3-19-2009

Forecasting USAF JP-8 Fuel Needs

Omer Saglam

FORECASTING USAF JP-8 FUEL NEEDS

THESIS

Ömer Sağlam, First Lieutenant, TuAF

AFIT/GLM/ENS/09-9

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT/GLM/ENS/09-9

FORECASTING USAF JP-8 FUEL NEEDS

THESIS

Presented to the Faculty

Department of Logistics Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics Management

Ömer Sağlam, BS

First Lieutenant, TuAF

March 2009

AFIT/GLM/ENS/09-9

FORECASTING USAF JP-8 FUEL NEEDS

Ömer Sağlam, BS
First Lieutenant, TuAF

Approved:

_________// SIGNED//__________________	19 MARCH 2009
Lt. Col. Bradley E. Anderson (Chairman)	date
_________// SIGNED//__________________	19 MARCH 2009
Dr. Raymond R. Hill	date

AFIT/GLM/ENS/09-9

Abstract

Oil is still one of the strategic energy resources for both the U.S. and the USAF today. Accurate oil prediction is important for the U.S. in order to improve the national strategy and the related budget concerns. Today, the U.S. is roughly importing 58% of its petroleum products. Moreover, in Fiscal Year (FY) 2007 the USAF total energy costs exceeded $6.9 billion. Aviation fuel accounted for approximately 81% of the total AF energy costs. Fluctuations in oil prices have huge impacts on the USAF's JP-8 budgetary calculations. In order to handle this problem, the need for accurate forecasts arises.

In this study, we forecast the USAF's JP-8 consumption and costs for the next five year period. The study shows that JP-8 consumption figures will go on to follow the recent trend via Holt's Linear Method. Also, the study shows that good short-term predictions can be obtained with more simple and easy-to-implement methods, versus complex ones. When we consider long-term forecasts, 5-years in this case, multiple regression outperforms ANN modeling within the specified forecast accuracy measures. Our results indicate that the USAF's JP-8 cost for each of the next 5 years will be somewhere between 6.3 and 7.5 billion dollars.

To Family and Friends!

Acknowledgments

I would like to express my sincere appreciations to my faculty advisor, Lt. Col. Bradley E. Anderson, and Dr. Raymond R. Hill for their guidance and support throughout the course of this thesis effort. The insight and experience was certainly appreciated. Special thanks to my Turkish peers for their continuous support and help during this long journey. Your support and being here with me meant a lot for me! Also, I would like to express my sincere appreciations to those Turkish Citizens who let me have this opportunity for such a valuable education with their tax Lira's. Finally and most importantly, to my family and friends: Thanks for all your support and prayers. Now it's time to come back home safely and payback period to serve for my country begins!

Ömer Sağlam

Table of Contents

Page

List of Figures

Page

List of Tables

Page

FORECASTING USAF JP-8 FUEL NEEDS

I. Introduction

"Oil in the next war will occupy the place of coal in the present war… The only big potential supply that we can get under British control is the Persian and Mesopotamian supply… The control over these oil supplies becomes a first-class British war aim.

Sir Maurice Hankey, British War Cabinet Secretary, 1918

"Developing aircraft indicate that our national defense must be supplemented, if not dominated, by aviation. It is even probable that the supremacy of nations may be determined by the possession of available petroleum and its products."

President Coolidge, 1924

"Keeping America competitive requires affordable energy. And here we have a serious problem: America is addicted to oil, which is often imported from unstable parts of world. The best way to break this addiction is through technology."

President George W. Bush, State of the Union Address, 31 Jan 2006

Background

As emphasized by many of the worldwide well-known leaders through history, the importance of having sufficient energy resources for a country has been critical for decades. Although there have been many improvements for finding new energy resources, oil is still one of the core energy resources in today's global and competitive environment. Moreover, it is still the main cause of disputes between countries worldwide.

The United States (U.S.), by being the world's number one consumer and importer of oil, is also cognizant of the fact that having sufficient volumes of energy resources is absolutely vital for national security, economic improvement, a transportation network, and for sustaining the "super power" role on earth. In order to take precautionary measures for preserving the current position, the U.S. has to forecast its energy needs and costs. At the same time, the world's organic production capability and demand as far as 25 years into the future should be taken into account for having an immediate, aggressive, and effective strategy to become significantly less dependent on foreign oil.

The United States Air Force (USAF) has initiated an Energy Program that supports the creation of a National Energy Strategy. The overarching vision of the AF Energy Program is "Make Energy a Consideration in all We Do". As stated in the Energy Program, a significant percent of the world's petroleum supply is vulnerable to terrorist attack, natural disasters and ongoing political instability. Therefore, the USAF aims to "synchronize and integrate communications to increase awareness and understanding" in order to reduce demand, increase supply and change the organizational culture. The point that should be highlighted for the purposes of this study is the fact that the USAF is committed to reducing aviation and ground fuel demand for the near future. Moreover, alternative fuels usage is being explored (USAF Energy Program Policy Memorandum, 2008).

It seems clear that accurate oil prediction is important for the U.S. in order to improve the national strategy and the related budget concerns. Today, the U.S. is roughly importing 58% of its petroleum products. In Fiscal Year (FY) 2007, USAF total energy costs exceeded $6.9 billion: $1.1 billion for facility energy, $5.6 billion for aviation fuel; and $229 million for ground fuel. Aviation fuel accounted for approximately 81% of total AF energy costs (USAF Energy Program Policy Memorandum, 2008). For that reason, if a $1/barrel increase occurs for the actual expense of fuel, versus the budgeted amount, the USAF's annual bill instantly skyrockets.

Fluctuations of oil prices have huge impacts on USAF's budgetary calculations. Hence, in order to handle the problem the need for decision support tools arises. One of the best systematic approach tools for this kind of a problem is forecasting. Forecasting can help us to take precautionary actions relating to ambiguities that may occur in the future. However, forecasting should not be confused with planning. Forecasting is only concerned with determining what the future value will be, whereas plans are sets of actions to help prepare for and deal with the future. In order to have insight about a future plan, one should first look at and evaluate the current situation. Then we can try to make educated guesses on the future with the appropriate tools provided by the forecasting discipline.

In this study, we forecast the USAF's JP-8 (as a sub product of crude oil) fuel costs and consumption for the near future. This study will help decision makers when they are planning to allocate resources and develop budgets for the future. It will also present the performance of various forecasting model types. The forecasting will involve many factors, such as price, consumption, production, cost, supply and demand issues under different conditions. That is why it will enable us to understand the variables that affect the problem and the related difficulties in obtaining accurate forecasts.

The Problem and the Research Questions

"Who controls the food supply controls the people; who controls the energy can control whole continents; who controls money can control the world".

Henry Kissinger

The U.S. Air Force spends vast amounts of money on fuel. In Fiscal Year 2007 (FY-07) the Defense Energy Support Center (DESC) purchased 5.87 billion dollars worth of Jet Propellant-8 (JP-8) and Jet Propellant Thermally Stable (JPTS) (DESC Fact Book, 2007: 19). In the presence of such a huge expense, a ten cent per gallon price increase for oil will most assuredly have deep impacts on the overall budgetary concerns.

That's why, under the current rising trend for oil demand and the high fuel costs, both the Department of Defense (DoD) leaders and the government lawmakers should pay special attention to increases in funding for the USAF fuel budget. Certainly, they should concentrate on finding better and, more importantly, efficient ways for spending the American tax payer's money. At this point, the need for more accurate JP-8 forecasting emerges. The USAF must have accurate predictions for JP-8, as a sub-product of crude oil, in order to assess the energy resources needed and their costs.

This thesis attempts to analyze and make comparisons between some of the well-known forecasting models of Multiple Regression Analysis, Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Average (ARIMA), based on historical JP-8 related data. The main aim is enlightening the readers/decision makers with insight on USAF JP-8 fuel costs and needs for the next 5-year period. Here, the overall question of the study is:

- How much will the USAF need to budget in the future to cover needs and rising fuel prices and what can be done to mitigate these rising costs?

Methodology

To answer the overall research question, many things are considered and analyzed. First of all, it is important to clarify the appropriate factors that exert influence over jet fuel prices. Then, choosing the appropriate method and the components of the problem is carefully examined. The following research sub-questions are addressed, which will help during the study to find the answer for the established overall research question:

- What will USAF JP-8 demand be in the future?
- What factors affect the price of JP-8 fuel?
- What will the projected cost of JP-8 be in the future?
- What can be done to reduce JP-8 consumption in the future?
- What JP-8 alternative fuels will exist in the future and how much might be available?

The study aims at gaining insight about the supply, demand, and the related cost of JP-8 for the next 5-year period. First, USAF's JP-8 demand is explored. Then we'll try to look at the factors that may affect the cost of JP-8, and at the same time we'll try to forecast the future cost of JP-8. Methods for reducing JP-8 consumption are investigated and finally, we'll look at whether there are any alternative JP-8 fuels that can be manufactured in sufficient volumes. The forecasting projections will give clues to the need for the more efficient and effective use of resources. Hopefully, they will also help us to identify the necessary actions for DoD/USAF leadership in order to allocate the resources more accurately. From a broader view, this will help to improve decisions for lessening energy dependency.

Assumptions

Undoubtedly, one of the most important steps in the problem solving process is establishing the assumptions that are related to the problem. It is impossible to find the exact solution for a problem that has many different variables and also many aspects without identifying the necessary assumptions concerned with it. Forecasting, by being a complicated problem solving process, also needs some assumptions that should be considered by the researcher during the study.

The appetite for oil and other energy sources is growing rapidly. Each year the people of the industrialized world go on to drive their cars more and also are equipped with an increasing array of energy demanding appliances. Hence, the rise of energy demand from economic output and improved standards of living put more pressure on energy supplies. In this study we will assume that emerging technologies will serve to augment petroleum and will not lead to significant decreases/increases in oil consumption. Secondly, it is assumed that the data gathered from the data providers are reliable and accurate. For the third assumption, current conditions of the political environment worldwide are assumed to be the same as today, and there won’t be any big conflicts and/or devastating wars which can affect the entire supply and demand of oil in the near future. Fourth, the JP-8 demand for the USAF is assumed to follow the current trend and there won’t be any major acquisitions of new weapon system or any big operations changes in the short term. Finally, some inherent assumptions of the models used are taken as they are currently implicit in the model.

Scope and Limitations

The scope of this thesis is limited to forecasting JP-8 costs and needs. Although, many factors are used to construct a forecast, factors other than the demand and cost of JP-8 are not forecasted where reasonable forecasts exist. This may include prices for substitutes, production quantities, oil products, and the economy.

Implications

Effective and efficient management relies heavily on decision making. In order to make sound decisions, a wise manager should apply the appropriate decision support tool as an aid. Strategic decision making involves "doing the right things" instead of "doing things right". Hence, DoD/USAF leadership should not only carefully examine the current conditions, identify the needs, and allocate the resources properly, but also try to achieve more accurate forecasting projections for the future.

For that reason, this analysis is aimed at providing basic insight to decision makers for the USAF's short-term JP-8 cost, needs. Also, methods for constructing the best model, which may enable more reliable decision making in a complex, and competitive environment, is explored.

II. Literature Review

Overview

The purpose of this section is to develop an understanding for the importance of JP-8 and future JP-8 cost forecasting for the USAF. We begin with a brief summary of the history of oil and then provide an explanation about the importance of oil and JP-8 for the U.S. in today's globally competitive environment. The study continues by introducing the need for forecasting and some well-known forecasting methods. Finally, we conclude with a brief summary of the findings and the gaps from some previously done research.

The Emergence of Oil for the United States through History

Crude oil is identified as: *'A mixture of hydrocarbons that exists in liquid phase in natural underground reservoirs and remains liquid at atmospheric pressure after passing through surface separating facilities. Crude oil is refined to produce a wide array of petroleum products, including heating oils; gasoline, diesel and jet fuels; lubricants; asphalt; ethane, propane, and butane; and many other products used for their energy or chemical content'* (Energy Information Administration Glossary, 2008). Jet fuel is: *'Kerosene-type; high-quality kerosene product used primarily as fuel for commercial turbojet and turboprop aircraft engines'* (New York Mercantile Exchange Glossary, 2008).

JP-8 is essentially commercial kerosene Jet A/ Jet A-1 fuel with three military specified additives: a corrosion inhibitor/lubricity improver, an anti-static additive, and a fuel system icing inhibitor. JP-8 replaced JP-4 in general AF use in the 1980's, primarily to reduce the risk of fire encountered with the low-flash-point of JP-4 (Edwards and others, 2001: 1).

"Two hundred million years ago the foundations of modern civilization were laid. Not only was it the evolution of man that gave us our world as we know today, but also the life, death, and decay of nondescript vegetation, creatures, and microbes that would eventually become the 2 trillion barrels of crude oil man discovered and harnessed to write his modern history" (Hornitschek, 2007: 5).

"Petroleum derivatives have been exploited since the emergence of human civilization, particularly in ancient Mesopotamia and elsewhere in the Middle East. At that time the primitive oil industry supplied asphalt for building roads, mastic for waterproofing ships and architecture, as well as essential components for many medicines and treatments. However, paradoxically, after having been widely used in ancient times its eventual applications throughout the centuries were marginal and mainly confined to those places where oil was easily available through surface seepage"(Maugeri, 2006: 3).

As the world became more industrialized in the past century, the prominence of oil has moved from a basic need for a cheaper and more flexible source of illumination to an important energy resource. In the mid-1850s parallel experiments by chemists were undertaken in Europe and the U.S. to refine oil for obtaining an illuminating oil fuel. In 1854, Abraham Gesner patented a new oil product in the U.S., called kerosene, for "illuminating or other purposes which was safer, cheaper and better than any existing illuminant. Hence, its use spread in Western Pennsylvania and New York City", while whale oil was preferred by the wealthy people and caused over-whaling in the Atlantic (Maugeri 2006: 3).

As time went on through history, demand for oil rose. People attempted to procure additional supplies from far away countries, like South Africa, which increased oil prices. Yet, producing petroleum in sufficient volumes still became an issue.

All the extraction techniques previously applied were involved in the collection of surface crude seepage with primitive instruments. A great revolution occurred in Pennsylvania in 1859 when Edwin Drake (who was also founder of the barrel as the quantity for measuring oil) first succeeded in extracting oil from its rocky underground prison with a drilling machine. Drake's experiment was considered the birth of the oil industry. In 1861 the first oil refinery showed up and the first cargo of oil exported from the U.S. sailed for London from Philadelphia with the oil loaded in barrels (Maugeri, 2006: 4).

In 1860, the price of oil was about ten cents per barrel. In 1861 it skyrocketed to ten dollars and in 1862 the price fluctuated between 10 cents and $2.25 per barrel, averaging $1.5 per barrel. The average price of a barrel of oil at the wellhead was $3.5 in 1863, $8 in 1864, $4 in 1866, $2.8 in 1867, $5.8 in 1869, $4.2 in 1871, and less than $2 in 1873. "The arithmetic average, however, hides dramatic ups and downs within each single year that gave the U.S. Oil Market a rollercoaster shape during its formative years. Paradoxically, the cost of the wooden barrel itself fluctuated between $2.50 and $3.50 which far exceeded the value of its contents for some time" (Maugeri, 2006: 5-6).

In the beginning of the 1900s, the U.S. started "to show the striking sign" of the shift from a business society to an industrial power. Global oil production had reached nearly 430,000 barrels per day (bpd), with Russia providing around 200,000 bpd and the U.S. delivering around 165,000 bpd. However, five years later, the U.S. had dramatically jumped ahead of Russia, reaching 370,000 bpd (Maugeri, 2006: 13).

During World War I petroleum products emerged as the leading fuels for moving people, armies, airplanes and naval fleets throughout the world. "It soon became clear that both the wealth of modern economies and mechanized war based on mass mobilization could be sustained only with access to ample sources of oil" (Maugeri, 2006: 24).

Between 1948 and 1970 even the U.S., the most "tapped" region in the world, registered almost a doubling of oil production. But "the superstar of the era" was to be Persian Gulf petroleum, with its unrivalled low cost. In the same period, the average production costs in the Middle East declined from about 20 cents per barrel in 1948 to around 11 cents in 1970, versus more than one dollar in Venezuela or nearly $1.30 in Texas (1970). Global proven oil reserves jumped from nearly 70 billion barrels in 1948 to 667 billion barrels in 1973, "extending their life-index" from 20.5 to 32.7 years. More than half of this quantity, or 355 billion barrels, was concentrated in the Middle East. In 1956, because of the cheaper oil prices, the American oil industry as a whole invested more abroad than domestically for the first time (Maugeri, 2006: 80-83).

The crude oil future prices had been extremely volatile since the first oil price shock in 1973 when the price almost quadrupled, rising from $3.40 to $12 per barrel. The collapse of the pro-American Iranian regime in 1979 and the beginning of the Iraq-Iran

War in 1981 both contributed to the more than doubling of oil prices as they reached $35 per barrel. In 1985 when the world's largest producer, Saudi Arabia, "abandoned its role as the swing producer in Organization of the Petroleum Exporting Countries (OPEC) and increased its production from 2 million barrels/day (mbd) to 5 mbd, oil prices plummeted below $10". Despite some movements, the price remained weak until 1999 before rising again in the early years of the new century (Moshiri and Foroutan, 2006: 83). In 2008, according to the analysts, oil prices reached record highs because of many different factors such as: rising demand, low stocks, OPEC strategy, action of speculators, violence in the Middle East, and political tension. In the beginning of 2009, because of the ongoing global economical crisis and the related turmoil in the economical markets, the price of oil plummeted below $50/barrel.

Understanding the Problem and Its Importance for the USAF

From the time that oil was first drilled and began to be used, we all have been hearing the speeches of worldwide leaders mentioning the necessity of having enough oil for continuous improvement. In today's global, competitive, and complex economical environment, the energy sources and their importance for global economies are undoubtedly more vital than ever before.

"Oil is a strategic commodity to the U.S. and its free flow represents a vital national interest, as oil is the lifeblood necessary for America's economic survival. The United States' homeland, industry, markets, military, and its extensive transportation networks demand and depend on the uninterrupted flow of oil" (Walsh, 2007: 1) . Even today, the U.S. still stands as the world's largest consumer of oil, using approximately 869 million gallons annually or 20.7 million barrels of petroleum products per day as shown in Table 1 below:

Table 1 - Top World Oil Consumers 2006 (Thousand barrels per day)

Rank	Country	Consumption
1	United States	20,687
2	China	7,201
3	Japan	5,198
4	Russia	2,811
5	Germany	2,692

Source: Energy Information Administration

The U.S. also imports approximately 12.36 million barrels of oil per day from foreign sources equating to 60% of its total daily requirements (see Table 2). Nearly half of the crude oil is imported from OPEC countries as seen in Table 3.

Table 2- Top World Oil Net Importers 2006 (Thousand barrels per day)

Rank	Country	Imports
1	United States	12,357
2	Japan	5,069
3	China	3,356
4	Germany	2,540
5	Korea, South	2,162

Source: Energy Information Administration

Table 3-U.S. Total Crude Oil and Products Import by Origin (Annual-thousand barrels)

Origin	2002	2003	2004	2005	2006	2007
All Countries	4,208,538	4,476,501	4,811,104	5,005,541	5,003,082	4,915,957
Persian Gulf	828,226	912,749	912,447	851,855	807,172	789,607
OPEC	1,680,889	1,884,084	2,086,462	2,039,288	2,013,603	2,182,607
Non-OPEC	2,527,649	2,592,417	2,724,642	2,966,253	2,989,479	2,733,350

Source: Energy Information Administration

Foreign oil dependency "leaves the American lifestyle, its freedoms, and its economy extremely vulnerable to risk and exposed to factors outside the United States' immediate control" (Walsh, 2007: 1). Foreign political or military action, acts of terrorism abroad, or the world's growing and competing demands for oil supplies are factors that could affect America's energy security. More than that, "acts of terrorism on American soil directed at its vast petroleum distribution infrastructure could have a devastating impact on transportation and industry, bringing the nation and economy to a virtual stand still". The United States' dependence on foreign oil is a significant security threat facing the nation (Lopez, 2007).

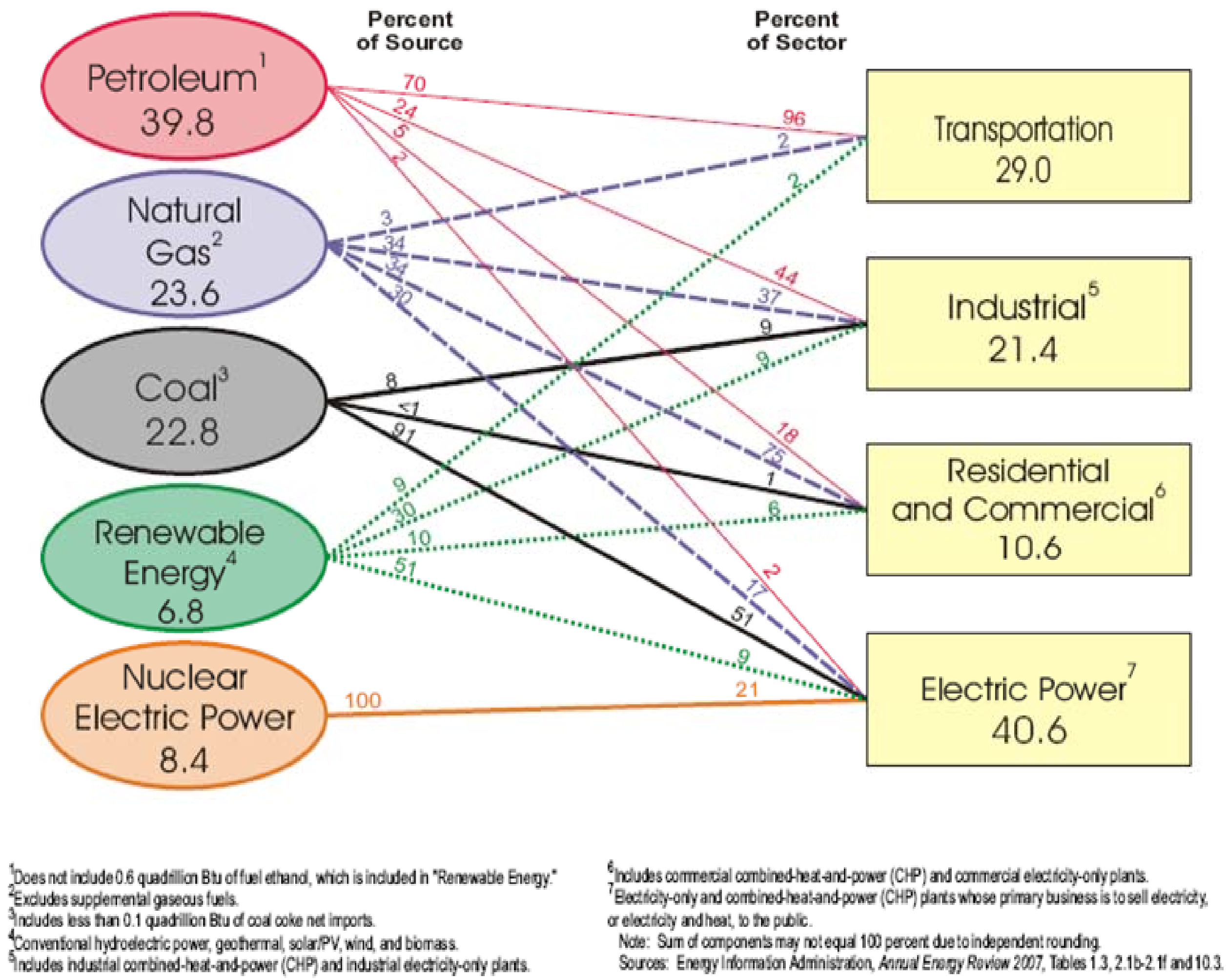


Figure 1- U.S. Primary Energy Consumption by Source and Sector (Quadrillion Btu)
Source: Energy Information Administration

Energy, more specifically oil, is not merely important for the security of the U.S. It is also important for sustainable economical growth and preserving the global power role of the country. The transportation and industry sectors are the two indisputable locomotive factors of U.S.'s sustainable economical growth. Notice that petroleum accounts for 96% of the transportation sector's and 44% of industrial sector's energy need, as it is shown in Figure 1.

The Department of Defense (DoD) is one of the largest single institutional energy customers and uses approximately 1.8% of the 20 million barrels of crude oil consumed each day in the U.S. (Lovins and others, 2005). The cost of jet fuel is one of the largest single expenses in the USAF budget. For relatively low-maintenance aircraft, such as transports, fuel cost is often the largest fraction of an aircraft's operations and support cost, which are typically 60% of an aircraft's life cycle cost (Edwards and others, 2001: 1). Within the Federal Government, the USAF is the single largest user of aviation fuel, using an estimated 2.3 billion gallons per year. Whenever the price of oil goes up $1 per barrel, it costs an additional $55 million for fuel.

In the presence of high fuel expenses and the current demand figures, DoD and the USAF leadership should focus on being 'scientific' in their decision making process for the future. The need for being scientific is most assuredly rooted in many reasons ranging from efficient use of taxpayer's money to more accurate budget planning. Thus, in this study the need for forecasting in managerial decisions is investigated. Specifically, the area of concern is the USAF JP-8 fuel needs, costs and the related budgetary issues in the presence of currently relatively stable JP-8 demand, parallel to the high fuel costs.

What Can Affect Jet Fuel Prices?

In her study Kasprzak claims that: "both heating oil and jet fuel can be categorized as light distillates and are formed by the same chemical process called hydro-cracking. Because of the substitution relationship between the distillates, if the production of one distillate is increased, the production of the other is decreased by the same amount". When there is a higher demand than normal due to severe weather conditions in winter, refineries operating at maximum capacity can not satisfy the demand because of the substitution effect. The seasonality ends up with an increase for both the heating oil and the jet fuel prices" (Kasprzak, 1995: 4).

According to Kasprzak there are many variables that can affect jet fuel prices. One of them is the "Iron Law" of energy and economic growth. It suggests that, there is an "inevitably and inescapably close relationship between economic growth rates and the growth rates for energy and oil use". She claims that there is a positive correlation between the economic growth and oil demand, as in the China case. Moreover, according to her, oil analysts suggest that jet fuel prices have a relationship with past jet fuel prices, crude oil prices, heating oil prices, gasoline prices, the current demand and supply of heating oil, political events, weather, and natural disasters (Kasprzak, 1995: 4-5).

We utilize the ideas of Kasprzak on her findings of what factors can affect the JP-8 prices. More broadly, one can try to introduce economical indicators such as Gross Domestic Product (GDP), or some demographic factors, such as population growth, into the modeling process. Also, we can consider alternative fuels such as biofuels. However, finding the related historical data to these factors may become a roadblock in our modeling process.

Hubbert's Peak

Hubbert's Peak is another major concern for oil related forecasts. The main idea behind the theory is applicable to all types of finite resources. The theory dates back to

1950s. In 1956 the geologist M. King Hubbert predicted that U.S. oil production would peak in the early 1970's. He made this announcement during a meeting of the American Petroleum Institute (API) in San Antonio. Five minutes before beginning his talk, the Shell Oil head office was on the phone asking Hubbert to withdraw his prediction (unsuccessfully). Since then, almost everyone inside and outside the oil industry rejected Hubbert's analysis. The controversy raged until 1970, when the U.S. production of crude oil started to fall. Hubbert was right in his theory (Deffeyes, 2000).

Hubbert's Theory is that oil is a finite resource, and as such its depletion is subjected to basic laws. These simple statements were described in the 1950's by Dr. Hubbert, and apply to any relevant system including the depletion of the world's petroleum resources (www.hubbertpeak.com, accessed in 2009):

- Production starts at zero.
- Production rises to a peak.
- After production passes that peak, it declines until the resource is depleted.

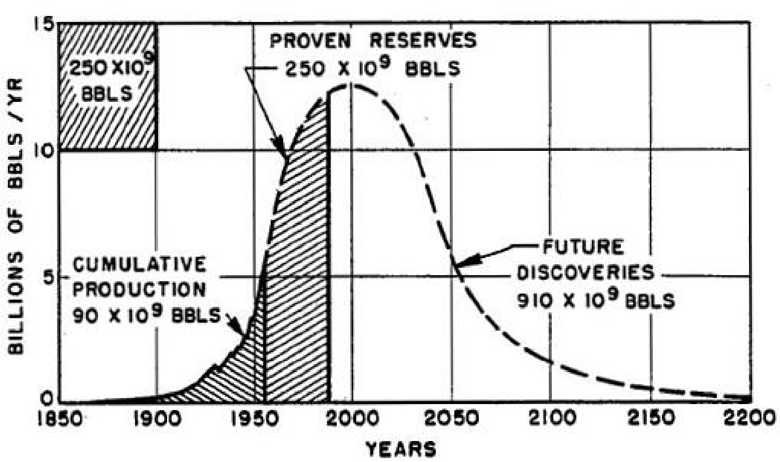


Figure 2- Ultimate World Crude Oil Production Based Upon Initial Reserves of 1250 Billion Barrels

Source: Hubbert, 1956.

The basic idea, according to Hubbert, is that this behavior can be expressed as a bell shaped curve which describes oil production over time, in this case years. The area under the curve represents the cumulative production of oil removed from the ground (called "ultimate"). Hubbert's method consists basically in fitting a bell shaped curve whose area represents the total oil reserves to be found under the earth's crust.

Hubbert also proposed that oil production was symmetric. The point of maximum production tends to coincide with the midpoint of depletion. Thus, peak production can be identified if one knows the total ultimate reserves located under the earth.

During the 1990's industry analysts began to apply his method to estimate world oil production peak (see Figure 3), which based on the previous analysis was supposed to peak between 2004 and 2008 (Deffeyes, 2000). Most recent studies, however, show that a peak will now take place sometime in the future. For example, the USGS studies show that this peak will occur some when between 2021 and 2112 (Wood, 2004). As of today almost all industry analysts accept that a peak in oil production will occur at some point, but at this time there is no firm date. Current studies focus on trying to use the Hubbert model and to accurately predict when this peak will occur.

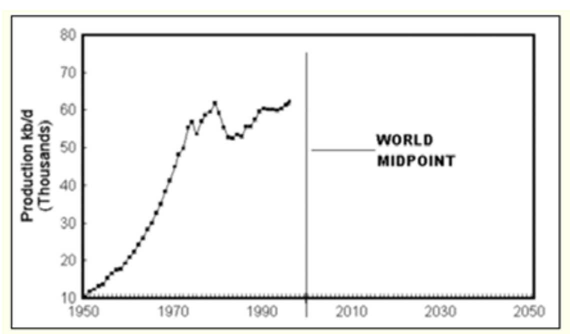


Figure 3- World Oil Production to Date

Source: www.hubbertpeak.com, accessed in 2009.

* Vertical line in Figure 3 indicates the probable midpoint of depletion by Campbell and others, 1997

If we knew the ultimate for oil production, we would be able to tell when we had reached the midpoint of oil production when the cumulative production had reached half of the ultimate. However, the biggest problem is that no one is certain about the size of the ultimate. Most studies propose a simple estimator:

Ultimate = Cumulative Production + Reserves + Undiscovered

Estimating ultimate is almost as difficult as estimating when Hubbert's peak will occur. The problem is that none of the three components are readily available. Cumulative production is the most available resource, but still there are some "gaps" in the production data due to lack of reporting by some countries and also lack of data for the time during World War I and II. Reserves reports tend to be biased, since they represent a large portion of the negotiation power for oil producing countries. Undiscovered oil that will be recovered is almost impossible to address and depends on a lot of factors other than market forces, like technology, alternative sources of energy, etc.

Hubbert proposed that the curve is bell shaped with a rounded top and tails on both ends. He also proposed that the declining side of the curve is a mirror image of the initial increase. However, there are some studies that show that this is not always the real case. In fact, some cases show that linear and exponential curves have a better fit than the bell shaped curves like Lorentz, Gaussian or Logistic.

The values or reserves reported by oil production nations may or may not represent reality. While these estimates are generally accepted without discussion, there is a chance that they may be artificially inflated (Greene and others, 2003). Since reserves confer bargaining power in negotiating production quotas within oil producing organizations, members have an incentive to inflate their reported reserve estimates to gain better bargaining positions. Campbell has estimated the overstatement of world reported reserves at about 360 billion barrels (35%). Several examples of possible bias in this data are:

- Iraq announced an increased reserved from 29.7 Gb to 41.0 Gb from 1982 to 1983.
- Kuwait from 63.9 Gb in 1984 to 90.0 Gb in 1985.
- In 1988, increases of more than 100% in reserves.

In summary, Hubbert's Peak is a major concern that we should take into consideration in oil related forecasts. However, we should be aware of the fact that, with the politically motivated alteration of data, the final numbers are difficult to estimate (www.hubbertpeak.com, accessed in 2009).

What is Forecasting?

"Those who fail to study the past are condemned to repeat it"

Famous Philosopher George Santayana, 1905

"Frequently there is a time lag between awareness of an impending event or need and occurrence of that event. This lead time is the main reason for planning. If the lead time is zero or very small, there is no need for planning. If it is long and the outcomes of the final event are conditional upon identifiable factors, planning can perform an important role" (Makridakis and Wheelwright, 1978: 4).

The need for forecasting is simple. It will help management to achieve better and more efficient planning as they attempt to decrease dependence on chance and try to become more scientific in dealing with the surrounding environment. Some of the well-known areas which forecasting plays a significant role for short, medium, and long-terms are: scheduling existing resources, acquiring additional resources, and determining what resources are desired. However, it can be stated that despite the need for better forecasting accuracy and the related benefits, there is no one model that can be adaptable to different circumstances.

What are the Descriptions for Short Term and Long Term Forecasting?

According to Xenakis (2008), "short-term forecasting can be defined as what everybody uses. In order to use it, one should examine the recent previous trends and extrapolate them forward from the present time into the future to make a forecast. Most of the time, it works well for growth trends, but not for chaotic trends like weather and politics" (Xenakis, 2008). For example, suppose that during a heat wave in Istanbul, the outside temperature increases everyday for 2 weeks. However, if one extrapolates the recent trend forward and forecasts that the temperature will continue to increase in December and January, obviously the forecast will fail.

Figure 4 below shows an increase in the period just before "today". In short term forecasting, the increasing amount is extrapolated forward, and the value is predicted to continue increasing.

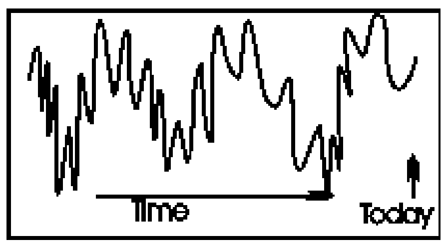


Figure 4- Short-Term Forecast Trend Line

In the short-term "forecasting can benefit by extrapolating the inertia that exists in economic and business phenomena. As changes in established patterns are not likely over a short time span, extrapolating them provides us, most often, with accurate and reliable forecasts. Empirical findings show that seasonality can be predicted accurately and reliably in the majority of the changes in a short forecasting horizon. Moreover, the uncertainty of our predictions can be estimated reliably in terms of prediction intervals around the most likely prediction(s)" (Makridakis and others, 1997: 553). Remember that although few things may happen that can change the existing patterns and relations in the short-term, unexpected events such as a war or an earthquake may occur and those can dramatically affect all the existing patterns with a result to invalidating forecasts.

“A long term forecast uses a different technique and one that is rarely used by analysts. The technique is to examine previous trends far into the past to establish long-term cycles and patterns and extrapolate them into long-term trends in the future. To make short-term forecasts, current trends should be matched to the long-term trends” (Xenakis, 2008).

Figure 5 below shows the same graph as the preceding one, except that a long-term trend line is added. Following the long-term trend line allows us to forecast that the value will fall, despite the recent increase.

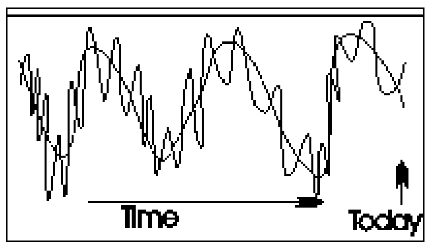


Figure 5- Long-Term Forecast Trend Line

Long-term forecasts are generally used for capital extension plans, selecting Research and Development (R&D) projects, launching new products, formulating long-term goal and strategies and deciding the best way of adapting organizations to environmental changes. They are based on the extrapolation of mega trends and analogies. “The farther away the time horizon of our predictions, the lesser the accuracy of our forecasts, since many things can happen to change established patterns and relationships. The purpose of forecasting in such cases is to build scenarios that provide general directions for the decision makers” (Makridakis and others, 1997: 558). It helps organizations to anticipate forthcoming major changes and prepare them to adapt to such changes in a proactive way. Long-term forecasts need a significant amount of data in order to draw any conclusions about the long-term trend. According to Makridakis et. al. long-wave cycles that are often observed in economic data series can last for more than 60 years (Makridakis and others, 1997: 454).

