Modelling and Forecasting Energy Intensity, Energy Efficiency and CO_2 Emissions for Pakistan

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To Parents and Siblings

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Abstract

The aim of this thesis is to examine the significant environmental issues, especially, Green House Gases (GHGs) emissions and specifically Carbon Dioxide (CO_2) emissions which are mainly caused by energy use. This thesis consists of three core chapters. Chapters 2 and 4 discuss how to stabilize and forecast CO_2 emissions for Pakistan while chapter 3 discusses the energy efficiency of Asian developing countries.

Exogenous Technical Change (TC) and endogenous TC models are considered in the chapter 2 for the stabilization of CO_2 emissions. Specifically, the estimated results show that endogenous TC model (which is estimated by following the Kalman Filter (KF) technique) does a better job in comparison. The results also point out the existence of a trade-off between GDP growth and fuel prices. Inter-fuel substitutions are estimated using the Almost Ideal Demand System (AID). Results suggest that stabilization can be achieved just in short run but it needs too much time for the implementation in the long run plans.

In chapter 3, a parametric Stochastic Frontier model Approach (SFA) is used for a panel of 19 countries including Pakistan over the period of 1980 to 2013. The individual and relative energy efficiency over time of all counties is estimated. The focus is to find either energy intensity a good indicator of energy efficiency or not. According to the estimated results, energy intensity is not a good indicator of energy efficiency but the energy efficiency estimated using SFA after controlling for some of the economic factors (fuel prices, population, income, etc.) it is.

In chapter 4, the relationship between CO_2 emissions and income, and energy consumption and income are found to support the Environmental Kuznets Curve (EKC) hypothesis. Univariate (Grey Prediction Model (GM), Exponential Smoothing (ES), Holt-Winter (H-W)) and multivariate model solving techniques are used to predict CO_2 emissions and their forecasting abilities are compared. A new technique, Out Of Sample Grey Prediction (OOSGP), is introduced after providing a critique of the GP model to get better forecast results. The findings of this study provide a valuable reference with which Pakistan's government could formulate measures to reduce CO_2 emissions by curbing the unnecessary consumption of energy.

JEL Classification Codes: C32, C53, Q41, Q43, Q55, Q58

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Chapter 1

Introduction

Environmental degradation can be seen as a direct result of the increase in consumption of non-renewable energy sources; there being a close connection between energy, environment and economics. Because the energy sector has contributed greatly to the global Green House Gases (GHGs) and there being financial and infrastructural pressure on developing countries to mitigate against global warming and climate change, there has been a worldwide demand for energy system analysis, when dealing with energy consumption and Carbon Dioxide (CO_2) emissions. A number of measures have been introduced by developed economies of the world in order to control emissions, chief among them being the Kyoto Protocol (1997). The aim and objectives of the protocol are to concentrate on reducing the level of GHGs responsible for climate change and is based on the belief that global warming exists, and that it is a result of manmade CO_2 emissions. Although the developed economies that are a part of the Protocol have an obligation to reduce current emissions due to the fact that they are considered responsible, historically developing economies also have their part to play in reducing these emissions.

In December 2015, the United Nations Framework Convention on Climate Change (UNFCCC) conducted a conference known as Paris Agreement[1]. 195 countries were invited of which Pakistan was one of them. The agreement was to reduce CO_2 emissions and commit to controlling global warming by reducing the world's surface temperature by 2 Degree Celsius (2°C). In order to achieve this, developing countries were to be given $100 billion towards new technologies and adopting new processes. Pakistan has subsequently signed the agreement and committed herself to the climate action plan which will come into effect in 2020. Energy plays an important role in driving economic growth and development, and growing economies have an ever increasing demand for energy products. It is clear that with the increase in utilization and consumption of energy resources, there is a corresponding increase in pollutants, mainly CO_2 emissions, which require balancing in order to reduce the risk of

[1] United Nations Climate Change Conference was conducted in France (Paris) in December, 2015 with the aim of environmental concerns but the discussed concerns are yet to be adopted by the world (those were agreed though)

environmental degradation. This balance is ignored by many governments in preference to production of products. However, it is very apparent that global fossil fuel CO_2 emissions are increasing rapidly and there is a 24 percent increment in world's CO_2 emissions from 1958 to date (NOAA, 2015). According to Carbon Dioxide Information Analysis Centre (CDIAC)[2], total global emissions have increased from 9.4 billion metric tons to 9.6 billion metric tons in the space of a year and it is estimated that there will be an 11.5 percent rise globally in the next ten years equating to a 14 inch thick layer of pure CO_2 at the earth's surface. Whilst developed economies are in a position to address this issue, the view is that the developing economies are still prioritizing increased production whilst disregarding the knock on effects of their production processes.

Sheikh (2010) argues that currently, Pakistan fulfills more than 99 percent of its energy requirements with fossil fuels and 54 percent of this relating to oil and gas ((Pakistan Energy Yearbook, 2011). In recent years this had led to an increase of 167 million tons of CO_2 emissions (Qudrut Ullah and Karahul, 2007). The challenge then, is for Pakistan to improve, adopt and change to alternative, renewable, non-pollutant energy sources, and its environmental energy policy requires an accurate forecast of CO_2 emissions. Although currently it is considered that developing countries, Pakistan included, do not contribute greatly to energy consumption and CO_2 emissions, that view will change and it is likely that they will consume a significant part of the world's energy. The prediction is that developing countries share of oil consumption will rise by up to 35.8 percent by 2020 in comparison to the rest of the world. If this continues, then global energy consumption will increase up to 50 percent by 2030. It is expected that the world's marketed energy consumption will increase from 447 Quadrillion British thermal units (QBtu) in 2004 to 702 QBtu in 2030 (Riaz, 2008).

With this increase in energy consumption, so there will be an increase in environmental degradation. It is essential that efficient ways to use energy are adopted to promote a cleaner, better environment. Energy systems need to be reviewed and improved if there is to be any control over the threat to our environment. Further to this, studies in efficiencies of energy utilization will provide a framework that improves the effectiveness of ecological tax reforms. In 2015 China agreed to invest approximately 30.7 billion Pounds in Pakistan's infrastructure over the next 20 years. The spending on

[2] Department of Energy of CDIAC came in to existence in 1982 based in U.S. They have been collecting and maintaining the data on the CO_2 emissions, atmospheric gases which affect the climate.

roads and rail networks, and electricity generation is aimed at strengthening Pakistan's struggling economy and ending the power shortages currently experienced. This investment (Murshid Hussain Sayed, chairman of the Pakistani parliament's defence committee) will strengthen the struggling economy and help end chronic power shortages in Pakistan. Although Pakistan is growing economically strong, this investment will boost their economy further and make them a key partner in China's economic and strategic ambitions. Also, with this investment, Pakistan can have greater focus on its plans to reduce CO_2 emissions. For this to happen, there is a need to revise CO_2 emissions estimates which can only be done if baseline forecasts are available.

