University of Alberta

Stochastic Modeling and Forecasting of Energy Prices

by

©

Ogochukwu Nneka Maduekwe

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of Master of Science

in

Mining Engineering

Department of Civil and Environmental Engineering

Edmonton, Alberta

Fall 2004

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Library and Archives Canada

Published Heritage Branch

395 Wellington Street
Ottawa ON K1A 0N4
Canada

Bibliothèque et Archives Canada

Direction du Patrimoine de l'édition

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file Votre référence
ISBN: 0-612-95812-4
Our file Notre référence
ISBN: 0-612-95812-4

The author has granted a non-exclusive license allowing the Library and Archives Canada to reproduce, loan, distribute or sell copies of this thesis in microform, paper or electronic formats.

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque et Archives Canada de reproduire, prêter, distribuer ou vendre des copies de cette thèse sous la forme de microfiche/film, de reproduction sur papier ou sur format électronique.

The author retains ownership of the copyright in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

L'auteur conserve la propriété du droit d'auteur qui protège cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou aturement reproduits sans son autorisation.

In compliance with the Canadian Privacy Act some supporting forms may have been removed from this thesis.

Conformément à la loi canadienne sur la protection de la vie privée, quelques formulaires secondaires ont été enlevés de cette thèse.

While these forms may be included in the document page count, their removal does not represent any loss of content from the thesis.

Bien que ces formulaires aient inclus dans la pagination, il n'y aura aucun contenu manquant.

Canada

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

ABSTRACT

Energy price fluctuations affect government and business policies, effective planning and implementation of strategic decisions and industrial growth and competitiveness of business enterprises. Energy is a major input in national and global economies and business growth and expansion, and thus, the ability to forecast energy prices is a critical component of major budgetary policies. Governments and industry continue to struggle in dealing with energy prices. Toward, the solution of this problem, many efforts are currently being made to provide some tools for guiding governments and industry in this domain. Energy prices are affected by a number of unforeseeable future events that are hardly predictable. However, modern science and economics have provided tools that can be used to provide forecasts with a reasonable degree of confidence. This research contributes toward this important issue of energy price forecasts. A number of statistical and econometric methods, including GARCH, ARIMA, PCR and neural networks modeling techniques, have been used to develop energy forecasts models. These energy models include electricity, coal, crude oil and natural gas prices and total energy consumption for Alberta and Canada. The determinants of energy prices in these models are the energy production, OPEC prices, the price of other energy products, personal income, GDP, number of oil and gas wells drilled (westca), personal income, unemployment and number of degree days. The models are verified and validated with data from CANSIM, Alberta Energy Library, EUB, Energy Prices and Taxes periodical, Annual Oil Market Report and OPEC bulletin. The results show that the PCR and neural networks techniques provide the best forecasts and could be used for developing reasonable energy price forecast for guiding regional, national and business policies.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

ACKNOWLEDGEMENT

I wish to acknowledge the help of Davison whose neural network software I used for my forecasts. Also, Laura of the Alberta Energy Library was very helpful with some of the data I used for my work, like Westca, the number of oil and gas wells drilled. My supervisor, Dr. Frimpong was also very supportive of all the work I did and his suggestions were most helpful. I appreciate the favour I had with most of my colleagues and would like to thank them all. The advise I got from some of them especially Eric helped me through out my study. And I wish to thank my younger ones for their prayerful support.

Most of all, I want to thank God for his patience and kindness.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

TABLE OF CONTENTS

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 3 ECONOMICS OF FOSSIL FUELS ENERGY AND ELECTRICITY INDUSTRY

CHAPTER 4 MATHEMATICAL FORMULATION OF ENERGY PRICE MODELS

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

LIST OF TABLES

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

LIST OF FIGURES

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

NOMENCLATURE

S_0	Price of Oil
λ_0	lags
g_0	production
d_0	consumption
ρ_0	population
p_0	price of other energy products
ϕ_0	GDP
φ_0	Personal income
μ_0	Unemployment rate
ν_0	Degree days
Q_0	OPEC quota
ω_0	number of oil and gas wells drilled
β	variables for energy price including lags, price of other energy products etc.
α	variables for total energy consumption including lags and price of other energy products etc.
ENT_{ind}	the energy intensity in ktoe/billion 1970 GDR
E_{ind}	the energy consumption in ktoe/year
GDP_{ind}	the gross domestic product in billion 1970 GDR/year
PR_{ind}	the energy price in GDR/ktoe
HFO_{ind}	the heavy fuel oil consumption in ktoe/year
PR_{HFO}	the heavy fuel oil price in GDR/ktoe
DSL_{ind}	the diesel consumption in ktoe/year
PR_{DSL}	the diesel price in GDR/ktoe
$ELEC_{ind}$	the electricity consumption in ktoe/year
PR_{ELEC}	the electricity price in GDR/ktoe
K	the saturation level of energy intensity
b	the growth factor
CANSIM	Canadian Socio-economic Information Management System
EUB	Energy Utilities Board
OPEC	Organization of Petroleum Exporting Countries
GDP	Gross Domestic Product
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
ARCH	Autoregressive Conditional Heteroskedasticity

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
CAODC	Canadian Association of Oil Well Drilling Contractors
DRNN	dynamical recurrent neural networks
MEM	mixture of expert models
PSC	predictive stochastic complexity
NYMEX	New York Mercantile Exchange
IPE	International Petroleum Exchange
SIMEX	Singapore Mercantile Exchange
NOC	National Oil Company
DSI	Dynamic System Imitator
MPEEE	mathematical programming energy economy environment
AEP	American Electric Power
LEN	logs of total energy
LPEN	logs of aggregate DPI of energy
LVA	logs Industrial value added
DPI	divisia Price Index
QSI	first round quantity shares
GQ	Goldfeld-Quandt
RSTAT	prints residual summary statistics (Durban-Watson etc.) option
OLS	ordinary least squares option
AR	autoregressive process
OTC	over the counter
NGX	Natural Gas Exchange
IEA	International Energy Agency
SSE	sum of squares error
COINT	cointegration command
OECD	Organization for Economic Co-Operation and Development
NWP	Numerical Weather Predictions
SI	Statistical Interpretation
PPM	Perfect Prog Method
MOS	model output statistics
EM	Europe Model
PoP	Probability of Precipitation
NCMRWF	National Centre for Medium Range Weather Forecasting
API	American Petroleum Institution

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 1.0
INTRODUCTION

1.1 Background History

Energy is pervasive and a very strategic element in our universe today. Crude oil is used in the manufacture of heating oil, aviation fuel, and gasoline for transportation. The industrial sector uses crude oil as a raw material for the production of various items like ointments, sweets, petrochemicals and a host of other products. The residential sector employs natural gas as a heating fuel as well as for the manufacture of electricity. Coal is also significant for commercial and residential purposes. Metallurgical coal is used in the manufacture of steel fabrications. Thermal coal is also used for the production of electricity. Electricity is an important factor in the industrial and residential sectors and so it is a raw material for many manufacturing companies. Current production of crude oil outside the Organization of Petroleum Exporting Countries (OPEC) come from Canada, United Kingdom, Mexico, Norway, China, the USA, and Russia. Each country produced between 1.9 million and 6.1 million barrels per day (mb/d) of crude oil in 1999. With the total world production standing at 67.7 million barrels per day, the individual shares of these countries of world production ranges from 2.8% to 9% in 1999 (Klein, 2001).

For the energy sector, a number of expert systems have been developed for carrying out various tasks such as system design, diagnosis and trouble shooting, demand forecast and planning. Oil and natural gas prices are volatile. This volatility is typical of the world oil and gas market. Coal and electricity prices are usually stable. Crude oil, as a strategically important commodity, depends on developments in its production, and pricing and is crucial to the global economy as a whole. These commodities form the foundation and growth of industrialization. Modeling, evaluation and analysis that lead to clear understanding are important to global, domestic and industrial policies for growth and sustainability. Expert systems are needed in the development of strategic planning and energy planning. Applications dealing with long-term energy planning, energy demand analysis and forecasting are numerous but most of them deal with power.

1.2 Statement of Problem

Supply and demand fluctuations affect the price of energy products because it is the state of the market that determines the price of any traded goods or services. If there are fluctuations in demand and supply then the prices of these energy products will be volatile. These fluctuations are due to the cyclic nature of the energy business, within various

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

seasons of the year. For instance, within the summer months, energy is used heavily for transportation and exploration and heating is required during the winter months. Volatile oil prices are due to the difficulties of predicting demand and supply worldwide, coupled with the secrecy surrounding market developments, the compliance of members of OPEC to their production quota system and political developments. Most 'spikes' in oil prices are associated with political crises. Crude oil availability and its price therefore impact the general economy in many ways. The most important channel of influence is that rising crude oil prices feed price inflation in consumer and other intermediate goods, which in turn impacts on other final commodity prices. This inflation then fuels demands for wage hikes to maintain consumer purchasing power.

Firms make business and investment decisions based on their expectations of energy prices. Investments that are surprised by unexpected low energy prices, result in marginal growth, losses and bankruptcies. However, unexpected high energy prices result in high profit margins, growth, buoyancy and competitiveness. Industrial growth and competitiveness are affected by crude oil that is a strategic commodity. The prices of crude oil is crucial to the economy due to its importance to the transportation sector, as well as being both an energy output and input in the production of other commodities. The stability of political and social structures is important in the oil sector. If the social and business structures are unstable the exploitation of the natural resource will slow down or stop altogether. With an unstable environment, investments will not be encouraged, and as such growth will be minimal if not negative. Unstable national governments and national economies, systematic erosion of fundamental social policies and lack of competitiveness among companies can cause unstable environments. In Alberta, the oil sands industry thrives on high market prices for sustainable profit margins. These and other problems necessitate the search for adequate and comprehensive methodologies to model, evaluate, analyze and use energy pricing models for making strategic, economic, business, social and political decisions.

1.3 Objective of Study

The objectives of this study are to: (i) examine the essential elements of oil, natural gas, coal and electricity pricing that play a major role in its determination and establish how to reduce the effects in adverse situations of high or low prices; (ii) develop energy price forecast models for energy planning, business planning and investment; (iii) develop computational and algorithmic efficiencies and statistical control paradigms for solving the forecast models, and (iv) generate appropriate forecast techniques for guiding Alberta and Canadian energy policy makers.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

1.4 Scope and Limitations of Study

This study deals with the forecast of energy prices for oil, natural gas, coal, electricity and energy consumption using linear and nonlinear methods. Mathematical and computer models are developed using Shazam, Matlab, Fortran and @Risk. In the case where the appropriate software was not available, codes were developed in Shazam, Matlab and Fortran. The energy data was obtained from Canadian Socio-economic Information Management System (CANSIM), Alberta Energy Library, Energy Utilities Board (EUB), Energy Prices and Taxes periodical, Annual Oil Market Report and OPEC bulletin with the period between 1982 and 1997. This study determines the factors affecting the time series, prices of oil, natural gas, coal and electricity for Alberta and Canada. Estimations and forecasts are made using GARCH (1,1), ARIMA and principal component regression (PCR). Independent component analysis (ICA) was carried out to give ore regular and structured models. This study also investigates the nonlinear characteristics of the forecast models. PCR and ICA are used to investigate the chaotic behavior of the time series models. PCR was also used to obtain the series forecasts.

1.5 Contributions and Industrial Significance of Study

The contribution of this study include: (i) detailed forecast models for investment decisions and planning of business strategies and budgeting; (ii) advances in knowledge and frontiers in energy economics; and (iii) a strong basis for formulating domestic and foreign policies on energy production, consumption, exports and inventory management. Most models comprise few parameters but do not show the complete picture of those parameters that affect energy product prices. The relationship among energy product prices and their derivative forecasts are treated in order to hedge and so reduce losses or increase gains. Expert systems can be developed for demand forecast and strategic planning. This mostly concentrates on energy planning in particular involving energy demand analysis and forecasting. Most national governments pursue a policy of sustainable development. This means that they harness and use natural resources in a responsible manner, which results in a wealth of natural resources for exploitation for future generations. These decisions require comprehensive forecasting methods, for which this study make significant contributions.

1.6 Research Methodology

The initial part of this thesis reviews the literature in pricing models. This is then followed by the economic structure of fossil fuels and electricity. Most of the input data are economic indicators, productivity and exploration, energy cycle determinants, prices of other alternative sources of energy. The mathematical and computer modeling involve the use of GARCH

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

modeling techniques. The ARIMA model was used to forecast prices of the different energy products, oil, natural gas, coal and electricity. PCR and neural networks were also used to obtain energy prices forecast in the short term. This forecast can then be used in business planning and investment decisions. Where the prices are high, adequate measures are taken to lock in prices at the energy market so that there is not too much loss if prices continue to rise. When prices are low then prices are locked in so as to ensure that losses are not incurred if the prices rise.

1.7 Report Structure

Chapter 1 deals with the background and problems the study will address, as well as the scope and limitations, contributions and industrial significance of the study. Chapter 2 contains a literature survey on fossil fuel energy and electricity pricing statistical and probability modeling. Factors affecting oil and gas prices and some energy price models were investigated and the economic structure of fossil fuels – the oil, gas, coal and electricity industry was researched in Chapter 3. It dealt with the economic structure of the oil industry, the spot and contract market and property evaluation. The essential elements of energy policy were also dealt with later in this chapter. Chapter 4 contains the mathematical modeling theory and computer software for GARCH, ARIMA, PCA and ICA models. The GARCH and ARIMA models are subjected to linear analysis while PCA and ICA models were subjected to nonlinear analysis. Chapter 5 deals with computer modeling and experimentation involving the strategies and methods used to tackle the issues that arise in this study. The results, analysis and discussion of the results are presented in chapter 6. Chapter 7 consists of the conclusion and recommendations.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 2.0

ANALYTICAL SURVEY OF THE LITERATURE

This chapter deals with analytical survey of the literature of previous studies in this research domain. It focuses on statistical and probabilistic, econometric, option pricing, energy forecast, and electricity pricing models. It also focuses on correlation dimension and forecasting, principal and independent component analyses and wavelet time series analysis.

2.1 Statistical and Probability Forecast Modeling

Sharma (2000a) carried out a study to develop a framework for rainfall probabilistic forecasting using available hydro-climatic information. The study presents an approach for identifying optimal predictors that can be used to formulate a robust and efficient probabilistic forecast model. He presents a statistical framework for identifying model predictors of a general linear or nonlinear system. The approach presented is based on the use of nonparametric kernel methods for multivariate probability density estimation. The approach quantifies dependence using a probability density formulation, in contrast to the usual use of deviations about a curve of best fit. The use of the probability density framework makes the proposed approach ideal for identifying predictors, which are used to formulate a probabilistic or stochastic forecast model. The proposed approach is a stepwise predictor selection scheme and is termed the partial mutual information (PMI) predictor identification approach.

He presents some background information required to describe the theoretical foundation of the partial mutual information (PMI) predictor identification approach. The PMI approach is applied to samples from selected stochastic models where the predictors are known before hand. The PMI criterion is used to quantify the dependence between an independent and a dependent variable conditioned on the presence of existing system predictors. A stepwise approach for identifying system predictors based on the partial information criterion was proposed and tested on several artificial data sets with known dependence characteristics. Results indicated that the criterion was effective and accurate in identifying predictors of all the models considered (Sharma, 2000a).

Sharma (2000b) also presented a nonparametric probabilistic forecast model based on accurate estimation of the conditional probability distribution of rainfall through the use of nonparametric kernel density estimation techniques. The kernel approach is data driven and avoids prior assumptions as to the form of dependence (e.g. linear or nonlinear) or of the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

probability density function. He presents a method for probabilistic forecasting of rainfall for lead times ranging from 3 to 24 months. The method involves estimation of the probability densities of the rainfall conditioned on the current values of the selected predictors. Nonparametric kernel methods for probability density estimation are used in formulating the conditional probability density. These methods allow a data based representation of the shape of the probability density function, thus leading to forecasts that represent the true variability in rainfall. Some background information on the kernel density estimation procedure and how it is used to estimate the conditional probability of a variable is presented in Sharma (2000b). The kernel procedure was used to estimate the conditional probability of the Warragamba rainfall time series for selected seasons.

Krzysztofowicz (1999) also presented the fundamentals of two Bayesian methods for producing a probabilistic forecast via any deterministic model. The Bayesian Processor Forecast (BPF) quantifies the total uncertainty in terms of a posterior distribution, conditioned on model output. It couples a deterministic model with a post-processor. The Bayesian Forecasting System (BFS) decomposes the total uncertainty into input uncertainty and model uncertainty, which are characterized independently and then integrated into a predictive distribution. The BFS is compared with Monte Carlo simulation and 'ensemble forecasting' technique, none of which can alone produce a probabilistic forecast that quantifies the total uncertainty, but each can serve as a component of the BFS. The BFS approach formulates a probabilistic forecasting system that includes an input forecaster, a deterministic model, a co-processor, a post-processor, and an integrator. This formulation reveals certain desired normative properties of any probabilistic forecaster and also identifies a proper and limited role of Monte Carlo simulation and the so-called "ensemble forecasting" technique.

Raible et al. (1999) introduced the short-term weather forecast and statistical single-station models and applied them to real-time weather prediction. Numerical weather prediction (NWP) models are very good in very short-term forecasting (up to 24 hours). However, they do require a substantial amount of computation time and the forecasts are not always stable at this time scale. In contrast, statistical schemes require little computation time to make a forecast and are adapted to the station's climate, but in general, they do not include nonlinear behavior. Another advantage of statistical methods over NWP models is that the latter often produces biased forecasts, in contrast to the former. They developed a multiple regression (R) model for predicting the temperature anomaly and a multiple regression Markov (M) model for forecasting the probability of precipitation. The following forecast experiments were conducted for central European weather stations are analyzed: (a) the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

single-station performance of the statistical models, (b) a linear error minimizing combination of independent forecasts of numerical weather prediction and statistical models, and (c) the forecast representation for a region deduced by applying a suitable interpolation technique. These forecasts were combined with the numerical weather prediction (NWP) model forecasts of the Europe model (EM) to improve the forecast accuracy. These two statistical methods has been applied to several weather stations of central Europe to obtain the regional forecast for this area, including the Hamburg Fuhlsbüttel weather centre.

The combination temperature forecast yields a 14% gain for the 24-h prediction with respect to the R model alone, and 17% gain with respect to NWP model. The combined probability of prediction forecast achieves 18% with respect to the R model and 33% with respect to NWP model. While statistical models, based only on observations, are independent of NWP models, the model output statistics technique for providing the best results requires a re-computation whenever the NWP model is changing. Therefore, the linear combination scheme offers an alternative way to improve the direct model output instead of the widely used model output statistics or Kalman filtering methods. The forecasts lead to an operational weather forecasting system for the temperature anomaly and the probability of precipitation. The statistical techniques demonstrated provide a potential for future applications in operational weather forecasts (Raible et al., 1999)

Kumar et al. (1999) developed an operational system for forecasting probability of precipitation (PoP) and a "yes/no" forecast over 10 stations during the monsoon season in India. The development of the PoP forecast equations involves two major steps. The first step is the interpolation of predictor fields to the station location and the second step is the development of multiple regression equations through a screening procedure. A perfect programming method (PPM) approach is developed for statistical interpretation of numerical weather prediction products. Precipitation is intermittent and highly variable in space and time. Local topographic and environmental conditions play an important role in precipitation distribution. For these reasons, the direct prediction of precipitation amounts with a numerical model becomes difficult, particularly for tropical regions. To overcome this difficulty, empirical relationships can be developed between the concurrent circulation, certain thermodynamic quantities, and the resulting precipitation.

The PPM-based operational system for forecasting occurrence of precipitation in probabilistic and categorical terms is the first time an objective interpretation system for precipitation prediction has been introduced in India. The regression equations have selected physically

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

relevant predictors such as relative humidity, vorticity, vertical velocity, and temperature. The forecasts have the desired reliability for most of the stations but the reliability actually decreases with increasing projection except in a few cases. They also discriminate satisfactorily between the occurrence and nonoccurrence of precipitation. It indicates that this PoP forecasting system has a satisfactory and desirable performance. Moreover the PoP forecasts have played an important role in the operational weather forecasting system at National Centre for Medium Range Weather Forecasting (NCMRWF).

Kumar et al. (1999) also developed a statistical interpretation (SI) of numerical weather prediction (NWP) model products. This model has a built-in accounting capability for the local topographic and environmental conditions controlling the precipitation and other surface weather. The uncertainties in the circulation and weather can also be formally expressed through such SI. The SI schemes are classified into two broad classes: (i) PPM and (ii) the model output statistics (MOS), depending on whether the observed or numerically predicted circulation is used in developing the empirical relationships. PPM develops a relation between the parameter to be predicted and the observed circulation around the location of interest using several years of data. The relationship is applied to the NWP output to obtain the forecast. The statistical interpretation scheme and the bias correction method were developed using at least 5-year data of the monsoon season (Kumar et al, 1999).

2.2 Energy Econometric models

Hsiao and Hsiao (1985) examined some commonly used econometric models of energy and found possible sources of use and abuse of elasticity. They derived a formula that clearly relates the income elasticity to the energy-income ratio. The difference of elasticities among the developing and developed countries can be explained directly from the formula. For data on energy consumption and GDP for a certain period, they calculated elasticities and ratios for each year, using all the past available information to minimize the sample errors. The results of econometric method depend on the specification of the model and the techniques of estimation. With all its limitations, the econometric method is only one of the energy modeling techniques and should be used and evaluated as such along with the results obtained from other techniques like input-output models, linear programming models and system models.

Elkhafif (1992) and Sioshansi (1985) used econometric energy models to evaluate past policy experiences, assess the impact of future policies and forecast energy demand. He estimated an industrial energy demand model for the province of Ontario using a linear-logit

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

specification for fuel type equations, which are embedded in an aggregate energy demand equation. Short- and long-term, and own- and cross-price elasticities are estimated for electricity, natural gas, oil and coal. Own- and cross-price elasticities are disaggregated to show the overall price elasticities and the "energy-constant" price elasticities when aggregate energy use is unchanged. These disaggregations suggest that a substantial part of energy conservation comes from the higher aggregate price of energy and not from interfuel substitution. Sharp fluctuations in energy prices in the past two decades have given rise to a variety of government policies regarding energy pricing and supply. Such policies could be counterproductive if they turned out to be too protective, especially in the industrial sector. A policy that significantly alters the price signals to producers could result in inefficient energy uses.

The model in the previous section was estimated using annual data for the 1963-1990 period. Two dummies were incorporated in the model. The first dummy (D69) was included to model the impact of the strike of steel workers in 1969, which substantially reduced the demand for coal and oil in this year. D69 is equal to 1 in 1969 and zero otherwise. The second dummy (D86) was added to represent the influence of the natural gas market deregulation after 1986. This study relies on the two-stage optimization approach to model industrial energy demand in Ontario, Canada. Annual data for the 1963-1990 period was used for the model estimation. The model was simulated to estimate two sets of price elasticities of demand: overall price elasticities and energy constant price elasticities. The results of the study showed that misspecification of the natural gas market deregulation in 1986 results in serious autocorrelation. In addition, the long-term own-price elasticities all fuels (electricity, natural gas, oil and coal) are less than one in absolute value. The capital stock adjustment in Ontario's industrial sector occurs mainly in response to changes in total energy price. This implies that the industrial sector becomes more energy efficient in the long-term in response to higher average energy prices. Very little capital adjustment occurs in the interfuel substitution sub-model. The results also showed that electricity, coal, natural gas and oil are symmetric complements, most likely reflecting the fuel and material mix in the production process of the steel and chemicals industries.

Elkhafif (1993) explained the distortions of the outcomes of price sensitivity analysis and forecasting when the model is used for forecasting simulations without adjusting the Divisia Price Index (DPI). The conclusions showed that the results could be misleading when a two-stage optimization model with an aggregate DPI is used for simulation without adjusting for the DPI. The study also provided an alternative technique that could produce more

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

reasonable results from the price sensitivity analysis and better simulation output. According to the study, the most widely used econometric energy forecasting model is based on the two-stage optimization approach. An aggregate energy DPI is used to link the two stages. Although the use of the DPI is necessary and has its advantages in estimation of the model, it results in misleading forecasts when the model is simulated without adjusting the DPI. The new formulation uses the same estimated coefficients as the conventional formulation. The study shows that demand sensitivity to price shocks obtained from simulating the conventional formulation indicates a bias towards less elastic own-price elasticity, and more negative (complementary) and less positive (substitute) cross elasticities. As a consequence, simulations based on the conventional formulation tend to over-forecast fuels with relatively high real prices and under-forecast fuels with relatively low real prices. To overcome these shortcomings, the study suggests an alternative formulation in which a disaggregated total energy equation is utilized to generate forecasts.

Vaage (2000) formulated the structure of the household's energy demand as a discrete/continuous choice, and on this basis, established an econometric model suitable for the data available in the Norwegian Energy Surveys. He specified the discrete appliance choice as a multinomial logit model, with a mixture of appliance attributes and individual characteristics as explanatory variables. In the next step the continuous choice of energy use is modeled conditioned on the appliance choice. The energy prices turned out to be significant both when estimating the appliance choice and the conditional energy demand. The estimated price elasticity for energy exceeds minus unity. The paper discusses how this relatively strong price response should be interpreted in the context of other econometric analysis with no explicit appliance dependence. Finally, the significance of the many household characteristics at both stages of the model signals a high degree of heterogeneity within the households, which justifies the use of detailed micro-data in the modeling of the energy demand. Time series studies lack data concerning stock appliance, building characteristics, and are usually aggregates over the entire country's consumption. Aggregation and missing variables lead, potentially, to mis-specification bias. In addition, on the basis of the information from time series data the planning authorities are unable to evaluate the effect of their intervention *across* the households.

2.3 Energy Forecast Modeling

Dieck et al. (1985) presented a study for selecting the most appropriate time series model to forecast total energy usage at the University of Missouri-Columbia Power Plant. The Energy Management Department provided the monthly data on total energy usage (megawatts) at

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

the University of Missouri-Columbia from January 1973 to December 1983. This data set was used to initialize the final models selected using a rollover forecast (updating every year the model if necessary and/or the parameters). These models included the Box-Jenkins ARIMA, Winters, Harrison and the Naïve models. Each of these models was described and an approach was developed for selecting the most appropriate model. Once the time series has been analyzed and identified using the autocorrelation analysis, the model fitting process is performed for the five planning horizons chosen. The models are used to forecast 12 periods ahead after each horizon (Dieck et al., 1985).

McElroy et al. (1986) developed a regional economic and demographic modeling system used to generate model inputs for forecasting internal energy sales and peak demands for the American Electric Power (AEP) System. Using standard econometric and component modeling techniques, the models forecast employment and output by detailed industry classification in manufacturing, employment by other major industry division, population, components of population change, labor force by age and personal income. A distinguishing feature of these models is that they explicitly incorporate quantitative estimates of both national and intra-regional linkages in the simulation process. Many electric utilities consider the methods for selecting economic and demographic forecast inputs to drive their service-area energy and demand projections. Since this regional economic and demographic modeling system is relatively new at AEP, its range of applications for developing improved energy and demand forecasts has yet to be fully explored.

Rastogi et al. (1990) suggested a total energy requirement model for the electric utility planning process. This model requires very little data input and time, and can be developed on a personal computer with the help of electronic spreadsheet and/or statistical program. Inputs used in determining the energy forecast for the suggested model includes population, weather, income, and a major economic activity. This study used the regression analysis to develop kWh sales models for twenty cooperatives. The following variables were included in the model development: (i) number of residential consumers; (ii) heating and cooling-degree days; (iii) electricity price; (iv) per capita income; (v) crude oil price; and (vi) previous electricity use. Their method has been tested on 20 rural electric cooperatives with satisfactory forecast results and explanations. A slight improvement to this method could be made by first excluding the large commercials in the total sales model and then adding back projected large commercial load to the projected sales (Rastogi et al., 1990)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Skiadas et al. (1997) examined the impact of energy prices in energy consumption in selected Greek industries in the 1978-1991 period. An index, called energy intensity, is developed to quantify energy-saving efforts, and it is examined for the whole industry and for two general divisions: the energy-intensive and the non-energy-intensive sectors. The energy-intensive sector contains those industries examined by OECD in the following sub-sectors: a) paper and paper products; printing and publishing; b) chemicals and petroleum, coal, rubber, and plastic products; c) non-metallic mineral products; and d) basic metal industries. The non energy-intensive sector contains all the other sub-sectors. Growth functions are used to examine the evolution of energy intensity. These growth functions provide an S-shaped time-pattern where a saturated level is finally reached. The saturation level is the most critical factor for understanding the behavior of the system under consideration, and knowledge of its variation would lead to improve forecasting. The study used two models to predict energy intensity. The results of the models are useful for formulating energy policy. Price-adjusted diffusion models seem to have predictive validity to be used to forecast changes in energy intensity. Pricing and taxation policies can be used as instrumental tools to promote specific energy-conservation measures. Applying the proposed models, one can predict the effectiveness of such measures. Supply-demand models can also be used to analyze the effects of a lower demand in the whole energy system for designing effective energy strategies (Skiadas et al., 1997).

Suganthi et al. (1999) developed a modified model to correct the deficiency in the econometric demand models used in developed countries, which consider only price and national income. Their modified model linked energy consumption with the economy, technology and the environment gave the best results, which were then compared with the results from a Mathematical Programming-Energy-Economy-Environment (MPEEE) model to find the optimum energy required based on certain environmental standards. The actual requirements of coal, oil and electricity from the modified model were used as input in the MPEEE model. The model maximizes the GNP-Energy ratio that is conceptually related to energy efficiency. The constraints limit the emissions of CO_2, SO_2, NO_2, total suspended particles (TSP), CO and volatile organic compounds (VOC). The difference between the actual requirement from the modified model and optimum from the MPEEE model will have to be supplied by the non-conventional energy sources. The historic commercial energy consumption in India from 1953 to 1989 is used in projecting the requirement to 2010-11.

An electricity constraint based on the existing generation capacity is introduced in the MPEEE model. Different scenarios evolved for different levels of electricity generation

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

capacity. A critical electricity generation capacity to be maintained for optimum GNP-Energy ratio was also established. The modified model (MM) gave the best result compared to the econometric and time series models. The predicted values from MM, compared to the actual, showed very little deviation. The GNP-Energy ratio is a maximum in the case of coal, while emissions were a maximum in the case of electricity generation. Hence in the MPEEE model the maximum allocation goes to coal. The critical values of electricity generation for different percentage reductions of pollutants give the policy maker a tool for taking appropriate decisions (Suganthi et al., 1999).

China is the world's second largest pollution source of CO sub 2 (Doug, 2000). It is estimated that 85-90% of the SO sub 2 and CO sub 2 emissions of China results from coal. With high economic growth and increasing environmental concerns, China's energy consumption in the next few decades has become an issue of active concern. Energy demand forecast over long periods, however, is getting more complex and uncertain. It is believed that the economic and energy systems are chaotic and nonlinear. Traditional linear modeling for energy demand forecasts, therefore, is not a useful approach. Stochastic dynamic models must be used to account for uncertainty and imperfect information about future economic growth and energy development. Doug (2000) developed a dynamic system model to predict China's energy demand in the next 25 years. The model predicts that China's energy demand in 2020 will be about 2,700-3,000 Mtce, coal demand 3,500 Mt, increasing by 128% and 154%, respectively, compared to that of 1995. The model can be used effectively for limited-data and ill-defined target system conditions. His results also showed that the GDP growth and energy economic efficiency improvements are two key factors in reducing energy consumption (Doug, 2000).

2.4 Electricity Pricing Modeling

Rudkevich et al. (1998) presented estimates for the price of electricity dispatched and sold through a poolco on the basis of bids made by rational, profit-maximizing generating firms. Advancing theoretical concepts developed by Klemperer and Meyer (1989) and Green and Newbery (1992), they developed a new formula for the instantaneous market clearing price that generating firms adopt bidding strategies given by Nash Equilibrium. They quantified the average price mark-up, relative to the "perfectly competitive" price, that would result from Nash equilibrium-based bidding strategies over the course of one year as a function of the number of identical firms in the poolco market. Their model is validated using data for Pennsylvania. The results showed that the Nash Equilibrium-based prices are sensitive to such factors as the average reliability of generating units, the amount of reserve capacity in

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

the system, and the precision with which generating firms are able to predict demand for electricity on a daily basis.

The results also showed that, in markets with relatively high number of firms, the price of electricity was significantly higher than the short-run marginal cost of generation. However, even with a relatively low market concentration (high number of competing firms), the market clearing prices are still significantly higher than "perfectly competitive" prices. Their findings have important implications for the design and operation of future electricity markets. Moreover, the findings suggested that the guidelines used by the Department of Justice and the Federal Energy Regulatory Commission to characterize market power in electricity markets may require revision if they are to prevent the exercise of market power in poolco-type markets (Rudkevich et al., 1998).

Breipohl (2002) proposed that the price of electricity should comprise two components: energy price and "reliability price". From the supply point of view, in addition to the energy price, there is a cost associated with reliability, or continuity of supply. This cost, which differs from other commodities, arises because electricity cannot be stored. From the demand point of view, electricity is an essential commodity, while others may want a choice of how much reliability they are willing to pay for. This study is based on the premise that, as long as the price of electricity is based solely on a price for electrical energy; the electricity market will not function properly. Consumers want electrical energy, but most consumers also want electrical energy instantaneously upon demand. Suppliers have to supply electrical energy, but they also must supply reliability. That is, they have to supply other services, spinning, ready, and planning reserve in addition to regulation and reactive power in order for the electrical energy system to be reliable. From regulatory rate hearings, the study reviews the capital costs and the cost of unserved demand and the traders "spark spread" as the reliability price.

Finally from the supply side, the study dealt with the price of ancillary services and suggested a price-reliability quantification as well as electrical energy price. Customers must also reimburse suppliers for subscribing to the reliability product for the ancillary services. On the demand side, electricity should be sold separately as electrical energy and reliability with customers being offered a choice of whether to subscribe to the reliability product or products. While this proposal has some notable difficulties, it offered a promise of having markets that logically address the two distinct products one of which certain customers may or may not want. In addition suppliers furnish electrical energy and reliability through ancillary

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

services. Thus each of these two markets can converge. Energy and reliability should be the two products that are bought and sold in the electricity market (Breipohl, 2002).

According to Davison et al. (2002), in recent years a great deal of interest has been paid to the market-based pricing of electrical power. Electrical power contracts often contain embedded options, the valuations of which require a stochastic model for electricity prices. Efficient stochastic models exist for modeling price variations in traditional commodities. Electricity is critically different from these commodities as it is difficult to store and, on short time scales, its price is highly inelastic. This has important implications for stochastic spot price models of electricity. In these random models, price returns play a dominant role. The authors developed a new stochastic electricity price model for forecasting electricity prices. The model incorporates four main assumptions: (i) price spikes exist; (ii) off-peak electricity prices are often zero; (iii) electricity prices are sometimes even negative; and (iv) electricity prices don't drift indefinitely.

The model combined the top-down aspect through examination of price series for key characteristics and through the use of price series to estimate model parameters. It also includes power demand and generating capacity, which are characteristics of the bottom-up approach, resulting in a hybrid model. Their preliminary results indicate that it has the potential to be a very powerful tool for pricing contracts and options on electrical power. The fact that the model is based on real physical aspects of the power markets, such as demand for power and generating capacity, means that it can be readily adapted to particular markets of interest, or to changing conditions within the same market. A number of aspects of the model require improvement if the model is to realize its full potential. The model does an adequate job of pricing calls but a poor job of pricing puts. A put-pricing model would need to incorporate a better model of "low" prices (Davison et. al., 2002).

Ko et al. (2002) presented a fuzzy regression model to estimate uncertain electricity market prices in deregulated industry environment. In the modeling of spot price of electricity, one common approach is to observe the price for a long period of time and fit a statistical model based on the observed time series. The estimated price depends on many factors such as demand periodicity, temperature and other meteorological influences and the loading order of generators. Production cost is used to represent the main variables that affect the spot price of electricity. Artificial neural network is applied to predict electricity prices based on past price, demand, and estimated reserves. In this paper, the authors used a time series model with fuzzy parameters to represent the uncertain market. A fuzzy number applies the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

autoregressive model to estimate a market price with the most likely price as its mean value and interval. To find the crisp mean value of fuzzy number, neural network is adapted with linear activation function and Levenberg-Marquart algorithm is applied to train the neural network.

The proposed model is applied to the California Power Exchange (CalPX) market data to predict the next days' maximum forward price ranges of wholesale electricity using the past seven-day data. A data set from May to June 1999 is used for training neural network and the autoregressive model is validated with data set from July to December 1999. Finally, the range of market prices is estimated for the year 2000. Despite the increased parameters and complexity of their computations for a linear regression model, the autoregression parameters obtained by the neural network seem to work better than those of simple linear autoregression based on a straightforward least square minimization. The current fuzzy autoregression model naively provides the information of "possible" ranges of highest and lowest forecasted prices (Ko, et. al., 2002).

2.5 Correlation Dimension and Forecasting

Sivakumar et al. (1999) investigated the existence of the number of essential and sufficient variables to model the dynamics of the daily rainfall process. Their paper investigated the existence of chaotic behavior in the daily rainfall data of Singapore. They determined whether the behavior of rainfall process variation is observed for different record lengths, and the effects of the data size and the delay time on the correlation dimension estimate. They used the correlation dimension method, the nonlinear prediction method, and the method of surrogate data to detect non-linearity in the analysis. The first objective was analyzed using all three methods, whereas the remaining three objectives were analyzed only through the correlation dimension method. Daily rainfall data from six rainfall stations in Singapore were analyzed in this study, and the data set covers 30,20, 10, 5, 4, 3, 2, and 1-year periods from each of the six stations.

The correlation dimension method provided a low fractal-dimensional attractor for the different data sets from the six stations, thus suggesting a possibility of chaotic existence. Based on the resulting attractor dimensions, the minimum number of variables essential to model the daily rainfall dynamics of Singapore was identified as 3 and the number of variables sufficient ranges from 11 to 18. Significant improvement can be achieved when additional variables, up to the number of variables sufficient (11 to 18), are included in the model. The results also indicated that data for longer record lengths exhibit a higher

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

attractor dimension than those of shorter record lengths. The effects of the delay time value, used for the phase-space reconstruction, on the attractor dimension estimate were investigated, and the results provided additional support to some claims from previous studies. A total of about 1,500 data points is suggested as the minimum number for the computation of correlation dimension.

The inverse approach of the nonlinear prediction method used three different approaches to identify the existence of chaos. These approaches check the prediction accuracy with respect to the number of neighbors, the embedding dimension and the lead time. The results indicate the existence of chaotic behavior with some amount of noise in the rainfall data. The low prediction accuracy could be due to the presence of noise in the data and the use of the first-order approximation for prediction. The surrogate data method for detecting non-linearity provided significant differences in the correlation exponents between the original data series and the surrogate data sets. This finding indicated that the null hypothesis (linear stochastic process) can be rejected. Their results also indicated that the daily rainfall data of Singapore exhibited a nonlinear behavior and possibly low-dimensional chaos. Thus, a precise short-term prediction based on nonlinear dynamics is possible. Noise reduction methods, for instance, can be employed to achieve more accurate results than those obtained in Sivakumar et al. (1999).

Lisi et al. (2001) considered the problem of forecasting the daily discharge of a river according to methods based on the theory of nonlinear dynamic system. Lyapunov exponents are used to quantify the exponential divergence of initially close trajectories and estimate the amount of chaos in the data. For time series generated by deterministic dynamical systems, positive characteristic exponents indicated the presence of chaos. The prediction method used the nearest neighbors and represented an attempt to locally approximate the dynamic system by autoregressive linear polynomials, where parameters are time-variable. The peculiarity of this methodology is that the coefficient parameters are locally estimated so that the global nonlinear model is composed of local linear models. Since, the medium-long term unpredictability is typical feature of the chaotic time series, these results can be considered as a further indication of the presence of positive Lyapunov exponents, and thus, of a linear deterministic component in the data (Lisi et al., 2001).

Recent empirical studies have shown that the chaotic behavior and excess volatility of financial series are the result of interactions between heterogeneous investors. Kyrtsou et al. (2002) proposed a verification hypothesis based on the model by Chen et al. (2000) to

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

show that the modification of the agents' homogeneity hypothesis can result in stochastic chaotic evolution of price series. Then, through an econometric procedure, they identified the underlying process of the Paris Stock Exchange returns series (CAC40). To this end, they applied several different tests dealing with: (i) long-memory components derives from the fractional integration test of Geweke and Porter-Hudak (1983); (ii) the chaotic structures from the work on correlation dimension by Grassberger and Procaccia (1983); and (iii) the Lyapunov exponents method by Gençay and Dechert (1992). Finally, they forecast the CAC40 return series using the recent methods of Principal Components Regression (PCR) and Radial Basis Functions (RBF).

According to the Takens' (1981) theorem when $m2n+1$, there exists an m-dimensional deterministic map g: $R^m \rightarrow R^m$, which governs the evolution of the states $\boldsymbol{X}_t=(x_t, x_{t-1},\ldots, x_{t-m+1})$, whose trajectory is diffeomorphic. Thus, given the properties of a diffeomorphism, there exists a map g such that $\boldsymbol{X}_{t+1}=g(\boldsymbol{X}_t)$ or equivalently $x_{t+1}=G(x_t, x_{t-1},\ldots,x_{t-m+1})$, where the function G: $R^m \rightarrow R^m$ is one of the components of g. Because G is deterministic, the problem of forecasting the component x_{t+1} reduces to the estimation of G. Following the technique of nearest neighbors, the system dynamics can be approximated by a polynomial function. Therefore, in predicting any forecasts with noisy data, the least-squares method may have a high variance. For this reason, Kugiumtzis, Lingjaerde, and Christopheresen (1998) applied the regularization methods of PCR, Partial Least-Squares Regression (PLS), and Ridge Regression (RR), which seem to be more robust against noise. For comparison reasons, the forecasts are reported by using the method of RBFs as proposed by Casdagli (1989).

Kyrtsou et al. (2002) investigated whether the behavior of the CAC40 returns series is governed by chaotic dynamics. Their method also explored the difficulties for distinguishing between chaotic and ARCH processes when traditional econometrical tests are applied. During recent years, "the family" of ARCH models has offered the best solution to detect heteroscedasticity and leptokurtosis in financial series. Therefore, it has been recently shown that structural nonlinear models can lead to market instability and chaos and mimic empirical time series properties. Kyrtsou et al. (2002) primary findings are as follows: (i) the CAC40 returns series exhibits short memory, as the deterministic Feigenbaum, noisy Feigenbaum, and ARCH processes; (ii) correlation dimension and Lyapunov exponents provide evidence that the CAC40 returns series could be generated from either a noisy chaotic or a pure stochastic process; and (iii) according to the normalised MSE criterion, chaotic models outperform the GARCH and naive prediction models.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The Paris stock market has become increasingly complex and is therefore less amenable to forecasting over long time periods. This is confirmed by examining the variation intervals. Kyrtsou's out-of-sample predictions are very sensitive to dynamic noise amplified in stock series. Even if the methods are used based on chaotic models, forecast values will never be identical to real prices. Noise and uncertainty play an important role in financial markets. Complex systems, such as stock markets, cannot be described by a purely deterministic system. It would be more realistic to consider that prices are stochastic realizations and agents' beliefs follow adaptive learning mechanisms. Then, high-dimensional underlying structures could be the root cause of the resulting price dynamics. Consequently, the Paris Stock Exchange can be modeled as a nonlinear system buffeted with noise (noisy chaos), providing explanations of the observed fluctuations (Kyrtsou et al., 2002).

Kuan et al. (1995) investigated the out-of-sample forecasting ability of feed-forward and recurrent neural networks based on empirical foreign exchange rate data. A two-step procedure is proposed to construct suitable networks, in which networks are selected based on the predictive stochastic complexity (PSC) criterion. The selected networks estimated use both recursive Newton algorithms and the method of nonlinear least squares. They investigated possible nonlinear patterns in foreign exchange data using feed forward and recurrent networks. The first step of the proposed procedure uses the recursive Newton algorithms of Kuan and White (1994a). The model by Kuan (1994) was then applied to estimate a family of networks and compute the PSC to select suitable network structures can easily be selected. In the second step, statistically more efficient estimates for networks selected from the first step are obtained by the method of nonlinear least squares using recursive estimates as initial values.

Second, they investigated the forecast performance of networks selected from the proposed procedure. Financial economists are usually interested in sign predictions (i.e. forecasts of the direction of future price changes), which yield important information for financial decisions such as market timing. Their results show that network models perform differently for different exchange rate series and that PSC is a sensible criterion for selecting networks. A two-step procedure was developed to estimate and select feed-forward and recurrent networks and carefully evaluate the forecasting performance of selected networks in different out-of-sample periods. The networks with significant market timing ability and/or significantly lower out-of-sample relative to the random walk model in only two out of the five series are evaluated. For other series, neural models do not exhibit superior forecasting performance.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Nevertheless, their results suggest that PSC is quite sensible in selecting networks and that the proposed two-step procedure may be used as a standard network construction procedure in other applications (Kuan et al., 1995).

Embrechts (1995) illustrates techniques for establishing predictability and predictability windows for time series of daily Yen/Dollar (¥/$) currency fluctuations by determining the correlation dimension ("chaos analysis") and the Hurst coefficient ("fractal analysis"). Preprocessing techniques and several non-conventional enhancements to the application and implementation of the back-propagation algorithm are explained. Time series foreign exchange rates are indeed predictable on a weekly or biweekly basis with artificial neural networks. From the study, time series prediction relies only on past data for just one type of financial commodity. While forecasting financial time series such as exchange rates and interest rates is an obvious and tempting application for artificial neural networks (ANN), not all financial time series are predictable. Time series related to stock market indicators are often not predictable at all. Given a sufficiently large database, financial time series related to interest rates and currencies are often reasonably predictable by using a proper predictability window.

The first step is to apply signal processing tools such as chaos and fractal analyses to determine whether the time series might be predictable at all, and on which time scale successful predictions might be forecasted. Forecasting financial times series – and foreign exchange rates in particular – with or without neural nets is challenging. Several unconventional enhancements to feed-forward ANN's trained with back-propagation are furthermore necessary to improve the profitability of time series forecasting. These include: (i) weight decay and threshold pruning; (ii) many hidden ANN layers; and (iii) multiple indicators. These modifications allow neural nets to consistently make profitable forecasts for ¥/$ biweekly exchange rate fluctuations. The most common pitfall to be avoided for forecasting financial time series is over-training. Monitoring actual trading performance, rather than the least squares error might prove to be a profitable compromise to overcome this hurdle (Embrechts, 1995).

According to Essawy et al. (1996), chaotic systems are known for their unpredictability due to their sensitive dependence on initial conditions. When only time series measurements from such systems are available, neural network-based models are preferred due to their simplicity, availability, and robustness. However, the type of neural network used should be capable of modeling the highly non-linear behavior and the multi-attractor nature of such

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

systems. They used a special type of recurrent neural network called the "dynamic system imitator (DSI)", that is capable of modeling very complex dynamic systems. The DSI is fully recurrent neural network that is specially designed to model a wide variety of dynamic systems. Their prediction method predicts one step ahead in the time series, and the predicted value is used to iteratively predict the subsequent steps. This method was applied to chaotic time series generated from the logistic, Henon, and the cubic equations in addition to experimental pressure drop time series measured from a Fluidized Bed Reactor (FBR).

The DSI is biologically motivated with both short-term and long-term memory mechanisms that enable the modeling of a system's transient and steady state behavior. In addition, the DSI behavior depends on its initial conditions like any differential equation model, even though no explicit differential solving is incorporated in this case. The dynamics of a chaotic time series were modeled by training the DSI to perform a one step prediction. However, at any point of time, the DSI response depends on the initial conditions at time zero, the history of inputs, the network state variables, and the current network input. The trained network with any set of initial conditions can be implemented assuming the network was able to capture the dynamics in the time series. The model can use a number of initial data points to put the network on track, and iteratively feed the output of the network back to compute next predicted values. Even though this methodology is applied to several theoretical systems, the main idea was to use it in a strategy to identify certain chaotic behavior modes encountered in a fluidized bed reactor (FBR) system (Essawy et al., 1996).

2.6 Principal Component Analysis and Independent Component Analysis

Biswajit (2002) developed a technique that combines principal component analysis (PCA) and time-series for constructing control charts in multivariate situations to alleviate grade control problems in the mineral industry. The method involved two stages, in which the data were fitted with a time series model and the one step ahead forecast residuals were then monitored over time by the use of traditional control charts. This technique produced the best grade control chart because it handled any type of adverse situation, such as cross-correlation, autocorrelation and non-normality of the data. The basic purpose of PCA is to project variable information, which is highly correlated, into a low-dimensional subspace by creating a new set of variables called 'principal components' or 'latent variables'. Though the principal components are uncorrelated, the problem remains that the autocorrelation is not removed completely from the data set. One advantage of this new method is that it can alleviate problems of cross-correlation, auto-correlation and normality of data (Biswajit 2002).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Lesch et al. (1999) produced two methods for feature extraction: PCA and independent component analysis (ICA), and applied them to univariate financial time series data. These feature extraction techniques decompose a financial time series into interesting components, which could be connected to political, economic or psychological factors influencing financial markets. Taken's theorem develops an embedding matrix which reconstructs the system dynamics under appropriate embedding conditions and assumptions. These include the presence of infinite, noise-free and stationary data and the usage of arbitrary values for the embedding dimension and delay. Unfortunately, the correct embedding parameters are hardly known for real-world data like financial time series, nor can the mentioned requirements easily be assumed for them.

In this methodology, the eigen vectors (also called principal components), were computed and form the columns of the eigen matrix whose inverse maps the data set into the feature space. In this feature space, the signal is represented by the most important components, while the noise is accounted for in least ones. In PCA analysis, importance is defined as the size of the eigen value, since it represents the proportion of variance captured by the corresponding principal component. The plot of the sorted eigen values against their number is called the eigen spectrum, which can be used to perform a signal-noise-decomposition. For a stochastic system, a smooth exponential decline of the eigen values is expected. Any deviation from that, in the form of a sharp discontinuous decline, is an indication of linear or nonlinear deterministic structure in the data. In independent component analysis the equivalence to the eigen matrix in PCA is a matrix with its columns as the independent components. Its inverse demixes linearly the embedding matrix into statistically "independent" sources. In contrast to PCA the demixing matrix diagonalizes the covariance matrix and the higher-order cumulant tensors.