Why Do We Need Forecasts?

Forecasting is an important aid for effective and efficient planning. It is an integral part of the decision-making activities of management. When an organization establishes goals and objectives it seeks to predict environmental factors and then selects actions that will hopefully result in attainment of the goals and objectives. “The need for forecasting is increasing as management attempts to decrease its dependence on chance and becomes more scientific in dealing with its environment”. More specifically, forecasting plays significant roles about scheduling existing resources, acquiring additional resources and determining what resources are needed (Makridakis and Wheelwright, 1978: 4).

The U.S. Government Accountability Office (GAO) highlights the importance of better fuel pricing practices to improve budget accuracy. In its report of April 2007, the GAO highlighted the problem produced by inaccurate fuel predictions and their consequences in the official budget system. The report indicates that the DoD identified and evaluated alternative crude oil forecasts by other federal departments and forecasts from 38 private organizations in an effort to forecast more accurately (GAO Report, 2007).

Fluctuations in crude oil prices could bring about economic instability in both oil exporting and oil consuming countries in developed and developing parts of the world. That's why oil price forecasting is vital to economic agents and policy makers "in order to mitigate the macroeconomic impacts on aggregate output, prices and employment for the countries worldwide" (Moshiri and Foroutan, 2006: 82).

Up until now, there have been many efforts to develop models for explaining the changes in crude oil prices and forecasting them accurately in spot and exchange markets. These models can be grouped into three categories; structural, linear, and nonlinear time series models. Structural models have been able to provide fairly reasonable explanations of the factors underlying movements in demand and supply, but they have not usually been successful in forecasting oil prices (Pindyck, 1999). Another researcher, Gately (1995), shows that model parameters play a significant role on the projection of oil prices in a structural model. Linear and non-linear time series models have been able to produce more accurate forecasts. However if the underlying data generating process of oil prices is non-linear and chaotic, they are also not ideal (Moshiri and Foroutan, 2006: 82).

Clemen et al (1995) state that in a given forecasting situation, we might consider a variety of forecasting methods. Because we want to choose a single method, "casting a wide net will help us wind up with good forecasts". Alternatively, looking at multiple forecasting methods opens the possibility of generating forecasts from two or more methods and then combining these forecasts. "The appropriate forecast evaluation methodology will depend on whether one must choose a single forecast or may combine multiple forecasts. In the choosing scenario, one can evaluate each method individually and then compare methods. On the other hand, in the combining scenario one must evaluate the methods simultaneously in order to consider interrelationships among the methods, as well as their individual performance" (Clemen and others, 1995).

In order to make sound decisions in the future for the demand and cost of JP-8, professional managers should focus on having the appropriate type of forecasts which can be called decision support tools. Therefore, from a macro perspective for the U.S., future oil forecasts can be clearly stated as an important decision support tool to overcome the current energy dependency on foreign oil.

Brief Analysis of Some Well-Known Forecasting Models

There are different types of forecasting models in the literature from relatively simple to the highly complex for different forecasting horizons. For instance, moving averages is a simple method to forecast the next period. This procedure is called as 'moving average' because "as each new observation becomes available, a new average is computed by dropping the oldest observation and including a new one". The average in this method includes the most recent observations. Moving averages deal with the latest k periods of known data and the number of data points in each average doesn't change as we go further in time. One of the main drawbacks of using moving averages as a forecast tool would be the fact that "they cannot handle trend and seasonality well enough, although they can do better than the total mean". But, they can produce surprisingly good results for short-term forecasting horizons (Makridakis and others, 1997: 89-94).

An extension of the moving average methods can be identified as exponential smoothing methods. They're called 'exponential methods' because of the fact that, these methods use exponentially decreasing weights as the observations get older. For all exponential smoothing methods the recent values are given relatively more weight in forecasting than the older observations. The smoothing parameter(s) in these methods should be determined explicitly, which has an effect on the forecasts. Some of the well-known exponential smoothing methods are simple exponential smoothing, Holt's Linear Method, and the Holt-Winter's method (Makridakis and others, 1997: 136).

The major advantages of smoothing methods are their simplicity and low cost. We are aware of the fact that better forecasting accuracies may be obtained via more sophisticated and highly complex models in some cases. However, when we need forecasts for a large number of items in a relatively short-time, smoothing methods are often one of the valid methods that can be applied for a rapid response in support of decision making processes.

"Models are only simplifications of the real world, and these simplifications are necessary because otherwise they would be as complex and unwieldy as the natural setting itself" (Michalewicz and Fogel, 2004). Many complex, often intractable models have been created to predict oil prices and its derivatives, Artificial Neural Networks (ANN) (Kasprzak, 1995), econometric forecasting, intertemporal optimization (Powell, 1990; Gately, 1995), behavior simulation, and multiple regression models (Salaverry, 2007) have shown very good results when used to forecast jet fuel prices in the U.S. and Argentinean market.

Econometric Forecasting:

Econometric forecasting is perhaps one of the earliest methods developed to forecast the price of oil and its derivatives. The technique involves the application of statistical and mathematical models "to construct a cause and effect map" that helps to predict the analyzed dependent variable. The necessity to find causality forces analysts to choose from a large variety of variables which affect the model's complexity and the number of required equations to predict results. "It is important to recall that statistics techniques capture correlation, not causation. Correlation is only one of the elements required to establish a cause and effect relationship between two variables, showing that precedence exists and removing all the other alternative explanations are also necessary conditions" (Leedy and Ormrod, 2005: 181-182).

As Moshuri and Foroutan stated, oil price movements are very complicated and, therefore, hard to predict. Thus, one of the main challenges facing econometric models is to forecast such "seemingly unpredictable" economic series. (Moshiri and Foroutan, 2006: 81). Supporting Moshuri and Foroutan, Burke states that "there is no single rule to build the model". "Models representing the same phenomenon vary in their forms, involve different variables, and are composed of a varied number of equations. Econometric forecasting has proved to be effective in samples but not to extrapolate out of them" (Burke, 2005: 14).

Intertemporal Optimization:

Intertemporal optimization took place in the theoretical literature but wasn't applied much for practical purposes. Powell (1990) and Gately (1995) state that the application of intertemporal optimization to forecast oil prices is based on three assumptions in relation to the owner of oil: perfect knowledge, perfect foresight, and maximum return on investment as a goal. "The theory behind the model offers a rational explanation of the actors in the model, but its unrealistic assumptions have made it difficult to be applicable for solving the real world problems" (Powell, 1990; Gately, 1995). Hence this model is not investigated in detail.

Behavioral Simulation:

Another well-known model is behavior simulation. It is a dynamic model that has been developed for "incorporating system dynamics and the bounded rationality school of thought". Its dynamism permits the model to encircle the uncertainty of the market, which is useful to show the market changes over time. The *U.S. National Energy Modeling System (NEMS)* has designed a behavioral simulation model to represent the important interactions of supply and demand in the U.S. energy markets. The description of the system establishes that "NEMS represents the market behavior of the producers and consumers of energy at a level of detail that is useful for analyzing the implications of technological improvements and policy initiatives" (Salaverry, 2007: 19). NEMS is composed of several modules, one of which is used to predict the price of oil derivatives.

The U.S. Energy Information Administration (EIA) has developed the *Short-Term Integrated Forecasting System (STIFS)* as a part of its integrating module of the National Energy Modeling System. STIFS permits the U.S. government to generate short-term (up to eight quarters) monthly forecasts of U.S. supplies, demands, imports, stocks, and prices of various forms of energy. The model contains more than 300 equations, of which over 100 are estimated. The estimated equations are linear regression equations interrelated to provide a system of forecasting equations. Estimation techniques are generally done on a one by one equation basis using the least squares method (Salaverry, 2007: 19).

Multiple Regression Model:

In statistics, the general purpose of multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent criterion variable. Simple regression is a special case of multiple regression. "In multiple regression there is one variable to be predicted, but there are two or more explanatory variables" (Makridakis and others, 1997).

Multiple regression models allow analysts to include both qualitative and the quantitative variables in their model (McClave and others, 2005). This is an important aspect for the researchers who are planning to conduct analyses with qualitative variables.

The general form of a linear multiple regression model can be written as:

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + ... + \beta_k x_{k,i} + \varepsilon_i$$

where y represents the dependent variable (in our case USAF JP-8 cost), i=1,…,n represent subjects, β_0, …, β_k are the regression coefficients, x_1, …, x_k symbolize the independent variables or predictors, and ε is an error term that captures the effects of all omitted variables.

The β coefficients in the formula are indicators of each independent variable's contribution to the model. There are many ways to find the value of these coefficients, but the most common method is ordinary least squares (OLS). The best fit in the least-squares sense is that instance of the model for which sum of squared errors has its least value, an error being the difference between the observed value and the value given by the model. This can be expressed mathematically as:

$$SSE = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 \text{ where } \varepsilon_i = y_i - \hat{y}_i \text{ and } \hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{1,i} + \hat{\beta}_2 x_{2,i} + \ldots + \hat{\beta}_k x_{k,i}$$

At this point it is important to mention that the application of OLS is subject to the following basic assumptions and one should check for all these assumptions in the model building process.

Model Form

The assumption here refers to the form of the relationship between the forecast variable and the explanatory variables. "If the assumed form is incorrect, then the forecasts may be inaccurate and the F-test, t-tests, and confidence intervals are not strictly valid any longer" (Makridakis and others, 1997: 260).

Independence

This assumption is strictly tied to the validity of t-tests, and F-tests. Here, Ordinary Least Squares (OLS) assumes that the random errors are independent in the probabilistic view that there shouldn't be a correlation or association between the residuals. It is difficult to test this assumption, however if the data can be gathered at equal time intervals, Durbin-Watson test or Runs tests may be reasonable to apply for checking this assumption. If data is not equally spaced in time, the researcher should analyze the scatter plots of residuals in great detail to investigate any trends, patterns, or anomalies (Salaverry, 2007: 27).

Constant Variance (Homoscedasticity)

The regression model assumes that all the residuals have the same population variance. The best way to check this assumption requires a descriptive plot (response versus residual) and the Breusch-Pagan Test. When this assumption is violated, often times the best way to overcome this problem is applying mathematical transformations. Also, it should be kept in mind that for many time series the raw data itself shows a multiplicative trend or any type of seasonality which can cause the equal variance assumption to be violated (Makridakis and others, 1997: 260).

Normality

Many regression models assume a normal distribution on the error term. It doesn't make any difference to the estimates of the coefficients, or the ability of model to forecast, but major differences from normality should be taken into account since it can affect the F-test, t-tests, and the confidence intervals. There are several methods to test this assumption. Some of the well-known methods to test this assumption are: goodness of fit tests, and the graphical representations of the residuals. Shapiro-Wilkinson, Kolmogorov-Smirnov and the Chi-Square tests can also be used to test the normality of the error terms. P-values higher than the chosen significance level allows us to conclude that there is not enough evidence to reject the null hypothesis (H_0) which claims that the error terms are normally distributed (McClave and others: 2005: 790).

Multicollinearity

This assumption is a very common problem in many of the regression analysis. It exists when:

- "Two explanatory variables are perfectly correlated",

- “Two explanatory variables are highly correlated”,
- “A linear combination of some of the explanatory variables are highly correlated with another explanatory variable”,
- “A linear combination of one subset of explanatory variables is highly correlated with a linear combination of another subset of explanatory variables”

There are two important concerns with this issue. When multicollinearity exists in a regression model, it is not possible to carry out the Least Squares solution. Multicollinearity affects stability of the model (Makridakis and others, 1997: 288).

Mostly, multicollinearity is checked via VIF (Variance Inflation Factor) scores which compute “how much the variance of the estimated β coefficients are magnified compared to the β coefficients when the explanatory variables are not linearly related”. At this point, “high VIF scores (higher than 10) indicates the presence of linear redundancy in the explanatory variables which has to be removed” (Kutner and others, 2005: 409-410).

Detecting for Outliers and Influential Data Points

Other than the assumptions above, the researcher should pay attention to the outliers and the influential data points in the model. Outliers indicate the data points that lay more than three standard deviations ($\pm 3\sigma$) away from the mean of the distribution of the residuals. This assumption can be checked through an analysis of the residual distribution plot. “If there seems to be an outlier in the plot, the researcher should investigate the cause of that point, and if the probability that in n observations an outlier will be obtained by chance is small, the data point considered an outlier can be eliminated, otherwise it has to be retained” (Kutner and others, 2005: 115, 390-400).

If there is a presence of influential data points in the model, it may seriously affect the robustness of the regression line. This may happen either by "pulling" or "pushing" the line in a biased way. The Cook's Distance Approach can be used for testing the influential data points. Here, Cook's distance values smaller than 0.25 are "preferable", values between 0.25 and 0.50 are " moderate" and values greater than 0.50 are considered "major" influential data points (Kutner and others, 2005: 402-403).

After meeting these assumptions, the overall fit of the model which can be stated as: whether the observed relation between the response variable and the predictors should be examined. Hence, the F-test allows us to test the significance of the overall regression model:

$$F = \frac{\exp lainedMS}{un\exp lainedMS} = \frac{\dfrac{\sum(\hat{Y}_i - \overline{Y})^2}{m-1}}{\dfrac{\sum(Y_i - \hat{Y}_i)^2}{n-m}}$$

, where m is the number of parameters (coefficients) in the model (Makridakis and others, 1997: 211-213).

As Makridakis and others claim, the p-value is presented with the F-statistic result in the computer software packages. The p-value gives "the probability of obtaining an F-statistic as large as the one calculated for your data, if in fact the true slope is zero. So, if the p-value is small, then the regression is significant". Given a 95% confidence interval, most of the time we can conclude that the regression is significant, if the p-value is less than 0.05 (Makridakis and others, 1997: 213).

After concluding that the overall model is significant based on an F-test result, the focus moves to whether the predictor terms have a significant effect in the overall model. If there seems to be no significant effect, then excluding them from the model building process should be considered. The best way to do such a comparison is to conduct t-tests on the predictor terms. P-values for the t-statistics lower than the chosen level of significance indicate same predictor terms have a significant effect on the overall model and should be kept in the model, otherwise it should be excluded from the overall model.

Generally, JP-8 forecasting involves many different variables and a complex modeling process. Kutner (2005), and Salaverry (2007) state that multiple regression analysis is one of the widely accepted methodologies for jet fuel price forecasting by several different disciplines. However, successful application of the method requires both a deep understanding of the underlying theory and its practical uses. Also it's hard to predict/project predictor variables. Anyway, we do believe that regression analysis is useful in many cases because of its high level of satisfactory among users and being applicable most often for medium and long-term forecasting horizons.

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) is based on "simple mathematical models of the way brains are thought to work". They are defined as information processing systems that are originally inspired by biological cognitive systems and have the ability to "learn". In Neural Networks (NN) we have a different terminology than the common forecasting terminology. For example, instead of a "model", we have a "network". Instead of "parameters", networks have "weights". And instead of "talking about "estimating parameters", NN forecasters talk about "training the network".

ANN's are composed of a number of interconnected simple processing elements operating in parallel, which are called "neurons" or "nodes". The neuron performs a simple processing of the signal it receives and then sends this signal forward. Then, by the help of a local activation or transfer function, an output signal for the other nodes or external outputs is produced (Zhang et al, 1998). Although each individual neuron implements its function rather slowly and imperfectly, collectively a network can perform a surprising number of tasks quite efficiently.

NN's have been used in various types of problems such as pattern recognition, identification, classification, speech vision, and control systems. Zhang (1998) states that, they have been used in a wide variety of areas such as forecasting bankruptcy and business failure, foreign exchange rate, stock prices, electric load consumption, international airline passenger traffic, personnel inventory and so on. With the learning and generalizing capability, today they are still valid for various types of problems which are difficult to solve for conventional computers or human beings (MATLAB Help Pages).

If the economic structure underlying the nonlinear process is known, forecasting the series accurately is more likely, at least in the short run. Unfortunately, the tests developed for nonlinearity are not able to point to a specific economic structure. They only tell us about the likely existence of nonlinear stochastic or nonlinear deterministic processes underlying the data. Therefore, as Moshuri and Foroutan stated, "forecasting a complex nonlinear series without knowledge of its specific structure would require a flexible, nonlinear, and local optimizer model such as an ANN model which outperforms the linear and nonlinear models" (Moshiri and Foroutan, 2006). To forecast a highly complex and dynamic series, an analyst needs "a flexible nonlinear and local optimizer model, such as an artificial neural network (ANN) model, which has demonstrated prowess to explore the data locally and forecast it more accurately than other competing linear and nonlinear models" (Kuan and White, 1994; Swanson and White, 1997; Moshiri and Brown, 2004).

Time after time, many different ANN models have been proposed for forecasting purposes. Some of the most well-known models are: multi-layer perceptrons (MLP), Hopfield Networks, and Kohonen's self organizing networks. Among those, most of the time MLP networks are used in different types of problems in forecasting because of "their inherent capability of arbitrary input-output mapping" (Zhang et al, 1998).

MLPs are typically composed of several layers of nodes. The first one is an input layer, "where external information is received". The second one is an output layer "where the problem solution is obtained", and the last one is the hidden layer which separates the input and output layers (Zhang et al, 1998). There are two stages in the MLP network. First of them is the running stage in "which the input pattern is presented to the trained network and transmitted through successive layers of neurons until reaching an output". The second one is the training or learning stage in which "the weights or the parameters of the network are iteratively modified on the basis of a set of input-output patterns known as a training set, in order to minimize the deviance or error between the output obtained by the network and the user's desired output". At this point, the learning rule most commonly used in this kind of a network is the backwards propagation of errors (backpropagation) algorithm or gradient descent method which were developed and introduced by Rumelhart, Hinton, and Williams (1986) (Palmer and others, 2006). We will identify backpropagation in the NN structure part in detail.

In 1995, Kasprzak makes a comparative analysis of her ANN model to the DOE's STIFS model. In her study, she concludes that an ANN model outperforms the STIFS model in six out of seven areas of measured effectiveness. She adds that an ANN model can provide a useful planning and decision aid for decision makers (Kasprzak, 1995: 39-40). However, Salaverry states that the utility of ANN models lie in the fact that "they can be used to infer a function from observations. This seems particularly useful in applications where the complexity of the data or tasks makes them impractical to design such a function by hand, as is the case of oil derivatives. Here the main drawbacks are: the requirement of specific software packages, high level of training, and unpredictable behavior when the network is poorly designed" (Salaverry, 2007: 18).

Much research has been conducted to test the performance of forecasting with ANN modeling in comparison with other models. According to Zhang et al (1998), ANNs have some distinguishing features which make them valuable for forecasting problems. First, they are "data-driven self-adaptive methods" which means that "they can learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. Therefore, they are well-suited for problems whose solutions require knowledge that is difficult to specify, and at the same time which have enough data or observations" (Zhang et al, 1998). Second, they have the ability to learn from the experience. Third, they can generalize the data presented to them. This enables the model "to infer the unseen part of a population even if the sample data contain noisy information". Finally, ANNs are nonlinear. The underlying mechanism for a forecasting process can sometimes be nonlinear. In these problems traditional methods such as Time Series Analyses and ARIMA, which assumes the underlying process as linear, can not work well. In fact, it can be stated that most of the real world systems are nonlinear (Zhang et al, 1998). In addition Nelson et al (1994) state that, “NNs are promising since they attempt to learn the essence of the seasonal movements, rather than making assumptions” (Nelson and others, 1994).

The need and performance of the ANN modeling has been investigated many times in the literature. One of the best researches on this subject is Zhang et al (1998)’s study which gives a brief summary of the relative performance of ANNs with traditional statistical methods. The summary of their conclusions in their study are:

- ANN’s give satisfactory performance in forecasting, but it is not clear whether or when they are better than classical methods.
- ANNs can be more appropriate for large data sets, nonlinear problem structure, and the multivariate time series forecasting.
- “ANN’s are nonlinear methods. For static linear processes with little disturbance, they may not be better than linear statistical methods”.
- “ANN’s are blackbox methods. There is no explicit form to explain and analyze the relationship between inputs and outputs.
- “ANNs are prone to have over-fitting problems due to their typical, large parameter set to be estimated”.
- “ANN’s usually require more data and computer time for training”.
- “ANNs are data driven and model free, that’s why they can suffer high variance in the estimation, whereas model-based methods such as Box-Jenkins are bias prone” (Zhang et al, 1998).

In another study Zhang and Qi (2005) conclude that, “neural networks with both detrending and deseasonalization are able to significantly outperform seasonal ARIMA models in out-of-sample forecasting. However, without appropriate data preprocessing neural networks may yield much worse forecasting performance than ARIMA models (Zhang and Qi, 2005). In their more recent study Qi and Zhang (2008) conclude that, the most effective way for NNs to significantly outperform other methods in out-of-sample forecasting depends mostly on differencing of the data (Qi and Zhang, 2008).

Neural Network Structure

According to Grudnitski and Osburn, "neural networks are particularly well-suited for finding accurate solutions in an environment characterized by complex, noisy, irrelevant, or partial information" which in our case are well-fitted for the underlying conditions (Grudnitski and Osburn, 1993). As Kasprzak stated, "a neural network is a parallel distributed information processing structure in the form of a directed graph". Here the nodes of the graph are commonly called processing elements while the arcs are called connections. Weight, w_{ij} is associated with each connected processing element and represents the strength of the connection. The processing elements are organized into layers (Kasprzak, 1995).

"For an extrapolative or time series forecasting problem, the inputs are typically the past observations of the data series and the output is the future value. The ANN performs the following function mapping:

$$y_{t+1} = f(y_t, y_{t-1,\dots,} y_{t-p}),$$

where y_t is the observation at time t. Thus, ANN's are equivalent to the nonlinear autoregressive models for the time series forecasting problems" (Zhang et al, 1998).

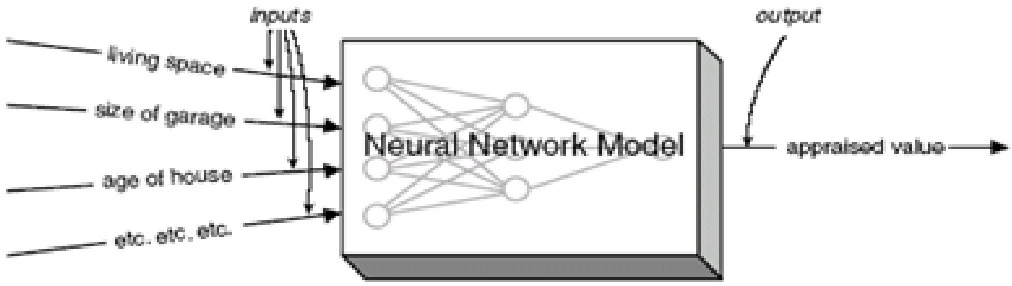
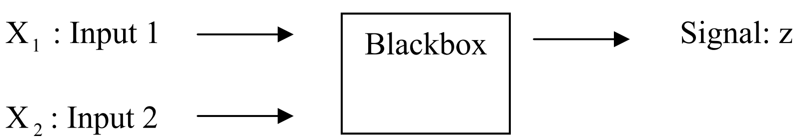


Figure 6- Basic ANN Structure

Here one can think of a neuron as a black box which takes its inputs and converts them into a signal. Since the interpretations of NN's are quite difficult, "they're often used as black-box solutions where only the inputs and outputs are deemed important" (Nelson et al, 1994).



The typical processing in the black-box can be explained as;

- First form a weighted combination of the inputs;

$$S = W_o(bias) + W_1X_1 + W_2X_2$$

- Then transform S;

$$f(S)=\frac{1}{1+e^{-s}}\equiv Z$$

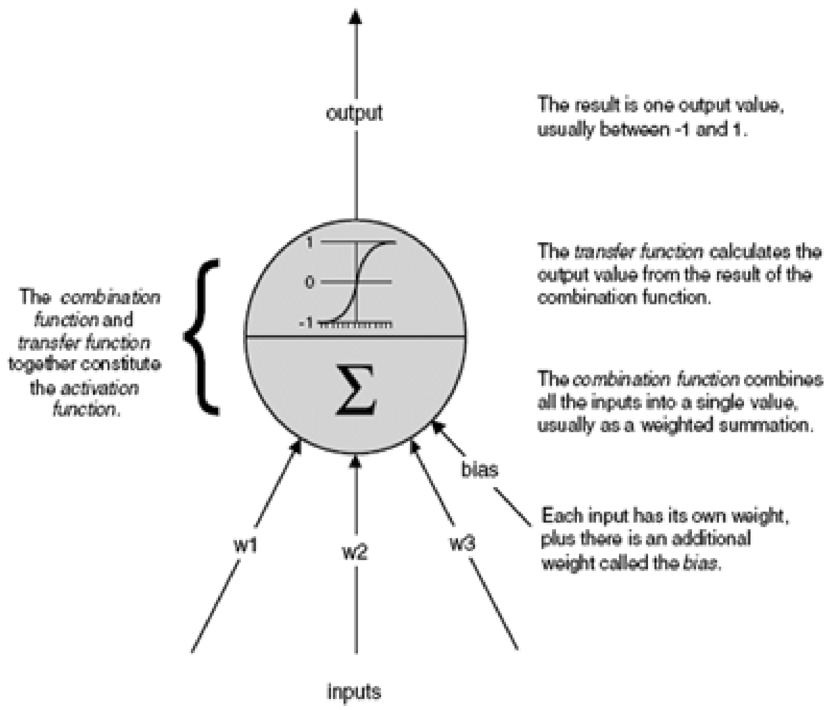


Figure 7- The Artificial Neuron

Prior to using ANN for performing any desired task, it must be trained. Training is the process of determining the arc weights which are the key elements of an ANN. The knowledge learned by a network is stored in the arcs and nodes in the form of arc weights and node biases.

"The training process is usually as follows. First, examples of the training set are entered into the input nodes. The activation values of the input nodes are weighted and accumulated at each node in the first hidden layer. The total is then transformed by an activation function into the node's activation value. It in turn becomes an input into the nodes in the next layer, until eventually the output activation values are found. The training algorithm is used to find the weights that minimize some overall error measure such as the sum of squared errors (SSE) or mean squared errors (MSE)" (Zhang et al, 1998).

Simply put, common Neural Networks are adjusted and trained so that a particular input leads to a specific output as shown in Figure 8.

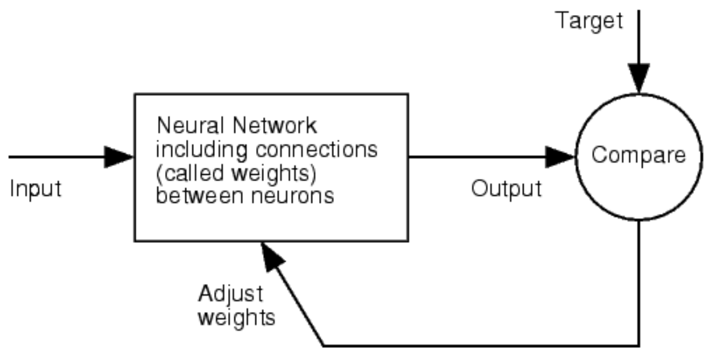


Figure 8- ANN Process Structure

Issues Concerned with Neural Network Architecture:

Preprocessing the Data

Prior to beginning the network architecture, raw data for input and output variables should be analyzed and transformed in order to detect trends, minimize noise, underline important relationships and flatten the variable's distribution. Most of the time this helps the model to learn relevant patterns. Two of the most popular transformation techniques in NNs are logarithmic transformation and differencing.

In their research about investigating whether prior statistical deseasonalising of data is necessary for producing more accurate forecasts with neural networks, Nelson et al (1994), found evidence that prior deseasonalising of data improves forecasting accuracy of NN models. Therefore, "it would be okay to first deseasonalising data, modeling time series, producing forecasts, and finally reseasonalising the forecasts".

Identifying the Number of Input Nodes/Hidden Layers/Output Nodes

In MLP design, the number of input nodes, the number of hidden layers/nodes, and the number of output nodes which are problem dependent should be determined. However as Zhang et al (1998) stated, "to date there is no simple clear-cut method for determination of these parameters". In Zhang et al (1998)'s paper it is stated that, one or at most two hidden layers may be enough for most forecasting problems. They also claim that for most of the time series problems that they have looked at, the optimal number of nodes is mostly between two and five.

Also, McMenamin et al (1998) state that, "as you add nodes, the in-sample fit always improves. That is, the sum of squared errors will always decline if you add more parameters. However, beyond a point, the coefficients have the freedom to specialize in order to explain specific events in the sample period, and these specialized results do not necessarily generalize to out-of-sample conditions".

Zhang et al (1998) found no consistent results for determining the number of input nodes through the literature. However, for the number of output nodes they concluded that this parameter often corresponds to the forecasting horizon.

Interconnecting the Nodes

Basically, the connections between the nodes identify the behavior of the network. The researcher should be aware of the fact that "all the nodes are fully connected in that all nodes in one layer are only fully connected to all nodes in the next higher layer except for the output layer" (Zhang et al, 1998).

Choosing the Transfer (Activation) Function

In their paper Zhang et al (1998) state that the activation function which is also known as transfer function, determines the relationship between inputs and outputs of a node and a network. There are only a small number of "well-behaved" activation functions. These are: sigmoid (logistic) function, hyperbolic tangent (tanh) function, the sine or cosine function and the linear function. From those, the most popular is the logistic transfer function but there is no accepted consensus on this subject among researchers.

Determining the Training Algorithm

One of the pros of ANN modeling lies in its ability to discriminate one pattern from another, and then using that discriminating advantage to tell something about a new pattern that hasn't been seen before. Grudnitski and Osburn give a very simple explanation of the process: "Consider the following situation where there are two patterns, PT1 and PT2. A neural network can be trained to recognize these patterns consistently by telling it every time it sees PT1 to relate it to the values 1 and 0 of its two output nodes, and every time it sees PT2 to relate it to the values 0 and 1 of these nodes. After the network is trained, assume a third pattern, PT3, is introduced. The neural network can determine how similar this pattern is to the two it has learned. Using the derived weights from training, it will produce a value between 1 (completely similar) and 0 (completely dissimilar) for each of the output nodes, which can be interpreted as the third pattern's similarity to PT1 and PT2, respectively" (Grudnitski and Osburn, 1993).

During the training algorithm, "arc weights of a network are iteratively modified to minimize the overall mean or total squared error between the desired and actual output values for all output nodes over all input patterns". But there is no algorithm currently available that can guarantee the global optimal solution in a reasonable time. Notice that, an excessive number of parameters/weights in hand and to the training data may cause over-fitting.

At this point the most popular algorithm used for the training algorithm is the backpropagation algorithm. This is a learning algorithm for updating weights in a feed-forward network. ANN that minimizes the mean squared mapping error. However, because of the problems related to slow convergence, inefficiency, and lack of robustness, some modifications or variations of this algorithm such as adaptive method and second-order methods are proposed. According to some researchers second-order methods such as Levenberg-Marquardt are more efficient in nonlinear optimization methods because of their faster convergence, robustness and the ability to find good local minima (Zhang et al, 1998).

Also in their study about "Short-Term Energy Forecasting with Neural Networks", instead of using backpropagation method which is believed to be "slow and cumbersome", McMenamin and Monforte chose to use Levenberg-Marquardt (LM) algorithm (McMenamin and Monforte, 1998). Because of the lack of a consensus on this issue, backpropagation method is assumed to be a reasonable method and is applied in this study.

Data Normalization

Data normalization often takes place prior to the training process. Here, when linear transfer functions are used at the output nodes, the desired output values must be transformed to the range of the actual outputs of the network. There are four methods for input normalization: Along channel normalization, across channel normalization, mixed channel normalization and external normalization. Among these, the external normalization in which all the training data are normalized in a specific range seems as the appropriate normalization procedure (Zhang and others, 1998).

Determining the Training Sample and Test Sample of the Data

In ANN modeling the data set is divided in three sub-components: training, validation, and test sets. This enables the network to generalize and perform well with the new cases.

Training sample and the test sample division of the data is an important concern which can affect the selection of optimal ANN structure. The literature offers little guidance on the issue but most authors select the training and test sample based on the rule of 90% vs.10%, 80% vs. 20% or 70% vs. 30% etc. Also, it can be stated that there is no definite rule for determining the sample size. As a general rule of thumb, most of the time “the larger the sample size, the more accurate the results will be”. But “ANNs do not necessarily require a larger sample than is required by linear models in order to perform well”. For small data sets it is also common to use one test set for both validation and testing purposes (Zhang et al, 1998).

Although ANN modeling seems to fit well for the overly complex and non-linear processes, there is no evidence that such methods do better than simple methods such as exponential smoothing. Note that Makridakis states, "most of the time the satisfaction of users concerning expert systems and neural networks is not high: 21.7% and 30% respectively" (Makridakis and others: 1997: 519). However, because of the underlying complex environment for JP-8 forecasting, we think that the performance of ANN modeling is still worth investigating in our case.

Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA method is one of the most popular model building processes in time series forecasting and analyses. This type of model was popularized by Box and Jenkins in the early 70s. Before delving into the subject, perhaps we should begin with describing fundamental terminology for time series and more specifically about ARIMA models.

"In order to examine the theoretical properties of a moving average series, values for the correlation between x_t and x_{t-j} are required, the so-called autocorrelations of the series, because the series x_t is checked to see if it is correlated with its own past" . If two random variables X and Y are correlated, the formula used is,

$$corr(X,Y) = \frac{\operatorname{cov} ariance(X,Y)}{\sqrt{\operatorname{var} iance(X) \operatorname{var} iance(Y)}},$$

In time series analysis, another important term is called autocorrelation function; which indicates the correlation of the time series with itself, lagged by 1, 2 or more periods as shown in the formula box below:

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \overline{Y})(Y_{t-k} - \overline{Y})}{\sum_{t=1}^{n}(Y_t - \overline{Y})^2}$$

Here "r_1 indicates the successive values of Y that relate to each other, and r_2 indicates how Y values of two periods apart relate to each other, and so on. Together, the autocorrelations at lags 1, 2,…, make up the autocorrelation function which is a valuable tool for investigating the properties of an empirical time series (Makridakis and others, 1997: 31).

Another important measure that is useful in time series analysis is the partial autocorrelation coefficient. These are used "to measure the degree of association between Y_t and Y_{t-k}, when the effects of other time lags- 1, 2, 3…, k-1- are removed". The partial autocorrelation coefficient of order k is denoted by α_k and can be calculated by regressing Y_t against, Y_{t-1} … Y_{t-k}, :

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + ... + b_k Y_{t-k}$$

Although it seems like a regression model, this is not the usual regression form as it can be observed from the formula because "the independent variables on the right hand sides of the equation are time-lagged values of the forecast variable". Thus, the name autoregression (AR) is used to define the type of equations of the form shown above (Makridakis and others, 1997: 321).

As Makridakis et al state, “Autoregressive (AR) models can be effectively coupled with moving average (MA) models to form a general and useful class of time series models called autoregressive moving average (ARMA) models. However, they can only be used when the data are stationary, which means that there is no growth or decline in the data”. The stationarity property of the data can be achieved either by normal or seasonal differencing according to the relevant conditions. Basically, the differenced series is called as “the change between each observation in the original series” as shown in the formula box below:

$$Y_t' = Y_t - Y_{t-1}$$

There are various types of ARIMA models. The basic non-seasonal ARIMA format can be shown as ARIMA (p,d,q):

AR : p= order of the autoregressive part.

I : d= degree of first differencing involved.

MA : q= order of the moving average part.

In a wide range of modeling options, it is quite difficult to decide which model to use given a set of data. For that reason, Makridakis et al (1997) outline the steps for choosing the right model:

- "Plot the data and check for any unusual observations. Decide if a transformation is necessary to obtain stationarity,
- Consider if the (possibly transformed) data appear stationary from the time plot and ACF and PACF,
- If the data is non-stationary, try differencing. For non-seasonal data, take first differences of the data, and for the seasonal data, take the seasonal differences. If they are still not stationary, try to take the second differences,
- When stationarity is achieved, check the autocorrelation to see if any pattern remains. Here, there are three options: First, seasonality may suggest itself, second, AR or MA models may be revealed- the pattern of autocorrelations will indicate a possible model, and third, if there is no clear MA or AR model suggested, a mixture of models may be necessary" (Makridakis and others, 1997: 347-348).

During the search for an appropriate forecasting model with ARIMA, the researcher should try to begin with simple structures at first. Moreover, we should be aware of the fact that first or the second order differencing of the model is an appropriate preprocessing tool for many of the time series analysis. Often times, there can be more than one model appropriate for the data series. In such situations the analyst should consider about a method for selecting the most preferable model. As Makridakis et al (1997) state, one can come up with a conclusion about choosing the model with the smallest sum of squared errors. However, this approach doesn't always work. Hence in ARIMA context, a penalty should be considered for the number of terms included in the model. "The likelihood should be penalized for each additional term in the model. If the extra term doesn't improve the likelihood more than the penalty amount, it is not worth adding". Thus, one of the most common penalized likelihood procedures is the Akaike's Information Criterion (AIC):

$$AIC= -2 \, LogL+2m,$$

where L denotes the likelihood. In the literature, there are many criterions other than AIC such as, Schwarz Bayesian Information Criterion (BIC) and Final Prediction Error (FPE) for evaluating model performance, but AIC is the most preferred one in many of them. Usually, "the less the AIC score, the better the model fit" is the basic rule of thumb for model selection. Also, a difference in AIC values of 2 or less is not important and we would be better off by choosing the simpler model.