Chapter 2 looks to examine exogenous and endogenous trend effects on Carbon Dioxide (CO_2) emissions and how this impacts economic growth in Pakistan. We have modelled the energy demand in Pakistan by adopting the small branch of methodology of Environmental Global Econometric Model (EGEM)[3] model. When total energy consumption is broken down into its share components, CO_2 emissions can be forecast for each energy type[4] in use. By using the technique known as the Kalman Filter (KF) technique[5], endogenous Technical Change (TC) can be estimated. In this way, the stabilisation of CO_2 emissions can be determined when there is an increase in both carbon and energy taxes. Using the Almost Ideal Demand Systems (AIDS)[6] as a means of estimating fuel share equations for oil, gas and coal, inter-fuel substitution possibilities can be identified which in turn influence policy where CO_2 emissions are concerned. If we know technological change, then, it could stabilise the CO_2 level over next 100 years after institutional and socio economic changes (Anderson et al., 2002). We examine the possibility of both exogenous and endogenous trend effects on CO_2

[3] EGEM model is based on rich econometric derivations of hundreds of equations. One branch of this model can be used as the estimation of energy demand model, which is used in present study for Pakistan. Also see chapter 4&5 of Mabey et al. (1997) for complete derivation and implication of the (EGEM) in the light of energy economics.

[4] In our study, we are taking three types of fossil fuel energy as Oil, Coal and Gas. These three variables are chosen on the basis of availability of data during 1971-2013 for Pakistan.

[5] To find out the detailed description of Kalman Filter technique, See Cuthbertson et al. (1992), Currie and Hall (1994), Harvey (1987), Lawson (1980), Hamilton (1994) and some more useful information and contributions in Kalman Filter could also be found in Aoki (1991), Lutkepohl (1993) and Harvey (1989) etc.

[6] Almost Ideal Demand System (AIDS) was developed by Deaton and Muellbauer in (1980). AIDS model is used extensively in different fields of economics and consumer demand systems and it also describes the underlying equilibrium structure of interrelated consumer demand (Akmal, 2002). The most appropriate and slightly better functional form between Almost Ideal Demand System (AIDS), linear, log-linear and translog functional is said to be AIDS forms when the relationship between energy consumption and energy prices or other explanatory variables is estimated (Xiao et al., 2007).

emissions. By breaking down total energy consumption in to its share components, CO_2 emissions can be forecast based on different types of energy (Oil, Coal and Gas) in use. Energy demand models provide valuable information about the overall energy intensity and CO_2 emissions but price changes induce substitution possibilities between the energy products. Historically, the macroeconomic models have been applied in different fields and a great deal of work has been done in which the economic systems are modelled with special featured models as: energy-environment-economy models. Two major approaches are adopted in these models 1) to combine the aggregated models of energy systems, climate change, economic activity and emissions, 2) to take the energy sector and technology models and focus on the climate change policy as well as the energy sector policy. It is worth clarifying why some studies have been using the endogenous technical progress model and others have been using induced technical change model. There is no real answer for this question but one of the reasons could be because path dependence is introduced and non-linearity is implemented immediately after the incorporation of the induced technological change in the model and the model is solved with qualitative steps.

Choosing the right modelling (exogenous or endogenous) and methodologies for TC is open for debate, so, it is very important to choose the appropriate way to model TC for perfect policy implications. The focus of this chapter is not to find out whether technological development is important or not, but on how the occurrence of technological development can be represented and used in the models and also to find out the policy implications about economic policy conclusions for the reduction in CO_2 emissions. The demand for energy products is increasing to fulfil the needs of growing economies. However, increase in the utilization and consumption of energy resources creates pollution due to carbon dioxide (CO_2) emissions. Therefore, energy consumption requires balancing in a way that production activities are performed smoothly and issues of environmental degradation do not hurt the social welfare of societies. However, that balance is being ignored and companies as well as governments remain biased towards production. Global fossil fuel CO_2 emissions are estimated by Carbon Dioxide Information Analysis Centre (CDIAC) and analysis shows how quickly CO_2 emissions are increasing. They have found that total global emissions have increased from 9.4 billion metric tons to 9.6 billion metric tons from 2011 to 2012 and over ten years, globally, there will be 11.5 percent increment in CO_2 emissions which means 14” (36cm) thick layer of pure CO_2 at the surface. There has been a 24 percent increase in world's CO_2 emissions from 1958 to date (NOAA, 2015). A continuous increase in CO_2 emissions is very worrying (Zhang and Cheng, 2009). Developed countries are in a position to address this issue, however developing economies are only concerned about the increase in production and ignore the issue of negative externalities of this production process. Therefore, energy consumption is not a country specific issue the whole world is included as stakeholders. Environmental degradation is the result of increase in non-renewable energy generation worldwide. In fact, there is a direct relationship between energy, environment and economics, being closely connected.

As the primary energy source is fossil fuel, so, the energy sector has become a great contributor to global anthropogenic Green House Gases (GHG) emissions (IPCC, 2011b; IEA and OECD, 2010). Financial and infrastructure resources are also the major issues for developing countries to mitigate the climate change (IPCC, 2007). Due to the aforementioned issues, energy system analysis has become a worldwide concern and deals with energy consumption, economic growth, CO_2 emissions and other economic variables.

Some studies (Hussain et al. (2012), Saidi (2015), Ali et al. (2015), Alam et al. (2007) etc) have evaluated the impact of energy demand on the reduction of carbon emissions in Pakistan. These studies lack provision of concrete results in explaining the correct reasoning between energy demand and carbon emissions in pure form. Moreover different authors have adopted simple methodologies (e.g. simple regression analysis) and data sets to find out only the energy demand and carbon emissions relationship.

We have modelled the energy demand in Pakistan by adopting the small branch of methodology of Environmental Global Econometric Model (EGEM) model. EGEM model is based on rich econometric derivations of hundreds of equations. One branch of this model is used as the estimation of the energy demand model. This model is used for the developed economies (Mabey et al., 1997) but this is the first attempt in this current study to use it for the developing economy (Pakistan). In general, all the models represent the reality in the simplest form but there remain gaps in some models in the way of presentation or because of complexity of the models. The purpose to develop a model is representation of economy. But sometimes it become very difficult to understand. Therefore a model is always chosen for the study which is relevant and efficient in nature.