The FastICA and JADE algorithms were used in this study for estimating the demixing matrix. The underlying assumptions include: (i) the sources are statistically independent; (ii) there is at most one source with a Gaussian distribution and the signals are stationary; and (iii) there are many signals as sources and that the mixing occurs instantaneously. The JADE algorithm performs a joint diagonalisation of the eigen matrices as slices of the 4^{th}-order cumulant. This requires complex tensorial operations and substantial computation power such that there are practical restrictions in the usage of this algorithm. In contrast, the FastICA algorithm estimates the non-Gaussian sources in the data set once at a time in an iterative way. This achieves a reduction in computation time by two orders of magnitude. Both methods were able to detect deterministic structure in the data using the eigen

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

spectrum for the PCA. The plot of the Euclidean norm of the independent components was much closer in their morphology to signals.

2.7 Artificial Neural Network and Forecasting

Kaastra et al. (1996) provided a practical introductory guide in the design of a neural network for forecasting economic time series data. They explained an eight-step procedure to design a neural network forecasting model. The back propagation (BP) neural network is used to illustrate the design steps since it is capable of solving a wide variety of problems. The first four steps are variable selection, data collection data preprocessing, and training, testing, and validation sets. The last four are neural network paradigms: number of hidden layers, number of output neurons, transfer functions, evaluation criteria, neural network training: number of training iteration, learning rate and momentum, and implementation. The success of neural network applications for an individual research depends on three factors. First, the researcher must have the time, patience and resources to experiment. Second, the neural network software must allow automated routines such as walk-forward testing, optimization of hidden neurons, and testing of input variable combinations; either through direct programming or the use of batch/script files. Third, the researcher must maintain a good set of records that list all parameters for each network tested. In this way a library of what is successful and what is not is built up (Kaastra et al. 1996).

2.8 Wavelet Transform and Forecasting Time Series

Milidiú et al. (1999) described a system formed by a mixture of expert models (MEM) for time series forecasting. The idea is to construct a specific predictive model for each input space. A complex problem is divided into simpler sub-problems that are treated individually. The implementation of the MEM method is made in five phases. The first phase centers on changing the base of the input vector space. The Haar wavelets transform is applied to change the base of the input vector space to provide sample description using an overall shape plus details. Thus, it allows the cluster algorithm to group patterns that have closer shapes. This approach enables a better modeling for the following phases. The second phase deals with input space partitioning. The transformed data plus any pertinent data available for the training of the expert models are partitioned by Isodata algorithm into a predefined number of classes. The samples and the centers of mass for each cluster (input space classes) are obtained as outputs. If Isodata is provided with an arbitrarily high number of initial random seed classes, it may be observed that many classes turn out to be empty (no samples associated).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The third phase centers on the training of expert models. Several categories of predictive models, such as neural networks, statistical models were used in this phase. For each model type, one specific model was constructed and trained for each input space class identified in phase 2, using its corresponding training samples. A set of models are generated $\{m_{ij}\}$ with i = 1,...,c, and j = 1,...,m, where c is the number of effective input space classes identified in phase 2 and m is the number of model categories used in MEM. The fourth phase is used for testing and benchmarking. Given an independent set of test patterns, they are classified among the input space classes identified in phase 2. The corresponding centroid that has the minimum Euclidean distance is selected for each test pattern. Next, each expert model m_{ij} is tested using the test patterns belonging to class i, obtaining the performance measure value $RMSE_{ij}$, (root mean squared error). Finally, for each selected class I, the winner expert model denoted as B(i) is that one presenting the minimum $RMSE_{ij}$, for j = 1,...,m. The vector B(i), for i = 1,...,c, works as the gating mechanism of MEM and indicates the winner expert model for each space class. The next phase is forecasting. Given a wavelet-transformed pattern, taken from a time series, its input space class i is identified by selecting its corresponding nearest centroid. Then the model B(i) is selected to treat this sample and produce the required forecast.

Two different time series were experimented with, including a laser data and a financial data. The first series was approximated using deterministic equations, while the financial time series used stochastic approximation. Three types of predictive models: partial least squares, K-nearest neighbors and carbon copy are utilized in this process. The main advantages of the MEM method include: (i) the use of Haar wavelet transform to perform a base change of the input vector space, giving an overall shape description of each pattern to the clustering algorithm; (ii) the independent of models and data that makes it possible to train and adjust the predictive models in a individualized form and in parallel; and (iii) the possibility of using different classes and variations of adaptive models, selecting those ones that best fit to particular regions of the input space (Milidiú et al., 1999).

Aussem et al. (1997) developed a simple strategy for improving neural network prediction accuracy, based on the combination of predictions at varying resolution levels of the domain under investigation. First, a wavelet transform is used to decompose the time series into varying scales of temporal resolution. The latter provides a sensible data decomposition so that the underlying temporal structures of the original time series become more tractable. Then, a dynamic recurrent neural network (DRNN) is trained on each resolution scale with the temporal-recurrent back-propagation algorithm. The forecasting strategy is based on the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

subdivision of the prediction task into elementary tasks. A wavelet transform, for this purpose, is used aimed at laying bare useful information, which is then treated by neural networks. Like the Fourier transform, the wavelet transform has proven to be a versatile tool, which gives a better handle on data. It has been effectively used for image compression, noise removal, object detection and large-scale structure analysis, among other applications.

The wavelet transform is a redundant transform (i.e. decimation is not carried out). It decomposes the input signal into detailed signals and residuals. The original signal can be expressed as an additive combination of the wavelet coefficients at the different resolution levels. The latter provides a sensible decomposition of the signal, or time series, so that faint temporal structures may be revealed. Statistical models may also be used to process these structures. Therefore, it suffices to run a DRNN model on each resolution level and then recombine the individual predictions to form the final forecast. Wavelet transform provides decomposition in terms of time and frequency, or of scale and position. A wavelet transform for discrete data is provided by the particular version known as the algorithm with holes. The combination of several DRNN, aimed at capturing the dynamics of several multi-resolution versions of a data signal, can aid in improving the prediction accuracy. This innovative approach combines data analysis and prediction in an integrated fashion. It leads to a combination of connected engines, with outputs combined in a natural way (Aussem et al. 1997)

2.9 Stochastic Processes

Any variable whose value changes over time in an uncertain way is said to follow a stochastic process. Stochastic processes can be classified as “discrete time” or “continuous time”. A discrete time stochastic process is one where the value of the variable can only change at certain fixed points in time, whereas a continuous time stochastic process is one where changes can take place at any time. A Markov process is a type of stochastic process where only the present state of the process is relevant for predicting the future. The past history of the process and the way in which the present has emerged from the past are irrelevant. Stock prices are usually assumed to follow a Markov process (Hull, 2000). The Markov property of stock prices corresponds to the weak form of market efficiency. This states that the present price of a stock impounds all the information contained in a record of past prices. Models of stock price behavior are usually expressed in terms of what are known as Wiener processes. A Wiener process is a type of Markov stochastic process used to describe the motion of a particle that is subjected to a large number of small molecular shocks and is sometimes referred to as Brownian motion.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

2.9.1 The Black-Scholes Option Pricing Model

Black and Scholes (1976) developed their options pricing model using the assumptions that asset prices adjust to prevent arbitrage, that stock prices change continuously, and that securities follow log normal distribution. From the original Black-Scholes formula, scholars and industry practitioners have developed a number of options pricing models suited for the different needs of the financial commodity industry. Fusaro (1998) simplified the option pricing model to capture essential elements of the Black and Scholes' formulation. The problems with options pricing models are the underlying assumptions about futures distribution of the forward price, security prices patterns, correlation between forward rates and interest rates, or about the normal distribution of option prices. These assumptions could lead to wrong option valuation. For example, the use of the Black-Scholes options pricing model over time has repeatedly confirmed that this model undervalues call options and overvalues put options.

This particular handicap of the Black Scholes model arises from the fact that expected volatility remains unknown, even with the underlying assumptions. As a result, a number of extensions of the Black-Scholes pricing model have followed since 1973 for dealing with volatility, including: (1) variations of the Black-Scholes pricing model and (2) the binomial model (Cox, 1976,). There are two basic approaches to estimating the volatility. The first approach is to use historic volatility to estimate the expected volatility. The second approach is to use fresh data from the options market itself. The second method uses options prices to find the option market's estimate of the underlying commodity price standard deviation that is drawn from the option market, which is called an "implied volatility" (Fusaro, 1998). The most important application of options pricing models is to estimate fair value prices in illiquid markets. The option pricing models can be applied to futures and forwards, options and other derivative securities.

Engle et al. (1993) forecast future option prices by using autoregressive models of implied volatility derived from observed option prices (Day and Lewis, 1990; Harvey and Whaley, 1992). In contrast, Engle (1982) proposed the ARCH model to develop the dynamic behavior in volatility and forecast the future volatility using only the return series of an asset. The performance of these two volatility prediction models from S&P 500 index options market data are assessed over the period from September 1986 to December 1991. The straddling trading strategy is used to achieve this assessment. Straddle trading is employed since a straddle does not need to be hedged. Each agent prices options according to its

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

chosen forecast method, buying and selling straddles when the forecast price for tomorrow is higher (lower) than today's market closing price. The results showed that the agent using the GARCH forecast method earns higher profit (in excess of a cost of $0.25 per straddle) than the agent using the implied volatility regression (IVR) forecast model (Engle et al. 1993).

2.9.2 Special Stochastic Process Problems

Several problems are encountered in the formulation and solution of stochastic problems of derivative securities. These include correlation dimension and correlation integral and dimension problems. Two methods for analyzing chaotic times series are the correlation dimension and nonlinear forecasting (Yunfan et al., 1998). Correlation dimension is a measure of the extent to which the presence of data point affects the position lying on the attractor. It uses the correlation integral for differentiating chaotic from stochastic behavior (Grassberger and Procaccia 1983). Grassberger and Procaccia (1983) and Theiler (1987) also developed special algorithms for the computation of the correlation dimension to compute the correlation dimension of energy prices and energy consumption time series. There are two sources of error in the estimation of the dimension from real data: statistical error and systematic error. Sources of systematic error include noise and autocorrelation (Theiler, 1986). Majski (1997) developed a probability measure for estimating the correlation dimension using N independent and identically distributed points, $x_1, x_2, \ldots, x_N \in R^M$.

Theiler et al. (1992a,b) also developed the method of surrogate data that makes use of the substitute data generated in accordance to the probabilistic structure underlying the original data. This means that the surrogate data possess some of the properties, such as the mean, the standard deviation, the cumulative distribution function and the power spectrum, but are otherwise postulated as random, generated according to a specific null hypothesis. Here, the null hypothesis consists of a candidate linear process, and the goal is to reject the hypothesis that the original data have come from a linear stochastic process. Since the primary interest is to identify chaos in the time series, it would be desirable to use any of the statistics used for the identification of chaos, such as the correlation dimension, the Lyapunov exponent, the Kolmogorov entropy, and the prediction accuracy. If the discriminating statistics obtained for the surrogate data are significantly different from those of the original time series, then the null hypothesis can be rejected, and original time series may be considered to have come from a nonlinear process. On the other hand, if the discriminating statistics obtained for the original and surrogate data are not significantly different, then the null hypothesis cannot be rejected, and the original time series is

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

considered to have come from a linear stochastic process as suggested by Theiler et al. (1992a,b) and Kyrtsou (2002).

2.10 Risk Quantification and Characterization

Virtually all investment decisions in the petroleum industry are made under conditions of risk and uncertainty. The decision maker must choose a course of action from among those available even though the final outcome of the decision is not known with certainty. A specific example is the decision to drill an exploratory well to test a geologic prospect. The process begins with an estimate of the reserves the well or field would likely produce if the prospect contained oil or gas. These reserves are apportioned into annual production-rate schedules. After accounting for crude and gas-sales prices, royalties, taxes, and operating expenses these annual production rates are converted to a series of annual cash flows and the associated measures of profitability (Newendrop, 1981). This is followed with application of risk and uncertainty methods. These methods include (i) use of a risk-adjusted input parameters; (ii) use of a higher discounting rate as a hedge against risk; (iii) use of "profit/risk ratios" which express likely return from a successful discovery as a multiple of the amount of exposed capital they l; and (iv) detailed stochastic process modeling (Newendorp, 1981).

2.11 Conclusion

The literature survey focused on energy forecasting using statistical and probability models, energy econometric models, option pricing models, correlation dimension and modeling using principal component analysis and independent component analysis and their effect on forecasting. Neural network forecast models and wavelet analysis of time series were also surveyed to provide comprehensive basis for this study. The prediction or forecast of a time series data involves the use of linear and non-linear analysis and methods. Algorithms are used in independent component analysis, correlation dimension and Radial Basis Function (RBF). PCA, ARIMA and GARCH are all linear methods except for PCA. All these methods have contributed in their various domains to advance knowledge and frontiers and to assist analyst with appropriate tools for solving various problems. However, there is no comprehensive tool available for helping mineral and energy economists for dealing with energy pricing and policies for managing mineral and energy projects in competitive markets. This fundamental problem forms the basis of this research study.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 3.0

ECONOMICS OF FOSSIL FUELS ENERGY AND ELECTRICITY INDUSTRY

This chapter reviews the determinants of energy prices. The factors that affect the energy demand and prices are presented, as well as the expanded use of energy products, which include crude oil, natural gas, coal and electricity. The chapter also covers the evolution of the energy map of Canada and Alberta.

3.1. Determinants of Oil Pricing Models

The factors that affect crude oil pricing include: (i) Organization of Petroleum Exporting Countries (OPEC) and non-OPEC production capacity; (ii) weather and production failures; (iii) market conditions, political and economic stability; and (iv) technological innovations. Throughout its history, the price of oil has practically never kept up with inflation. That is to the advantage of the customers, but of great concern to exporting countries. Forecasting crude oil prices over the productive life of an oil field of twenty or more years is a complicated task. Economic theory states that, in the long run, prices will settle at a level whereby the efficient firms will continue to replace their non-renewable natural resource reserves and earn a reasonable return on their shareholder's equity commensurate with the associated geological and financial risks. This may hold true ten or twenty years into the future. Unfortunately, in the critical near term, world crude oil prices forecasting has become a little more than a guessing game with inordinately high stakes (Breton, 1985).

Forecasting of gas prices with deregulation and the growing trend of producers to sell directly to major natural gas purchasers rather than the gas pipeline companies makes the historical prices inadequate for future price projections. Opinions differ widely on natural gas future pricing. One important factor that is considered in price projections is the basic realization that, as the industry finds more gas relative to oil with time, this may affect the supply and demand price relationship with the growing market for the product. A further stabilizing factor has to be the tremendous reserves of natural gas locked up in overseas locations such as the Persian Gulf, Russia, Australia, Algeria and Indonesia due to lack of market.

3.2 Demand for Oil and Gas

The demand for domestic crude oil in any country depends on several major factors including domestic and international demand and the total amount of crude in a country relative to discoveries in other countries. The degree of market freedom in the movement of crude oil and its products in international trade is an important factor. Demand is also

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

affected by the development of other energy sources such as shale, tar sands, atomic fission or fusion, and solar energy, hydro dams and wind power (Campbell, 1959). Much of the changes in the 21st century may be credited to the remarkable expansion in the use of energy. The volume of energy used is a measure of the real wealth of a country or a civilization.

The first half of the 20th century can be classified as the period when people turned increasingly larger proportions of total industrial production into energy-consuming machines. These machines led to still greater increases in industrial production to supply both consumer goods and still more energy-consuming machines (Campbell, 1959). Population is one of the basic factors in the growth of consumer demand and also the growth in the use of energy. Figure 3.1 illustrates the growth comparisons of population, total energy, oil and gas (Campbell, 1959). Population changes have brought about important economic shifts such as higher ratios of consumers to producers. However, population increases have not had any great influence on demand for petroleum products (Campbell, 1959).

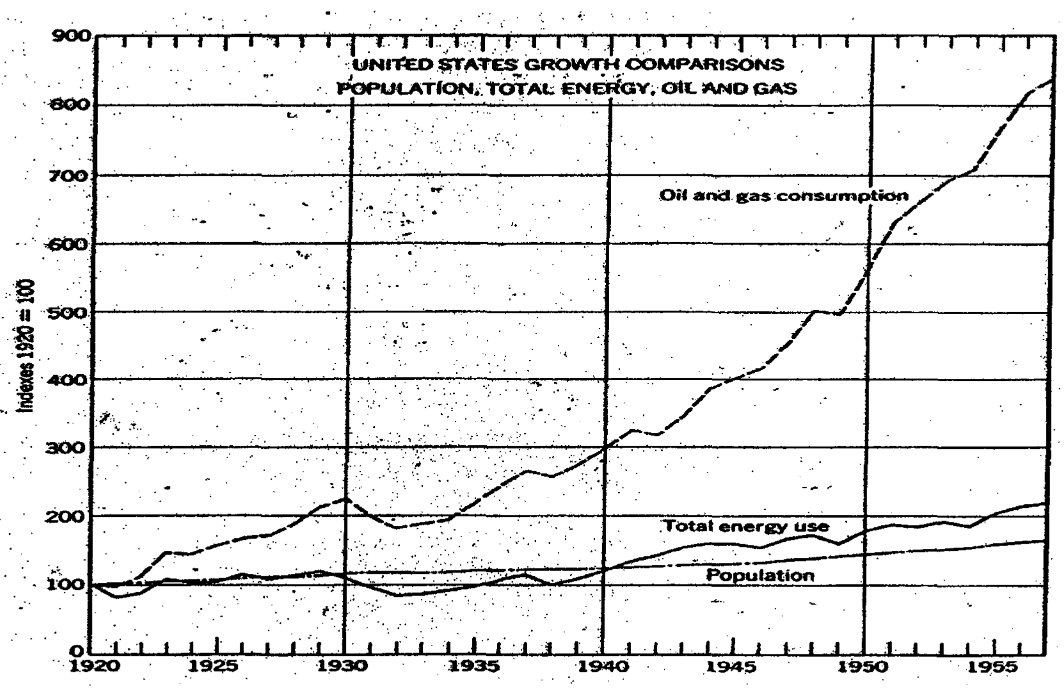

Figure 3.1 Growth Comparisons: Population, Total Energy, Oil and Gas
(Source: Campbell, 1959)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

3.3 Expanded Use of Petroleum Products

Figure 3.1 also shows that oil and gas made big gains after the 1940s. Also, petroleum consumption did not lose its momentum during the depression of the thirties. Total energy consumption in 1938 was almost identical with that of 1920. Oil and gas demand showed 200% gains by 1950. The recession of 1938, civilian rationing in 1942, and the economic dip of 1949 were only minor rest periods in the steady upward demand trend. There is the relationship between oil and gas demand and the value of all goods and services in the United States. Figure 3.2 shows this comparison in terms of the number of gallons of oil and gas used per thousand dollars of gross national product[1] (Campbell, 1959).

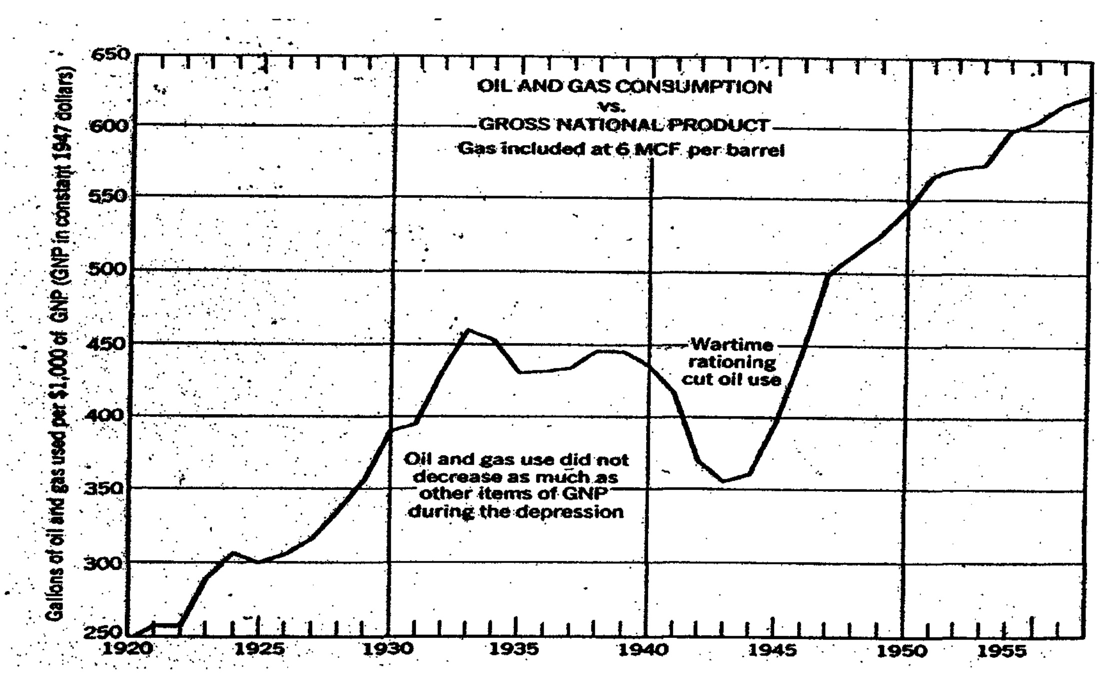

Figure 3.2 Oil Gas consumption versus Gross National Production
(Source: Campbell, 1959)

There is a direct comparison between oil and gas consumption and population. The per capita consumption of oil and gas is estimated by dividing the yearly demand by the estimated population. In the early twenties, consumption averaged less than 250 gallons per person per year. Those were the days of the T-Model Ford when total motor vehicle registration averaged only about 10,000,000 cars and trucks. Data on distillate production were lumped in with residual fuels until 1930. When refiners first reported distillate production that year, the total represented only 8.8% of a barrel of crude. Refiners turned

[1]Since the value of goods and services is expressed in dollars and oil and gas is measured in terms of physical volume the dollar values were corrected for inflation or deflation with all values stated in 1947 dollars.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

about 23.1% of the average barrel of crude into distillate fuels in 1957, and even this yield did not include the light material that went into jet fuel. The once-prosperous oil and gas industry of Iran has suffered great setbacks since 1979. Prior to the revolution, Iran was the second largest oil exporter and the fourth largest oil producer in the world. Today, however, 24 years after the revolution, the Iranian oil and gas industry has suffered massive losses from lack of professional and experienced management and definitely an acute lack of domestic and foreign investments. Technically, it is an internationally accepted fact that current Iranian output has reached a plateau and production is declining. In addition, fast-growing domestic oil and gas consumption due to the increasing population in Iran has also caused the reduction of oil exports and the shrinkage of oil revenue. Within the next few years, Iran is set to reach a rare moment in the history of its oil industry, as domestic oil consumption overtakes exports (Kashfi, 2003).

Domestic demand for petroleum products was only 1,250,000 bbl daily in 1920, but the rate of gain was rapid for the next decade. The total demand in 1929 was almost exactly double that of 1920. There is little wonder that some drillers and car manufacturers in the twenties began to worry about a probable shortage of oil (Campbell, 1959). Gasoline was the only major petroleum product to sustain growth in 2002 API Overall demand for petroleum increased by 0.1% in 2002 API, For the 10 years prior to 2000, US petroleum-demand growth had averaged about 1.5 percent per year.

Gasoline demand had its strongest showing in four years API Domestic deliveries again lagged behind historic growth trends. API also reported that US petroleum inventories during 2002 fell by more than 100 million barrels, or about 10% (Anon., 2003). The growth trend of demand is shown in Figure 3.3. While demand for petroleum is not influenced by changes in the general economy as much as other production items, the chart shows an important dip in the economy between 1920 and 1955. The biggest drop came during the depression years of the early thirties. The slight dips in the demand curve were due to the 1938 recession, 1942 civilian rationing, loss of 1946 military demand, 1949 recession, the rolling recession of 1954, and the period of adjustments, which started in 1956. If domestic demand were to continue gaining at the 1921-55 rate, the 1965 average would have been almost 15,000,000 bbl per day (Campbell, 1959).

3.4 Breakdown of Demand

The change in composition of domestic demand for petroleum is shown in Figure 3.4, which portrays the portions of domestic demand represented by gasoline and distillate fuels.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Gasoline had its greatest relative growth in the twenties. In 1920, gasoline represented only 23.9% of domestic demand for all oils. By 1931, the gasoline portion had climbed to 45.3% of the total (Campbell, 1959). The oil embargo and subsequent inflation in 1973-1974 had a severe impact on the US automobile industry. US auto sales fell from a high of 9.67 million units in 1973 to a low of 5.8 million units in 1982. During the period 1970-1982, sales of small cars increased, as did sales of foreign cars. Three factors contributed to the change in the composition of US car sales. These factors include: (i) the recession; (ii) the increase in government regulations; and (iii) the rise in oil prices. The economic recovery and the decline in the real price of petroleum have changed the outlook for the US auto industry. Continued expansion in the US economy will accelerate this trend. However, several factors threaten to disrupt an otherwise optimistic outlook for the American auto industry, including: (i) quotas on foreign steel; (ii) federal corporate fuel economy requirements; and (iii) domestic content laws (Laffer, 1985).

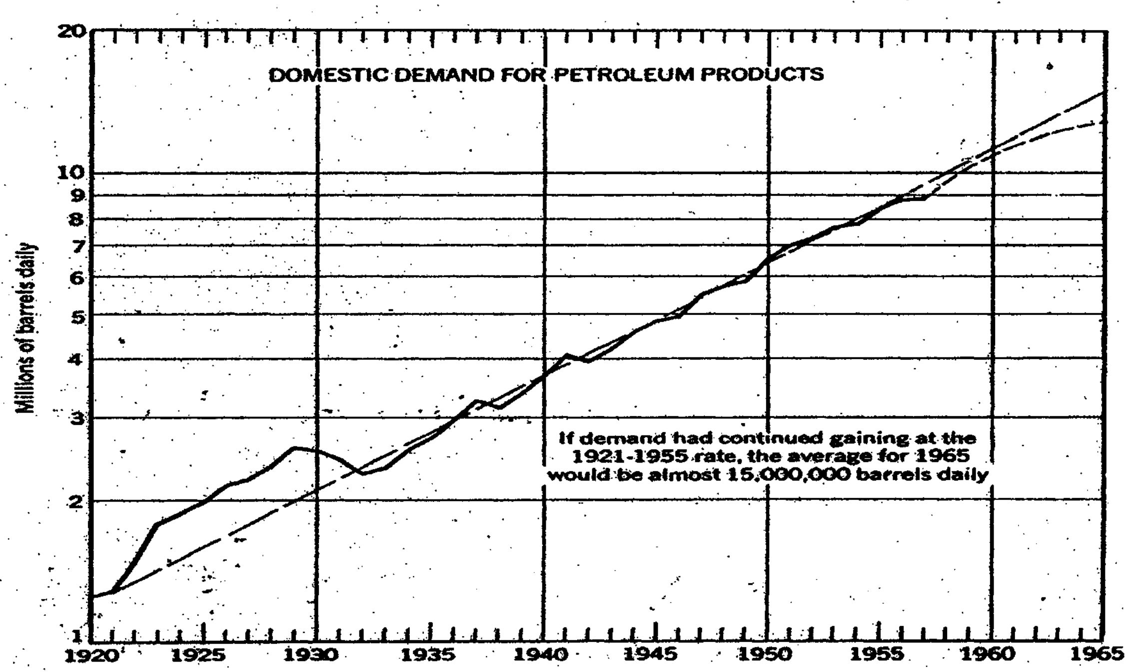

Fig. 3.3 Percentage Gains in Domestic Demand From 1920-1965
(Source: Campbell, 1959)

Rapid growth in demand for distillate fuels was the main reason for the leveling of the gasoline percentage after 1930. In 1933, the first year the Bureau of Mines separated distillate fuel from residual, distillate demand was only 7.5% of the total for all oils. Distillate accounted for 19.1% in 1957. It is this shift in the percentage composition of domestic demand that made possible the rapid gains in the overall total. Diesel fuel sales to railroads

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

climbed from less than half a million barrels in 1936 to almost 85,000,000 bbl in 1956. However, residual fuel sales dropped to 57,000,000 bbl in the same period. The greatest gain in consumption of distillate has been for use as heating oils. Distillate sales for heating gained 420% in the 20-year period while residual sales increased by 208%. Domestic demand for all products increased to 194 %. Sales of anthracite coal, used mostly for domestic heating, dropped from 54,200,000 tons in 1936 to almost 29,000,000 tons in 1956 and to 25,500,000 tons in 1957. Either distillate fuel or natural gas replaced most of this coal for heating purposes (Campbell, 1959).

Table 8.3 shows the domestic product Supply by year (Anon, 1996). Figure 3.5 shows the trend in annual changes in domestic demand for petroleum products in the U.S. from 1933 through 1957. Actual decreases in domestic demand came during the recession of 1938 and at the start of civilian rationing in 1942. For the 12-year period 1945-57, there were six years with annual gains of about 3.5 % or less. There was only one year with an increase better than 10 %. In the period 1948-57, there were only two years with large increases: 1951 with 8.2 % and 1955 with 9.0 % (Campbell, 1959). Even the pressure from new car drivers did not keep percentage gains in line with those of the big growth period that lasted from the low point of the depression in 1932 to 1955.

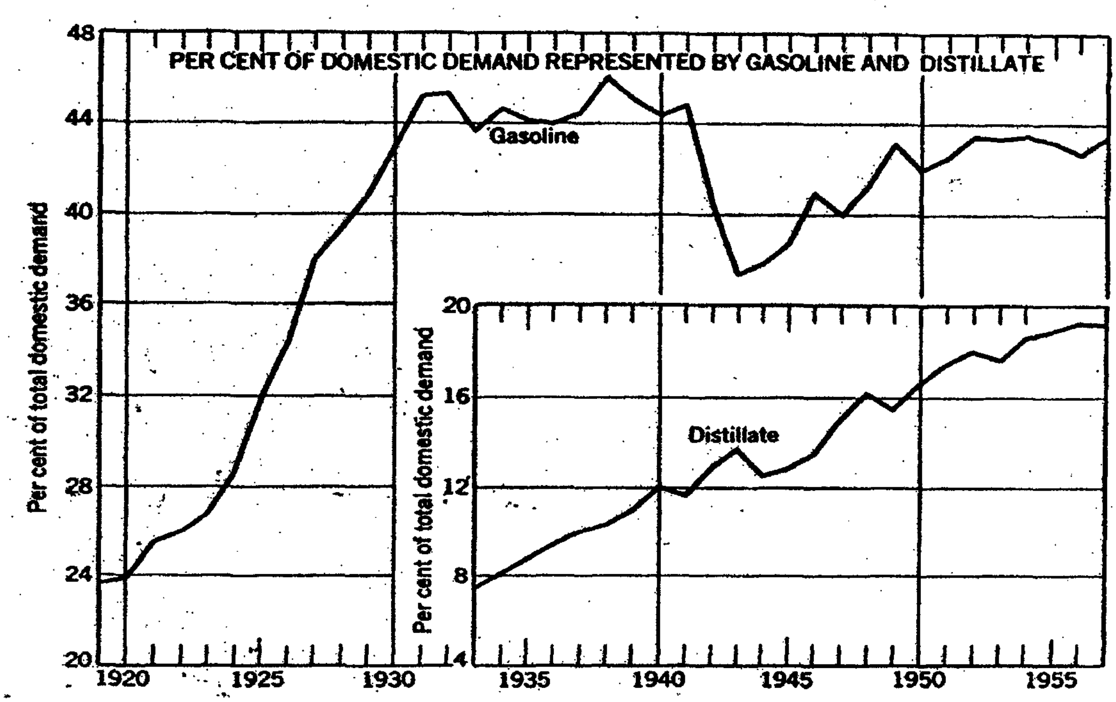

Fig. 3.4 Percentage Domestic Demand for Gasoline and Distillate.
(Source: Campbell, 1959)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Oil and gas accounted for 17.7% of the total energy in 1920 and climbed to 45.4% by 1938. For the period from 1938 through 1943, World War II forced gains in fuel consumption that was met only through rapid increases in coal production. Production of bituminous coal and lignite increased to 336,281,000 net tons in 1938 and to 593,797,000 tons in 1943. The big gains for coal resulted in the drop in percentage of the total energy supplied by oil and gas, down to 39.7% for 1943. After 1943, oil and gas returned to its upward trend. By 1956, these fuels were supplying 67.5% of total energy from fuels and waterpower.

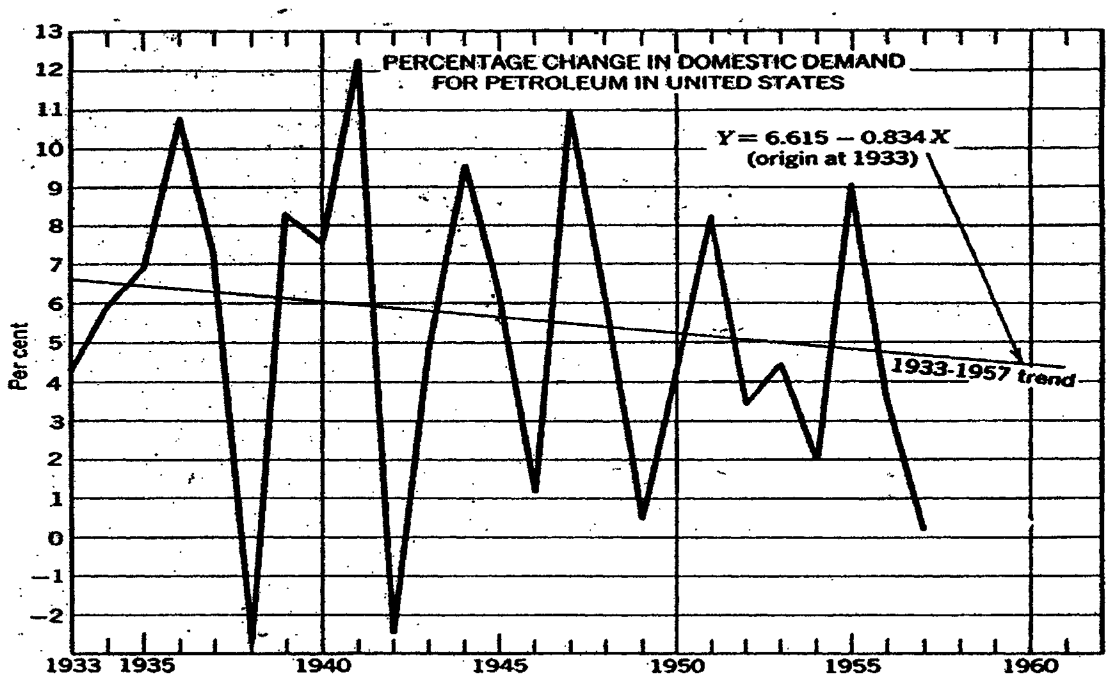

Fig. 3.5 Percentage Gains in US Petroleum Domestic Demand
Source: (Campbell, 1959)

3.5 Energy Demand Outlook

Figure 3.6 shows the marketed production of natural gas. Consumption of natural gas reached 2 trillion cubic feet a year for the first time in 1936. Demand for petroleum products and marketed production of natural gas are combined in Figure. 3.7 to show the overall gain in demand for oil and gas. Projected lines at the right of the chart show three totals of oil and gas demand for 1965 based on three conditions: (i) if the 1942-57 rate of gains were to continue the 1965 total would be about 23,300,000 bbl daily; (ii) actual gains were expected to give a total of 19,300,000 bbl daily; and (iii) if low gains of 1957 and early 1958 were to govern the trend, the total for 1965 may be as low as 17,000,000 bbl daily. In 1958, the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

combination of stagnating product demand, crude supply fluctuations, feed stock and product price volatility created tremendous swings in profit margins. The API reported that US gasoline demand in 2002 was strong but that demand for all other petroleum products was much lower than previous years. In terms of supply, the US has become more dependent on imports. Different regions have also built up different degrees of conversion capacity depending on the regional product slates and type of crude processed. The US has the most mature refining industry compared to other regions. Events in Iraq and Venezuela will have the biggest impact on future refinery profitability. In the absence of a war in Iraq or with a short war, refining margins should recover fairly quickly but remain in the lower end of the historical range (Nakamura, 2003).

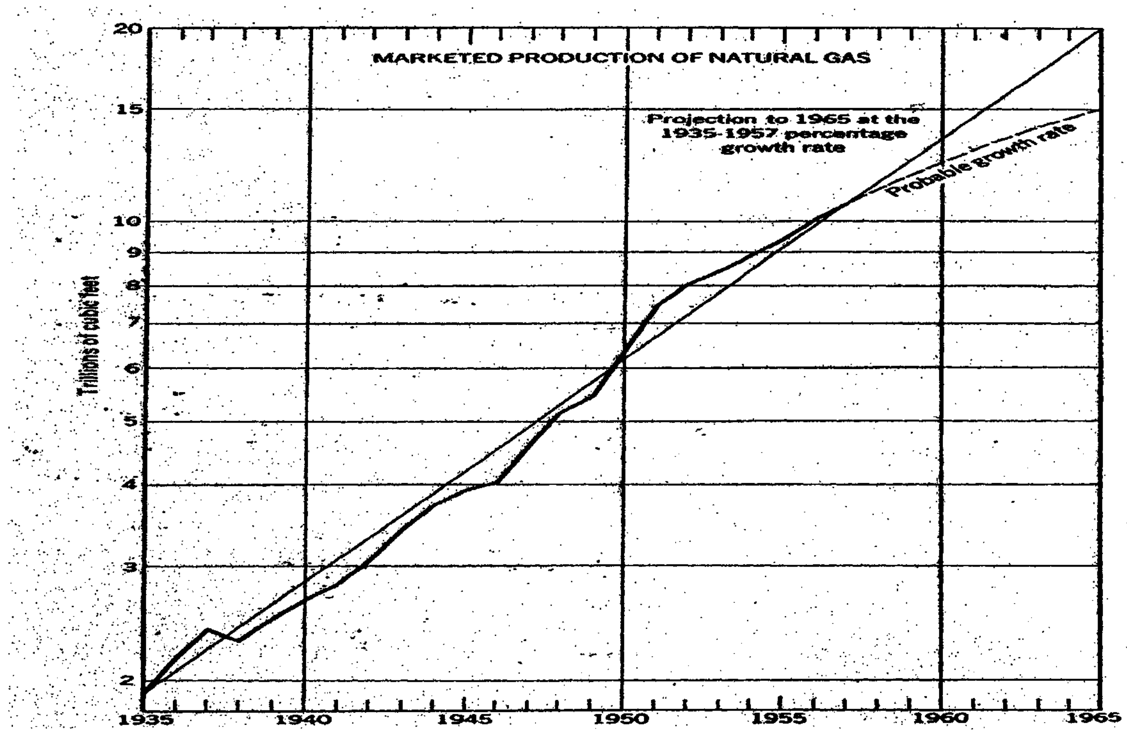

Fig. 3.6 Marketed Production of Natural Gas between 1935 and 1965
(Source: Campbell, 1959)

3.6 Competition from Gas

There are at least three factors, which indicate a greater growth for natural gas and gas liquids than for petroleum products. Figure 3.8 compares marketed production of natural gas with domestic demand for petroleum products. The comparison is made by expressing production of natural gas as a percentage of domestic demand for products. The US exploration and production industry increased capital spending in 2000 versus 1999. This was due largely to the availability of attractive drilling prospects, expectations for a steady

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

increase in US oil and natural gas demand, and continued strength in oil and gas prices (Anon, 1999). This ratio remained below 35 from 1918 until World War II. The sharp upward trend started in 1941 when natural gas production was 31.5 % of the energy from all petroleum products used in the United States. Except for minor adjustments in the late years of World War II and in 1955, gas gained steadily on oil through 1957. Crude make up 41.4 % and natural gas liquids the remaining 7.6 %.

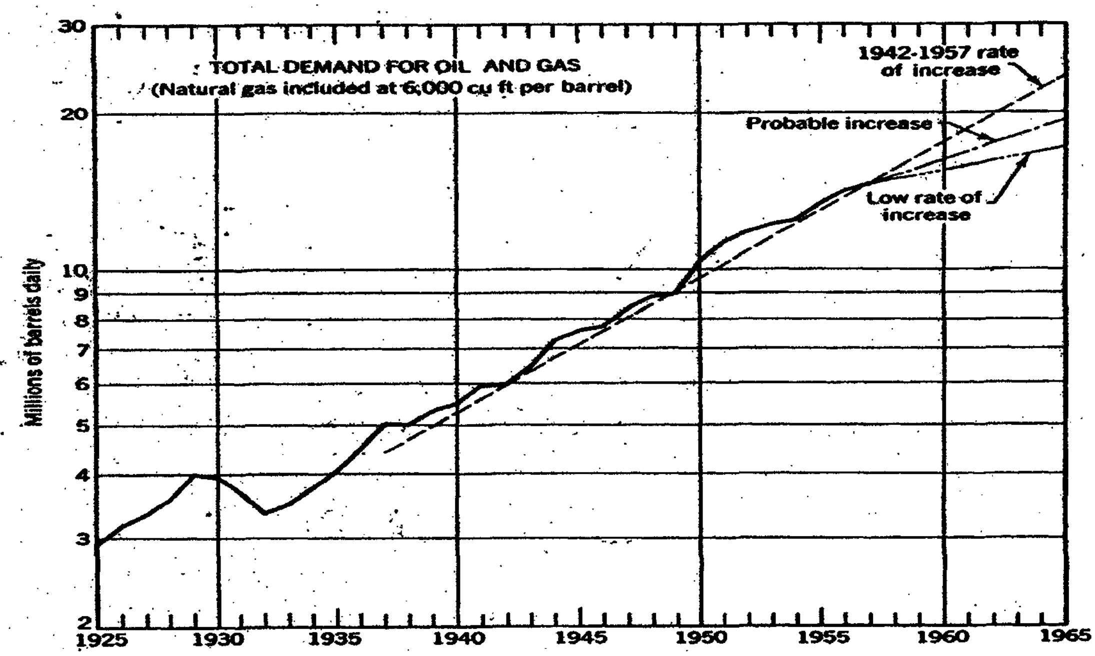

Figure 3.7 Total Demand for Oil and Gas.

(Source: Campbell, 1959)

3.7 Ultimate Production

The second biggest factor in US future demand for crude from the oil fields is the availability of crude and natural gas. This availability depends on the total volume of petroleum contained in the sedimentary deposits of the US and the cost of finding and producing the hydrocarbons from these deposits. As long as these raw materials can be found and produced below the price refiners and processors will pay for them, production is limited only by demand. Operators have discovered 153 gas fields in the Sacramento basin of northern California. Of these, 114 fields have a combined probable ultimate recovery of 9,545.3 billion cubit feet (BCF) of gas. Some 95% of the cumulative production is from the 46 fields that have a field size greater than 25 BCF. From recent Sacramento basin highlights, it is reasonable to expect another 500 BCF of new ultimate production (MacKevett, 1998).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

3.8 Factors Affecting Drilling

The total amount of oil found depends on the results of drilling and the number of wells drilled. The number of wells drilled depends on income from production and this income is determined by crude volume and unit price. The volume of crude depends on demand and producibility and is related to oil/gas reserves. Estimates of ultimate production from a given reservoir will tend to rise in the future as production engineers develop more and better secondary-recovery methods (McKechnie, 1983). Wells drilled in new areas will encounter geothermal gradients that are unknown. The required temperature and pressure prediction methods must, for economic reasons, obtain the required input data from temperature logs while drilling (Kutasov, 2002).

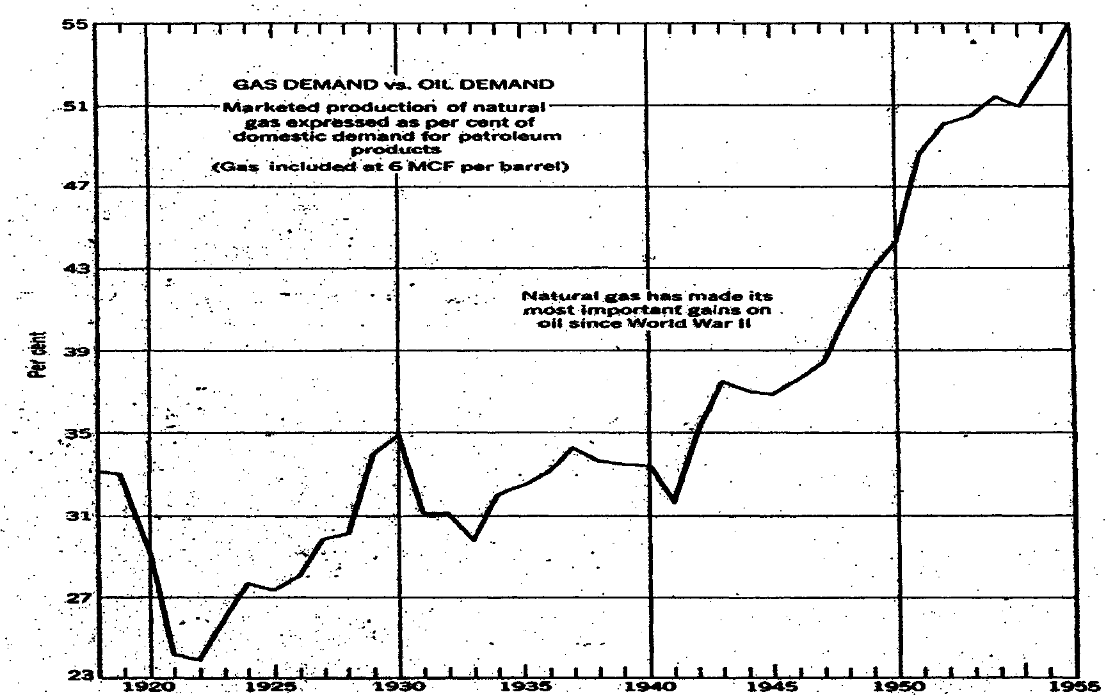

Fig. 3.8 Natural Gas Demand versus Crude Oil Demand
(Source: Campbell, 1959)

Drilling depends on capital availability, which also depends primarily on the general level of the economy. Neither this factor nor others based on income from oil and gas are of great value in predicting drilling for a given year since they do not take into account short term factors such as unusual flow of oil capital to foreign drilling; shortage of materials; short term business cycles and rush to drilling in "hot areas". Starting from 1997, Alberta's oil capital tumbled as the price of benchmark West Texas Intermediate crude tumbled from more than US $22 last fall, to a nine-year-low of US$13.21 in mid-March, before recovering last week to bob around US $16. The bounce came on news that two OPEC giants, Saudi Arabia and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Venezuela, along with Mexico, had secretly brokered a multinational deal to cut oil production by at least 1.1 million barrels a day beginning on April 1 1998 (Nemeth, 1998).

US Oil operators are finding less oil per well drilled than in the past. As a result, total reserves will not keep up with production unless the percentage gain in well completions climbs faster than production increases. Producers are also using up a larger percentage of proven reserves each year than they were in the late thirties and the years just after World War II. If oil operators are failing to maintain a constant ratio of oil reserves to production, the change can be due to either of two factors. To date most of the oil produced has been conventional crude. There is an increasing need to distinguish it from non-conventional oil made up of heavy oil, tar sand oil and enhanced recovery oil. It may be concluded that the world's political and economic stability, which relies on an abundant supply of cheap oil, is in serious jeopardy (Campbell, 1997).

Nominal and real crude oil prices (US$) are shown in Figure A.1 see the Appendix. From 1971 to 1999, world oil production increased by 1.1 % a year from 2.48 billion tonnes to 3.45 billion tonnes, with dips following the oil shocks of 1974 and 1979 (Figures A.2 and A.3 See Appendix). OPEC's share of the world oil production shrank from 50% to 40% but it is expected to increase in the next two decades. OECD countries continue to use more than half the world's oil, but the share of developing countries rose significantly as shown in Figure A.4 (See Appendix). The International Energy Agency (IEA) estimates OPEC's overall production capacity at 31.4 million barrels of crude a day, a third of the total by Saudi Arabia, and another third by Iran, Iraq, Venezuela and the United Arab Emirates. Figure A.5, (See Appendix) shows that OPEC's spare capacity is 2.2 million barrels a day. Figure A.6 (See Appendix) shows OPEC's crude production capacity beyond its target for October 1, 2000.

3.9 Drilling and Crude Prices

To raise the ratio of drilling to production would call for higher crude prices or lower drilling costs or both. Drilling contractors and oil-company crews have been and are continuing to cut drilling costs, but this is not enough. Despite the large percentage gain in well completion, reserves are not keeping pace with production. This is shown in Figure 3.9. Improvements in drilling quality will lead to reductions in the cost of drilling wells. It will mean better selection of drilling locations, greater knowledge of prospective producing formations that will be tapped by the drill and better testing of these formations (Campbell, 1959). Another aspect that influences the reserve portion of the ratio as well as production capacity

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

is the rapid growth in secondary recovery. These programs add to total recoverable reserves. The rate and gain in production by secondary recovery projects will be determined by the cost of finding new crude oil. As long as the operator can find new crude oil cheaper than he can add to reserves by secondary recovery method, he will only have conservation as an incentive for initiating secondary projects (McKechnie, 1983). Production in the future will be influenced by the relative quantities of oil and gas in the total reserve. Figure 3.10 shows the remarkable gains in consumption of natural gas since 1935. The annual percentage gains have been consistently high.

3.10 Foreign Production

Anon (1976) has observed that the American petroleum industry in its early phases was not involved in any significant way in the foreign relations or policy of the United States. In his view, there was no specific public interest in the acquisition of foreign petroleum reserves because during the period from 1860 to 1920 domestic supplies were abundant and continually increasing, and the strategic character of petroleum had not yet been realized. It was only after the experience of World War I that general awareness of the vital role-played by the current technology of warfare developed. The reason for developing pressure from foreign crude is shown in Figure 3.10. In 1918, when US crude production was just under a million barrels daily, total foreign production was less than half the US production. Some of the larger gains have been in the Middle East since the end of World War II.