For the last part, after choosing the appropriate model for the data series, the analyst should perform a diagnostic checking in order to verify that the model is valid. This process consists of checking the residuals and the outliers. For a good forecasting model, we may expect to have no significant autocorrelations (ACF) and partial autocorrelations (PACF) by the time we plot the ACF and PACF of the residuals.

When looking for outliers, it should be more wise to standardize (or scale) the residuals in order to make it simpler to detect outliers. "Any residual smaller than -3 or greater than 3 is an outlier and may be worth investigating" (Makridakis and others, 1997: 364).

In Box-Jenkins methodology the model building process for time series analysis can be summarized shown in Figure 9:

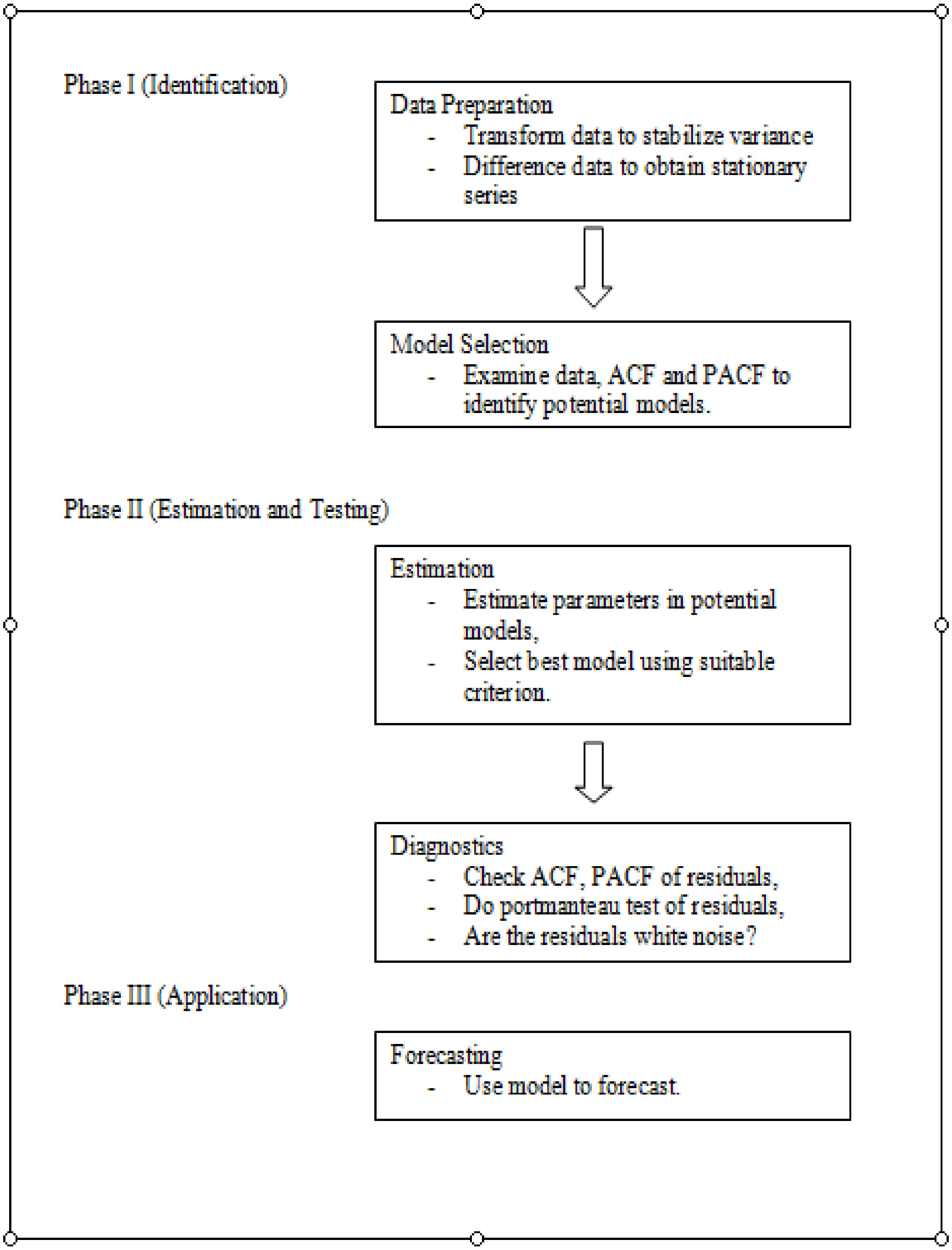


Figure 9- Schematic Representation of the Box-Jenkins Methodology

Source: (Makridakis and others, 1997: 314)

According to Burke, Autoregressive Integrated Moving Average (ARIMA) is a method that uses past values of the data being forecasted and the moving average of error to generate predictions about the future. This technique can perform very accurate forecasts including the capture of some natural fluctuations; however, it doesn't offer an explanation about why the dependent variable is changing (Burke, 2006: 24). Also the method is mathematically sophisticated in theory and requires a deep knowledge of the method. Plus it has a need for at least 50 and preferably 100 or more observations that should be used. In their study, Ediger et al (2006) developed a decision support system for forecasting Turkey's fossil fuel production by applying a regression, ARIMA and SARIMA (Seasonal Time Series ARIMA) method to the historical data from 1950 to 2003 in a comparative manner. At the end of their study, they conclude that a comparative regression and the ARIMA method with a decision support system give good results for long-term fossil fuel production forecasting (Ediger and others, 2006: 3838).

In summary, ARIMA modeling is a widely accepted modeling process for time series analyses. However, according to Mentzer and Cox's study (1984) the practitioners are not so much familiar with ARIMA modeling as a forecasting method (Makridakis and others, 1997: 518). Other than that, the model contains several assumptions which may not be met, such as the assumption that assumes the historical patterns of the data remains constant during the forecast period. However, for many real world scenarios this seems quite impossible.

Although there are inherent problems for ARIMA modeling, every model has its own benefits and drawbacks. Since it has shown good results for time series analysis and oil related problems in the literature, we find ARIMA modeling worth investigating and will use this method as one of our forecasting tools in our problem solving process.

Other Literature Findings for Oil and JP-8 Forecasting

The next models are beyond the scope of this research. However, we try to filter the necessary information relevant to our modeling to improve our insight for the underlying conditions.

Autoregressive Conditional Heteroskedastic (ARCH) type linear and nonlinear time series models have been able to generate accurate forecasts (Abosedra and others, 1997; Sadrosky, 2002). But, if the underlying data generating process of oil prices is nonlinear and chaotic, using linear or nonlinear parametric ARCH-type models with changing means and variances is not ideal.

Since Black Monday, (stock market crash of October 1987) when the stock markets plummeted, researchers have also become interested in applying chaos theory and have examined new ways of using elements of the theory to analyze economic and financial time series. According to chaos theory, the very complex behavior of economic series, which appears to be random, may be explained by a deterministic nonlinear system. Moshuri and Foroutan state that Chaos Theory can be applied to energy markets. Chwee (1998), and Serletis and Gogas (1999) found evidence of chaos in natural gas futures and the North American natural gas liquid markets. Panas and Ninni (2000) found strong evidence of chaos in a number of oil products in the Rotterdam and Mediterranean petroleum markets. Adrangi and Chatrath (2001) also reported evidence of chaos in oil prices in the futures markets, However, very few studies have been carried out to forecast nonlinear dynamic economic series (Moshiri and Foroutan, 2006).

Other than those, using hybrid models or combining several models has become a "common practice" for enhancing the forecasting accuracy. "The basic idea of the model combination in forecasting is to use each model's unique features to capture different patterns in the data. Both theoretical and empirical findings suggest that combining different methods can be an effective and efficient way to improve forecasts". Under current conditions, quantitative methods have become important decision support tools for financial markets forecasting and for improving decisions and investments.

In their retrospective study, Koomey et al (2003) point to factors like technological innovation and human behavior for inaccuracy of oil forecasts. Tang and Hammoudeh (2002) show that, "omission of market participants' expectations" contributes to forecasting errors.

Georgoff and Murdick (1986) claims that; "A forecaster should incorporate subjective judgments in dynamic situations when the statistical models can not reflect significant internal and external changes". Besides, Edmundson and others (1988) comment that "the well-structured judgmental process can consistently outperform the statistical model based extrapolation". Wolfe and Flores (1990) have shown that the Autoregressive Integrated Moving Average Model (ARIMA) based forecasts can be enhanced by adopting the Analytical Hierarchy Process (AHP) for the judgmental adjustment. They argue that the accuracy of unadjusted statistical forecasts can be improved by the judgmental adjustment. In their study, Lee and Yum (1998) found evidence that the additive adjustment of judgmental effects on the neural network based main trend forecast can provide the best forecasts (Lee and Yum, 1998).

On the contrary, Sanders and Manrodt claim that "a large portion of the forecasting literature points to the information processing limitations and biases inherent in human decision making. Biases inherent in judgmental forecasting include optimism, wishful thinking, political manipulation, overreacting to randomness and lack of consistency". Moreover, they add that many of the researchers show disapproval for the use of a judgmental process in forecasting, indicating that the shortcomings of human decision making. Hence, because of the existing potential for inaccuracy, judgmental revision of statistically generated forecasts, which is known as a common organizational practice, has been discouraged by many researchers (Sanders and Manrodt, 2002).

Comparison of the Models for JP-8 Forecasting

It is important to recognize that forecasting is not an exact science, and its accuracy is largely dependent on underlying economic and political assumptions. While this always introduces some degree of uncertainty, the range is, on average, relatively narrow. No matter what technique is used, there are some underlying conclusions with respect to the predictor variables:

- Jet fuel prices have strong correlation with crude oil prices (Kasprzak, 1995: 3-4; Salaverry, 2007: 21).

- Supply is influenced by the total capacity to produce jet fuel in accordance with the other oil products obtained with the same process (Kasprzak, 1995: 3-4; Salaverry, 2007: 21).

Due to the presence of a dominant producer and high degree of volatility, the real price of oil is difficult to forecast. Supply and demand for oil are influenced by outside factors such as political tension, seasonality, natural disasters etc. (Kasprzak, 1995: 3-4; Salaverry, 2007: 21).

Summary

Forecasting is not an exact science as mentioned many times before. However, it provides a good insight for future planners and decision makers. JP-8 cost forecasting revolves around many different factors. Hence, it is not a clear-cut process. Through the literature, many models were developed for forecasting such a complex environment. But for the purposes of this study, our focus will be mainly on 3 different models. First, we'll look at multiple regression analysis due to it being widely-accepted and providing a high level of satisfaction to the users. We do believe that regression shows effective results for JP-8 forecasting and balances the trade-off between complexity and accuracy. Second, we'll use ANN modeling which is proved to be effective in complex and dynamic situations. Finally, knowing that it doesn't capture why the dependent variable is changing, we will use ARIMA modeling as a sophisticated method for time series analysis.

The United States' homeland, markets, military, industry, and its extensive transportation networks demand and depend on the uninterrupted flow of oil. In order to preserve the current global power position, the U.S. has to forecast the need for oil and oil-related expenses that are responsible for an important part of the government budget. Moreover, being the number one oil importer and consumer, the U.S. has to look for the alternative energy resources in order to reduce the current level of oil dependency on other countries.

To begin with we should take one step back and look at the big picture. In this study, our overall problem is to determine how much money the USAF needs to budget in the future to cover its needs and rising fuel prices. Our decision support tool for the problem is forecasting. For finding viable solutions to our forecasting problem, first we should begin with determining the JP-8 needs and identifying the factors that affect the price of JP-8. Second, we should choose the most appropriate model that is capable of yielding the best forecasts. Third, we should gather necessary JP-8 related historical information to enable the forecast. Fourth, we should use the model, and validate it. Following the identification of future JP-8 costs, effective budget planning and reducing JP-8 consumption are explored.

Following the problem statement and its underlying setting in Chapter I, the detailed history of oil, the importance of it for both the U.S. and the USAF, and the motivation for more accurate oil forecasting were explored in Chapter II. In addition to this, a wide range of forecasting methods from relatively simple to the highly complex that are available to forecast jet fuel prices are investigated. In Chapter III, our focus will be mainly on the multiple regression analysis, ANN modeling, and ARIMA techniques that are implemented for the investigation of the research questions.

III. Methodology

"An unsophisticated forecaster uses statistics as a drunken man uses lamp-posts- for support rather than illumination".

Andrew Lang

Introduction

In the first chapter of the research, the overall research question and the investigative questions were presented. In the second chapter we begin with describing the history of oil. Then, we tried to understand the research questions and their importance. Following this, we presented our literature findings for JP-8 modeling and discussed their possible application for our research problem. This chapter presents the methodology implemented in this study.

Data Collection Information

The most important decision to make in the data collection process is to decide which variables to include. This search for the appropriate data set is not an easy matter. The availability of historical data is a problem, as we try to decide the variables included for the research problem. We should keep in mind that Granger states, "the search should be for a causal series or a leading indicator of the series to be forecast". We need to use judgmental inputs for the problem solving process and try to come up with reasonable outcomes.

The characteristics of this study can be identified as an “exploratory observational study”. Thus, we try to find explanatory variables related to the response variable. The response variable for the study is the USAF JP-8 consumption cost. Taking into consideration the effect of crude oil on JP-8 consumption as a major impact, variables chosen for the study are:

- Real Imported Crude Oil Price (Real $/barrel) NOV-08=1,
- U.S. Refinery and Blender Net Production of Crude Oil and Petroleum Products (thousand barrels per day),
- U.S. Crude Oil and Petroleum Products Ending Stocks (thousand barrels),
- U.S. Kerosene-Type Jet Fuel Ending Stocks (thousand barrels),
- U.S. Refinery and Blender Net Production of Kerosene-Type Jet Fuel (thousand barrels per day),
- U.S. Natural Gas Wellhead Price (dollars per thousand cubic feet),
- Kerosene Type Jet Fuel Spot Price FOB (cents per gallon).
- Consumer Price Index (CPI) 1982-1984=1,
- Europe Brent Spot Price FOB (dollars per barrel),
- U.S. FOB Costs of Crude Oil (dollars per barrel),
- Real Gasoline Price (real cents/gallon) NOV08=1,
- Real Heating Oil Price (real cents/gallon) NOV08=1
- U.S. Crude Oil Field Production (thousand barrels per day),
- U.S. Crude Oil Imports (thousand barrels per day),
- GDP (in billion dollars-seasonally adjusted),

- U.S. Kerosene-Type Jet Fuel Product Supplied (thousand barrels per day),
- U.S. Natural Gas Imports (MMcf),
- Cushing, OK WTI Spot Price FOB (dollars per barrel).

Data were collected from internet sites administered by the Energy Information Administration (http://www.eia.gov), U.S. Bureau of Labor Statistics (http://www.bls.gov), and actual JP-8 cost and consumption data from the Air Force Petroleum Office (AFPET). In total, the study extracted 19 possible predictor variables.

In the study, monthly measures of the predictor variables are used because of "their wide utilization in most of the economic and business time series analysis" as Zhang and Qi state. Also, our models need a significant amount of historical data points. As claimed in literature review, for instance ARIMA needs at least 50 or more and more preferably 100 or more data points. Hence, the data set uses monthly measures of data from September 1978 until the end of August 2007. Appendix A provides the detailed names and sources of the 19 possible predictor variables.

Kerosene type jet fuel prices are gathered from five different sources or spots- Los Angeles, U.S. Gulf Coast, New York, Singapore, and Amsterdam-Rotterdam-Antwerp. The data is sorted and ordered by daily date because of the trading day's differences in 5 different markets which can be called as 'calendar adjustment' as Makridakis et al (1997) claim. The five spot price locations are averaged to provide a single day point value. After all single day values are calculated, the data is averaged by month to provide a continuous pool and a robust monthly measure.

Potential Errors and Limitations within the Data

All the predictor input variables' historical values are obtained in monthly measures as needed for our model building process. However, our output data set for USAF's JP-8 cost from AFPET includes yearly measures. Hence, the study relies on linearly interpolating the missing monthly measures from the yearly charts for problem solving.

One important limitation of the EIA's database is that some predictor variables have missing values that correspond to each month during the time-period selected for the study. Also, some other variables have no recent values. Hence, missing data imputation is applied for the potential predictor variables as necessary.

There are three well-known imputation methods established for the missing data: "simply deleting the offending row", "regression analysis for predicting the column as a function of the remaining full columns and filling the holes with predictions", and "substituting the mean". In our study, whenever historical data is not available for a predictor variable, we simply delete the row for all predictor variables until the time data becomes available for all variables. For the output variable, JP-8 cost, missing values are obtained by linear interpolation of the yearly figures to obtain monthly figures via Microsoft Excel's 'interpolate' function.

A great deal of national and worldwide data is available from government databases related to the topic. While this is a positive aspect in some sense, this abundance of information makes identifying the correct information needed to forecast USAF JP-8 consumption cost more difficult. We attempt to overcome this problem with a detailed literature review. For future studies it should be kept in mind that it may be infeasible to try and access every fuel contract for every region. Talking with the people in the field would help to enhance the model's face validity, which is one of the key processes of model building.

Statistical Software Used in the Study

During the study, the main statistical aid for the Multiple Regression and ARIMA analysis is JMP 7.0®. The reason for choosing JMP 7.0® to perform our analysis is because: it is readily available, widely-accepted and easy-to-use. For ANN modeling there are several software packages for preparing a Neural Network and computing the performance of the model in the software arena. The Statistical Neural Network Analysis Package (SNNAP) is one of them and has been chosen to perform our analysis. This package is "a software environment for developing and analyzing neural network models of decisions, time-series phenomenon, system control, and other input-output relationships. It implements training heuristics developed in prior research, which significantly improve the performance of neural networks in areas with high degrees of stochastic noise" (Wiggins and others, 1995: 1). SNAPP can be used everywhere by copying a folder to your personal computer.

Modeling Process

"Any astronomer can predict just where every star will be at half past eleven tonight; he can make no such prediction about his daughter".

James Truslow Adams

Our research focus is determining the USAF JP-8 needs and forecasting the cost of JP-8 for the next 5-year period. This period is fairly long-term when we consider JP-8 forecasting. The reasons behind selecting a long-term forecasting period for the problem is discussed in the literature review part of the study.

There are many different ways to construct long-term forecasts for jet fuel consumption and prices. Considering the related pros and cons for model selection, an analyst should try to make the model as simple and understandable as possible. This in turn will enable the analyst to communicate well with the decision makers who are not the SME's (Subject Matter Expert).

According to Banks et al, there are three steps in the model building process. "The first step consists of observing the real system and the interactions among their various components and of collecting data on their behavior. The second step is the construction of a conceptual model, and the third step is the implementation of an operational model". According to them, a researcher should return to each of these steps many times while building the model (Banks and others, 2005: 355).

To perform our analysis in the data analysis part, we'll use a 5-step systematic approach in order to make things clearer and more easily understandable.

Step 1:

In our study, we begin with identifying the USAF JP-8 consumption amounts by looking at the recent trends. The historical data for USAF JP-8 consumption is gathered from AFPET for the years between 1996 and 2008. First, we plot the historical USAF JP-8 cost and try to understand the recent trends. Following the identification of recent historical consumption, we model the USAF's JP-8 costs via Holt's Linear Method and project for the next 5-year period.

Step 2:

In the second step, we begin our modeling process to forecast the cost of JP-8 via Multiple Regression Analysis. Recall that we have 19 potential predictor variables to construct a regression model. Before beginning model building, the number of potential predictor variables that will be included in regression model should be reduced and the best predictor variables for our modeling purposes should be determined. Thus, we use the Multivariate Analyses Platform of JMP 7.0® in order to reduce the number of predictor variables with VIF scores. After finding the most relevant predictor variables to our problem, we build our model for USAF JP-8 cost. For the model building process, inherent assumptions for multiple regression analysis are checked in order to perform the diagnostic checking step in model building process. Verifying that our model is valid, in-sample performance measures of the model are calculated and kept for further comparisons with other models. At last, future projections of the model are explored. But, remember that we have two main drawbacks here: First, our model is able to generate reliable forecasts only for one-month ahead. Second, in order to make future projections for JP-8 cost, we need to know the future values for the predictor variables. Thus, Holt's Linear Method is applied to overcome this problem and helps us to determine the future values of the predictor variables.

Step 3:

After regression, we construct a model with ANN modeling. The same predictor variables used in multiple regression analysis are introduced to the ANN model. This time, our statistical software aid is SNAPP in our model building process. Remember that, SNAPP uses tab-delimited information in its background and data should be introduced to the software in a text format. In order to convert our data set accordingly to SNAPP's needs, our data set is coded to tab-delimited text format via Microsoft Visual Basic program. After that, predictor variables are introduced to the model and the parameters of the network are identified with the help of SNAPP's expert 'suggest' system. Following the model building and running stage, the model in-sample performance results are captured for further future comparisons. To make projections for the future, the same problem that we face in Multiple Regression Analysis emerges here again. Because the future values of the predictor variables are not available, once again Holt's Linear Method is applied to solve this problem.

<u>Step 4:</u>

Finally, we perform an ARIMA analysis as our third model. In ARIMA modeling there is no need to investigate the causal effects of the predictor variables to the process. Therefore, our only data set that we investigate in this modeling process is the actual JP-8 cost of the USAF. First, we begin our analyses by obtaining the inherent conditions such as stationarity for ARIMA modeling. Then, in order to find the best model, we check the ACF and PACF for each of the potential models. After that, having the adequate tools for identifying the best model in hand, we choose the most appropriate model and finally perform diagnostics for validation purposes.

<u>Step 5:</u>

In the final step, forecast accuracy measures of the different models are compared for different forecast horizons. At the same time, MA3, MA6, MA12 type of moving averages, simple exponential smoothing (SES), and Winter's additive model type of exponential smoothing methods are also explored and compared for different forecasting horizons. First, we compare the models for different forecasting horizons according to their Theil's U-values' as it is shown in Table 4 below.

Table 4- Comparison Table for Theil's U-Values

	THEIL'S U VALUES				
	Forecast Horizon				
MODELING TYPE	1-month	2-months	1-year	5-years	10-years
ANN with Raw Data	X	X	X	X	X
ANN with 3MA Smoothed	X	X	X	X	X
ANN with 12MA Smoothed	X	X	X	X	X
Multiple Regression	X	X	X	X	X
Seasonal ARIMA	X	X	X		
Holt-Winters (additive)	X	X	X		
SES	X				
MA3	X				
MA6	X				
MA12	X				

After Theil's U-values' comparison, we look at the MAPE scores of the models for different forecasting horizons again as shown in Table 5. This process enables us to come up with the best model for our modeling purposes. Choosing the best model, we perform our forecasts with it. After finding the USAF JP-8 consumption and cost, we discuss the findings of our analysis in an attempt to answer our overall and investigative research questions.

Table 5- Comparison Table for MAPE Scores

	MAPE SCORES				
	Forecast Horizon				
MODELING TYPE	1-month	2-months	1-year	5-years	10-years
ANN with Raw Data	X	X	X	X	X
ANN with 3MA Smoothed	X	X	X	X	X
ANN with 12MA Smoothed	X	X	X	X	X
Multiple Regression	X	X	X	X	X
Seasonal ARIMA	X	X	X		
Holt-Winters (additive)	X	X	X		
SES	X				
MA3	X				
MA6	X				
MA12	X				

The AF is constantly looking at alternative fuels and has successfully used a mix of synthetic fuel and JP-8 to fly aircraft. Therefore, how much the USAF decides to use alternative fuels with or without JP-8 is going to affect the answers to the investigative questions of the study. Hence, what has been done so far for alternative fuel usage at the Federal level is discussed and what future plans that the U.S. and the USAF have on this subject is presented in parallel to the investigative questions at the end of our modeling process.

Tools for Measuring Forecast Accuracy

Another fundamental concern about forecasting is measuring the suitability of a particular forecasting method, given a set of data. Often times goodness of fit, which refers to "how well the forecasting model is able to reproduce the data that are already known", is used synonymously with the word accuracy. However, there are many measures to evaluate the forecast accuracy. The forecast accuracy measures that are used in this study are mathematically expressed as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} {e_t}^2$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t|$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |PE_t|,$$

where $PE_i = \left(\frac{Y_i - \hat{Y}_i}{Y_i}\right) \times 100$, and n represents the number of data points used in the error calculations. "The Mean Absolute Error (MAE) has the advantage of being more interpretable and is easier to explain to non-specialists". But, the Mean Squared Error (MSE) has the advantage of being easier to handle mathematically and emphasized larger errors. Another common measure is the Mean Absolute Percentage Error (MAPE) which is only meaningful if the scale has a meaningful origin (Makridakis and others, 1997: 45-46).

Theil's U-statistic is another measure which "allows a relative comparison of formal forecasting methods with naïve approaches and also squares the errors involved so that large errors are given much more weight than small errors". This statistic is mathematically identified as:

$$U = \sqrt{\frac{\sum_{i=1}^{n-1}\left(\frac{\hat{Y}_{i+1} - Y_{i+1}}{Y_i}\right)^2}{\sum_{i=1}^{n-1}\left(\frac{Y_{i+1} - Y_i}{Y_i}\right)^2}}$$

The value of the U-statistic will only be '0' when the forecasts are exact, and it will have a value 1 "if the errors in the forecasting method are the same as those that would be obtained by forecasting no change at all in the actual values". U-values greater than 1 indicate the naïve approach produces better results and U-values smaller than 1 indicate the applied forecasting method is better than the naïve approach (Makridakis and others, 1997: 50). The most frequently used performance measures for ANN modeling are the mean absolute deviation (MAD), the sum of squared error (SSE), the mean squared error (MSE), the root mean squared error (RMSE= $\sqrt{MSE}$) and the mean absolute percentage error (MAPE). Among these, MSE is the most frequently used accuracy measure in the literature.

Recall that in forecasting an MSE or MAPE of zero for a model can be achieved by using a higher order polynomial term in the fitting phase. However, as Makridakis et al states "having a model that fits well for historical data is not a guarantee of more accurate post-sample predictions". Hence, in reality we would be better-off by comparing each model's performance for the out-of-sample data which compares the actual forecasts of different models. The model would be built with the initialization data set and actual forecasts are compared via the hold-out set. For Multiple Regression and ANN modeling we build our model for the entire data set without dividing the data into a test and a hold-out set. Thus, since we don't know the future values of the predictor variables we'll be performing in-sample comparisons within the entire data set for Multiple Regression and ANN modeling. For moving averages, exponential smoothing methods and ARIMA modeling, the data set is divided into an initialization and a hold-out set. For each model we calculate MAPE, Theil's U, MSE and ME as the selected forecasting measures because of their being widely-accepted use in the literature. While evaluating the forecast accuracy of different models, we will be specifically interested in MAPE, Theil's U or both as the appropriate comparison criteria.

Summary

Our methodology for model building process needs a systematic approach that will be our roadmap for the data analysis part. In this chapter we identify the methodology that will drive our data gathering process, and identification of the potential predictor variables. We also develop a 5-step systematic approach for our data analysis, comparisons, and justification of our results.

IV. Data Analysis and Results

"A good forecaster is not smarter than everyone else; he merely has his ignorance better organized".

Anonymous

Introduction

In the first three chapters, the problem was defined and the related importance of delving into it was claimed. The literature findings from many different sources were investigated and finally the methodology that will be used in the next part of the research was introduced. In this chapter, first we'll look at USAF JP-8 needs for the future. Then, we will illustrate the model building process which will allow us to predict the cost of JP-8 for the USAF in the next five year period.

Step 1: USAF JP-8 Consumption Figures and Forecast for Future

Before beginning our model building process for USAF JP-8 cost analysis, it would be better to first look at the demand figures by looking at the historical consumption of JP-8. This enables us to capture the recent demand trend which has a direct effect on costs and lets us gain some insight for future projections.

The historical JP-8 consumption data was obtained from AFPET for the years between 1996 and 2008 in terms of gallons per year and plotted in Figure 10.

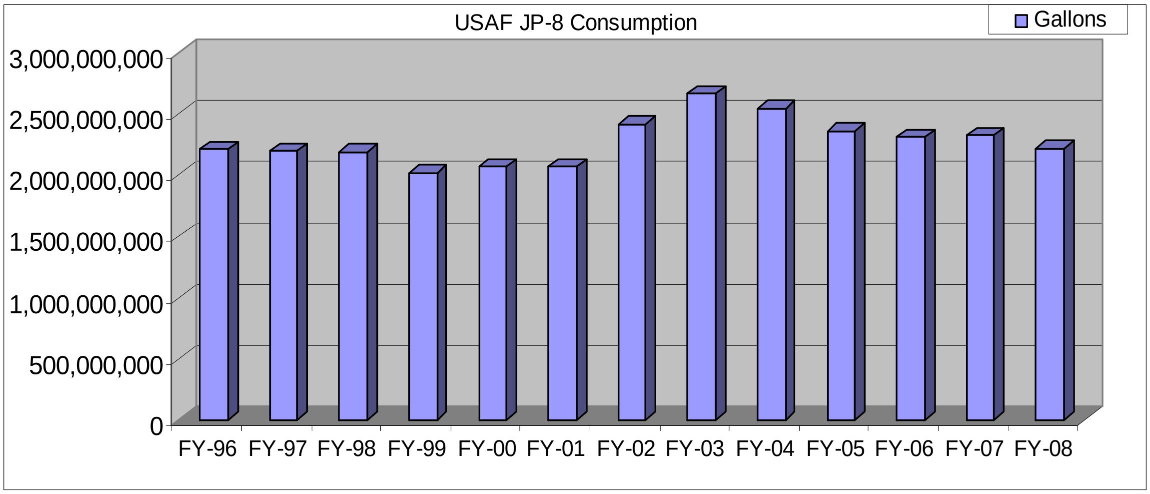


Figure 10- USAF JP-8 Consumption

Figure 10 shows that USAF JP-8 consumption follows a quite stable trend with an average of 2,277,505,456 gallons/year for the last 12 years. The total sum of consumption over that period is 29,607,570,932 gallons. We can divide the consumption pie into pieces for fly-aviation, non-fly aviation, equipment, vehicles and utilities. The consumption pieces are illustrated in Figure 11 below.

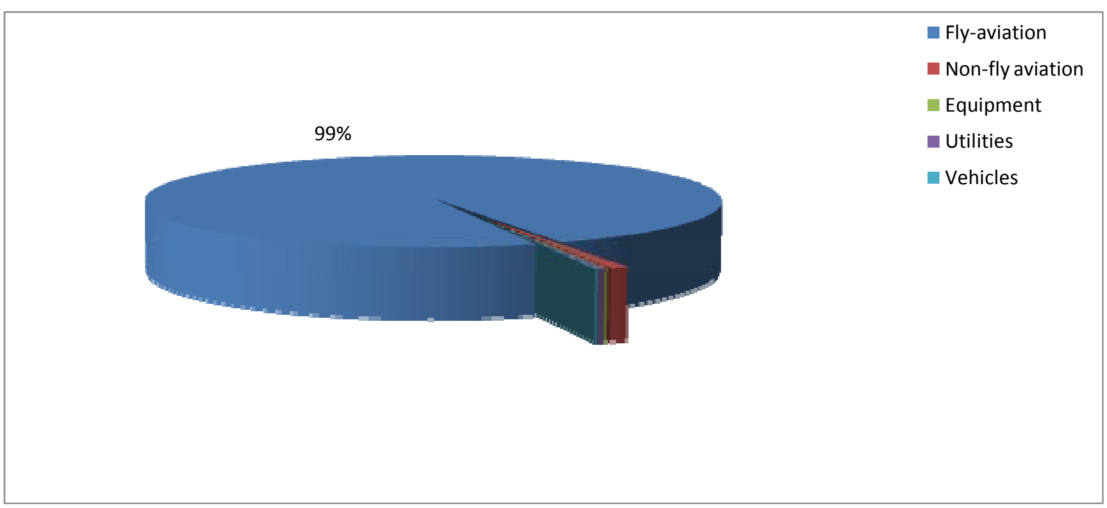


Figure 11- JP-8 Consumption Areas

Based on Figure 11, it is obvious that most of the JP-8 consumption is for fly-aviation, as expected. The total amount corresponding to fly-aviation is 29,174,297,452 gallons, 271,794,993 gallons for non-fly aviation, 33,709,040 gallons for equipment, 81,911,366 for utilities, and 45,858,081 gallons for vehicles for the last 12 years.

Now that we have looked at the previous trend for JP-8 consumption, let's try to identify the future needs for JP-8. This analysis is performed with the help of Holt's Linear Method.

Holt's Linear method is used to forecast JP-8 consumption. Basically, Holt's method allows us to forecast data with trends. The model uses two smoothing constants, α and β (with values between 0 and 1) with three equations:

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1}),$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1},$$

$$F_{t+m} = L_t + b_t m$$

Here, "L_t denotes an estimate of the series at time t and b_t denotes an estimate of the slope of the series at time t. The first equation adjusts L_t directly for the trend of the previous period, b_{t-1}, by adding it to the last smoothed value, L_{t-1}. This helps to eliminate the lag and brings L_t to the approximate level of the current data value" (Makridakis and others, 1997: 158). Here one problem arises in finding the best values for the alpha and beta. Thus, we use Microsoft Excel's Solver to overcome this problem. When the constraints and the variables are identified in Solver, the objective function is to minimize the Mean Absolute Percentage Error (MAPE). The alpha and beta values for the analysis are found as 0.967 and 0.159, respectively via the MS Excel Solver. Following the identification of alpha and beta values, future predictions for JP-8 consumption are found with a MS Excel Spreadsheet and the results are presented in Figure 12:

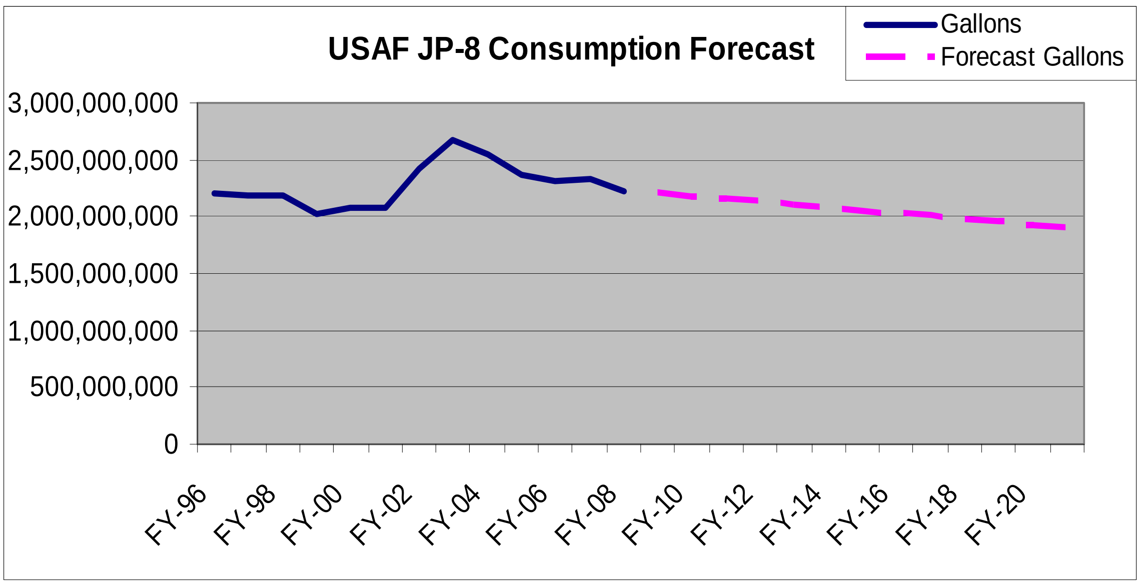


Figure 12- USAF JP-8 Consumption Forecast

From Figure 12, assuming that there won't be any major new conflicts and the Global War on Terror (GWOT) goes on with the current ops-tempo, we see that JP-8 consumption figures of USAF will remain mostly the same as the current and previous amounts. However, with an increasing amount of alternative fuel usage in AF ops-tempo, the above-stated consumption figures may face a change. According to available information, a significant change is not likely in the short-term. We believe that JP-8 will continue to be one of the leading fly-aviation fuels for the near future and that fossil fuels will be used for many years to come.

Step 2: Multiple Regression Model to Predict the USAF JP-8 Fuel Cost

The study uses collected information to create a data set of 244 observations. Because of the potential outliers, 183 data points were used to build the model and test the model assumptions during the validation process. The reason for not using all the data points in the model building process is because there are obvious outliers in the overlay plot before and following the Gulf War period. Since we don't divide the entire data into a test and a hold-out set, the entire data set is used to calculate the forecast error measures.