The results obtained from the Kalman Filter technique (endogenous TC) show that past changes in energy intensity are in response to long run factors, but also show how important innovation is to energy efficiency rather than looking at reduction in energy demand (Mabey et al., 1997, Romer (1986) and, Emonds et al. (2000)). The long run factors in this case could be innovation in technology, slow impact of economy in policy change, infrastructure of whole economy, plans, influence of structural economic changes etc. Same results are also obtained from the present research after applying the both exogenous TC model and KF technique (endogenous TC model) to find the projected energy intensity for the simulation period from 1971-2030. However, it can be considered that although increased changes in energy prices stimulate research and development that result in technological progress, this technological improvement leads to reduce emissions even when there is an increase in energy consumption, and due to inter-fuel substitution, anticipated cost of pollution are not as apparent. KF technique is used to find how CO_2 emissions are stabilised with an increase in carbon and energy taxes in relation to Pakistan's economy. Kalman Filter technique implies for greater technical innovations, structural economic changes and policy purposes (explicitly) and stem from increased energy prices. The results availed from this technique show that all past changes in energy intensity are in response to long run factors and also shows the importance of innovation in energy efficiency when analysed by using simulation of future carbon taxes. However, on the basis that changes in energy prices induce research and development that result in technological progress, sometimes, increase in energy consumption reduces emissions because of technological improvement. Almost Ideal Demand System (AIDS) was developed by Deaton and Muellbauer in (1980). AIDS model is used extensively in different fields of economics and consumer demand systems and it also describes the underlying equilibrium structure of interrelated consumer demand (Akmal, 2002). The most appropriate and slightly better functional form between Almost Ideal Demand System (AIDS), linear, log-linear and translog functional is said to be AIDS forms when the relationship between energy consumption and energy prices or other explanatory variables is estimated (Xiao et al., 2007). We try identify the Inter-fuel substitution using the Almost Ideal Demand System (AIDS) model as a means to estimate the fuel share equations. Three share equations are estimated for Oil, Coal and Gas to identify the substitution possibilities between them and also to find out the policy implication for CO_2 emissions. The study also aims to predict the energy needs under policy scenarios by using the econometric model. The models identified are also used to find out the results from the estimated elasticities around change in prices, taxes, income, weather, demand for energy resources etc.

Howath (1997), Pearce (1998) and Herring (1998) discussed about the link between energy efficiency and energy consumption and economics growth in UK. Herrring (1998), Brooks (1979, 1990), khazzoom (1980, 1987), Saunders (1992), Sutherland (1994, 1996) and Schurr (1982, 1990) discussed that energy use could not be reduced because of increase in energy efficiency on national and macroeconomics level, but it could do some reduction in energy use at microeconomic level. This concept is also known as Khazzoom-Brookes Postulates. This debate was printed in the newspapers (The New York Times) first time in early 1990's. Brookes (1990) and Rees (1998) agreed that increase in consumption could be possible because of energy efficiency. Brookes did not agree with the people who were thinking for the reduction in consumption because of improved energy efficiency, as per fear of loss of economic output. Rees further discussed the idea of computers that how efficient technology encourage the consumers to use less energy. Bates (1998) and Goldemberg (1998) argued about the energy efficiency and energy consumption. According to them, efficient use of energy would allow the nations to consume less energy. Energy efficiency has been given very less importance until (early year 2000). Harrison et al. (1992) discussed that there was not proper definition of energy efficiency in New Zealand's three reports during 1990's, while focus of all three reports was energy efficiency. Patterson (1996) defines energy efficiency as "the ratio between useful output of a process and energy input into a process". In general, energy intensity is defined as "the ratio between energy consumption and GDP". Wilson et al (1994) discussed the ratio of GDP and energy and they also used this ratio as an indicator of energy efficiency by having some factors as energy input mix, labour substitution etc. Jenne and Cattlell (1983), Renshaw, (1981), Liu et al. (1992) discussed that these factors had nothing to do with the energy efficiency. They claimed that these factors could influence the movement of ratio. Patterson (1993b) excluded these factors and get the results for the underlying energy efficiency. A debate to differentiate energy efficiency and energy intensity is discussed in 4th chapter of the present study. Khazzoom (1980,1982) and Miller (1982) introduced the concept of energy efficiency under the "rebound" or "takeback" effect. They said that higher energy consumption could become possible because of the improvements in energy efficiency. Greene et al. (1999) introduced three types of rebound effect as direct, indirect and general equilibrium. They suggested that rebound effect could be used for the energy efficiency to determine the reduction in greenhouse gas emissions. Energy efficiency was discussed in detail via rebound effect by (Greening et al., 2000 and Sauders, 2000).

Chapter 3 focuses on the estimation of income and energy demand price elasticities, and energy efficiencies of 19 developing countries. The stochastic frontier approach initially introduced by Aigner et al. (1977)[7] is used where the objective is to improve estimation procedures. This method constructs the frontier from best practice within industry. The greater the distance from the 'norm' of best practice, the more inefficient the process is considered to be. A parametric frontier approach is followed in this study to estimate the energy demand frontier function. This approach provides the maximum attainable output using given inputs and in the case of energy demand provides the minimum level of energy required to achieve a given level of output. Hence, this approach identifies countries where best technology is used to produce a specific output. This then provides a benchmark with which to compare to. There are other important factors to consider apart from economy and technology that may influence energy consumption levels which include exogenous regulatory and institutional factors. The impact of these exogenous changes are not necessarily consistent over a period of time and although the use of time dummies has been suggested in order to capture the impact of these sometimes unobserved exogenous factors, using a large number of time dummies in itself can cause estimation problems. Therefore, an alternative would be to use time trends.

In order to obtain the results of different influences, the relationship between energy consumption of activities and energy prices is estimated using an energy demand model. Also to control the effect of other factors in energy demand, additional variables such as economy structure, area size and population need to be introduced. The framework adopted in this study attempts to isolate the "Underlying Energy Efficiency" by using control variables including energy price, income and population. This underlying energy efficiency is then used to verify how the estimated efficiency has

[7] Aigner et al. (1977) introduced the frontier function approach which was developed within the neo-classical production theory. This approach has been used to estimate the level of inefficiency (allocative and technical inefficiency) by using the production and cost frontier. In the present study, a stochastic frontier approach is used within the empirical approach traditionally and just the concept of neo-classical production theory is used in the estimation of economy wide energy demand function while the neo-classical production theory is discarded. Of course the, the underlying energy inefficiency concept which is developed here still follows a production process.

changed over the estimation period and how efficiency moves across a panel of 19 Asian developing countries[8].

Chapter 4 performs empirical analysis on the relationship between environmental pollution and economic growth and checks the validity of Environmental Kuznets Curve (EKC)[9] hypothesis. This can be explained thus: environmental pollution levels increase to the point where income passes a turning point from when it starts to decrease again forming an inverted U-shape. However, as an increase in national income does not always reduce pollutant emissions, a time series dynamic model is used as an overview. Analysis of the empirical relationship between energy consumption and output suggests that there is a positive relationship between output and economic development. However, as energy consumption is closely related to economic growth, it follows that higher economic development requires more energy consumption, and energy use is more efficient if there is a higher level of economic development.

