174804	95170	299802	394972	0,555		
15	13	302452	302452	394972	92520	312767,5	405607	103155	291225,6	-93973,8	190188	112264	713276,4	0,406		
16	14	315745	315745	302452	13293	315447,3	312767	2978	303895,7	-8658,69	197252	118493	690435,5	0,459	327394	11649
17	15	557148	557148	315745	241403	532977,9	315447	241701	530956,9	179917,2	295237	261911	729693,4	0,759	524041	33107
18	16	642080	642080	557148	84932	631169,8	532978	109102	648959,4	130385,5	710874	68794	810051	0,785	572080	70000
19	17	1003366	1003366	642080	361286	966146,4	631170	372196	980963,9	291680,7	779345	224021	812795,5	1,234	999603	3763
20	18	1047568	1047568	1003366	44202	1039426	966146	81422	1070076	129625,6	1272645	225077	824821,5	1,268	1030625	16943
21	19	1208997	1208997	1047568	161429	1192040	1039426	169571	1208067	136318,5	1199701	9296	848208,6	1,421	1172071	36926
22	20	1427984	1427984	1208997	218987	1404390	1192040	235944	1419624	196509,1	1344386	83598	875704,3	1,626	1378339	49645
23	21	1298645	1298645	1427984	129339	1309219	1404390	105745	1330394	-32082,5	1616133	317488	830596,8	1,572	1377483	78838
24	22	949270	949270	1298645	349375	985265	1309219	359949	984174,1	-283392	1298311	349041	749994,1	1,279	1063995	114725
25	23	540201	540201	949270	409069	584707,4	985265	445064	556259,1	-399010	700782	160581	838234,7	0,638	477746	62455
26	24	419054	419054	540201	121147	435619,3	584707	165653	392873,5	-210511	157249	261805	763370,5	0,554	465220	46166
27	25			419054			435619				182363				309928	
28				N :	1		alfa :	0,9			alfa :	0,9			Sea.Lengt	12
29				MAD :	167671,8		MAD :	180717			beta :	0,8			alfa :	0,9
30				MSE :	4,53E+10		MSE :	5,03E+10			MAD :	176610,2			gama :	0,1
31				MAPE :	0,248		MAPE :	0,271			MSE :	4,13E+10			MAD :	47656
32											MAPE :	0,282			MSE :	3,24E+09
33															MAPE :	0,063

Figure B.4. The Iteration Results of Sample Run 2 (MSE)