Oil and gas producing enterprises outside the US had their output increased and yet the profits in 2001 were generally lower (Radler, 2002). Important producing areas other than the Middle East are Canada, Mexico, Venezuela, Indonesia and Russia. Worldwide drilling activities will increase in 2003 with more than 20% higher rig forecasts in North America, solid gains in international markets, and slightly higher offshore rig utilization. Exploration and production spending will grow by more than 10% in 2003, following the 2.5% 2002 world decline. The drilling industry is well positioned for profitable growth as economic recovery gains momentum in 2003. Commodity prices and industry activity will likely remain volatile. Analysts point to a myriad of interrelated factors and variables influencing supply and demand forces. The petroleum industry should view the volatility as normal and build it into future plans (Sumrow, 2002).

3.11 Determinants of Global Energy Pricing

There are six factors that determine the price of crude oil. They are market (supply/demand); quality (refining cost and yield); location (transportation); reliability

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

(production rate); availability (reserves) and exploration and development (costs and quality of wells). Supply/demand relationship of the world's crude oil production is cyclic and complex. When oil prices are low (less than $15/bbl), the demand varies directly with the basic economic cycle country by country (Seba, 1998). There are marked seasonal cycles of consumption – heavy gasoline demand for summer driving and heavy home heating loads in winter – which must be anticipated in planning refinery runs months ahead of time. Crude oil quality reflects the products that can be refined from a particular crude oil and the cost to the refiner. Location determines the transportation cost to move crude oil and/or petroleum products from the point of production/refining to the customer. Reliability is controlled by production rate and production capacity, while availability refers to reserves. Exploration and well development help in determining the productive capacity. Productive capacity influences prices in the short term while reserves influence prices in the long term.

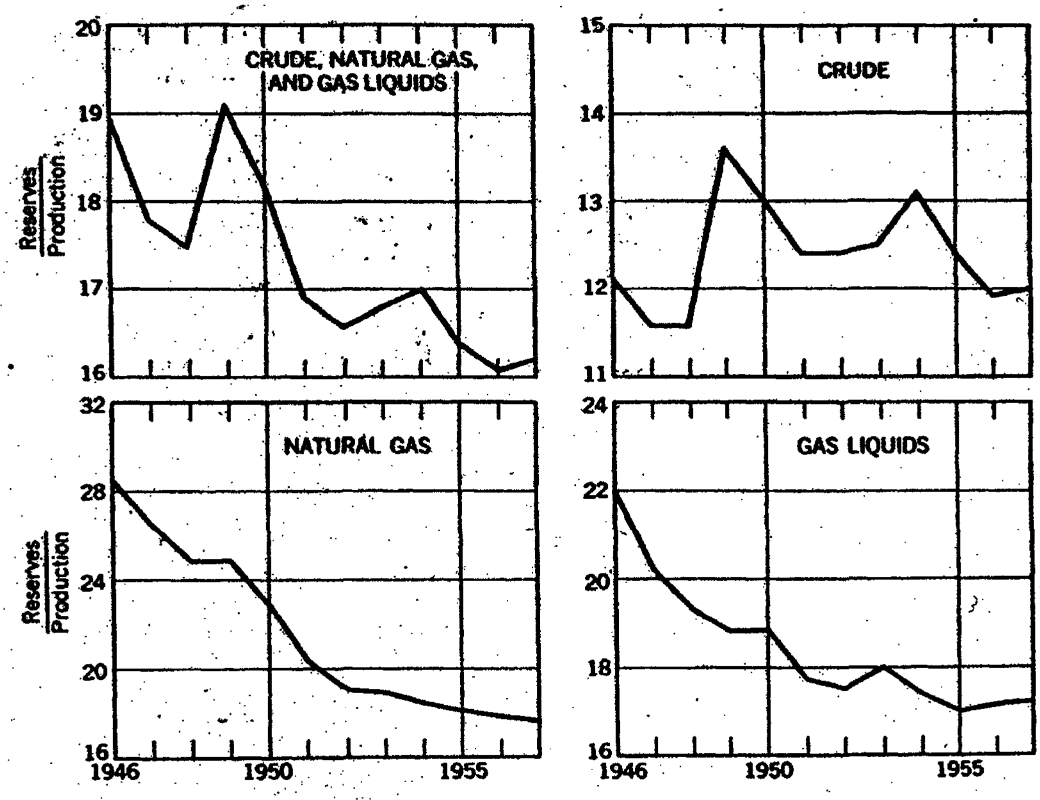

Fig.3.9 Reserves-Production Ratios Decline
(Source: Campbell, 1959)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The unprecedented price volatility, which has occurred since the "price shocks" of the 1970's, and more particularly since crude oil began to trade as a commodity in the 1980's, has had a dramatic impact on the industry (Seba, 1998). As a result, company profits, the revenues of oil-exporting countries and the availability of investment funds have been severely affected (Pearce, 1983; Seba, 1998). Due to the length of time for crude oil supply through high seas, suppliers and refiners tend to lock in prices of the crude oil. This has led to extensive use of options and futures for price hedging for the longer haul crude. When prices plummet exploration is the first activity to be curtailed to preserve the oil company's profits under the western world's system of accounting. The long lead times of five to ten years between exploration and discovery and actual production imposes another almost irreversible cyclic factor into the equation.

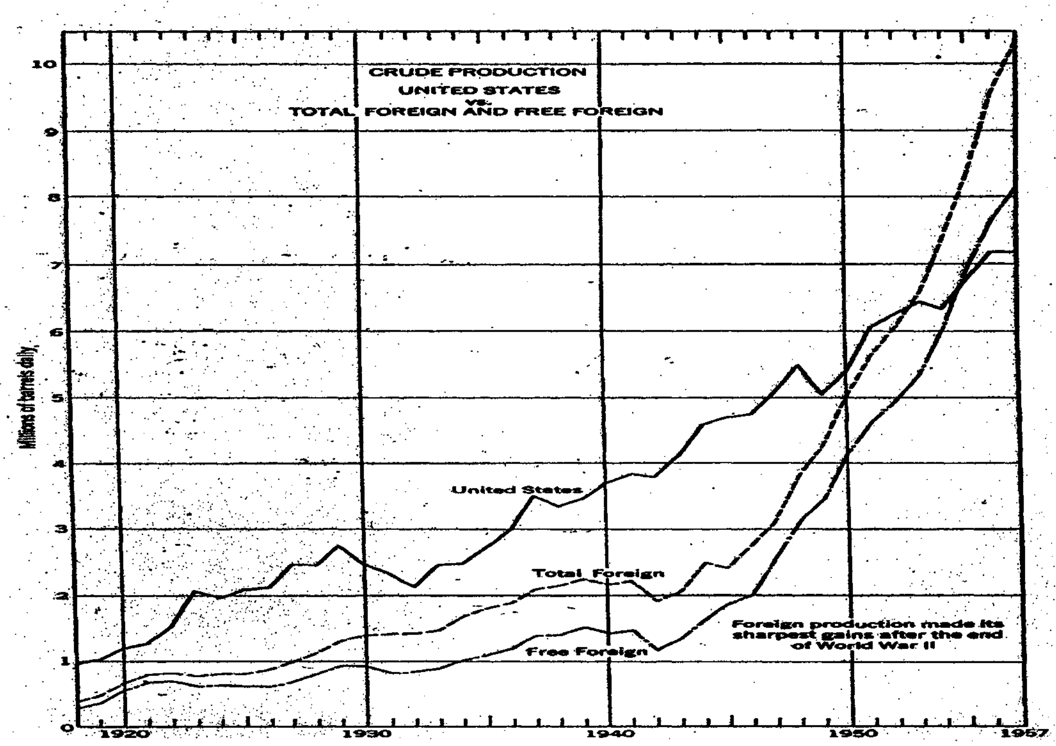

Figure 3.10 U.S. Crude Oil Production Rate Drop Below the World Total in 1953
Source: Campbell, 1959

3.12 Marketing of Natural Gas

Natural gas has been largely used as a fuel, although an increasing amount is being processed for by-products. When used for fuel, it is transported through a producer-owned or independent gathering system to the pipeline. The pipeline then sells it to local or regional

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

distributors who, in turn, sell it to the consumer. When it is used for processing, no distributor is usually involved. In some places the producer sells directly to the plant, and in others the plant operates its own pipeline system. The demand for gas as fuel varies with the time of day and season. Thus, gas transmission lines have generally developed underground storage to handle seasonal peak loads. Gas reserves are depleted over a long period of time and it is uneconomic to have to wait 15 to 30 years to recover his initial investment, in view of the associated risks. The price of gas varies with the quantity, transportation facilities, and geographical location.

3.13 The Risk Structure of the Oil Industry

The petroleum exploration and production industry is characterized by many risks. There are many geological risks in drilling non-productive wells. With the growing volatility in oil and gas prices, financial risk is increasingly becoming another risk source. The traditional way of coping with risk has been through diversification, sheer size and vertical integration of oil and gas production and downstream refining and marketing. The decision to undertake a project is not only affected by the anticipated gain but also the degree of uncertainty of both the timing of events and the ultimate outcome. There are many types of risks under technical, economic and political are summarized in Table A.4 (See Appendix) (Seba, 1998). There are three significant types of uncertainties in the evaluating of exploration and production ventures. These uncertainties include: (i) occurrence uncertainty, (ii) uncertainty of magnitude and (iii) production rate uncertainty (Seba, 1998). During the exploratory phase, uncertainty of occurrence is a major concern and will probably dominate exploratory evaluations. Once a discovery is made, uncertainty of magnitude, which includes both volume and value, and the rate of production become the dominant uncertainties. These uncertainties will remain throughout the entire producing life of a project, but will diminish with time as producing performance tends towards zero at abandonment (Campbell, 1982).

Political risks involve the uncertainty arising from possible changes in the policies of regulatory authorities and the degree to which such changes may affect the project revenues. Regulatory considerations can be subdivided into fiscal and non-fiscal considerations. The fiscal aspects primarily include continuity in the levels of local and national taxation, exchange controls and limitations on import and export of foreign and local currencies. They also include changes in levels of custom duties on imported equipment and supplies, and possible imposition of locally denominated prices for the production. Non-fiscal political risks may relate to possible interruptions by regulatory authorities over environmental matters, disagreements over hiring or firing of local personnel and outright

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

nationalization. Matters such as the provisions for transfer of operatorship to the National Oil Company (NOC) and the potential for political unrest in the host country also fall under this category (Seba, 1998).

Economic risk also covers the present and future levels of oil and gas prices and the physical nature of the project. For instance, the principal economic risk associated with an infrastructure project may be confined to the possibility of capital cost overrun and timing of completion. In the case of a depleting asset, such as mining or petroleum production, the prime economic concerns will probably involve drilling and operating costs. It also includes inflationary effects and interest rates, as well as the product prices and demand over the life of the project. Technical risks involve the operational nature of the project and may include the capability and experience of the engineering talent assigned to the project. In the case of reserve estimation, the degree of technical risk may involve the hydrocarbon volumes in place and whether the producing rates and ultimate recoveries projected by the engineers will actually be realized (Seba 1998).

One of the greatest risks faced by the petroleum industry is the price that will be obtained for oil and gas products. The other side of the issue is the price risk that the consumer is exposed to in the markets. The individual consumer might not be overly concerned with this issue, but it is a major concern of electric companies and airlines. Oil and gas derivatives have been developed to provide "insurance" against price fluctuations, with an associated premium. The premium covers the price of the option of the underlying asset bought or sold to manage price risk. Oil and gas options are a form of forward contract which convey to the holder the right, but not the obligation to buy or sell a certain quantity of oil or gas at a specified price (strike price) on a scheduled date (settlement date). The value of an option depends on four elements: time, prices, interest rates and volatility (Seba, 1998). As the expiration date approaches, its time value diminishes and only the intrinsic value remains. As each day passes, the option's time value reduces. This may either work in favor of the sellers or the buyers.

3.14 The Spot and Contract Markets

Most of oil and gas trading occurs in the spot and contract markets. Spot markets facilitate cash trading for immediate delivery while contract markets facilitate financial instrument trading for delivery at some future date. In the spot market, the buying, selling and trading of crude oil have undergone many changes in the past 140 years of its history. At the start of the US oil history, the refiners who are the purchasers, published crude oil postings, which

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

were the price a buyer was willing to pay for each barrel, provided that it met the required specifications. Buyers outside the US, who were also producing companies, made similar postings for the purchase of their production. In more recent times host governments have insisted that the crude oil prices for their countries' production have to be the subject of formal agreements between the government and the producer. In OPEC countries, the price is established solely between governments (Fesharaki and Razavi, 1986).

3.14.1 Forward and Futures Markets

Petroleum transactions in the forward market are arranged as freely negotiated contracts between parties from a group to which members are co-opted. Members include crude oil producing companies, petroleum refiners, commodity trading companies, and investment banks. The clearinghouse defines the rules governing the transactions and assures their observance. The three principal commodity exchanges for petroleum are NYMEX (New York Mercantile Exchange), IPE (International Petroleum Exchange) and SIMEX (Singapore Mercantile Exchange).

Heating oil, natural gas, crude oil gasoline, propane, and gas oil are traded on energy futures and options. Energy futures and options contracts are traded on futures and options markets, which are composed of exchanges and brokers that facilitate buying and selling of contracts. They are primarily exchanged in Chicago, New York, London, Tokyo, Beijing, Frankfurt, Paris, and São Paolo. Futures markets are primarily financial markets that trade commodity futures and options contracts. The economic purpose of futures markets is to provide an arena for transferring risk among market participants (Errera and Brown, 1999). Airlines and other large users of fuel, as well as the independent petroleum refiners, are increasingly relying on financial arrangements designed to minimize the price risk. With the advent of the futures market in crude oil doors opened to hedging operations in a manner similar to the trading in other commodities. There are two prime reasons for hedging, one to protect inventory and the other to fix ahead of time the cost of purchases (Seba, (1998).

Successful futures contract require three important factors: (i) the commodity must be homogeneous and fungible; (ii) there must be significant hedger interest in the market; and (iii) there must be price volatility. Homogeneity is required because the futures market must have a standardized grade of the commodity to trade. The price of a particular futures contract will reflect the grade specified in the contract as satisfying the requirements for delivery. If delivery should occur, appropriate discounts and premiums from the price of the specified grade insure that delivery is convenient for wide spectrum of market participants

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

(Errera and Brown, 1999). Firms with substantial cash market positions view price volatility as undesirable and use futures markets to reduce the risk of price changes in the cash market. The rationale for the existence of future markets is that they provide a vehicle for the transfer of price risk from hedgers to speculators. Price risk in futures markets attracts speculators who hope to profit from it. In general, the greater the price volatility the greater the potential profits to speculators.

3.14.2 Options and Swap Options

Two classes of options are increasingly used in the energy trade: (i) exchange-traded options; and (ii) over the counter (OTC) options. The buyer of a put has the right to sell the underlying commodity. The buyer of a call has a right to buy the underlying commodity. The seller of a put must stand ready to buy the underlying commodity. The buyer of a call must stand ready to sell the underlying commodity. OTC options offer a distinct advantage over forwards, futures, and swaps in that the need to arrange back-to-back transactions is eliminated. This offers a particular advantage to producers and consumers because there is little chance of doing back-to-back transactions due to mismatched cash flow of the market makers. This greater flexibility makes OTC options easier to market than other instruments. As energy trading instruments continue to become more sophisticated, swap options are being used to structure swaps deals in ways that increasingly protect borrowers. Swap options are options on swaps that allow the writer of the swap the option of either increasing or decreasing the swap volume or increasing the period of the swap. They are written as part of an option portfolio which must be managed actively to limit credit exposure and keep the books balanced. Options on swaps are used because they limit risk factors and add more certainty to the market.

3.14.3 Spread Trading

Spreads are another means to limit price risk in rapidly changing markets. A spread is the simultaneous purchase and sale of futures or options contracts in the same or related markets using intra-market, inter-market, and inter-exchange arbitrages. Purchasing futures contract with one expiration while selling a contract in a different expiration would be an intramarket spread. This strategy would be useful where there are seasonal variations in demand for a commodity. Crack spreads are inter-market spreads, where opposite positions are taken in crude and oil products to take into account refining margins. The NYMEX trades options on #2 heating oil/crude and New York Harbour unleaded gasoline/crude crack spreads. Inter-exchange arbitrage consists of opposite positions in similar contracts on the NYMEX and IPE. The objective of a spread trade is to profit from a change in price

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

differential between contracts, or between futures and options. In natural gas, the wide basis risk of the North American markets has created an active market in spreads trading for differential to NYMEX. In electricity, it is anticipated that there is an active market in seasonal spreads and in spreads between contracts covering different delivery points, as well as inter-commodity spread trading (Fusaro, 1998).

3.15 World Oil Pricing

Crude oil prices in international trade are universally quoted in US dollars per API barrel of 42 US gallons at 60°F. Actual monetary settlements are generally made in currencies other than U.S. dollars. Currently in the global economy, and most particularly in the developing world, settlements for crude oil imports involve barter arrangements for exportable goods from the purchasing country (Seba, 1998). The world's petroleum industry has endured a cyclic and complex supply/price/demand situation since its inception in the last century. When oil prices are low ($15/bbl) demand varies directly with the basic economic cycle country by country. When prices are high it has been demonstrated that conservation measures by the consumer will cut back on demand (Hampton, 1991; Seba, 1998).

3.15.1 Netback and Formula Pricing Contracts

In a netback transaction, crude is sold on the basis of the price the buyer expects to receive for his final products, rather than at a price set by the producer at the time of crude sale (Seba, 1998). Some netbacks are negotiated on the basis of actual "after the fact" refinery yields and product sales. Netbacks deals have five basic constituents, which are refinery yield, product prices, timing, transportation, profit margin, and other fees (Fesharaki, 1986; Seba, 1998). The timing component of the netback incorporates an agreed time lapse after loading, which is typically 10 to 60 days from the time of lifting the cargo. The timing factor includes the number of days for which the product price quotes will be averaged in determining the product values. The crude transport factor is the cost of a spot market charter of an appropriate sized tanker for a single voyage. This cost is a negotiated fraction of the current world scale rate (Seba, 1998). The marketing costs associated with sales to the ultimate consumer of the products are not a factor in netback since it is assumed that the finished products will be moved at wholesale, from the refinery gate (Seba, 1998).

3.15.2 Residual, Marginal and Major Spot Markets

Almost all oil companies face the problem of matching their refinery output with the market's current demand for various products. They have deficits of some products and surpluses of others. Companies may balance these deficits and surpluses through the use of storage

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

and/shipment facilities. But quite often it is more economical to balance them by swapping or selling and buying some products on the spot market. This was primarily the function that the spot market served in its early stages of development in the 1950's and 1960's (Razavi and Fesharaki, 1991). After the 1973-1974 oil crisis, the spot market began to play a marginal role in petroleum trading. The shift of spot market from residual to marginal markets occurred in 1975-1978, when low spot prices were used as indicators of soft market conditions by both the petroleum industry and the governments of consuming countries. The shift accelerated after 1979 when it was demonstrated that the spot market could play this role under both tight and soft market conditions (Razavi and Fesharaki, 1991).

Despite the significance of spot transactions to the industry's planning and pricing policies, their volume remained small during the second stage of market development. Between 1983 and 1985, spot and spot-related transactions grew to account for 80 to 90% of internationally traded oil. Excess capacity in the refining industry forced refiners to fight for their survival. Refiners were forced to use the most economical way of procuring crude oil. They increased their refinery throughput to the point where the price of a marginal barrel of product covered the marginal operating cost. This brought about a shift from term-contract arrangements to spot purchasing of crude to take advantage of flexible spot prices over rigid contract prices. In addition, as OPEC member countries of began to lose their market share, they began to engage in spot-related sales in order to recapture lost sales (Razavi and Fesharaki, 1991).

3.16 Oil Property Evaluation

Investors use the discounted cash flow technique based on either rate of return, present, annual and future values, or other breakeven analyses to make economic decisions (Seba, 1998; Thompson, and Wright, 1985). The market emphasis has however evolved with time. In addition, analysts differ on the relative importance of one evaluation method from another. Some analysts focus on a method that deals with reserves; others focus on one that deals with the company's growth capacity while others look at underlying value with growth potential. Financial analysis of the oil and gas sector tends to focus on the payoff side of the cycle, namely, reserves, production and cash flow. The ratios used by analysts in relative valuations of one stock to another or when examining assets and corporate acquisitions are Price/Cash flow Multiple, Price discretionary Cash flow Multiple and Enterprise Value/ Debt-Adjusted cash flow multiple where price is price per share and cash flow is cash flow per share (Karkkaainen, 1997).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

In the US the Crude Oil Windfall Profit Tax of 1980 (WPTA) was passed by Congress as part of the oil decontrol package and is applied to all domestic production of crude oil. The windfall profit tax is calculated by multiplying the windfall profit per barrel by the appropriate tax rate. The windfall profit is the removal price less an adjusted base price and an amount called the severance tax adjustment. Base prices for a barrel of oil are established for three categories of production, tier 1, tier 2 and tier 3. Once a base price is established, this base price is then adjusted by an inflation adjustment factor to determine the adjusted base price, which is used to calculate the windfall profit. Severance tax adjustment prevents the producer from paying windfall profit tax on the amount he pays to the state government as severance tax on the difference between the removal price and the adjusted base price. Severance taxes in excess of 15% also do not qualify for the severance tax adjustment.

In Canada's oil sector, royalties on Crown oil and gas are added to those collected through bidding received on the sale of Crown leases of oil and gas production rights. The second category of rents estimated by the economic council, those accruing to consumers, reflects particular domestic pricing policies used in the oil and gas sector and the hydroelectricity sector. Artificially low prices for hydroelectric power transfer rents from the producing provinces to consumers, some of them in the U.S. In this case the artificially low prices stems from average cost pricing applied by provincial power utilities. If electricity price is set on the basis of the average cost of power generation from different sources, including a normal rate of return on capital invested in generating stations and distribution networks, economic rent on hydro sites is automatically passed forward to consumers in reduced power prices. The size of economic rents in Canada is quite large – approximately 10 percent of Canadian GNP in 1980 or more than $1,200 per capita ($4,800 for a family of four). Of the total rents, the amount that was collected as provincial resources revenues made up 2.5 percent of GNP or $300 per capita.

Three-quarters of economic rents were passed forward in reduced product prices and a large proportion of benefits of Canadian resources production were received outside the provinces in which the rents were actually generated. For example, Alberta, whose main resource is oil and gas generated $20.645 billion in economic rent (about 75 percent of the Canadian total). But most of the benefits of reduced oil and gas prices flowed to other provinces, so that Alberta retained only $7.928 billion. On a smaller scale, Newfoundland's hydroelectric power industry generated $.737 billion in economic rent, of which $.603 billion (82 percent) was transferred to other provinces or to U.S. consumers. The dispute between the Canadian and Alberta governments has produced much more "natural resources consciousness" in

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

other provinces and has been an important factor in discussions leading to patriation of the British North America Act as the Constitution Act (amended in 1982). Under that Act, the Canadian provinces assume exclusive responsibility for nonrenewable resources exploration, management of nonrenewable resources, forests, and electrical energy, taxes, as well as making non-discriminating laws concerning export of primary products derived from these resources.

3.17 Coal Pricing Models

Coal will continue to make a significant contribution to Canadians energy supply. Technological advances in the way coal is used in electricity generation are anticipated (Patching et al. 1980). Low rank coals, such as lignite and sub-bituminous, are characterized by higher moisture levels and lower energy content. They are used in power generation and cement manufacturing. Higher rank coals, which include bituminous and anthracite, are lower in moisture, higher in carbon and energy content. These coals are used in power generation and the production of coke, which is a reducing agent and heat source for the steel industry. Canadian deposits of anthracite are currently not exploited. Increasing concern over sulfur dioxide emissions and acid rain places a premium value on reserves from western Canada that generally have a low-sulfur content (Patching et al. 1980). Almost 95% of coal resources of immediate interest are located in Western Canada as illustrated in Table A.5 (appendix). About 60% of these consist of low-quality lignite. Remaining reserves would be about 90 times the 1997 Canadian production of 79 megatonnes. Lignite reserves are mainly found in Saskatchewan, whereas all sub-bituminous reserves are located in Alberta. Most of Canada's bituminous reserves are in British Columbia with smaller volumes located in Alberta and Nova Scotia.

3.17.1 Coal Prices

Canada is both an importer and exporter of coal; thus, domestic prices tend to reflect developments in international markets. Many countries, including the US, have unused productive capacity that can be activated when prices rise sufficiently. This potential production tends to limit sustained price increases. The principal Canadian purchasers of coal are electric utilities. Productivity improvements in coal mining operations, industry rationalization and improved productivity in rail transportation are a boon to the coal mining industry. Coal prices vary among provinces due to transportation costs, quality differences and specific contractual terms. In recent years, average Canadian prices have fluctuated between $1.15 and $1.20 per gigajoule. The prices of domestic and imported bituminous coal in Ontario varied between $1.80 and $2.20 per gigajoule in 1997. Utilities in Alberta and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Saskatchewan have been paying \$0.50 to \$1.00 per gigajoule for sub-bituminous coal and lignite (Anon., 1999b).

Coal demand is caused by electricity generation and industry requirements. In 1997, electricity generation consumed 49 Mt of coal, about 84% of domestic coal demand. Ontario, Alberta and Saskatchewan accounted for 91% of this consumption, with the remainder in Nova Scotia and New Brunswick. Coal-fired generation is expected to remain competitive with other fuels, particularly in existing facilities, although little growth is expected. Metallurgical coal demand is currently about 11% of the domestic requirements mainly used by the iron and steel industry in Ontario. Improving technology in the steel making process will cause a moderate increase in demand. In 1997, less than 2 Mt of coal was used to generate process heat in the cement, smelting and other industry, mostly in Quebec, Ontario and British Columbia (Anon., 1999b). In 1997, Canada's coal exports were 36 Mt while imports were 14 Mt. Metallurgical coal accounted for 82% of exports in 1997, mostly from Alberta and British Columbia to Japan and the Republic of Korea. Most thermal coal exports were also shipped to Japan and Korea. Alberta is the largest coal-producing province in Canada producing 34 million tones of coal in 1999, which is 47% of Canada's total coal production with revenues of \$430 million (Frimpong et al., 2001).

3.18 North American Gas Supply and Markets

Natural gas markets in North America are well developed in that there are transmission networks in nearly all the provinces in Canada, as well as the northern part of the US connecting the supply sources with the market and customers. Natural gas in Canada is primarily located in the Western Canada Sedimentary Basin (WCSB). This is a geological region that includes most of Alberta, significant portions of British Columbia and Saskatchewan, as well as of Manitoba and the Northwest Territories. Other areas containing natural gas reserves are Ontario and offshore Nova Scotia (Anon., 2000f). Remaining gas reserves in Canada are estimated to be 1 606 $\times$ 10^9 m^3 as of year-end 1999. WCSB accounts for 1 517 $\times$ 10^9 m^3 of natural gas reserves. Offshore Nova Scotia is estimated to hold 85 $\times$ 10^9 m^3 of gas reserves while Ontario is estimated to have 13 $\times$ 10^9 m^3 as of year-end 1999. Since 1985, natural gas production has more than doubled. Canadian natural gas production in 1999 totaled 170.3 $\times$ 10^9 m^3 essentially all of which was produced from the WCSB. This corresponds to an average production of about 465 $\times$ 10^6 m^3, causing the WCSB to rank as one of North America's most productive basins. Moreover, the WCSB accounts for a quarter of North American gas production. Of this, Alberta accounted for 83%

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

of total Canadian production while British Columbia and Saskatchewan contributed 12% and 4%, respectively.

3.18.1 Canadian Gas Transportation Systems

Canada is part of an integrated North American natural gas market due to the many thousands of kilometres of pipelines that connect supply basins with regional markets. The Canadian pipeline grid consists of gas gathering, transmission and distribution systems that transport processed natural gas. These transmission pipelines transport large volumes of gas at high pressure over long distances from supply sources to market centres (See Fig 8.9 in the Appendix) (Anon., 2000f). Several major transmission pipelines serve the Canadian gas market, which also interconnect with the US pipeline grid at many export points. TransCanada Pipelines Limited (TCPL) is one of the largest carriers of natural gas in North America. Production is concentrated in the west and principal markets are in the east, requiring long transmission lines. The major natural gas pipeline transmission systems are Westcoast Energy Inc. in British Columbia, NOVA Gas Transmission in Alberta and TransCanada Pipelines Ltd. in Alberta (Anon., 2000f). Distribution systems are the retail component of the pipeline industry. Local distribution companies (LDCs) receive gas off the transmission pipelines and deliver it to end-users, such as homes, within a franchise area. The LDCs are regulated by provincial regulatory boards or commission or directly by a provincial government. Gas Storage facilities are also used for pipeline load balancing, supply security and price risk management (Anon., 2000f).

3.18.2 Natural Gas Trading Dynamics in Canada

Canada's natural gas pricing is dependent on three trading systems in Alberta. The natural gas market is the second largest in Alberta and serves 82% of the retail market. Since 1985, contracts have become increasingly short-term. Furthermore, pricing is market responsive as prices are determined through index-based mechanisms, which fluctuate either monthly or daily. The homogenous nature of natural gas has permitted the development of a larger and more competitive gas market (Anon., 2000f). There are three main trading systems in Alberta: Natural Gas Exchange (NGX), Enron-on-line and Altrade (Anon., 2000f). Since 1985, the Canadian and US market have become more integrated. In a fully integrated competitive gas market, the price of gas in one should differ from the price in another region by the cost of transportation (Anon., 2000f).

The demand for natural gas is very seasonal, mainly because of weather patterns. The consumption profile of each market sector is important because it defines the type of

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

contracting practices and risk management, which each sector will pursue. This seasonality may result in higher prices during the winter season. Peak requirements are usually met by gas in storage. Traditionally, storage is used to balance seasonal demands through injection, storage and withdrawal. This reduces the need for additional pipeline capacity to meet peak requirements, improves the reliability of supply and dampens price spikes that occur in tight supply conditions. These services add flexibility and provide arbitrage opportunities (Anon., 2000f).

Alberta is the second largest gas market in the country, representing about one-third of Canada's natural gas demand. Natural gas met 43% of its total energy requirements in 1998. Coal and oil each accounted for 27% and 26%, respectively, while other forms of energy accounted for 4% of total energy needs. Electricity generation is mostly coal-fired (Anon., 2000f). In 1999, Alberta consumed 20 114 $\times$ 10^6 m^3 (710 BCF) of natural gas. The industrial sector is the largest user of natural gas in Alberta accounting for 70% of total consumption. Industrial consumers include petrochemical and fertilizer manufacturers, oil producers, electrical power generators and pipelines. The balance, about 30%, is used for heating in residential and commercial enterprises. ATCO Gas is the largest local distribution company in Alberta and serves 82% of the retail gas market.

3.18. 3 Natural Gas Prices

Alberta consumers have generally paid lower prices for natural gas than other consumers have in North America. The most commonly quoted intra-Alberta price for natural gas is the Alberta Energy company/Nova Inventory Transfer (AECO-C/NIT) market price. AECO-C/NIT prices have been lower than NYMEX prices until late 1998. The recent rise in the AECO-C/NIT price has resulted in an increase in the price of gas paid by Alberta consumers. The price of gas paid by Alberta utility customers is based on a portfolio of AECO-C/NIT daily and monthly price indices (Anon., 2000f). The Alberta Energy and Utilities Board (AEUB) regulates natural gas rates charged to consumers by investor-owned gas utilities such as ATCO Gas and AltaGas Utilities Inc. Rate paid by consumers of natural gas marketers, rural gas co-ops and municipal gas utilities are not regulated by the AEUB. Also excluded from regulation is the wholesale market (Anon., 2000f). Natural gas marketers only sell gas; the utility company continues to provide gas delivery. The AEUB sets utility company gas prices at least twice a year at rates similar to market rates, to reflect winter and summer market conditions. Individual customers must decide whether the price options offered by natural gas marketers or utility companies meet their needs (Anon., 2002).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

3.18.4 Impact on Consumers

Using long term gas delivery contracts and futures commodity contracts, many of Alberta's major industrial users have locked in gas prices at rates lower than the current market prices at AECO-C/NIT. However, if a high gas prices environment endures after the expiry of these arrangements, industrial users will assess their alternatives. Coal is a competitive energy source for large industrial fuel consumers and utilities in the medium to long term. However, in the short term, many companies are not equipped to burn coal. Natural gas demand is expected to increase in Alberta. There are currently many proposed gas-fired electricity generation plants. Furthermore, strong oil prices provide support to current expansions to Alberta's oil sands extraction industry and to the development of heavy oil projects. These oil extraction processes use large amounts of natural gas for fuel (Anon., 2002)

3.18.5 Natural Gas and Electricity Deregulation

Natural gas market has increasingly been deregulated since 1985 to meet the ever-increasing demand for natural gas. Electricity deregulation has been on going since the mid-1990s to keep pace with the worldwide changes and consumer benefits. The flourishing Alberta economy is straining the province's existing energy infrastructure. New industries and residents demand increasing amounts of power and heat. Large and small industrial consumers have negotiated short and long-term contracts with suppliers since 1998 (Anon., 2002). From 1975 to 1985, the Governments of Alberta and Canada regulated the price of Alberta natural gas sold to other provinces. The governments of Canada, British Columbia, Alberta and Saskatchewan signed the *Agreement on Natural Gas Markets and Prices* in October 1985. For the first time, end-users in non-producing provinces were able to purchase gas directly from producers at negotiated prices (Anon., 2000f). Table 8.6 and Table 8.7 (See Appendix) shows the import and export volume and value of electricity in Canada (Anon., 2002).

During the 1990s, natural gas has been increasingly used to generate electricity, particularly in the United States. In recent years, there has been the greater reliance on natural gas to provide the energy for new electricity generation projects. Natural gas combined-cycle and cogeneration power plants can be built more quickly and with lower capital costs than alternatives. Also, clean air legislation in the United States favors the use of natural gas (Anon., 2000f). For decades, natural gas has competed with fuel oil in industrial markets. For this reason, a number of large industrial users have developed the capability to quickly switch between these fuels, depending on price and availability. Changes in oil prices will

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

tend to affect natural gas prices to the extent that oil products and gas compete in end-use markets. Trends show that when both markets are tight, a close relationship exists between higher oil and higher gas prices (Anon., 2000f). Increased use of gas for power generation has caused natural gas prices to be influenced by electricity prices due to the convergence of gas and electricity markets.

3.19 Risk Management

Commodity producers and consumers are constantly exposed to risk in their buying and selling transactions. This risk can be broken down into three parts: price risk, basis risk, and credit risk (Fusaro, 1998). Price risk refers to exposure to adverse price moves in the cash market. Basis risk refers to the difference between the prices used as a benchmark in a transaction and the price for actual goods changing hands. The difference is a function of location, quality, and supply/demand for each. Credit risk refers to the ability of a transaction to keep their contractual obligations. While a hedge on the NYMEX will allow the trader easy, anonymous entrance and exit from trades, as well as the virtual elimination of counterparty credit risk, it cannot eliminate geographic basis risk. A natural gas producer in Alberta, Canada, for example, may wish to hedge part of its production on NYMEX, but the hedge will only be effective to the extent that there is reliable, high level of price correlation between Alberta and Henry Hub, the active NYMEX contract delivery point.

The natural gas production, pipeline, and storage infrastructure in North America, however, creates distinctive patterns of trade by geographic area. There are limitations and constructions on natural gas transportation that tend to regionalize trade, in some areas more than others. Market conditions in Alberta, for instance, are affected by such local factors as the level of snowfall in the Canadian Rockies that will be utilized to produce hydropower, potentially displacing gas-fired electric power generation in the Northwest. Transportation limitations localize this trade, isolating it to some extent from the Henry Hub delivery area. These issues serve to create different price relationships between geographic areas, with varying degrees of correlation depending on local demand patterns, the integration of the local pipelines with other trading hubs, available storage facilities, and local production (Fusaro, 1998).

The risk management process reduces financial exposure associated with price volatility by substituting a transaction made now for one that would have been made at a later date. Control over price changes is managed by using financial instruments. The application of risk management tools allows companies to purchase downside protection, though opportunity

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

for gain. Some factors to consider in applying risk management tools include profit margins, credit exposure, cash flow requirements, debt service obligations, project economics, and planning requirements (Fusaro, 1998). The energy industry is developing new financial instruments for both producers and consumers to manage short and long-term risk. These financial tools and techniques have been applied to the currency markets since the 1970s. Now they are becoming part of the once heavily regulated electric utility industry.

3.20 Fundamental Continental Energy Policy

Energy plays an important role in economic and social development. The identification and analysis of energy issues, and the development of energy policy options, are therefore important areas of study by governments, researchers, and the development community. Neither developed nor developing countries conducted sector-wide energy planning until after the 1973 oil embargo. Such planning was left to the sub-sectoral institutions with little attempt at coordination or central planning. All that changed in the aftermath of the first oil crisis, and countries everywhere struggled with the establishment of effective policies and institutions to deal with energy sector problems (Munasinghe et al., 1993, Toman, 1993). Governments' role in the pricing of commercial energy resources, and the relative neglect of issues relating to traditional forms of energy is vital. Governments exercise direct influence over energy pricing, usually through the ownership of energy sources or price controls. Indirect influences occur through such means as taxes, import duties, subsidies, market quotas, taxes on energy-using equipment, and government-guided investments in energy resources (Munasinghe et al., 1993). Most often certain fuels such as kerosene, rural electricity and agriculture pumping, and diesel tend to be subsidized. Cross-subsidies exist between different fuels, user groups, and geographic regions. High-priced gasoline may finance the subsidy on kerosene, industrial electricity users may subsidize household consumers. A uniform national pricing policy usually implies subsidization of energy users in remote areas by those living in urban centers.

Import and export duties, excise taxes, and sale taxes are levied, at various stages in the production, processing, distribution, and retailing chain by several government agencies. Several less obvious methods, such as property taxes, water rights and user charges, and franchise fees are also used to influence energy use. Energy prices are also affected by the wide range of royalty charges, profit sharing schemes, and exploration agreements that are made for the development of oil and gas resources between governments and multi-national companies (Munasinghe et al, 1993). Other policy instruments are often used to reinforce pricing policies, such as quotas on imported or scarce forms of energy, coupled with high

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

prices. Conservation regulations may affect depletion rates for oil and gas, while availability of hydropower from some multipurpose dams may be subordinate to the use of water for irrigation or river navigation. Many special policies involving tax holidays and concessions, import subsidies, export bonuses, government loans or grants, high taxes on automobiles, are also used to affect energy use.

The evolution of energy planning in developing countries had as one of its main roots the need to deal with the macroeconomic impact of the sharp oil price increases that occurred in the mid-1970s. For the typical small oil-importing developing country, the most immediate point of impact whenever a change occurs in the world oil price is the balance of payments. One of the major problems faced by energy and macroeconomic planners is how developing countries should adjust to such changes is: modeling such impacts, and quantifying the impacts of the policies that might be appropriate to mitigate the macroeconomic consequences, proves to be exceptionally difficult (Munasinghe et al, 1993). From Figure A.10 (See Appendix), there was a drop in oil prices to $20 in 1986 which gave great relief to oil-importing countries. Since then, prices have gradually risen, and by end of the 1980s stabilized in the $18-22/bbl range. Yet the Iraqi invasion of Kuwait in August 1990 and major damages to production facilities in Kuwait and Saudi Arabia, illustrated the volatility of world oil markets, with spot prices staying well above $30/bbl for extended periods in late 1990.

Information is actually the most essential element of all policy making and their accuracy, timeliness and appropriateness are daunting. Policy makers and researchers have an urgent need for exact, swift, detailed and scientifically correct data. In addition, decision makers in companies and their technicians have their specific information needs. Finally, it is also vital that the public has access to sufficiently detailed and understandable information to provide the electoral support without which no policies would be possible. These are needed in order to investigate local problems, set priorities and provide information to foster a democratic debate on environmental issues (Sterner, 1994). Governments' most powerful tool is through the direct use of economic resources, through public spending and investments in infrastructure such as roads, railways, telecommunications and research.

3.21 Macroeconomic Impact of Varying Oil Prices

Large increase in oil price raises the general price level and simultaneously transfers income from consumers to energy producers. Oil exporting countries begin to increase purchases from oil-importing countries. Energy producers in the consuming countries begin to expand their production facilities and/or begin an active search for fossil fuels, in response to the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

higher prices of their products. The magnitude of the second oil price increase in the 1979-1980 period was significantly affected by the energy policy responses on the part of the consuming countries. Thus, the frenzied panic on the spot market, the lack of a strategic petroleum reserve, and the inability of the IEA to function effectively contributed to OPEC's ability to increase official prices in from October 1978 to February 1979, as prices soared to the $38-40/bbl range (Munasinghe et al, 1993).

Non-producing developing countries suffer severe impact on foreign exchange earnings and reserves, rather than on aggregate demand in periods of higher energy prices. Economic growth in these countries is heavily dependent on the availability of foreign exchange, which in turn is a major factor determining their capacity to import capital goods, to support investment, and to generate economic growth. First, the oil induced recession in the industrial countries shrinks their export markets and thereby reduces their ability to import. Second, out of their reduced foreign earnings, a larger fraction has to be devoted to paying for oil, leaving a smaller amount available for the other imports needed to meet development plans. Third, adverse changes in their trade balances can impair the ability of developing countries to borrow in private capital markets. Fourth, the transfer of income from Organization of OECD countries to OPEC can affect the flow of concessional aid to the developing countries (Munasinghe et al, 1993).

Since 1980, the real price of oil has fallen. In the period 1980-5 the nominal price was roughly constant, the real dollar price therefore fell. Then in 1986 both nominal and real prices fell sharply, and more recently showing a gradual rise in nominal terms but staying roughly constant in real dollar terms. However, in a period of falling oil prices and increasing value of the dollar, the principal beneficiary of the falling oil price was the US. Elsewhere, the decline in the crude oil price was offset by the dollar appreciation. According to IEA, the weighted average of crude oil prices in the 1981-5 period incurred by the European members of the IEA increased by 30%, and it remained constant when expressed in dollars.

3.22 Evolution of the Energy Maps of Canadian and Alberta

The overriding feature of Canada's energy map is that the industrial core of southern Ontario and Quebec is almost devoid of fossil-fuel resources and has had to secure them from elsewhere or find substitutes. When coal became the principal energy source of this industrializing region in the late nineteenth century, the lowest-cost supplies were (and remain today) the US Appalachian mines south of Lake Erie, readily accessible by rail and/or water. To compete, even in the Montreal market in the 1920s, Cape Breton coal required a

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

federal transportation subsidy. More recently, Alberta coal purchased by Ontario Power (formerly Ontario Hydro) has carried a higher delivered price than coal imported from the United States, but one justified commercially by its lower sulphur content. The development of hydroelectric power in Quebec compensated for the lack of coal. Total energy consumption consists of oil, gas, electricity and coal. Coal and the use of coal for electricity have the upper hand and thus the price of coal will increase.

The development of Alberta's oil and gas fields in the 1950s posed new political challenges concerning the relation the relation between Canada's industrialized core and its resource-rich western periphery. At the time, to provide a large and secure market for Alberta's fuels and stimulate the economic development of the province, it was necessary to construct pipelines to link producers to distant Ontario consumers. In 1959, when the 'Ottawa Valley Line' was instituted as a regulatory device to preserve the Ontario market west of Ottawa for Alberta producers, leaving Canada east of that line to be supplied by imported, and then slightly cheaper, oil. In this respect, federal policy discriminated against Ontario consumers for the sake of stimulating Alberta's oil industry.

The impact of the oil price increases in the 1970s induced by OPEC massively reversed this price discrimination and created a highly charged geopolitical challenge to Ottawa. Although Canada is a net exporter of energy, this is achieved only because exports of oil, gas and coal from Western Canada and of electricity, principally from Quebec, exceed imports of oil into the eastern and central provinces and coal into Ontario. The rapid escalation of world oil prices in 1973 and 1979 generated vast resource royalties for the Alberta, but it increased energy costs for Canadians, especially Central and Eastern Canada. The competitiveness of Ontario's manufacturing sector was threatened, and industries and domestic consumers in Atlantic Canada became more vulnerable. Because of the lack of alternative cost-competitive energy sources in that region, oil became the preferred fuel for electricity generation.

The federal government responded to the new global oil price regime by regulating domestic prices. A 'made in Canada' oil price, set below world levels with the intention of benefiting Canadian manufacturers (primarily in Ontario and Quebec), was financed by increasing federal taxation of western oil production (at the expense of producers and the Alberta government) and using these funds to subsidize the cost of imported oil consumed in eastern Canada. Yet the huge oil revenues of Alberta government Ottawa with a further threat: under the formula for regional equalization payments, the federal government was facing massive obligations to transfer funds to the have-not provinces, and by 1977 this group could

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

technically have included Ontario. Ottawa's response was unilaterally to impose new fiscal arrangements that had the effect of ensuring that Ontario would not become eligible for equalization payments. Whatever the merits of the federal government's arguments for moderating the domestic impact of higher world oil prices and protecting the weaker economies of Atlantic Canada (and to a lesser extent Quebec) from their consequences, its policy aroused deeply felt resentment in Alberta. It appeared that, yet again, the interests and prosperity of westerners were being sacrificed for the sake of Central Canadians.

The National Energy Program (NEP), instituted in 1980, capped Ottawa's response to the energy crises of the 1970s and reinforced western alienation. Its encouragement of greater Canadian ownership of the oil industry, including an element of state ownership through the creation of Petro-Canada (which was privatized in the 1990s) was philosophically at odds with the outlook of Calgary business community and was anathema to the multinational oil industry. The NEP's lavish subsidies for the high-cost energy exploration in the Arctic and Atlantic offshore frontiers was seen as undermining continued investment in the oil and gas sector in Alberta and adjacent provinces. Moreover, westerners noted that whereas the federal government was greatly increasing its intervention in, and revenues from, the oil and gas sectors, it was doing little to interfere with the expansion and revenues of provincial hydroelectric utilities, notably Hydro-Quebec. Completion of the first stage of the James Bay hydro-electric project in 1981 allowed the Quebec utility to sell large quantities of power into the high-priced market of the Northeastern United States at a time when oil and gas exports from western provinces were being curbed.

The return to a lower and more stable world oil price regime after the mid-1980s and the changed political climate in Ottawa reduced the intergovernmental and interregional frictions associated with national energy policy. Concerns about the adequacy and security of Canadian energy supplies have subsided since the 1970s. This is partly due to the gains in efficiency of energy use and the structural change in the national economy, which lowered the growth rate of demand from 2.6 per cent per year in the 1970s to 0.8 per cent per year in the 1980s and the technological progress. By the late 1990s Alberta's conventional oil output was gradually declining, but since the opening of the Suncor plant near Fort McMurray in 1967 and the larger Syncrude plant in 1978, major efficiency gains have been made in the technology of processing the province's vast oil-sands deposits.

Western Canadian gas reserves have continued to expand in British Columbia and southern Yukon. With the demand for gas in North America continuing to grow rapidly, proposals

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

were reviewed in 2000 to build two pipelines from the Arctic. The Alaska Highway and Mackenzie Valley routes would bring supplies from the Alaskan North Slope and the Mackenzie Delta region into Alberta, for onward distribution through the existing continental pipeline network. In Eastern Canada, much developments gave that region the security of more energy options should there be another crisis in world markets in the future. The inter-provincial natural gas grid was extended further east in Quebec in the 1980s, and in 1997 the first barrel of east coast offshore oil was pumped from the Hibernia field. Gas production fields off Sable Island reached the mainland of Nova Scotia in 2000, a project made financially attracted by the exports that the pipeline will carry to the New England market.

3.23 Conclusion

This chapter provides a broad overview of the nature, composition and the determinants of the energy industry and their effects on energy pricing mainly in the Canadian and North American context. The determinants of energy pricing models, demand and supply, and the expanded use of energy have been the focus of this chapter. Factors affecting drilling, as well as the risk in the oil industry under technical, economic and political were dealt with. Energy consumption in Alberta is ever increasing. Virtually all investment decisions in the petroleum industry are made under conditions of risk and uncertainty. The energy industry is developing financial instruments to meet the needs of customers and producers to manage short and long-term risks. The government has a role to play in energy pricing, through ownership of energy sources and price controls.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 4.0

MATHEMATICAL FORMULATION OF ENERGY PRICE MODELS

4.1 Introduction

This chapter focuses on mathematical models of oil, natural gas, coal price, and electricity prices and total energy consumption for Alberta and Canada in a North American context. The primary reason for time series modeling and analysis is to understand the patterns of events over a period of time. Time series modeling involve the consolidation of historical experiences into mathematical system that describes the behavior of events over time. These mathematical models are utilized to forecast what is likely to occur within a specific future time period. The determinants are the prices of crude oil, natural gas, coal and electricity and the total energy consumption. Energy prices are influenced by conservation incentives, the state of the world economy, successful exploration and production in non-OPEC countries, OPEC's production quota, substitution of alternate fuels for industrial, residential, and commercial use. The mathematical models are converted into computer models and solved using multivariate regression and forecast using Shazam (White, 1997).

4.1.1 The Determinants of Oil Prices

The relationship between energy system and spatial organization of society is complex, dynamic and not yet fully analyzed or understood, but its main features are clear. The nature and availability of energy resources have always influenced the environment and distribution of human activities. During the 20th century, cheap energy permitted the outward spread of urban areas at decreasing densities. In the last decade, studies have focused on global energy analysis to lay the groundwork for building a city's sustainable energy future. It is generally regarded that changes on energy consumption are mainly influenced by the scale of economic activities (activity effect), sectorial technology level (intensity effect) and the economic structure (the structural effect) (Bending et al., 1987).

Since the early 1970s, the Western world became aware of the necessity to conserve fossil fuels. Energy conservation in those days was mainly dictated by the idea that energy resources were being exhausted. Nowadays, environmental problems associated with fuel use such as acid rain, enhanced greenhouse effect, impose even more stringent limitations upon the use of fossil-fuel derived energy. Retrospective studies, in which the developments of the energy intensity of a country are unraveled, have been conducted by several authors from many countries [Jenne and Cattell, 1983; Bending et al., 1987; Howarth et al., 1991;

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Raggi and Barbiroli, 1991; Schipper et al., 1992; Sinton and Levin, 1994]. In most of these studies, the focus is on monetary indicators to describe the activity level of most sectors.