It is also attempted to explore the dynamic relationship between energy consumption, economic growth and CO_2 emissions, specifically in relation to Pakistan. The forecasting models used to forecast the energy system and environmental protection is categorized in two ways, namely multivariate analysis[10] and univariate time-series analysis. Multivariate model techniques are used in a number of studies to forecast energy consumption whereas future values of variables of interest can be forecast using historical time series data of the same variables by using the univariate models.

For the purpose of performing this task, univariate Grey Prediction (GP)[11] model, Exponential Smoothing (ES)[12] and Multivariate model solving techniques are used. Furthermore, these two models are then compared. Many of the methods used for forecasting use only current or past values of variables, as these are all that are provided. Of these, ES is well known for introducing some of the most successful

[8] See the table 1, tables (3.5 to 3.7) and figures (3.1 to 3.4) for the detailed data description and name of the countries

[9] See Kuznets (1955),Grossman and Kruger (1991), Stern (2004) and Dinda (2004), Mangi and Jena (2008), Martinez and Benguchea (2004), and Dinda and Coondoo (2006)

[10] See Amarawickrama (2008), Pao (2006) and Bianco, and Manca and Nardini (2009))

[11] See Deng (1989), Lee (1986), Song (1992), Morita et al. (1996), Mon et al. (1995), Hsu et al. (1998), Wu (1994), Chew (1995)

[12] See Holt 1957, Brown 1959, Winter 1960, Chatfield 1978, Montgomery and Johnson 1976, Granger and Newbold 1977

forecasting methods by using weighted averages of past observations. A univariate model used for single variable forecasting is called Grey Prediction (GP) model and literature suggests univariate time series can be estimated when using a limited amount of data. Although in Far East and developing countries, this technique has been considered, it has attracted many researchers and has become a popular model particularly when forecasting energy demand.

GP has been the subject of many papers and is claimed to be a simple technique that can characterize unknown systems by using few data points. However, the argument here is that this claim is incorrect and used the wrong concept which is shown with the help of numerical examples and tables in chapter 4. Motivated by the importance of forecasting the CO_2 emissions, this study proposes an Out Of Sample Grey Prediction model (OOSGP model) which criticizes the methodology of GP model. As GP model is being used in different fields but with wrong methodology. The aim is to attempt to provide a better way of using this technique (GP model) with Out Of Sample forecasting. The new model is established to improve the predictive accuracy of the GP model. An OOSGP model has been introduced to solve this problem which is explained in sections (4.4.4 & 4.4.5).

By following the rule of GP model, the errors among the actual and predicted values are calculated for different n's. To enhance the effectiveness and accuracy in errors for GP model, some studies have been developed to improve this model by Hsu and Chen (2003), Hsu (2003), Hsu and Wang (2007), Wang and Hsu (2008), Bianco et al. (2010), Tan and Chang (1996), Tan and Lu (1996), Guo, Song and Ye (2005), Yao and Chi (2004), Huang and Wang (2001), Lin, Su and Hsu (2001), Yao, Chi and Chen (2003), Yao and Chi (2004), Pao, Chang and Tsai (2008) and Fu and Tseng (2012) but they also used the future values to predict for the present. Modified grey prediction model has been introduced by them with some additional information but with the same methodology. The same GP system is followed by all of them and in all of the studies minimum data is used to forecast. Fewer errors are given by using minimum data thus, it is preferred and suggested by all researchers to use a small amount of data.

Out Of Sample Grey Prediction model (OOSGP model) is introduced by us, which criticizes the methodology of GP model. This is even a first attempt to apply this model to get the forecast results.

With the increase in energy consumption there will be an increase in environmental degradation. It is essential that efficient ways to use energy are adopted to promote a cleaner, better environment. Energy systems need to be reviewed and improved if there is to be any control over the threat to our environment. Although Pakistan is growing economically strong, huge investment will boost their economy. For this to happen, there is a need to revise CO_2 emissions estimates which can only be done if baseline forecasts are available.

The aim and objective of this thesis is to examine the significant environmental issues, especially, Green House Gases (GHGs) emissions and specifically Carbon Dioxide (CO_2) emissions which are mainly caused by energy use. In this thesis, all three chapters are interlinked with each other. Chapters 2 and 4 discuss how to stabilize and forecast CO_2 emissions for Pakistan while chapter 3 discusses the energy efficiency of Asian developing countries. In chapter 2, debate starts from the discussion of Exogenous Technical Change (TC) and endogenous TC models for the stabilization of CO_2 emissions and estimation results are found by using the methodology of Kalman's Filter (KF) technique and Almost Ideal Demand Systems. Results suggest that stabilization can be achieved just in short run but it needs too much time for the implementation in the long run plans. In chapter 4, it is tried to forecast CO_2 emissions by using several methodologies as Univariate (Grey Prediction Model (GM), Exponential Smoothing (ES), Holt-Winter (H-W)) and multivariate model solving techniques and, a new technique Out Of Sample Grey Prediction (OOSGP) and forecasting abilities of all the models are compared. In chapter 3, the focus is to find either energy intensity a good indicator of energy efficiency or not. According to the estimated results, energy intensity is not a good indicator of energy efficiency but the energy efficiency estimated using SFA after controlling for some of the economic factors (fuel prices, population, income, etc.) it is.

After explaining the background and overview of the topic in the introduction, the difference between exogenous and endogenous technical progress model, and also the stabilisation of CO_2 emissions can be seen in the second chapter. Furthermore, the working of KF technique, AIDS model with the help of share equations is also shown in detail. Comparison between 19 Asian developing countries regarding energy efficiency is discussed in chapter 3, and also, relative comparison between all the countries for different decades is estimated by using stochastic demand frontier technique. Chapter 4 presents the forecasting of CO_2 emissions for Pakistan by introducing new model. Finally, chapter 5 concludes all the findings of this present research.