The regression model in this study revolves around using predictor values to forecast expected future USAF JP-8 cost. To accomplish this, the study uses one month old data -which is called lagged-one-month data- for all predictive variables. The reasoning behind this is the fact that one would expect the data for the current month to be available next month. Thus, using month-old data to predict the current month helps to mitigate this problem by increasing the probability that the data are available when needed.

Sometimes adjusting the historical data may lead to a simpler and more interpretable forecasting model. As Makridakis et al state: "A mathematical transformation is a convenient method for accounting the increasing variation". In our multiple regression analysis, all the variables in the model are mathematically transformed by taking their natural logs and back-transformed later to obtain forecasts on the original scale.

Figure 13 gives USAF JP-8 consumption cost. From Figure 13, we see that the Gulf War and the Iraq War have huge impacts on the USAF's JP-8 expenditures. Despite the fluctuations, it is not hard to note a rising trend during the last decade.

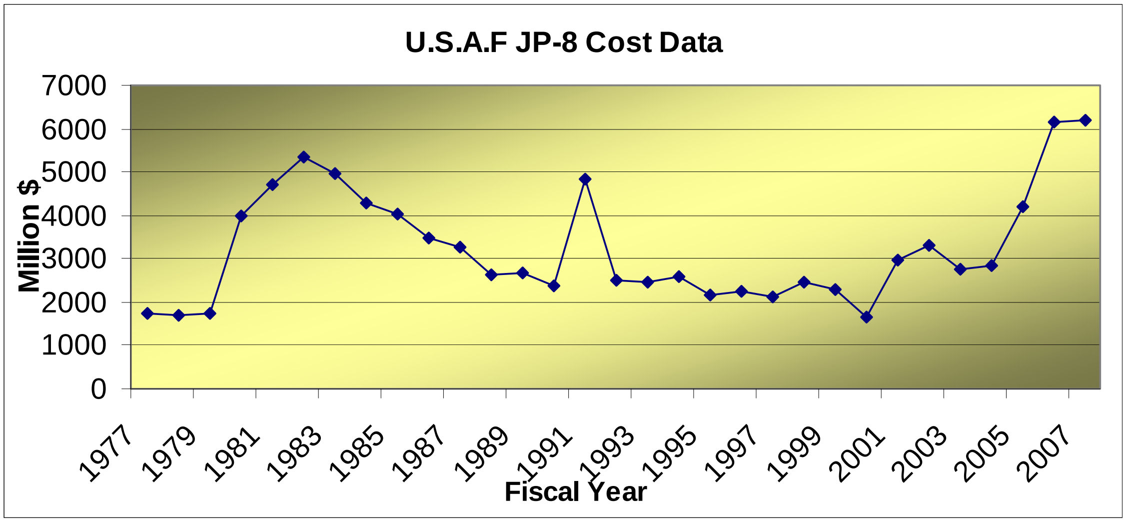


Figure 13- USAF JP-8 Costs (in million $)

Because of the large number of predictor variables related to our problem, the model building process is divided into 2 parts: reducing the number of predictor variables and the model building process. For the first part, there are some reliable proposals in the literature regarding how to select appropriate variables for the analysis. These can be listed as: doing best subsets regression, doing a step-wise regression and performing a principal components analysis for all variables, which in turn enables us to decide the key variables. Performing a distributed lag analysis may help us to decide which leads and lags are more appropriate (Makridakis and others, 1997).

Another formal method of reducing the number of predictor variables is by simply looking at the Variance Inflation Factor (VIF) scores. VIF scores detect the presence of multicollinearity. It measures "how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related". The largest VIF value among all x variables is often used as an indicator of the severity of multicollinearity. "A maximum VIF value in excess of 10 is frequently taken as an indication that multicollinearity may be unduly influencing the least squares estimates. Hence, VIF scores of more than 10 detect instances where an x variable should not be allowed into the fitted regression model because of excessively high interdependence between this variable and the other x variables in the model" (Kutner and others, 2005: 409-410).

For selecting the best predictor variables, we obtain inverse correlation matrixes by using JMP 7.0® as the statistical software aid (the inverse correlation matrix obtained for all the predictor variables is presented in Appendix B). Then, by excluding the predictor values with a VIF score more than 10 and rerunning the Multivariate Analysis Platform of JMP 7.0®, the best predictor variables will be implemented in our model are determined. The last step for reducing the number of predictor variables is shown in Table 6.

Table 6 - Inverse Correlation Matrix for Potential Predictor Variables

Variable	x1	x2	x3	x4	x5	x6	Y
x1	2.9082	0.4252	-0.1476	-0.0218	0.5506	-2.2178	-0.8088
x2	0.4252	4.8587	-0.8571	0.1153	-2.8094	-2.1757	-0.1929
x3	-0.1476	-0.8571	1.9282	-0.4925	0.5461	0.6082	-1.1174
x4	-0.0218	0.1153	-0.4925	1.4002	-0.8995	0.5919	0.0076
x5	0.5506	-2.8094	0.5461	-0.8995	4.3229	-1.2314	1.0178
x6	-2.2178	-2.1757	0.6082	0.5919	-1.2314	5.1966	-0.9559
Y	-0.8088	-0.1929	-1.1174	0.0076	1.0178	-0.9559	2.8211

During the model building process, the stepwise regression is applied to the various combinations of the predictor variables as the second variable reduction methodology.

As a result of the VIF scores analysis, selected variables that are introduced to the model are: JP-8 cost lagged one month (in million \$) as ylag1, Real Imported Crude Oil Price lagged one month as x1lag1 (real \$/barrel), U.S. Refinery and Blender Net Production of Crude oil as x2lag 1 (thousand barrels/day), U.S. Crude Oil and Petroleum Products Ending Stocks as x3lag1 (thousand barrels), U.S. Kerosene-type Jet Fuel Ending Stocks as x4lag1 (thousand barrels), U.S. Refinery and Blender Net Production of Kerosene-type Jet Fuel as x5lag1(thousand barrels/day), and U.S. Natural Gas Wellhead Price as x6lag1 (\$/thousand cubic feet). We also attempt to introduce a conditional variable called ‘conflict’ into the model. The reason for this variable is to verify that the Gulf and Iraq Wars are considered as ‘conflict’ and can be modeled with a predictor variable for the JP-8 consumption cost model. Having this in mind, the related formula introduced to the model is shown in Figure 14:

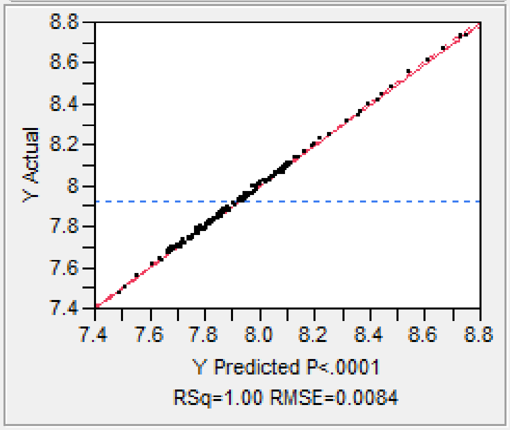
If Date MDY(5, 15, 1990) < *x1* <= Date MDY(4, 15, 1991) | Date MDY(1, 15, 2003) < *x1* <= Date MDY(12, 15, 2007) ⇒ 1
else ⇒ 0

Figure 14- Formula Box for Conflict Variable in JMP 7.0®

After numerous runs to find the most reasonable and accurate model for our case, the model variables are calculated using JMP 7.0® and the model result is shown in Figure 15:

Response Y

Actual by Predicted Plot



Summary of Fit

RSquare	0.998909
RSquare Adj	0.998727
Root Mean Square Error	0.008414
Mean of Response	7.919716
Observations (or Sum Wgts)	183

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	26	10.111270	0.388895	5492.626
Error	156	0.011045	0.000071	**Prob > F**
C. Total	182	10.122316		<.0001*

Figure 15- Model Summary

It can be stated that the model presents a high adjusted- R^2 (0.998727), which implies a good overall fit for the regression model. However, recall that the best model fitting to the past data doesn't guarantee the most accurate forecast for the future. A high adjusted- R^2 can be obtained in the fitting phase by using a polynomial of sufficiently high order which leads us to over-fitting. The result of the F-test (p-value is lower than the stated level of significance, which is 0.05) for the model indicates that the regression model is quite significant.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	22983.746	4247.945	5.41	<.0001*
YLAG1	-1016.683	189.9056	-5.35	<.0001*
X1LAG1	-13.07118	1.690038	-7.73	<.0001*
X2LAG1	-1571.475	384.0187	-4.09	<.0001*
X3LAG1	-1595.82	296.9994	-5.37	<.0001*
X4LAG1	-743.545	139.9475	-5.31	<.0001*
X5LAG1	-2063.083	506.5634	-4.07	<.0001*
X6LAG1	2.7533543	0.165681	16.62	<.0001*
CONFLICT	-61.47463	14.06525	-4.37	<.0001*
YLAG1*X2LAG1	1.2328667	0.113426	10.87	<.0001*
YLAG1*X3LAG1	69.98715	13.25348	5.28	<.0001*
YLAG1*X4LAG1	96.436876	17.89528	5.39	<.0001*
YLAG1*X6LAG1	-0.349026	0.021148	-16.50	<.0001*
YLAG1*CONFLICT	8.2715466	1.742542	4.75	<.0001*
X1LAG1*X2LAG1	-0.230075	0.055925	-4.11	<.0001*
X1LAG1*X3LAG1	1.0693764	0.119677	8.94	<.0001*
X1LAG1*CONFLICT	0.0672543	0.012213	5.51	<.0001*
X2LAG1*X3LAG1	108.99403	26.8632	4.06	<.0001*
X2LAG1*X5LAG1	213.55038	52.43351	4.07	<.0001*
X2LAG1*CONFLICT	6.3621412	1.458929	4.36	<.0001*
X3LAG1*X4LAG1	51.725835	9.771271	5.29	<.0001*
X3LAG1*X5LAG1	143.89977	35.4475	4.06	<.0001*
X6LAG1*CONFLICT	-1.715208	0.257241	-6.67	<.0001*
YLAG1*X2LAG1*CONFLICT	-0.859163	0.180886	-4.75	<.0001*
YLAG1*X3LAG1*X4LAG1	-6.709883	1.24936	-5.37	<.0001*
YLAG1*X6LAG1*CONFLICT	0.2210108	0.032231	6.86	<.0001*
X2LAG1*X3LAG1*X5LAG1	-14.89491	3.669079	-4.06	<.0001*

Figure 16- Model Parameter Estimates

As observed from Figure 16, it can be stated that the selected exploratory variables for the model are all significant with a significance level of 0.05 or better.

The Model Validation Process

Validation is important in model building. It can be defined as comparing the model behavior to the real system behavior. This process consists of: demonstrating that the model has high face validity, meeting the model assumptions, and given the same inputs, providing the same outputs like the real system. Since the model parameters match expected predictors suggested by the literature and the model R^2 is so high we assume a reasonable level of face validity. Now, assuming the model has face validity, we can perform the validation tests to ensure the model's feasibility.

Testing Normality of Studentized Residuals

Many regression models assume a normal distribution for the error term. It doesn't make any difference to the estimates of the coefficients, or the ability of model to forecast, but major differences from normality should be taken into account since it can affect the F-test, t-tests, and the confidence intervals. The study analyses the distribution of Studentized Residuals in a histogram as shown in Figure 17, and tests for normality using a Shapiro-Wilkinson test illustrated in Figure 18.

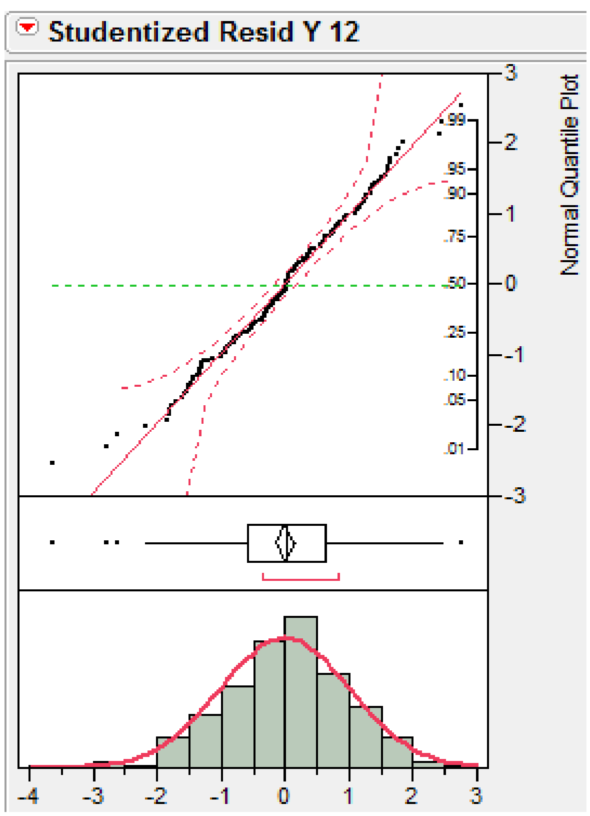


Figure 17- Distribution and Quantile Plot of Residual JP-8 Cost

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	-0.002987	-0.151554	0.1455802
Dispersion	σ	1.0185964	0.9238376	1.1351861

Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.990764	0.2886

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure 18- Shapiro-Wilkinson Test Results

The Shapiro-Wilkinson Test has a goodness of fit p-value of 0.2886 at a 0.05 significance level, indicating that the study must fail to reject the hypothesis that the data is from a normal distribution.

Plot of Residuals

A visual analysis of the scatterplot of the residuals to test the presence of any pattern, trend, or abnormality is presented in Figure 19. Thus, in Figure 19 no significant trend, pattern, or abnormality can easily be observed. A D-W Test applied to the entire data set has a value of 1.49 which indicates a small potential for autocorrelation. Further, the error variance appears well-behaved.

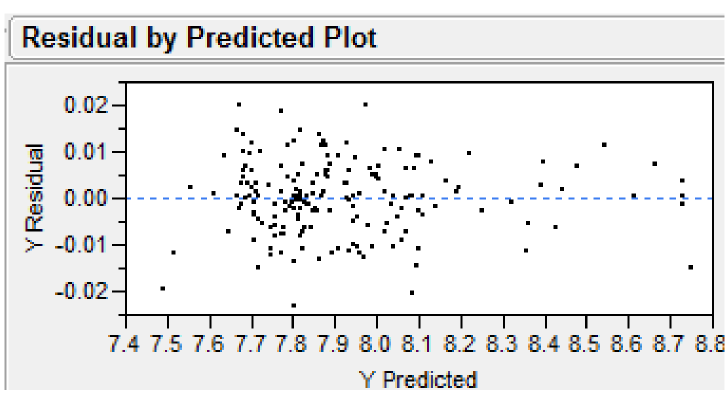


Figure 19- Run Plot of Residuals

Testing Constant Variance (Homoskedasticity) on Residuals

"When a residual plot gives the impression that the variance may be increasing or decreasing in a systematic manner, a simple test based on the rank correlation between the absolute values of the residuals and the corresponding values of the predictor variable may be conducted" (Kutner and others, 2005: 115). Since our descriptive plot shown in Figure 19 doesn't show such a systematic manner, the study finds no significant identifiable pattern within the residuals.

Testing for Multicollinearity

If two vectors point in the same direction, they can be called collinear. This test is very important because the presence of multicollinearity affects the calculations of ß coefficients. In order to detect multicollinearity, Variance Inflation Factor (VIF) scores of the variables are used.

Table 7 - VIF Scores for the Predictor Variables

Variable	YLAG1	X1LAG1	X2LAG1	X3LAG1	X4LAG1	X5LAG1	X6LAG1	CONFLICT
YLAG1	2.333	-0.813	-0.189	-0.795	-0.128	0.835	-0.862	0.104
X1LAG1	-0.813	2.726	0.458	0.184	0.031	0.475	-1.328	-0.788
X2LAG1	-0.189	0.458	4.498	-0.716	0.166	-2.608	-2.277	0.348
X3LAG1	-0.795	0.184	-0.716	1.740	-0.504	0.560	0.796	-0.642
X4LAG1	-0.128	0.031	0.166	-0.504	1.467	-0.929	0.464	0.200
X5LAG1	0.835	0.475	-2.608	0.560	-0.929	4.025	-0.809	-0.207
X6LAG1	-0.862	-1.328	-2.277	0.796	0.464	-0.809	5.081	-1.273
CONFLICT	0.104	-0.788	0.348	-0.642	0.200	-0.207	-1.273	2.411

JMP 7.0® provides the VIF scores for the model variables which are shown in the diagonal of Table 7. Recall that Kutner et al state: “A maximum VIF value in excess of 10 is frequently taken as an indication that multicollinearity may be unduly influencing the least squares estimates” (Kutner and others, 2005: 409-410). From Table 7, it can be observed that none of the variables have a VIF score higher than 10, which indicates that there seems to be no multicollinearity issue between the model variables.

<u>Testing for Existence of Outliers and Influential Data Points</u>

The study uses Cooks-D plot to test for influential data points. Recall that, Cook’s Distance values smaller than 0.25 are “preferable”, values between 0.25 and 0.50 are “moderate” and values greater than 0.50 are considered “major” influential data points (Kutner and others, 2005: 402-403).

The Cooks-D plot in Figure 20 shows that all variable values are less than 0.4, with the majority of points falling below 0.02. Only one point of interest has an influence of approximately 0.4 and it represents a point during the conflict period. However, excluding this data from calculations doesn’t cause an important change to the model parameters. Hence, keeping this data point in the model is preferred.

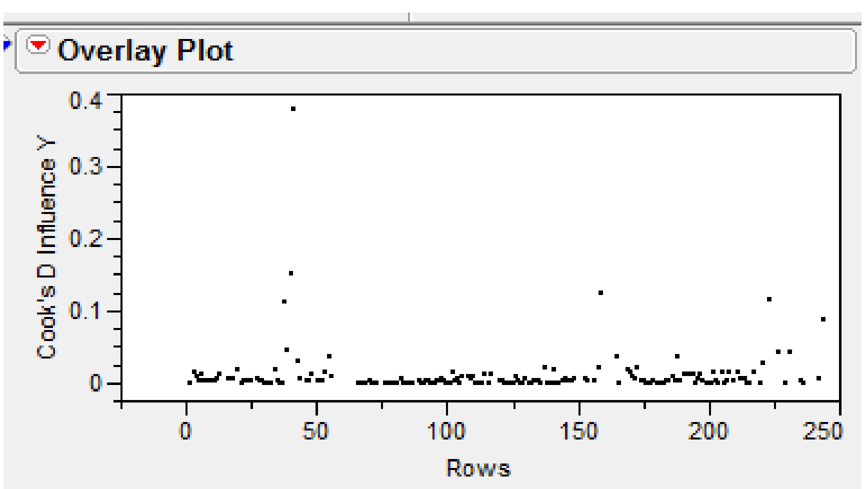


Figure 20- Cook’s Distance Overlay Plot

Multiple Regression Model Findings Discussion

This model is useful for forecasting the following month's JP-8 cost based on the current month's values of the predictors, such as real crude oil price (x1) and so on (see Appendix C). For instance, any time a major conflict occurs for the U.S., the resulting changes in crude oil and JP-8 usage affect the cost of operations for the USAF. In addition, some peculiar, observable and repeatable situations also affect the JP-8 cost.

Because the regression model is a causal model, the forecasting period can be extended by projecting the predictor variables' future values. However, we should be aware of the fact that each of these predictor variables' predicted values includes an inherent error. Hence, adding these individual errors may have an overall multiplicative error impact for our overall model.

The study finds that the JP-8 cost is susceptible to change and subjected to unexpected fluctuations. Despite these abrupt price changes, the forecasting model is still reasonable, successfully forecasting 209 of 243 points (86.1%) using a 95% individual prediction confidence interval for one month ahead (see Appendix D).

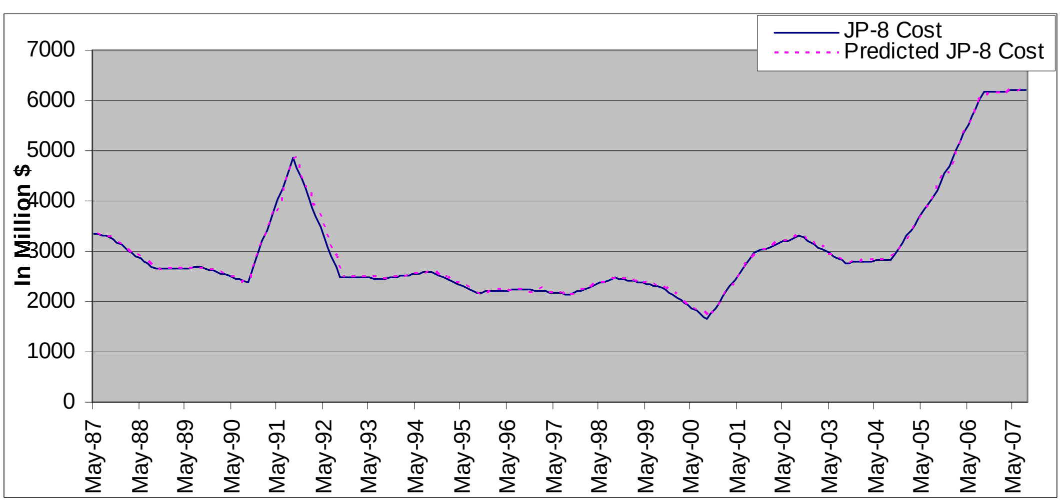


Figure 21- Real and Predicted JP-8 Cost Comparison

The forecasting capability of the model for the in-sample data is shown in Figure 21; Table 8 provides the corresponding Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's U statistics.

Table 8- Summary of Model Behavior Results

MAE	MAPE	Theil's U	% Inside CI.
31.73	1.05	0.65	86.01

From Table 8, it can be observed that the MAPE is 1.05%. This measure shows that the model behavior is good compared to the real data. Remember that such a low MAPE value doesn't always necessarily imply good forecasting because of the relevant over-fitting problem. It can be added that having a Theil's U statistics value of 0.65, which is lower than 1, indicates that the regression model provides better outcomes than the naïve approach. Recall the naïve approach uses the most recent observation available as a forecast.

To forecast with this model, we need the future values of the predictor variables. Holt's Linear Method is used to forecast the future values of the predictor variables (inputs: x1, x2, x3, x4, x5, x6) for the next 5 years. Associated alpha and beta values for each predictor variable are found as seen in Table 9.

Table 9- Alpha and Beta Values for Predictor Variables

Variable	α	β
x1	0.994838	0.014158
x2	0.980783	0.040313
x3	0.990611	0.045276
x4	0.989694	0.02397
x5	0.973069	0.067787
x6	0.997403	0.007452

The error percentages of the predictor variables via Holt's Linear Model are shown in Table 10.

Table 10- Holt's Linear Method Scores

Variable	ME	MAE	MPE	MAPE
x1	-0.12553	0.144654	-0.29002	0.406899
x2	-25.0515	30.33931	-0.15475	0.187189
x3	-2232.93	3466.823	-0.13338	0.214969
x4	-58.0424	82.31862	-0.1358	0.19993
x5	-3.75995	5.86446	-0.29031	0.441436
x6	-0.00107	0.010786	0.183219	0.390997

Now that we have the predictor variables' future values for the next 5-years, we can perform a regression analysis for the JP-8 cost during the next 5-year period. Remember that in our multiple regression model, other than those shown in Table 10, we introduce a variable called "conflict" which indicates any major conflict involving the

U.S. Assuming the current GWOT continues, which has an obvious effect on USAF ops-tempo and fuel usage, the "conflict" variable is assumed to have an impact for the future with an assigned value of "1", and the future JP-8 cost is calculated accordingly. Plugging the future values of each predictor variable in the model, the regression line is found, as shown, in Figure 22. From the figure it can be seen that the regression line shows a quite steep upward trend. Most of this is due to the recent upward trend in oil prices.

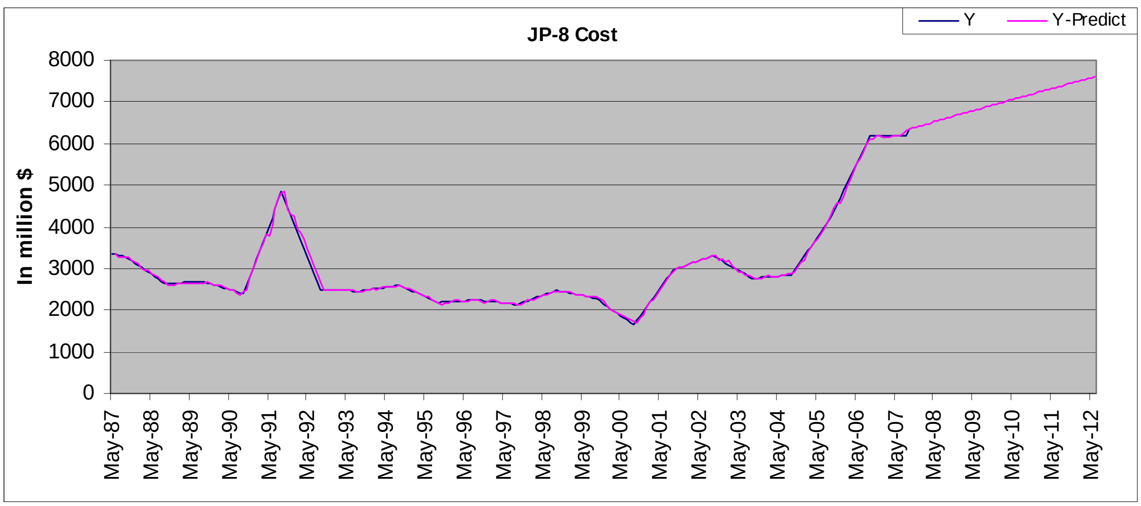


Figure 22- Multiple Regression Model Forecast

Step 3: ANN Model to Predict the USAF JP-8 Fuel Consumption Cost

<u>Introduction</u>

This part of the research focuses on fitting a NN model that can discover the related pattern for JP-8 cost data. Using the NN for forecasting purposes is explored and empirical evidence about the accuracy of NN forecasts is investigated.

Model Building Process

In our case, the data is divided into two parts. The model is fit to the first part, and then genuine out-of-sample forecasts are made in the second part. For the model fitted, a variety of statistical measures were computed to measure the fit of the model.

There are many software applications for developing and analyzing NN's. At this point, we make a decision about the software environment after talking with SME's. Because of the Statistical Neural Network Analysis Package (SNAPP)'s characteristics of being simple, easy-to-use, containing an expert system, and more importantly, doing the same job as other software in a simpler way, we choose it as the software aid. SNAPP's expert system's suggest feature 'suggest' a specific structure and set of parameters for any particular model. "The expert system's suggestions and default parameters have proven to be suitable and relatively stable over a wide range of problems"(Wiggins and others, 1995: 1).

In order to analyze a data set, SNAPP needs two different types of data: delimited and fixed format data. Hence, the data is transformed accordingly to SNAPP's identification needs via a Visual Basic coded converter spreadsheet (see Appendix-E). Following this procedure, the variables from the data set, which will be used as the inputs and the outputs, are specified as it can be seen in Figure 23.

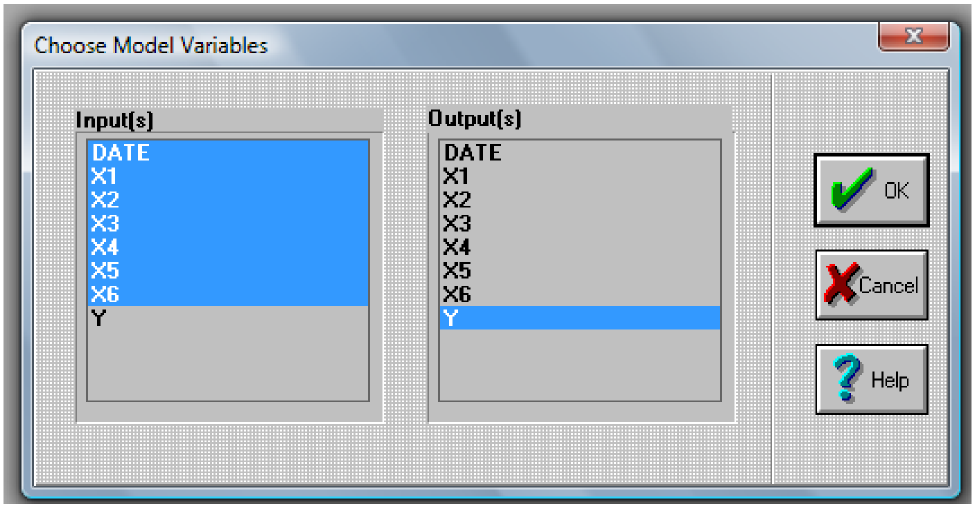


Figure 23- Identifying the Inputs and Outputs for the Model

To compare ANN model with the Multiple Regression Model, and also since the predictor variables of the regression model are found to have an impact on the JP-8 cost, the same variables used in the Multiple Regression Model are introduced to the NN. The output of the model is JP-8 cost (y), and the inputs (independent variables) are;

- Date,
- Real Imported Crude Oil Price (Real $/barrel) NOV08=1, as x1,
- U.S. Refinery and Blender Net Production of Crude Oil and Petroleum Products (thousand barrels per day) as x2,
- U.S. Crude Oil and Petroleum Products Ending Stocks (thousand barrels) as x3,
- U.S. Kerosene-Type Jet Fuel Ending Stocks (thousand barrels) as x4,
- U.S. Refinery and Blender Net Production of Kerosene-Type Jet Fuel (thousand barrels per day) as x5,
- U.S. Natural Gas Wellhead Price as x6 (dollars per thousand cubic feet).

Since backpropagation is the most preferred NN structure in the literature, we use the backpropagation NN structure during our study (see Figure 24).

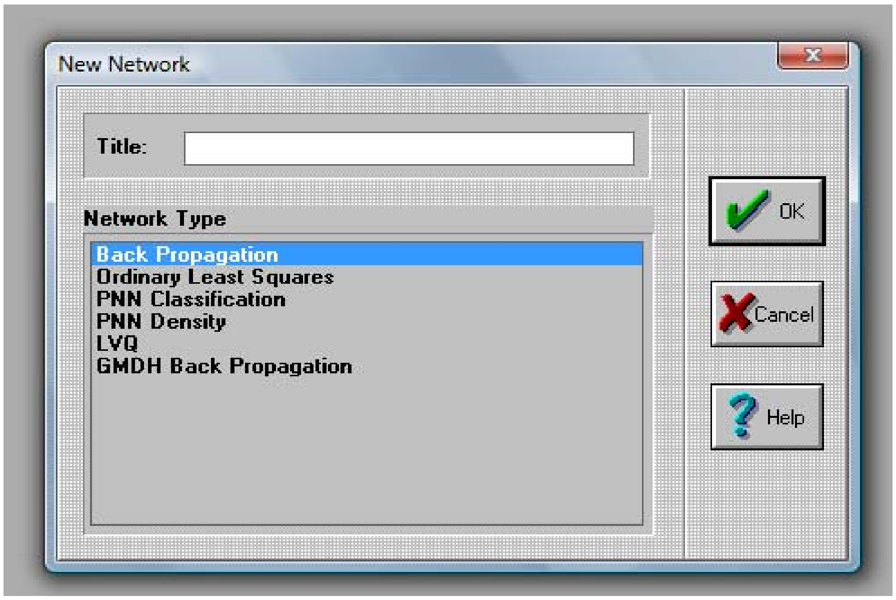


Figure 24- Identifying the Structure for the Model

A backpropagation network is composed of several layers which are aimed to feed information forward from the input to the output layer.

SNAPP allows users to set the number of layers, the types of activation functions, and the interconnections among layers. However, this work accepted SNAPP default (suggested) settings for the NN structure in our study (see Figure 25). Our transfer function is identified as a linear transfer function with seven neurons and one hidden layer, via SNAPP's expert system for our data set.

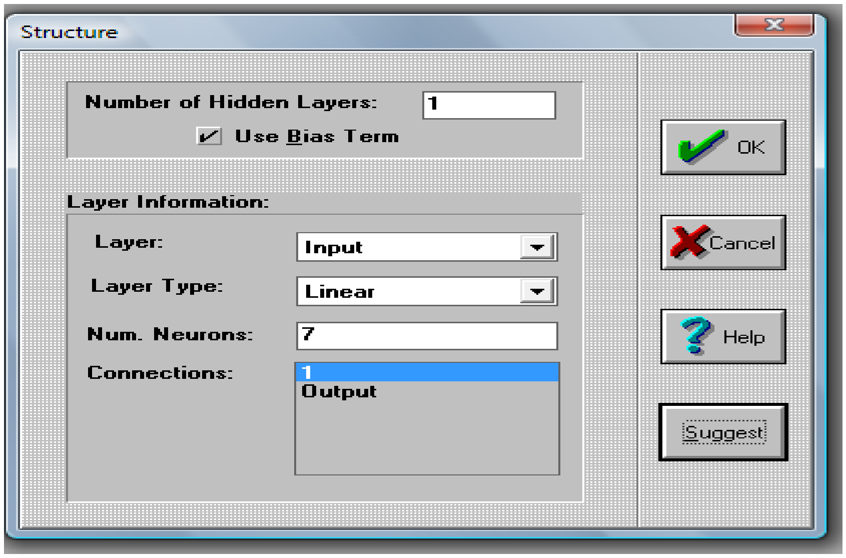


Figure 25- Using SNAPP's Suggest Option

Validation samples are used to gauge the progress of a network and help to evaluate the networks ability to generalize outside of the training sample. SNAPP is capable of tracking performance on two different validation samples. However, in this study, only one validation sample is used and the type of validation sample is identified as "modulus". Here, the validation sample is every jth record in the training file, starting with the kth element (where k<j). "j" is called the divisor and "k" is called the remainder, since the nth record is in the sample when n divided by j has the remainder k. The default value for the divisor and remainder used in the study are 3 and 0 (see Figure 26).

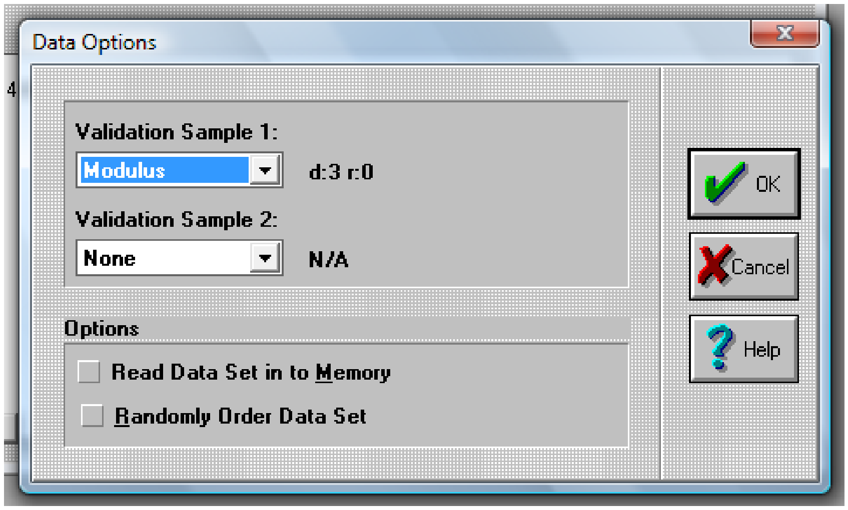


Figure 26- Specifying the Validation Sample

The training algorithms for the NN architectures are highly susceptible to the scale of the input variables. To address this problem SNAPP has the capability to scale the data sets to ranges specified by the user. During the study all input variables are scaled between the range of 0.10 and 0.90 (SNAPP's default) and for the output variables no transformation is used (see Figure 27).