4.1.2 Formulation of a General Forecast Model

Models have been used to provide inputs for industrial decisions. The main scrutiny of forecast models centers on their accuracy and validation process. The usefulness of energy models for policy analysis or technology assessment lies in the comparative results generated for alternative scenarios, initiatives and actions. There are several energy models available for forecasting and policy analysis. However, a small number of these are used by decision makers. Decision makers believe that these models lack the rigor to provide appropriate information for better energy decisions. Comprehensive models, which capture the stochastic processes governing the evolution of determinant variables, are required to solve the problems volatile energy pricing.

4.1.3 Description of the Effects on Energy Price

The price of a unit energy and the total energy consumption are functions of total energy consumption, energy price lags, energy production, population, alternative fuel prices, GDP, personal income, unemployment, weather conditions, the level of OPEC production, and number of wells drilled (exploration), Westca. During winter heating oil is in higher demand than gasoline. In summer, gasoline is in high demand. The price of crude oil varies with the season, winter, spring, summer, and fall. If the production capacity is high then the price of crude oil will be lower when compared with a lower production capacity. The price of the energy product rises with a small population and falls when the population is high. If the price of the other energy product rises it will cause the energy product being considered to rise if it can be substituted with the other energy products.

4.2 Generalized Multivariate Regression Model

The multiple regression theory is used to formulate energy price models based on relevant dependant variables. These variables periodic lags, production and consumption capacities, population and growth, price of other energy products, GDP, personal income, unemployment rate, degree days, OPEC quota and number of oil and gas wells drilled. The generalized energy regression model is formulated in equation (4.1). Energy can be represented as oil, natural gas, coal and electricity, and thus, equation (4.1) can be written for each type of energy. The total energy consumption can also be written as equation (4.2). From equation (4.1), the model for oil pricing is given by equation (4.3).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$\textit{Energy Price} = \begin{aligned}&\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \\ &+ \beta_8 X_8 + \beta_9 dX_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \varepsilon\end{aligned} \quad (4.1)$$

$$\textit{Energy consumption} = \begin{aligned}&\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \\ &+ \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + \alpha_9 dX_9 + \alpha_{10} X_{10} + \varepsilon\end{aligned} \quad (4.2)$$

$$\begin{aligned}S_o = {} & \beta_0 + \beta_1\lambda_0 + \beta_2 g_0 + \beta_3 d_0 + \beta_4\rho_0 + \beta_5 p_0 + \beta_6\phi_0 + \beta_7\varphi_0 + \beta_8\mu_0 + \beta_9 v_0 + \\ & + \beta_{10} Q_0 + \beta_{11}\omega_0 + \varepsilon_l\end{aligned} \quad (4.3)$$

Lags of the different price variables and energy consumption were used in the mathematical model. Conservative incentives are the improvements on drilling and exploration technology and the use of other energy fuels or products. The state of the economy is described by GDP, personal Income, population and unemployment. Successful exploration has the number of wells drilled, Westca, as a proxy. Production of the different energy products was used and no variable was used as a proxy for wars between OPEC members. The generalized multiple linear regression model can be expressed as equation (4.4).

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik} + \varepsilon_i \quad (4.4)$$

4.2.1 Quantitative Least Squares Error Modeling

When a predictor is used to predict the dependent function Y_1, an error, ε_i, is made in the process. The objective is to choose β_0, β_1..., such that ε_l is minimized in the process. In order to achieve this objective, the least square estimation is obtained from equation (4.4). Let the vector of estimated regression coefficients be β_0, β_1,..., β_{k-1} be β. Whenever the commodity price estimates, $\hat{S}_i$, is used to forecast the price in any particular period, an error ε_l is made because the true price S_i is unknown as illustrated in equation (4.5). The least square function, L, is given by equation (4.6).

$$\hat{S}_i = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j \alpha_{ij} + \varepsilon_i \quad (4.5)$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left[\hat{S}_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j \alpha_{ij} \right]^2 \tag{4.6}$$

To minimize the error, L must be differentiated with respected to β_0 and β_j and set to zero as illustrated in equation (4.7) and (4.8). For the regression model, these least squares estimators are also maximum likelihood estimators and are unbiased, minimum variance unbiased consistent and sufficient.

$$\frac{\partial L}{\partial \beta_0} = -2\sum_{i=1}^{n} \left[y_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \right] = 0 \tag{4.7}$$

$$\frac{\partial L}{\partial \beta_j} = -2\sum_{i=1}^{n} \left[y_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \right] x_{ij} = 0 \text{ , j=1,2,...,k} \tag{4.8}$$

Equations (4.7) and (4.8) yield the system of linear equations in equation (4.9). Equations (4.7) and (4.8) can be represented in matrix form as in equation (4.9). In a matrix from, equation (4.9) becomes (4.10).

$$\begin{array}{l}
n\beta_0 + \beta_1 \sum_{i=1}^{n} x_{i1} + \beta_2 \sum_{i=1}^{n} x_{i2} + \ldots + \beta_n \sum_{i=1}^{n} x_{ik} = \sum_{i=1}^{n} y_i \\
\beta_0 \sum_{i=1}^{n} x_i + \beta_1 \sum_{i=1}^{n} x_{i1} + \beta_1 \sum_{i=1}^{n} x_{i1}.x_{i2} + \ldots + \beta_1 \sum_{i=1}^{n} x_{i1}.x_{ik} = \sum_{i=1}^{n} x_{i1} y_1 \\
\quad . \qquad . \qquad . \qquad . \qquad . \qquad . \\
\quad . \qquad . \qquad . \qquad . \qquad . \qquad . \\
\quad . \qquad . \qquad . \qquad . \qquad . \qquad . \\
\beta_0 \sum_{i=1}^{n} x_{ik} + \beta_1 \sum_{i=1}^{n} x_{ik} x_{i1} + \beta_1 \sum_{i=1}^{n} x_{ik}.x_{i2} + \ldots + \beta_1 \sum_{i=1}^{n} x_{ik}^2 = \sum_{i=1}^{n} x_{i1} y_1
\end{array} \tag{4.9}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_{i1} & \sum_{i=1}^{n} x_{i2} \cdots & \sum_{i=1}^{n} x_{ik} \\ \sum_{i=1}^{n} x_{i1} & \sum_{i=1}^{n} x_{i1}^2 & \sum_{i=1}^{n} x_{i1}x_{i2} \cdots & \sum_{i=1}^{n} x_{i1}x_{ik} \\ \sum_{i=1}^{n} x_{i2} & \sum_{i=1}^{n} x_{i1}x_{i2} & \sum_{i=1}^{n} x_{i2}^2 \cdots & \sum_{i=1}^{n} x_{i2}x_{ik} \\ \vdots & \vdots & \vdots & \vdots \\ \sum_{i=1}^{n} x_{ik} & \sum_{i=1}^{n} x_{ik}x_{i1} & \sum_{i=1}^{n} x_{ik}x_{i2} & \sum_{i=1}^{n} x_{ik}^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_{i1}y_i \\ \sum_{i=1}^{n} x_{i2}y_1 \\ \vdots \\ \sum_{i=1}^{n} x_{i1}y_i \end{bmatrix} \tag{4.10}$$

When the matrix multiplication is done, the scalar form of the normal equations will result. X'X is a k × k matrix, and the diagonal elements are the sums of squares of the elements in column X and the off-diagonal elements are the sums of the elements of the cross products. X'y is a k × 1 column vector and is the sums of the cross products of X and the observations $\{y_i\}$. In scalar notation, the fitted model is given by equation (4.11).

$$\hat{y}_i = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \quad i = 1, 2, \ldots, n \tag{4.11}$$

The difference between the observation and the fitted value $\hat{y}_i$ is a residual, $e_i = y - \hat{y}_i$. These models are validated with real-world data on the regressor variables within a period from 1982 to 1997.

4.3 Stationary Time-Series Modeling

The difference equation is used to ensure stationarity in the multiple regression equation. The theory of linear difference equations can be extended to allow the forcing process $\{x_t\}$ to be stochastic. This class of linear stochastic difference equations underlies much of the time-series econometrics. Especially important is the Box-Jenkins (1976) methodology for estimating time-series models in equation (4.12).

$$y_t = a_o + a_1 y_{t-1} + \ldots + a_p y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q} \tag{4.12}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Such models are called autoregressive integrated moving average (ARIMA) time-series models. A stationary ARIMA model is called an ARMA model.

4.3.1 ARMA Models

It is possible to combine a moving average process with a linear difference equation to obtain an autoregressive moving average. Consider the pth-order difference equation (Enders, 1995), the particular solution can be written as equations (4.13) and (4.16). Now let $\{x_t\}$ be the moving average (MA)(q) process given by equation (4.14) so that equation (4.12) becomes equation (4.15).

$$y_t = a_0 + \sum_{i-1}^{p} a_i y_{t-i} + x_t \tag{4.13}$$

$$x_t = \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \tag{4.14}$$

$$y_t = a_o + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \tag{4.15}$$

$$y_t = \frac{a_0}{1 - \sum_{i=1}^{p} a_i} + \sum_{i=0}^{\infty} \alpha_i \varepsilon_{t-i} \tag{4.16}$$

If the characteristic roots of equation (4.15) are all in the unit circle, $\{y_t\}$ is called an autoregressive moving average (ARMA) model for y_t (Enders, 1995). The autoregressive part of the model is the "difference equation" given by the homogeneous portion of equation (4.13) and the moving average part is the $\{x_t\}$ sequence. If the homogeneous part of the difference equation contains p lags and the model for x_t is q lags, the model is called an ARMA(p,q) model. If q = 0, the process is called a pure autoregressive process denoted by AR(p), and if p = 0, the process is a pure moving average process denoted by MA(q).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

4.3.2 Parsimony

A fundamental idea in the Box-Jenkins (1976) approach is the principle of parsimony. Parsimony (sparseness or stinginess) comes as second nature to economists. Incorporating additional coefficients will increase fit (e.g. the value of R^2 will increase) at a cost of reducing the degrees of freedom. Box and Jenkins argue that parsimonious models produce better forecasts than over-parameterized models. A parsimonious model fits the data well without incorporating many coefficients. The aim is to approximate the true data-generating process but not to pin down the exact process. The goal of parsimony is to eliminate the MA(12) coefficient in the simulated AR(1) model. In order to ensure that the model is parsimonious, the various a_i and β_i should all have t-statistics of 2.0 or greater (so that each coefficient is significantly different from zero at the 5% level). Moreover, the coefficients should not be strongly correlated with each other. Highly collinear coefficients are unstable; usually a few can be eliminated from the model without reducing forecast performance (Enders, 1995).

4.4 Modeling Economic Time Series: Volatility and Trends

Many economic time series do not have a constant mean and most exhibit periods of relative tranquility followed by high volatility periods. Much of the current econometric research is concerned with extending Box-Jenkins methodology to analyze this type of time-series behavior. The key features are as follows (Enders, 1995):

1. Most of the series contain a clear trend. Real GNP and its components and the supplies of short-term financial instruments exhibit a decidedly upward trend. For some series (interest and inflation rates), the positive trend is interrupted by a marked decline, followed by a resumption of the positive growth. Nevertheless, it is hard to maintain that these series have a time-invariant mean.

2. The UK £/US $ exchange rate shows no particular tendency to increase or decrease. The pound seems to go through sustained periods of appreciation and then depreciation with no tendency to revert to a long-run mean. This type of "random walk" behavior is typical of non-stationary series.

3. Any shock to a series displays a high degree of persistence. The federal fund rate experienced a violently upward surge in 1973 and remained at the higher level for nearly 2 years. In the same way, the UK industrial production plummeted in the late 1970s, and it did not return to its previous level until the mid-1980s.

4. The volatility of many series is not constant over time. During the 1970s, US producer prices fluctuated wildly as compared with the 1960s and 1980s. Real investment grew

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

series are called conditional heteroskedastic if the unconditional variance is constant but there are periods in which the variance is relatively high.

5. Some series share common movements with other series. Large shocks to US industrial production appear to be timed similarly to those in the UK and Canada. Short- and long-term interest rates track each other quite closely. The presence of such movements should not be too surprising.

4.5 ARCH Processes

Instead of using adhoc variable choices for x_t and/or data transformations, Engle (1982) showed that it is possible to simultaneously model the mean and variance of a series. As a preliminary step to understanding Engle's methodology, note that conditional forecasts are vastly superior to unconditional forecasts. To elaborate, suppose you estimate the stationary ARMA model $y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$ and want to forecast y_{t+1}. The conditional forecast of y_{t+1} is given by (4.17).

$$E_t y_{t+1} = a_0 + a_1 y_t \tag{4.17}$$

If this conditional mean is used to forecast y_{t+1}, the forecast error variance is $E_t (y_{t+1} - a_0 - a_1 y_t)^2] = E_t \varepsilon^2_{t+1} = \sigma^2$. Instead, if unconditional forecasts are used, the unconditional forecast is always the long-run mean of the $\{ y_t \}$ sequence that is equal to $(a_0)/(1-a_1)$. The unconditional forecast error variance is given by equation (4.18).

$$E_t \{[y_{t+1}-(a_0)/(1-a_1)]^2\} = E[(\varepsilon_{t+1} + a_1\varepsilon_t + (a_1)^2\varepsilon_{t-1} + (a_1)^3\varepsilon_{t-2} + \ldots)^2 = \sigma^2/(1 - (a_1)^2) \tag{4.18}$$

Since $1/(1-(a_1)^2)>1$, the unconditional forecast has a greater variance than the conditional forecast. Thus, conditional forecasts are preferable because they take into account the known current and past realizations of the series. Similarly, if the variance of $\{\varepsilon_t\}$ is not constant, one can estimate any tendency for sustained movements in the variance using an ARMA model. For example, let $\{\hat{\varepsilon}_t\}$ denote the estimated residuals from $y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$, so that the conditional variance of y_{t+1} is given by equation (4.19).

$$Var(y_{t+1}/y_t) = E_t [(y_{t+1} - a_0 - a_1 y_t)^2] = E_t (\varepsilon_{t+1})^2 \tag{4.19}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Suppose the conditional variance is not constant, one simple strategy is to model the conditional variance as an AR(q) process using the square of the estimated residuals as illustrated in equation (4.20)

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1\hat{\varepsilon}_t^2 + \alpha_2\hat{\varepsilon}_{t-1}^2 + ..\alpha_q\hat{\varepsilon}_{t-q}^2 + v_t \qquad (4.20)$$

v_t is a white-noise process. If the values of α_1, α_2..., α_n are equal zero, the estimated variance is simply the constant α_0. Otherwise, the conditional variance of y_t evolves according to the autoregressive process given by equation (4.20). As such, you can use *equation (4.20)* to forecast the conditional variance at t + 1 as in equation (4.21).

$$E_t\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1\hat{\varepsilon}_t^2 + \alpha_2\hat{\varepsilon}_{t-1}^2 + ...\alpha_q\hat{\varepsilon}_{t+1-q}^2 \qquad (4.21)$$

Equation (4.21) is called an autoregressive conditional heteroskedastic (ARCH) model. The unconditional variance is $E\varepsilon_t^2 = \alpha_0 /(1-\alpha_1)$.

4.6 The GARCH Model

Bollerslev (1986) extended Engle's work to develop a technique that allows the conditional variance to be an ARMA process. Let the error process be given by equation (4.22).

$$\varepsilon_t = v_t\sqrt{h_t} \qquad (4.22)$$

$$\sigma_v^2 = 1 \text{ and } h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \qquad (4.23)$$

Since $\{v_t\}$ is a white-noise process that is independent of past realizations of ε_{t-i}, the conditional and unconditional means of ε_t are equal to zero. Taking the expected value of ε_t, results in equation (4.24).

$$E\varepsilon_t = E\, v_t\sqrt{h_t} = 0 \qquad (4.24)$$

The conditional variance of ε_t is given by $E_{t-1}(\varepsilon_t)^2 = h_t$. This generalized ARCH(p,q) model called GARCH(p,q) allows for both autoregressive and moving average components in the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

heteroskedastic variance. Setting p = 0 and q = 1, it is clear that the first-order ARCH model given by equation (4.25).

$$\varepsilon_t = v_t(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^{1/2} \tag{4.25}$$

If all the β_i equal zero, the GARCH(p,q) model is equivalent to an ARCH(q) model. A high-order ARCH model may have a more parsimonious GARCH representation that is much easier to identify and estimate. The key feature of GARCH models is that the conditional variance of the disturbances of the $\{y_t\}$ sequence constitutes an ARMA process. Hence, it is expected that the residuals from a fitted ARMA model should display this characteristic pattern. The ordinary least squares (OLS) command will run an ordinary least squares regression. The linear regression model can be restated as equation (4.26).

$$Y_t = \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \ldots + \beta_K X_{Kt} + \varepsilon_t \qquad \text{for } t = 1,\ldots,N \tag{4.26}$$

There are N observations and Y_t is observation t on the dependent variable, X_{Kt} is observation t on the X^{th} explanatory variable; k =1,...,K, β_K are parameters to estimate and ε_t is a random error that is assumed to have zero mean and variance σ^2.

4.7 Independent Component Analysis (ICA)

Imagine two people speaking simultaneously into two microphones. The microphones give two recorded time signals denoted by $x_1(t)$ and $x_2(t)$, with x_1 and x_2 as the amplitudes and t the time index. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, denoted by $s_1(t)$ and $s_2(t)$. $x_1(t)$ and $x_2(t)$ are given by equation (4.27) and (4.28).

$$x_1(t) = a_{11}s_1 + a_{12}s_2 \tag{4.27}$$

$$x_2(t) = a_{21}s_1 + a_{22}s_2 \tag{4.28}$$

a_{11}, a_{12}, a_{21}, and a_{22} are some parameters that depend on the distances of the microphones from the speakers. If there are n linear mixtures x_1, ..., x_n of n independent components, such that equation (4.29) is true.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$x_j = a_{j1}s_1 + a_{j2}s_2 + ... + a_{jn}s_n \quad \textit{for all } j \tag{4.29}$$

Then each mixture x_j, as well as each independent component s_k is a random variables, instead of a proper time signal. It is assumed that both the mixture variables and the independent components have zero mean (i.e. the observeable variables x_i can always be centred by subtracting the sample mean). Using vector-matrix notation, the random vector x whose elements are the mixtures of x1,...xn, and the random vector s with elements s1,...,sn are related and given by equation (4.30). A is the matrix with elements a_{ij}. All vectors are column vectors.

$$X = A \bullet s \tag{4.30}$$

Sometimes the columns of matrix A is denoted by a_j and the model can be written as equation (4.31).

$$\mathbf{x} = \sum_{i=1}^{n} \mathbf{a}_i s_i \tag{4.31}$$

The statistical model in equation (4.30) is called the independent component analysis model. The starting point of ICA is that the components s_i are statistically independent and must have non-Gaussian distribution. After estimating the matrix A, the inverse, W is computed and the independent component is obtained by equation (4.32).

$$S = W \bullet x \tag{4.32}$$

In many applications, there are some noise measurements. For simplicity, the noise term is omitted, since the estimation of the noise-free model is difficult enough in itself, and seems sufficient for many applications.

4.7.1 Principles of ICA Estimation

Assume that the data vector x is distributed according to equation (4.30). That is, it is a mixture of independent components and that all the independent components have independent distributions. To estimate one of the independent components, a linear combination of x_i is considered as given by equation (4.33).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$y = \mathbf{w}^{\mathbf{T}}\mathbf{x} = \sum_i w_i x_i \qquad (4.33)$$

w is a vector to be determined. If w were one of the rows of the inverse of A, this linear combination would actually equal one of the independent components. How can the central limit theorem be used to determine w so that it would equal one of the rows of the inverse of A? In practice, w cannot be determined exactly, because there is no knowledge of matrix A, but an estimator that gives a good approximation can be found. To see how this leads to the basic principal of ICA estimation, some changes to the variables as given in equation (4.34) and (4.35)

$$z = A^T \bullet w \qquad (4.34)$$

$$y = w^T \bullet x = w^T \bullet As = z^T \bullet s \qquad (4.35)$$

y is thus a linear combination of s_i, with weights given by z_i. Since a sum of two independent random variables is more Gaussian than the original variables, $z^T s$ is more Gaussian than any of the s_i and becomes least Gaussian when in fact equals one of the s_i. In this case, obviously only one of the elements z_i of z is non-zero (s_i is assumed to have identical distributions). Therefore, w is a vector that maximizes the non-Gaussianity of $w^T \bullet x$. Such a vector would necessary correspond (in the transformed coordinated system) to a z which has only one non-zero component. This means that $w^T \bullet x = z^T \bullet s$ equals one of the independent components. Maximizing the non-Gaussianity of $w^T \bullet x$ thus gives one of the independent components. The optimization landscape for non-Gaussianity in the n-dimensional space of vectors w has 2n local maxima, two for each independent component, corresponding to s_i and - s_i. To find several independent components, all the local maxima are found. This corresponds to orthogonalization in a suitably transformed (i.e. whitened) space.

4.7.2 Preprocessing for Independent Component Analysis

Before applying an ICA algorithm on the data, it is usually very useful to do some preprocessing. These preprocessing techniques that make the problem of ICA estimation simpler and better conditioned include centering and whitening. The most basic and necessary preprocessing is to center x (i.e. subtract its mean vector m = E{x}) to make x a zero-mean variable. This implies that s is zero-mean, as well as can be seen by taking expectations on both sides of equation (4.30). This preprocessing is made solely to simplify

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

the ICA algorithms: It does not mean that the mean could not be estimated. After estimating the mixing A with centered data, the estimation can be completed by adding the mean vector of s back to the centered estimates of s. The mean vector is given by $A^{-1} \bullet m$, where m is the mean that was subtracted in the preprocessing.

Another useful preprocessing strategy in ICA is to first whiten the observed variables. This means that before the application of the ICA algorithm and after centering, the vector x is transformed linearly and the new vector $\tilde{\mathbf{x}}$ which is white. In other words, the covariance matrix of $\tilde{\mathbf{x}}$ equals the identity matrix, and is given by equation (4.36).

$$E\{\tilde{\mathbf{x}}\tilde{\mathbf{x}}^T\} = \mathbf{I} \tag{4.37}$$

4.8 The FastICA algorithm

The FastICA algorithm is a variant of the ICA algorithm for fast process implementation. The data is preprocessed by centering and whitening before using FastICA.

4.8.1 FastICA for One Unit

A "unit" means a computation unit, eventually an artificial neuron, having a weight vector w that the neuron is able to update by a learning rule. The FastICA learning rule finds a direction, i.e. a unit vector w such that the projection w^Tx maximizes non-Gaussianity. Non-Gaussianity measured by the approximation of negentropy (based on the information-theoretic quantity of (differential) entropy) $J(w^Tx)$ is given by equation (4.37).

$$J(y) \propto [E\{G(y)\} - E\{G(v)\}]^2 \tag{4.37}$$

The variance of w^Tx must be constrained to unity. For whitened data this is equivalent to constraining the norm of w to be unity. The FastICA is based on a fixed-point iteration scheme for finding a maximum non-Gaussianity of w^Tx, as measured in equation (4.37). It can also be derived as an approximate Newton iteration denoted by g, which is the derivative of the non-quadratic function G used in equation (4.37) and expanded in equation (4.38).

$$G_1(u) = \frac{i}{a_1}\log\cosh a_1 u, \qquad G_1(u) = -\exp(-u^2/2) \tag{4.38}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$1 \leq a_1 \leq 2$ is some suitable constant; often $a_1 = 1$. For example the derivatives of the functions in equation (4.38) are given by equation (4.39).

$$g_1(u) = \tanh(a_1 u), \text{ and } g_2(u) = u\exp\left(-u^2/2\right) \tag{4.39}$$

The basic form of the FastICA algorithm is as follows: (i) choose an initial (e.g. random) weight vector w; (ii) let $\mathbf{w}^+ = E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}$ and $\mathbf{w} = \mathbf{w}^+ / \|\mathbf{w}^+\|$; and (iv) if not converged, go back to (ii).

4.8.1 FastICA for Several Units

The one-unit algorithm estimates just one of the independent components. To estimate several independent components, the one-unit FastICA algorithm must be run using several units with weight vectors $w_1,\ldots,w_n$. To prevent different vectors from converging to the same maxima, the outputs $\mathbf{w}_1^T\mathbf{x},\ldots,\mathbf{w}_n^T\mathbf{x}$ must be decorrelated after every iteration. A Matlab implementation of the FastICA algorithm was used which is available at http://www.cis.hut.fi/projects/ica/fastica/.

4.8.2 Principal Component Analysis

Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components.* The first principal component accounts for as much variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. The mathematical technique used in PCA is called eigen analysis, which solves for the eigen values and eigen vectors of a square symmetric matrix with sums of squares and cross products. The eigen vector associated with the largest eigen value has the same direction as the first principal component. The eigen vector associated with the second largest eigen value determines the direction of the second principal component. The sum of the eigen values equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of this matrix.

4.8.3 Neural Networks for Time Series Forecasting

An artificial neural network (ANN) is an information processing paradigm that is inspired by the way the brain processes information. The key element of this paradigm is the novel structure of the information processing system. It is composed of highly interconnected

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

processing elements (neurons) working in unison to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. In statistical parlance, the ANN network corresponds to a nonlinear model and the learning process to parameter estimation. Recently, ANNs have been investigated as a tool for time series forecasting. The most popular class, used exclusively in this study, is the multilayer perceptron, a feedforward network trained by backpropagation. This class of network consists of an input layer, a number of hidden layers and an output layer as illustrated in Figure 4.1.

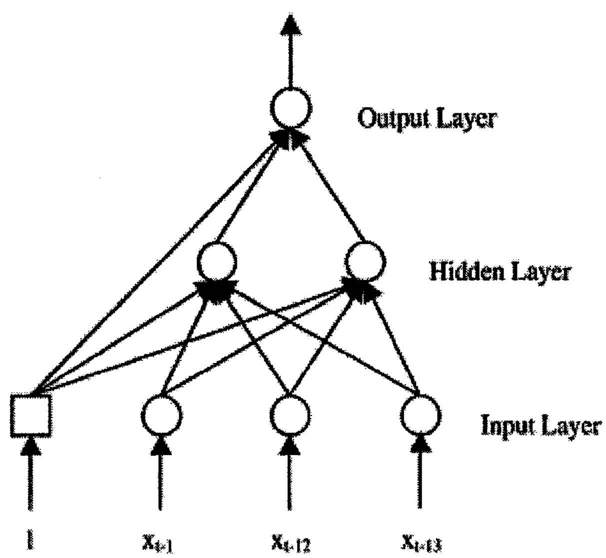

Figure 4.1 Multilayer Feedforward Neural Networks

Since ANNs learn by example, it is vital that the inputs characterize the important relationships in the time series being forecast. Forecasts are generated iteratively by performing successive one-step ahead forecasts using previous forecasts as estimates of observables. This paradigm attempts to provide an intelligent choice of inputs using recognized statistical procedures. An ANN typically has more parameters than most time series models. Therefore, it is expected that they will perform better on longer series with stable patterns. By construction, the ANN is expected to provide superior forecasts when the process is nonlinear. The reason for using a complex method must be that a process contains elements not captured by simple forecasting methods, notably nonlinearity in the case of ANNs. For an ANN to outperform simple methods, there must be sufficiently long series to detect the nonlinearity and to provide reliable estimates of the parameters.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

4.9 Summary and Conclusion

The mathematical formulation for energy price models used in this study were ARCH and GARCH models, Principle Component Regression model, Independent Component Analysis model and Neural Network models. Stationary time series modeling was discussed and trends and volatility of modeling economic time series were dealt with. The theory of ARCH and GARCH models, ICA and PCA were also discussed.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 5.0

COMPUTER MODELING AND ALGORITHMIC EFFICIENCY

In this chapter the mathematical models are translated into computer models in order to obtain solutions to the energy time series models outlined in Chapter 4.0 using SHAZAM, MATLAB, Fortran and @Risk software. The models are verified and validated using data from CANSIM for both Alberta and Canada.

5.1 Modeling and Computational Efficiency

Robustness, rigor, computational time and systematic procedures for arriving at solutions with a higher degree of confidence ensure modeling and computational efficiency, which is important in any scientific research. In order to attain efficiency, a number of procedures are followed in this research phase. These procedures include systematic mathematical and computer modeling, verification and modification of algorithms, validation with real-world data, experimental design and experimentation for generating relevant information for understanding the system. The verification and modification of algorithms and validation ensure confidence and integrity in the models with regards to functional accuracy and relevance to real-world systems. The experimental design stage defines the control environment, stable and unstable regimes and full scale parameterization of algorithms for efficient process control. The selection of appropriate software is critical to achieve computational efficiency. In this research, the selected software packages were carefully selected based on their computational platforms, reliability and the author's thorough understanding. An equally important consideration is the real-world data for validation. Appropriate data is collected, processed and formatted for validating the models. See Fig. 5.1, Fig. 5.2 and Fig. 5.3 for the flow charts.

5.2 Random Field Sampling and Stochastic Simulation

The Monte Carlo sampling technique was chosen for simulating the random phenomena underlying the functional variables. This simulation technique is well known for its reliability, rigor and efficiency. However, for few random samples, Monte Carlo can generate cluster population, which is non-representative of the underlying stochastic process. In order to overcome this problem, stratified sampling using the Latin Hypercube technique can be used

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

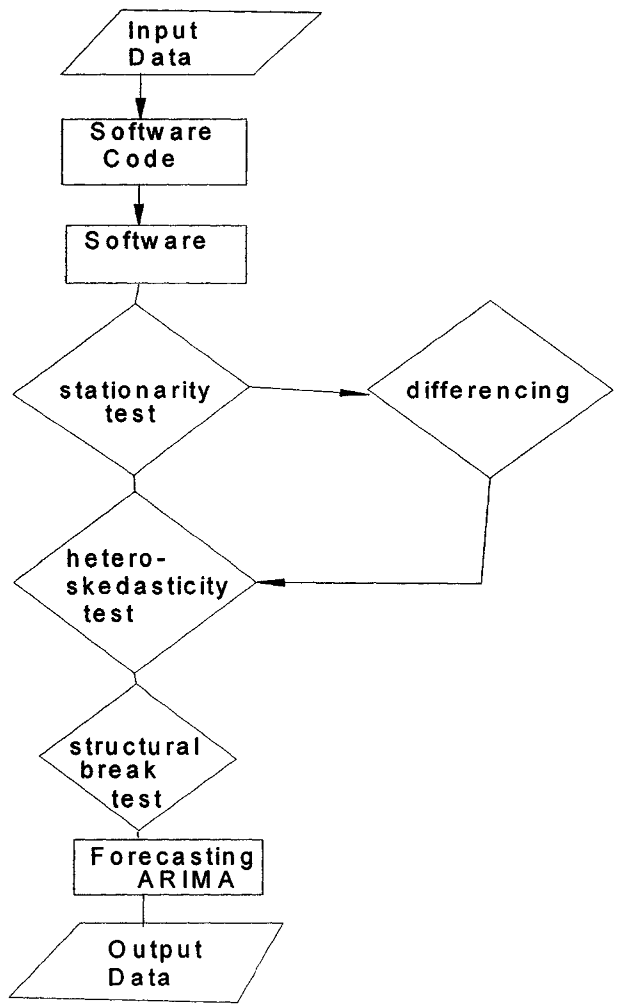

Figure. 5.1 Flow Chart for the Development of Energy Price Model using SHAZAM

to control random sampling over the whole distribution [Palisade, 2003]. In this study, large number of iterations was generated to avoid the cluster problem. The Monte Carlo technique for this study uses the multiplicative congruential methodology as a random number generator and the inverse transform method for generating unbiased samples from a cumulative uniform conversion of all probability density functions in the model. At the end of each sampling iteration, a functional value is estimated as a probable outcome, out of many outcomes, that define the output random process. The expected value and variance of a generalized continuous random multivariate function are given by equations (5.1) and (5.2)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

[Frimpong and Akihiro, 1998]. These equations consist of the functional component, $\phi(\gamma_i)$, the probability density function, $f(\gamma_i)$, and the continuous operator, $d\gamma_i$.

$$E[\phi(\gamma_i)] = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \phi(\gamma_1, \gamma_2, \cdots, \gamma_n) * f(\gamma_1) d\gamma_1 * f(\gamma_2) d\gamma_2 * \cdots * f(\gamma_n) d\gamma_n \tag{5.1}$$

$$VAR[\phi(\gamma_i)] = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} [\phi(\gamma_1) - E(\phi)]^2 * [\phi(\gamma_2) - E(\phi)]^2 * \cdots * [\phi(\gamma_n) - E(\phi)]^2 * f(\gamma_1) d\gamma_1 * f(\gamma_2) d\gamma_2 * \cdots * f(\gamma_n) d\gamma_n \tag{5.2}$$

Equations (5.1) and (5.2) do not have analytical solutions, and thus, numerical approximations and simulation experiments are used to obtain approximate solutions. The use of stochastic simulation requires that a large number of sampling iterations are carried out to replicate the input probability density functions. Thus, increasing sampling iterations increase the confidence in the results. For this experiment, 500 iterations were judged to be the minimum that ensures variance stability in the process.

5.3 Hybrid Stochastic-Optimization Process

A hybrid stochastic-optimization process was used to optimize the random field [Frimpong, Szymanski and Whiting, 1998]. This process combines the power of stochastic simulation with optimization to ensure that a series of optima are generated to represent the random field. At the end of each stochastic event, the process is optimized and the latter is stored as the functional output. This process results in a series of optimized stochastic results, which must be analyzed for its expected value and associated variability. The process of econometric analysis benefits from this hybrid process because of its inherent randomness, complexities and functional representations. The main problems that are encountered in econometric time series data include: (i) flawed measurements; (ii) immeasurable variables; (iii) improper functional representations; (iv) violation of the underlying stochastic processes; and (v) missing relevant variables.

To maximize or minimize a function, f(x), its corresponding slope, f'(x), is set to zero(i.e. f'(x) = 0). Otherwise, the function will be increasing or decreasing in x. This situation implies the first-order or necessary condition for an optimum. For a maximum, the function must be concave and convex for a minimum. This situation leads to a sufficient condition for an optimum as illustrated in equations (5.3) and (5.4).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

For a maximum, $\dfrac{d^2y}{dx^2} < 0;$ *(5.3)*

For a minimum, $\dfrac{d^2y}{dx^2} > 0.$ *(5.4)*

Some functions, such as the sine and cosine functions have many local optima. A function such as (sinx)/x, which is a damped sine wave, differs in that although it has many local maxima. However, the maximum at x = 0 is greater than it is at any other point. Thus, x = 0 is the global maximum, whereas the other maxima are only local maxima. Certain functions, such as quadratic, have only a single optimum. These functions are globally concave if the optimum is a maximum and globally convex if it is a minimum. For maximizing or minimizing a function of several variables, the first-order condition is defined by equation (5.5).

$$\frac{\partial f(x)}{\partial x} = 0. \tag{5.5}$$

This result is interpreted in the same manner as the necessary condition in the univariate case. At the optimum, it must be true that no small change in any variable leads to an improvement in the function value. In the single-variable case, d^2y/dx^2 must be positive for a minimum and negative for a maximum. In the multivariate case, a similar condition is attached to the second derivatives matrix of the objective function. The second-order conditions for an optimum are that, at the optimizing value, equation (5.6) must be positive definite for a minimum and negative definite for a maximum.

$$H = \frac{\partial^2 f(x)}{\partial x \partial x'} \tag{5.6}$$

5.4 Experimental Design

Experimental design is the design of a logical structure, dimension and the control environment for experimentation. It involves the selection of parameter values to use in the computer runs, the sampling technique to apply to the experiment and the determination of the amount of replication. It also defines the domain and boundaries of stable and unstable regimes for conducting extensive experiments using various tests. In this study, these tests include stationarity, structural break, autocorrelation, heteroskedasticity, cointegration and the principal component regression test.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The next critical step is to generate the experimental phases, which include planning, design, construction, debugging, execution, data analysis and reporting of results. The planning phase involves the evaluation of the various approaches that might solve the problem. In the design phase the information found in the planning phase is used to specify the instrumentation needed and the details of the configuration of the experimental approach. The test plan is identified and decisions made on the ranges of conditions to be run, the required data, and the experimental sequence. During the construction stage, the individual components are assembled into the overall experimental approach for performing the associated instrumentation. In the debugging stage, initial runs using the computer models are made for the appropriate software programs, with modifications. The stage will then be set for detailed experimentation of the models. During the execution stage, the experimental runs are made to generate appropriate results. Often, the runs are monitored using checks that are designed into the system to guard against inaccurate models.

5.4.1 Test for Stationarity

The test for stationarity is done using the COINT command. The COINT command implements tests for unit roots and cointegration including Dickey-Fuller root tests. Finding unit root in a time series indicate non-stationarity.

5.4.2 Test for Structural Change (Chow Test)

The F test is used for achieving structural change. In specifying a regression model, the assumption is that it applies to all the observations. Structural change test ensues that when the data is split into two sub-samples, the coefficients are the same in the two sub-samples. The full sample estimate of the model is obtained through restricted regression. The unrestricted regression is when the coefficients are allowed to differ in the two sub-samples by estimating the two sub-samples separately. The test statistics must be based on a comparison of sum of squared errors (SSE) for the restricted and unrestricted models rather than a comparison of R^2 values. The F test statistics is obtained as equation (5.7).

$$F = \frac{(SSE_R - (SSE_1 + SSE_2))/k}{(SSE_1 + SSE_2)/(df_1 + df_2)} \qquad (5.7)$$

SSE_R is the SSE in the restricted model estimated using all observations, while the sum (SSE_1+ SSE_2) is the SSE in the unrestricted model estimated for each sub-sample. K is the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

number of parameters in the restricted model; df_1 and df_2 refer to the degrees of freedom in the two sub-samples (White, 1997).

5.4.1 Testing for Autocorrelation

The test for autocorrelation is based on the principle that if true disturbances are autocorrelated, this fact will be revealed through the autocorrelations of the least square residuals (White, 1997). When the classical assumption, Cov (e,e) = 0, is violated, where e_i and e_j arre the error terms for the i^{th} and j^{th} observations, (i, j = 1,..., n), the error terms are said to be autocorrelated or serially correlated. In this case, OLS is no longer efficient and estimated standard errors are incorrect. The most common specification of autocorrelation is where the error term for observation at any time, e_t, depends only on the error term in the previous period, e_{t-1}. With a firsr-order autoregressive process, AR(1), which is given by et = e_{t-1} + e_t, ρ, the first-order autoregressive parameter lies in the range ($-1 < \rho < 1$), and ε_t is a random error term that satisfies the classical assumptions. H_0: $\rho = 0$ (no autocorrelation) and H_1 : $\rho > 0$ (positive autocorrelation). The Durbin-Watson test statistic, d, is obtained in SHAZAM by using the option RSTAT on the OLS command. With a Durbin-Watson statistic of d=2.6852, it is compared with the upper and lower bound, d_U and d_L. Between these bounds, $d_U < d < d_L$, the test is inconclusive. If $d > d_U$, the null hypothesis is not rejected and there is no evidence of positive autocorrelation. The null hypothesis is rejected if $d < d_L$. The Cochrane-Orcutt estimation method is the remedial method used for AR(1) errors (White, 1997).

5.4.2 Heteroskedasticity – Testing and Remedial Action.

When the classical assumption $Var(e_i) = \sigma^2$ for all i = 1, ... , n, is violated, the variance of the error terms differs for different observations ($Var(e_i) = \sigma^2$), e_i is the error term for the ith observation, and the error terms are said to be heteroskedastic (White, 1997). In this case, OLS is unbiased but no longer efficient and the estimated standard errors are incorrect. The basis of the Goldfeld-Quandt (GQ) test is that if there is no heteroskedasticity, the variance should be the same for two separate sub-samples taken from the original sample. The test involves splitting the sample into two sub-samples, obtaining an estimate of the variance $\left(\hat{\sigma}^2\right)$ for each sub-sample, and using these two values to test whether the true variances $\left(\sigma^2\right)$ differ for each sub-sample. The observations were sorted against Westca, which is number of wells drilled in the regression for oil price and production for the rest of energy product prices. Energy consumption was sorted against the energy product that is most consumed, oil production.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Two sub-samples are selected from the sorted data by taking the first (n-c)/2 and last (n-c)/2 observations. c is typically about 20% of the sample, so that with 60 observations c = 12 such that (n-c)/2 is an integer. Both sub-samples have the same degrees of freedom. The OLS is used to estimate the model for each sub-sample to obtain $\hat{\sigma}^2$ in each case. The ratio of the two $\hat{\sigma}^2$ values are calculated in equations (5.8) and (5.9) and compared to critical values from F tables.

$$GQ_1 = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2} = \frac{SSE_1}{SSE_2} \tag{5.8}$$

$$GQ_2 = \frac{\hat{\sigma}_2^2}{\hat{\sigma}_1^2} = \frac{SSE_2}{SSE_1} \tag{5.9}$$

The degrees of freedom are 24 – 10 = 14 in each sub-sample regression. $GQ^* = F_{14,14,0.05}=$ 2.48. To test $H_0 : \sigma_1^2 = \sigma_2^2$ against $H_1 : \sigma_1^2 > \sigma_2^2$, the variance is decreasing with increasing values of Westca use GQ_1. Alternatively, to test $H_0 : \sigma_1^2 = \sigma_2^2$ against $H_1 : \sigma_1^2 < \sigma_2^2$, the variance is increasing with increasing values of Westca use GQ_2. For $H_1 : \sigma_1^2 > \sigma_2^2$, GQ_1 test statistic is 1.6584, while for $H_1 : \sigma_1^2 < \sigma_2^2$, the GQ_2 test statistic is 0.6030. The critical value is GQ^* is 2.48 and the null hypothesis is not rejected. There is no evidence of heteroskedasticity (After Ryan, 1999).

5.4.3 Tests for Cointegration

If the Dickey-Fuller unit root tests statistic is smaller than the critical value then there is evidence for cointegration (evidence of a long run relationship between non-stationary variables). This is the test for stationarity. If this is the case the data is transformed using differencing. First differences can be obtained by using the NDIFF = 1 option on the COINT command (White, 1997)

5.4.6 Principal Component Regression Test

A consequence of multicollinearity is that the OLS estimators may have large standard errors. A solution is to consider a restricted least squares estimator. One approach is to use PCA to reduce the data set dimensionality. Principal components are generated and a sub-

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

set is selected to include as regressors in an OLS regression. The estimators are then transformed to obtain estimators for the coefficients of the original model. The resulting estimator has an interpretation as a restricted least squares estimator and therefore has smaller sampling variance compared to the unrestricted OLS estimator (White, 1997).

5.5 Experimentation

This experiment is designed for 64 observations a span of 16 years. Most observations were obtained from CANSIM. The observations were limited to this number by the personal income which stops at 1997. The regression was run using the mathematical models in Chapter 4. The purpose is to obtain unbiased estimates of the different variables under investigation and to generate reproducible results. The software packages used include SHAZAM, MATLAB, Fortran and @Risk software for solving various sections of the problem. Figure 5.1 illustrates how SHAZAM was used. Fig. 5.2 and Fig. 5.3 show the use of @Risk and MATLAB were used in this experiment.

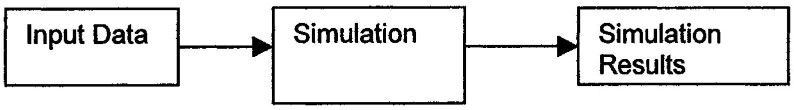

Figure. 5.2 Simulation Data Flow Chart using @Risk.

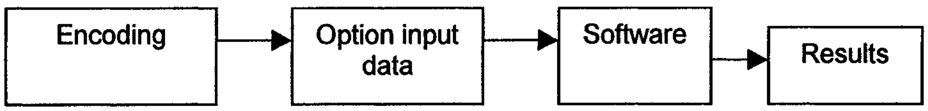

Figure. 5.3 Forecasting options using Matlab

The most convenient way to run SHAZAM is in BATCH mode using three files: data file, SHAZAM command file and SHAZAM output file. This means that SHAZAM commands are typed into a file called a SHAZAM command file and SHAZAM is instructed to process the command file and to place all the output results of the command file in another file, the SHAZAM output file. In this way, errors in the SHAZAM command file, or if SHAZAM does not produce the required output, or if additional SHAZAM commands are needed, the command file can easily be edited, and have SHAZAM process the command file again. Although data can be included in a command file, it is usually more convenient to have the data in separate file called a data file (White, 1997).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The @Risk software was used to analyze the stochastic models in this research. This software used the Monte Carlo simulation technique for sampling. It consists of building systems by computer calculations and evaluating the performance of such systems. If, for instance, a system has 500 components and there are 500 of each component available. 500 different systems can be built and 500 measurements of system performance. Actually, system performance can be measured without building the systems if the relationship between the component variables is known. If, instead of having 500 samples of each component, we know the distribution for each variable, synthetic measurements can be obtained, 500 random values from each distribution. These random values are used to calculate performance.

The neural network forecasting model was built using FORTRAN programming language. Time series forecasting formulation is intended to capture the underlying mechanism that drives the process. And then the ability to forecast becomes possible. The input comprise of several time series. The number of input layer nodes largely dictates the design of subsequent layers. If the total number of weights in the network are too few then the network will not have the capability to solve the forecasting problem. A model with a large number of weights can map the input vectors' corresponding target outputs, without necessarily extracting any meaningful relationships. The key factor is the ratio of input training vectors to weights. The higher this ratio is the better. Once the neural network has been trained to forecast a time series, a time series of forecasts over the same time period can be created.

5.5.1 Using Data Retrieved from CANSIM

The CANSIM database from Statistics Canada was used to validate these models. Access to CANSIM is obtained through an internet connection from the electronic database of the library at the University of Alberta.

Although price series are usually available monthly, GDP is only available on a quarterly or annual basis. All the data series obtained were processed to have the same frequency. Monthly or quarterly data can be converted to annual series, but the reverse is not possible.

5.6 Conclusion

The process required for modeling and computational efficiency has been provided for this study. The random field sampling technique and stochastic simulation bases have been developed, as well as the hybrid stochastic-optimization process. The experimental design

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

and the experimentation process have also been outlined to provide the underpinning foundation for the study. The theoretical basis of the various tests, including stationarity, structural break, autocorrelation, heteroskedasticity, cointegration and the principal component regression have also been covered for reliable experimental design.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 6.0

ANALYSIS AND DISCUSSION OF RESULTS

The models in Chapter 4.0 are validated with CANSIM data based on the algorithmic efficiency and control environments outlined in Chapter 5.0. Energy price models for electricity, coal, crude oil, natural gas and the total energy consumption have been formulated within the economic environments of Alberta (in Section 6.1) and Canada (in Section 6.2). The models are constructed using GARCH, ARIMA, PCR and neural networks (NN) for each economic environment. The most important features of that indicate the suitability of these models are the mean, volatility, trend cycle and trend direction. This section also deals with the associated risks and uncertainties, the forecasting of energy prices with the Black-Scholes formulation and their impact on energy in Alberta and Canada. The structural break, heteroskedasticity, autocorrelation for both Alberta and Canada are in Tables B.1 and B.2 in Appendix B.

6.1 Energy Pricing Model Results for Alberta

The energy price models for Alberta focus on the variations in energy prices within the economy of Alberta. Alberta is the dominant source of Canada's fossil fuel industry, with about a tenth of Canada's population. The booming economy of Alberta has spurred industrial growth, population increase, and thus, increase in energy demand at the commercial and residential levels. The deregulation of electricity in Alberta also introduced some shock into the energy markets causing volatility in energy pricing. These models are therefore unique from that of Canada wide models.

6.1.1 Electricity Pricing Model Results for Alberta

Electricity Price is in $/GigaWatt-Hour for Alberta and Canada. Figures 6.1, 6.2, 6.3 and 6.4 show the electricity price forecasts using GARCH, ARIMA, PCR and NN. The forecast models incorporate the effect of Production, OPEC prices, the price of other energy products, personal income, GDP on electricity prices. Price volatility is precipitated by resource scarcity, and artificial scarcity created by transmission constraints, fuel supply, generation availability, and electricity transmission. The GARCH model in Figure 6.1 shows complete departure below the 30^{th} quarter and overall shows an unacceptable prediction model for electricity prices. The ARIMA model in Figure 6.2 under-predicts the observed electricity prices and may provide severely optimistic prices for future models, which could prove to be economically inappropriate for marginal profit companies. The PCR model in Figure 6.3 captures the mean, the volatility the trend direction and provides an appropriate

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

model for future predictions. The NN model in Figure 6.4 shows much volatility than the observed pattern even though the trend cycle and direction are captured in this model.