CHAPTER 2

Modelling of Energy Consumption in Pakistan

2.1 Introduction

The aim of this study is to examine the possibility of both exogenous and endogenous trend effects on CO_2 emissions and economic growth in Pakistan. By breaking down total energy consumption in to its share components, CO_2 emissions can be forecasted based on different types of energy in use.[13] For the purpose of this study, endogenous technical change is estimated using the Kalman Filter (KF) technique.[14] This technique is not widely used in macroeconomic and energy economics because of the complex nature of systems of equations, but this is not the reason to use this technique in our study. The only reason to use KF technique is given in the literature (Currie and Hall (1994), Lutkepohl (1993), Aoki (1991), Harvey (1987&89), Cuthbertson et al. (1992), Lawson (1980), Hamilton (1994)) as, Kalman Filter technique does a better job as compare to the conventional energy demand model in filtering out the true relationship of the variables and also show exactly what is going on in the economy of country. Simple theoretical frame work may not provide the best solution and econometric estimation of the economic variables with interaction terms may also introduce large errors, while the econometric modelling for the energy sector measure such relationship with accuracy. The main objective of using KF technique is to find how CO_2 emissions are stabilised with an increase in carbon and energy taxes in relation to Pakistan's economy, and also, to identify, the inter-fuel substitution using the Almost Ideal Demand System (AIDS)[15] model introduced by Deaton and Muellbauer (1980) as a means to estimate the fuel share equations. Three share equations are estimated for Oil, Coal and Gas to identify the substitution possibilities between them and also to find out

[13] In our study, we are taking three types of fossil fuel energy as Oil, Coal and Gas. These three variables are chosen on the basis of availability of data during 1971-2013 for Pakistan.

[14] To find out the detailed description of Kalman Filter technique, See Cuthbertson et al. (1992), Currie and Hall (1994), Harvey (1987), Lawson (1980), Hamilton (1994) and some more useful information and contributions in Kalman Filter could also be found in Aoki (1991), Lutkepohl (1993) and Harvey (1989) etc.

[15] Almost Ideal Demand System (AIDS) was developed by Deaton and Muellbauer in (1980). AIDS model is used extensively in different fields of economics and consumer demand systems and it also describes the underlying equilibrium structure of interrelated consumer demand (Akmal, 2002). The most appropriate and slightly better functional form between Almost Ideal Demand System (AIDS), linear, log-linear and translog functional is said to be AIDS forms when the relationship between energy consumption and energy prices or other explanatory variables is estimated (Xiao et al., 2007).

the policy implication for CO_2 emissions. The study also aims to predict the energy needs under policy scenarios by using the econometric model. The models identified above are also used to find out the results from the estimated elasticities around change in prices, taxes, income, weather, demand for energy resources etc.

For this study, two types of energy demand models are used to estimate energy intensity, these being exogenous and endogenous technical progress models. Dynamic energy demand model is estimated by considering technological progress as exogenous. We estimate the long run relationship in the exogenous technical progress model (conventional energy demand model) by using cointegration analysis. It can be investigated that either time trend is the only reason for changes in the energy intensity over time or not. Here exogenous trend is modelled as time trend. Alternatively, Error Correction Model (ECM) technique is used to find the short run relationship by using the residual term from the long run relationship. This technique provides the coefficient of speed of adjustment towards the equilibrium as a result. To contrast, we try to solve the problem by using the second model as endogenous technical progress model. Secondly, we take the energy demand equation in production function and consider the endogenous Technical Change (TC). Furthermore, we take the aggregate consumption which depends on fuel prices, lagged differences in consumption and time trend, while the time trend depends on endogenous trend determinants (manufacturing components of GDP, investment, trade, non-fossil fuel supply, etc.) and lagged fuel prices. The endogenous technical progress model is estimated using the Kalman Filter (KF) technique. State space models are estimated in Kalman Filter (KF) technique which was originally used for chemistry and engineering applications by Kalman (1960, 1962) and Wiener (1949). The Kalman Filter gradually became popular (very slowly) in economics when econometricians started to use this technique in 1980s as by (Currie and Hall (1994), Cuthbertson (1988), Cuthbertson et al (1992), Harvey (1987)).

Kalman Filter technique implies for greater technical innovations, structural economic changes and policy purposes (explicitly) and stem from increased energy prices. The results availed from this technique show that all past changes in energy intensity are in response to long run factors and also shows the importance of innovation in energy efficiency when analysed by using simulation of future carbon taxes, while the conventional energy demand model focuses on energy demand reductions and measures the elasticities. However, on the basis that changes in energy prices induce research and development that result in technological progress, sometimes, increase in energy consumption reduces emissions because of technological improvement. However, anticipated costs of pollution show up less because of inter fuel substitution and how best use of technology can be achieved with less energy cost and if we know technological change, then, it could stabilise the CO_2 level over next 100 years after institutional and socio economic changes (Anderson et al., 2002). Energy demand models provide valuable information about the overall energy intensity[16] and CO_2 emissions but price changes induce substitution possibilities between the energy products. As for policy implications, CO_2 emissions can be reduced in the long run by following the energy model based on Environmental Global Econometric Model (EGEM)[17] model as; use efficient ways of production, substitute fuel to non-fuel energy or use less environmentally damage energy inputs as compared to high damage ones, use improved technology etc.

Energy plays an important role in deriving Economic growth and hence paving the way for socio economic development. The demand for energy products is increasing to fulfil the needs of growing economies. However, increase in the utilization and consumption of energy resources creates pollution due to carbon dioxide (CO_2) emissions. Therefore, energy consumption requires balancing in a way that production activities are performed smoothly and issues of environmental degradation do not hurt the social welfare of societies. However, that balance is being ignored and companies as well as governments remain biased towards production. Global fossil fuel CO_2 emissions are estimated by Carbon Dioxide Information Analysis Centre (CDIAC)[18] and analysis shows how quickly CO_2 emissions are increasing. They have found that total global emissions have increased from 9.4 billion metric tons to 9.6 billion metric tons from 2011 to 2012 and over ten years, globally, there will be 11.5 percent increment in CO_2 emissions which means 14” (36cm) thick layer of pure CO_2 at the surface. There has been a 24 percent increase in world’s CO_2 emissions from 1958 to date (NOAA, 2015). A continuous increase in CO_2 emissions is very worrying (Zhang and Cheng, 2009). Developed countries are in a position to address this issue, however developing economies are only concerned about the increase in production and ignore the issue of

[16] Energy intensity is taken as the ratio of energy consumption and real GDP of Pakistan.

[17] EGEM model is the model with rich econometric derivations of hundreds of equations. One branch of this model can be used as the estimation of energy demand model, which is used in present study for Pakistan. Also see chapter 4&5 of Mabey et al. (1997) for complete derivation and implication of the (EGEM) in the light of energy economics.

[18] Department of Energy of CDIAC came in to existence in 1982 based in U.S. They have been collecting and maintaining the data on the CO_2 emissions, atmospheric gases which affect the climate.

negative externalities of this production process. Therefore, energy consumption is not a country specific issue the whole world is included as stakeholders. Environmental degradation is the result of increase in non-renewable energy generation worldwide. In fact, there is a direct relationship between energy, environment and economics, being closely connected.