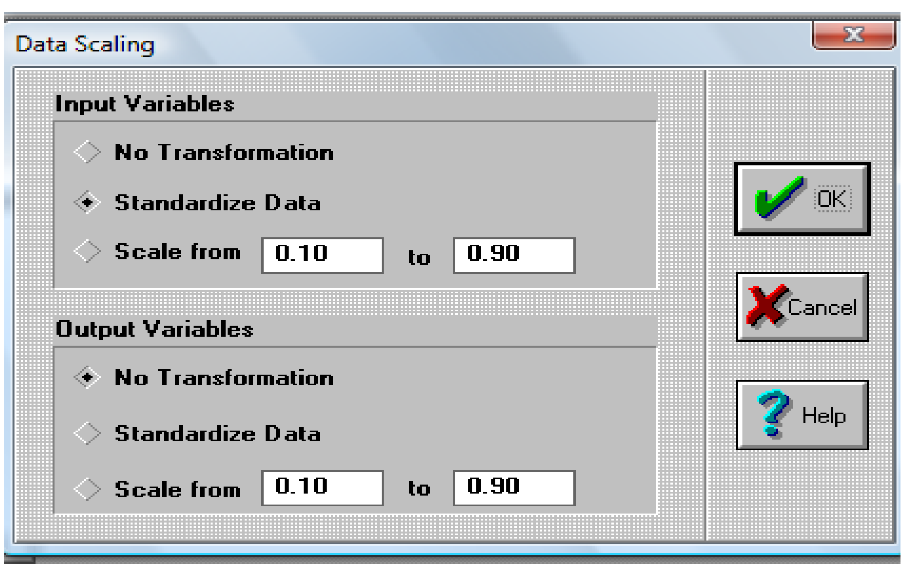


Figure 27- Data Scaling and Standardizing

Two parameters help us to determine how training proceeds in a backpropagation network. These are the training rate and the momentum factor. “The training rate essentially determines how much of the network’s error is attempted to be solved by each weight being adjusted in the network (Wiggins and others, 1995: 16).

“The momentum term helps us to smooth the network’s training path by remembering the past weight adjustments (Wiggins and others, 1995: 1). Hence, during the study the default values suggested by SNAPP’s expert system are used for the training and momentum terms (see Figure 28).

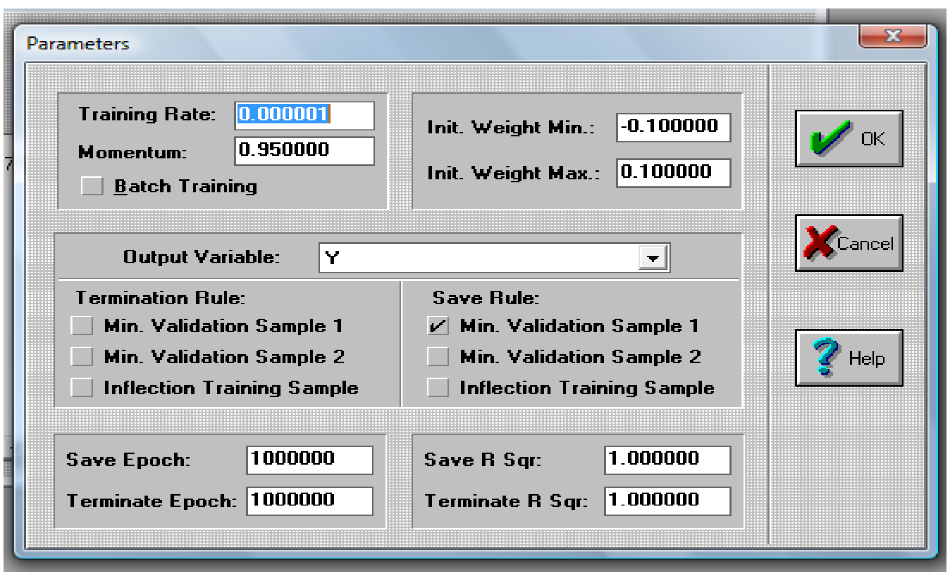


Figure 28- Identifying the Training Parameters

The amount of time required for a training epoch depends on: the number of output and input variables introduced to the model, the complexity of the model, and the size of the data set. Therefore, the maximum training epoch is identified as 1200 where no further improvement of the model seems to be possible, as observed from run plots.

Results

During the research, three different networks are formed to make comparisons of the model's performance. In the first one, we introduce the raw data to the model and evaluate the network's performance. In the second one, input variables are smoothed via 3MA and in the third one they're smoothed via 12MA. Then they're introduced to the model. The smoothed graphs of the predictor variables can be seen in Appendix F.

In practice we need to find the smooth patterns in the data and deal with the randomness inherent in the time series. Data averaging process reduces the variation in the series due to randomness, allowing one to make the trend-cycle more distinct and thus easier to estimate. These methods smooth the "past history" of the data. The trade-off with moving averages is how smooth to make the data. The smoothest is the simple average but there is a loss of information whenever you average. Since the moving average technique presumes an odd number of observations, there is a loss of data at the beginning and end of the time series.

Recall that our data set dates back to May 1987. For 3MA, the trend-cycle for April of year 1 is estimated to be the average of the values for March, April and May. For 12MA we have a significant data loss at the beginning and end of our observation period. Thus, to overcome the data loss that we face in a 12MA smoothed average, the first data point is taken as the average of the months through October 1987 with 1/2 of the month of November 1987. The second 12MA data point adds an additional month to the average. This continues until the November data point when we are sufficiently into the series to obtain the complete 12MA.

In short, the reason to use a 3MA and 12MA weighted moving average in our model is to reduce the short-term fluctuations of the variables and have the ability to compare both options with each other and also with the raw data. This enables us to focus on the trend-cycle. In addition, it helps us to identify whether smoothing the data allows us to have more robust forecasts with NNs.

The problem that we encounter in multiple regression analysis shows up again in NN modeling. Since we don't know the future values of the predictor variables, we are not able to compare the performance of the model for the out-of-sample data. Thus, the same future values of the predictor variables that we've already determined for the regression analysis via Holt's Linear Method will be used for the NN forecasting. Now that we have the future values of the predictor variables in hand, all of the conditions are met to make predictions of JP-8 cost for the next 5-year period.

First, we begin with introducing the raw data to the NN. The graph of the NN forecast with the raw data for the next 5-years is shown in Figure 29:

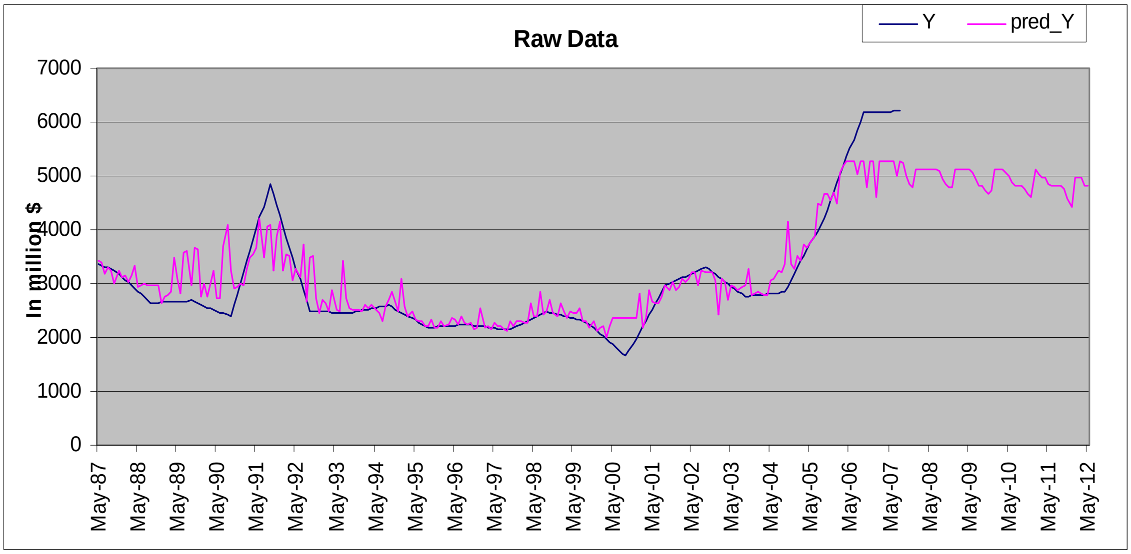


Figure 29- NN Forecast with Raw Data

Based on Figure 29, it can be stated that, generally the NN model captures the trend of the real data. However, there are variations of the in-sample forecast from the actual amounts. Our model forecast shows a horizontal pattern for the future JP-8 cost. Figure 30 and 31 show the graph of our NN forecast for the in-sample data using the 3MA and 12MA smoothed data.

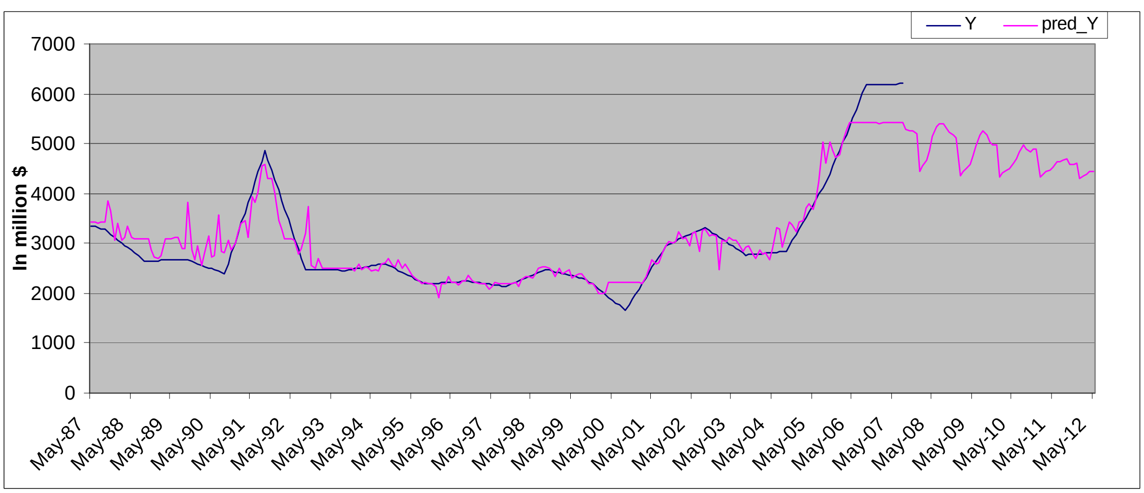


Figure 30- NN Forecast via 3MA Smoothed Data

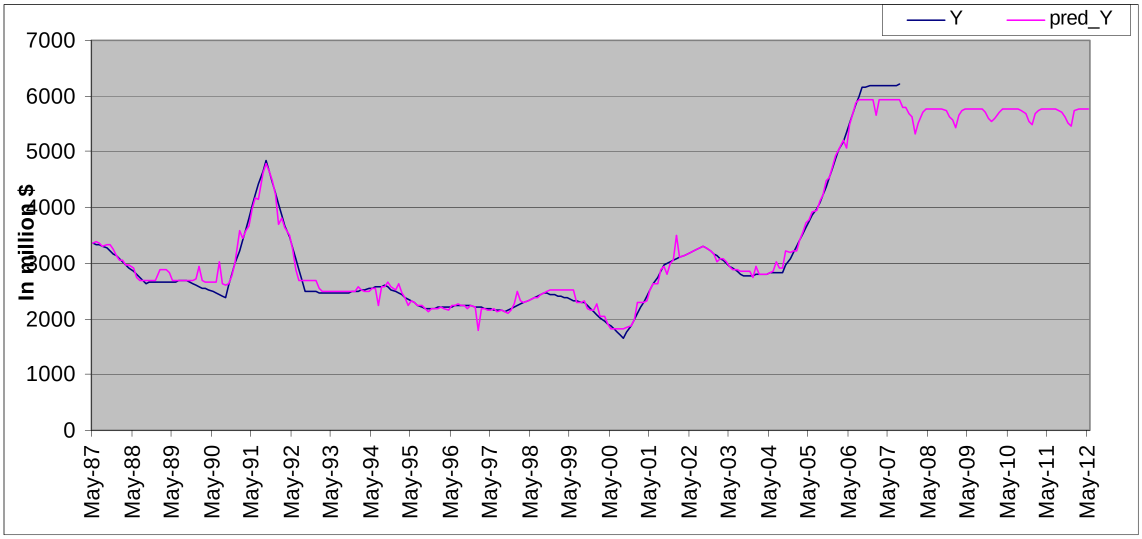


Figure 31- NN Forecast via 12MA Smoothed Data

From Figure 30 and 31, we see that the predictions of the NN model for the in-sample data look better than the one with the raw data. The variation from the real values for the in-sample data is relatively small if we compare it with the raw data. As the smoothing period increases, the data set shows a better fit for the in-sample data. The forecasting performance of three different NN models is provided below in Table 11 and 12.

Table 11- NN Forecast Performance Comparisons 1

Data Type	ME	MAE	MPE	MAPE	MSE	Theil's U
Raw Data	-52.85	267.25	-4.24	8.73	186077.45	5.42
3MA	-41.51	201.42	-2.87	6.49	100996.81	3.97
12MA	-11.52	76.41	-0.86	2.58	15512.86	1.63

Table 12- NN Forecast Performance Comparisons 2

Data Type	RMSE (Train)	RMSE (Validate)	R-square (Train)	R-square (Validate)
Raw Data	350.31	559.97	0.89	0.71
3MA	268.56	398.97	0.93	0.84
12MA	107.96	142.13	0.99	0.98

Our findings indicate that, before introducing a data set to a NN, we should reduce the short-term fluctuations somehow in order to make the trend-cycle distinct for our analyses. This enables us to have more robust forecasts than by simply using the raw data. In our NN model, the smoother the model, the better the results we get from our network, as it is shown in Table 11 and 12. The above-shown forecast accuracy measures such as MAPE and Theil's U-value indicate the relative improvement with the increased smoothing period as you move down in the columns. Beyond the three different smoother data sets that are introduced to the model, we try four additional data sets to be used in the model. These are: detrended, deaseasonalized, and both detrended and deaseasonalized data sets with a mathematical transformation of the data based on the natural log. However, none of these models produced better results. So, they will not be shown here.

Step 4: ARIMA Model to Predict the USAF JP-8 Fuel Consumption Cost

The third model considered was an ARIMA model. ARIMA modeling requires stationarity of the data series. In practice, most non-stationary series can be made sufficiently stationary by means of differencing, curve fitting, removal of trend, or by taking logarithms (Granger, 1989: 65-66).

In this ARIMA modeling we use the JP-8 cost time series beginning from the year 1977, different from our previous analysis. Because ARIMA modeling is not a causal model, we divide our data set into two sets, a model build set and a model check set. The data for years between May-77 to May-95 is the model building set and the rest of the data set is the model check set. Once again, JMP 7.0® Time Series Analysis Platform is used as the statistical aid for this analysis. The modeling process begins with the time series plot of historical JP-8 cost shown in Figure 32.

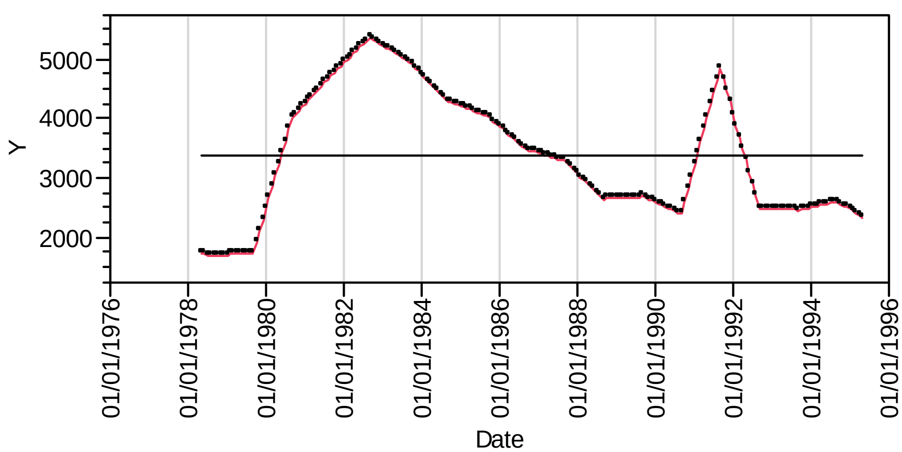


Figure 32- Time Series Plot of JP-8 Historical Cost

From the time series figure, it can be stated that the series doesn't seem stationary in the mean. Thus, prior to performing ARIMA modeling, transformation of the series should be considered in order to have the stationarity condition met.

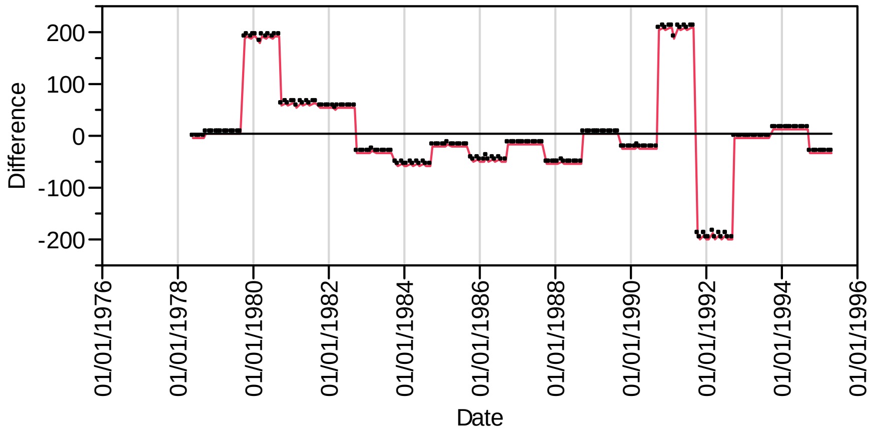
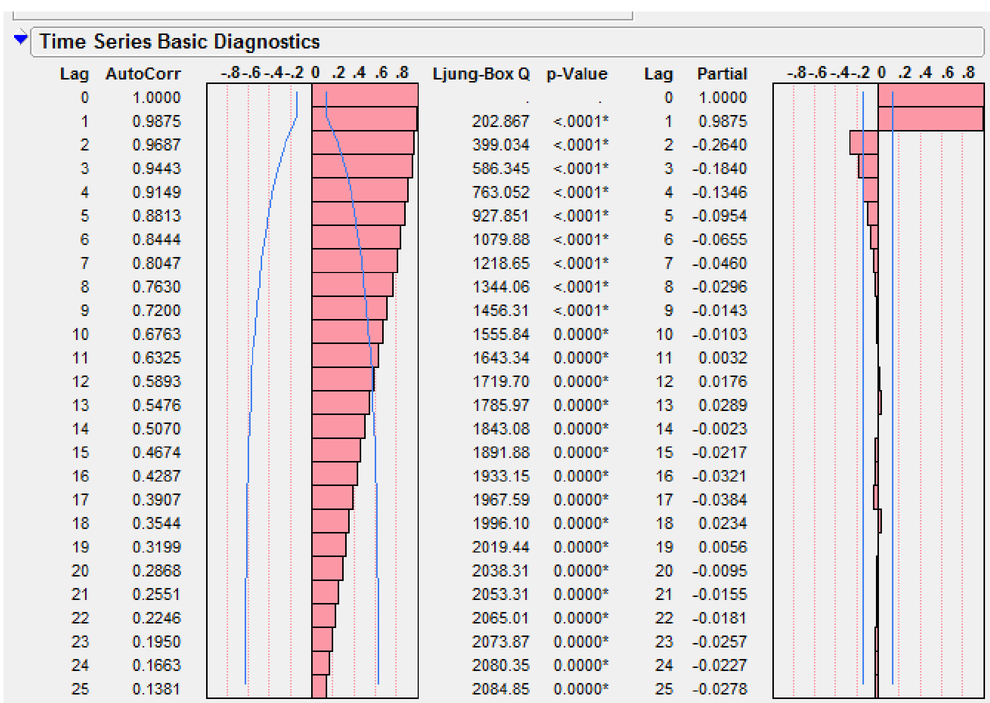


Figure 33- First-Differenced Series

As it can be observed from Figure 33, after taking the first differences of the time series, the series seems stationary in the mean. The ACF and the PACF plot of the historical JP-8 cost time series is presented in Figure 34.



Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.9875	202.867	<.0001*	1	0.9875
2	0.9687	399.034	<.0001*	2	-0.2640
3	0.9443	586.345	<.0001*	3	-0.1840
4	0.9149	763.052	<.0001*	4	-0.1346
5	0.8813	927.851	<.0001*	5	-0.0954
6	0.8444	1079.88	<.0001*	6	-0.0655
7	0.8047	1218.65	<.0001*	7	-0.0460
8	0.7630	1344.06	<.0001*	8	-0.0296
9	0.7200	1456.31	<.0001*	9	-0.0143
10	0.6763	1555.84	0.0000*	10	-0.0103
11	0.6325	1643.34	0.0000*	11	0.0032
12	0.5893	1719.70	0.0000*	12	0.0176
13	0.5476	1785.97	0.0000*	13	0.0289
14	0.5070	1843.08	0.0000*	14	-0.0023
15	0.4674	1891.88	0.0000*	15	-0.0217
16	0.4287	1933.15	0.0000*	16	-0.0321
17	0.3907	1967.59	0.0000*	17	-0.0384
18	0.3544	1996.10	0.0000*	18	0.0234
19	0.3199	2019.44	0.0000*	19	0.0056
20	0.2868	2038.31	0.0000*	20	-0.0095
21	0.2551	2053.31	0.0000*	21	-0.0155
22	0.2246	2065.01	0.0000*	22	-0.0181
23	0.1950	2073.87	0.0000*	23	-0.0257
24	0.1663	2080.35	0.0000*	24	-0.0227
25	0.1381	2084.85	0.0000*	25	-0.0278

Figure 34- First Differenced Time Series ACF PACF

From Figure 34, it can be seen that the autocorrelations are exponentially decaying and there is only one important non-zero partial autocorrelation at lag 1. “In reality, we don’t know the order of the ARIMA model. However, we can use the ACF and PACF to infer an AR (1) model, when the autocorrelations are exponentially decaying and there is a single partial autocorrelation” (Makridakis and others: 1997: 338).

After meeting the stationarity condition for model building, we perform and compare different types of models in an attempt to identify the best model that fits our historical JP-8 cost time series. From the 18 different types of models shown in Table 13, the best models are identified via the lowest AIC and MAPE score and the highest R-squared value.

Table 13- Performance of Various Models

Model Comparison

Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	AIC Rank	SBC Rank	MAPE	MAE
AR(1)	203	7985.3055	2430.6347	2437.2807	0.991	2426.6347	10	10	1.882351	60.724180
MA(1)	203	278797.27	3159.4218	3166.0678	0.730	3155.4218	15	15	15.719076	466.18134
ARI(1, 1)	202	1534.234	2079.0345	2085.6708	0.999	2075.0345	3	3	0.403592	12.995124
IMA(1, 1)	202	3399.6287	2240.7129	2247.3492	0.997	2236.7129	6	6	1.092835	36.417890
ARMA(1, 1)	202	3404.6585	2258.7780	2268.7471	0.994	2252.778	7	7	1.280827	39.185584
ARIMA(1, 1, 1)	201	1535.8573	2080.2489	2090.2033	0.999	2074.2489	4	4	0.406583	13.101066
Seasonal ARIMA(0, 0, 0)(1, 0, 0)12	203	618645.12	3325.2174	3331.8634	0.387	3321.2174	17	17	19.951078	606.36010
Seasonal ARIMA(0, 0, 0)(0, 0, 1)12	203	697891.48	3347.2667	3353.9127	0.326	3343.2667	18	18	23.740791	704.52561
Seasonal ARIMA(0, 0, 0)(1, 1, 0)12	191	723926.69	3153.8269	3160.3523	0.262	3149.8269	12	12	17.738382	610.33317
Seasonal ARIMA(0, 0, 0)(0, 1, 1)12	191	724568.1	3153.9793	3160.5047	0.262	3149.9793	13	13	17.781810	612.73969
Seasonal ARIMA(0, 0, 0)(1, 0, 1)12	202	593161.74	3318.1695	3328.1386	0.406	3312.1695	16	16	19.836542	590.77821
Seasonal ARIMA(0, 0, 0)(1, 1, 1)12	190	727150.16	3155.6844	3165.4725	0.263	3149.6844	14	14	17.684826	608.19733
Seasonal ARIMA(1, 1, 0)(0, 0, 1)12	201	682.37595	1948.4185	1958.3729	0.999	1942.4185	1	1	0.290074	9.615880
Seasonal ARIMA(1, 0, 0)(0, 0, 1)12	202	7755.6911	2425.8728	2435.8419	0.991	2419.8728	9	9	1.960112	63.543276
Seasonal ARIMA(1, 0, 0)(0, 1, 1)12	190	143757.04	2842.7315	2852.5196	0.854	2836.7315	11	11	10.352902	331.25777
Seasonal ARIMA(0, 1, 1)(1, 0, 0)12	201	3088.8722	2223.4099	2233.3643	0.997	2217.4099	5	5	1.151806	38.646081
Seasonal ARIMA(1, 0, 1)(0, 1, 0)12	190	9283.9015	2318.9735	2328.7616	0.991	2312.9735	8	8	1.857973	59.861421
Seasonal ARIMA(2, 1, 0)(0, 0, 1)12	200	685.66919	1950.4075	1963.6799	0.999	1942.4075	2	2	0.289747	9.612134

From our findings, the best model with the lowest AIC, MAPE and also the highest R-squared value is the Seasonal ARIMA (1,1,0)(0,0,1)12 model. The numbers in the first parenthesis respectively indicate the autoregressive, differencing, and the moving average orders of the model and the second parenthesis respectively represent the seasonal components of the model. The number '12' outside the parenthesis indicate the order of periodicity or seasonality of the model. The model has a p-value less than 0.05 (95% C.I) that indicates the significance of the model. Detailed model information is shown in Figure 35.

Model: Seasonal ARIMA(1, 1, 0)(0, 0, 1)12

Model Summary

DF	201	Stable	Yes
Sum of Squared Errors	137157.565	Invertible	Yes
Variance Estimate	682.375946		
Standard Deviation	26.1223266		
Akaike's 'A' Information Criterion	1948.41852		
Schwarz's Bayesian Criterion	1958.37288		
RSquare	0.99927668		
RSquare Adj	0.99926948		
MAPE	0.29007409		
MAE	9.61588033		
-2LogLikelihood	1942.41852		

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate
AR1,1	1	1	0.973753	0.019826	49.11	<.0001*	
MA2,12	2	12	1.000000	0.106810	9.36	<.0001*	-0.0051431
Intercept	1	0	-0.195949	5.000828	-0.04	0.9688	

Figure 35- Model Summary and Parameter Estimates

Now that we have selected our model, which appears to be the best among the models being considered, we should perform diagnostics to verify that the model is adequate. As previously mentioned, this process is carried out by studying the residuals and detecting if any pattern remains unaccounted for. Certainly ARIMA model residual computation is not as easy and straightforward as regression modeling. However, JMP

7.0® performs the tedious math calculations for us. The residual plot of the model is as follows.

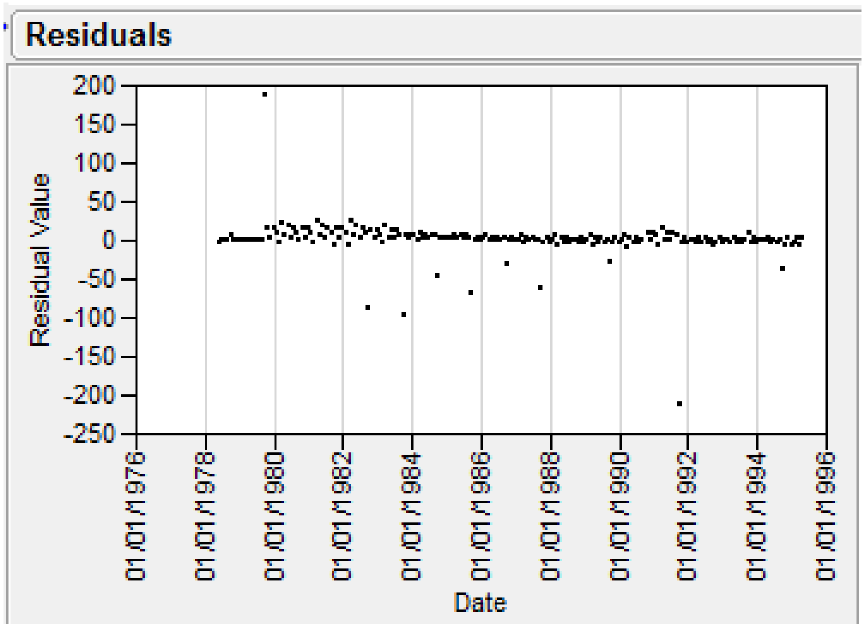
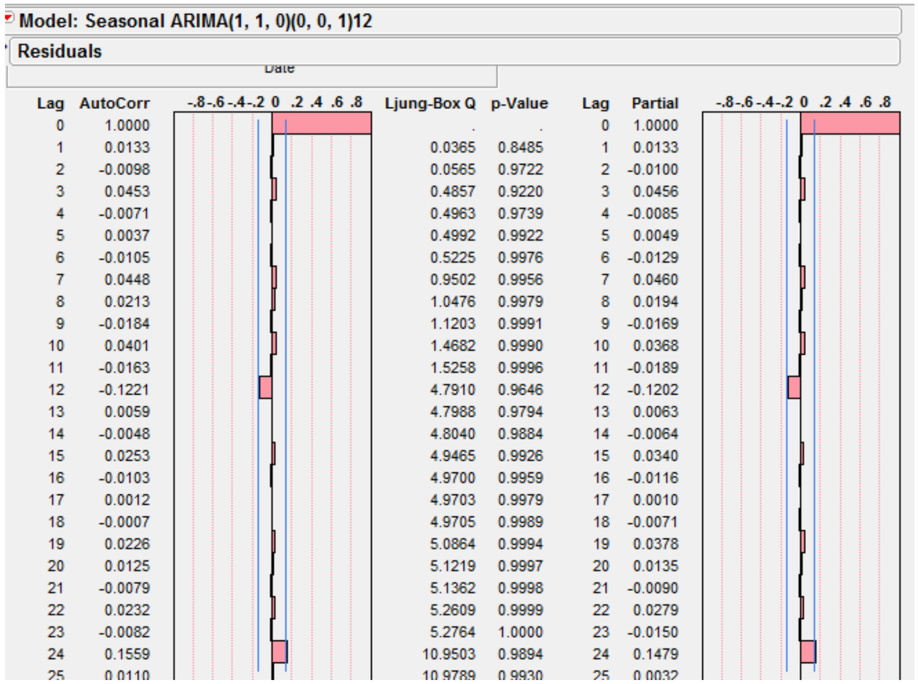


Figure 36- Residual Plot

After fitting the model, the residuals should be white noise in a good forecasting model. It can be seen in Figure 36 that the residual plot of our model looks like white noise, which means the residuals are random. There are only two important outliers in the residual plot. Removing them from our model building process doesn't make any significant difference, thus we consider them as not worthy for deeper investigations.

After fitting the model, the ACF and PACF of the residuals are obtained via JMP 7.0® shown in Figure 37.



Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.0133	0.0365	0.8485	1	0.0133
2	-0.0098	0.0565	0.9722	2	-0.0100
3	0.0453	0.4857	0.9220	3	0.0456
4	-0.0071	0.4963	0.9739	4	-0.0085
5	0.0037	0.4992	0.9922	5	0.0049
6	-0.0105	0.5225	0.9976	6	-0.0129
7	0.0448	0.9502	0.9956	7	0.0460
8	0.0213	1.0476	0.9979	8	0.0194
9	-0.0184	1.1203	0.9991	9	-0.0169
10	0.0401	1.4682	0.9990	10	0.0368
11	-0.0163	1.5258	0.9996	11	-0.0189
12	-0.1221	4.7910	0.9646	12	-0.1202
13	0.0059	4.7988	0.9794	13	0.0063
14	-0.0048	4.8040	0.9884	14	-0.0064
15	0.0253	4.9465	0.9926	15	0.0340
16	-0.0103	4.9700	0.9959	16	-0.0116
17	0.0012	4.9703	0.9979	17	0.0010
18	-0.0007	4.9705	0.9989	18	-0.0071
19	0.0226	5.0864	0.9994	19	0.0378
20	0.0125	5.1219	0.9997	20	0.0135
21	-0.0079	5.1362	0.9998	21	-0.0090
22	0.0232	5.2609	0.9999	22	0.0279
23	-0.0082	5.2764	1.0000	23	-0.0150
24	0.1559	10.9503	0.9894	24	0.1479
25	0.0110	10.9789	0.9930	25	0.0032

Figure 37- ACF and PACF of Residuals

Although there seems to be a slight autocorrelation and partial autocorrelation for period twelve in the ACF/PACF plot of Figure 37, these are within the limits and look acceptable.

Following the model identification and verification, the future projection of the JP-8 cost is obtained using the JMP 7.0® Time Series Analysis Package. The future projection of the model is presented in Figure 38 and the performance measures of the forecast accuracy are calculated via a MS Excel Spreadsheet and exhibited in Table 14.

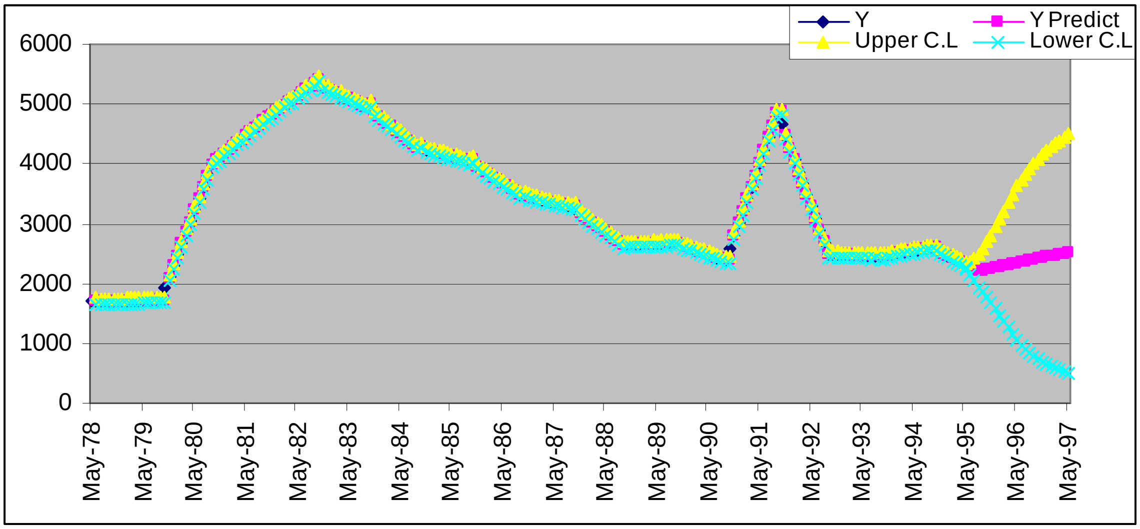


Figure 38- Seasonal ARIMA (1,1,0)(0,0,1)12 Model Projection

Table 14- Performance Measures of Seasonal ARIMA (1,1,0)(0,0,1)12 Model

ME	MAE	MPE	MAPE	MSE	Theil's U
1.286	9.568	0.067	0.290	591.094	0.374

The performance measures of the model indicate good results, as it can be observed from the fit of the model with the real data in Figure 38. Also, the model's U-statistic value of 0.37 indicates that the model is better than simply using the naïve approach. The error statistics are good as shown in Table 14.

Step 5: Comparison of the Model Findings and Choosing the Best Model

We compare our different forecast models by identifying a comparison timeframe within the in-sample data. The comparisons are executed for the years between May-95 and May-05 within our data set. Other than our three core models, which are Multiple Regression, ANN modeling and ARIMA modeling, we also try to utilize moving averages and smoothing methods (Holt-Winters, SES) for our short-term model performance comparisons. The reason for utilizing them is to check whether more simple methods can provide accurate enough forecasts for the short-term. These methods are applied with the help of JMP 7.0® time series analysis package. Here we use five different forecasting horizons for model comparisons. We begin with comparing the Theil's U-values' of the models for different forecasting horizons. The results are presented in Table 15.

Table 15- In-Sample Comparison of Theil's U-values for Different Forecast Horizons

	THEIL'S U VALUES				
	Forecast Horizon				
MODELING TYPE	1-month	2-months	1-year	5-years	10-years
ANN with Raw Data	0.003	1.191	3.653	5.337	5.301
ANN with 3MA Smoothed	0.009	0.471	4.471	3.472	3.675
ANN with 12MA Smoothed	0.003	0.424	1.411	3.137	1.737
Multiple Regression	0.011	0.561	1.049	0.909	0.622
Seasonal ARIMA	0.002	0.185	2.442		
Holt-Winters (additive)	0.000	0.037	8.415		
SES	0.030				
MA3	0.030				
MA6	0.052				
MA12	0.077				

A graphical comparison of Theils's U-Values for different models within different forecasting horizons is presented in Figure 39 and 40.