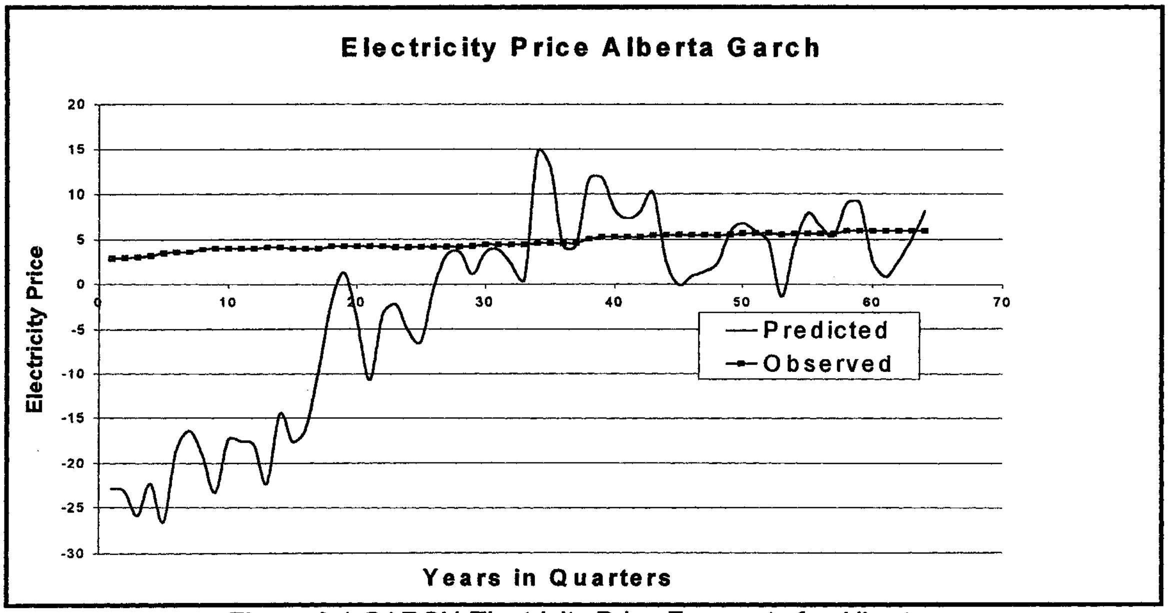

Figure 6.1 GARCH Electricity Price Forecasts for Alberta

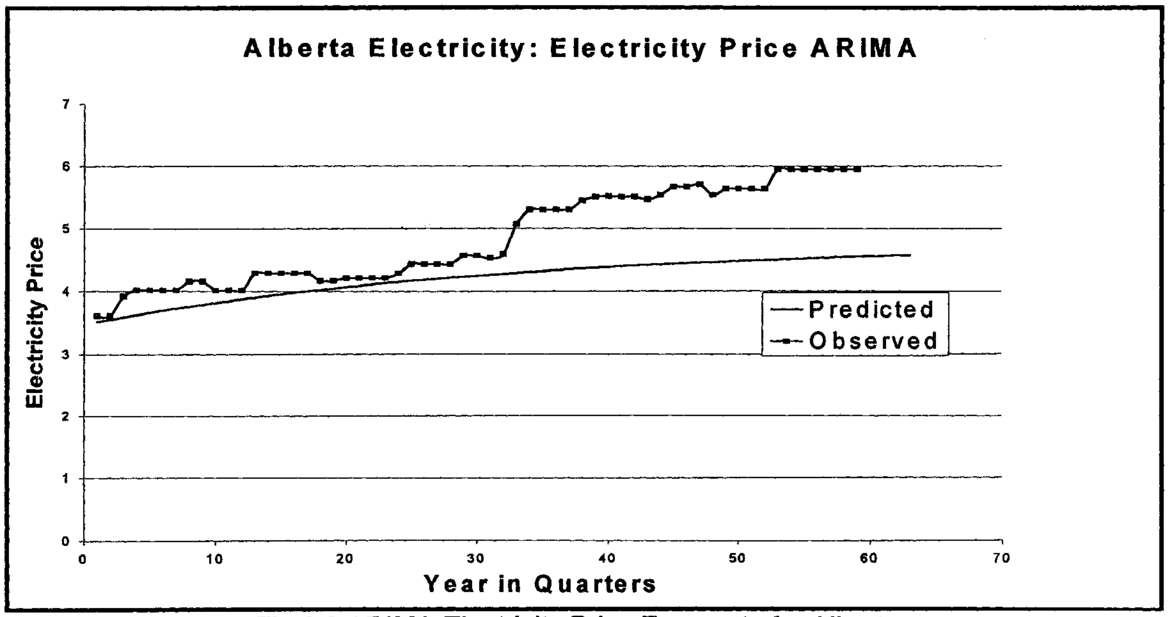

Fig 6.2 ARIMA Electricity Price Forecasts for Alberta

There is a general increase electricity price over time. The coefficients of the independent variables in the electricity model that are significant are price of natural gas (used to produce electricity), oil price, coal price and westca (number of oil and gas wells drilled). Coal and natural gas are used in the production of electricity, and thus, an increase in their prices

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

increases the price of electricity. The price of electricity in the third quarter, natural gas, oil, and coal price, electricity production, total consumption, population, GDP, personal income, unemployment OPEC quota and number of wells drilled are all elastic. The elasticities at the means shown in Tables B.6 and B.7 represent the changes in the dependent variable following a 1 % change in the independent variables. For example, a 1% change in production of electricity brings about a 1.3 % change negatively in the price of electricity. Population brings about more than 40% decrease and unemployment brings about approximately 33% increase in the price of electricity. A 1 % change in natural gas price brings about a 3.6% increase in electricity price. The coal price, population, and unemployment variables have the biggest change or effect on the price of electricity followed by price of natural gas, total energy consumption, OPEC quota, GDP and personal income.

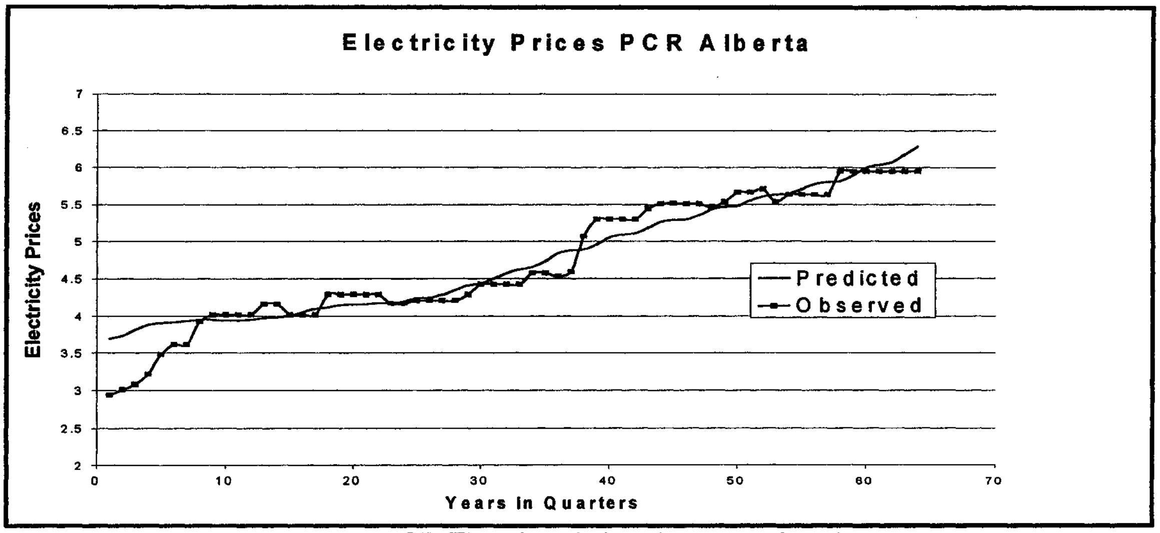

Figure 6.3 PCR Electricity Price Forecasts for Alberta

6.1.2 Coal Pricing Model Results for Alberta

Coal price is in $/kilotonnes for Alberta and Canada. Figures 6.5, 6.6, 6.7 and 6.8 show the coal price forecasts using GARCH, ARIMA, PCR and NN. The GARCH model in Figure 6.5 captures the mean, volatility, trend cycle and direction in the observed coal prices and may be a suitable model for predicting future coal prices in Alberta. The ARIMA model in Figure 6.6 captures a stationary mean without the volatility and the trend characteristics of the observed coal prices. This model presents only a simplistic explanation to the behavior of coal prices and may not be helpful for predicting future prices. The PCR model in Figure 6.7 also captures a stationary mean without the volatility and the trend characteristics of the observed coal prices and has the same weakness associated with the ARIMA model. The NN model in Figure 6.8 captures the mean, volatility, trend cycle and direction in the

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

observed coal prices and may be a suitable model for predicting future coal prices in Alberta. However, it under-predicts the coal price for the period below the 15th quarter. The NN coal price model has 10 hidden layers that give the best results.

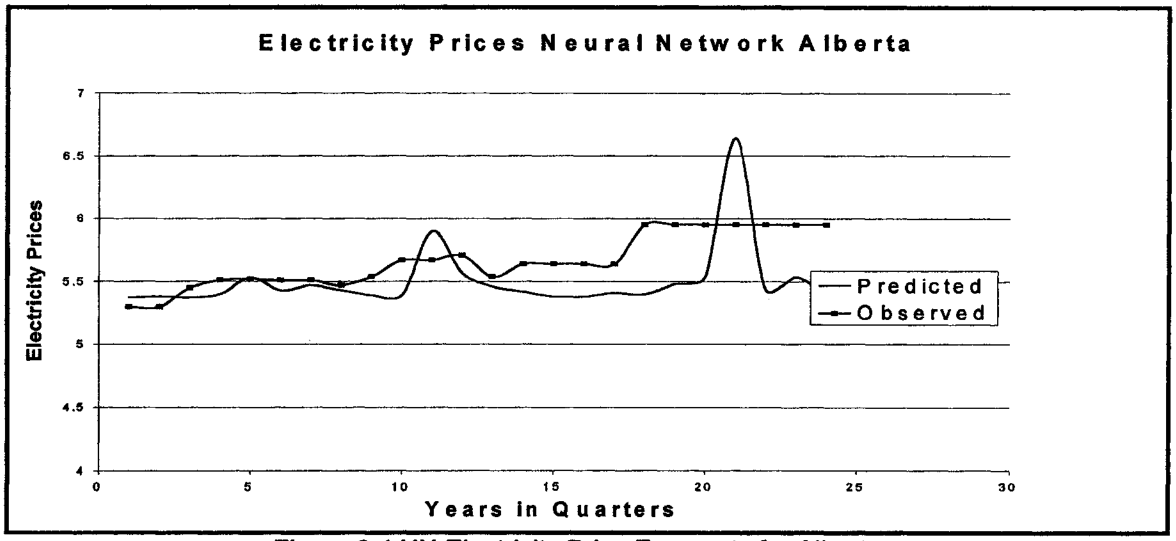

Figure 6.4 NN Electricity Price Forecasts for Alberta

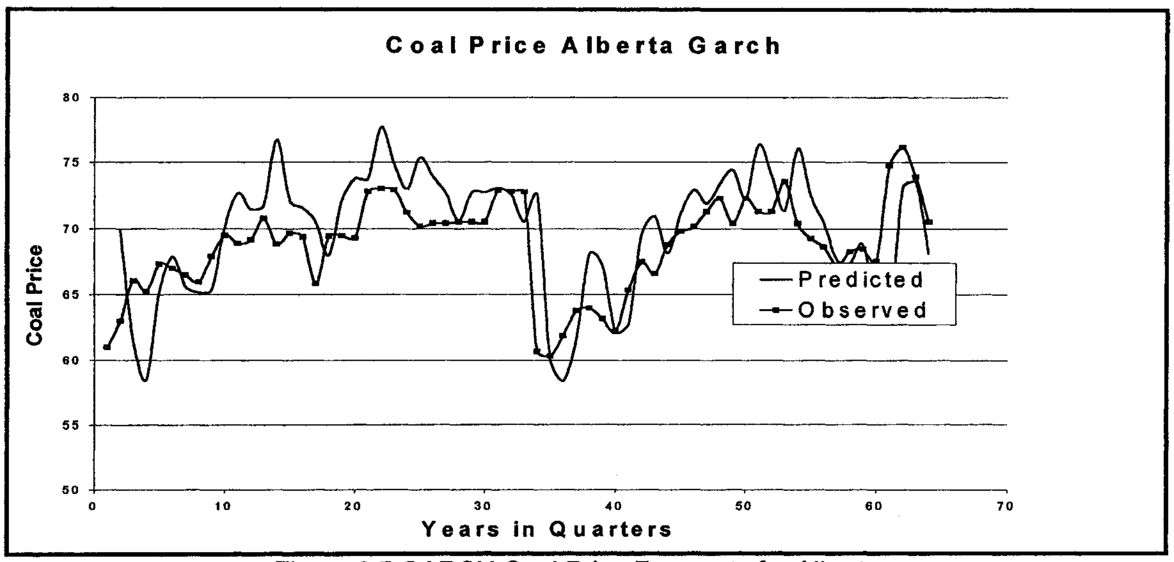

Figure 6.5 GARCH Coal Price Forecasts for Alberta

The independent variables that significantly increase the price of coal are the first lag in coal prices and total energy consumption. The independent variables that decrease the price of coal are GDP and OPEC quota. The price of electricity generation does not affect coal prices because the price of electricity is determined by EPCOR, a monopoly. The only parameter that is elastic is the first lag of the price of coal. An increase in consumption of energy and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

the coal price of first lag brought about an increase in the coal price. OPEC quota and GDP brought about a decrease in the price of coal. Population is correlated with technological change. Therefore, increases in population (advancement in technology and the passage of time) have resulted in shifts away from the use of coal. This decreased demand in coal decreases the price of the commodity. While increases in total energy consumption brought about an increase in the price of coal.

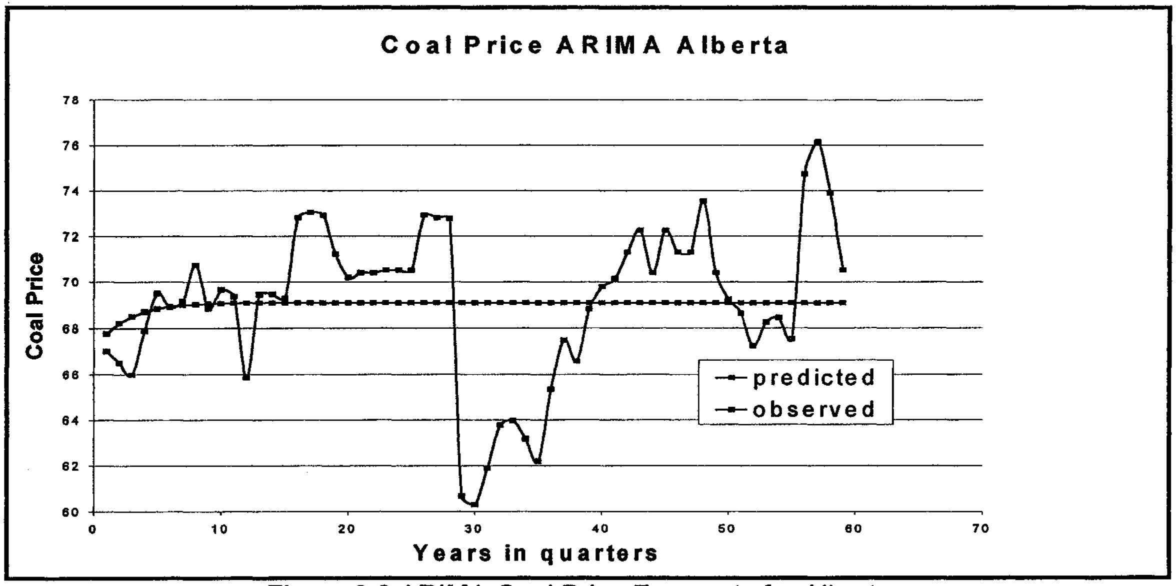

Figure 6.6 ARIMA Coal Price Forecasts for Alberta

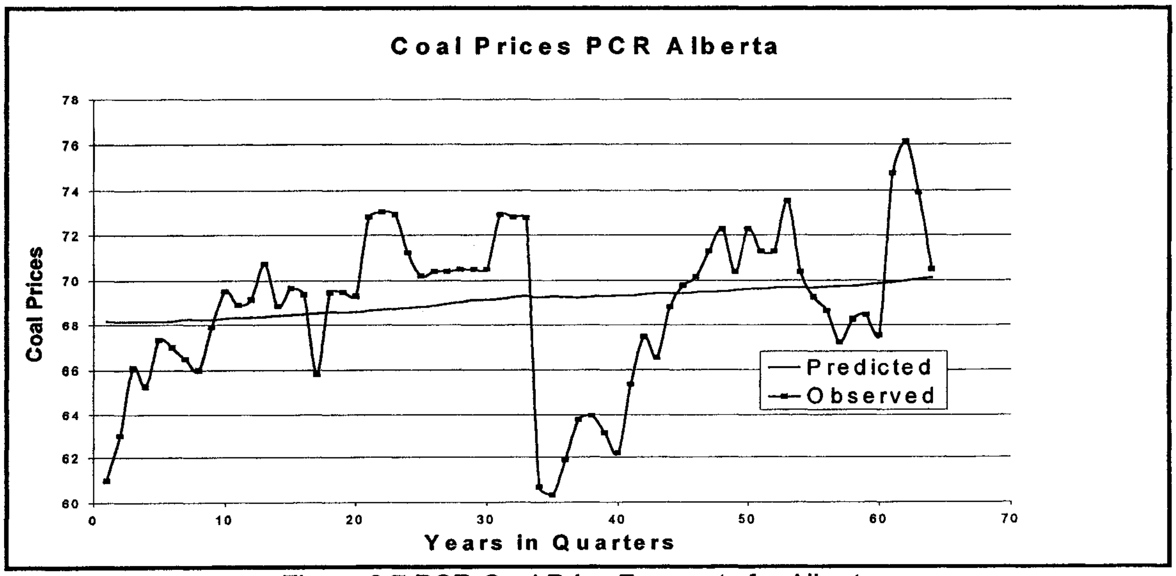

Figure 6.7 PCR Coal Price Forecasts for Alberta

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The length of a single cycle is generally longer than one year. The cyclic pattern is often difficult to predict because it does not lend itself to repetition at constant intervals of time and its duration is not uniform. The cyclical factors represent the ups and downs caused by economic or industry specific conditions like GDP, product production, demand and interest rates. Historically, coal price fluctuations in have tracked the changes in corresponding Middle Atlantic sector coal prices in both direction and magnitude. Canada is a small portion of the total Middle Atlantic coal use.

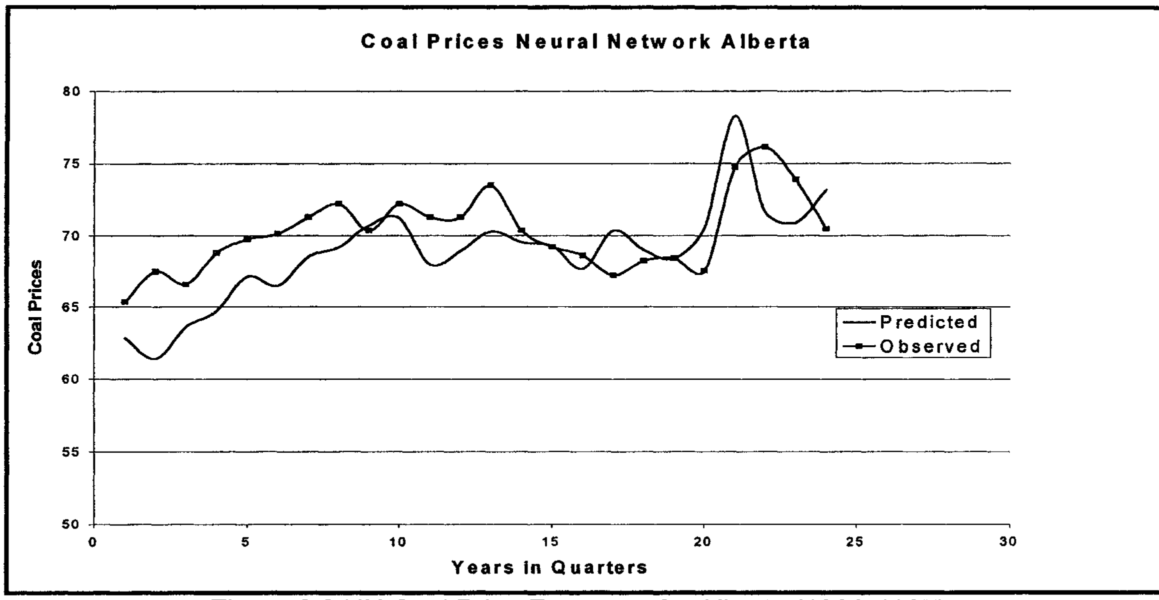

Figure 6.8 NN Coal Price Forecasts for Alberta (1990-1997)

6.1.3 Crude Oil Pricing Model Results for Alberta

Crude oil is in $/barrel for Alberta and Canada. Figures 6.9, 6.10, and 6.11 show the crude oil price forecasts using ARIMA, PCR and NN. The GARCH model for crude oil did not give good results. The ARIMA model in Figure 6.9 captures a stationary mean without the volatility and the trend characteristics of the observed crude oil prices. This model presents only a simplistic explanation of the behavior of crude oil prices and may not be helpful for predicting future prices. The PCR model in Figure 6.10 captures the mean, a damped volatility, trend cycle and direction in the observed crude oil prices and may be a suitable model for predicting future coal prices in Alberta. The damped volatility underestimates high crude prices and overestimates low crude prices but overall the effects may be negligible. The NN model in Figure 6.11 captures the mean, volatility, trend cycle and direction in the observed crude prices and may be a suitable model for predicting future crude oil prices in Alberta. The NN oil price model also has 10 hidden layers that give the best results.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The variables that affect the price of crude oil negatively include the 4th quarter oil price, oil production, population, and GDP. However, the 2nd quarter crude oil price, the price of natural gas, personal income, unemployment, and the number of degree days affect the price of oil positively. The parameters that are elastic are oil production, population and unemployment, number of wells drilled, number of degree days, electricity price, coal price changes, natural gas price and changes in of OPEC quota. A 1 % increase in oil production brings about a 3% decrease in the price of oil and a decrease in oil price of about 17.5% is brought about by a 1% increase in population. Unemployment increase by 1% increases oil price by 19%. There is a closely matched New York and Middle Atlantic prices have been over the period the 1970-1999 period (Anon, 2002c).

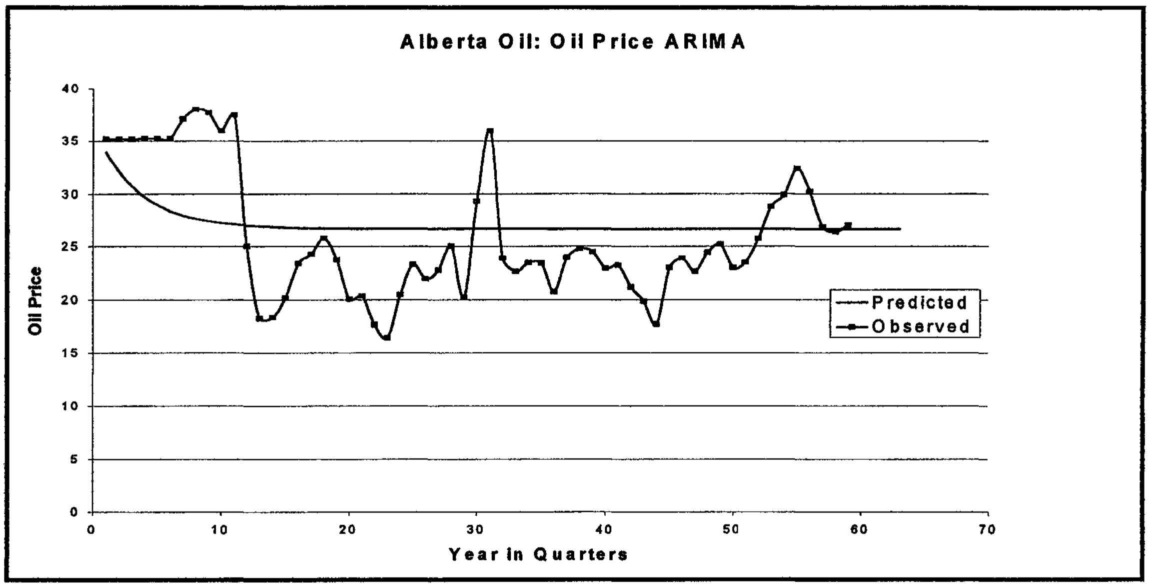

Figure 6.9 ARIMA Crude Oil Price Forecasts for Alberta

6.1.4 Natural Gas Pricing Model Results for Alberta

Natural Gas price is in ¢/m^3 for Alberta and Canada. Figures 6.12, 6.13, 6.14 and 6.15 show the natural gas price forecasts using GARCH, ARIMA, PCR and NN. The GARCH model in Figure 6.12 displays complete departure below the 20th quarter and between the 30th and 40th quarters, but otherwise it captures the mean, volatility, trend cycle and direction in the observed natural gas prices for Alberta in the remaining quarters. The ARIMA model in Figure 6.13 captures a stationary mean without the volatility and the trend characteristics of the observed natural gas prices. This model presents only a simplistic explanation to the behavior of coal prices and may not be helpful for predicting future prices. The PCR model in Figure 6.14 also captures a stationary mean, a damped volatility and the trend

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

characteristics of the observed natural gas prices. This model may be used to predict future natural gas prices in Alberta with a high degree of confidence. The NN model in Figure 6.8 captures the mean, volatility, trend cycle and direction in the observed coal prices and may be a suitable model for predicting future natural gas prices in Alberta. The NN natural gas price model also has 10 hidden layers that give the best results.

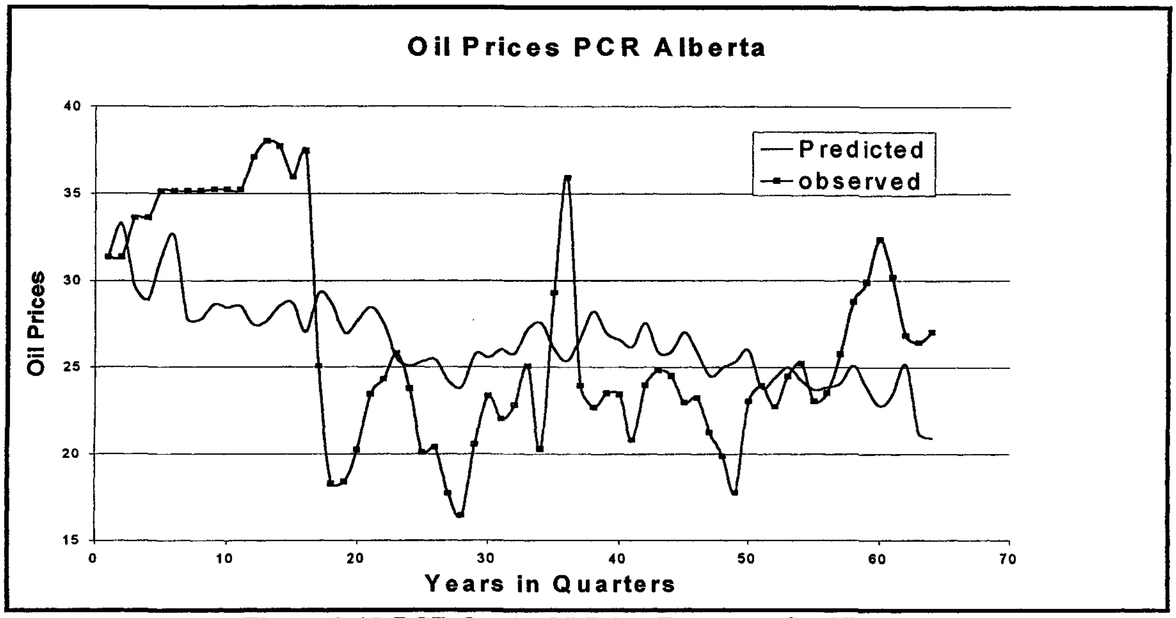

Figure 6.10 PCR Crude Oil Price Forecasts for Alberta

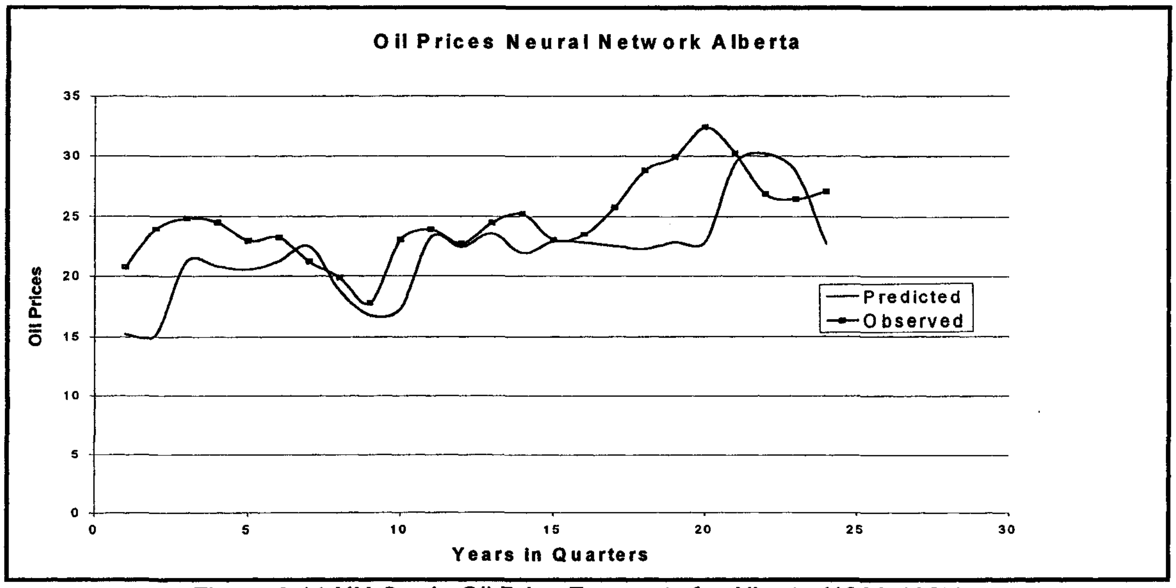

Figure 6.11 NN Crude Oil Price Forecasts for Alberta (1990-1997)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The GDP, total energy consumption, natural gas price in the 3rd quarter, and coal price are the only independent variables that affect the price of natural gas significantly and positively. The fourth quarter lags in the price of natural gas, oil price, natural gas production, personal income and OPEC quota affect the natural gas price significantly and negatively. Both oil and gas are usually found simultaneously and can be termed as complementary substitutes. An increase in natural gas production, personal income and the OPEC quota produces a decrease in the price of natural gas. The only elastic parameters are the 3rd and 4th quarter lags, oil price, coal price, electricity price, natural gas production, total energy consumption, population, GDP, personal income, unemployment and OPEC quota. These variables are positive except for the 4th quarter lag, crude oil price, natural gas production, personal income, unemployment and OPEC quota. As the population increases, the housing needs will increase and there will be a need for electricity and heating devices.

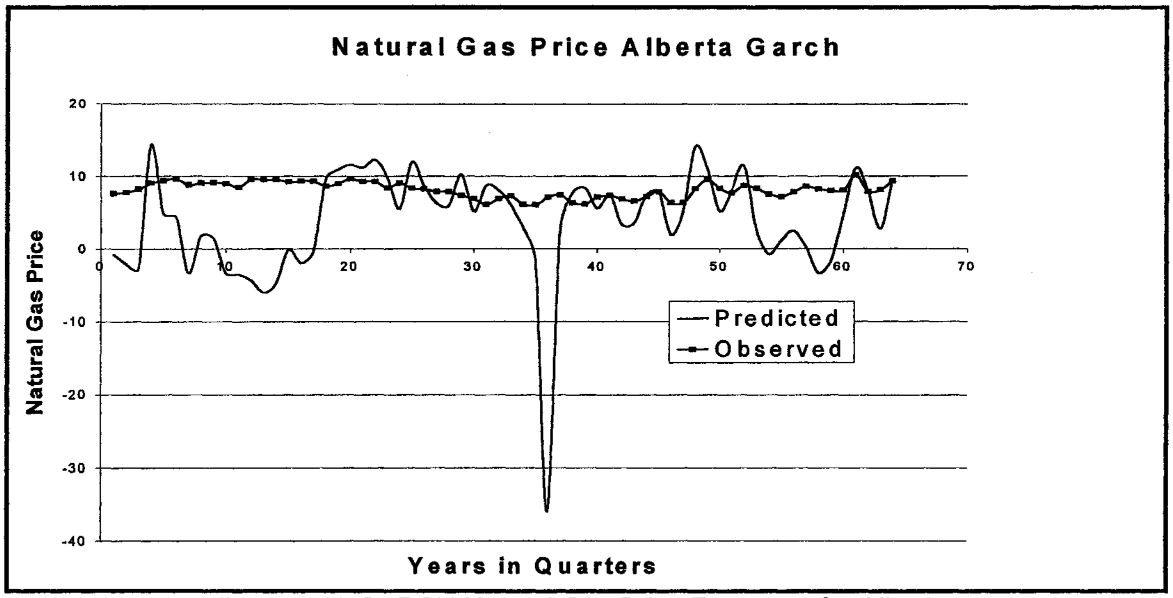

Figure 6.12 GARCH Natural Gas Price Forecasts for Alberta

6.1.5 Total Energy Consumption Model Results

Total Energy Consumption is in petajoules for Alberta and Canada. Figures 6.16, 6.17, 6.18 and 6.19 show the total energy consumption forecasts using GARCH, ARIMA, PCR and NN. The GARCH model in Figure 6.16 displays complete departure below the 20th quarter, but it captures fairly well the mean, volatility, trend cycle and direction in the observed total energy consumption for Alberta in the remaining quarters. The ARIMA model in Figure 6.17 captures a stationary mean without the volatility and the trend characteristics of the observed total energy consumption. This model presents only a simplistic explanation and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

undervalues the total energy consumption of the total energy consumption. The PCR model in Figure 6.18 captures the mean, volatility and the trend characteristics of the observed total energy consumption. This model is appropriate for predicting the future total energy consumption in Alberta with a high degree of confidence. The NN model in Figure 6.19 also captures the mean, volatility, trend cycle and direction in the observed energy consumption and may be a suitable model for predicting future energy consumption in Alberta. The NN total energy consumption forecast model uses two hidden layers.

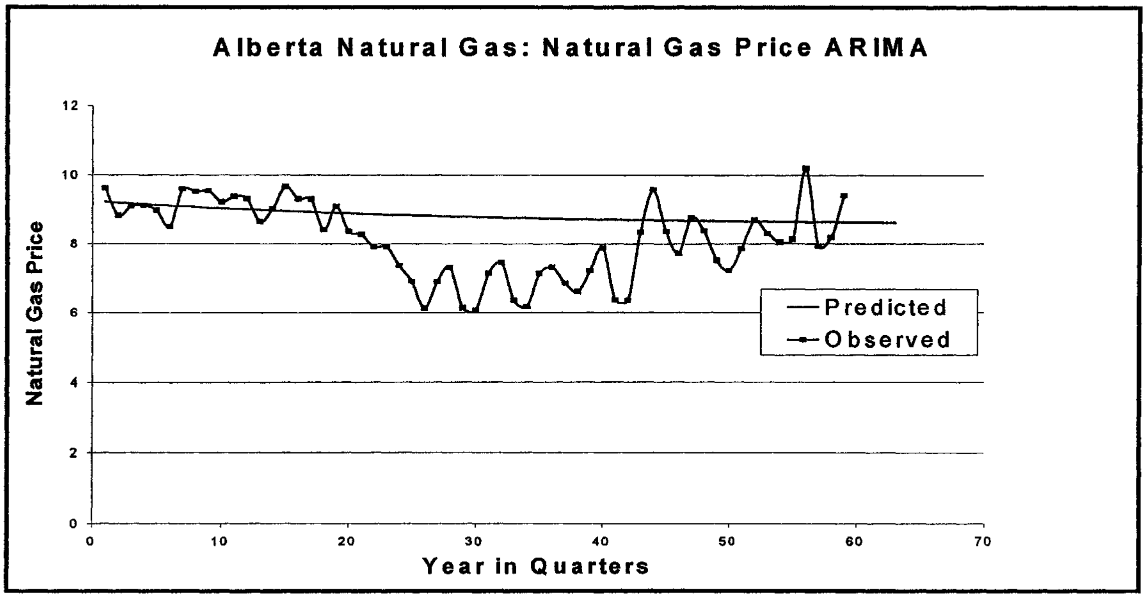

Figure 6.13 ARIMA Natural Gas Price Forecasts for Alberta

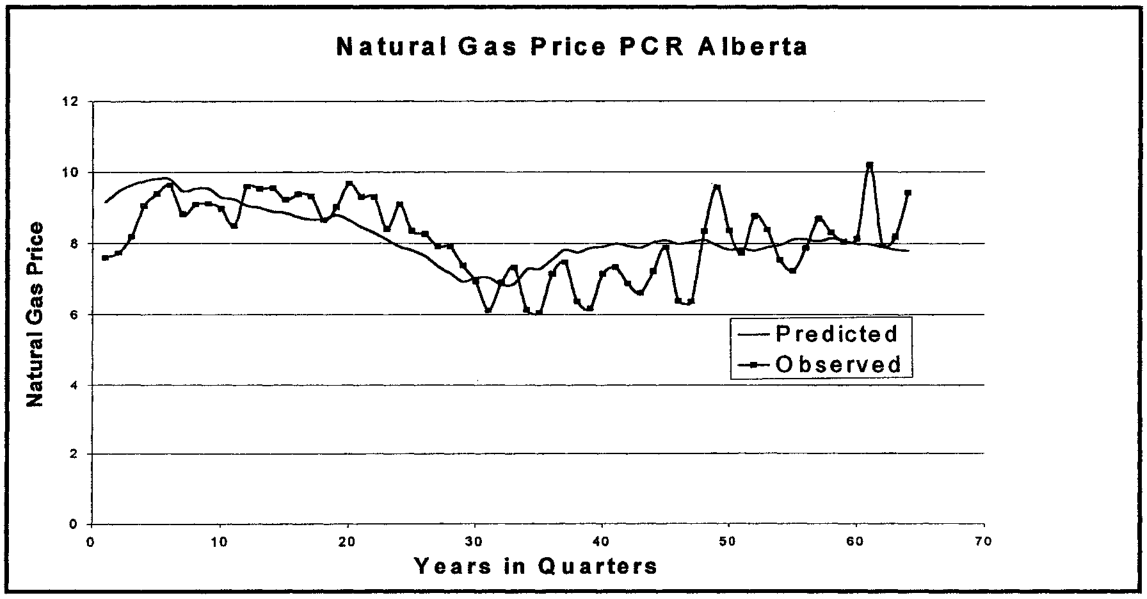

Figure 6.14 PCR Natural Gas Price Forecasts for Alberta

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The parameters that are significant in this model include the 1st lags of the dependent variables, oil and coal price variations, electricity production, GDP, and personal income. The 1st quarter lag, coal price and personal income negatively affect energy consumption, while oil price, electricity production, and GDP positively affect energy consumption. An increase in total energy consumption in the 1st quarter and coal price, and personal income decreases total energy consumption. An increase in price of oil, electricity production, and GDP increases total energy consumption. The elastic variables are population and personal income. An increase of 1 % in population, and personal income results in a 1.9 % increase, and 1.07 % decrease in energy consumption respectively.

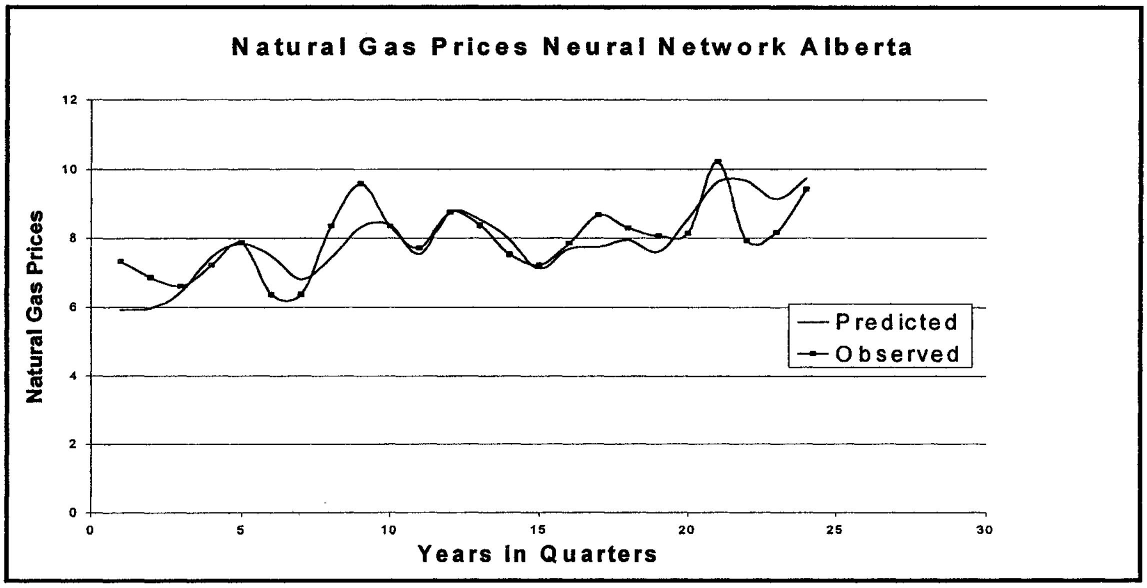

Figure 6.15 NN Natural Gas Price Forecasts for Alberta (1990-1997)

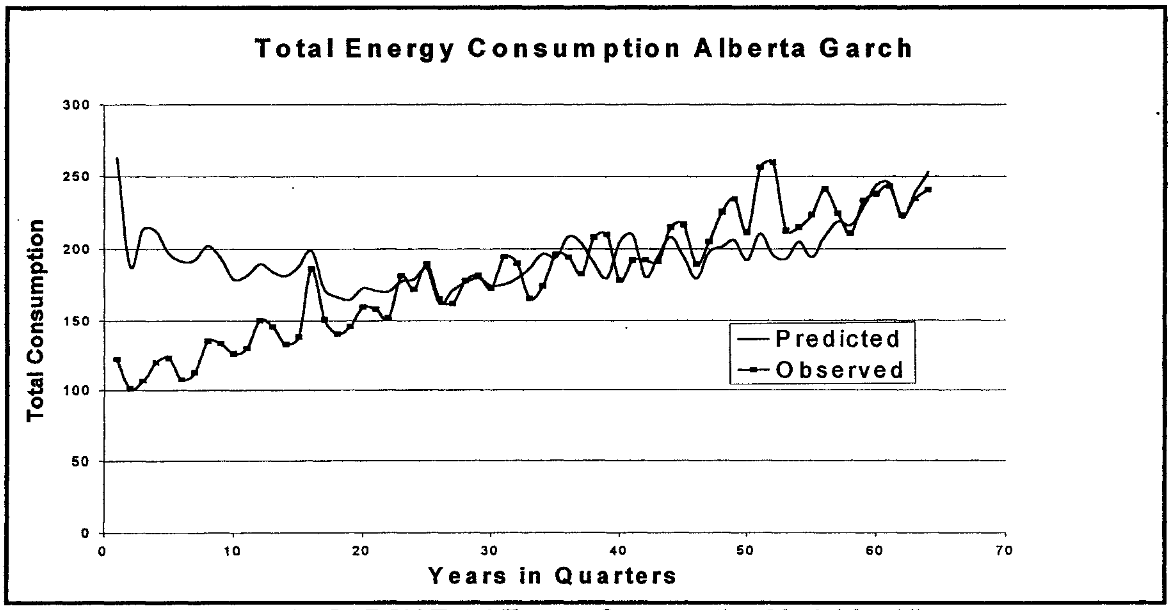

Figure 6.16 GARCH Total Energy Consumption Model for Alberta

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

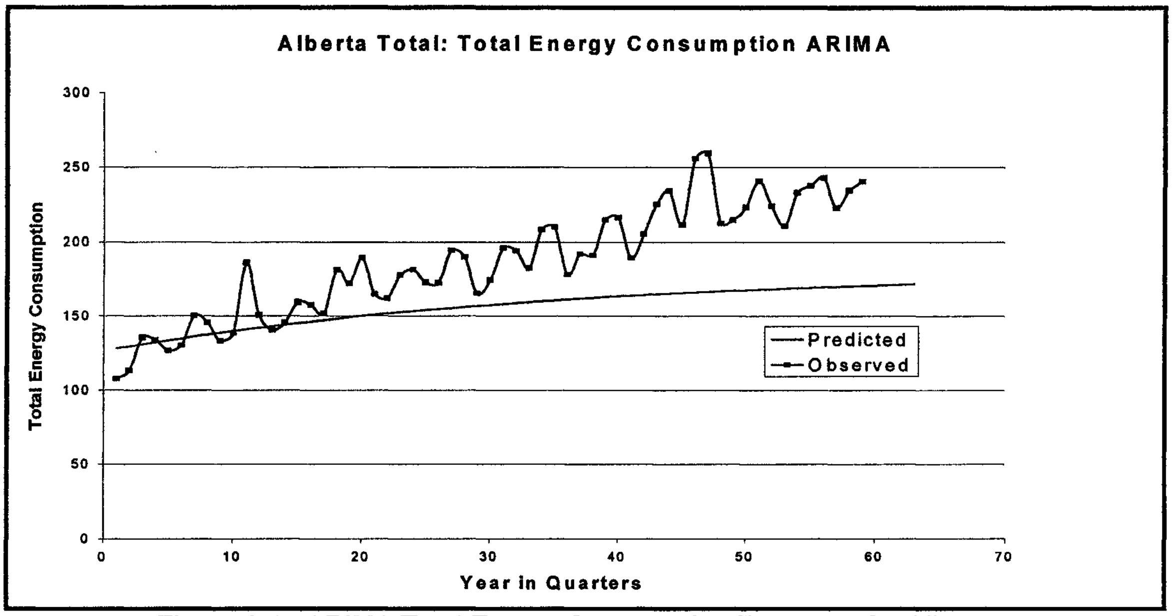

Figure 6.17 ARIMA Total Energy Consumption Forecasts for Alberta

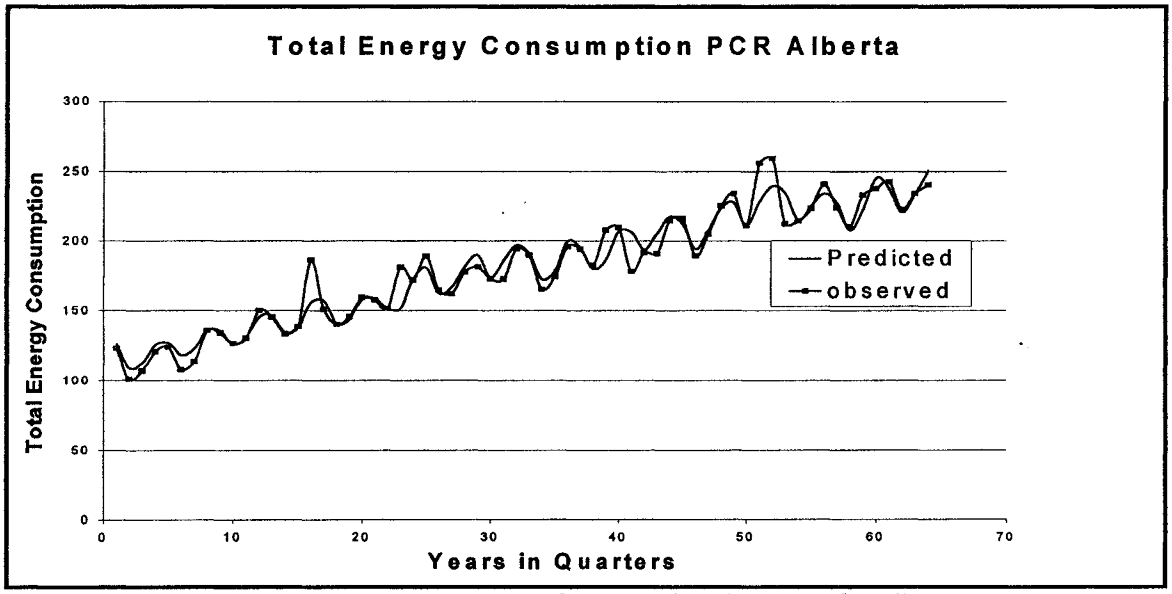

Figure 6.18 PCR Total Energy Consumption Forecasts for Alberta

6.2 Energy Pricing Model for Canada

Canadian energy price models focus on the variations in energy prices within the Canadian economy. Canada's energy sources, unlike Alberta, comes from other sources including hydro and nuclear power sources, even though attention is given to the fossil fuel

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

components of the energy spectrum. Canada has enjoyed expanded economy within the last decade, and thus, the demand for energy for both residential and commercial purposes has increased significantly.

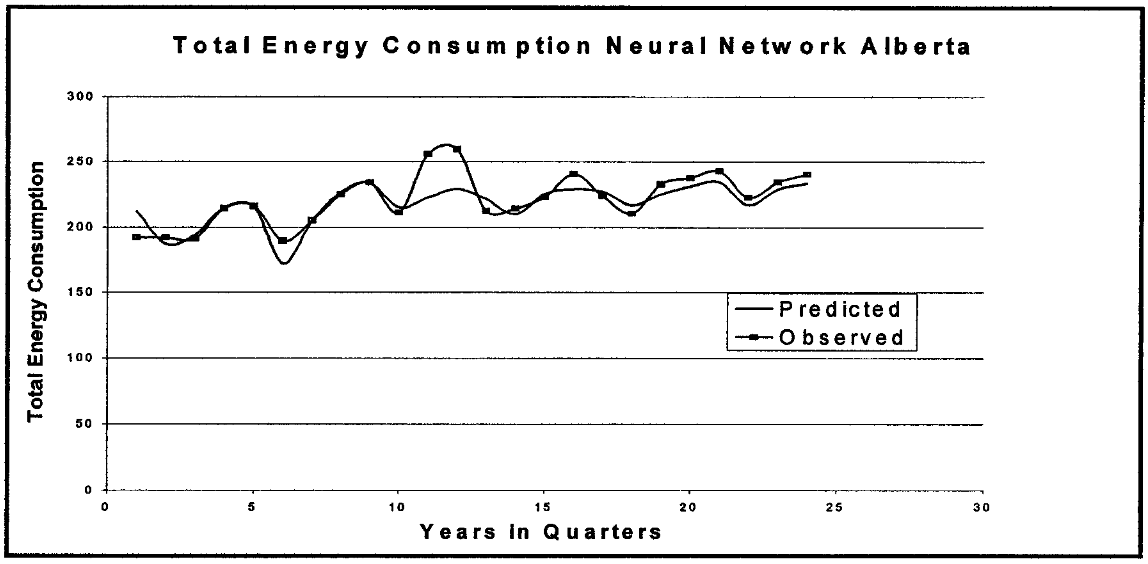

Figure 6.19 NN Total Energy Consumption Forecasts for Alberta (1990-1997)

6.2.1 Electricity Pricing Model Results for Canada

Figures 6.20, 6.21, 6.22 and 6.23 show the electricity price forecasts using GARCH, ARIMA, PCR and NN. The GARCH model in Figure 6.20 shows complete departure below the 30th quarter and an unacceptable prediction model for electricity prices. The ARIMA model in Figure 6.21 under-predicts the observed electricity prices and may provide severely pessimistic prices for future models, which are economically inappropriate for marginal profit companies. The PCR model in Figure 6.22 captures the mean, the volatility and the trend direction and provides an appropriate model for future predictions.