Microsoft Excel - Sample Run 2 - MSE.xls

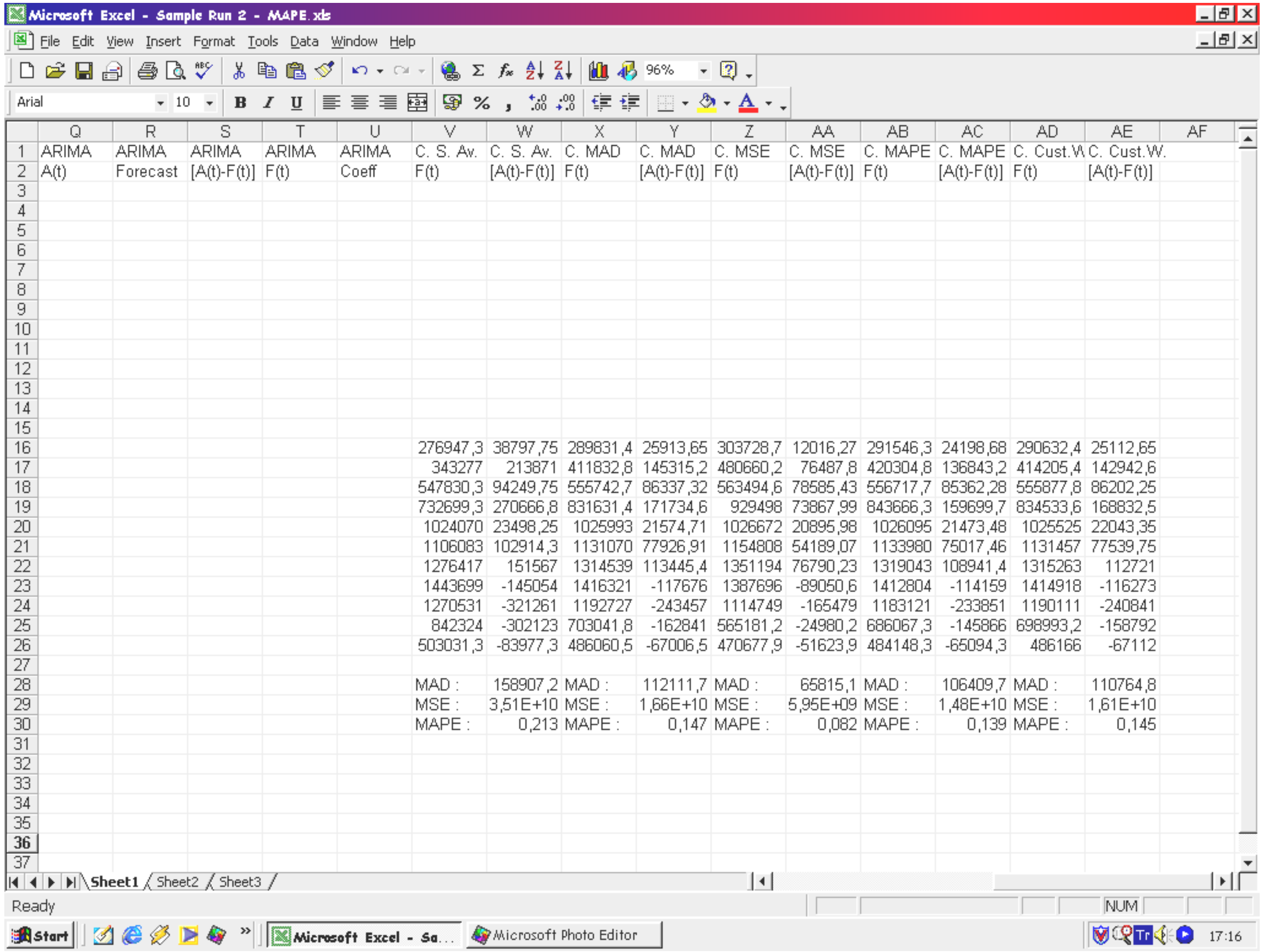
	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
1	ARIMA	ARIMA	ARIMA	ARIMA	ARIMA	C. S. Av.	C. S. Av.	C. MAD	C. MAD	C. MSE	C. MSE	C. MAPE	C. MAPE	C. Cust.W	C. Cust.W.
2	A(t)	Forecast	[A(t)-F(t)]	F(t)	Coeff	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]
16						284966,3	30778,75	302053,3	13691,7	316743	-997,995	304696,5	11048,54	301937,4	13807,65
17						362617,5	194530,5	427246,6	129901,4	485925,6	71222,42	434842,1	122305,9	427186,9	129961,1
18						593270	48810	584675,9	57404,08	578090,4	63989,56	582679,3	59400,7	584794	57286
19						763049,5	240316,5	857556,4	145809,6	944768,5	58597,53	867619,7	135746,3	857670,9	145695,1
20						1068196	-20627,5	1052935	-5367,37	1041230	6337,876	1049430	-1861,55	1053167	-5599,3
21						1114692	94305,5	1137463	71534,45	1159484	49513,31	1139150	69846,7	1137643	71353,7
22						1280941	147043,5	1319794	108189,7	1356286	71697,71	1323416	104567,8	1319900	108084,1
23						1456498	-157853	1424709	-126064	1397300	-98654,6	1419824	-121179	1424892	-126247
24						1242543	-293273	1171042	-221772	1105962	-156692	1162809	-213539	1171124	-221854
25						778265,8	-238065	658207,4	-118006	546854,5	-6653,54	645938,4	-105737	658057,9	-117857
26						436844,3	-17790,3	448561,4	-29507,4	456084,9	-37030,9	452367,3	-33313,3	448194,6	-29140,6
28						MAD :	134853,8	MAD :	93386,2	MAD :	56489,8	MAD :	88958,8	MAD :	93353,1
29						MSE :	2,71E+10	MSE :	1,26E+10	MSE :	5,08E+09	MSE :	1,14E+10	MSE :	1,26E+10
30						MAPE :	0,171	MAPE :	0,116	MAPE :	0,066	MAPE :	0,11	MAPE :	0,115