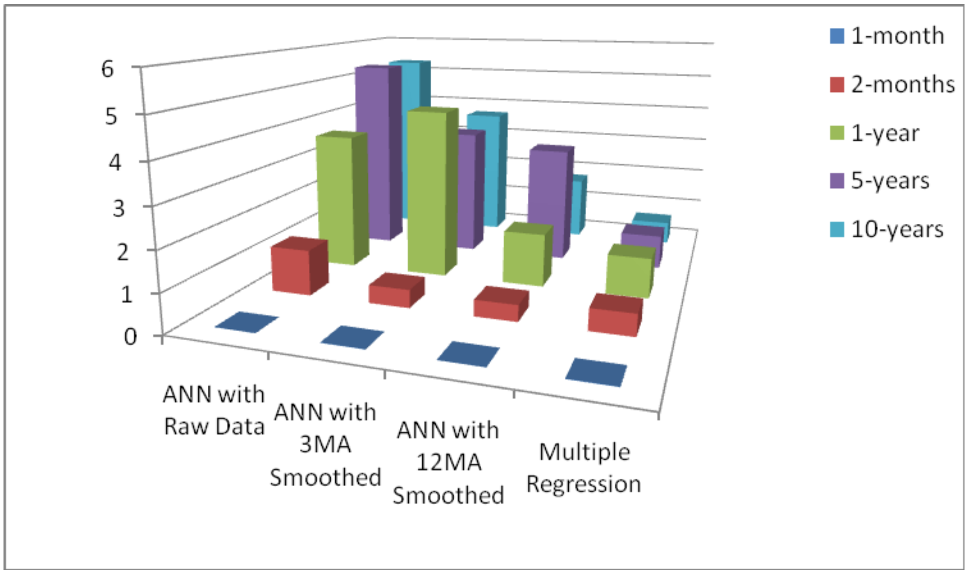


Figure 39- Comparison of Theil's U-Values for ANN and Regression

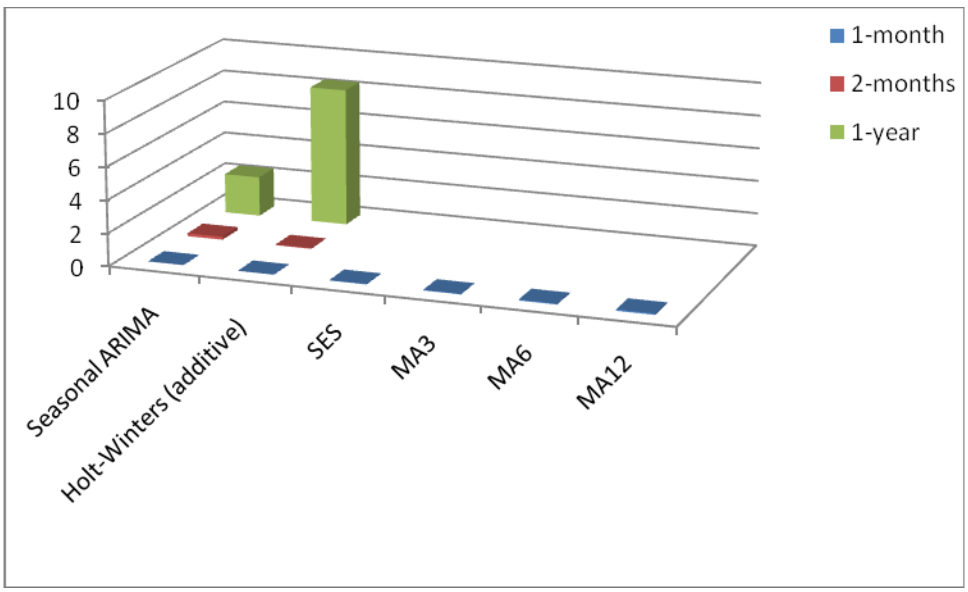


Figure 40- Comparison of Theil's U-Values for Other Models

The Theil's U-values shown both in Table 15, Figure 39 and 40 indicate that, for the in-sample data all of the models give approximately the same results for a month ahead forecast horizon. Hence, we would be better-off by utilizing more simple methods for short-term forecasts especially when time is a considerable constraint for decision making. When we consider a 2 month ahead forecast horizon, our results show that all of the models, except ANN with raw data, are better than the naïve approach. Seasonal ARIMA and Holt-Winters Method have the best scores for Theil's U-values for this period. When we compare the models for 1 year ahead forecasting horizon, multiple regression outperforms the other models. ANN with 12MA smoothed and the regression model show better results than the naïve approach. When we extend our forecasting horizon to 5 years, which is our goal, and even 10 years ahead, regression model once again performs better than both the naïve approach and the different type of ANN models. Also, it should be kept in mind that the ANN model with raw data shows poor results for all of the forecasting horizons in comparison to the smoothed models. This confirms that prior to beginning the analysis with ANN modeling, preprocessing of the data is necessary. Finally, as the forecasting horizon increases, the data should be smoothed for more periods in order to get better results.

The MAPE scores of the models for the same forecasting horizons are shown in Table 16 and a graphical comparison is presented in Figure 41 and 42.

Table 16- In-Sample Comparison of MAPE Scores for Different Forecast Horizons

	MAPE SCORES				
	Forecast Horizon				
MODELING TYPE	1-month	2-months	1-year	5-years	10-years
ANN with Raw Data	0.316	1.065	2.161	3.883	6.409
ANN with 3MA Smoothed	1.557	1.210	2.166	2.418	4.441
ANN with 12MA Smoothed	0.256	0.462	0.875	2.083	2.177
Multiple Regression	0.835	0.742	0.768	0.802	0.940
Seasonal ARIMA	0.141	0.209	1.753		
Holt-Winters (additive)	0.042	0.052	5.178		
SES	2.257				
MA3	3.002				
MA6	5.233				
MA12	7.482				

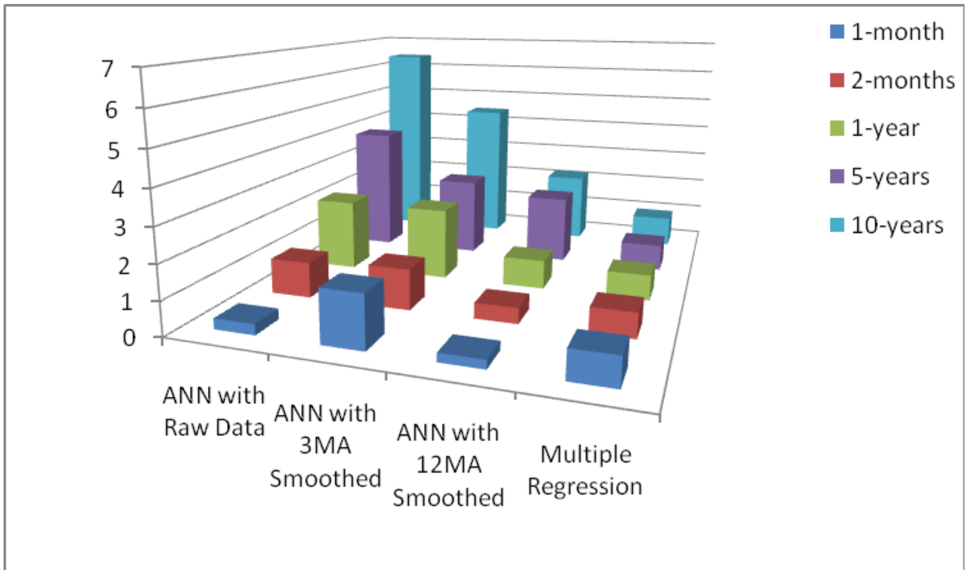


Figure 41- Comparison of MAPE Scores for ANN and Regression

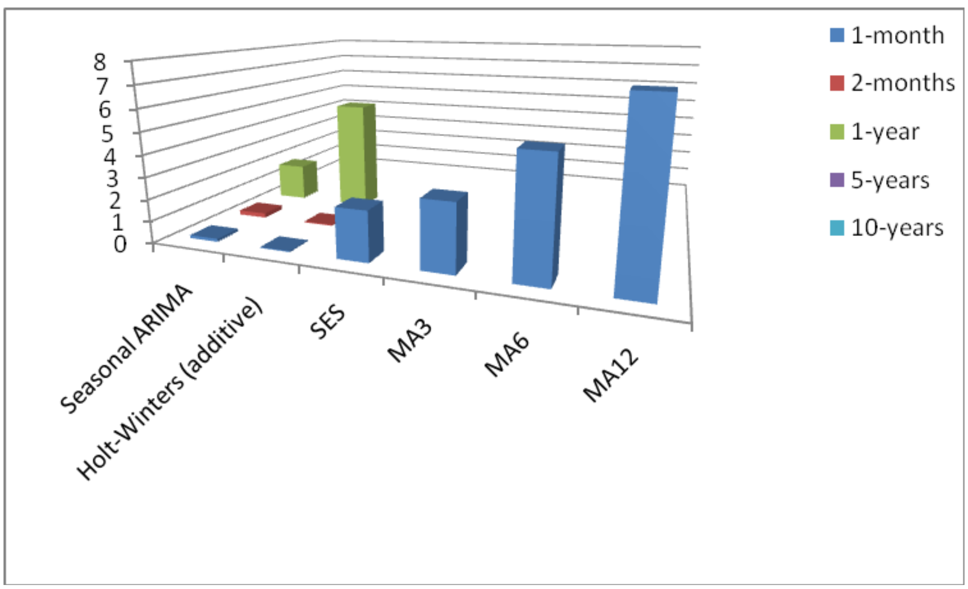


Figure 42- Comparison of MAPE Scores for Other Models

From Table 16, Figure 41, and 42 the MAPE scores reveal the same conclusions as the Theil's U-values for the performance of models. The MAPE scores for moving averages and exponential smoothing methods seem higher than other methods for the 1 month ahead forecast horizon. But when we check 2-month ahead forecasts' MAPE scores, our results reveal that the decision makers would be better-off by using relatively simple models for short-term (a month or a two month ahead) forecasting horizons. Again, it is clear that prior to beginning ANN modeling, short-term fluctuations of the variables should be removed.

The purpose of this study is to forecast the cost of JP-8 for the next 5-years. From what we have found so far, multiple regression analysis outperformed other models according to the specified forecasting accuracy measures for both 5-year and even 10-year forecasting horizons. Also, the regression model shows better results than simply using the naïve approach. Hence, we conclude that the Multiple Regression Analysis model represents the recent and future trends for USAF JP-8 cost figures better than other models for the next 5-year period. Before beginning the analysis, it was thought that ANN models would present a better forecast because of the underlying non-linear process in the JP-8 forecasting environment. However, regression outperforms ANN modeling within the chosen forecast accuracy measuring tools. As Makridakis et al state, "NN techniques are sometimes better than competing methods, but not always". Our results seem to indicate the later of the two.

V. Conclusions and Recommendations

Chapter Overview

After constructing various models in an attempt to shed light on our overall problem, this chapter is aimed at answering the overall research question and the investigative questions already proposed in Chapter I. Following the answers to the questions, possible areas of further research will be discussed and a summary of the research will be presented.

Conclusions of Research

<u>What will USAF JP-8 demand be in the future?</u>

In order to answer this question we obtained the related data from AFPET for the years between 1996 and 2008. At first, we tried to identify the recent trends which give us insight for the consumption figures during the past 12 year period. Our findings indicate that USAF JP-8 consumption follows a quite stable trend in the last decade. When we look at the next 10-year period via Holt's Linear Method, consumption figures follow a stable trend with a very small amount of decrease for the upcoming years. Hence, assuming there won't be any new major conflicts for the U.S. and the GWOT goes on with the current ops-tempo, the USAF yearly JP-8 consumption will go on to be somewhere between 2,000,000 and 2,500,000 gallons per year. While, the increased amount of alternative fuels usage in AF operations may have an impact on these figures, JP-8 will continue to be one the main fuel resource in USAF operations, at least in the short-term.

<u>What factors can affect the price of JP-8 fuel?</u>

Both the literature review and the analysis results reveals that there are many factors that may impact JP-8 prices and these change from one market to another. In this study, 19 possible predictor variables (see Appendix A) are considered, as they may have an impact. Obtaining historical data for different variables over the same time frames is not always possible. Also we need some sort of judgmental input to choose the most suitable variables relevant to our research problem. We should begin with investigating various data streams to find the related historical data, and then we should look through the literature and find out which variables to include in the modeling process. Following the identification of the most relevant variables for the problem, another problem arises for the missing parts of the data. We need to consider the proper data imputation methods in order to have a clean data set.

In this study, as a result of the VIF analysis and numbers of trial-and-error stepwise comparisons, the final selected variables introduced to the model are: JP-8 cost lagged one month (in million $) as ylag1, Real Imported Crude Oil Price lagged one month as x1lag1 (real $/barrel), U.S. Refinery and Blender Net Production of Crude oil as x2lag 1 (thousand barrels/day), U.S. Crude Oil and Petroleum Products Ending Stocks as x3lag1 (thousand barrels), U.S. Kerosene-type Jet Fuel Ending Stocks as x4lag1 (thousand barrels), U.S. Refinery and Blender Net Production of Kerosene-type Jet Fuel as x5lag1(thousand barrels/day), and U.S. Natural Gas Wellhead Price as x6lag1 ($/thousand cubic feet). We also introduced a conditional variable called “conflict” into the model to identify the Gulf and Iraq Wars as “a war” and to use as a predictor variable for the JP-8 consumption cost model. The findings from the Multiple Regression Analysis reveal the effect of all these variables to the overall JP-8 cost model with an Adjusted R-squared value of 99% and U-statistic of 0.65.

Which of the models seem more plausible for the problem’s solution?

As mentioned time after time by many of the SME’s, forecasting and modeling is not a clear-cut process. It includes many factors that are difficult to define and figure out. To date, there is no exact and accurate science that we can apply for our forecasting purposes, nor will there be in the foreseen future. Hence, the forecasting process is complex, and many judgmental inputs are involved. Our study indicates that the Multiple Regression model outperforms ANN modeling for the next 5-year period for both of the selected accuracy measures.

From the basic comparison of the models, it can be stated that the Multiple Regression Model demonstrated a better fit for the JP-8 cost modeling with a U-Statistic value of 0.90, and a MAPE of 0.80 within the model check set (May-95 to May 00). Our findings from the comparison of the models indicate that ANN Modeling doesn’t perform as well as we expected. There may be many causes for these results, including poorly designed networks. In the earlier stages of ANN modeling, we try to use raw data for forecasting purposes; however, we didn’t achieve satisfactory results. By smoothing all input variables for the model build data set via a 3MA and a 12MA approach, we come up with more reasonable solutions relative to the raw data usage. In addition, we find that, as we use smoothing for more periods, the forecasting results tend to get better in the long run.

From our findings we conclude that although ANN models show some good results for non-linear processes in the literature, there is no evidence to conclude that they're better than the Regression models in the long-term. In order to develop a good NN, the data should be purified from short-term fluctuations and the network should be well-designed.

<u>How much will the USAF need to budget in the future to cover needs and rising fuel prices and what can be done to mitigate these rising costs?</u>

Budget estimation and funding allocation is not a clear-cut process. Debates and negotiations related to this matter cost hours of work, even for the well-known SME's. Undoubtedly, potential variable factors and uncertainties involved in the problem make it even harder to solve. From a micro perspective, JP-8 cost forecasting and allocation is also an arduous process which constitutes an essential portion of the USAF budget. Most assuredly, the USAF leadership is searching for better ways to overcome this problem which will enable them to plan and use resources in a more effective and efficient manner.

According to the Office of Management and Budget (OMB)'s latest release for Financial Year 2009; the DoD's base budget is estimated to be $515.4 billion, which indicates a 74% increase over 2001, plus $70.0 billion as an emergency allowance to support activities related to the GWOT. Operation and Maintenance activity expenses for the DoD was 146,155 million dollars in the year 2007, whereas those are estimated to be 164,171 in year 2008, and 179,788 in the year 2009[1].

---

[1] Retrieved from the Office of Management and Budget official website (http://www.whitehouse.gov/omb/) accessed on Dec 29, 2008.

Looking from the demand side, the relatively stable trend for JP-8 consumption is clearly observed from the future projections and the relevant budgetary sums. However, from the supply side there are many factors involved in the issue, such as Hubbert Peak, existence of dominant oil producer countries, alternative fuel usage opportunities etc.

According to the latest EIA reports issued in January 2009, "in the past 6 months, the monthly average price of West Texas Intermediate (WTI) crude oil has fallen from $133/barrel in July to $41 in December. WTI prices are projected to average $43/barrel in 2009 and $55 in 2010. Also, the downward trend in oil prices continued in December, as the worsening global economy weakened. The outlook for supply and demand fundamentals indicates a fairly loose oil market balance over the next 2 years. The oil price path going forward will be driven mainly by the depth and duration of the global economic downturn, the pace and timing of the recovery, and actual OPEC production".

Moreover, there are many Federal and USAF initiatives to enhance alternative fuels usage which may lead to dramatic changes in JP-8 cost for the future. However, as mentioned before this won't likely happen in the near future. JP-8 will continue to be the leading fuel resource for the USAF. Assuming there won't be any new major conflicts, any major acquisitions of weapon systems, and the on-going GWOT follows the current ops-tempo, USAF's JP-8 cost will go on to increase for the next 5-year period. Our results indicate that the USAF's JP-8 cost for each of the next 5 years will be somewhere between 6.3 and 7.5 billion dollars, via a multiple regression model. Our analysis doesn't take the recent global economical crisis of 2009 into account for the model building process. Although, the oil prices had reached a record high in summer 2008, nowadays the price of oil is fluctuating between $35 to $45/barrel. But, our results indicate that these figures are temporary and the price of oil will go on to increase for the next 5-years.

Supporting our findings, the Energy Information Administration's (EIA) crude oil price projection shows an increasing trend for the upcoming years. Despite the global economical crisis that the world faces today, the latest EIA's Energy Outlook Analysis for January 2009 indicates that the crude oil prices will show a rising trend in the next 2-year period, as shown in Figure 43.

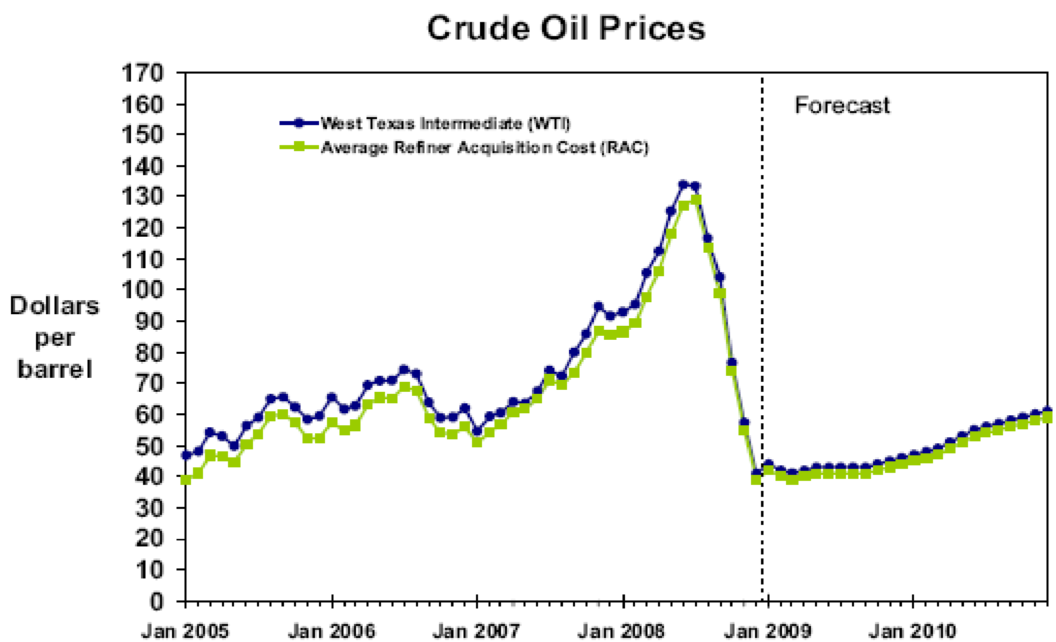


Figure 43- EIA Crude Oil Price Forecast

Source: Energy Information Administration, January 2009 Outlook

<u>What JP-8 alternative fuels exist? What can be done to reduce JP-8 consumption in the future?</u>

The primary alternative fuels are defined as follows:

'Methanol, ethanol, or other alcohols, natural gas, liquefied petroleum gas, hydrogen, coal derived liquid fuels, fuels (other than alcohol) derived from biological

materials, electricity (including electricity from solar energy), ethers, or any other fuel the Secretary determines, by rule, is substantially not petroleum and would yield substantial energy security benefits and substantial environmental benefits…(Congress, 1992)'.

Today one of the first priorities for the U.S. Government is to take necessary actions to "reduce foreign oil dependency" and "be energy independent". At this point we'll bring some of the actions to decrease foreign oil dependency (whether they're taken or not) into focus. Below is a summary of what has been done so far on the subject, according to the latest White House reports:

- "Ethanol production has quadrupled from 1.6 billion gallons in 2000 to an estimated 6.5 billion gallons in 2007. In 2007, the United States accounted for nearly half of worldwide ethanol production".
- "In 2007, the U.S. produced about 490 million gallons of biodiesel – up 96 percent from 2006. Today, there are more than 968 biodiesel fueling stations, and hundreds of fleet operators use biodiesel to fuel their trucks".
- "Over the last five years, the Federal Government has invested approximately $1.2 billion in hydrogen research and development to help bring hydrogen fuel cell vehicles to market. These vehicles use no gasoline at all and emit clean, pure water".
- In 2007, President Bush signed the Energy Independence and Security Act (EISA), which responded to his "Twenty in Ten" challenge to expand alternative fuels and improve vehicle fuel economy".
- Since 2001, the U.S. has increased wind energy production by more than 400 percent. Last year, more than 20 percent of new electrical generating

capacity added in the U.S. was wind. Wind power now supplies one percent of the U.S' electricity".

- Between 2000 and 2007, the U.S' solar energy capacity doubled. In 2007 the U.S' solar installations grew by more than 32 percent".

- The Bush Administration also launched the Nuclear Power 2010 program and other significant efforts that helped to encourage industry to submit 17 applications for 26 new nuclear reactors in the U.S." (The White House Official Website, retrieved 18 January 2009).

From the private companies' perspective, many important improvements have taken place concurrently with the government efforts. As an example of private company efforts, the Exxon Mobil Corporation's activities on the subject are brought into focus. In his address to Woodrow Wilson International Center for Scholars, Rex W. Tillerson, Chairman and the Chief Executive Officer (CEO) of the Exxon Mobil Corporation states that: "It is estimated that there is enough oil and natural gas off-shore and in non-wilderness and non-park lands to fuel 50 million cars and heat nearly 100 million homes for the next 25 years, providing an important link of time and resources as we work toward future energy solutions. The U.S. demand will decrease to 17 million barrels a day (18% less) by the year 2030 with significant innovations in energy efficiency (assuming today's consumption as 20 mbd)". He adds that, "since 2004, ExxonMobil has invested more than $1.5 billion in activities that improve energy efficiency with a companion reduction in greenhouse-gas emissions, and we will be spending about half-a-billion dollars over the next few years" (Tillerson, 2009).

Some of the projections and the improvements of Exxon Mobil in an effort to gain energy efficiency from Tillerson's own words are as follows.

"A technology recently developed by ExxonMobil has made it economically possible to produce natural gas "trapped" in extremely tight rock formations far below the earth's surface. In Colorado, the amount of gas from one field alone will be enough to heat 50 million U.S. homes for the next decade" (Tillerson, 2009).

"The new Q-Max ships that we have developed in conjunction with our partner Qatar Petroleum can transport 80 percent more LNG cargo than current conventional-size ships, yet they require approximately 40 percent less energy per unit of cargo" (Tillerson, 2009).

"Another improvement is a new engine technology called Homogeneous Charge Compression Ignition, or HCCI, which combines the best features of gasoline- and diesel-powered engines. The results could be up to 30 percent better fuel economy and lower emissions" (Tillerson, 2009).

"And finally, our scientists and engineers are working with those from other industries on breakthrough technology that could advance the use of hydrogen fuel cells. This new technology, which has been under development for more than a decade, will be applied first to industrial vehicles, such as forklifts" (Tillerson, 2009).

The literature review on oil shale development in the U.S. indicates that "the largest oil shale deposits in the world are in the Green River Formation, which covers portions of Colorado, Utah, and Wyoming. Estimates of the Green River Formation range from 1.5 to 1.8 trillion barrels. For potentially recoverable oil shale resources, it is possible to derive an upper bound of 1.1 trillion barrels of oil and a lower bound of about

500 billion barrels. For policy planning purposes it is enough to know that any amount in this range is very high if one thinks that the middle point of 800 billion barrels is more than triple the proven reserves of Saudi Arabia. More than that, supposing the daily usage for petroleum products is about 20 million barrels, it can be stated that 800 billion barrels of recoverable resources would last for more than 400 years" (Bartis and others: 2005: IX).

The AF has successfully completed test flights on three airframes using a 50/50 blend of traditional JP-8 jet fuel and synthetic fuel on March 19, 2008. In August 2007, the new fuel was certified for operational use in the B-52H Stratofortress and in December 2007, for the use in the C-17 Globemaster (Bates and others, 2008: 18-20). Furthermore, at Nellis AFB, Nevada, the use of solar panels is explored in parallel with the governmental initiatives on energy efficiency. The Secretary of the Air Force (SECAF) has recently signed the AF Energy Program Policy (AFEP) which is "the blueprint for the AF Officials as they keep their goal to keep energy initiatives in the forefront". The policy goals are planned to be met by reducing demand, increasing supply and changing the culture within (USAF Energy Program Policy Memorandum, 2008).

Currently, it is clear that the new administration will also pay special attention to this subject as it is pinpointed in their Strategic Energy Plan. Shortly, the new administrations' energy goals for the next decade will be:

- "Saving more oil than U.S. currently imports from the Middle East and Venezuela combined".

- Helping to create five million new jobs by strategically investing $150 billion over the next ten years to catalyze private efforts to build a clean energy future".
- "Putting 1 million Plug-In Hybrid cars – cars that can get up to 150 miles per gallon – on the road by 2015"[2].

From the detailed investigation of what was planned and done so far and what is planned to be implemented in the near future, it is clear that the U.S. is most assuredly cognizant of its energy needs. The U.S. realizes the challenge that they face and the vital importance of having enough conventional fuels while exploring alternative fuels usage. Simply put, having enough energy and oil resources is a key element for its security and sustainable economical wealth. A basic investigation of both government and private corporation activities reveals that the U.S. is determined to take every necessary action, such as oil shale development, off-shore drilling, enhancing biofuels use, and diversifying energy resources in an attempt to reduce its foreign oil dependency. The degree of consistency in the subject can be observed in every speech of the new administration, the actions that have taken so far, and from the massive amount of money that is planned to be invested in the near future for the exploration of solutions. So far, there are many different fuels being developed along with different propulsion methods. The development of hydrogen and full electric automobiles is quite promising. However, the technology is many years from maturity and a full working system is even further away.

---

[2] Retrieved from Obama-Biden Website (http://my.barackobama.com/page/content/newenergy. accessed on Dec 27, 2008.

Recommendations for Future Research

The USAF has initiated a Strategic Energy Plan and outlined the overarching and implementation goals for the plan. The overarching goal of the plan is stated as "reducing aviation, ground fuel, and installation energy demand".

Implementation goals for 'reducing the demand' are:

- Reducing aviation fuel-use/hour operation by 10% (from a 2005 base line) by 2015,
- Implementing pilot fuel efficiency measures in all standardization and evaluation flights by 2010,
- Incorporating pilot fuel efficiency elements in the Undergraduate Pilot Training (UPT) training syllabus by 2011,
- Reducing motor vehicle fleet petroleum fuel use by 2 percent per annum,
- Reducing installation energy intensity 1 by 3 percent per annum.

For 'increasing the supply' part of the strategy, there are also implementation goals. These are:

- Increasing non-petroleum-based fuel use by 10% per annum in the motor vehicle fleet,
- Increasing facility renewable energy use at annual targets of 5% by FY10, 7.5% by FY13, and 25% by FY25 – 50 percent of the increase must come from new renewable sources,
- By 2016, being prepared to cost competitively acquire 50% of the AF's domestic aviation fuel requirement via an alternative fuel blend in which the alternative component is derived from domestic sources produced in

a manner that is greener than fuels produced from conventional petroleum.

All of these implementation goals are worth investigating in future studies. Also, for future studies one would try to use software other than SNAPP for ANN modeling. Here our suggestion would be to use Matlab's Neural Network Toolbox. Matlab would enable the researcher to form different types of networks and let the researcher compare the performance of differently trained networks, instead of just simply relying on SNAPP's expert system.

Summary

Aviation fuel is an important asset for the USAF to accomplish the assigned global missions and accounts for approximately 81% of the total AF energy costs. JP-8 is the main oil derivative product that is used as an aviation fuel. Crude oil price instability and conflicts, added to the high consumption rates and many different factors, result in many problems that have a direct effect to USAF's logistics planning and budgetary sums. This is a challenging problem for the planners and decision makers working in the USAF tasked to acquire needed JP-8. They have been trying to accurately forecast the consumption and cost figures of JP-8 for years. However, the complex environment, great number of variables involved in the process, volatilities in the economical figures and lack of an adequate methodology have been the biggest impediments to achieve an acceptable solution.

This research shows that there is no single way to forecast accurately, however we can come up with reasonable results with the appropriate forecasting tools. Our results indicate that the USAF JP-8 consumption for the near future can be predicted via Holt's

Linear Method. From the different types of models applied to accurately predict USAF's JP-8 cost for the next five year period, our multiple regression model outperforms other models within the selected forecasting accuracy measures. Also, it should be added that for short-term forecasting, simple methods such as moving averages and smoothing methods may present adequate results, versus the highly-complex models. The model in this thesis can help USAF planners/decision makers with insight on the future JP-8 consumption and cost figures which may have a positive impact on the logistics planning processes and the related budgetary allocations.

Appendix A: Collected Data Sources

Indicator	Variable Name	Document	Source
X1	Real Imported Crude Oil Price (Real $/barrrel) NOV08=1	real_prices.xls	http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html
X2	U.S. Refinery and Blender Net Production of Crude Oil and Petroleum Products (Thousand Barrels per Day)	mttrpus2m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mttrpus2M.htm
X3	U.S. Crude Oil and Petroleum Products Ending Stocks (Thousand Barrels)	mttstus1m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mttstus1M.htm
X4	U.S. Kerosene-Type Jet Fuel Ending Stocks (Thousand Barrels)	mkjstus1m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mkjstus1M.htm
X5	U.S. Refinery and Blender Net Production of Kerosene-Type Jet Fuel (Thousand Barrels per Day)	mkjrpus2m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mkjrpus2M.htm
X6	U.S. Natural Gas Wellhead Price (Dollars per Thousand Cubic Feet)	n9190us3m.xls	http://tonto.eia.doe.gov/dnav/ng/hist/n9190us3M.htm
X7	Kerosene-Type Jet Fuel Spot Price-Averaged (Cents per Gallon)	rjetara5m.xls	http://tonto.eia.doe.gov/dnav/pet/pet_pri_spt_s1_d.htm
X8	Consumer Price Index (CPI) 1982-1984=1	-	http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html
X9	Europe Brent Spot Price FOB (Dollars per Barrel)	rbrtem.xls	http://tonto.eia.doe.gov/dnav/pet/hist/rbrteM.htm
X10	U.S. FOB Costs of Crude Oil (Dollars per Barrel)	i000000004m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/i000000004M.htm
X11	Real Gasoline Price (Real cents/gallon) NOV08=1	real_prices.xls	http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html
X12	Real Heating Oil Price (real cents/gallon) NOV08=1	real_prices.xls	http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html
X13	U.S. Crude Oil Field Production (Thousand Barrels per Day)	mcrfpus2m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mcrfpus2M.htm
X14	U.S. Crude Oil Imports (Thousand Barrels per Day)	mcrimus2m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mcrimus2M.htm
X15	Gross Domestic Product (GDP) (in billion $-seasonally adjusted	-	http://www.bea.gov/regional/gsp/
X16	U.S. Kerosene-Type Jet Fuel Product Supplied (Thousand Barrels per Day)	mkjupus2m.xls	http://tonto.eia.doe.gov/dnav/pet/hist/mkjupus2M.htm
X17	U.S. Natural Gas Imports (MMcf)	n9103us2m.xls	http://tonto.eia.doe.gov/dnav/ng/ng_move_impc_s1_m.htm
X18	Cushing, OK WTI Spot Price FOB (Dollars per Barrel)	rwtcm.xls	http://tonto.eia.doe.gov/dnav/pet/hist/rwtcM.htm
Y	JP-8 Monthly Cost Data (in million $) interpolated		AFPET

*** All data was extracted from the websites as of the 13-14 November 2008 information.

Appendix B: Inverse Correlation Matrix for Potential Predictor Variables

Variable Name	Kerosene-Type Jet Fuel Spot Price-Averaged (Cents per Gallon)	Consumer Price Index (CPI) 1982-1984=1	Europe Brent Spot Price FOB (Dollars per Barrel)	U.S. FOB Costs of Crude Oil (Dollars per Barrel)	Real Gasoline Price (Real cents/gallon) NOV08=1	Real Heating Oil Price (real cents/gallon) NOV08=1	Real Imported Crude Oil Price (Real $/barrel) NOV08=1	U.S. Refinery and Blender Net Production of Crude Oil and Petroleum Products (Thousand	U.S. Crude Oil Field Production (Thousand Barrels per Day)	U.S. Crude Oil Imports (Thousand Barrels per Day)	GDP (IN BILLION $ (SEASONALLY ADJUSTED)	U.S. Kerosene-Type Jet Fuel Product Supplied (Thousand Barrels per Day)	U.S. Natural Gas Imports (MMcf)	U.S. Crude Oil and Petroleum Products Ending Stocks (Thousand Barrels)	U.S. Kerosene-Type Jet Fuel Ending Stocks (Thousand Barrels)	U.S. Refinery and Blender Net Production of Kerosene-Type Jet Fuel (Thousand Barrels per Day)	U.S. Natural Gas Wellhead Price (Dollars per Thousand Cubic Feet)	Cushing, OK WTI Spot Price FOB (Dollars per Barrel)	JP-8 Cost Data (in million $) interpolated
Kerosene-Type Jet Fuel Spot Pri	108.981	-16.02	-53.86	-20.832	-8.24	-22.94	31.202	2.9682	3.126	6.723	31.88	-1.885	-2.66	-5.6705	2.6662	-10.46	-2.606	-41.851	3.873
Consumer Price Index (CPI) 1982-	-16.025	385.48	-32.47	-123.22	-33.9	23.054	237.84	10.9955	19.73	-14.51	-186	11.753	-63.4	8.5062	5.6175	-15.6778	25.039	-142.18	-11.8
Europe Brent Spot Price FOB (D	-53.859	-32.47	450.7	-200.3	6.481	0.8907	52.451	-15.9919	-37.7	36.18	9.429	-1.73	-6.41	-1.5615	-6.8279	9.1114	-4.191	-269.75	-1.37
U.S. FOB Costs of Crude Oil (Dol	-20.832	-123.2	-200.3	646.326	20.23	20.148	-474.3	0.7416	38.62	-7.567	-83.6	1.041	11.1	0.1825	4.0702	6.6428	19.112	133.01	4.923
Real Gasoline Price (Real cents/	-8.2432	-33.87	6.481	20.2296	21.31	-5.986	-42.26	-5.896	3.643	-2.161	20.43	-0.794	4.28	-1.0531	-0.8643	4.3982	-1.658	21.071	0.097
Real Heating Oil Price (real cents	-22.937	23.054	0.891	20.1481	-5.99	26.09	-0.429	6.6665	-6.04	2.823	-28	-1.707	0.21	-0.0077	0.4012	1.3337	-3.491	-16.993	-1.92
Real Imported Crude Oil Price (R	31.2017	237.84	52.45	-474.33	-42.3	-0.429	522.68	5.9788	-18.3	8.754	8.307	-1.763	-15.1	4.5414	1.2171	-10.4372	0.9139	-241.58	-2.55
U.S. Refinery and Blender Net Pr	2.9682	10.996	-15.99	0.7416	-5.9	6.6665	5.9788	13.34	-6.62	-8.49	-12.8	-0.815	1.4	-1.2837	0.5974	-4.0151	-2.036	3.7372	-0.82
U.S. Crude Oil Field Production (	3.126	19.727	-37.65	38.6186	3.643	-6.039	-18.33	-6.6224	44.81	-0.317	16.51	5.5117	-1.37	4.382	1.2882	-4.1854	4.1692	22.503	-3.42
U.S. Crude Oil Imports (Thousand	6.7226	-14.51	36.18	-7.5667	-2.16	2.8231	8.7542	-8.4895	-0.32	34.9	-17.6	0.7232	7.01	-2.1553	-0.1726	0.4359	-0.763	-43.199	5.813
GDP (IN BILLION $ (SEASONALL	31.8751	-185.5	9.429	-83.618	20.43	-28.01	8.3069	-12.8254	16.51	-17.59	234	-10.73	16.3	0.3999	-3.4738	6.8093	-24.2	48.516	-4.82
U.S. Kerosene-Type Jet Fuel Pro	-1.8845	11.753	-1.73	1.041	-0.79	-1.707	-1.763	-0.8149	5.512	0.723	-10.7	11.914	-4.51	0.5837	0.3785	-5.9829	1.3681	7.2379	1.002
U.S. Natural Gas Imports (MMcf)	-2.6634	-63.36	-6.412	11.1147	4.285	0.2136	-15.09	1.3951	-1.37	7.011	16.26	-4.514	34.7	-0.9628	0.2321	-0.7409	-3.962	19.652	3.247
U.S. Crude Oil and Petroleum Pro	-5.6705	8.5062	-1.562	0.1825	-1.05	-0.008	4.5414	-1.2837	4.382	-2.155	0.4	0.5837	-0.96	3.1292	-0.45	0.3433	1.8235	1.4381	-2.01
U.S. Kerosene-Type Jet Fuel Endi	2.6662	5.6175	-6.828	4.0702	-0.86	0.4012	1.2171	0.5974	1.288	-0.173	-3.47	0.3785	0.23	-0.45	1.7976	-2.2147	0.6353	-0.9808	-0.21
U.S. Refinery and Blender Net Pr	-10.46	-15.68	9.111	6.6428	4.398	1.3337	-10.44	-4.0151	-4.19	0.436	6.809	-5.983	-0.74	0.3433	-2.2147	12.382	0.4276	1.2941	1.811
U.S. Natural Gas Wellhead Price (	-2.6061	25.039	-4.191	19.1116	-1.66	-3.491	0.9139	-2.0362	4.169	-0.763	-24.2	1.3681	-3.96	1.8235	0.6353	0.4276	14.673	-16.296	0.855
Cushing, OK WTI Spot Price FOB	-41.851	-142.2	-269.7	133.009	21.07	-16.99	-241.6	3.7372	22.5	-43.2	48.52	7.2379	19.7	1.4381	-0.9808	1.2941	-16.3	505.47	-3.65
JP-8 Cost Data (in million $) inte	3.8733	-11.8	-1.373	4.923	0.097	-1.923	-2.549	-0.815	-3.42	5.813	-4.82	1.0022	3.25	-2.0107	-0.2061	1.8113	0.8551	-3.6456	5.853