As the primary energy source is fossil fuel, so, the energy sector has become a great contributor to global anthropogenic Green House Gases (GHG) emissions (IPCC, 2011b; IEA and OECD, 2010). Financial and infrastructure resources are also the major issues for developing countries to mitigate the climate change (IPCC, 2007). Grubb et al. (2002) discussed the Energy-Environment-Economy (EEE) system models and categorised them in three groups[19] as: Macroeconomic Models (e.g. AEEI, EGEM, WARM etc.), Integrated Assessment Models (IAMs) and Energy Sector Models.

Due to the aforementioned issues, energy system analysis has become a worldwide concern and deals with energy consumption, economic growth, CO_2 emissions and other economic variables. The developed economies of the world have introduced various methods[20] of controlling emissions. These measures include the Kyoto Protocol amongst the various control programs. The objectives of the Kyoto Protocol (1997) are to concentrate on the reduction of Green House Gases (GHGs), which are responsible for changes in climate. The aim of the Kyoto Protocol is to set a specific target in the reduction of GHGs and achieve it. Reducing Carbon Dioxide (CO_2) emissions has always been given more importance among all GHGs (Beer 2000). The share of carbon dioxide (CO_2) emissions is 58.8 percent among all the GHGs (World Bank report (2007)). It is a fact that developed economies have shown more concerns about these environmental issues.

Although developing economies do not formulate plans in line with developed economies, these developing economies have not ignored the problem. Instrument of accession to the Kyoto Protocol is deposited by Pakistan to the United Nations (UN) Secretariat on 11th Jan, 2005. The Kyoto Protocol (KP), adopted in Kyoto, Japan on 11th December 1997, is an international treaty that commits state parties (of which there are

[19] Some other categories of the models are also presented in the literature as: Edenhofer et al. (2006) categorised the models in four groups, optimal growth models, simulation models, energy system models and general equilibrium models.

[20] There are also three further ordinary methods which are used for the reduction in CO_2 emissions mentioned as: 1) employing energy efficiency and conservation practices, 2) using carbon-free or reduced-carbon energy resources, and 3) capturing and storing carbon either from fossil fuels or from the atmosphere.

currently 192) to reduce Green House Gases (GHGs) emissions. This is based on the premise that global warming actually exists and that it is a result of manmade CO_2 emissions. The objective of KP is to fight global warming by reducing the concentration of GHGs in the atmosphere to "a level that would prevent dangerous anthropogenic interference with the climate system". Developed countries are obligated to reduce current emissions based on the fact that they are considered responsible, historically, for the existing levels of GHGs in the atmosphere.

The Duration of the Protocol's first commitment period was 2008 to 2012. The second commitment period was agreed in 2012 and is known as the Doha Amendment. As part of this second commitment period, 37 countries have binding targets, although some of these countries have suggested they may withdraw and not put their target into force. Only 7 of these countries have ratified. Negotiations have been held on measures to be taken after the second commitment period ends in 2020, and resulted in the adoption of the Paris Agreement[21] in 2015. This is a separate instrument and not a further amendment to the original Protocol.

To reduce and control global warming and GHGs emissions on the planet, United Nations Framework Convention on Climate Change (UNFCCC) conducted a Conference in December, 2015 known as Paris Agreement. 195 counties were invited to the conference all of them signed the agreement. They agreed to reduce emissions as soon as possible and also committed to bringing the temperature of the earth's surface below 2 degree Celsius (°C)/3.6 degree Fahrenheit (F) to control global warming of the planet. Developing countries will be given $100 billion in a year for the adoption of new procedures to reduce GHGs emissions. This agreement will come into effect in 2020 and 161 countries have signed the agreement to date out of 195. The Prime Minister of Pakistan also attended the conference and signed the agreement submitted for the climate action plan.

The Clean Development Mechanism (CDM) project is also filled by Pakistan to become a part of it. The purpose of adopting this strategy is to fulfil the requirements of establishing a Designated National Authority (DNA). It attempts to have transparent, participatory and effective management of CDM processes in the country. The details of the functions and powers of the DNA are described in the strategy that is based on

[21] United Nations Climate Change Conference was conducted in France (Paris) in December, 2015 with the aim of environmental concerns but the discussed concerns are yet to be adopted by the world (those were agreed though).

preliminary studies which include the initial project, namely Asia Least Cost Greenhouse Gases Abatement Strategy (ALGAS), 1998. The establishment of DNA is being implemented by the government of Pakistan within the Ministry of Environment to manage CDM. GHGs emissions were not considered an important issue in Pakistan before the establishment of the CDM project. Global warming can be controlled by managing GHGs emissions.

The share of energy use of developing countries is not very high, but they will soon be consuming a major part of world’s energy in the future because of rapid income growth (Dahl, 1994). In the next three decades the share of energy demand from developing countries will increase from 30 percent to 40 percent. It is expected that the world’s marketed energy consumption will increase from 447 Quadrillion British thermal units (QBtu) in 2004 to 702 QBtu in 2030 (Riaz, 2008). Pakistan is the 31st largest energy consumer in the world and it ranks 40th in the import of energy products. There have been many changes in the energy demand policies in Pakistan because of the heavy imports of energy (more likely import of oil). The purpose of the changes in policy was to encourage the inter fuel and non-fuel substitution for energy consumption, to focus on the determination of energy demand in Pakistan, and highlight such taxation policies that help in controlling the CO_2 emissions.

There is a 54 percent use of gas and oil from the primary energy consumption in Pakistan which causes CO_2 emissions which becomes higher with the additional use of coal (Pakistan Energy Yearbook, 2011). In the last year, there has been an increase of 167 million tons in CO_2 emissions because of energy consumption (Qudrut Ullah and Karahul, 2007). A serious challenge for Pakistan is to improve the energy sector with a clean environment. Because of high energy consumption there is significant increase in CO_2 emissions. But, unfortunately, the policy makers have remained biased in favour of enhancing growth and ignore the issue of controlling CO_2 emissions in Pakistan. Economic surveys in Pakistan (2012-2013) clarify that there is a huge contribution of the energy sector in Pakistan to greenhouse gas emissions, and also globally, the demand for liquid oil consumption has increased from 88.4 million/barrels/day to 89.0million/barrels/day in 2011-2012. It shows that the demand for liquid oil has increase by 0.8% globally and Pakistan also contributes to this increment because the major source of energy consumption in Pakistan is oil, gas and coal. Further, recent historical low level energy prices have also been an important factor that may result in the over utilization of energy products in Pakistan.

Energy is recognised and considered as an important strategic commodity and it is thought to be life line of the economy (Sahir and Qureshi, 2007). Energy is essential in almost all fields of economics, especially, to keep the environment clean. In the present era, a rapid increase in demand for energy indicates that CO_2 emissions are also increasing and both of them will become the biggest problem in the world in the next thirty years. Sheikh (2010) argues that Pakistan fulfils more than 99 percent of its energy requirements with fossil fuels. CO_2 emissions and total GHGs emissions increase due to the combustion of fossil fuels. It is the largest single contributor to CO_2 emissions and the impact of this has grown more rapidly since 1970. Therefore, Pakistan's environmental energy policy requires an accurate estimation, forecast and stabilisation of CO_2 emissions.