Figure B.4. (continued)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	# of perioc	24	MA	MA	MA	S. Ex. Sm	S. Ex. Sm	S. Ex. Sm	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(Tr	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S	Ex.Sm.(S .
2	Period	A(t)	MA	F(t)	[A(t)-F(t)]	S(t)	F(t)	[A(t)-F(t)]	S(t)	T(t)	F(t)	[A(t)-F(t)]	S(t)	I(t)	F(t)	[A(t)-F(t)] .
3	1	287178	287178			287178			287178	0				0,404		
4	2	326487	326487	287178	39309	322556,1	287178	39309	322556,1	10613,43	287178	39309		0,459		
5	3	539738	539738	326487	213251	518019,8	322556	217182	519081,2	66386,92	333170	206568		0,759		
6	4	557846	557846	539738	18108	553863,4	518020	39826	560608,2	58928,96	585468	27622		0,784		
7	5	878197	878197	557846	320351	845763,6	553863	324334	852331	128767,1	619537	258660		1,234		
8	6	902258	902258	878197	24061	896608,6	845764	56494	910142	107480,3	981098	78840		1,268		
9	7	1011137	1011137	902258	108879	999684,2	896609	114528	1011786	105729,3	1017622	6485		1,421		
10	8	1155810	1155810	1011137	144673	1140197	999684	156126	1151980	116069	1117515	38295		1,625		
11	9	1118972	1118972	1155810	36838	1121095	1140197	21225	1133880	75818,05	1268049	149077		1,573		
12	10	911022	911022	1118972	207950	932029,3	1121095	210073	940889,6	-4824,41	1209698	298676		1,281		
13	11	453461	453461	911022	457561	501317,8	932029	478568	501721,4	-135128	936065	482604		0,637		
14	12	394972	394972	453461	58489	405606,6	501318	106346	392134,2	-127465	366594	28378	394972	0,555		
15	13	302452	302452	394972	92520	312767,5	405607	103155	298673,7	-117264	264669	37783	677909,3	0,408		
16	14	315745	315745	302452	13293	315447,3	312767	2978	302311,5	-80993,4	181410	134335	685899,9	0,459	311160	4585
17	15	557148	557148	315745	241403	532977,9	315447	241701	523565	9680,65	221318	335830	724424,3	0,76	520598	36550
18	16	642080	642080	557148	84932	631169,8	532978	109102	631196,6	39065,92	533246	108834	800068,5	0,786	567949	74131
19	17	1003366	1003366	642080	361286	966146,4	631170	372196	970055,7	129003,9	670262	333104	810494,1	1,234	987285	16081
20	18	1047568	1047568	1003366	44202	1039426	966146	81422	1052717	115101,2	1099060	51492	823025	1,268	1027707	19861
21	19	1208997	1208997	1047568	161429	1192040	1039426	169571	1204879	126219,4	1167818	41179	845250,7	1,422	1169519	39478
22	20	1427984	1427984	1208997	218987	1404390	1192040	235944	1418295	152378,5	1331099	96885	872057,7	1,626	1373532	54452
23	21	1298645	1298645	1427984	129339	1309219	1404390	105745	1325848	78930,67	1570674	272029	834879,4	1,571	1371747	73102
24	22	949270	949270	1298645	349375	985265	1309219	359949	994820,9	-44056,6	1404779	455509	759806,5	1,278	1069481	120211
25	23	540201	540201	949270	409069	584707,4	985265	445064	581257,3	-154909	950764	410563	830392,7	0,638	483997	56204
26	24	419054	419054	540201	121147	435619,3	584707	165653	419783,5	-156878	426349	7295	770120,3	0,554	460868	41814
27	25			419054			435619				262905				314209	
28				N :	1		alfa :	0,9			alfa :	0,9			Sea.Lengt	12
29				MAD :	167671,8		MAD :	180717			beta :	0,3			alfa :	0,8
30				MSE :	4,53E+10		MSE :	5,03E+10			MAD :	169537,1			gama :	0,1
31				MAPE :	0,248		MAPE :	0,271			MSE :	5,15E+10			MAD :	48770,2
32											MAPE :	0,254			MSE :	3,34E+09
33															MAPE :	0,063
34																
35																
36																
37																

Figure B.5. The Iteration Results of Sample Run 2 (MAPE)



	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
1	ARIMA	ARIMA	ARIMA	ARIMA	ARIMA	C. S. Av.	C. S. Av.	C. MAD	C. MAD	C. MSE	C. MSE	C. MAPE	C. MAPE	C. Cust.W	C. Cust.W.
2	A(t)	Forecast	[A(t)-F(t)]	F(t)	Coeff	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]	F(t)	[A(t)-F(t)]
16						276947,3	38797,75	289831,4	25913,65	303728,7	12016,27	291546,3	24198,68	290632,4	25112,65
17						343277	213871	411832,8	145315,2	480660,2	76487,8	420304,8	136843,2	414205,4	142942,6
18						547830,3	94249,75	555742,7	86337,32	563494,6	78585,43	556717,7	85362,28	555877,8	86202,25
19						732699,3	270666,8	831631,4	171734,6	929498	73867,99	843666,3	159699,7	834533,6	168832,5
20						1024070	23498,25	1025993	21574,71	1026672	20895,98	1026095	21473,48	1025525	22043,35
21						1106083	102914,3	1131070	77926,91	1154808	54189,07	1133980	75017,46	1131457	77539,75
22						1276417	151567	1314539	113445,4	1351194	76790,23	1319043	108941,4	1315263	112721
23						1443699	-145054	1416321	-117676	1387696	-89050,6	1412804	-114159	1414918	-116273
24						1270531	-321261	1192727	-243457	1114749	-165479	1183121	-233851	1190111	-240841
25						842324	-302123	703041,8	-162841	565181,2	-24980,2	686067,3	-145866	698993,2	-158792
26						503031,3	-83977,3	486060,5	-67006,5	470677,9	-51623,9	484148,3	-65094,3	486166	-67112
28						MAD :	158907,2	MAD :	112111,7	MAD :	65815,1	MAD :	106409,7	MAD :	110764,8
29						MSE :	3,51E+10	MSE :	1,66E+10	MSE :	5,95E+09	MSE :	1,48E+10	MSE :	1,61E+10
30						MAPE :	0,213	MAPE :	0,147	MAPE :	0,082	MAPE :	0,139	MAPE :	0,145

Figure B.5. (continued)