Appendix C: Prediction Expression of the Multiple Regression Model

Prediction Expression

```
22983.7456114624
+-1016.6833128431*YLAG1
+-13.071179457167*X1LAG1
+-1571.4749552923*X2LAG1
+-1595.820129305*X3LAG1
+-743.54499222419*X4LAG1
+-2063.0833237821*X5LAG1
+2.75335433754865*X6LAG1
+-61.474629074121*CONFLICT
+YLAG1*X2LAG1*1.23286666727899
+YLAG1*X3LAG1*69.9871496699324
+YLAG1*X4LAG1*96.4368756735296
+YLAG1*X6LAG1*-0.3490262985988
+YLAG1*CONFLICT*8.27154664584695
+X1LAG1*X2LAG1*-0.2300753261809
+X1LAG1*X3LAG1*1.06937641909321
+X1LAG1*CONFLICT*0.0672543163737
+X2LAG1*X3LAG1*108.994033391273
+X2LAG1*X5LAG1*213.55037832961
+X2LAG1*CONFLICT*6.36214122048198
+X3LAG1*X4LAG1*51.7258350346725
+X3LAG1*X5LAG1*143.899766417081
+X6LAG1*CONFLICT*-1.7152077970747
+YLAG1*X2LAG1*CONFLICT*-0.8591630762634
+YLAG1*X3LAG1*X4LAG1*-6.709883175407
+YLAG1*X6LAG1*CONFLICT*0.2210107859968
+X2LAG1*X3LAG1*X5LAG1*-14.894908259408
```

Appendix D: Multiple Regression Analysis Results

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
May-87	3351.324										
Jun-87	3334.482	3333.210	1.272	1.272162	0.038152	0.038152	0.0001	0.0000	3398.662	3269.019	Yes
Jul-87	3318.184	3287.867	30.317	30.31687	0.913659	0.913659	0.0001	0.0000	3348.554	3228.280	Yes
Aug-87	3301.342	3271.537	29.805	29.8054	0.902827	0.902827	0.0000	0.0000	3329.712	3214.378	Yes
Sep-87	3284.5	3263.799	20.701	20.70055	0.63025	0.63025	0.0002	0.0003	3320.590	3207.980	Yes
Oct-87	3231.934	3279.059	-47.125	47.12451	-1.45809	1.45809	0.0000	0.0003	3336.575	3222.534	Yes
Nov-87	3177.617	3200.278	-22.662	22.66165	-0.713165	0.713165	0.0000	0.0003	3256.504	3145.023	Yes
Dec-87	3125.051	3138.469	-13.418	13.41782	-0.429363	0.429363	0.0001	0.0003	3193.661	3084.231	Yes
Jan-88	3070.733	3102.955	-32.222	32.22179	-1.049319	1.049319	0.0000	0.0003	3155.962	3050.839	Yes
Feb-88	3016.416	2995.421	20.995	20.99475	0.696017	0.696017	0.0000	0.0003	3048.059	2943.692	Yes
Mar-88	2965.602	2950.906	14.696	14.69601	0.495549	0.495549	0.0001	0.0003	3004.334	2898.429	Yes
Apr-88	2911.284	2942.182	-30.898	30.89759	-1.061304	1.061304	0.0002	0.0003	2993.819	2891.436	Yes
May-88	2858.719	2895.311	-36.592	36.59212	-1.280018	1.280018	0.0001	0.0004	2946.231	2845.271	Yes
Jun-88	2804.401	2835.326	-30.925	30.92479	-1.102724	1.102724	0.0001	0.0004	2886.009	2785.533	Yes
Jul-88	2751.836	2782.573	-30.737	30.73743	-1.116979	1.116979	0.0001	0.0004	2830.530	2735.429	Yes
Aug-88	2697.518	2727.123	-29.605	29.60533	-1.097503	1.097503	0.0001	0.0004	2774.261	2680.786	Yes
Sep-88	2643.2	2674.151	-30.951	30.95078	-1.170959	1.170959	0.0001	0.0000	2720.639	2628.456	Yes
Oct-88	2646.405	2616.599	29.806	29.80647	1.1263	1.1263	0.0002	0.0000	2662.164	2571.814	Yes
Nov-88	2649.718	2614.161	35.556	35.55646	1.341896	1.341896	0.0002	0.0000	2660.845	2568.296	Yes
Dec-88	2652.923	2620.162	32.761	32.76092	1.234899	1.234899	0.0000	0.0000	2667.424	2573.738	Yes
Jan-89	2656.236	2642.562	13.674	13.67368	0.514776	0.514776	0.0000	0.0000	2687.619	2598.260	Yes
Feb-89	2659.548	2643.409	16.139	16.13897	0.606831	0.606831	0.0000	0.0000	2688.778	2598.806	Yes
Mar-89	2662.54	2647.301	15.239	15.23917	0.572355	0.572355	0.0000	0.0000	2693.521	2601.873	Yes
Apr-89	2665.852	2651.190	14.662	14.66218	0.55	0.55	0.0000	0.0000	2698.002	2605.190	Yes
May-89	2669.058	2656.959	12.098	12.09835	0.453282	0.453282	0.0001	0.0000	2704.686	2610.075	Yes
Jun-89	2672.37	2651.636	20.734	20.73405	0.775867	0.775867	0.0001	0.0000	2700.160	2603.984	Yes
Jul-89	2675.575	2645.795	29.780	29.77986	1.113027	1.113027	0.0001	0.0000	2691.738	2600.637	Yes
Aug-89	2678.888	2659.823	19.064	19.06419	0.711646	0.711646	0.0001	0.0000	2706.094	2614.344	Yes
Sep-89	2682.2	2657.941	24.259	24.25942	0.90446	0.90446	0.0000	0.0001	2703.814	2612.845	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Oct-89	2658.258	2665.315	-7.057	7.057189	-0.265482	0.265482	0.0000	0.0001	2711.755	2619.670	Yes
Nov-89	2633.517	2630.491	3.026	3.025831	0.114897	0.114897	0.0000	0.0001	2676.427	2585.344	Yes
Dec-89	2609.575	2608.903	0.672	0.671618	0.025737	0.025737	0.0000	0.0001	2654.530	2564.060	Yes
Jan-90	2584.834	2591.903	-7.069	7.069115	-0.273484	0.273484	0.0002	0.0001	2637.552	2547.044	Yes
Feb-90	2560.093	2594.539	-34.446	34.44594	-1.345495	1.345495	0.0000	0.0001	2641.031	2548.866	Yes
Mar-90	2537.747	2554.330	-16.582	16.58247	-0.653433	0.653433	0.0000	0.0001	2598.688	2510.728	Yes
Apr-90	2513.007	2516.616	-3.610	3.609508	-0.143633	0.143633	0.0000	0.0001	2561.601	2472.421	Yes
May-90	2489.064	2490.674	-1.610	1.610024	-0.064684	0.064684	0.0001	0.0001	2534.962	2447.160	Yes
Jun-90	2464.324	2491.227	-26.903	26.90317	-1.091706	1.091706	0.0001	0.0001	2542.205	2441.271	Yes
Jul-90	2440.381	2412.460	27.921	27.92138	1.14414	1.14414	0.0003	0.0001	2458.686	2367.103	Yes
Aug-90	2415.641	2370.621	45.019	45.01947	1.863666	1.863666	0.0005	0.0001	2416.804	2325.321	Yes
Sep-90	2390.9	2446.439	-55.539	55.53899	-2.322932	2.322932	0.0019	0.0072	2495.658	2398.191	No
Oct-90	2593.116	2490.002	103.115	103.1146	3.976473	3.976473	0.0000	0.0065	2540.639	2440.374	No
Nov-90	2802.073	2785.829	16.244	16.24441	0.579728	0.579728	0.0000	0.0052	2842.527	2730.262	Yes
Dec-90	3004.29	2992.401	11.889	11.88881	0.395728	0.395728	0.0002	0.0048	3049.867	2936.018	Yes
Jan-91	3213.247	3173.481	39.766	39.76628	1.237573	1.237573	0.0000	0.0042	3232.326	3115.707	Yes
Feb-91	3422.204	3428.645	-6.441	6.44072	-0.188204	0.188204	0.0000	0.0030	3494.379	3364.146	Yes
Mar-91	3610.939	3605.683	5.257	5.256586	0.145574	0.145574	0.0000	0.0033	3676.060	3536.652	Yes
Apr-91	3819.896	3829.664	-9.768	9.768139	-0.255717	0.255717	0.0046	0.0028	3910.264	3750.726	Yes
May-91	4022.113	3764.383	257.729	257.7295	6.407814	6.407814	0.0021	0.0027	3836.579	3693.546	No
Jun-91	4231.07	4048.177	182.892	182.8925	4.322606	4.322606	0.0000	0.0023	4120.694	3976.936	No
Jul-91	4433.286	4421.273	12.013	12.01324	0.270978	0.270978	0.0000	0.0022	4504.109	4339.960	Yes
Aug-91	4642.243	4634.520	7.723	7.723182	0.166367	0.166367	0.0001	0.0020	4723.796	4546.931	Yes
Sep-91	4851.2	4817.986	33.214	33.21372	0.68465	0.68465	0.0018	0.0016	4909.562	4728.119	Yes
Oct-91	4657.462	4864.919	-207.457	207.4568	-4.454289	4.454289	0.0001	0.0018	4958.831	4772.785	No
Nov-91	4457.267	4423.460	33.807	33.80712	0.758472	0.758472	0.0000	0.0019	4511.703	4336.942	Yes
Dec-91	4263.529	4286.946	-23.417	23.41743	-0.54925	0.54925	0.0022	0.0022	4368.333	4207.076	Yes
Jan-92	4063.333	4265.540	-202.207	202.2071	-4.976386	4.976386	0.0003	0.0024	4343.359	4189.116	No
Feb-92	3863.138	3927.888	-64.750	64.74984	-1.676094	1.676094	0.0020	0.0024	4002.674	3854.498	Yes
Mar-92	3675.858	3847.959	-172.102	172.1015	-4.681942	4.681942	0.0038	0.0030	3928.418	3769.149	No

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Apr-92	3475.662	3700.946	-225.284	225.284	-6.481757	6.481757	0.0027	0.0031	3772.162	3631.075	No
May-92	3281.925	3461.392	-179.468	179.4678	-5.468372	5.468372	0.0040	0.0037	3526.964	3397.040	No
Jun-92	3081.729	3289.364	-207.635	207.6345	-6.737599	6.737599	0.0036	0.0040	3346.585	3233.121	No
Jul-92	2887.991	3072.169	-184.177	184.1774	-6.377352	6.377352	0.0050	0.0048	3125.467	3019.780	No
Aug-92	2687.796	2892.239	-204.443	204.443	-7.606345	7.606345	0.0045	0.0055	2942.032	2843.288	No
Sep-92	2487.6	2667.589	-179.989	179.9894	-7.235464	7.235464	0.0000	0.0000	2713.008	2622.931	No
Oct-92	2484.97	2472.433	12.537	12.53722	0.504522	0.504522	0.0000	0.0000	2514.816	2430.763	Yes
Nov-92	2482.252	2481.988	0.264	0.26442	0.010652	0.010652	0.0000	0.0000	2525.204	2439.510	Yes
Dec-92	2479.622	2479.425	0.197	0.196899	0.007941	0.007941	0.0000	0.0000	2521.742	2437.818	Yes
Jan-93	2476.904	2483.098	-6.194	6.193501	-0.25005	0.25005	0.0001	0.0000	2525.286	2441.614	Yes
Feb-93	2474.186	2492.292	-18.106	18.10609	-0.7318	0.7318	0.0000	0.0000	2535.532	2449.790	Yes
Mar-93	2471.732	2472.357	-0.626	0.625798	-0.025318	0.025318	0.0000	0.0000	2514.549	2430.873	Yes
Apr-93	2469.014	2478.267	-9.253	9.253358	-0.37478	0.37478	0.0000	0.0000	2520.724	2436.525	Yes
May-93	2466.384	2477.744	-11.361	11.36087	-0.460629	0.460629	0.0001	0.0000	2520.099	2436.102	Yes
Jun-93	2463.666	2482.202	-18.537	18.53653	-0.752396	0.752396	0.0000	0.0000	2524.953	2440.175	Yes
Jul-93	2461.036	2466.481	-5.446	5.44584	-0.221282	0.221282	0.0000	0.0000	2508.782	2424.894	Yes
Aug-93	2458.318	2449.397	8.921	8.920695	0.362878	0.362878	0.0000	0.0000	2491.881	2407.637	Yes
Sep-93	2455.6	2456.376	-0.776	0.775527	-0.031582	0.031582	0.0000	0.0000	2499.169	2414.315	Yes
Oct-93	2467.353	2462.565	4.788	4.788428	0.194071	0.194071	0.0000	0.0000	2505.834	2420.044	Yes
Nov-93	2479.499	2478.719	0.779	0.779432	0.031435	0.031435	0.0000	0.0000	2523.490	2434.743	Yes
Dec-93	2491.252	2487.334	3.918	3.918196	0.157278	0.157278	0.0000	0.0000	2532.036	2443.421	Yes
Jan-94	2503.397	2505.535	-2.137	2.137436	-0.085381	0.085381	0.0001	0.0000	2549.117	2462.698	Yes
Feb-94	2515.542	2496.919	18.624	18.62369	0.740345	0.740345	0.0000	0.0000	2541.084	2453.521	Yes
Mar-94	2526.512	2525.884	0.628	0.628468	0.024875	0.024875	0.0000	0.0000	2571.016	2481.544	Yes
Apr-94	2538.658	2546.520	-7.863	7.862747	-0.309721	0.309721	0.0000	0.0000	2592.269	2501.579	Yes
May-94	2550.411	2557.123	-6.712	6.71242	-0.26319	0.26319	0.0000	0.0000	2601.297	2513.700	Yes
Jun-94	2562.556	2560.480	2.076	2.07629	0.081024	0.081024	0.0000	0.0000	2603.889	2517.795	Yes
Jul-94	2574.31	2565.835	8.475	8.474651	0.329201	0.329201	0.0000	0.0000	2609.458	2522.941	Yes
Aug-94	2586.455	2572.609	13.846	13.8462	0.535335	0.535335	0.0000	0.0000	2616.538	2529.417	Yes
Sep-94	2598.6	2585.194	13.406	13.40606	0.515896	0.515896	0.0000	0.0002	2629.703	2541.439	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Oct-94	2564.384	2570.650	-6.267	6.266689	-0.244374	0.244374	0.0000	0.0002	2615.290	2526.772	Yes
Nov-94	2529.027	2532.858	-3.832	3.831618	-0.151506	0.151506	0.0000	0.0002	2577.000	2489.472	Yes
Dec-94	2494.81	2510.541	-15.730	15.73039	-0.630524	0.630524	0.0001	0.0002	2554.001	2467.820	Yes
Jan-95	2459.453	2479.281	-19.828	19.82763	-0.80618	0.80618	0.0000	0.0002	2522.374	2436.924	Yes
Feb-95	2424.096	2428.828	-4.732	4.732134	-0.195212	0.195212	0.0000	0.0002	2470.819	2387.551	Yes
Mar-95	2392.161	2394.271	-2.111	2.110649	-0.088232	0.088232	0.0001	0.0002	2435.603	2353.642	Yes
Apr-95	2356.804	2374.554	-17.750	17.74967	-0.753125	0.753125	0.0000	0.0002	2415.266	2334.527	Yes
May-95	2322.587	2336.293	-13.706	13.7058	-0.590109	0.590109	0.0001	0.0002	2376.333	2296.928	Yes
Jun-95	2287.23	2311.938	-24.707	24.70714	-1.080221	1.080221	0.0000	0.0002	2351.973	2272.583	Yes
Jul-95	2253.014	2265.539	-12.525	12.52528	-0.555935	0.555935	0.0000	0.0002	2304.491	2227.246	Yes
Aug-95	2217.657	2219.326	-1.669	1.66866	-0.075244	0.075244	0.0000	0.0003	2257.715	2181.589	Yes
Sep-95	2182.3	2182.382	-0.082	0.081903	-0.003753	0.003753	0.0004	0.0000	2220.167	2145.239	Yes
Oct-95	2187.366	2144.451	42.915	42.91494	1.961946	1.961946	0.0001	0.0000	2181.449	2108.080	No
Nov-95	2192.6	2171.140	21.460	21.45968	0.978732	0.978732	0.0002	0.0000	2208.509	2134.404	Yes
Dec-95	2197.666	2167.841	29.825	29.82478	1.357112	1.357112	0.0000	0.0000	2204.961	2131.345	Yes
Jan-96	2202.9	2196.206	6.694	6.694004	0.303872	0.303872	0.0001	0.0000	2233.747	2159.296	Yes
Feb-96	2208.134	2228.698	-20.563	20.56317	-0.931246	0.931246	0.0001	0.0000	2268.625	2189.473	Yes
Mar-96	2213.031	2239.730	-26.699	26.69906	-1.206448	1.206448	0.0000	0.0000	2283.125	2197.160	Yes
Apr-96	2218.266	2226.194	-7.929	7.928597	-0.357423	0.357423	0.0000	0.0000	2271.118	2182.159	Yes
May-96	2223.331	2210.460	12.871	12.8708	0.578897	0.578897	0.0001	0.0000	2250.777	2170.866	Yes
Jun-96	2228.566	2207.231	21.334	21.33431	0.957311	0.957311	0.0000	0.0000	2246.629	2168.524	Yes
Jul-96	2233.631	2230.670	2.961	2.961104	0.132569	0.132569	0.0000	0.0000	2268.874	2193.109	Yes
Aug-96	2238.866	2248.682	-9.817	9.816562	-0.438461	0.438461	0.0000	0.0000	2287.200	2210.813	Yes
Sep-96	2244.1	2236.746	7.354	7.353779	0.327694	0.327694	0.0001	0.0000	2275.141	2198.999	Yes
Oct-96	2235.412	2209.508	25.904	25.90395	1.1588	1.1588	0.0004	0.0000	2248.581	2171.114	Yes
Nov-96	2226.435	2181.959	44.476	44.4756	1.997615	1.997615	0.0000	0.0000	2220.032	2144.540	No
Dec-96	2217.747	2212.448	5.300	5.299641	0.238965	0.238965	0.0002	0.0000	2250.432	2175.105	Yes
Jan-97	2208.77	2241.708	-32.938	32.93785	-1.491231	1.491231	0.0009	0.0000	2280.689	2203.394	Yes
Feb-97	2199.793	2265.190	-65.398	65.39753	-2.972895	2.972895	0.0001	0.0000	2308.631	2222.568	No
Mar-97	2191.684	2215.922	-24.238	24.23751	-1.105885	1.105885	0.0000	0.0000	2257.300	2175.302	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Apr-97	2182.707	2169.395	13.312	13.31193	0.609882	0.609882	0.0000	0.0000	2207.494	2131.954	Yes
May-97	2174.019	2164.357	9.662	9.662438	0.44445	0.44445	0.0000	0.0000	2202.150	2127.213	Yes
Jun-97	2165.042	2158.448	6.594	6.594441	0.304587	0.304587	0.0000	0.0000	2195.774	2121.756	Yes
Jul-97	2156.355	2159.776	-3.422	3.421871	-0.158688	0.158688	0.0000	0.0000	2197.362	2122.834	Yes
Aug-97	2147.377	2152.463	-5.086	5.085634	-0.23683	0.23683	0.0000	0.0000	2190.002	2115.567	Yes
Sep-97	2138.4	2137.217	1.183	1.183106	0.055327	0.055327	0.0002	0.0002	2174.160	2100.902	Yes
Oct-97	2166.222	2134.746	31.476	31.47605	1.453039	1.453039	0.0000	0.0002	2171.666	2098.453	Yes
Nov-97	2194.971	2180.424	14.547	14.54687	0.662736	0.662736	0.0000	0.0002	2218.271	2143.223	Yes
Dec-97	2222.793	2229.650	-6.857	6.857069	-0.308489	0.308489	0.0000	0.0002	2268.569	2191.399	Yes
Jan-98	2251.542	2250.382	1.161	1.160529	0.051544	0.051544	0.0001	0.0002	2289.692	2211.746	Yes
Feb-98	2280.292	2257.391	22.900	22.90034	1.004272	1.004272	0.0000	0.0001	2296.938	2218.526	Yes
Mar-98	2306.259	2299.485	6.774	6.773962	0.293721	0.293721	0.0000	0.0002	2340.204	2259.475	Yes
Apr-98	2335.008	2338.305	-3.297	3.296578	-0.141181	0.141181	0.0001	0.0001	2379.039	2298.268	Yes
May-98	2362.83	2381.391	-18.561	18.56072	-0.785529	0.785529	0.0000	0.0001	2422.913	2340.580	Yes
Jun-98	2391.579	2375.782	15.798	15.79762	0.660552	0.660552	0.0000	0.0001	2417.246	2335.029	Yes
Jul-98	2419.401	2408.354	11.048	11.04774	0.456631	0.456631	0.0000	0.0001	2451.039	2366.412	Yes
Aug-98	2448.151	2446.836	1.314	1.314328	0.053687	0.053687	0.0001	0.0001	2491.174	2403.288	Yes
Sep-98	2476.9	2447.220	29.680	29.68036	1.198287	1.198287	0.0000	0.0000	2491.947	2403.295	Yes
Oct-98	2461.234	2460.493	0.741	0.740818	0.030099	0.030099	0.0000	0.0000	2503.157	2418.557	Yes
Nov-98	2445.046	2450.639	-5.593	5.59278	-0.228739	0.228739	0.0000	0.0000	2492.910	2409.085	Yes
Dec-98	2429.381	2431.395	-2.014	2.014281	-0.082913	0.082913	0.0002	0.0000	2475.117	2388.445	Yes
Jan-99	2413.193	2446.860	-33.668	33.66762	-1.395149	1.395149	0.0000	0.0000	2490.642	2403.848	Yes
Feb-99	2397.005	2403.738	-6.733	6.733325	-0.280906	0.280906	0.0000	0.0000	2446.360	2361.859	Yes
Mar-99	2382.383	2379.337	3.047	3.046667	0.127883	0.127883	0.0000	0.0000	2421.672	2337.742	Yes
Apr-99	2366.195	2380.945	-14.750	14.74982	-0.623356	0.623356	0.0001	0.0000	2422.180	2340.413	Yes
May-99	2350.53	2378.555	-28.025	28.02546	-1.192304	1.192304	0.0000	0.0000	2419.547	2338.258	Yes
Jun-99	2334.342	2343.608	-9.267	9.266586	-0.396968	0.396968	0.0001	0.0000	2384.933	2303.000	Yes
Jul-99	2318.676	2337.812	-19.136	19.13634	-0.825313	0.825313	0.0000	0.0000	2378.114	2298.193	Yes
Aug-99	2302.488	2317.681	-15.193	15.19326	-0.659863	0.659863	0.0001	0.0000	2358.272	2277.789	Yes
Sep-99	2286.3	2314.418	-28.118	28.1177	-1.229834	1.229834	0.0005	0.0005	2354.651	2274.871	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Oct-99	2234.366	2286.645	-52.279	52.27931	-2.339783	2.339783	0.0006	0.0006	2327.166	2246.829	No
Nov-99	2180.7	2233.351	-52.651	52.65142	-2.414427	2.414427	0.0010	0.0006	2271.740	2195.611	No
Dec-99	2128.766	2198.367	-69.601	69.60129	-3.269561	3.269561	0.0000	0.0006	2236.103	2161.267	No
Jan-00	2075.1	2090.089	-14.989	14.98853	-0.722304	0.722304	0.0000	0.0007	2127.429	2053.404	Yes
Feb-00	2021.434	2019.182	2.252	2.252239	0.111418	0.111418	0.0000	0.0006	2059.980	1979.192	Yes
Mar-00	1971.231	1957.759	13.472	13.47169	0.683415	0.683415	0.0000	0.0007	1997.481	1918.828	Yes
Apr-00	1917.566	1913.514	4.052	4.05192	0.211305	0.211305	0.0006	0.0007	1948.885	1878.785	Yes
May-00	1865.631	1910.808	-45.177	45.17652	-2.421514	2.421514	0.0001	0.0008	1944.445	1877.752	No
Jun-00	1811.966	1833.722	-21.756	21.75633	-1.200703	1.200703	0.0004	0.0008	1867.249	1800.797	Yes
Jul-00	1760.031	1794.774	-34.743	34.74263	-1.973978	1.973978	0.0022	0.0009	1829.118	1761.074	No
Aug-00	1706.366	1789.341	-82.975	82.97496	-4.862672	4.862672	0.0014	0.0010	1823.497	1755.824	No
Sep-00	1652.7	1717.674	-64.974	64.97414	-3.931394	3.931394	0.0016	0.0042	1750.695	1685.276	No
Oct-00	1760.363	1695.101	65.262	65.26193	3.7073	3.7073	0.0009	0.0040	1729.282	1661.595	No
Nov-00	1871.615	1819.589	52.026	52.02579	2.779727	2.779727	0.0016	0.0033	1854.557	1785.281	No
Dec-00	1979.278	1905.280	73.998	73.99766	3.738619	3.738619	0.0001	0.0032	1941.004	1870.214	No
Jan-01	2090.53	2071.503	19.027	19.02697	0.910151	0.910151	0.0000	0.0028	2111.809	2031.966	Yes
Feb-01	2201.781	2201.008	0.773	0.773482	0.03513	0.03513	0.0007	0.0021	2245.153	2157.731	Yes
Mar-01	2302.267	2245.073	57.194	57.19388	2.484242	2.484242	0.0006	0.0023	2286.904	2204.007	No
Apr-01	2413.519	2357.127	56.392	56.39175	2.336495	2.336495	0.0002	0.0020	2399.105	2315.883	No
May-01	2521.182	2484.498	36.683	36.68329	1.455004	1.455004	0.0002	0.0019	2528.734	2441.037	Yes
Jun-01	2632.433	2596.590	35.843	35.84319	1.361599	1.361599	0.0001	0.0017	2642.579	2551.402	Yes
Jul-01	2740.096	2715.481	24.615	24.61515	0.898332	0.898332	0.0001	0.0016	2763.764	2668.042	Yes
Aug-01	2851.348	2826.302	25.046	25.04614	0.878396	0.878396	0.0004	0.0015	2876.086	2777.380	Yes
Sep-01	2962.6	2904.496	58.104	58.10409	1.961253	1.961253	0.0000	0.0001	2955.103	2854.755	No
Oct-01	2991.104	2975.987	15.117	15.11712	0.505403	0.505403	0.0001	0.0001	3028.329	2924.549	Yes
Nov-01	3020.558	3043.200	-22.642	22.64151	-0.74958	0.74958	0.0000	0.0001	3095.794	2991.499	Yes
Dec-01	3049.062	3044.924	4.138	4.138334	0.135725	0.135725	0.0000	0.0001	3099.813	2991.008	Yes
Jan-02	3078.517	3082.728	-4.211	4.211118	-0.13679	0.13679	0.0000	0.0001	3137.311	3029.095	Yes
Feb-02	3107.971	3106.633	1.338	1.337911	0.043048	0.043048	0.0001	0.0001	3160.035	3054.134	Yes
Mar-02	3134.575	3163.598	-29.023	29.02288	-0.925895	0.925895	0.0000	0.0001	3218.186	3109.935	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Apr-02	3164.029	3170.566	-6.537	6.536603	-0.206591	0.206591	0.0000	0.0001	3225.080	3116.973	Yes
May-02	3192.533	3193.200	-0.667	0.666926	-0.02089	0.02089	0.0000	0.0001	3248.706	3138.642	Yes
Jun-02	3221.987	3221.130	0.857	0.857257	0.026606	0.026606	0.0000	0.0001	3277.837	3165.405	Yes
Jul-02	3250.492	3249.554	0.938	0.937859	0.028853	0.028853	0.0000	0.0001	3307.146	3192.965	Yes
Aug-02	3279.946	3288.546	-8.600	8.600022	-0.2622	0.2622	0.0000	0.0001	3347.949	3230.196	Yes
Sep-02	3309.4	3321.588	-12.189	12.18851	-0.3683	0.3683	0.0001	0.0002	3380.626	3263.582	Yes
Oct-02	3264.638	3300.657	-36.019	36.01885	-1.103303	1.103303	0.0000	0.0002	3358.513	3243.798	Yes
Nov-02	3218.385	3198.663	19.722	19.72212	0.612796	0.612796	0.0004	0.0002	3255.820	3142.509	Yes
Dec-02	3173.623	3239.420	-65.797	65.79744	-2.07326	2.07326	0.0000	0.0002	3297.020	3182.827	No
Jan-03	3127.369	3140.168	-12.799	12.79914	-0.409262	0.409262	0.0011	0.0002	3196.856	3084.486	Yes
Feb-03	3081.116	3185.596	-104.480	104.4805	-3.390995	3.390995	0.0000	0.0002	3245.263	3127.026	No
Mar-03	3039.338	3055.661	-16.323	16.32258	-0.537044	0.537044	0.0000	0.0002	3115.143	2997.314	Yes
Apr-03	2993.084	2978.882	14.202	14.20206	0.474496	0.474496	0.0001	0.0002	3037.935	2920.978	Yes
May-03	2948.323	2922.356	25.966	25.9664	0.880718	0.880718	0.0000	0.0002	2981.743	2864.152	Yes
Jun-03	2902.069	2919.675	-17.606	17.60636	-0.606683	0.606683	0.0000	0.0002	2975.184	2865.203	Yes
Jul-03	2857.307	2854.771	2.536	2.536106	0.088759	0.088759	0.0001	0.0003	2906.285	2804.171	Yes
Aug-03	2811.054	2840.372	-29.319	29.31863	-1.042976	1.042976	0.0001	0.0003	2889.793	2791.797	Yes
Sep-03	2764.8	2795.955	-31.155	31.15508	-1.126848	1.126848	0.0000	0.0000	2845.659	2747.119	Yes
Oct-03	2771.046	2762.126	8.920	8.920322	0.321912	0.321912	0.0000	0.0000	2811.284	2713.826	Yes
Nov-03	2777.5	2777.107	0.393	0.393266	0.014159	0.014159	0.0000	0.0000	2825.620	2729.427	Yes
Dec-03	2783.746	2774.836	8.910	8.909927	0.32007	0.32007	0.0000	0.0000	2823.218	2727.283	Yes
Jan-04	2790.2	2791.429	-1.229	1.228796	-0.04404	0.04404	0.0001	0.0000	2841.223	2742.507	Yes
Feb-04	2796.654	2824.411	-27.757	27.75654	-0.992491	0.992491	0.0000	0.0000	2875.926	2773.818	Yes
Mar-04	2802.692	2816.183	-13.491	13.491	-0.481359	0.481359	0.0000	0.0000	2867.212	2766.062	Yes
Apr-04	2809.146	2814.291	-5.145	5.144825	-0.183146	0.183146	0.0001	0.0000	2864.032	2765.414	Yes
May-04	2815.392	2782.272	33.120	33.11995	1.176389	1.176389	0.0000	0.0000	2831.992	2733.425	Yes
Jun-04	2821.846	2820.852	0.994	0.993651	0.035213	0.035213	0.0000	0.0000	2871.069	2771.514	Yes
Jul-04	2828.092	2840.126	-12.034	12.03423	-0.425525	0.425525	0.0001	0.0000	2889.985	2791.127	Yes
Aug-04	2834.546	2867.781	-33.235	33.23486	-1.172493	1.172493	0.0002	0.0000	2919.135	2817.330	Yes
Sep-04	2841	2884.005	-43.005	43.00462	-1.513714	1.513714	0.0000	0.0016	2937.507	2831.477	Yes

Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Oct-04	2954.063	2935.660	18.403	18.40294	0.62297	0.62297	0.0001	0.0016	2987.660	2884.565	Yes
Nov-04	3070.895	3039.262	31.633	31.63282	1.030085	1.030085	0.0001	0.0014	3094.418	2985.089	Yes
Dec-04	3183.958	3150.215	33.743	33.7429	1.059778	1.059778	0.0009	0.0013	3205.468	3095.914	Yes
Jan-05	3300.79	3206.857	93.933	93.93259	2.845761	2.845761	0.0001	0.0013	3263.449	3151.247	No
Feb-05	3417.621	3391.246	26.375	26.37497	0.771735	0.771735	0.0000	0.0010	3451.116	3332.415	Yes
Mar-05	3523.147	3510.541	12.606	12.60566	0.357795	0.357795	0.0000	0.0011	3571.118	3450.992	Yes
Apr-05	3639.979	3631.407	8.571	8.571179	0.235473	0.235473	0.0001	0.0010	3695.274	3568.645	Yes
May-05	3753.042	3717.639	35.403	35.40277	0.943309	0.943309	0.0002	0.0010	3786.165	3650.353	Yes
Jun-05	3869.873	3815.339	54.534	54.53431	1.409201	1.409201	0.0002	0.0009	3888.790	3743.276	Yes
Jul-05	3982.936	3922.927	60.010	60.00965	1.506668	1.506668	0.0000	0.0009	4011.904	3835.923	Yes
Aug-05	4099.768	4103.717	-3.949	3.948952	-0.096321	0.096321	0.0001	0.0008	4180.916	4027.943	Yes
Sep-05	4216.6	4265.188	-48.588	48.58824	-1.152309	1.152309	0.0002	0.0015	4344.350	4187.469	Yes
Oct-05	4377.211	4437.433	-60.222	60.22217	-1.375811	1.375811	0.0000	0.0014	4526.027	4350.573	Yes
Nov-05	4543.176	4572.550	-29.374	29.37418	-0.646556	0.646556	0.0010	0.0012	4671.179	4476.003	Yes
Dec-05	4703.787	4560.889	142.898	142.8978	3.03793	3.03793	0.0010	0.0012	4656.737	4467.013	No
Jan-06	4869.751	4721.636	148.115	148.1148	3.041528	3.041528	0.0002	0.0012	4815.978	4629.143	No
Feb-06	5035.716	4959.647	76.069	76.06874	1.510584	1.510584	0.0001	0.0009	5064.462	4857.001	Yes
Mar-06	5185.619	5127.563	58.057	58.05688	1.119575	1.119575	0.0000	0.0010	5225.898	5031.078	Yes
Apr-06	5351.584	5336.157	15.428	15.42758	0.288281	0.288281	0.0000	0.0009	5443.769	5230.671	Yes
May-06	5512.195	5510.044	2.151	2.151321	0.039028	0.039028	0.0001	0.0009	5613.176	5408.807	Yes
Jun-06	5678.16	5632.923	45.237	45.23679	0.796681	0.796681	0.0001	0.0008	5739.386	5528.435	Yes
Jul-06	5838.771	5795.923	42.848	42.84794	0.733852	0.733852	0.0000	0.0008	5912.995	5681.168	Yes
Aug-06	6004.735	5991.510	13.225	13.2255	0.220251	0.220251	0.0001	0.0008	6106.798	5878.398	Yes
Sep-06	6170.7	6101.351	69.349	69.34899	1.123843	1.123843	0.0002	0.0000	6226.165	5979.039	Yes
Oct-06	6173.659	6096.200	77.459	77.45865	1.254664	1.254664	0.0000	0.0000	6229.185	5966.055	Yes
Nov-06	6176.716	6185.837	-9.121	9.121029	-0.147668	0.147668	0.0000	0.0000	6316.251	6058.117	Yes
Dec-06	6179.675	6177.620	2.056	2.055574	0.033263	0.033263	0.0000	0.0000	6313.348	6044.809	Yes
Jan-07	6182.733	6146.632	36.101	36.10059	0.583894	0.583894	0.0000	0.0000	6270.549	6025.164	Yes
Feb-07	6185.79	6164.756	21.035	21.03463	0.340048	0.340048	0.0000	0.0000	6287.082	6044.810	Yes
Mar-07	6188.552	6147.685	40.867	40.86715	0.660367	0.660367	0.0000	0.0000	6299.241	5999.775	Yes