Shyamal and Rabinda (2004) mention the factors which could become the reason for reduction of CO_2 emissions by using the decomposition method. According to their analysis, there should be a decrease in CO_2 emissions with improved technology, energy efficiency and fuel substitution. They also find a huge effect of energy intensity on energy induced CO_2 emissions but they find negligible effect of pollution and CO_2 emissions in agricultural sector. Sheinbaunm-Pardo et al. (2012) use the LMDI method to find out CO_2 emissions and energy consumption in the industrial sector and find the reason for the reduction in CO_2 emissions via structure effect. Fong et al. (2007) find the relationship between CO_2 emissions, energy consumption, economic growth, pollution and living standards. The results of their analysis suggest a positive relationship between all five variables. Shabbir et al. (2014) estimate the relationship between renewable and non-renewable energy consumption, CO_2 emissions and real GDP in Pakistan by using the structural VAR approach. According to their results the CO_2 emissions increases with the increase in energy consumption in the short-run but mostly the reduction in CO_2 emissions occur because of the substitution of non-renewable energy consumption to renewable energy consumption in the long run.

Some studies[22] discussed simple methodologies (e.g. simple regression analysis) and data sets to find out only the energy demand and carbon emissions relationship. These studies lack provision of concrete results in explaining the correct reasoning between energy demand and carbon emissions. In these studies, there is not proper answer that why energy demand and carbon emissions are positively or negatively related with each

[22] See Hussain et al. (2012), Saidi (2015), Ali et al. (2015), Alam et al. (2007) etc.

other. Moreover different authors have adopted simple methodologies (e.g. simple regression analysis) and data sets to find out only the energy demand and carbon emissions relationship.

We intend to discuss some of the controversial studies which have been carried out in the literature as: Soytas et al. (2007) applied the granger causality test between energy consumption, CO_2 emissions and economic growth. They should have realised that the concept of granger causality is not valid for energy consumption and CO_2 emissions. It is clear that consumption definitely causes CO_2 emissions but CO_2 emissions do not cause energy consumption. Later on, Soytas and Sari (2009) did the same analysis to check the causality between energy consumption and CO_2 emissions in Turkey. There is no achievement in these studies though. Lean and Smith (2009) found the causal relationship between CO_2 emissions and energy consumption for five ASEAN countries. The results suggested a positive and significant[23] relationship between both of them but they find no causal relationship between CO_2 emissions and fossil fuel consumption. Menyah and Rufael (2010) applied the granger causality test and found a positive effect of CO_2 emissions on energy consumption in the case of South Africa. Niu et al. (2011) estimated the result for eight Asian economies of energy consumption and CO_2 emissions by applying granger causality test and found a positive relationship between both of them. Similarly, a branch of literature[24] that has been doing the same granger causality test for energy consumption and CO_2 emissions in an unusual manner, preceded their work in the wrong way. The idea to check such a type of relationship between energy consumption and CO_2 emissions is not productive. Unfortunately, all this work has been done but, we think, this work is not relevant. It could be argued that the results of these studies are ill conceived and offer zero percent economic impact due to the basic concept being fundamentally flawed.

The aim and objective of the study is to find how CO_2 emissions are stabilised with an increase in energy tax in relation to Pakistan's economy. The study also aims to predict the energy needs under policy scenarios by using the econometric model. The energy demand analysis of Pakistan's economy is divided in to two parts. First, the aggregate fossil fuel consumption is analysed by considering the exogenous and endogenous

[23] When fundamental concept of the model is wrong then we should not focus on the significance of the model and relationship of the variables.

[24] All of them have tried to find the causal relationship between energy consumption and CO_2 emissions: see Chang (2010), Halicioglu (2009), Acaravci and Ozturk (2010), Ang (2007), etc.

trend. Secondly, the analysis is extended to a system of fuel (Oil, Gas and Coal) shares. Fuel mix/fuel substitution is the response of distortion in the energy markets within the country in local markets and also between two counties. Three types of taxes are discussed in the simulation period (1971-2030) as, carbon tax, flat-rate tax and ad valorem tax. After analysing the results some policy implications are discussed.

The rest of this paper is organized as follows: Section 2 presents the model and methodological Issues in detail. Data and construction of variables are discussed in Section 3. Empirical findings and simulation properties are given in Section 4. The conclusion is presented in section 5.

2.2 Models presentation and Methodological Issues

2.2.1 Aggregate Energy Models for Pakistan

The energy demand analysis of Pakistan's economy is divided in to two parts. First, the aggregate fossil fuel consumption is analysed by considering the exogenous and endogenous trend. Secondly, the analysis is extended to a system of fuel (Oil, Gas and Coal) shares.

Choosing the right modelling (exogenous or endogenous) and methodologies for TC is open for debate, so, it is very important to choose the appropriate way to model TC for perfect policy implications. The focus of this chapter is not to find out whether technological development is important or not, but on how the occurrence of technological development can be represented and used in the models and also to find out the policy implications about economic policy conclusions for the reduction in CO_2 emissions. We have modelled the energy demand in Pakistan by adopting the small branch of methodology of Environmental Global Econometric Model (EGEM) model. EGEM model is based on rich econometric derivations of hundreds of equations. One branch of this model can be used as the estimation of the energy demand model, which is used in this current study for Pakistan. Also see chapter 4&5 of Mabey et al. (1997) for complete derivation and implication of the (EGEM) in light of energy economics.

According to the definition of autonomous Technical Change (TC), this exogenous (autonomous) technical change depends solely on economic growth which could be modelled as endogenous. When we talk about the CO_2 emissions and environmental change, the question arises, whether technical change affects economic growth in the long run or not with a change in prices. The answer is provided in the literature[25] as, induced TC is affected by conditions in the energy markets which does not happen in the case of autonomous TC, as the influence is restricted in its assumption. In practice, both technical changes (autonomous and induced) can be combined and the original innovation can be characterized over analysis. However proper attention is needed to make and develop the model for induced technical changes.