The NN model in Figure 6.23 shows severe departure from the observed pattern and may be unsuitable for Canadian electricity price forecasting. The lags in electricity prices are not significant. Electricity prices are affected positively by the price of oil, GDP, unemployment, and OPEC quota and negatively by coal prices and population. The 1st quarter lags in the price of electricity, natural gas prices, oil prices, coal prices, electricity production, total energy consumption, population, GDP, personal income, unemployment, number of degree days and OPEC quota are elastic in this model. An increase of 1 % in population and unemployment brings about 400% decrease and 360% increase in the price of electricity respectively.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

6.2.2 Coal Pricing Model Results for Canada

Figures 6.24, 6.25 and 6.26 show the coal price forecasts using ARIMA, PCR and NN. The GARCH model for coal did not give good results and so is not included in these results. The ARIMA model in Figure 6.24 captures a stationary mean without the volatility and the trend characteristics of the observed coal prices. This model presents only a simplistic explanation to the behavior of coal prices and may not be helpful for predicting future prices. The PCR model in Figure 6.25 also captures a stationary mean without the volatility and the trend characteristics of the observed coal prices and has the same weakness associated with the ARIMA model. The NN model in Figure 6.26 captures the mean, volatility, trend cycle and direction in the observed coal prices and may be a suitable model for predicting future coal prices in Alberta. However, it under-predicts the coal price for the period below the 5th quarter.

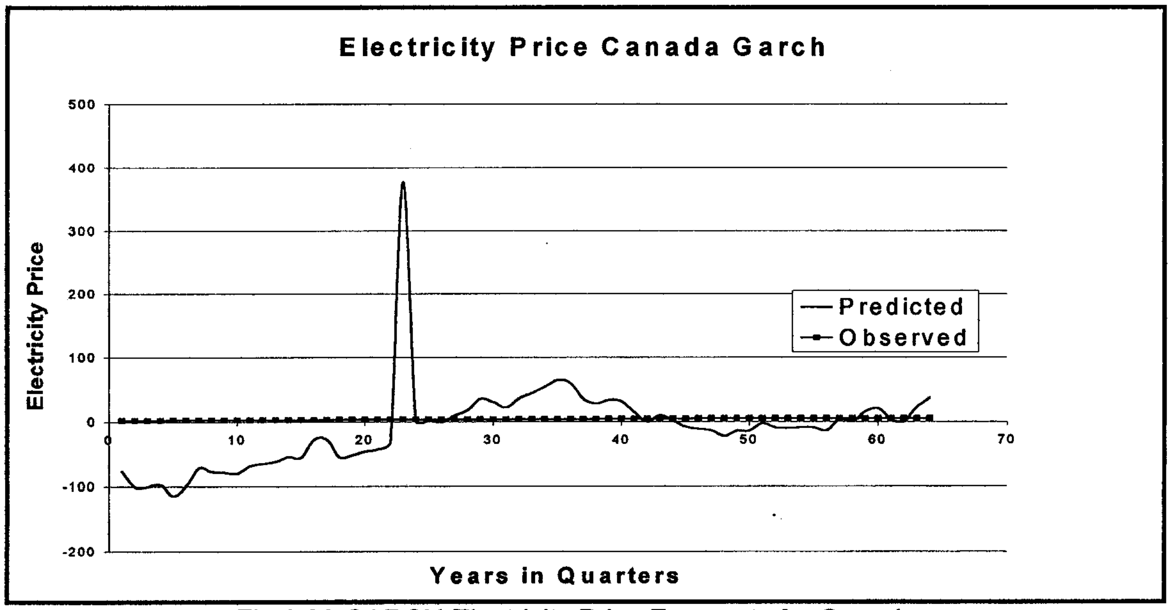

Fig 6.20 GARCH Electricity Price Forecasts for Canada

The independent variables that are significant are the 1st quarter lag, crude oil price, total energy consumption and the number of oil and gas wells drilled. The 2nd quarter lag in coal and crude oil prices affects the model positively. As the total energy consumption, and westca (number of oil and gas wells increases), the price of coal decreases. An increase in crude oil price and the 1st quarter lag results in an increase in the coal price. Unemployment is the only variable that is elastic. An increase in unemployment by 1% results in a decrease

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

of 1.52 % in coal price. Unemployment increases will bring about an increase in the use of coal since it is the cheapest source of all the energy products.

6.2.3 Crude Oil Pricing Model Results for Canada

Figures 6.27, 6.28, and 6.29 show the crude oil price forecasts using ARIMA, PCR and NN. The GARCH model for Crude Oil is not included because it did not give good results. The ARIMA model in Figure 6.27 captures a stationary mean without the volatility and the trend characteristics of the observed crude oil prices. This model presents only a simplistic explanation of the behavior of crude oil prices and may not be helpful for predicting future prices. The PCR model in Figure 6.28 captures the mean, a damped volatility, trend cycle and direction in the observed crude oil prices and may be a suitable model for predicting future coal prices in Alberta. The damped volatility underestimates high crude prices and overestimates low crude prices but overall the effects may be negligible. The NN model in Figure 6.29 captures the mean, volatility, trend cycle and direction in the observed coal prices and may be a suitable model for predicting future crude oil prices in Canada. The NN oil price model also has 10 hidden layers that give the best results.

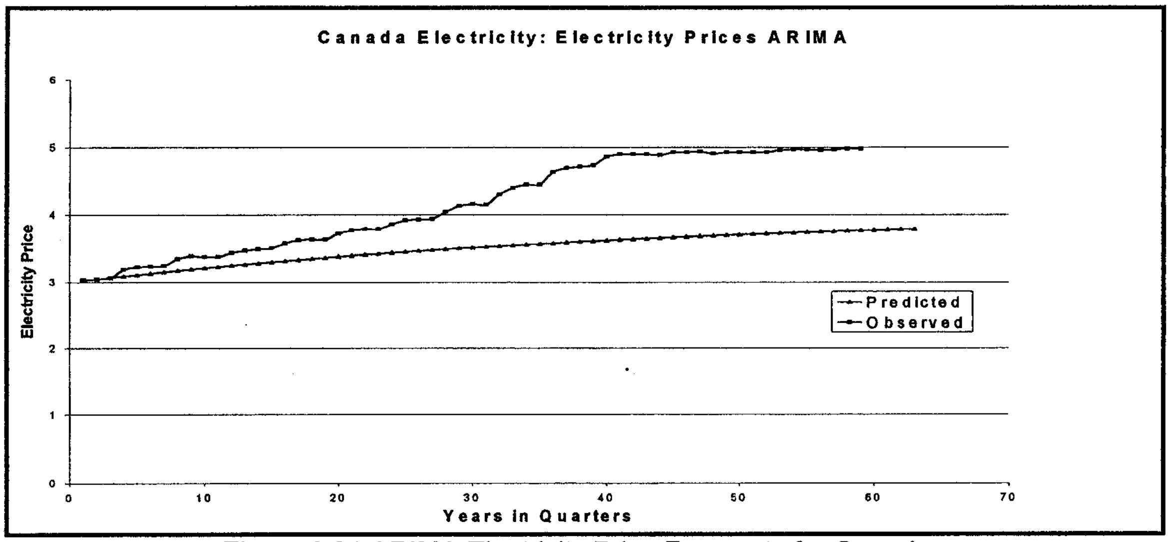

Figure 6.21 ARIMA Electricity Price Forecasts for Canada

The significant variables in this model are the changes in the 1st, 2nd and 3rd quarter lags, natural gas price, total energy consumption, number of degree days, and OPEC quota. An increase in the 1st and 3rd quarter lags and number of degree days results in an increase in crude oil price. An increase in the 2nd quarter lag, natural gas price, total energy consumption and OPEC quota results in a decrease in crude oil price. The elastic variables in this model are total energy consumption, population, personal income, and unemployment. An increase

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

in population results in an increase of 7.6% in crude oil price, while an increase in total energy consumption, personal income and unemployment results in a decrease of 1.62%, 1.88% and 3.43%, respectively in crude oil price.

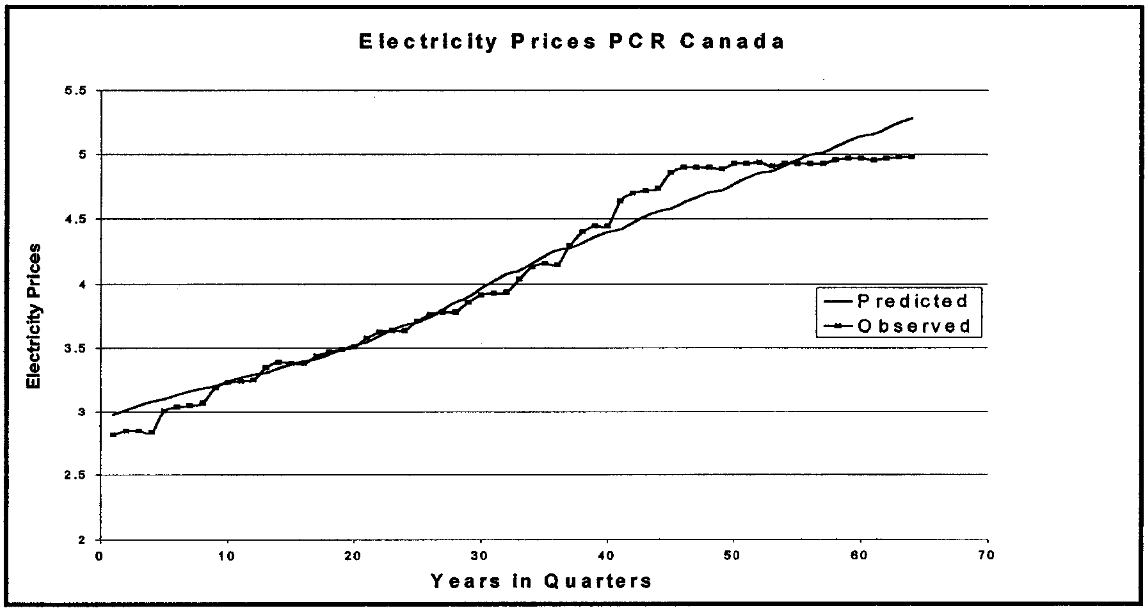

Figure 6.22 PCR Electricity Price Forecasts for Canada

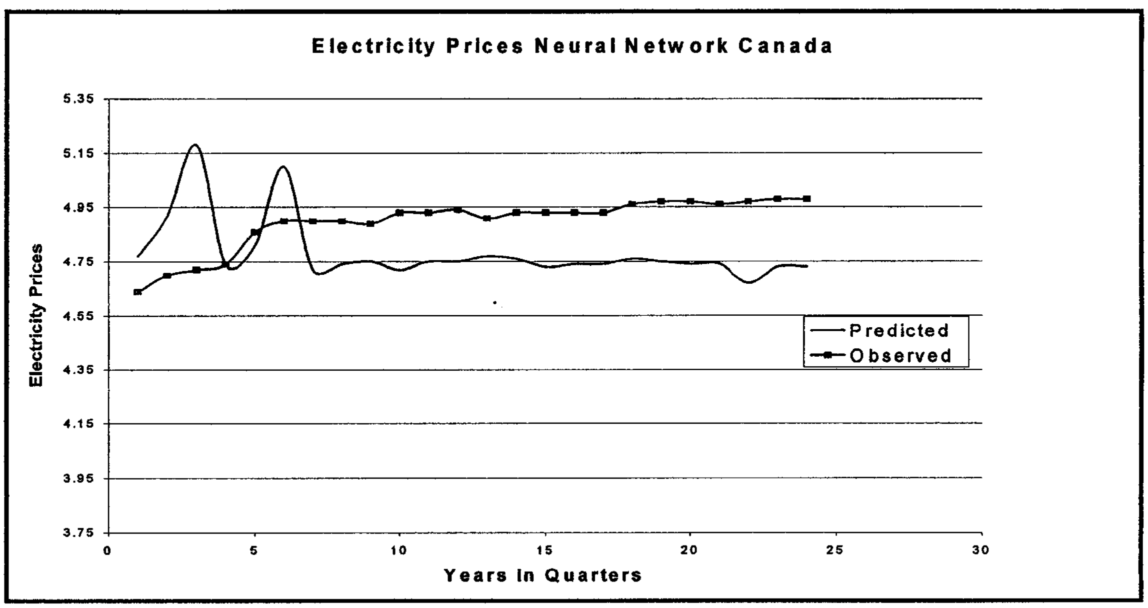

Figure 6.23 NN Electricity Price Forecasts for Canada (1990-1997)

6.2.4 Natural Gas Pricing Model Results for Canada

Natural Gas Price is in cents/m^3. Figures 6.30, 6.31 and 6.32 show the natural gas price forecasts using ARIMA, PCR and NN. The GARCH model for Natural gas Canada was not

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

included because it did not give good results. The ARIMA model in Figure 6.30 captures a stationary mean without the volatility and the trend characteristics of the observed natural gas prices. This model presents only a simplistic explanation to the behavior of natural gas prices and may not be helpful for predicting future prices. The PCR model in Figure 6.31 also captures a stationary mean, a damped volatility and the trend characteristics of the observed natural gas prices. This model may be used to predict future natural gas prices in Canada with a high degree of confidence. The NN model in Figure 6.32 captures the mean, volatility, trend cycle and direction in the observed natural gas prices and may be a suitable model for predicting future gas prices in Canada. The NN natural gas price model also has 5 hidden layers that give the best results.

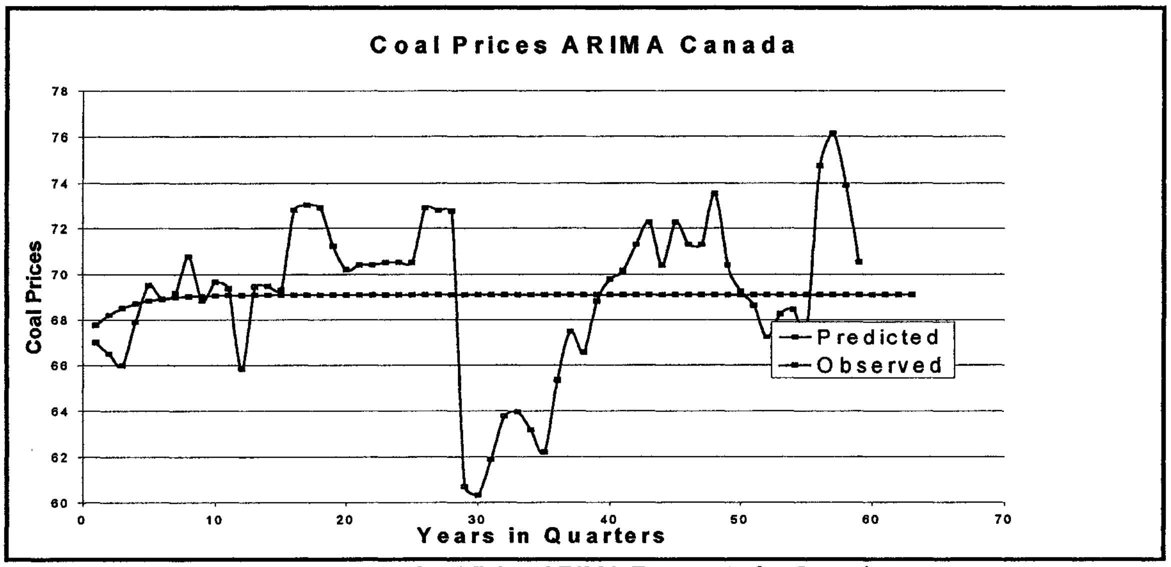

Figure 6.24 Coal Price ARIMA Forecasts for Canada

Population, GDP, personal income, unemployment, number of degree days and total energy production are the significant variables in this model. None of the lags are significant in this model. The crude oil price, coal price, total energy consumption, population, GDP, personal income, unemployment, number of degree days, OPEC quota and the number of oil and gas wells drilled are elastic variables. As population increases, the requirement for housing increases and so does energy consumption. As unemployment increases the use of energy by the unemployed will decrease. A 1 % increase in population and unemployment result a 207 % increase and a 166% decrease in the price of natural gas respectively.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

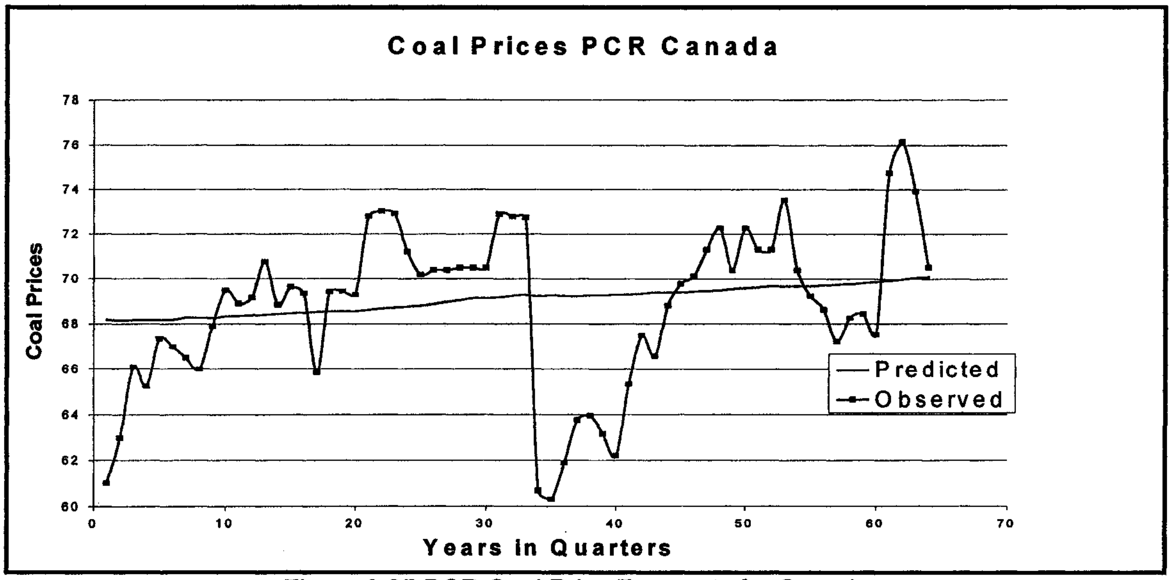

Figure 6.25 PCR Coal Price Forecasts for Canada

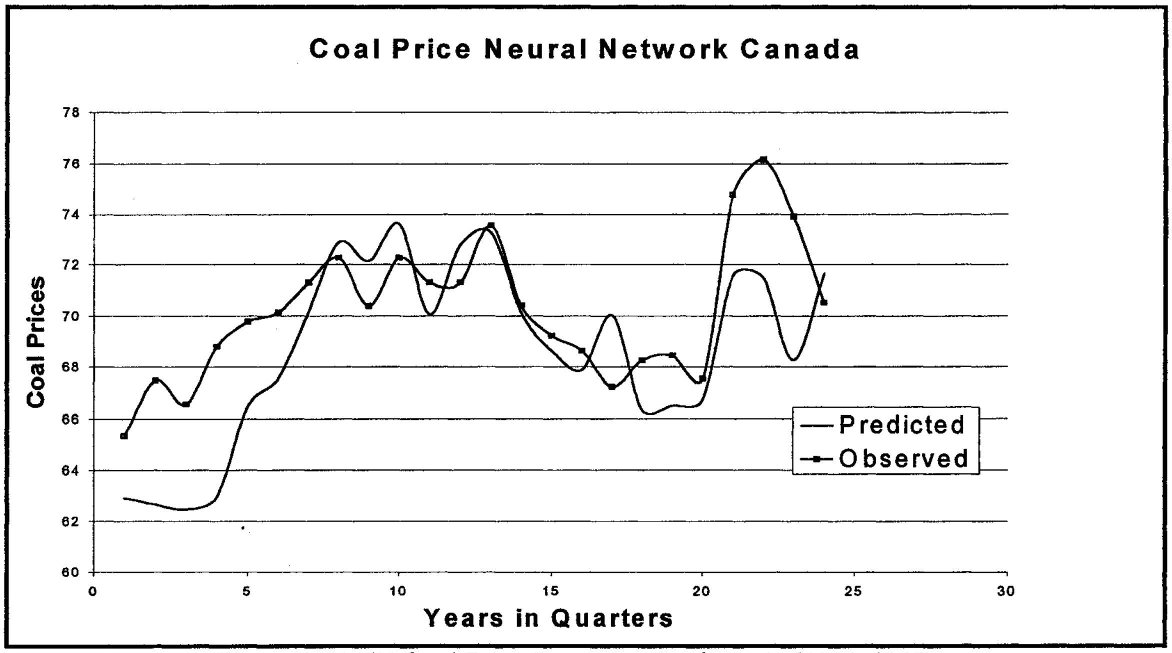

Figure 6.26 NN Coal Price Forecasts for Canada (1990-1997)

6.2.5 Total Energy Consumption Model for Canada

Total Energy Consumption is in Petajoules. Figures 6.33, 6.34, 6.35 and 6.36 show the total energy consumption forecasts using GARCH, ARIMA, PCR and NN. The GARCH model in Figure 6.33 captures fairly well the mean, volatility, trend cycle and direction in the observed total energy consumption for Canada with a complete departure within a small segment between the 20th and 30th quarters. The ARIMA model in Figure 6.34 captures a stationary mean without the volatility and the trend characteristics of the observed total energy

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

consumption. This model presents only a simplistic explanation and undervalues the total energy consumption of the total energy consumption. The PCR model in Figure 6.35 captures the mean, volatility and the trend characteristics of the observed total energy consumption. This model is appropriate for predicting the future total energy consumption in Canada with a high degree of confidence. The NN model in Figure 6.35 also captures the mean, volatility, trend cycle and direction in the observed energy consumption and may be a suitable model for predicting future energy consumption in Canada. The NN total energy consumption forecast model uses five hidden layers.

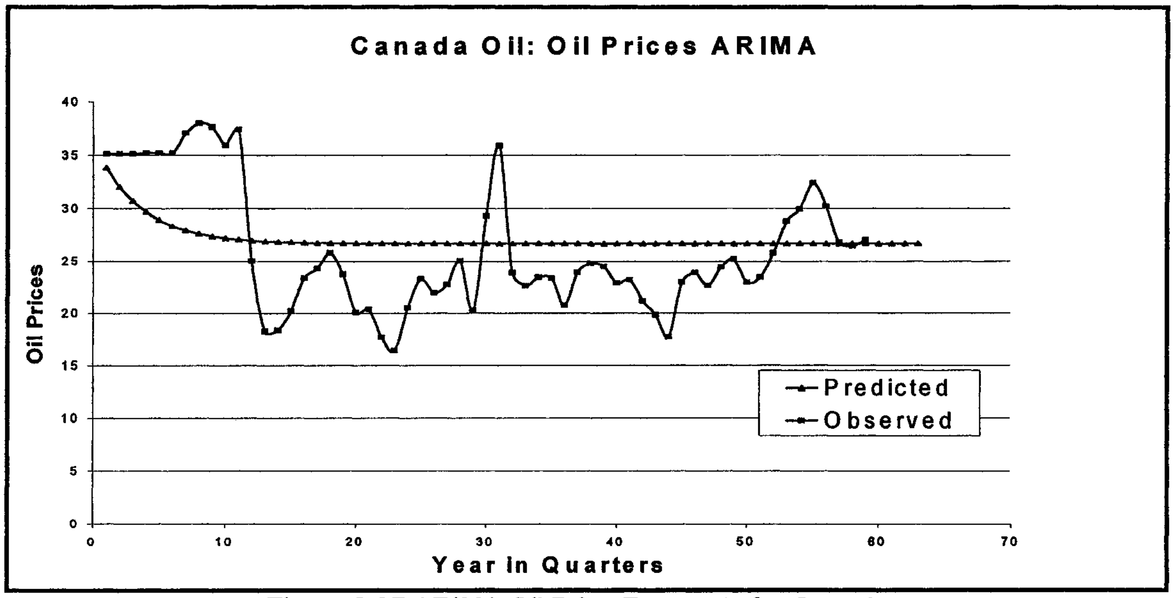

Figure 6.27 ARIMA Oil Price Forecasts for Canada

The 1st, 2nd, 3rd and 4th quarter lags, oil price, coal price, electricity production, population, GDP, unemployment, the number of degree days and the number of oil and gas wells drilled are all significant independent variables of this model. An increase in the 4th quarter consumption lag, price of oil, production of electricity, GDP, and personal income brings about an increase in energy consumption. An increase in the 1st, 2nd and 3rd quarter lags, coal price, population, number of degree days and the number of oil and gas wells drilled results in a decrease in total energy consumption. Population and personal income are the only independent variables that are elastic. A change of 1 % in their values results in a change of 2.1% (negatively) and 1.9% (positively) the total energy consumption, respectively.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

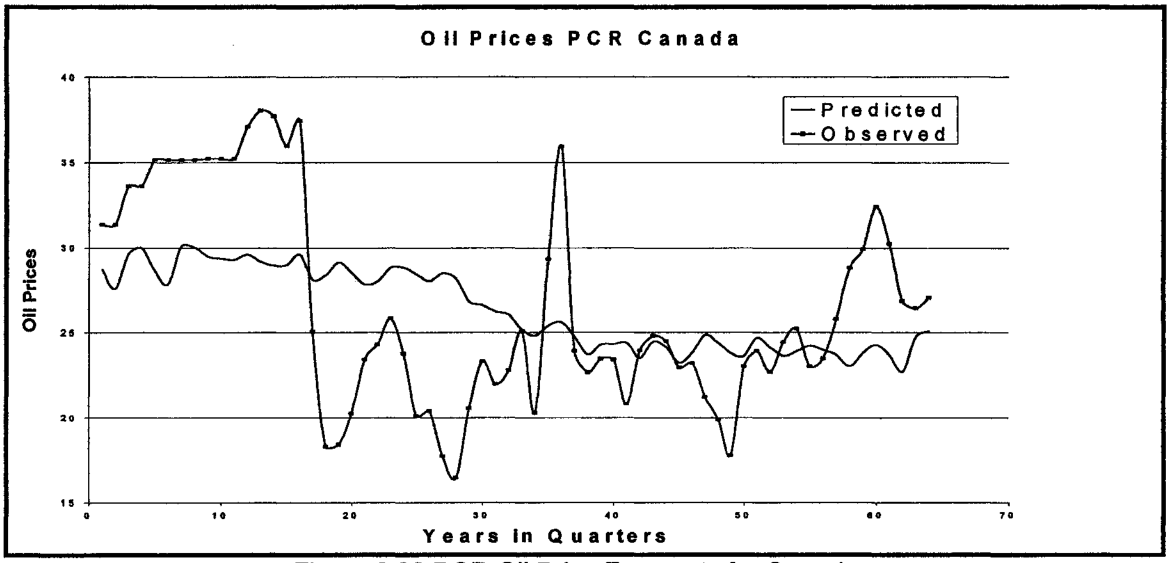

Figure 6.28 PCR Oil Price Forecasts for Canada

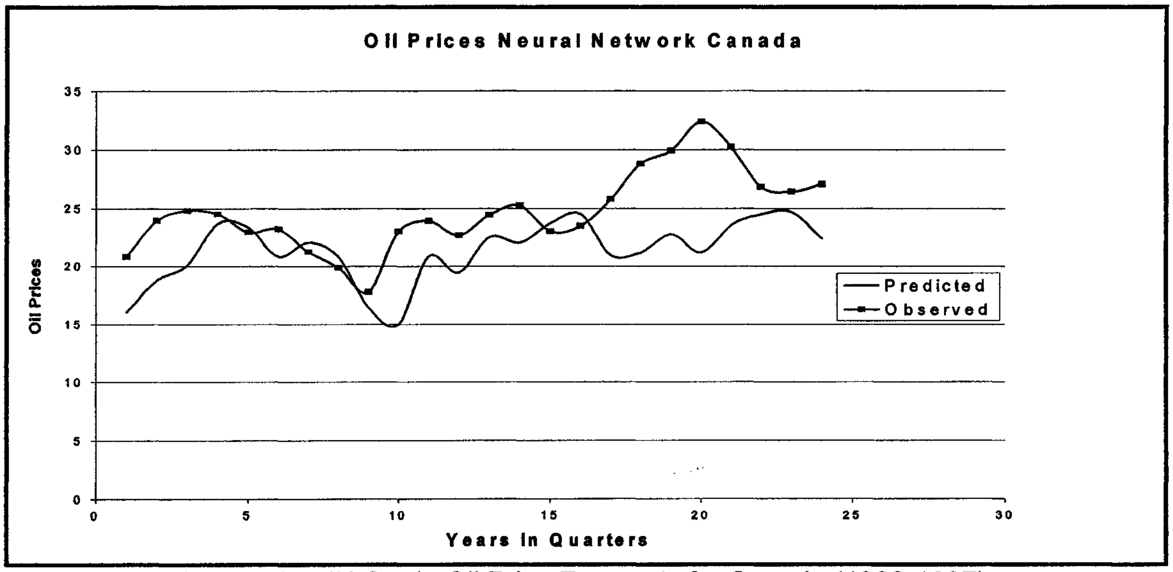

Figure 6.29 NN Crude Oil Price Forecasts for Canada (1990-1997)

6.3 Optimal Energy Price Predictors for Alberta and Canada

Detailed analysis of the energy price model results show that the PCR and NN predictors are suitable for predicting crude oil and natural gas prices and the total energy consumption for both Alberta and Canada, as well as the electricity prices in Alberta. The GARCH and NN predictors are suitable for predicting the coal prices in Alberta. The PCR predictor is suitable for predicting Canada's electricity prices. Finally, the NN is predictor is appropriate for predicting Canada's coal prices. With these predictors, analysts can model, simulate and analyze the energy prices and energy consumption levels for guiding government and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

company policies and for ensuring optimal investment decisions and performance of energy companies.

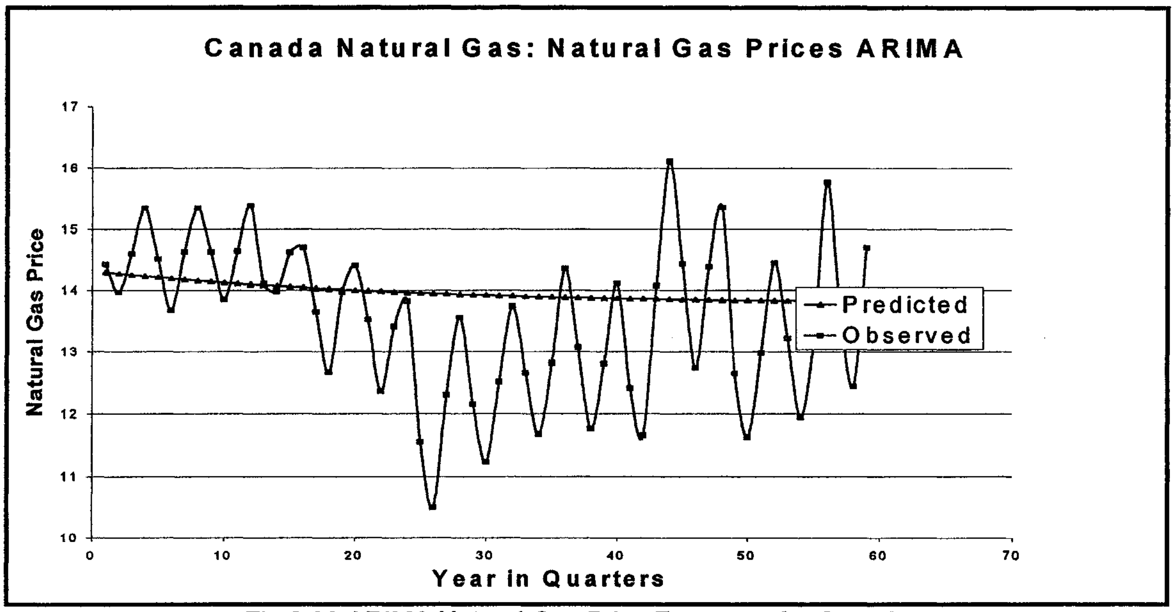

Fig 6.30 ARIMA Natural Gas Price Forecasts for Canada

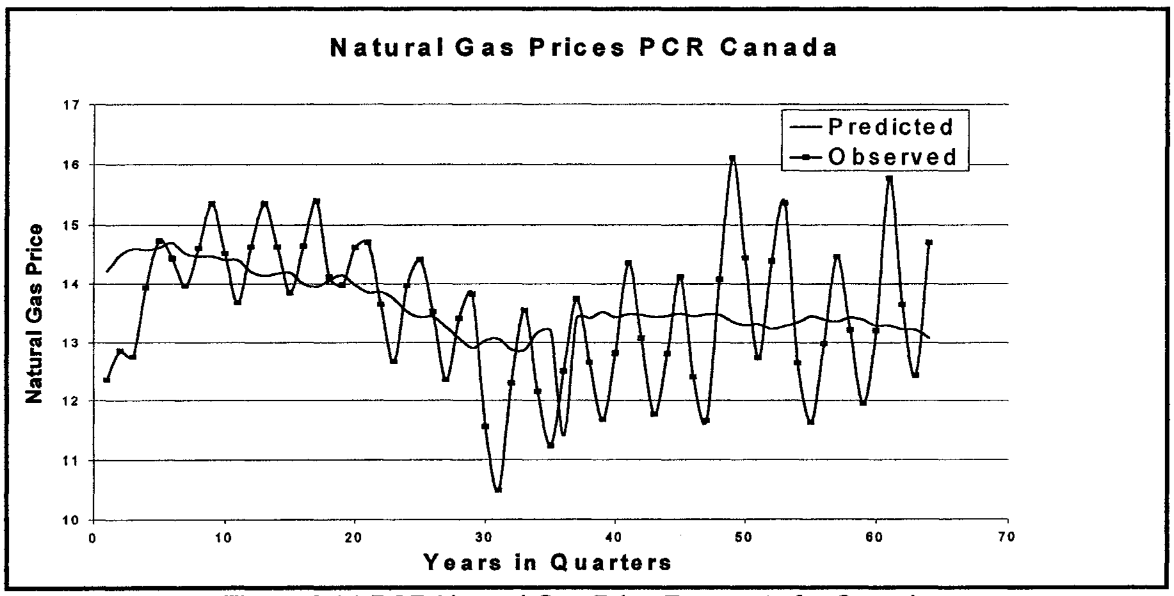

Figure 6.31 PCR Natural Gas Price Forecasts for Canada

6.4 Stochastic Characterization of Energy Price Volatility

Energy prices are volatile, and this volatility affects provincial and federal government and the energy businesses budgetary policies. In order to capture these energy price and total consumption volatilities, the random projections around the expected values of the models

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

were modeled and analyzed using the Monte Carlo simulation technique [Palisade, 2000]. The data sources included Canadian Socio-economic Information Management System (CANSIM), Alberta Energy Library, Energy Utilities Board (EUB), Energy Prices and Taxes periodical, Annual Oil Market Report and OPEC bulletin with the period between 1982 and 1997. Figures 6.37 and 6.38 illustrate the cumulative probabilities associated with the respective Alberta and Canadian energy prices and total energy consumption.

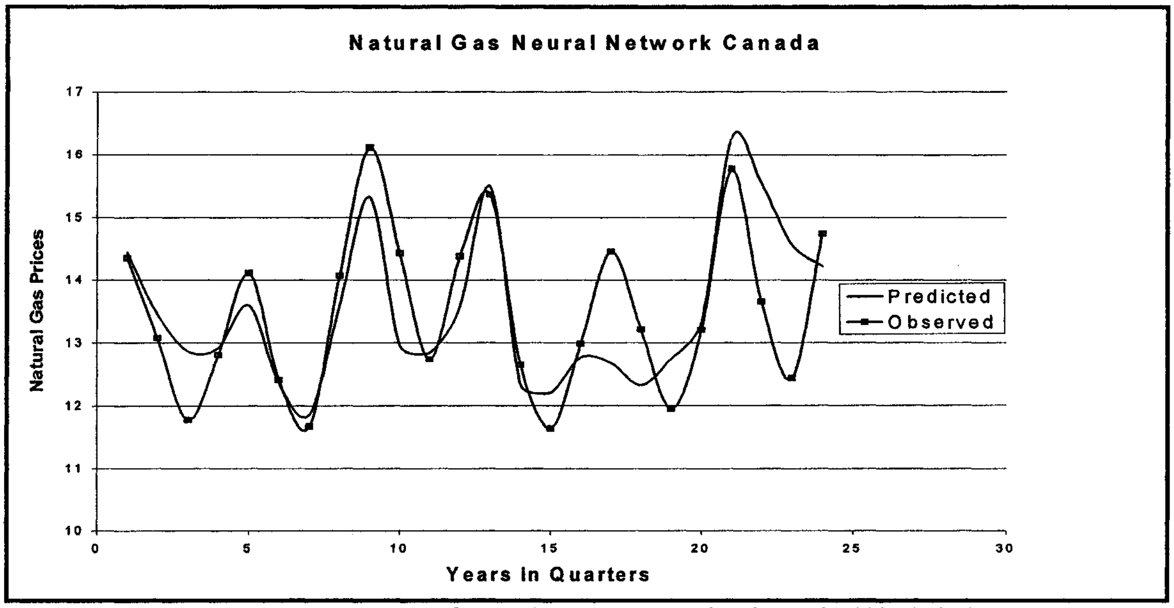

Figure 6.32 NN Natural Gas Price Forecasts for Canada (1990-1997)

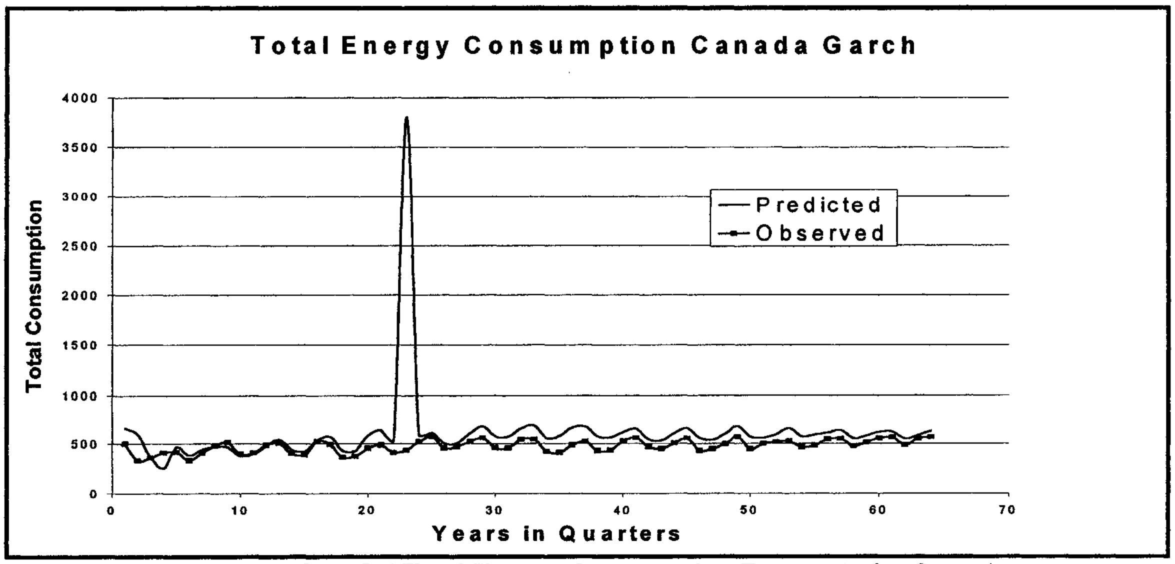

Figure 6.33 GARCH Total Energy Consumption Forecasts for Canada

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

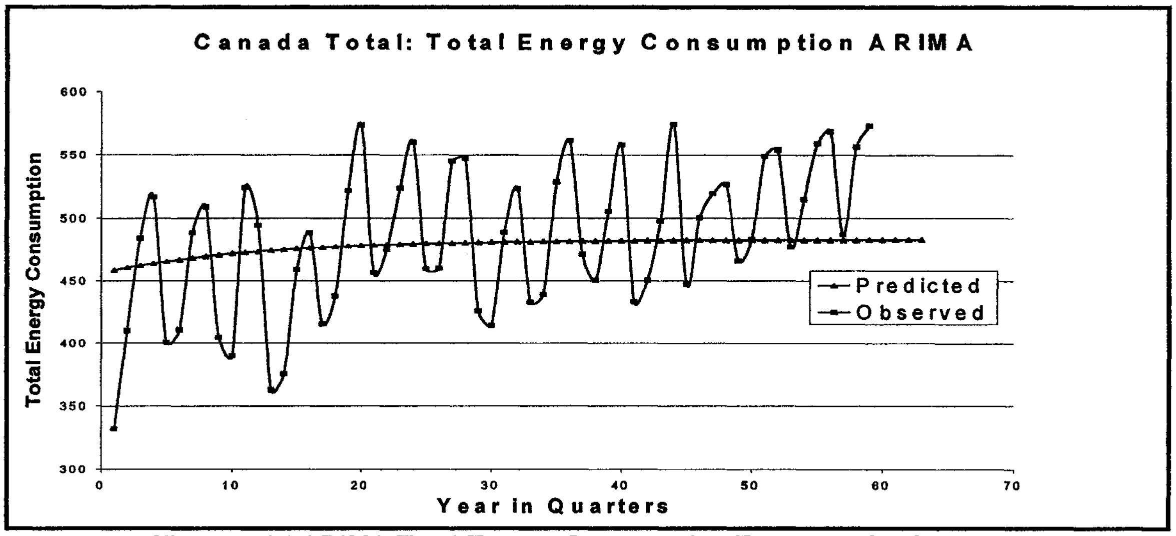

Figure 6.34 ARIMA Total Energy Consumption Forecasts for Canada

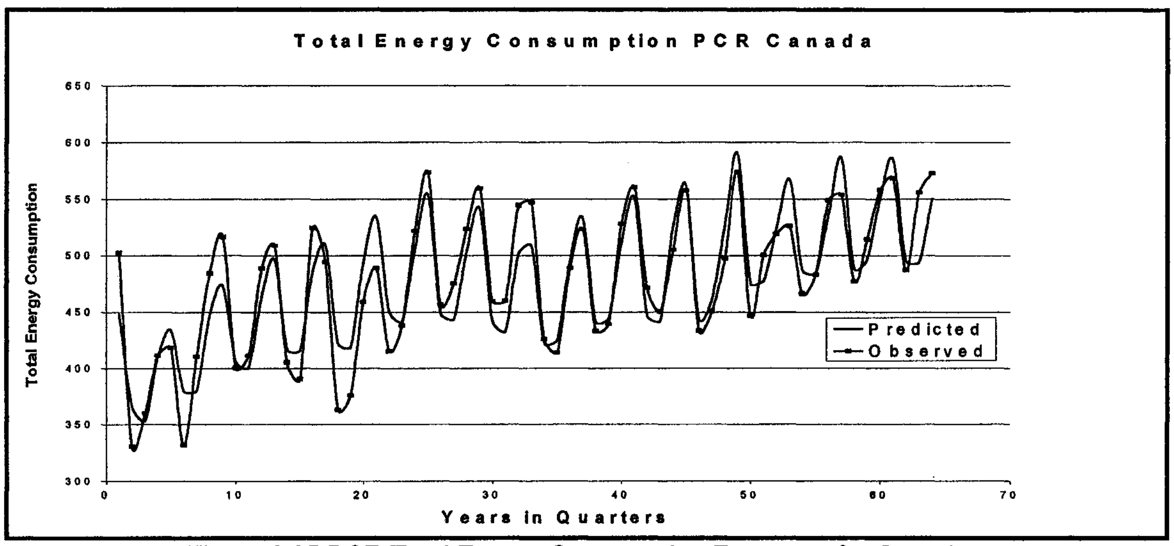

Figure 6.35 PCR Total Energy Consumption Forecasts for Canada

The abbreviations used are: Alberta Gas Prices (AB-Gas); Alberta Petroleum Prices (AB-Pet); Alberta Coal Prices (AB-Coal); Alberta Electricity Prices (AB-Elt) and Alberta Total Energy Consumption (AB-Total); Canada Gas Prices (CAN-Gas); Canada Petroleum Prices (CAN-Pet); Canada Coal Prices (CAN-Coal); Canada Electricity Prices (CAN-Elt) and Canada Total Energy Consumption (CAN-Total). The figures show much variability in all the energy centers including total energy consumption for Canada and Alberta within this period except natural gas prices in Alberta. This might not be the case after the deregulation because the markets tend to price commodities based on supply and demand. At 5% and 95% cumulative probability the price of natural gas is 6.5 ¢/m^3 and 10 ¢/m^3 or less respectively. The results are the same for AB-Pet, AB-Coal, AB-Elt and AB-Total, $14 and

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$34 for 5% and 95% respectively. At 5% and 95% probability Can-gas and Can-Total have the same results of $15 and $34 ¢/m^3. For Can-Pet Can-Coal and Can-Elt have $18 and $35 respectively for 5% and 95% cumulative probability.

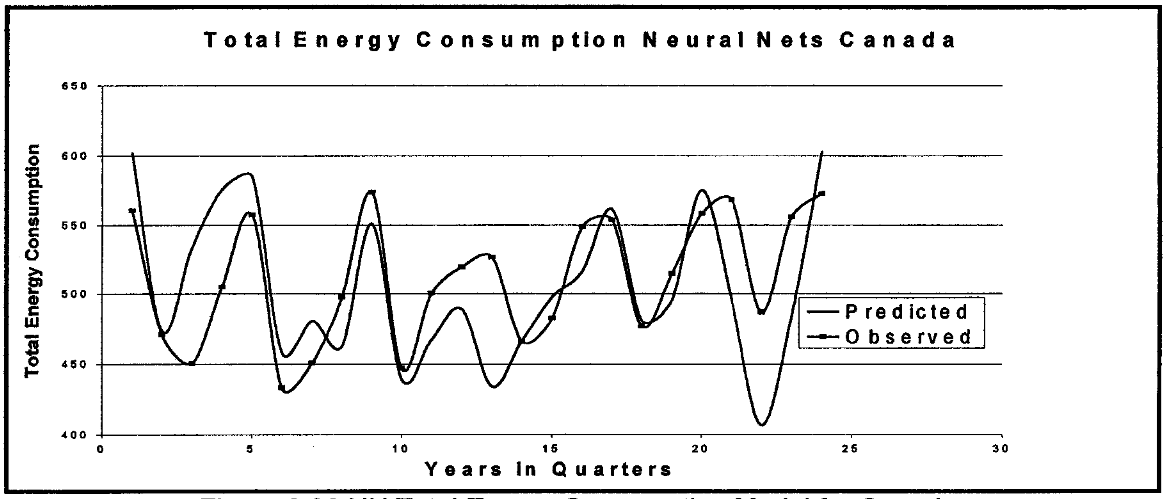

Figure 6.36 NN Total Energy Consumption Model for Canada

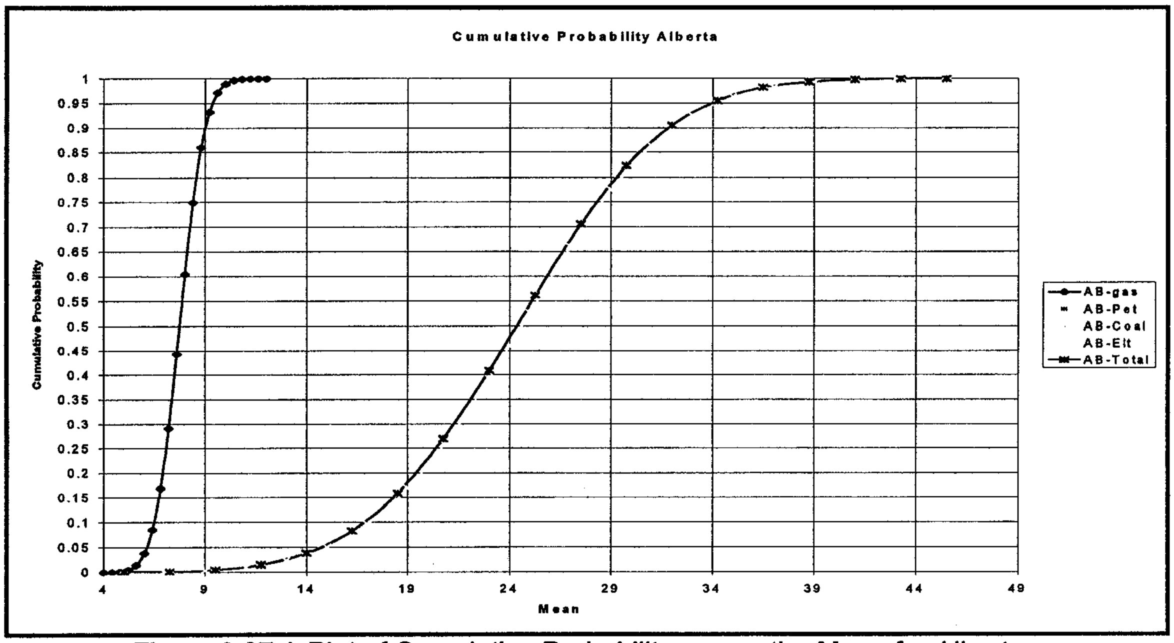

Figure 6.37 A Plot of Cumulative Probability versus the Mean for Alberta

Table B.3 (in Appendix B) shows the cumulative probabilities and the means of energy prices. The coal and oil prices for both Alberta and Canada are the same hence their similar results. The cumulative probability of 95% has an electricity price of $ 4.4/gigawatt hours for Alberta and $3.0/gigawatt hours for Canada. At a cumulative probability of 95% the natural gas prices are C$15.1 for Alberta and C$27.5 for Canada. Total energy consumption, even

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

at 5% cumulative probability, is high at 166 petajoules for Alberta and 656 petajoules for Canada. The other independent variables gave 5% and 95% cumulative probabilities as shown in Table B.4. Table B.5 (see Appendix B) shows the means of the different independent variables. The means of GDP, Income, OPEC quota and degree days are the same for Alberta and Canada. The number of wells drilled, westca, are nearly the same implying that a significant number of wells drilled are in Alberta. These results show similarity between the volatility profiles for Alberta and Canada.