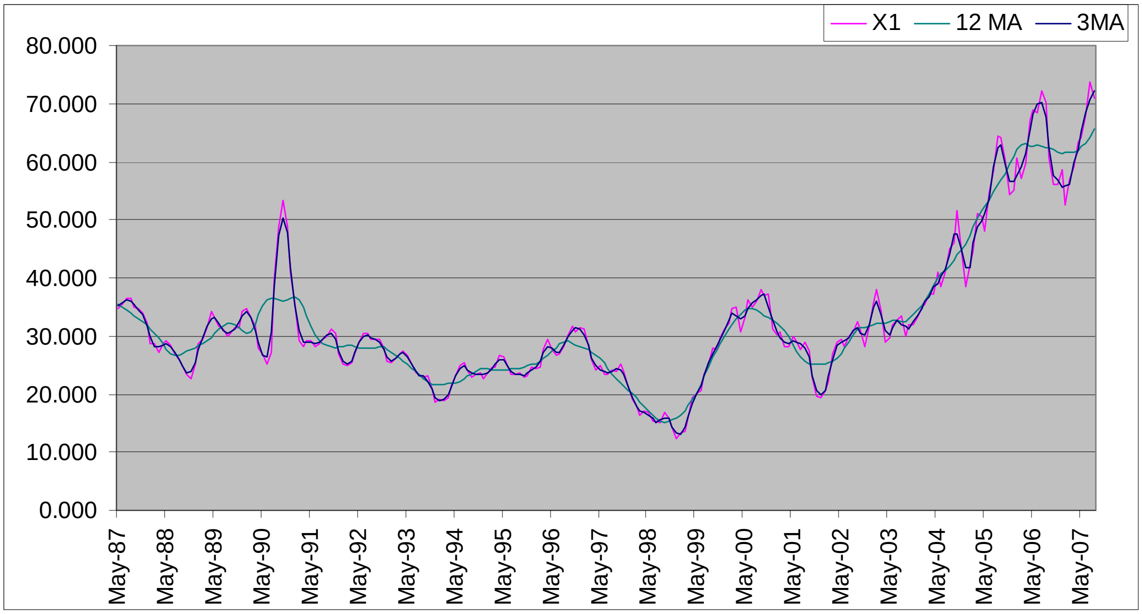
Date	JP-8 Cost	Predicted JP-8 Cost	e	|e|	PE	|PE|	THEIL'S U		Upper Bound	Lower Bound	Prediction included?
Apr-07	6191.61	6195.232	-3.623	3.62278	-0.058511	0.058511	0.0000	0.0000	6329.500	6063.813	Yes
May-07	6194.569	6199.529	-4.960	4.960117	-0.080072	0.080072	0.0000	0.0000	6325.010	6076.536	Yes
Jun-07	6197.626	6173.957	23.669	23.66941	0.381911	0.381911	0.0000	0.0000	6293.033	6057.133	Yes
Jul-07	6200.585	6212.973	-12.389	12.38854	-0.199796	0.199796	0.0002	0.0000	6330.647	6097.487	Yes
Aug-07	6203.642	6298.177	-94.535	94.5349	-1.523861	1.523861			6419.877	6178.785	Yes
							0.0689	0.1626			

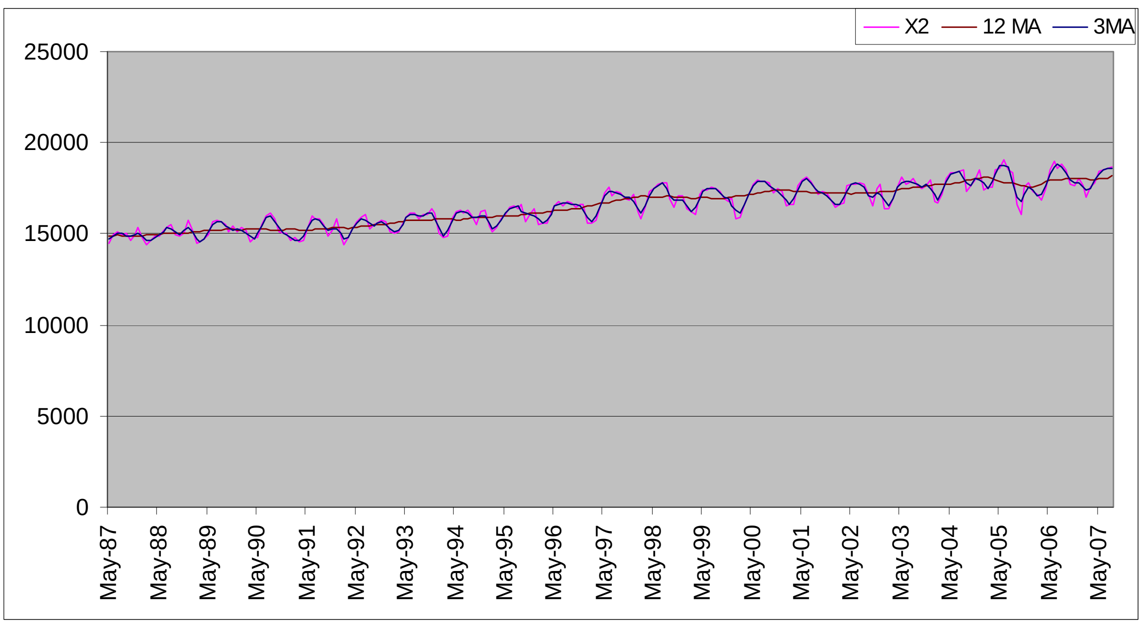
Appendix E: Visual Basic Codes for Obtaining Tab-Delimited Format in SNAPP

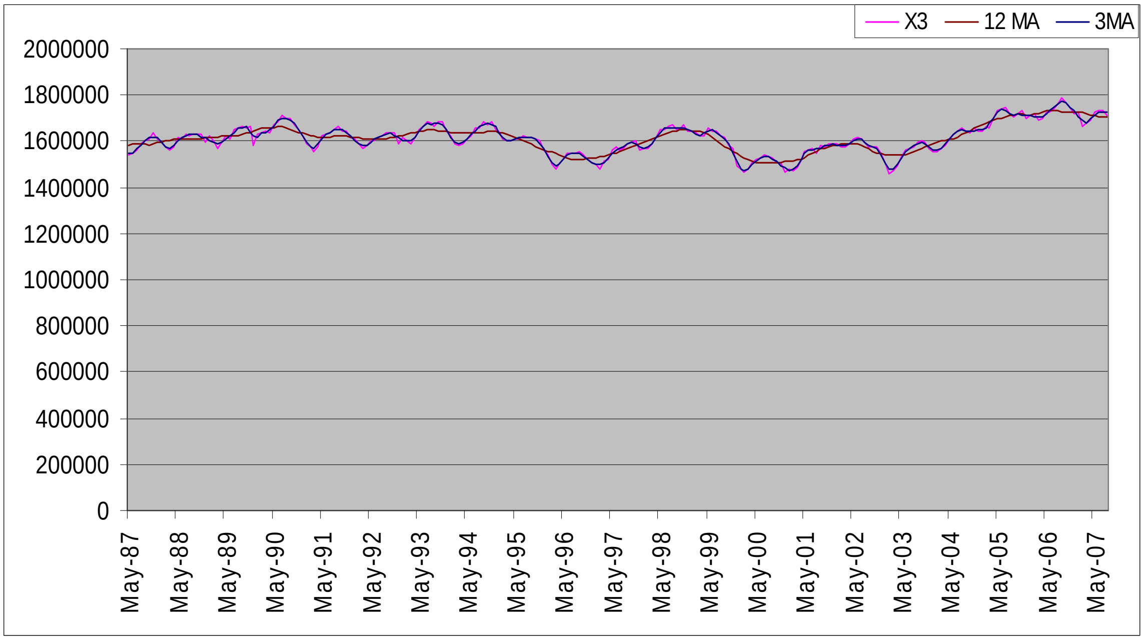
```
Private Sub CommandButton1_Click()

On Error Resume Next
Dim Col_Num_F As Integer
Dim Col_Num_L As Integer
Dim Row_Num_F As Integer
Dim Row_Num_L As Integer
Dim sFile
Dim Decim
Dim rng1 As Range
Dim iFileNum As Integer
Dim str1 As String

Set rng1 = Application.InputBox(Prompt:="Ilk satir veri basliklari olacak sekilde veri
araligini seciniz", Title:="Data", Type:=8)
If (Err.Number = 424) Or (Err.Number = 91) Then Exit Sub

sFile = Application.GetSaveAsFilename("SNNAP_Verisi", FileFilter:="Text Files
(*.txt), *.txt", Title:="SNNAP text dosyasi kaydediniz")
If sFile = False Then Exit Sub

Decim = InputBox("Virgulden sonra kac rakam istiyorsunuz? (Oldugu gibi birakmak icin
A yaziniz)", "Veri Formati", "A")
If Decim = "" Then
   MsgBox "Iptal edildi!", vbExclamation, "Iptal edildi"
   Exit Sub
End If

If Decim = "A" Then GoTo Decim_is_A
If Val(Decim) = 0 Then Decim = 0
Decim_is_A:

iFileNum = FreeFile
Open sFile For Output As iFileNum

Row_Num_F = 10000
Row_Num_L = 0
Col_Num_F = 10000
Col_Num_L = 0

For Each c In rng1.Cells
   If c.Row < Row_Num_F Then Row_Num_F = c.Row
   If c.Row > Row_Num_L Then Row_Num_L = c.Row
   If c.Column < Col_Num_F Then Col_Num_F = c.Column
```

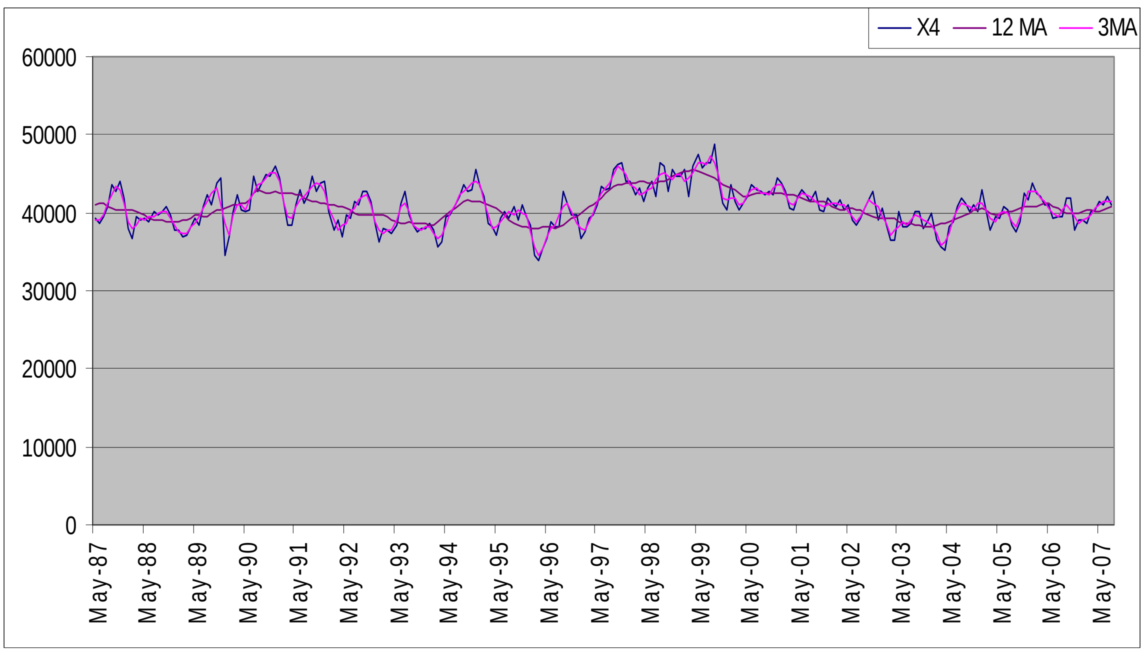
```
   If c.Column > Col_Num_L Then Col_Num_L = c.Column
Next

str1 = ""
Dim deger As String
'For j = 1 To Row_Num
'    For i = 1 To Col_Num
For Each c In rng1.Cells
        deger = Chr(9)
        If c.Column = Col_Num_L Then deger = ""
        If c.Row = Row_Num_F Then
           str1 = str1 & SNNAP_Data_Sheet.Cells(c.Row, c.Column) & deger
        Else
           If Decim = "A" Then
              str1 = str1 & Val(SNNAP_Data_Sheet.Cells(c.Row, c.Column)) & deger
           Else
              str1 = str1 & Round(Val(SNNAP_Data_Sheet.Cells(c.Row, c.Column)),
Decim) & deger
           End If
        End If
'    Next i
   If c.Column = Col_Num_L Then
      str1 = str1 & Chr(32)
      Write #iFileNum, str1
      str1 = ""
   End If
'Next j
Next

Close #iFileNum
ReplaceTextInFile sFile, " ", ""
ReplaceTextInFile sFile, Chr(34), ""
ReplaceTextInFile sFile, Chr(34), ""
MsgBox "Dosya Hazir!", vbExclamation, "Kayit"
End Sub
```

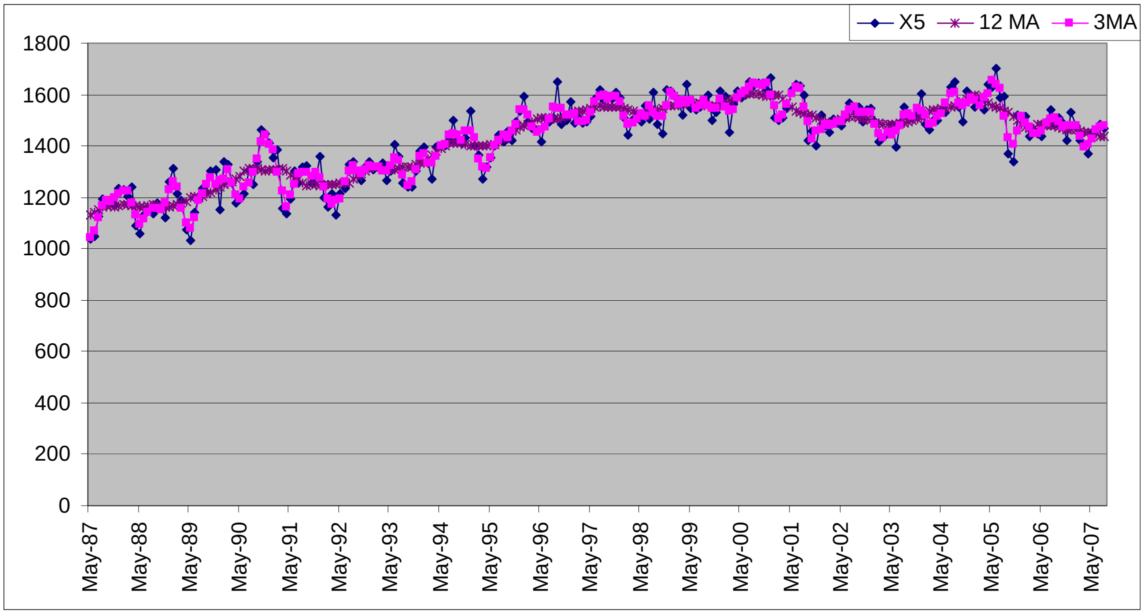
Appendix F: Smoothing Figures of Predictor Variables

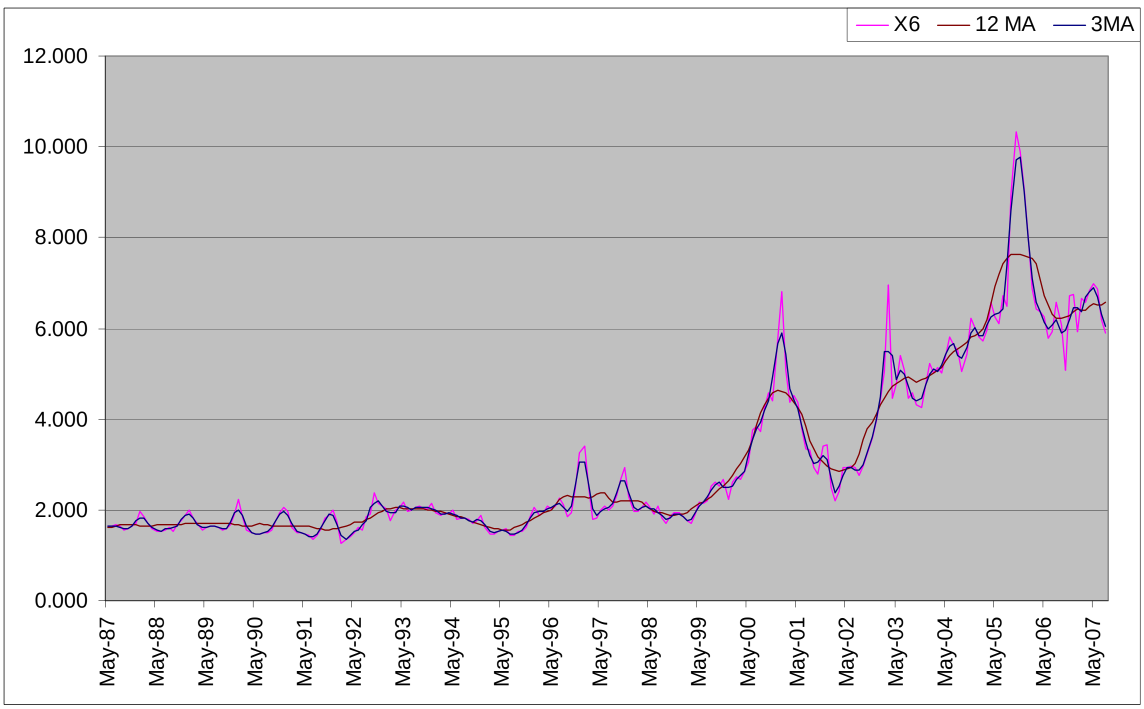





X3
12 MA
3MA
2000000
1800000
1600000
1400000
1200000
1000000
800000
600000
400000
200000
0
May-87
May-88
May-89
May-90
May-91
May-92
May-93
May-94
May-95
May-96
May-97
May-98
May-99
May-00
May-01
May-02
May-03
May-04
May-05
May-06
May-07


X4
12 MA
3MA
60000
50000
40000
30000
20000
10000
0
May-87
May-88
May-89
May-90
May-91
May-92
May-93
May-94
May-95
May-96
May-97
May-98
May-99
May-00
May-01
May-02
May-03
May-04
May-05
May-06
May-07


X5
12 MA
3MA
1800
1600
1400
1200
1000
800
600
400
200
0
May-87
May-88
May-89
May-90
May-91
May-92
May-93
May-94
May-95
May-96
May-97
May-98
May-99
May-00
May-01
May-02
May-03
May-04
May-05
May-06
May-07


X6
12 MA
3MA
12.000
10.000
8.000
6.000
4.000
2.000
0.000
May-87
May-88
May-89
May-90
May-91
May-92
May-93
May-94
May-95
May-96
May-97
May-98
May-99
May-00
May-01
May-02
May-03
May-04
May-05
May-06
May-07

Appendix G: Blue Dart Submission

First Name: Ömer Last Name: SAĞLAM

Rank: 1st LT Designator # AFIT/GLM/ENS/09-9

Students Involved in Research for Blue Dart: First Lieutenant Ömer SAĞLAM

Position/Title: AFIT Graduate Student

Phone Number: DSN:

E-mail: omer.saglam.tr@afit.edu

School/Organization: Air Force Institute of Technology

Status: [X] Student [ ] Faculty [ ] Staff [ ] Other

General Category / Classification:

[ ] core values	[ ] command	[ ] strategy
[ ] war on terror	[ ] culture & language	[ ] leadership & ethics
[ ] warfighting	[] international security	[ ] doctrine

[X] other: energy

Suggested Headline: A Closer Look to USAF's JP-8 Cost Figures. What Can Be Done to Reduce High Consumption Costs?

Keywords: Forecasting, Energy, Multiple Regression.

Do you know that in 2007 the U.S., with a population of 300 million people, consumed the same amount of oil as China, Japan, India, the Russian Federation and Germany all together, and they have a population of 2.8B people? The U.S. is roughly importing 58% of its petroleum products while consuming approximately 20 million barrels of crude oil each day. The USAF is consuming 2.5B gallons of aviation fuel in a year.

When you tie the consumption to the cost figures, the massive cost becomes apparent. In Fiscal Year (FY) 2007, the USAF total energy costs exceeded \$6.9 billion-\$1.1 billion for facility energy; \$5.6 billion for aviation fuel; and \$229 million for ground fuel. Aviation fuel accounted for approximately 81 percent of the total AF energy costs (USAF Energy Program Policy Memorandum, 2008).

Surely having sufficient volumes of energy resources is absolutely vital for the U.S.'s national security, economic improvement, transportation network, and for sustaining the "super power" role on earth. However, consumption and cost figures are incredibly high. Although the on-going GWOT follows a high ops-tempo that causes the high cost and consumption figures, it is clear that some of the cost may be saved by taking the necessary actions. So, what actions can be taken?

First, effective and efficient planning should be conducted in every oil related decision making process. In order to take precautionary measures for preserving the current position, the U.S. has to forecast its energy needs and costs. At the same time, the world's organic production capability and demand, as far as 25 years into the future, should be taken into account. Here the importance of forecasting emerges. To determine a budget for the upcoming years the USAF has to accurately forecast related JP-8 cost and needs in order to prevent funding shortfalls. There are many forecast modeling techniques for oil related forecasts in the literature. Our study for JP-8 cost forecasting indicates that a multiple regression model outperforms ANN modeling within the selected forecasting criteria for long-term forecast horizons. According to our results, short-term forecast horizons should utilize simpler models, such as moving averages and smoothing methods, as they give satisfactory results when compared to the highly complex models. Our forecast model shows that the USAF's JP-8 cost for each of the next 5 years will be somewhere between 6.3 and 7.5 billion dollars.

Second, cultural change is necessary. In a broader sense, every American needs to be aware of potential energy savings in their daily life. From a micro perspective, airman should also be aware of the costs of using official equipment as if they're using their own property. Saving opportunities for all areas should be screened, monitored, and initiated by the senior leadership of the organization. With the help of the right metrics, successful energy savings practices should be awarded and utilized by other partners of the organization.

Third, senior leadership should be patient and invest money on alternative sources of energy, realizing that it will take more time for alternative energy explorations to play a significant role in the overall goal of reducing foreign oil dependency. Leadership should not forget that the United States' dependence on foreign oil is a significant security threat facing the nation.

The overall goal of reducing foreign oil dependency can be achieved by a clear vision for the future. Determined strategic and tactical planning are the key aspects for achieving the organizational goals. The USAF initiated an Energy Program Policy which includes all the necessary steps that should be taken for achieving the overarching goals of the program. Aggressive pursuit of these goals by every member of the USAF will be the breakpoint for the success of the program.

Bibliography

Abosedra, S., and Nikiforos Laopodis "Stochastic Behavior of Crude Oil Prices: A GARCH Investigation," The Journal of Energy and Development, 21-2: 283 (1997).

Adrangi, Bahram, and C. Chatrath. "Chaos in Oil prices? Evidence from Futures Market," *Energy Economics* 23: 405-425 (2001).

Banks, Jerry, John S. Carson, Barry L. Nelson and David M. Nicol. *Discrete Event System Simulation.* Pearson Education Inc, 2005.

Bartis James T., Tom La Tourrette, Lloyd Dixon, D.J. Peterson and Gary Cecchine. *Oil Shale Development in the United States; Prospects and Policy Issues.* U.S.A.: RAND Corporation., 2005.

Bates Matthew, Roger Drinnon, Jason Hernandez and Air Force Flight Test Center, Edward AFB. "Air Force Soars toward Alternative Fuel Goals," *Defense Transportation Journal,* June (2008).

Burke Kenneth. *Building a Consensus Forecast for Crude Oil Prices*. MS thesis, AFIT/GLM/ENV/06-04. Air Force Institute of Technology, Wright Patterson Air Force Base OH, March 2005.

Campbell and Laherrere. *The End of Cheap Oil?*, Scientific American, March 1998.

Chwee, Victor. "Chaos in Natural Gas Futures," *The Energy Journal* 19-2: 149-164 (1998).

Clemen, Robert T., A. H. Murphy, and Robert L. Winkler "Screening Probability Forecast Contrasts between Choosing and Combining," *International Journal of Forecasting,* 11: 133-146 (1995).

Deffeyes, Kenneth S. *Hubbert's Peak: The Impending World Oil Shortage*, Princeton University Press, 2002.

Deutsch Philip J. "Think again: Energy Independence," *Foreign Policy*, 151: 20-24 (Nov/Dec 2005).

Ediger Volkan S., Sertac Akar, and Berkin Ugurlu. "Forecasting Production of Fossil Fuel Sources in Turkey Using a Comparative Regression and ARIMA model," *Energy Policy,* 34: 3836-3846 (2006).

Edwards Tim, Bill Harrison, and Lourdes Maurice. “Properties and Usage of Air Force Fuel: JP-8,” *American Institute of Aeronautics and Astronautics,* AIAA 2001-0498.

Energy Information Administration. *The U.S. Country Energy Profiles,* 2006, Official Energy Statistics from the U.S. Government.

Energy Information Administration. *U.S. Annual Kerosene- Type Jet Fuel Product Supplied,* Energy Glossary.

Energy Information Administration. *The U.S. Primary Energy Consumption by Source and Sector,* Annual Energy Review 2007.

Gately, Dermot. “Strategies for OPEC’s Pricing and Output Decisions,” *The Energy Journal* 16-3: 1-37 (1995).

Granger C.W.J. *Forecasting in Business and Economics* : Academic Press Inc., San Diego, 1989.

Greene, David L., Janet L. Hopson and Jia Li, *Running Out of Oil: Analyzing Global Oil Depletion and Transition through 2050*. Oak Ridge National Laboratory. ORNL/TM-2003/259. TN, USAA, October 2003.

Grudnitski Gary, and Larry Osburn. “Forecasting S&P and Gold Futures Prices: An Application of Neural Networks,” *The Journal of Futures Markets,* 13-6: 631-643 (1993).

Hornitschek Michael J. “War without Oil: Catalyst for Transformation,” *Air Force Journal of Logistics,* 30: 2-30 (Fall 2006).

Kasprzak Mary. *Forecasting Jet Fuel Prices Using Artificial Neural Networks.* MS Thesis. Naval Postgraduate School, Monterrey, California, March, 1995.

Koomey, Jonathan, Paul Craig, Ashok Gadgil, and David Lorenzetti, “Improving Long-Range Energy Modeling: A Plea for Historical Perspectives,” *The Energy Journal* 24-4: 75 -92 (October 2003).

Kuan Chung-Ming and Halbert White. "Artificial Neural Networks: An econometric Perspective,” *Econometric Reviews* 13: 93-97 (1994).

Kutner Michael H., Christopher J. Nachtsheim, John Neter, and William Li. *Applied Linear Statistical Models (5th Edition).* New York : McGraw-Hill, 2005.

Lee Jae Kyu, and Chang Seon Yum. “Judgmental Adjustment In Time Series Forecasting Using Neural Networks,” *Decision Support Systems* 22: 135-154 (1998).

Leedy Paul and Jeanne Ormrod. *Practical Research. Planning and Design (8th Edition).*Columbus OH: Pearson, 2005.

Lopez C. Todd. “Budget request: Air Force seeks $6.2 Billion Increase”, *Air Force Print News*, Washington D.C., 14 Feb 07

Lovins Amory B., E. Kyle Datta, Odd-Even Bustnes, Jonathan G. Koomey, and Nathan J. Glasgow, “Winning the Oil Endgame, Innovation for Profits, Jobs, and Security,” Report to public, Rocky Mountain Institute, 2005.

Makridakis Spyros and Steven C. Wheelwright. *Forecasting Methods and Applications*. U.S.A. : John Wiley & Sons. Inc., 1978.

Makridakis Spyros and Steven C. Wheelwright. *Forecasting Methods and Applications*. U.S.A. : John Wiley & Sons. Inc., 1997.

MATLAB 7^0 Software Neural Network Toolbox Help Pages.

Maugeri, Leonardo. The Age of Oil: The Mythology, History, and Future of the World’s Most Controversial Resource. Greenwood Publishing Group, 2006.

McClave James, P.George Benson, and Terry Sincich. Statistics for Business and Economics (9^{th} edition). New Jersey: Pearson, 2005.

McMenamin J. Stuart, and Frank A. Monforte. “Short Term Energy Forecasting with Neural Networks,” *The Energy Journal,* 19-4: 43-61 (1998).

Michalewicz Zbigniew and David Fogel. *How to solve it: Modern Heuristics (2^{nd} edition).* Germany: Springer, 2004.

Moshiri Saeed, and Faezeh Foroutan. “Forecasting Nonlinear Crude Oil Futures Prices,” *The Energy Journal*, 27: 81-95 (2006).

Moshiri Saeed, and Laura Brown. "Unemployment Variation over Business Cycles: A Comparison of Forecasting Models," *Journal of Forecasting* 23: 497-511 (2004).

Nelson Michael, Tim Hill, Bill Remus, and Marcus O’Connor. “Can Neural Networks Applied to Time Series Forecasting Learn Seasonal Patterns: An Empirical

Investigation,” *Proceedings of the Twenty-Seventh Annual Hawaii International Conference on System Sciences,* 649-655 (1994).

New York Mercantile Exchange Glossary. http://www.nymex.com/glossary.aspx#j (Retrieved Aug 23, 2008).

Palmer Alfonso, Juan Jose Montano, and Albert Sese. “Designing an Artificial Neural Network for Forecasting Tourism Time Series,” *Tourism Management,* 27: 781-790 (2006).

Panas Epaminondas and Vassilia Ninni. "Are Oil Markets Chaotic? A nonlinear dynamic analysis," *Energy Economics* 22: 549-568 (2000).

Pindyck, Robert S. "The Long-Run Evolution of Energy Prices," *The Energy Journal*, 20: 1-27 (1999).

Powell Stephen G. “The Target Capacity-Utilization of OPEC and the Dynamic of the World Oil Market,” *The Energy Journal,* 11(3): 27-37 (1990).

Qi Min, and G. Peter Zhang. “Trend Time-Series Modeling and Forecasting with Neural Networks,” *IEEE Transactions on Neural Networks,* 19-5: 808-816 (2008).

Sadrosky Perry. “Time Varying Risk Premium in Petroleum Futures Prices," *Energy Economics* 24: 539-556 (2002).

Salaverry Juan A. *Predicting Argentine Jet Fuel Prices*. MS Thesis, AFIT/GLM/ENC/07M-01. Air Force Institute of Technology, Wright Patterson Air Force Base OH, March 2007.

Sanders Nada R. and Karl B. Manrodt. “The Efficacy of Using Judgmental versus Quantitative Forecasting Methods in Practice,” *The International Journal of Management and Science, Omega* 31: 511-522 (2003).

Serletis, Apostolos and Periklis Gogas. "The North American Natural Gas Liquids Markets are Chaotic," *The Energy Journal* 20-1: 83-103 (1999).

Statistical Neural Network Analysis Package Users Manual, Texas: 1995.

Swanson Norman R. and Halbert White. "A Model Selection Approach to Real-Time Macroeconomic Forecasting Using Linear Models and Artificial Neural Networks," *The Review of Economics and Statistics* 79-4: 540-550 (1997).

Tang, Linghui, and Shawkat Hammoudeh. "An Empirical Exploration of the World Oil Price under the Target Zone Model," *Energy Economics* 24: 577 – 596 (2002).

The Energy Policy Act of 1992. U.S. Congress. Washington D.C, 1992.

The Obama-Biden Comprehensive New Energy Plan for America, 2008.

Available at their website:
http://my.barackobama.com/page/content/newenergy
(Retrieved Dec 27, 2008)

Tillerson Rex W., Chairman and the Chief Executive Officer of the Exxon Mobil Corporation. "Strengthening Global Energy Security." Address to Scholars. Woodrow Wilson International Center for Scholars, Washington D.C. 8 January 2009.

United States Government Accountability Office. *Defense Budget: Review of DoD's Report on Budgeting for Fuel Cost Fluctuations.* GA)-07-688R. Washington D.C: 26 April 2007.

U.S. Air Force Energy Communication Plan (November 2007)

Walsh Shawn P. "Oil Vulnerabilities and United States Strategy," *U.S. Army War College Research Project*. (February, 2007).

Wiggins Vincent L., Kevin M. Borden, Kathryn L. Turner, and Jeff Grobman. *Statistical Neural Network Package Users Manual).* Texas : Human Resources Directorate of the Armstrong Laboratory, 1995.

Wood, John H., Gary Long and David F. Morehouse. *Long Term World Oil Supply Scenarios: The future is neither as bleak nor rosy as some assert.* Energy Information Administration, 2004.

Available at EIA Website:
http://www.eia.doe.gov/pub/oil_gas/petroleum/feature_articles/2004/worldoilsupply/oilsupply2004.htm (Retrieved October 19, 2008)

Xenakis John J. *Generational Dynamics for Historians* (Online version of his draft book available for peer reviews).

Available at his website: http://www.generationaldynamics.com/cgi-bin/D.PL?d=ww2010.book2
(Retrieved Aug 25, 2008).

Zhang Guoqiang, B. Eddy Patuwo, and Michael Y. Hu. “Forecasting with Artificial Neural Networks: The State of the Art,” *International Journal of Forecasting,* 14: 35-62 (1998).

Zhang G. Peter, and Min Qi. “Neural Network Forecasting for Seasonal and Trend Time Series,” *European Journal of Operational Research,* 160: 501-514 (2005).

Vita

First Lieutenant Ömer Sağlam graduated from Maltepe Military High School in Izmir, Turkey. He entered to Turkish Air Force Academy in Istanbul, Turkey where he graduated with a Bachelor of Science degree in Industrial Engineering in August 2003.

His first assignment was at Cigli AFB, Izmir as a student in Basic Pilot Training in September 2003. In August 2005, he was assigned to the Supply Officer Basic Training School, Izmir, Turkey where he was a student supply officer for 6 months. After graduating from the school, he was assigned to 15th Missile Base Command located in Istanbul. In August 2007, he entered the Graduate School of Engineering and Management, Air Force Institute of Technology. Upon graduation, he will be assigned to his previous station.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 074-0188

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
10-08-2007	Master's Thesis	Sep 2007 – Mar 2009

4. TITLE AND SUBTITLE

Forecasting USAF JP-8 Fuel Needs

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Sağlam Ömer , 1st Lt., TuAF

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)

Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Way, Building 640
WPAFB OH 45433-8865

8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT/GLM/ENS/09-9

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

N/A

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Oil is still one of the strategic energy resources for both the U.S. and the USAF today. Accurate oil prediction is important for the U.S. in order to improve the national strategy and the related budget concerns. Today, the U.S. is roughly importing 58% of its petroleum products. Moreover, in Financial Year (FY) 2007 the USAF total energy costs exceeded $6.9 billion. Aviation fuel accounted for approximately 81% of the total AF energy costs. Fluctuations in oil prices have huge impacts on the USAF's JP-8 budgetary calculations. In order to handle this problem, the need for accurate forecasts arises.

In this study, we forecast the USAF's JP-8 consumption and costs for the next five year period. The study shows that the JP-8 consumption figures will go on to follow the recent trend via Holt's Linear Method. Also, the study shows that short-term predictions could be performed with more simple and easy-to-implement methods, versus complex ones. When we consider long-term 5-year forecasts, our multiple regression model outperforms ANN modeling within the specified forecast accuracy measures. Our results indicate that the USAF's JP-8 cost for each of the next 5 years will be somewhere between 6.3 and 7.5 billion dollars, via a multiple regression model.

15. SUBJECT TERMS

FORECASTING, REGRESSION ANALYSIS, AVIATION FUELS, ENERGY, NEURAL NETS, TIME SERIES ANALYSIS.

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Bradley E. Anderson, Lt.Col., USAF
U	U	U	UU	169	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 785-3636, ext 4646 (bradley.anderson@afit.edu)