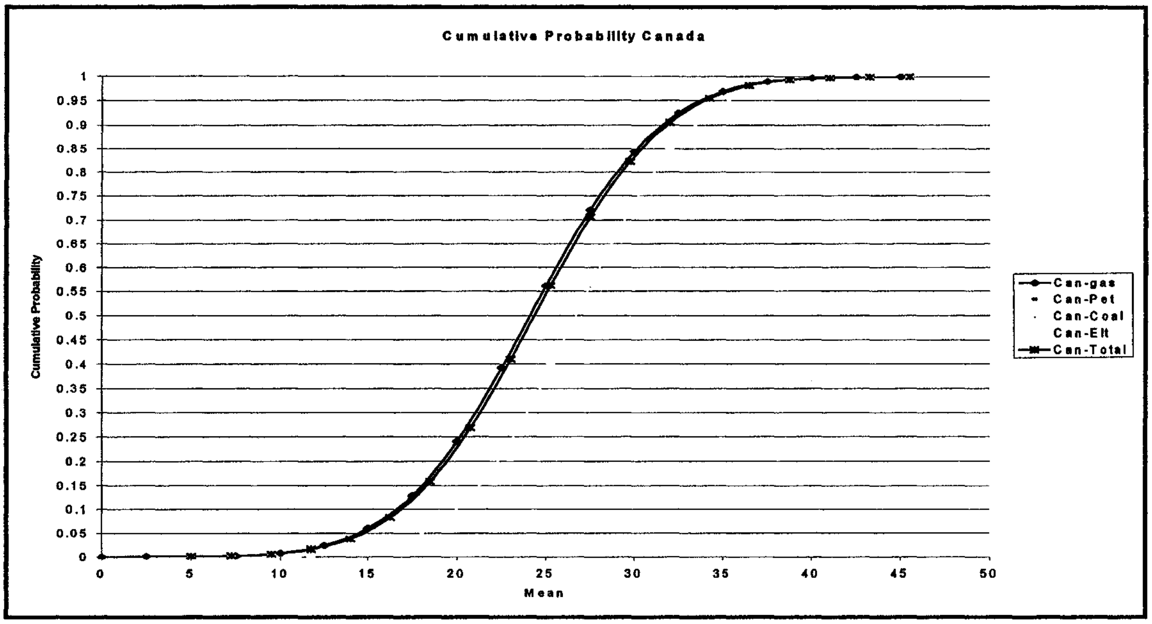

Figure 6.38 A Plot of Cumulative Probability versus the Mean for Canada

6.5 Conclusions

Detailed analysis of the results shows that, the PCR and NN predictors are suitable for forecasting future energy prices and consumption. These predictors are non-linear and they capture the means, volatility, trend cycles and directions to a reasonable degree of confidence. Energy pricing and budgetary policies must reflect the associated volatility to cushion government's and company budgets against shortfalls and undue erosion of their competitive edge and economic stability. Rigorous energy price and consumption modeling and diversification are strong economic strategies to deal with such volatility.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

CHAPTER 7.0
CONCLUSIONS AND RECOMMENDATIONS

Energy price fluctuations affect government and business policies, effective planning and implementation of strategic decisions and industrial growth and competitiveness of business enterprises. Many efforts have been made and are currently being made to provide some tools for guiding governments and industry in this domain. This research study used a number of statistical and econometric methods, including GARCH, ARIMA, PCR and neural networks modeling techniques, to develop energy forecasts models. The main objectives of this study were to: (i) examine the essential elements of oil, natural gas, coal and electricity pricing that play a major role in its determination and establish how to reduce the effects in adverse situations of high or low prices; (ii) develop energy price forecast models for energy planning, business planning and investment; (iii) develop computational and algorithmic efficiencies and statistical control paradigms for solving the forecast models, and (iv) generate appropriate forecast techniques for guiding Alberta and Canadian energy policy makers. A number of methodologies, procedures and analyses were carried out to achieve these objectives. Detailed literature survey, analysis of the energy sector, detailed mathematical and computer modeling of the problems, experimentation and analysis of results were carried out for generating the base for drawing conclusions.

7.1 Conclusions

The first and the most important conclusion of the study is that it has achieved all the objectives laid out in Section 1.3 of this thesis report.

1. A detailed examination of all the essential elements that determine the price, volatility and trend directions of energy have been carried out within the Alberta and Canada environments.

2. Energy price forecasts models have been developed using GARCH, ARIMA, PCR and NN techniques for guiding government and business organizations in planning, investment and policy making.

3. Computational and algorithmic efficiencies and statistical control paradigms have been developed for solving the forecast models.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

4. The forecasts modeling techniques have been compared and analyzed for generating the appropriate techniques for guiding forecasters within Alberta and Canada.

From detailed mathematical and computer modeling, experimentation, and analysis of the energy price model results, the following conclusions are also drawn:

5. The principal components analysis (PCR) and multi-layer feed-forward neural networks (NN) predictors are suitable for predicting crude oil and natural gas prices and the total energy consumption for both Alberta and Canada, as well as the electricity prices in Alberta.

6. The GARCH and NN predictors are suitable for predicting the coal prices in Alberta.

7. The PCR predictor is suitable for predicting Canada's electricity prices.

8. The NN predictor is appropriate for predicting Canada's coal prices.

With these predictors, analysts can model, simulate and analyze the energy prices and energy consumption levels for guiding government and company policies and for ensuring optimal investment decisions and performance of energy companies.

7.2 Contributions and Industrial Significance of Study

A number of contributions have been achieved to advance knowledge in this research domain and to assist business organizations and governments in energy price forecast modeling. These contributions include:

1. Development of detailed forecast models for investment decisions and planning of business strategies and budgeting

2. Advances in knowledge and frontiers in energy economics

3. Forecasts models provide strong basis for formulating energy price models for domestic and foreign policies on energy production, consumption, exports and inventory management. Most models comprise few parameters but do not show the complete picture of those parameters that affect energy product prices. The

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

relationship among energy product prices and the fundamental economic indicators are provided in a comprehensive manner to ensure robust models.

7.3 Recommendations

The following recommendations are made to ensure research continuity, advances in knowledge and research frontiers in energy economics:

1. The appropriate predictors for energy pricing in Alberta and Canada, PCR and NN predictors, must be subjected to rigorous modeling and testing with a large data base over a long period of time to ensure their stability and operating domain constraints.

2. Detailed reconciliation analysis must be carried out on the PCR and NN predictors over short future time periods. A 3-month future prediction can be carried out using these predictors and their results can be matched against the actual energy prices for calibration and use.

3. The radial basis function (RBF) should also be studied and used to forecast energy prices and total energy consumption and compare with other forecasting methods.

4. Correlation dimension should also be used to determine the extent of chaos in these forecasts.

5. Wavelet Analysis should also be used to determine the energy time series data.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

REFERENCES

1. Anon. (1976). U.S. Senate Special Committee Investigating Petroleum Resources, American Petroleum Interests in Foreign Countries, Arno Press Inc., New York: 297 Pages.
2. Anon. (1986), Coal Mining Research Company, Coal Mining in Alberta 1986-2035 Vol. 1, The Current Status of Coal Reserves Production Forecasts and Mining Technology in Alberta, CMRC Report # 8519-D3, Mining Division, Devon, AB: 19-45.
3. Anon. (1988) IEA Annual Oil Market Report, OECD Paris, FR
4. Anon. (1991) IEA Energy Prices and Taxes, IEA OECD, Paris, FR
5. Anon. (1995) OECD Environmental Performance Reviews: Canada, OECD, Paris, FR: 133.
6. Anon. (1996a) Harvard Business School Report, Phillips Petroleum Co. and Norwegian Oil Policy, Publishing Division, Harvard Business School, Boston, MA 02163. pp 2-3.
7. Anon. (1996b) IEA, Canada 1996 Review; Energy Policies of IEA Countries, Head of Publications Service, OECD 2, rue Andre-Pascal, 75775 PARIS CEDEX 16, FR: 47-84.
8. Anon. (1997a) OPEC Bulletin, Vienna, Austria.
9. Anon. (1997b) Shazam Econometrics Computer Program, User's Reference Manual Version 8.0, McGraw-Hill, (1997 by Kenneth White, Vancouver, BC.
10. Anon. (1997c) IEA International Coal Trade: The Evolution of a Global Market, IEA, Paris, FR: 51- 57.
11. Anon. (1999a) National Energy Board, (1999) Canadian Energy: Supply and Demand to 2025, (National Energy Board, The Publications Office, Calgary, AB: 3 Pages.
12. Anon. (1999b) Financial Engineering Ltd., Managing Energy Price Risk, 2nd Edition, Risk Publications, London, UK: 17- 19.
13. Anon. (1999c) IEA: The Future Role of Coal: Markets, Supply and the Environment, IEA. Paris, FR: 21 Pages.
14. Anon. (1999d); Industry E&P spending plan for 2000 reflect renewed optimism in Oil & Gas Journal, Tulsa; Dec 20, 1999; Vol. 97, Iss. 51; pg. 30, 1 pgs
15. Anon. (2000a) International Energy Agency Report, Oil Prices and Taxes in the Year 2000: An IEA Statistical Fact Sheet.
16. Anon. (2000b) International Energy Agency Report, (2000), Experience Curves for Energy Technology Policy, IEA, Paris, FR: 23 Pages.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

17. Anon. (2000c) International Energy Agency Report, (1996), International energy Technology Collaboration: Benefits and Achievements, IEA, Paris, FR: 17 Pages.
18. Anon. (2000d) International Energy Agency Report, (1999), International Collaboration in Energy Technology: A Sampling of Success Stories, IEA, Paris, FR: 13-22.
19. Anon. (2000e) Energy Policies of IEA Countries: Canada 2000 Review, IEA, Paris, FR: 71- 122
20. Anon. (2000f), National Energy Board Canadian Natural Gas Market, Dynamics and Pricing; An Energy Market Assessment (National Energy Board 2000, Publications Office, National Energy Board, Calgary, AB: 1 Page.
21. Anon. (2000g) Market Surveillance Administrator Report on Power Pool of Alberta Prices, University of Alberta, Edmonton, AB: 1 Page.
22. Anon. (2002a), Alberta Energy Board Website www.aeb.ca
23. Anon. (2002b), Website of The Canadian Association of Oilwell Drilling Contractors, Daily Oil Bulletin. www.caodc.ca
24. Anon. (2002c) All fuels Demand and Price Forecast Methodology, Forecast Appendix, New York State Energy Plan – June 2002, EIA/DOE, NY (Unpublished).
25. Anon. (2003); Deman for petroleum increased slightly in 2002, NPN, National Petroleum News, Chicago; Mar 2003; Vol. 95, Iss. 3; pg. 7, 2 pgs
26. Armstrong, M. (1988) The Canadian Economy and its problems, 4th Edition, Prentice-Hall Canada Inc., Ontario:151-176.
27. Ball, M., (1965), This Fascinating Oil Business, Bobbs-Merrill Co., New York: 202-236.
28. Bell, H. S. (1945) American Petroleum Refining, D. Van Nostrand Company, Inc., New York: 8-9.
29. Bending, R.C., Cattell, R.K., and Eden, R.J. (1987). Energy and structural change in the United Kingdom and Western Europe. Ann. Rev. Energy 12: 185-222.
30. Bhatia, R (1987), Energy Demand Analysis in Developing Countries: A Review, Energy Journal, 8 (Special LDC Issue),: 1-33.
31. Bollerslev, T., (1986) Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics 31 (Elsevier Science, North-Holland: 307-327.
32. Bollerslev, T., Engle, R.F. and Nelson, D.B. (1993) ARCH Models, Working Paper No. 154, Prepared for The Handbook of Econometrics, Volume 4, Elsevier Science, Pub. Co., New York, US. 110 pages

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

33. Breipohl, A.M. (2002) Electricity Price Forecasting Models, Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference, Vol. 2: 963-966.
34. Breton, T.R. (1985) World Oil Market; Low Prices Forecast in Short-Term, Petroleum Economist, Vol. 52 No. 12: 450-451.
35. Campbell, J. M. (1959) Oil Property Evaluation, Prentice-Hall, Inc., NJ: 42 Pages.
36. Campbell, J. M. (1982) Petroleum Evaluation for Financial Disclosures, Campbell Petroleum Series Inc., Norman, Oklahoma. P. 63-150.
37. Campbell, C. J. and Laherrere, J.H. (1998) The End of Cheap Oil, Scientific American, March 1998: 81-84.
38. Campbell, C. J, (1997); Better understanding urged for rapidly depleted reserves, Oil & Gas Journal, Tulsa; Apr 7, Vol. 95, Iss. 14; pg. 51, 3 pgs
39. Cullingworth, J.B. (1990) Energy, Land, and Public Policy Energy Policy Studies Volume 5, Transaction Publishers, London: 53-57.
40. Davison, M.; Anderson, C.L.; Marcus, B. and Anderson, K., (2002) Development of a Hybrid Model for Electrical Power Spot Prices, IEEE Transactions on Power Systems, Vol. 17 No. 2 May: 257-264.
41. Dilnot, A. and Helm, D. (1987), Energy Policy, Merit Goods and Social Security, Fiscal Studies, 8 (3), (August): 29-48.
42. Dieck, A.J.; Strickler, W.K., (1985) Evaluation of Time Series Models for Energy Usage Forecasting, Priceedings, American Institute of Industrial Engineers, Annual Conference and Convention, Norcross, GA, USA. No. 258: p 619-625.
43. Elkhafif, M. (1992) Estimating Disaggregate Price Elasticities in Industrial Energy Demand, Energy Journal, 13(4): 209-17.
44. Elkhafif, M. (1993) Energy Forecasting Models, Simulations and Price Sensitivity: New Formulation, International Journal of Forecasting, 9(2): 203-10.
45. Errera, S. and Brown S. L., (1999) Fundamentals of Trading Energy Futures & Options, Pennwell Publishing Co., OK: 95-169.
46. Enders, W. (1995) Applied Econometric Time Series, John Wiley & Sons, Inc. p. 63.
47. Embrechts, M.J. (1995) Forecasting foreign Exchange Rates with Artificial Neural Networks, Proceedings of the 1995 Artificial Neural Networks in Engineering, ANNIE'95. St. Louis, USA: 771-778.
48. Engle, R.F.; Kane, A. and Noh, J., (1993) A Test of Efficiency for the S&P 500 Index Option Market Using Variance Forecasts, National Bureau of Economic Research Working Paper: 4520 November: page 24.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

49. Essawy, M.A.; Bodruzzaman, M., Shamsi, A. and Noel, S., (1996) Iterative Prediction of Chaotic Time Series using recurrent neural network, Proceedings of the 1996 Artificial Neural Networks in Engineering, ANNIE'96. St.Louis, USA Vol. 6: 753-762.

50. Farla, J. Cuelenaere, R., and Blok K. (1998) Energy efficiency and structural change in the Netherlands, 1980-1990. Energy Economics 20 (1998) (Elsevier Science; Netherlands: 1-28.

51. Faruqui, A. and Eakin, K. (2000) Pricing in Competitive Electricity Markets, Kluwer Academic Publishers, Boston: 5-11.

52. Frimpong, S., J.M. Whiting and J. Szymanski (1998) Stochastic-Optimization Annealing of an Intelligent Open Pit Mine Design; Journal of Mineral Resources Engineering, Vol. 7, No. 1; © ICP, Imperial College, UK: 15-27.

53. Frimpong, S. and A. Hachiya, (1999) "Quantitative Risk Simulation of CO_2 Disposal Economic Models for Alberta"; *International Journal of the Society of Materials Engineering for Resources: Special Issue Vol. 7, No. 1; © Society of Material Resources Engineering of Japan: 55~72.*

54. Frimpong, S., A.Pop and R.Suglo, (2003) "Linear Optimization Modeling of Luscar-Sheritt Coal Production"; CAMI 2003, Calgary, Canada (September).

55. Fusaro, P.C. (1998) Energy Risk Management: Hedging Strategies and Instruments for the International Energy Markets, McGraw-Hill, NewYork: 133-143.

56. Gardner, D.T. and Elkhafif, M.A.T. (1998) Understanding Industrial Energy Use: Structural and energy intensity changes in Ontario industry, Energy Economics 20 (Elsevier Science; Netherlands: 29-41.

57. Gentry, D.W. and O'Neil, T. J. (1984) Mine Investment Analysis, SME-AIME, Inc., New York. pp. 31.

58. Greene, W. H. (2000) Econometric Analysis, 4th Edition, Prentice Hall, London: 760-810.

59. Haines, L. (1998) Is the World Running Out of Oil? Oil & Gas Investor 18, No. 1 (Jan. 1998): p.3

60. Hamilton, J.D. (1993) Time Series Analysis, Time Series Models of Heteroskedasticity, chapter 21, Princeton University Press, Princeton, New Jersey: 657-676.

61. Hampton, M. (1991) Oil Prices, Cycling Towards Low Prices, Petroleum Economist, London Vol. 58 No. 4: 9-11.

62. Helliwell, J.F., MacGregor, M.E., McRae, R.N. and Plourde, A., (1988) 'Oil and Gas Taxation', Osgoode Hall Law Journal, 26(3) No. 3: 453-494.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

63. Hotelling, H. (1993), The Economics of Exhaustible Resources, Journal of Political Economy, 39 (2), April: 137-75.

64. Howarth, R.B., Schipper, L., Duerr,P.A., Strom, S., (1991) Manufacturing energy use in eight OECD countries; decomposing the impacts of changes in output, industry structure and energy intensity, Energy Economics 13: 135-142.

65. Hough, G.V. (1988) World Survey, Liquified Natural gas: Optimism kept in bounds, Petroleum Economist, Vol. 55 No. 12: 391-393.

66. Hsiao, F.S.T. and Hsiao, M.W., (1985) Elasticities, Ratios and Energy Modelling, Energy Economics, July; 7(3): 153-58.

67. Hull, J. C. (2000) Options, Futures, and other Derivatives, Fourth Edition, Prentice Hall, New Jersey. pp. 218-295.

68. Huntington, H.G. (1994), Oil Price Forcasting in the 1980s: What Went Wrong?, Energy Journal, 15 (2), 1-22.

69. Jenne, C.A., Catell, R.K., (1983) Structural change and energy efficiency in industry. Energy Economic 5, 114-123.

70. Karkkainen, P. (1997) "Oil and Gas" in Handbook of Canadian Security Analysis, Volume 1, Kan, Joe, (Editor), John Wiley & Sons, Ontario: 142-180.

68. Kashfi M.S.(2003);Long decline in oil sector means shrinking role for Iranian supply in new world order Oil & Gas Journal, Tulsa; Feb 10, 2003; Vol. 101, Iss. 6; pg. 20, 2 pgs

69. Klein, S. (2001) Costly Energy: Why Oil and Gas are Rising and What we can do About It, Canadian Centre for Policy Alternatives, Ontario, Canada: 5-24.

71. Ko, H.S., Niimura, T. and Ozawa, K., (2002) A Day Ahead Electricity Price Prediction based on a Fuzzy-Neuro Autoregressive Model in a Deregulated Electricity Market, Proceedings of the International Joint Conference on Neural Networks, Vol. 2: 1362-1366.

72. Krzysztofowicz, R. (1999) Bayesian Forecasting via Deterministic Model, Risk Analysis, 19(4); 739-749.

73. Kumar, A.; Maini, P.; and Singh, S.V. (1999) Operational Model for Forecasting Probability of Precipitation and Yes/No Forecast, Weather and Forecasting, 14(1); 38-48

74. Kutasov, I.M. (2002) Downhole temperature, pressure methods are accurate for drilling, completion, cement design; Oil & Gas Journal, Tulsa; Sep 16, 2002; Vol. 100, Iss. 38; pg. 42, 3 pgs

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

75. Kyrtsou, C. and Terraza, M. (2002) Stochastic Chaos or ARCH Effects in Stock Series? A Comparative Study, International Review of Financial Analysis, 11(4): 407-31.

76. Labys, W. C. (1999) Modeling Mineral and Energy Markets, Kluwer Academic Publishers, Boston:1-3.

77. LaCasse, C. and Plourde, A. (1995) 'On the Renewal of Concern for the Security of Oil Supply', The Energy Journal, 16(2): 1-23

78. Laffer, A. B. (1985) High road for the American Automobile Industry; The World Economy, Oxford; Sep 1985; Vol. 8, Iss. 3; pg. 267, 20 pgs

79. Lariviere I. And Lafrance G. (1999) Modelling the electricity consumption of cities: Effect of urban density, Energy Economics 21 (1999) (Elsevier Science; Netherlands: 53-66.

80. Lich, M. and Gobert, W., (1997) "Oil Services" in Handbook of Canadian Security Analysis, Volume 2, Kan, Joe, (Editor) John Wiley & Sons, Ontario: 1-45.

81. Lisi, F. and Villi, V., (2001) Chaotic Forecasting of Discharge Time Series: A Case Study, Journal of the American Water Resources Association, 37(2): 271-279.

82. Lerche, I and Mackay, J.A. (1999) Economic Risk in Hydrocarbon Exploration, Academic Press, Sandiego: 1-20.

83. Mabro, R (1998) OPEC Behaviour 1960-1998: A Review of the Literature, The Journal of Energy 4(1): 3-27.

84. McElroy, R.K.; Villacis, E.; Yontz, R.E. and Musa, D.I. (1986) Integrated Regional Economic and Demographic Modeling System for Developing Long-Range Forecast Inputs to Sectoral Energy and Peak Demand Forecasting Models, Proceedings of the American Power Conference, Vol. 48: 382-398.

85. MacKevett, N.H. (1998) Gas reserves growth boosts Sacramento basin; Oil & Gas Journal, Tulsa; Jan 26, 1998; Vol. 96, Iss. 4; pg. 102, 4 pgs

86. Merklein, H. A. and Hardy, W. C. (1977) Energy Economics, Gulf Publishing Company, Texas: 8-10.

87. Meyer, R. A. (1981) Coal Handbook, (Marcel Dekker, Inc. New York: 76-79.

88. Micheal C. L., (1999) Oil Scarcity, Energy Security and Long-term Oil Prices – Lessons Learned (Unlearned), International Association for Energy Economics (IAEE) Newsletter, Third Quarter 1999.

89. Mork, K.A. (1994), Business Cycles and the Oil Market, Energy Journal, 15 (Special Issue): 15-38.

90. Munasinghe, M. and Meier, P. (1993) Energy Policy Analysis and Modeling, Cambridge University Press, U.K.: 3-19.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

91. Nakamura D.(2003) Refiners face continued uncertainty in 2003; Oil & Gas Journal, Tulsa; Mar 24, 2003; Vol. 101, Iss. 12; pg. 58, 5 pgs

92. Nemeth, M. (1998) Has Oil Hit Bottom, Maclean's v111 n14 p. 48

93. Newendorp, P. D. (1981) Risk Evaluation Helps Make Better Decisions, in Petroleum Exploration, by Takken, S. and Sengal, E.W., The Institute for Energy Development, Inc. Oklahoma City: 81-83.

94. Nordhaus, W.D. (1980), Oil and Economic Performance in Industrial Countries, Brookings Papers on Economic Activity, 2: 341-99

95. Nunn, S., Schlesinger, J. R.and Ebel, R. E. (2000) The Geopolitics of Energy in the 21st Century, Volume 2: The Supply-Demand Outlook, 2000-2020 (The Centre for Strategic and International Studies, Washington D.C.: 25-35.

96. Nunn, S., Schlesinger, J.R., Ebel, R.E. (2000) The Geopolitics of Energy in the 21st Century, Volume 3: The Geopolitical Outlook, 2000-2020 (The Centre for Strategic and International Studies, Washington D.C.: 64-67.

97. Pagá, E. and Gürer, N., (1996), Reassessing Energy Intensities: A Quest for New Realism, OPEC Review, XX (1), March: 47-86.

98. Pagan, A.R. and Schwert, G.W. (1990) Alternative Models for Conditional Stock Volatility, Journal of Econometrics 45 (Elsevier Science, North-Holland: 267-290.

99. Pagan, A. (1996) 'The Econometrics of Financial Markets', Journal of Empirical Finance 3: 15-102.

100. Palm, F.C. (1996) 'GARCH Models of Volatility', Handbook of Statistics, Vol.14 (Elsevier Science, Netherlands: 209-240.

101. Patching, T. H., Harrison, J. M., Mackay,I., and Beck, R.A.D.(1980) Western Canada's Coal: "The Sleeping Giant" Canada West Foundation, Calgary, Alberta: 135-141.

102. Plourde, A. (1988) 'On the Role and Status of Canadian Natural Gas Carriers Under Deregulation', The Journal of Energy and Development, University of Colorado: 1-25.

103. Plourde, A. and Ryan, D.L. (1995) 'Government Policy and Access to Natural Gas Service in Canada', Canadian Public Policy: 304 – 315.

104. Plourde, A. (1993) 'Natural Gas Trade in North America: Building up to the NAFTA', The Energy Journal, 14(3): 51-73.

105. Plourde, A. (1994) 'The Petroleum Industry Under NAFTA', The Impact of NAFTA: Economies in Transition, Proceedings of a Symposium held at the London School of Economics, September, 1994: 121-145.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

106. Plourde, A., Ryan, D.L. and Wang, Y. (1996) 'Asymmetric Price Responses of Residential Energy Demand in Ontario', Canadian Journal of Economics, XXIX, Special Issue, April: S317-323.

107. Radler, M. (2002) Production, reserves climb as profits ebb for OGJ100; Oil & Gas Journal, Tulsa; Sep 9, 2002 Vol. 100, Iss. 37; pg. 84, 6 pgs

108. Raggi, A. and Barbiroli, G., (1992). Factors influencing changes in energy consumption; the case of Italy, 1975-1985. Energy Economics 14, 49-56.

109. Raible, C.C.; Bischof, G.; Fraedrich, K. and Kirk, E. (1999) Weather and Forecasting, 14(2): 203-214.

110. Rastogi, S.; Roulet, G. and Ortbals, Marvin, (1990) Total Energy Forecast Model for Rural Distribution Cooperatives, 34th Annual IEEE Rural Electric Power Conference, New York.

111. Razavi, H. and Fesharaki, F., (1991) Fundamentals of Petroleum Trading, Prager Publishers, New York: 3-15.

112. Rosenberg, N. (1980) Historical Relations Between Energy and Economic Growth, in Dunkerley, J. (ed.), International Energy Strategies, Pcoceedings of the 1979 IAEE/RFF Conference, Cambridge, MA: Oelgesschlager, Gunn & Hain, Publishers, Inc.: 55-70.

113. Rudkevich, A.; Duckworth, M. and Rosen, R., (1998) Modeling Electricity Pricing in a deregulated generation Industry: The Potential for Oligopoly Pricing in a Poolco, Energy Journal, 19(3): 19-48.

114. Schipper, L., Howarth and R., Carlassare, E., (1992) Energy intensity, sectoral activity, and structural change in the Norwegian economy. Energy Economics 17: 215-233.

115. Sharma, A. (2000a) Seasonal To Interannual Rainfall Probabilistic Forecasts for Improved Water Supply Management: Part 1 – a Strategy for System Predictor Identification, Journal of Hydrology, 239(1-4): 232-239.

116. Sharma, A. (2000b) Seasonal to Interannual Rainfall Probabilistic Forecasts for Improved Water Supply Management: Part 3 – a Nonparametric Probabilistic Forecast Model, Journal of Hydrology, 239(1-4): 232-239.

117. Seba, D. R. (1998), Economics of Worldwide Petroleum Production, Oil and Gas Consultants International, OK.: 53-128, 203-269.

118. Sinton, J.E., Levine, M.D., (1994) Changing energy intensity in Chinese industry, Energy Policy 22: 239-255.

119. Sivakumar, B.; Liong, S.Y.; Liaw, C.Y. and Phoon, K.K. (1999) Singapore Rainfall, Behaviour: Chaotic? Journal of Hydrologic Engineering, 4(1): 38-48.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

120. Skeet, I. (1988) OPEC: Twenty-Five Years of Prices and Politics, Cambridge University Press, Cambridge, Great Britain: 7-16.

121. Stermole, F. J. and Stermole, J. M. (1990) Economic Evaluation and Investment Decision Methods, 7th Edition, Investment Evaluation Corporation, Golden, CO 80401: 6-21.

122. Sterner, T. (1994) Economic Policies for Sustainable Development, Kluwer Academic Publishers, Netherlands: 1-25.

123. Skiadas, C.H.; Papagiannakis, L and Mourelatos, A., (1997) Application of Diffusion Models to Forecast Industrial Energy Demand, Applied Stochastic Models and Data Analysis, v 13 n 3-4 Sep-Dec: 357-367.

124. Slade, M.E., Kolstad, C.D. and Weiner, R.J. (1993) Buying Energy and Nonfuel Minerals: Final, Derived, and Speculative Demand, in Handbook of Natural Resource and Energy Economics, Volume III, Editors: Kneese, A.V. and Sweeney, J.L., Elsevier, New York: 935-938.

125. Stevens, P. (2000) The Economics of Energy Vols. 1 and 2, Edward Elgar Publishing Ltd., U.K.: 1 - 135.

126. Suganthi, L. and Samuel, A.A., (1999) Optimal energy Forecasting Model for the Economy Environment Match, International Journal of Ambient Energy, Vol. 20 No. 3; 137-148.

127. Sumrow, M. (2002) Higher gas prices, drilling activity forecast – oil prices to trend lower; Oil & Gas Journal, Tulsa; Nov 11, 2002; Vol. 100, Iss. 46; pg. 58, 4 pgs

128. Sun, J.W. (1998) Changes in energy and energy intensity: A complete decomposition model. Energy Economics 20 (1998) (Elsevier Science, Netherlands: 85-100.

129. Toman, M.A. (1993) The Economics of Energy Security: Theory, Evidence, Policy, in Handbook of Natural Resource and Energy Economics, Volume III, Editors: Kneese, A.V. and Sweeney, J.L., Elsevier, New York.: 1167-1171.

130. Vaage, K. (2000) Heating technology and energy use: A discrete/continuous choice approach to Norwegian houshold energy demand in Energy Economics v 22 n 6 Dec.: 649-666.

131. Wallace, I., (2002) A Geography of the Canadian Economy, Oxford University Press, Canada: 152-164.

132. Walter Y. G. (1997) The Inevitable Control of Earth's Resources over Nations and Individuals (Portland, Oreg.: National Book Co.,)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

133. Watkins, G.C. and Plourde, A. (1998) 'Crude Oil Prices Between 1985 and 1994: How Volatile in Relation to other Commodities? Resource and Energy Economics, 20 p.245-262 (Elsevier Science Pub. Co, New York, US.: 245-262.

134. Ziemba, W.T. and Schwartz S.L. (1980) Energy Policy Models Volume 11, Martinus Nijhoff Publishing, London: 17-19.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

APPENDIX A

Table A.1: World Oil Production, Consumption and Reserves (percentages and totals for 1965)

Region	Production	Consumption	Reserves
North America	32.5%	40.6%	11.0%
South America	13.6	5.3	7.5
Western Europe	1.4	25.4	0.6
Middle East	26.4	2.3	62.7
Centrally Planned	17.0	14.6	9.1
Africa	7.1	1.9	5.7
Other	2.1	9.9	3.5

Total production: 31.7 million barrels/day
Total consumption: 31.3 million barrels/day
Total proven reserves: 338.7 billion barrels
(Source: Anon 2000d)

Table A.2: Average Nominal Prices of Crude Oil: 1951-1965 (US$/barrel)

	Arabian Light Official Price	Arabian Light Market Price	U.S. Average Wellhead Price
1951	1.75	1.71	2.53
1953	1.93	1.93	2.68
1955	1.93	1.93	2.77
1957	2.08	1.90	3.09
1959	1.90	1.70	2.90
1961	1.80	1.45	2.89
1963	1.80	1.40	2.89
1965	1.80	1.33	2.86

(Source: Anon, 1996a)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

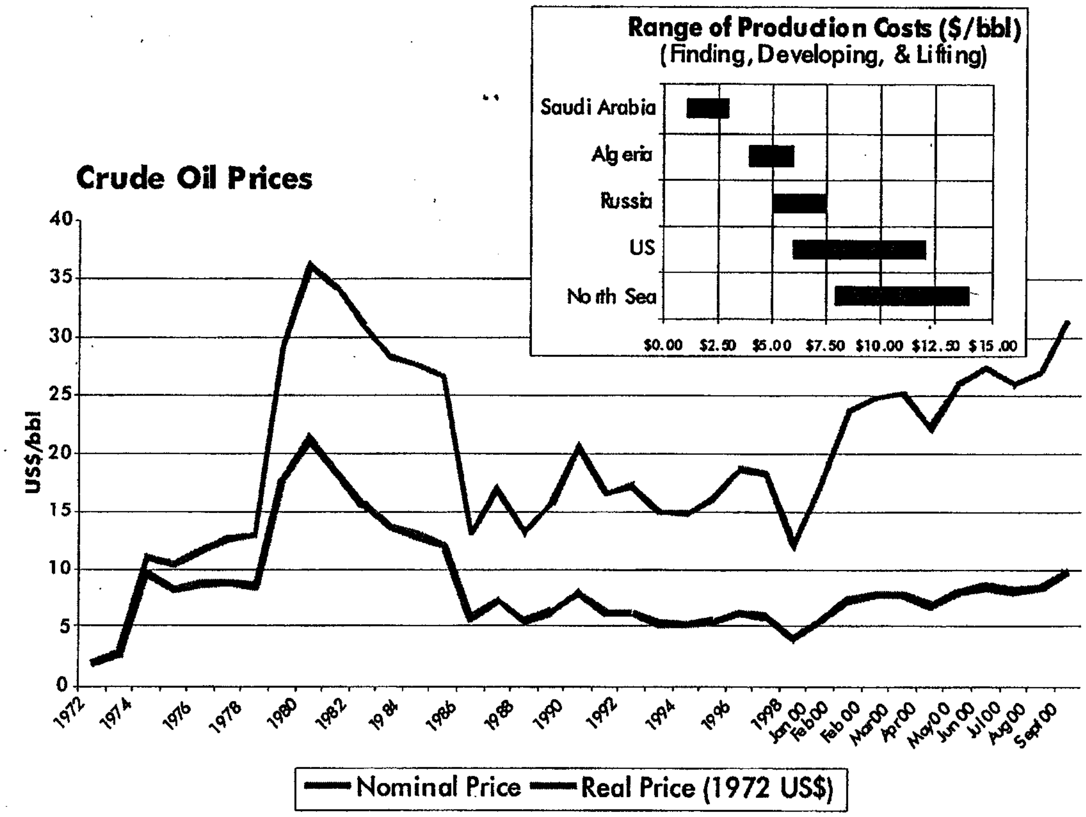

Figure A.1 Evolution of Oil prices from 1972 to 2000.
(Source Anon, 2000a)

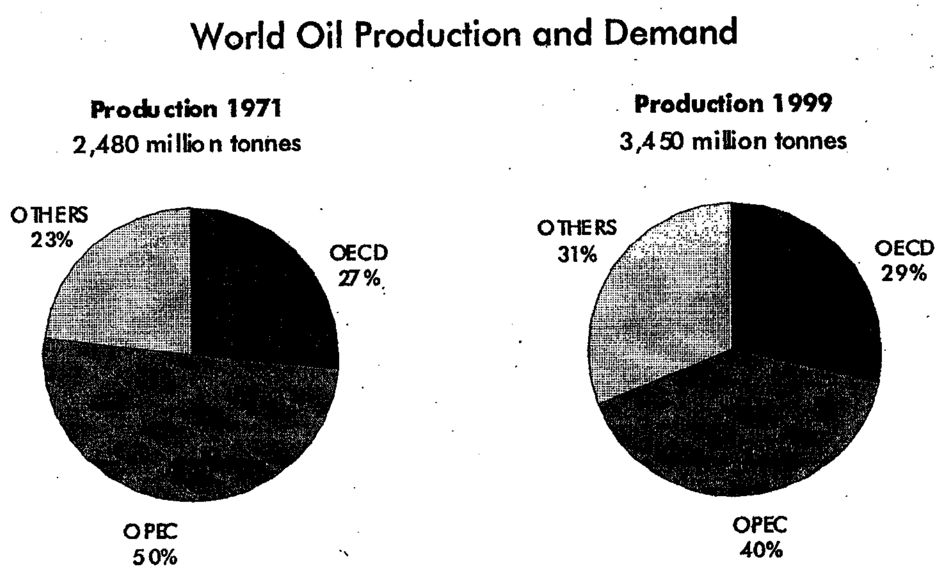

Figure A.2 World Oil Production and demand for 1971 and 1999

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

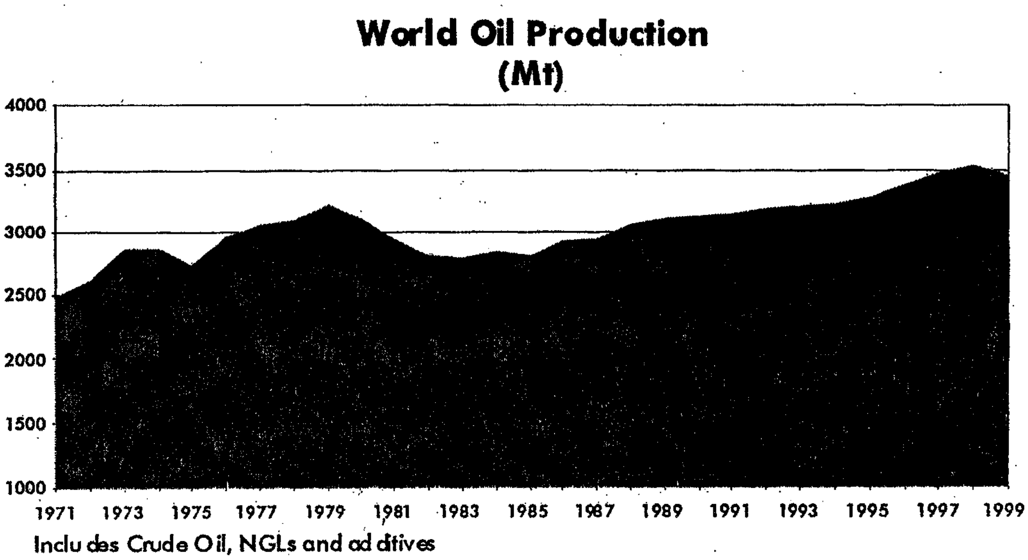

Figure A.3 World Oil Production

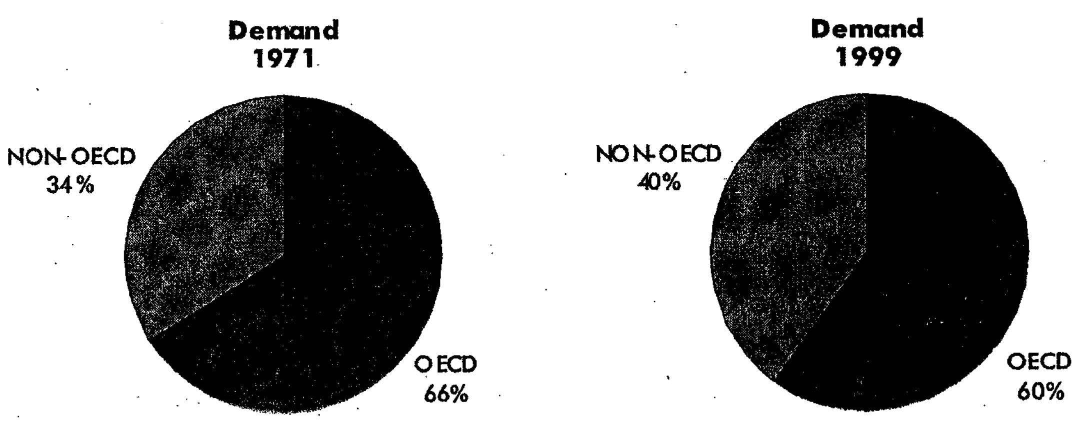

Figure A.4 Demand in OECD and Non OECD-Countries

(Source Anon. 2000a)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

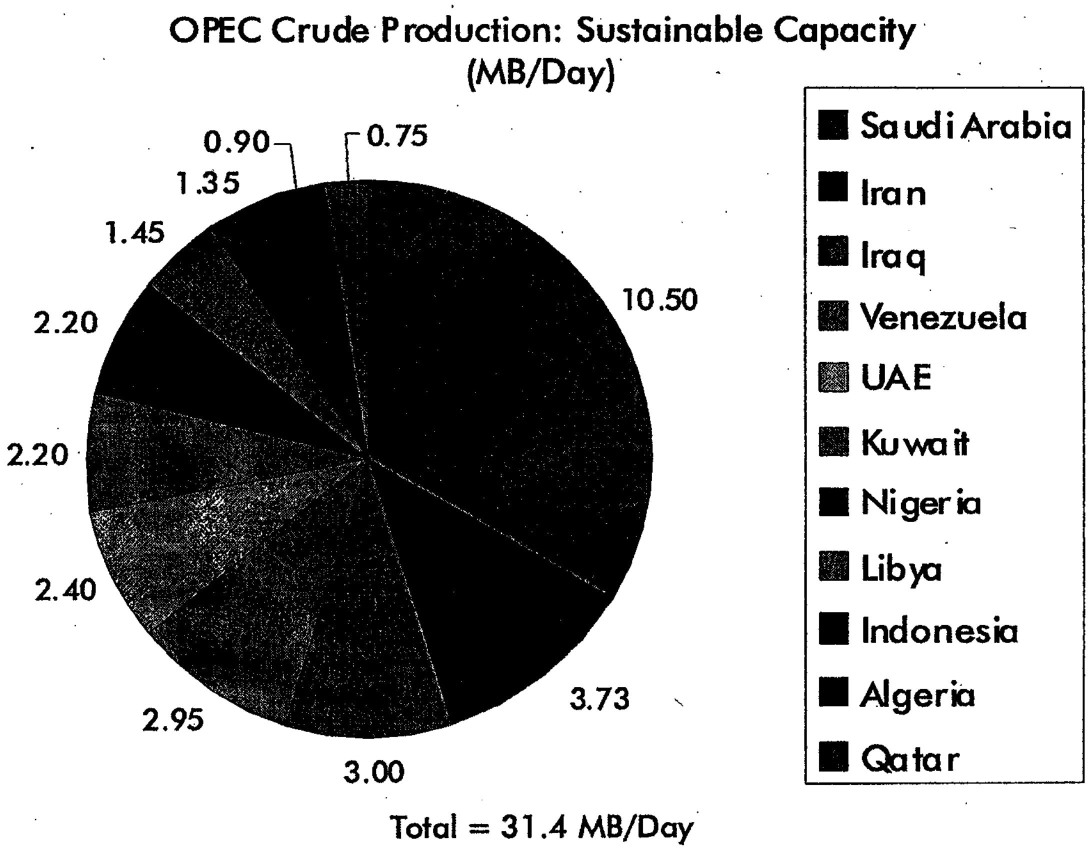

Figure A.5 OPEC's spare capacity
(Source Anon. 2000a)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

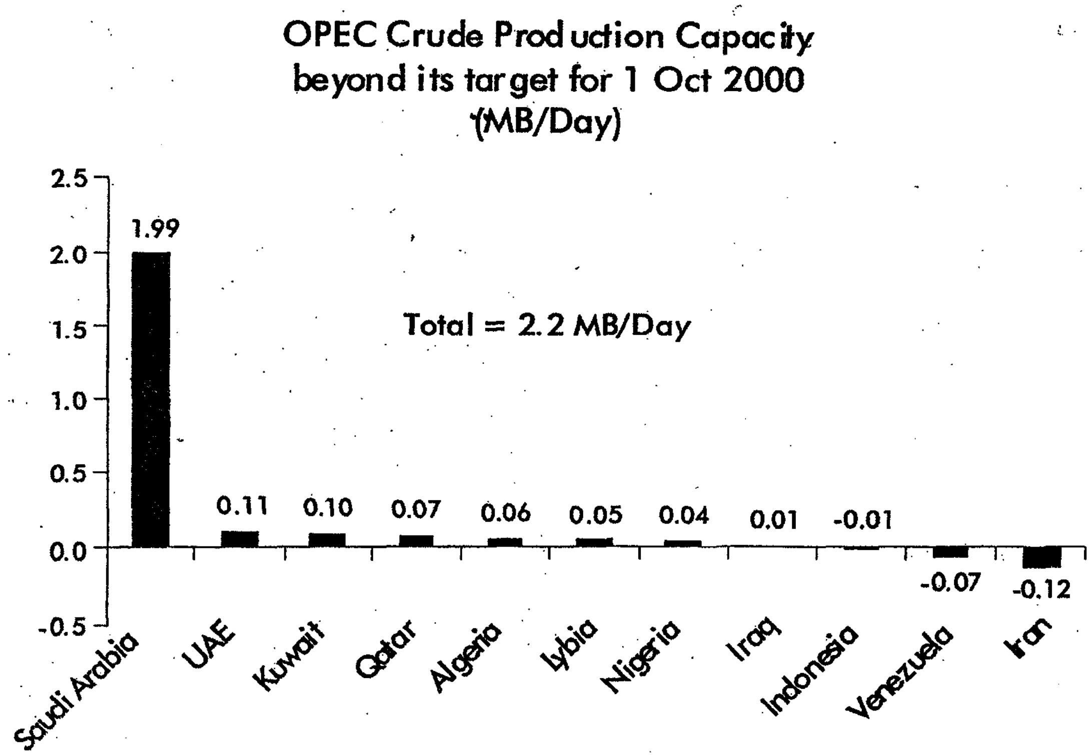

Figure A.6 OPEC Crude Production Capacity as of 1Oct 2000.
(Source Anon. 2000a)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

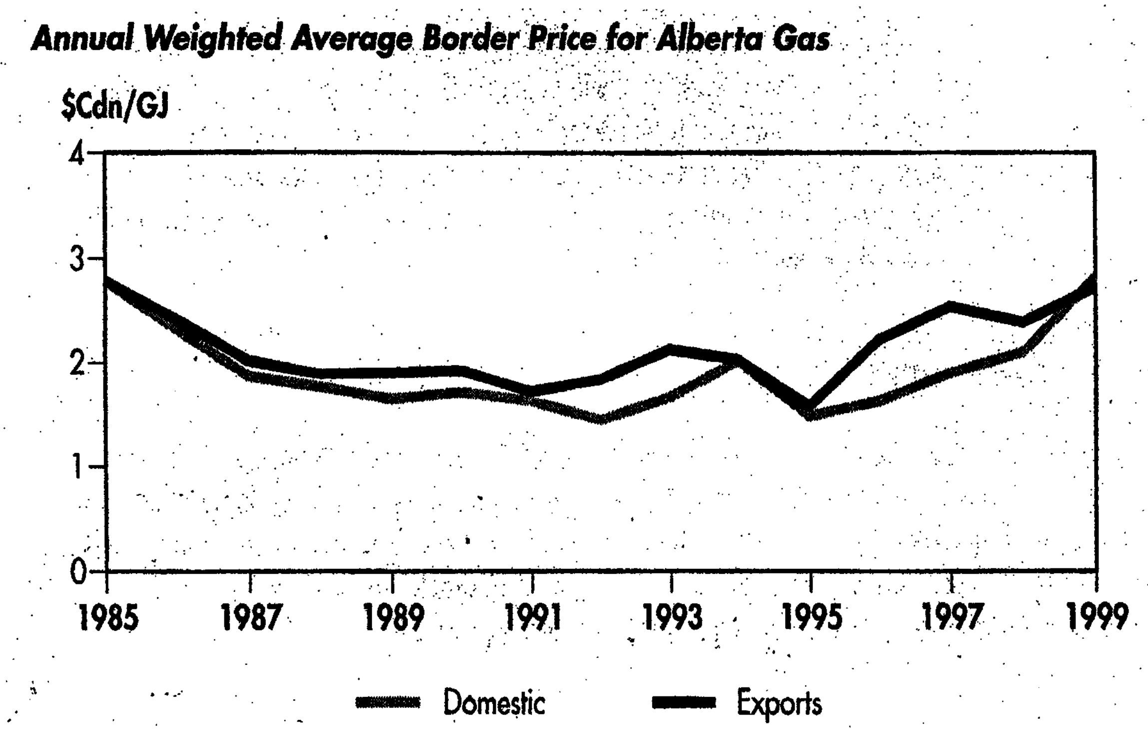

Figure A.7 Annual Weighted Average Border Price for Alberta Gas

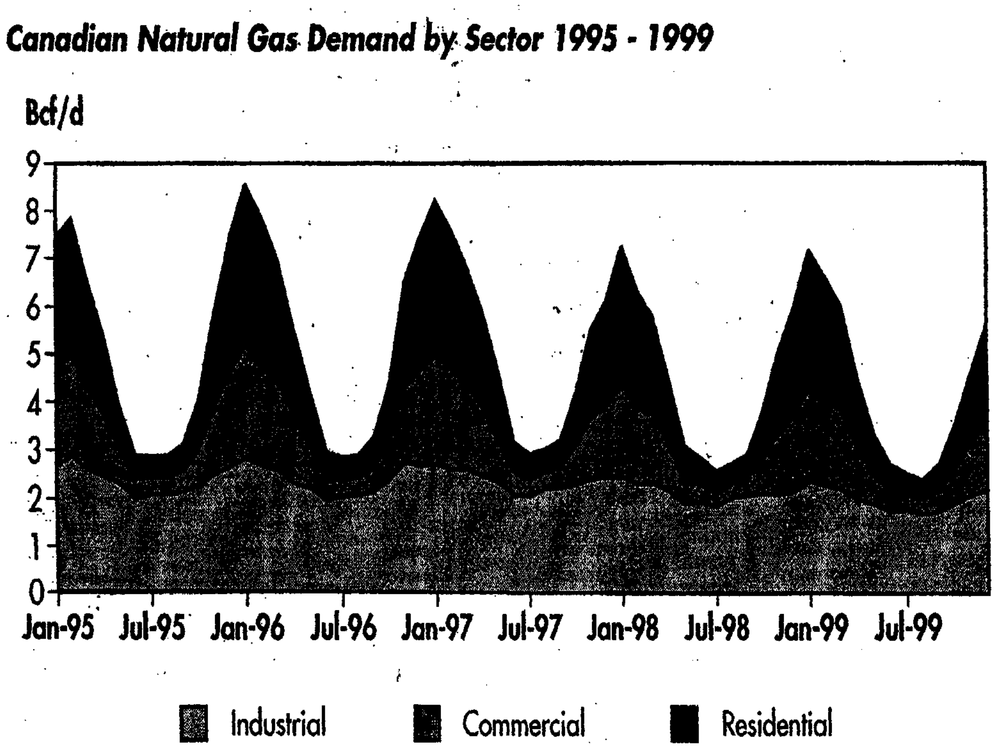

Figure A.8 Canadian Natural Gas Demand by Sector 1995 to 1999

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table A.3 Domestic Product Supply by Year

Year	All Products	Gasoline	Kerosene (a)	Distillate	Residual	LPG	Lubricants	Other
1995	6,459	2842	20	1168	311	693	57	1369
1994	6418	2769	574	1156	366	685	57	811
1993	6198	2664	553	1106	390	626	55	804
1992	6178	2654	545	1088	399	639	54	799
1991	6097	2625	552	1065	420	603	53	779
1990	6170	2633	569	1102	447	565	59	795
1989	6324	2675	543	1152	500	609	58	751
1988	6261	2670	481	1132	487	631	58	802
1987	6083	2630	465	1086	461	588	59	794

(Source: National Petroleum News, 1996. (a) – Aviation fuel included)

Table A.4 Types of Risk

Technical	**Economic**	**Political**
Dry holes	Inflation	Governmental policy
Geological	Oil and gas prices	Government regulations
Engineering	Gambler's ruin	Laws
Storm damage	Interest rates	Nationalization
Earthquake	Environmental	Environmental
Timing	Timing	Timing
	Exchange rate	Exchange rate
	Financing/capital	Financing/capital
	Supply/demand	Taxation
	Operating costs	Export/import
		Personnel

Source Seba (1998)

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table A.5 In-Place Coal Resources of Immediate Interest (megatonnes)

Province	Low volatile Bituminous -Anthracite	Medium-Low Volatile Bituminous	High Medium Volatile Bituminous	High Volatile Bituminous	Lignite-Sub-Bituminous	Total
British Columbia	1 610	9 270	7 190	645	1090	19 805
Alberta	815	3 515	1 710	7 420	33 475	46 935
Saskatchewan	-	-	-	-	7 595	7 595
Ontario	-	-	-	-	180	180
New Brunswick	-	-	75	-	-	75
Nova Scotia	-	-	1 405	-	-	1 405
Yukon and District of Mackenzie	90	-	150	350	2 290	2 880
Canada	**2 515**	**12 785**	**10 530**	**8 415**	**44 630**	**78 875**

Source: Coal Resources of Canada (Anon., 1989).

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table A.6 Alberta Existing Generation Capacity

Year End 2000 Capacity (MegaWatts)	**Coal**	**Gas**	**Hydro**	**Total installed**	**Available to AIES**
Generation					
ATCO Electric	1,563	104	-	1,667	1,667
EPCOR	768	841	-	1,609	1,609
TransAlta	3,290	-	795	4,085	4,085
Emergency Capability					126
City of Medicine Hat	-	211	-	211	40
Sub Total	**5,621**	**1,156**	**795**	**7,572**	**7,572**
Generation					
Industrial				958	100
Small power/independent power producers				111	111
New independent power producers				1,395	889
Sub Total				**2,464**	**1,100**
Interconnections					
British Columbia				800	800
Saskatchewan				150	150
Sub Total				**950**	**950**
Grand Total				**10,986**	**9,577**

Source: Anon., 2002

Table 8.7 Imports/Exports

	1999	2000
Export volume (MWh)	273,779	823,008
Exports value ($)	$4,261,938	$65,167,447
Imports volume (MWh)	2,211,217	1,386,112
Imports value ($)	$135,505,922	$331,158,297

Source: Anon., 2002

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

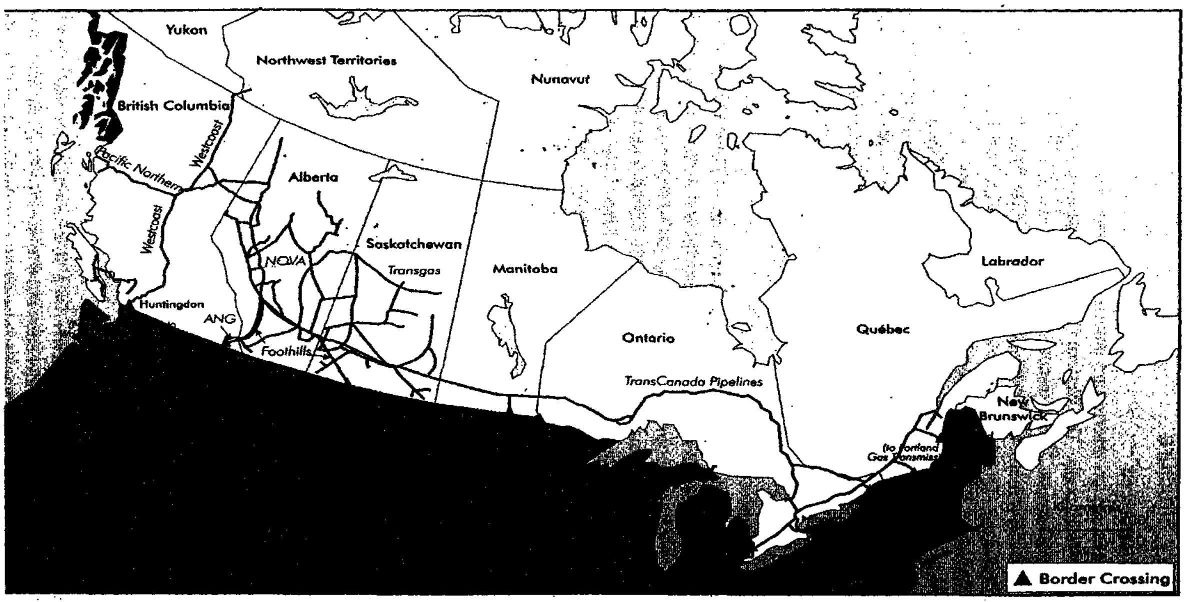

Figure A.9 Natural Gas Transmission Network
(Sources: Anon, 2000f)

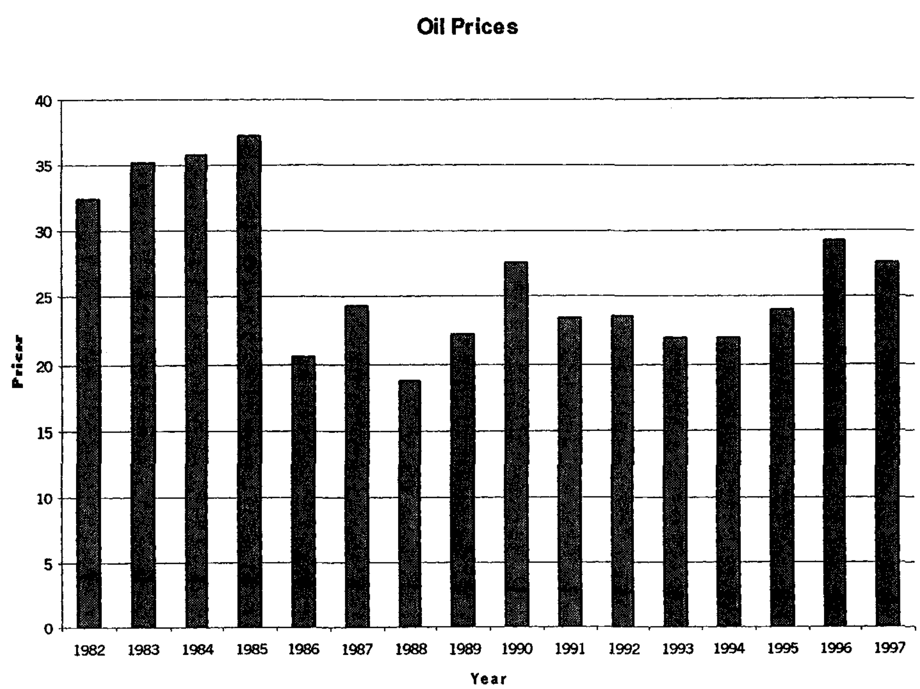

Figure. A.10 The Average Oil Price between 1982 and 1997 in Alberta and Canada.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table A.8 Description of Data

Variable	CANSIM Series Canada	Alberta	Period	Frequency	Unit
Price: Oil	E13041	E13041	1982 – 1997	Monthly	$
Natural gas	E13450	E13456	1982 – 1997	converted to	Cents/m^3
Coal	Periodical*	Periodical*	1982 – 1997	quarterly by	$/Kilotonnes
Electricity	P1900	P1911	1982 - 1997	averaging	$/GigaWattHour
Production					
1. Oil	D384710	D388339	1982 – 1997	Monthly	terajoules
2. Natural gas	E9001	E9601	1982 – 1997	converted to	Million m^3
3. Coal	E 12001	D2486	1982 – 1997	quarterly by	Kilotonnes
4. Electricity	D372136	D372016	1982 - 1997	summing	MegaWatt.Hour
Total Consumption	All energy products	All energy products	1982-1997	Quarterly	Petajoules
Population	D1	D10	1982 - 1997	Quarterly	Persons
GDP	E205000	E205000	1982 - 1997	Quarterly	Millions of $
Income	E205160	E205160	1982 - 1997	Quarterly	Millions of $
Unemployment	D980562	D983831	1982 - 1997	Monthly converted to quarterly by averaging	Thousand persons
Degree days	Historical energy tables	Historical energy tables	1982 - 1997	Quarterly	Number of days
OPEC quota	OPEC Bulletin	OPEC Bulletin	1982 - 1997	Quarterly	MBPD
Westca	CAODC	CAODC	1982 - 1997	Monthly	Number of wells

CAODC: Canadian Association Oilwell Drilling Contractors
*Energy Price and Tax Periodical

The Total Energy Consumption was obtained using the following chart. (Table A.8)

Energy Source	Conversion Factor (terajoules)	From
Natural Gas	38.13	Gigalitres
Electricity	3.60	Gigawatthour
Crude oil	39.08	megalitres

Coal consumption was added and the whole energy consumption was recorded in petajoules.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

APPENDIX B: STATISTICAL TEST RESULTS

Alberta

Table B. 1 Data Properties, Alberta

Structural Break

Energy Product	F Statistics	Structural Break?	5%	1%
Oil	1.41	No	2.07	2.80
Gas	3.186	Yes	2.07	2.80
Electricity	3.750	Yes	2.07	2.80
Coal	0.62	No	2.07	2.80
Total Energy Co	1.486	No	2.07	2.80

Heteroskedasticity

Energy Product	$\sigma1>\sigma2$	$\sigma1<\sigma2$	Heteroskedasticity?	GQ^* 5%	GQ^* 1%
Oil	1.758	0.569	No	2.48	3.70
Gas	0.768	1.302	No	2.48	3.70
Electricity	0.804	1.243	No	2.48	3.70
Coal	1.82	0.549	No	2.48	3.70
Total Energy Co	1.288	0.776	No	2.48	3.70

Autocorrelation

Energy Product	Durbin Watson	Autocorrelation	d_L d_U 5%	d_L d_U 1%
Oil	0.8874	positive	1.260 1.939	1.108 1.771
Gas	3.186	No positive	1.260 1.939	1.108 1.771
Electricity	3.750	No positive	1.260 1.939	1.108 1.771
Coal	0.62	positive	1.260 1.939	1.108 1.771
Total Energy Co	1.486	inconclusive	1.260 1.939	1.108 1.771

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Canada

Table B.2 Data Properties, Canada
Structural Break

Energy Product	F Statistics	Structural Break?	5%	1%
Oil	4.18	Yes	2.07	2.80
Gas	1.01	No	2.07	2.80
Electricity	16.83	Yes	2.07	2.80
Coal	0.66	No	2.07	2.80
Total Energy Co	1.18	No	2.07	2.80

Heteroskedasticity

Energy Product	$\sigma1>\sigma2$	$\sigma1<\sigma2$	Heteroskedasticity?	GQ^* 5%	GQ^* 1%
Oil	1.64	0.61	No	2.48	3.70
Gas	1.30	0.77	No	2.48	3.70
Electricity	2.21	0.45	No	2.48	3.70
Coal	4.05	0.25	Yes	2.48	3.70
Total Energy Co	1.0455	0.9564	No	2.48	3.70

Autocorrelation

Energy Product	Durbin Watson	Autocorrelation	d_L d_U 5%	d_L d_U 1%
Oil	0.6863	positive	1.260 1.939	1.108 1.771
Gas	1.39	Inconclusive	1.260 1.939	1.108 1.771
Electricity	0.52	positive	1.260 1.939	1.108 1.771
Coal	2.13	No positive	1.260 1.939	1.108 1.771
Total Energy Co	1.37	inconclusive	1.260 1.939	1.108 1.771

Table B.3 Energy Price Cumulative Probabilities

	Coal Prices			Electricity Prices			Oil Prices			Natural Gas Prices			Total Energy Consumption		
	5	95	Mean	5	95	Mean	5	95	Mean	5	95	Mean	5	95	Mean
Alberta	52.1	82.3	68.78	2.5	4.4	3.5	20.2	31.91	26.59	9.5	15.1	12.47	166	377	273
Canada	52.1	82.4	68.78	1.7	3.0	2.35	20.2	31.92	0.23	19	27.5	23.58	656	994	832

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table B.4 Independent Variables Cumulative Probabilities Continued

	GDP		Income		Population		Electricity Production		Natural Gas Production	
	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
Alberta	79409.66	159084.8	315806.1	398511.6	2285072	2793932	6662638	14102690	17325.16	44581.92
Canada	79409.66	159084.8	315806.1	398511.6	24.7×10^7	3.0×10^7	-7.13×10^7	3.33×10^8	6616.83	67129.53

Table B.4 Independent Variables Cumulative Probabilities Continued

	Crude Oil Production		Coal Production		Degree days		OPEC Quota		Unemployment	
	5%	95%	5%	95%	5%	95%	5%	95%	5%	95%
Alberta	3699860	639623	4956.24	9701.47	-41.53	2583.83	16.68	27.04	1224.18	1520
Canada	-2.42×10^7	7.58×10^7	8393.63	24423.02	-12.94	2562.18	16.79	27.05	12441.97	15272.44

Table B.4 Independent Variables Cumulative Probabilities Continued

	Westca	
	5%	95%
Alberta	601.76	3674.96
Canada	610.80	3691.95

Table B.5 Independent Variables' Mean

	GDP Mean	Income Mean	Population Mean	Electricity Production Mean	Natural Gas Production mean	Crude Oil Production Mean	Coal Production Mean	Degree days Mean	OPEC Quota Mean	Unemployment Mean	Westca Mean
Alberta	121117	357765	2.6×10^5	1.0×10^7	31214.8	5.1×10^6	7401.5	1290.1	22.07	89.8	2176.4
Canada	121117	357765	2.7×10^7	1.3×10^8	37696.0	2.8×10^7	16736.9	1290.1	22.07	13877.0	2166.0

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Table B.6 GARCH Estimation for Alberta

ALBERTA

Coal

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC1L	1.3133	0.1750	7.506	0.000	0.769	1.3255	1.3116
PRIC1L2	-0.16352	0.2188	-0.7473	0.455	-0.119	-0.1631	-0.1630
PRIC1L3	-0.83342E-01	0.2039	-0.4088	0.683	-0.065	-0.0819	-0.0828
PRIC1L4	0.61676E-01	0.2165	0.2848	0.776	0.046	0.0615	0.0611
PRIC3	0.27352E-01	0.6990	0.3913E-01	0.969	0.006	0.0090	0.0032
PRIC5	-0.78320E-01	0.8538E-01	-0.9173	0.359	-0.145	-0.1401	-0.0297
PRIC2	2.5139	4.804	0.5233	0.601	0.084	0.5679	0.1755
PROD1	0.55629E-03	0.6286E-03	0.8850	0.376	0.140	0.2179	0.0609
TOTAL	0.51130E-01	0.3078E-01	1.661	0.097	0.257	0.5777	0.1372
POP	-0.32370E-05	0.4431E-04	-0.7306E-01	0.942	-0.012	-0.1419	-0.1200
GDP	-0.12475E-03	0.6589E-04	-1.893	0.058	-0.290	-0.8351	-0.2234
INC	0.86425E-04	0.9203E-04	0.9391	0.348	0.149	0.5864	0.4509
UNEMP	-0.99502E-02	0.4863E-01	-0.2046	0.838	-0.033	-0.2567	-0.1995
DEGRDAY	-0.11517E-02	0.1276E-02	-0.9029	0.367	-0.143	-0.2641	-0.0212
QUOTA	-1.0764	0.3924	-2.743	0.006	-0.402	-1.0224	-0.3461
WESTCA	-0.82889E-03	0.1087E-02	-0.7625	0.446	-0.121	-0.1759	-0.0193
CONSTANT	0.14918	43.99	0.3391E-02	0.997	0.001	0.0000	0.0022
	VARIANCE EQUATION:						
ALPHA_	5.4987	2.021	2.720	0.007	0.39		
ALPHA_	1.9113	0.6659	2.870	0.004	0.41		
PHI_	0.23400E-02	0.6930E-03	3.377	0.001	0.47		
DELTA_	0.14523E+07	0.1059E+07	1.372	0.170	0.21		

Electricity

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC2L	0.20127	7.593	0.2651E-01	0.979	0.004	0.2047	0.1994
PRIC2L2	0.55086	9.062	0.6079E-01	0.952	0.010	0.5711	0.5402
PRIC2L3	1.4156	8.049	0.1759	0.860	0.028	1.4941	1.3739
PRIC2L4	0.81800	6.081	0.1345	0.893	0.022	0.8777	0.7854
PRIC3	2.1095	1.025	2.058	0.040	0.313	3.0669	3.5579
PRIC5	-0.33478	0.1564	-2.140	0.032	-0.324	-2.6518	-1.8169
PRIC1	-1.0072	0.2191	-4.596	0.000	-0.593	-4.4586	-14.4259
PROD2	-0.59526E-06	0.1825E-05	-0.3262	0.744	-0.052	-1.6411	-1.3194
TOTAL	0.61278E-01	0.5925E-01	1.034	0.301	0.163	3.0647	2.3557
POP	-0.76155E-04	0.7763E-04	-0.9810	0.327	-0.155	-14.7839	-40.4426
GDP	0.16415E-03	0.1044E-03	1.573	0.116	0.244	4.8645	4.2098
INC	0.13264E-03	0.1274E-03	1.041	0.298	0.164	3.9841	9.9129
UNEMP	0.11445	0.8832E-01	1.296	0.195	0.203	13.0711	32.8608
DEGRDAY	-0.74715E-03	0.2381E-02	-0.3139	0.754	-0.050	-0.7586	-0.1973
QUOTA	0.83065	0.6379	1.302	0.193	0.204	3.4929	3.8254
WESTCA	-0.33208E-02	0.1707E-02	-1.945	0.052	-0.297	-3.1202	-1.1078
CONSTANT	-0.12005	76.40	-0.1571E-02	0.999	0.000	0.0000	-0.0249
	VARIANCE EQUATION:						
ALPHA_	8.1796	3.336	2.452	0.014	0.36		
ALPHA_	1.2923	0.3952	3.270	0.001	0.46		
PHI_	0.24238E-01	0.4760E-02	5.092	0.000	0.63		
DELTA_	0.14525E+07	0.1069E+07	1.358	0.174	0.21		

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Oil

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC5L	0.24460	0.1489	1.643	0.100	0.254	0.2476	0.2456
PRIC5L2	0.35730	0.1852	1.929	0.054	0.295	0.3660	0.3604
PRIC5L3	0.16744E-03	0.1508	0.1111E-02	0.999	0.000	0.0002	0.0002
PRIC5L4	-0.49330	0.1127	-4.376	0.000	-0.574	-0.5091	-0.4994
PRIC3	2.5815	0.7012	3.682	0.000	0.508	0.4738	0.8022
PRIC1	-0.10341	0.1063	-0.9728	0.331	-0.154	-0.0578	-0.2729
PRIC2	2.4683	3.573	0.6908	0.490	0.110	0.3116	0.4548
PROD5	-0.92790E-04	0.1674E-04	-5.542	0.000	-0.664	-1.0628	-2.8065
TOTAL	0.26973E-01	0.2823E-01	0.9555	0.339	0.151	0.1703	0.1911
POP	-0.17892E-03	0.3978E-04	-4.497	0.000	-0.584	-4.3849	-17.5071
GDP	-0.17206E-03	0.5516E-04	-3.119	0.002	-0.447	-0.6437	-0.8131
INC	0.12541E-03	0.6919E-04	1.813	0.070	0.279	0.4755	1.7268
UNEMP	0.36118	0.5503E-01	6.564	0.000	0.724	5.2078	19.1084
DEGRDAY	0.54159E-02	0.1163E-02	4.656	0.000	0.598	0.6942	0.2635
QUOTA	-0.18775	0.3257	-0.5765	0.564	-0.092	-0.0997	-0.1593
WESTCA	-0.88304E-03	0.1347E-02	-0.6554	0.512	-0.104	-0.1047	-0.0543
CONSTANT	-0.16774	38.33	-0.4376E-02	0.997	-0.001	0.0000	-0.0064
	VARIANCE EQUATION:						
ALPHA_	2.7535	1.456	1.891	0.059	0.29		
ALPHA_	2.5763	0.6549	3.934	0.000	0.53		
PHI_	0.86592E-02	0.2192E-02	3.950	0.000	0.53		
DELTA_	0.14524E+07	0.1047E+07	1.387	0.165	0.21		

Total Energy Consumption

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
TOTALL	-0.47207	0.9699E-01	-4.867	0.000	-0.615	-0.4747	-0.4670
TOTALL2	0.96581E-01	0.8972E-01	1.076	0.282	0.170	0.0988	0.0944
TOTALL3	-0.13471	0.8551E-01	-1.575	0.115	-0.245	-0.1411	-0.1302
TOTALL4	-0.11785	0.9824E-01	-1.200	0.230	-0.189	-0.1227	-0.1127
PRIC2	3.5102	9.868	0.3557	0.722	0.057	0.0702	0.0913
PRIC3	2.7817	1.801	1.544	0.123	0.240	0.0809	0.1220
PRIC5	1.0187	0.2935	3.471	0.001	0.486	0.1613	0.1438
PRIC1	-1.4760	0.3369	-4.381	0.000	-0.574	-0.1306	-0.5499
PROD2	0.55309E-05	0.3028E-05	1.827	0.068	0.281	0.3049	0.3189
POP	0.13972E-03	0.1365E-03	1.024	0.306	0.162	0.5423	1.9301
GDP	0.73700E-03	0.2005E-03	3.675	0.000	0.507	0.4367	0.4917
INC	-0.55044E-03	0.2342E-03	-2.350	0.019	-0.352	-0.3306	-1.0701
UNEMP	0.79398E-02	0.1829	0.4341E-01	0.965	0.007	0.0181	0.0593
DEGRDAY	0.41307E-02	0.4223E-02	0.9782	0.328	0.155	0.0839	0.0284
QUOTA	0.44028	0.9797	0.4494	0.653	0.072	0.0370	0.0527
WESTCA	0.32480E-02	0.3366E-02	0.9649	0.335	0.153	0.0610	0.0282
CONSTANT	-0.62054E-01	123.1	-0.5040E-03	1.000	0.000	0.0000	-0.0003
	VARIANCE EQUATION:						
ALPHA_	10.405	6.163	1.688	0.091	0.26		
ALPHA_	0.92071	0.2210	4.166	0.000	0.55		
PHI_	0.12516E-01	0.3493E-02	3.583	0.000	0.49		
DELTA_	0.14522E+07	0.1055E+07	1.376	0.169	0.21		

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Natural Gas

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC3L	-0.42794	0.5522	-0.7749	0.438	-0.123	-0.4256	-0.4276
PRIC3L2	0.18613E-01	0.6998	0.2660E-01	0.979	0.004	0.0185	0.0186
PRIC3L3	1.6660	0.8152	2.044	0.041	0.311	1.6583	1.6642
PRIC3L4	-1.9531	0.9762	-2.001	0.045	-0.305	-1.8878	-1.9405
PRIC5	-0.63661	0.1143	-5.572	0.000	-0.666	-3.4685	-2.0485
PRIC1	0.56379	0.1273	4.429	0.000	0.579	1.7167	4.7880
PRIC2	2.7039	4.555	0.5937	0.553	0.095	1.8599	1.6032
PROD3	-0.10054E-02	0.2535E-03	-3.965	0.000	-0.536	-7.3853	-3.9270
TOTAL	0.90156E-01	0.3772E-01	2.390	0.017	0.357	3.1015	2.0550
POP	0.84266E-04	0.5106E-04	1.650	0.099	0.255	11.2518	26.5326
GDP	0.28069E-03	0.6685E-04	4.199	0.000	0.558	5.7215	4.2682
INC	-0.34359E-03	0.7430E-04	-4.624	0.000	-0.595	-7.0985	-15.2244
UNEMP	-0.84968E-01	0.6007E-01	-1.415	0.157	-0.221	-6.6750	-14.4651
DEGRDAY	0.22580E-02	0.1397E-02	1.616	0.106	0.251	1.5769	0.3535
QUOTA	-0.92846	0.3891	-2.386	0.017	-0.357	-2.6854	-2.5352
WESTCA	-0.10184E-02	0.1265E-02	-0.8049	0.421	-0.128	-0.6582	-0.2014
CONSTANT	0.83111E-01	48.62	0.1709E-02	0.999	0.000	0.0000	0.0102
	VARIANCE EQUATION:						
ALPHA_	2.5116	1.676	1.499	0.134	0.23		
ALPHA_	1.7994	0.4933	3.648	0.000	0.50		
PHI_	0.43786E-01	0.6115E-02	7.160	0.000	0.75		
DELTA_	0.14525E+07	0.1071E+07	1.357	0.175	0.21		

Table B.7 GARCH Estimation for Canada

Canada

Coal

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC1L	0.89610	0.2190	4.092	0.000	0.548	0.9044	0.8950
PRIC1L2	0.44411	0.2724	1.630	0.103	0.253	0.4430	0.4427
PRIC1L3	0.72388E-01	0.2316	0.3125	0.755	0.050	0.0711	0.0719
PRIC1L4	-0.94767E-01	0.2084	-0.4547	0.649	-0.073	-0.0944	-0.0939
PRIC3	0.79007	0.5846	1.351	0.177	0.211	0.2886	0.1550
PRIC5	0.43574	0.1136	3.837	0.000	0.524	0.7797	0.1651
PRIC2	3.9498	4.908	0.8047	0.421	0.128	0.8087	0.2374
PROD1	-0.33987E-03	0.5300E-03	-0.6413	0.521	-0.102	-0.2369	-0.0818
TOTAL	-0.35784E-01	0.2027E-01	-1.766	0.077	-0.272	-0.6264	-0.2500
POP	0.16830E-05	0.4288E-05	0.3925	0.695	0.063	0.7507	0.6715
GDP	0.18863E-03	0.1254E-03	1.505	0.132	0.234	1.2586	0.3376
INC	0.32308E-04	0.1007E-03	0.3209	0.748	0.051	0.2194	0.1686
UNEMP	-0.75064E-02	0.9689E-02	-0.7748	0.438	-0.123	-1.7659	-1.5183
DEGRDAY	0.10447E-02	0.1277E-02	0.8183	0.413	0.130	0.2396	0.0193
QUOTA	-0.46809	0.4133	-1.133	0.257	-0.178	-0.4446	-0.1505
WESTCA	-0.16690E-02	0.8557E-03	-1.951	0.051	-0.298	-0.4683	-0.0533
CONSTANT	-0.10217	67.75	-0.1508E-02	0.999	0.000	0.0000	-0.0015
	VARIANCE EQUATION:						
ALPHA_	6.9707	2.534	2.751	0.006	0.40		
ALPHA_	2.0914	0.7979	2.621	0.009	0.38		
PHI_	0.21196E-01	0.3676E-02	5.767	0.000	0.67		
DELTA_	0.14901E+07	0.1101E+07	1.353	0.176	0.21		

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Electricity

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC2L	1.1995	29.18	0.4111E-01	0.967	0.007	1.2199	1.1892
PRIC2L2	0.90783	33.46	0.2713E-01	0.978	0.004	0.9357	0.8923
PRIC2L3	0.14667	30.00	0.4889E-02	0.996	0.001	0.1528	0.1429
PRIC2L4	-0.17880E-01	31.72	-0.5637E-03	1.000	0.000	-0.0188	-0.0173
PRIC3	-0.56306	1.976	-0.2850	0.776	-0.046	-1.0046	-1.8379
PRIC5	1.5779	0.4699	3.358	0.001	0.474	13.7902	9.9484
PRIC1	-3.3070	0.5870	-5.634	0.000	-0.670	-16.1530	-55.0288
PROD2	0.39915E-06	0.4480E-06	0.8910	0.373	0.141	9.2177	11.7247
TOTAL	0.91803E-01	0.6321E-01	1.452	0.146	0.227	7.8498	10.6729
POP	-0.61528E-04	0.1859E-04	-3.310	0.001	-0.468	-134.0583	-408.4920
GDP	0.88699E-03	0.3840E-03	2.310	0.021	0.347	28.9075	26.4166
INC	0.33959E-03	0.2865E-03	1.185	0.236	0.186	11.2620	29.4835
UNEMP	0.10752	0.3595E-01	2.991	0.003	0.432	123.5450	361.8639
DEGRDAY	-0.79853E-02	0.4865E-02	-1.641	0.101	-0.254	-8.9454	-2.4497
QUOTA	2.5084	1.176	2.132	0.033	0.323	11.6377	13.4198
WESTCA	-0.12391E-02	0.2012E-02	-0.6158	0.538	-0.098	-1.6981	-0.6589
CONSTANT	-0.11841E-02	250.3	-0.4730E-05	1.000	0.000	0.0000	-0.0003
	VARIANCE EQUATION:						
ALPHA_	1.6896	4.461	0.3788	0.705	0.06		
ALPHA_	0.70087	0.1498	4.678	0.000	0.60		
PHI_	0.10051E-01	0.3022E-02	3.326	0.001	0.47		
DELTA_	0.14904E+07	0.1081E+07	1.379	0.168	0.21		

Oil

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC5L	0.95473	0.1697	5.625	0.000	0.669	0.9665	0.9587
PRIC5L2	-0.94829	0.2052	-4.622	0.000	-0.595	-0.9714	-0.9566
PRIC5L3	0.95560	0.2068	4.621	0.000	0.595	0.9840	0.9667
PRIC5L4	-0.15118	0.1505	-1.004	0.315	-0.159	-0.1560	-0.1531
PRIC3	-1.9053	0.7269	-2.621	0.009	-0.387	-0.3890	-0.9864
PRIC1	0.26391	0.1762	1.498	0.134	0.233	0.1475	0.6965
PRIC2	-1.2433	5.606	-0.2218	0.824	-0.035	-0.1423	-0.1972
PROD5	-0.56092E-06	0.2028E-04	-0.2766E-01	0.978	-0.004	-0.0108	-0.0210
TOTAL	-0.87807E-01	0.1894E-01	-4.637	0.000	-0.596	-0.8591	-1.6191
POP	0.71848E-05	0.4429E-05	1.622	0.105	0.251	1.7912	7.5656
GDP	0.11892E-03	0.1392E-03	0.8543	0.393	0.136	0.4435	0.5617
INC	-0.13683E-03	0.1117E-03	-1.225	0.221	-0.192	-0.5192	-1.8842
UNEMP	-0.64200E-02	0.9398E-02	-0.6831	0.495	-0.109	-0.8441	-3.4270
DEGRDAY	0.61299E-02	0.1500E-02	4.086	0.000	0.548	0.7857	0.2983
QUOTA	-0.95484	0.4395	-2.173	0.030	-0.329	-0.5069	-0.8102
WESTCA	-0.18495E-03	0.1188E-02	-0.1557	0.876	-0.025	-0.0290	-0.0156
CONSTANT	0.25361	79.93	0.3173E-02	0.997	0.001	0.0000	0.0097
	VARIANCE EQUATION:						
ALPHA_	7.3484	2.933	2.505	0.012	0.37		
ALPHA_	1.6655	0.5930	2.808	0.005	0.41		
PHI_	0.73713E-02	0.1907E-02	3.866	0.000	0.52		
DELTA_	0.14903E+07	0.1091E+07	1.366	0.172	0.21		

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Total Energy Consumption

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
TOTALL	-0.25586	0.6748E-01	-3.792	0.000	-0.519	-0.2537	-0.2544
TOTALL2	-0.53432	0.6793E-01	-7.865	0.000	-0.783	-0.5403	-0.5277
TOTALL3	-0.36480	0.6464E-01	-5.643	0.000	-0.670	-0.3867	-0.3583
TOTALL4	0.36555	0.7271E-01	5.027	0.000	0.627	0.3806	0.3582
PRIC2	1.2115	17.79	0.6810E-01	0.946	0.011	0.0142	0.0104
PRIC3	-2.2532	3.352	-0.6722	0.501	-0.107	-0.0470	-0.0633
PRIC5	2.3149	0.6407	3.613	0.000	0.501	0.2366	0.1255
PRIC1	-1.4313	0.6501	-2.202	0.028	-0.332	-0.0818	-0.2049
PROD2	0.33394E-05	0.5324E-06	6.272	0.000	0.709	0.9019	0.8437
POP	-0.37386E-04	0.2192E-04	-1.706	0.088	-0.263	-0.9526	-2.1350
GDP	0.10113E-02	0.5474E-03	1.847	0.065	0.284	0.3854	0.2591
INC	0.26049E-02	0.5271E-03	4.942	0.000	0.621	1.0103	1.9453
UNEMP	0.33797E-01	0.5426E-01	0.6229	0.533	0.099	0.4542	0.9784
DEGRDAY	-0.35837E-01	0.8253E-02	-4.342	0.000	-0.571	-0.4695	-0.0946
QUOTA	2.7783	2.600	1.069	0.285	0.169	0.1507	0.1279
WESTCA	-0.92022E-02	0.3342E-02	-2.754	0.006	-0.403	-0.1475	-0.0421
CONSTANT	0.97868E-01	302.6	0.3234E-03	1.000	0.000	0.0000	0.0002
	VARIANCE EQUATION:						
ALPHA_	3.8912	24.28	0.1603	0.873	0.02		
ALPHA_	0.68997	0.1526	4.522	0.000	0.58		
PHI_	0.96891E-02	0.3136E-02	3.089	0.002	0.44		
DELTA_	0.14897E+07	0.1081E+07	1.379	0.168	0.21		

Natural Gas

VARIABLE NAME	ESTIMATED COEFFICIENT	ASYMPTOTIC STANDARD ERROR	T-RATIO --------	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
	MEAN EQUATION:						
PRIC3L	0.23698	4.988	0.4751E-01	0.962	0.008	0.2354	0.2368
PRIC3L2	-0.25272	6.003	-0.4210E-01	0.966	-0.007	-0.2502	-0.2526
PRIC3L3	0.19003	5.559	0.3419E-01	0.973	0.005	0.1886	0.1897
PRIC3L4	0.35136	7.555	0.4651E-01	0.963	0.007	0.3412	0.3493
PRIC5	-0.60980	0.8916	-0.6840	0.494	-0.109	-2.9870	-1.1779
PRIC1	0.69684	1.410	0.4942	0.621	0.079	1.9076	3.5523
PRIC2	3.2224	45.86	0.7027E-01	0.944	0.011	1.8060	0.9872
PROD3	0.16263E-03	0.4847E-03	0.3355	0.737	0.054	2.4167	0.4622
TOTAL	0.69835	0.1173	5.955	0.000	0.690	33.4677	24.8731
POP	0.10202E-03	0.2835E-04	3.598	0.000	0.499	124.5818	207.5041
GDP	0.36832E-02	0.8604E-03	4.281	0.000	0.565	67.2780	33.6064
INC	-0.37230E-02	0.5929E-03	-6.279	0.000	-0.709	-69.1997	-99.0267
UNEMP	-0.16145	0.5079E-01	-3.179	0.001	-0.454	-103.9744	-166.4672
DEGRDAY	-0.25518E-01	0.9760E-02	-2.615	0.009	-0.386	-16.0218	-2.3983
QUOTA	1.4149	4.080	0.3468	0.729	0.055	3.6793	2.3191
WESTCA	-0.48898E-01	0.8119E-02	-6.023	0.000	-0.694	-37.5583	-7.9663
CONSTANT	-0.92790E-02	557.7	-0.1664E-04	1.000	0.000	0.0000	-0.0007
	VARIANCE EQUATION:						
ALPHA_	0.77346E-01	8.576	0.9019E-02	0.993	0.00		
ALPHA_	1.7646	0.3431	5.143	0.000	0.63		
PHI_	0.37838E-02	0.1516E-02	2.496	0.013	0.37		
DELTA_	0.14903E+07	0.1066E+07	1.398	0.162	0.21		

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

APPENDIX C: NUMERICAL EXAMPLE OF MULTIPLE REGRESSION

A Numerical Example of Multiple Regression Model

Suppose the price of crude oil depends on number of wells drilled and the crude oil production number of wells drilled. The multiple linear regression model

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \tag{C.1}$$

The following table lists the data: Table C.1 Data Set Numerical Example

Data number	Crude Oil Price y	No. of wells drilled X_1	Crude Oil Production X_2
1	31,37	2003	23.309806
2	31,37	1105	20.639047
3	33,62	1879	23.838222
4	33,62	1755	22.509869
5	35,16	2003	21.020729
6	35,16	1105	18.436885
7	35,16	1879	23.958647
8	35,16	1755	22.921693
9	35,24	2429	22.792125
10	35,24	1705	20.560944
11	35,24	2504	22.298096
12	37,09	2469	21.966392
13	38,02	3010	20.406928
14	37,7	2012	20.369222
15	35,97	3328	22.921220
16	37,45	3396	23.021160
17	25,05	3351	21.222122
18	18,29	1067	19.264941
19	18,39	790	23.076516
20	20,24	1067	21.415461
21	23,42	1432	22.244207
22	24,3	826	20.773807
23	25,8	1872	23.996720
24	23,75	2678	23.750569
25	20,1	2535	23.756000

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The X matrix and y vector for this model are

$$X = \begin{bmatrix} 1 & 2003 & 23.309806 \\ 1 & 1105 & 20.639047 \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ 1 & 2678 & 23.750569 \\ 1 & 2535 & 23.756000 \end{bmatrix} \quad y = \begin{bmatrix} 31.37 \\ 31.37 \\ \bullet \\ \bullet \\ \bullet \\ 23.75 \\ 20.10 \end{bmatrix}$$

The X'X matrix is

$$X'X = \begin{bmatrix} 1 & 1\bullet\bullet\bullet & 1 \\ 2003 & 1105\bullet\bullet\bullet & 2532 \\ 23.309806 & 20.639047\bullet\bullet\bullet & 23.756000 \end{bmatrix} \begin{bmatrix} 1 & 2003 & 23.309806 \\ 1 & 1105 & 20.639047 \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ 1 & 2532 & 23.756000 \end{bmatrix}$$

$$X'X = \begin{bmatrix} 25 & 49955 & 555.47 \\ 49955 & 1.1\times10^8 & 1.1\times10^6 \\ 555.47 & 1.1\times10^6 & 12177.45 \end{bmatrix}$$

The X'y vector is

$$X'y = \begin{bmatrix} 1 & 1\bullet\bullet\bullet & 1 \\ 2003 & 1105\bullet\bullet\bullet & 2532 \\ 23.309806 & 20.639047\bullet\bullet\bullet & 23.756000 \end{bmatrix} \begin{bmatrix} 31.37 \\ 31.37 \\ \bullet \\ \bullet \\ \bullet \\ 20.10 \end{bmatrix} = \begin{bmatrix} 761.91 \\ 1575446 \\ 16759.48 \end{bmatrix}$$

$$\hat{\beta} = (X'X)^{-1} X'y$$

$$\begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = \begin{bmatrix} 25 & 49955 & 555.47 \\ 49955 & 1.1\times10^8 & 1.1\times10^6 \\ 555.47 & 1.1\times10^6 & 12177.45 \end{bmatrix}^{-1} \begin{bmatrix} 761.91 \\ 1575446 \\ 16759.48 \end{bmatrix}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$= \begin{bmatrix} 3.7677 \\ 0.0059 \\ 0.6746 \end{bmatrix}$$

The regression model is

$$\hat{y} = 3.7677 + 0.0059X_1 + 0.6746X_2 \qquad \text{C.2}$$

4.2.1 Calculation of the Mean and Variance of Y.

$$E[\hat{y}] = E[3.7677] + 0.0059 \times E[X_1] + 0.6746 \times E[X_2]$$

= 3.7677+ (0.0059×1998.2) +0.6746 × 22.0188531

= 30.41

$$Var[\hat{y}] = Var[3.7677] + 0.0059 \times Var[X_1] + 0.6746 \times Var[X_2]$$

= 0.0059×613436.6 + 0.6746 × 2.3625 × 10^{12}

=3620.87

$R^2 = 1 - \frac{SS_E}{SS_{yy}}$

$$SS_{yy} = \sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}$$

$$SS_{yy} = 24320.63 - \frac{(761.91)^2}{25}$$

=1100.36

$SS_E = \frac{\sum (y_i - \hat{y}_i)^2}{n}$ = 1111.293/25=44.4517

R^2 = 1- 44.4517/1100.36 =0.9596

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

	Crude Oil	No. of Wells	Crude Oil Prod-	Estimation		Price-Estimated	
Data No.	Price y	Drilled X1	uction (10^6) X2	of yi	y^2	Price E	E^2
1	31.37	2003	23.309806	31.310195	984.0769	0.059804872	0.003577
2	31.37	1105	20.639047	24.210301	984.0769	7.159698894	51.26129
3	33.62	1879	23.838222	30.935065	1130.304	2.684935439	7.208878
4	33.62	1755	22.509869	29.307358	1130.304	4.312642373	18.59888
5	35.16	2003	21.020729	29.765984	1236.226	5.394016217	29.09541
6	35.16	1105	18.436885	22.724723	1236.226	12.43527738	154.6361
7	35.16	1879	23.958647	31.016303	1236.226	4.143696734	17.17022
8	35.16	1755	22.921693	29.585174	1236.226	5.574825902	31.07868
9	35.24	2429	22.792125	33.474368	1241.858	1.765632475	3.117458
10	35.24	1705	20.560944	27.697613	1241.858	7.542387178	56.8876
11	35.24	2504	22.298096	33.583596	1241.858	1.656404438	2.743676
12	37.09	2469	21.966392	33.153328	1375.668	3.936671957	15.49739
13	38.02	3010	20.406928	35.293214	1445.52	2.726786371	7.435364
14	37.7	2012	20.369222	29.379577	1421.29	8.320422839	69.22944
15	35.97	3328	22.92122	38.865555	1293.841	-2.895555012	8.384239
16	37.45	3396	23.02116	39.334175	1402.503	-1.884174536	3.550114
17	25.05	3351	21.222122	37.855044	627.5025	-12.8050435	163.9691
18	18.29	1067	19.264941	23.059129	334.5241	-4.769129199	22.74459
19	18.39	790	23.076516	23.996118	338.1921	-5.606117694	31.42856
20	20.24	1067	21.415461	24.50987	409.6576	-4.269869991	18.23179
21	23.42	1432	22.244207	27.222442	548.4964	-3.802442042	14.45857
22	24.3	826	20.773807	22.65511	590.49	1.644889798	2.705662
23	25.8	1872	23.99672	31.000687	665.64	-5.200687312	27.04715
24	23.75	2678	23.750569	35.590034	564.0625	-11.84003385	140.1864
25	20.1	2535	23.756	34.749998	404.01	-14.6499976	214.6224
	761.91				24320.63		1111.293

Principal Component Regression

$$R = \frac{N\sum X_1X_2 - \sum X_1 \times \sum X_2}{\left(\left(N\sum X_{1_1}^2 - \left(\sum X_1\right)^2\right)\times\left(N\sum X_2^2 - \left(\sum X_2\right)^2\right)\right)^{\frac{1}{2}}}$$

Where R is the correlation coefficient.

$$R = \frac{25 \times 1109385 - 49955 \times 550.47}{\left(\left(25 \times 114542559 - 49955^2\right)\times\left(25 \times 12177.45 - 550.47^2\right)\right)^{\frac{1}{2}}}$$

= 0.326495372

The 2 by 2 matrix of correlation coefficient is

$$\begin{bmatrix} 1.0000 & 0.3265 \\ 0.3265 & 1.0000 \end{bmatrix}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

the eigenvalues are obtained as follows

$$\begin{bmatrix} r_{11}-\lambda & r_{12} \\ r_{21} & r_{22}-\lambda \end{bmatrix} = (r_{11}-\lambda)(r_{22}-\lambda) - r_{12}r_{21} = \lambda^2 - (r_{11}+r_{22})\lambda + (r_{11}r_{22} - r_{12}r_{21}) = 0$$

Putting in the r values:

$$\lambda^2 - 2\lambda + 0.8934$$

a = 1, b = -2, c = 0.8934

$$\lambda = \frac{-b \pm (b^2 - 4ac)^2}{2a}$$

$\lambda = 1.4$ and 0.6

$\lambda_1 = 1.4$

$\lambda_2 = 0.6$

$\Sigma\lambda_i = 2$

Thus the first principal component λ_1 accounts for (1.4/2 $\times$100) of the total variance, 70%; likewise λ_2 accounts for (0.6/2 $\times$100) of the total variance, 30%.

$$\begin{bmatrix} e_{11} & e_{21} \\ e_{12} & e_{22} \end{bmatrix} * \begin{bmatrix} r_{11} & r_{21} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} * \begin{bmatrix} e_{11} & e_{21} \\ e_{12} & e_{22} \end{bmatrix}$$

After multiplying out it becomes

(1) $(r_{11} - \lambda_1)e_{11} + r_{21}e_{21} = 0$

(2) $r_{12}e_{11} + (r_{22} - \lambda_1)e_{21} = 0$

From standard scores of data, the correlation matrix remains

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$R = \begin{bmatrix} 1.0 & 0.83 \\ 0.83 & 1.0 \end{bmatrix}$$

(1) $-0.4e_{11} + 0.3265e_{21} = 0$

(2) $0.3265e_{11} - 0.4e_{21} = 0$

Making e_{21} the subject of equation (1) and setting it to 1 we have and :

$$e_{21} = \frac{0.4}{0.3265} = 1.225$$

$$\begin{bmatrix} e_{11} \\ e_{21} \end{bmatrix} = \begin{bmatrix} 1.225 \\ 1.000 \end{bmatrix}$$

Square e_{i1}	divide by sum of square roots	take square root of e_{i1}.
$\begin{bmatrix} 1.50 \\ 1.00 \end{bmatrix}$	$\begin{bmatrix} 0.6 \\ 0.4 \end{bmatrix}$	$\begin{bmatrix} 0.7746 \\ 0.6326 \end{bmatrix}$

The eigenvalues of the correlation matrix is

$$b = \begin{bmatrix} 0.1700 & 0 \\ 0 & 1.8300 \end{bmatrix}$$

The eigenvectors of the correlation matrix is

$$a = \begin{bmatrix} -0.7071 & 0.7071 \\ 0.7071 & 0.7071 \end{bmatrix}$$

The matrix of the principal component loadings, is designated as {L}.

$$\{L\} = \{a\} \cdot \{b\}^{1/2}$$

$$\{b\}^{1/2} = \begin{bmatrix} 0.4123 & 0 \\ 0 & 1.3528 \end{bmatrix}$$

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

$$\{L\} = \begin{bmatrix} -0.2915 & 0.9565 \\ 0.2915 & 0.9565 \end{bmatrix}$$

ARMA(1,1) Process

The combined AR(1) and MA(1) processes gives the ARMA(1, 1) scheme,

$$(y_t - \mu) = \alpha(y_{t-1} - \mu) + \varepsilon_t - \beta\varepsilon_{t-1} \tag{C.3}$$

The mean squared error (MSE) of a forecast is simply the average, or expected squared forecast error. This treats positive and negative forecast errors symmetrically and is widely used criterion for the choice of a forecasting rule. The minimum MSE forecast for period n+1 is then

$$\hat{y}_{n+1} - \mu = \alpha(y_n - \mu) - \beta\varepsilon_n$$

This result differs from the AR(1) forecast only by the term in $\beta\varepsilon_n$. The forecast error variance is $var(e_{n+1}) = \sigma^2$. Repeated use of C3 gives

$$(y_{n+2} - \mu) = \alpha^2(y_n - \mu) + \varepsilon_{n+2} + (\alpha - \beta)\varepsilon_{n+1} - \alpha\beta\varepsilon_n$$

The forecast period n+2 is then

$$(\hat{y}_{n+2} - \mu) = \alpha^2(y_n - \mu) - \alpha\beta\varepsilon_n = \alpha(\hat{y}_{n+1} - \mu) \tag{C.4}$$

Thus, as in the AR(1) case, successive forecasts deviate from the mean in a declining exponential fashion. The forecast error variance is $var(e_{n+2}) = \sigma^2[1+(\alpha-\beta)^2]$. Therefore

$$(\hat{y}_{n+s} - \mu) = \alpha^s(y_n - \mu) - \alpha^{s-1}\beta\varepsilon_n \tag{C.5}$$

Artificial Neural Network

Artificial neural networks are models (usually simulated on digital computers) composed of many nonlinear processing elements (called nodes or neurons) operating in parallel and arranged in patterns reminiscent of biological neuron interconnections. Neural networks typically have their nodes arranged in layers.

Each hidden layer node has one variable "weight" for each of its outputs, and exactly one variable "threshold". The neural network is "trained" by presenting to it data in the form of vectors. If there are N inputs to the network, then it is trained using vectors of N + 1 elements: one element for each input, plus the known output corresponding to the given input. Training consists of iteratively updating weights and thresholds in the hidden layer nodes as training vectors are applied, toward the goal of minimizing the difference between the network's actual and desired outputs.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

The operation of a network can be explained in geometric terms, beginning with the operation of a single neuron. The weights w and threshold θ are imagined residing within the summing node. The output Y of the node is a sigmoid function given by

$$Y = f(Z) = 1/[1 + \exp(-Z)] \quad \text{(C.6)}$$

When training is complete, all network weights are fixed and the network output is a complicated but deterministic function of the network inputs. The value S_{M+1} is then predicted as the network output corresponding to the input vector (S_{M-3}, S_{M-2}, S_{M-1}, S_M). The value S_{M+1} then serves as the last component of the next input vector, which is used to predict S_{M+2}. The prediction process continues as long as is desired. Prediction accuracy generally decreases with time due to incomplete training and numerical rounding.

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.