The major difference between exogenous and endogenous trend is explained as: the effect of exogenous trend is valid in both (short and long run) and it affects growth in both cases but, in the long run, it does not allow growth to vary and it fixes it while the effect of endogenous trend can be estimated and observed in the long run. If there is exogenous technical change then we cannot change the trend but for endogenous trend it can give very different implications. If we want to stabilise CO_2 emissions then it is impossible to do so in the exogenous technological model because GDP is dependent on trend or there is a limit of GDP growth and GDP cannot grow faster in a certain amount of time. Nothing can ever be done to allow GDP to grow faster than trend. If it is an endogenous trend then we allow certain factors (energy/fuel prices, energy tax, carbon tax etc.) which will allow the trend to grow faster and so will the GDP. Moreover, exogenous technical change follows the assumption of growth limit in the model. GDP growth only depends on trend with ratio of coefficients, which verifies the growth limit (either it reaches zero or infinity). To deal with both trends, different properties of Technical change (TC) are discussed. The occurrence of TC is not given much importance though in the field of economic modelling. In conventional economic models/conventional energy demand models, the famous assumption is to take TC as an exogenous variable. This assumption verifies that with time the efficiency is improved and costs of certain kinds of technologies also go down. The implication of this assumption verifies that technical change in modelling is mainly an autonomous process which happens in a way that it does not depend on any other policy or economic variable.

The addition of autonomous TC verifies that in the whole economy (or only in one sector), Autonomous Energy Efficiency Improvement (AEEI) parameter is included, which becomes the reason for the increment in the energy efficiency with some exogenous amount every year.

[25] See Mabey et al. (1997), Romer (1986) and, Emonds et al. (2000)

The exogenously imposed trend rate of non-price decline in energy intensity is generally interpreted as being a function of general technical progress, and so it is termed the Autonomous Energy Efficiency Improvement (AEEI) parameter. The AEEI parameter is an important determinant of CO_2 emissions in the baseline scenario. Higher value of AEEI give lower baseline CO_2 emissions, and therefore lower the cost of stabilising carbon emissions and concentrations into future. The AEEI in most studies is the same in the baseline scenario as in the constrained scenario. There is no reason why it should not be different in the two cases. For example, if in the base-case, energy intensity declines by 1 percent per annum (or AEEI is 1 percent per year), then with a constrain on carbon emissions the decline could be greater, say 1.5 percent per annum, due to greater emphasis on energy saving technological development. Exogenously determined, arbitrary decline in AEEI in the baseline scenario is questionable by itself, but the process becomes more dubious if a new set of rates for AEEI are specified for the constrained case, again exogenously. The basis for the link between the change in AEEI and the emission abatement strategy or policy is remote. It is therefore necessary to endogenise the factors responsible for a change in non-price induced energy intensity in a consistent manner, and see how they change in response to different policy options. In practice empirically measured estimates of the AEEI capture the changes in energy intensity due to irreversible technological progress, reversible technical diffusion due to price rises, structural change in the economy and other non-technological factors such as consumption trends. It is important to separate the purely technical factors from the other structural effects to see if they are price sensitive, which would be an intuitive assumption, and would greatly affect the impact of taxation policies.

The aggregated models are famous for using this AEEI parameter (MacCracken et al. (1999) and Nordhaus (1994)). There exist some serious problems with the AEEI that it does not take constant technology (which is good). The first problem with AEEI models is the long time periods (up to 100 years). If we carry out some minor changes in the model, the results of energy demand, economic growth and costs of emissions reductions change dramatically. So, there is no consensus that could be used for AEEI. Mabey et al. (1997) find that any change in AEEI over time is always arbitrary and when the policy variables are modelled, they turn up unconnected. They also observe that the working of AEEI could be different in different sectors and different regions of economies. Because a disaggregated AEEI is not always considered as different AEEIs are required at different levels of aggregations.

It is not possible to get the reasonable curve fitting approximation by using AEEI model, although the response of energy demand technology systems on energy prices could be checked (Dowlatabadi, 1998). Unfortunately, it is very difficult to model the technological evolution as discussed earlier and for that reason most of the time the energy models are incorporated with the autonomous assumption or exogenous assumption of TC (Salas, 2013). Azar and Dowlatabadi (1999) criticise the Autonomous Energy Efficiency Improvement (AEEI) approach and describes the working for TC modelling based on induced TC. Manne and Richels (1992) introduced the concept of technical progress which is represented by time trend in equation (1) and, in some models, it is also known as "Autonomous Energy Efficiency Improvement" (AEEI). Energy use can be reduced in the long run without increase in the cost of energy by having improved technology, because energy productivity increases with improved technology and ultimately the use of energy reduces. By using the model in equation (1), it is not impossible to find how the change in macroeconomic variables, change in policy and exogenous factors may affect technological development

However, it is confirmed in the wider literature[26] that TC is not an autonomous process. It is a response to identifiable processes which includes the effects of corporate technology investment, government Research and Development (R&D) and the effect of economy of scale. This is why, TC should be treated as endogenous in the modelling term, meaning it depends on the other parameters reflected in, with the model[27]. The main differentiation between exogenous and endogenous growth models is to make a significant effect on long run growth rates by using public policy which only happens in the case of endogenous TC (Pearce, 2002). It is very important to derive conclusion and policy implications that we choose the right way to model TC[28] as the wrong choice of modelling could provide the wrong conclusion and wrong policy implications proving counterproductive.

[26] See Sue Wing (2006), Azar and Dowlatabadi (1999), Grubler et al. (1999), Dowlatabadi (1998), Anderson D. (2001), Christiansen AC. (2001), Grubler and Messner (1998) etc.

[27] If we see the macroeconomic growth theory and the technical change in the Neoclassical growth models, then we come to know that Solow growth model and Cobb-Douglas specification TC is treated exogenously. Afterwards, the literature and empirical studies proved that some important components of growth were unexplained because of TC assumption and it became the important weakness of the growth models. Later on, Romer (1986) used the endogenous modelling of TC in the economic growth models first time.

[28] The literature on modelling for endogenous or exogenous assumption could be found as, see Salas (2013), De and Kucharavy (2011) Gillingham et al. (2008), Kohler et al. (2006), Edenhofer et al. (2006), Wegant (2004), Weyant and Olavson (1999), Emonds et al. (2000), and Popp (2006a,b)

Messner (1995) suggests that to include the induced TC in production and consumption will play an important and increasing role in future environmental modelling. Weyant and Olavson (1999) use the induced TC in energy environment debate, and suggest several factors in favour of this model whilst highlighting the outstanding issues[29] in recent modelling work. They also provide the implications and possible extension of the model as: heterogeneity of innovators, path dependence, complementary source of technical change and uncertainty from R&D. Hogan and Jorgenson (1991) measure the AEEI empirically and find inconclusive results[30].

Cointegration analysis has been used substantially in the last two decades in econometric modelling which was developed by Engle and Granger (1987) and Johansen (1991). Time trend was not treated as an exception in energy econometrics. Although stationarity of the series is the main feature of the popular Cointegration technique also, it is assumed that there is no change in the estimated parameters (averages of the estimated parameters is taken during the studied period) with the change in time. Because of these requirements, in some cases researchers started thinking about and doubting overdependence on cointegration analysis. Harvey (1997) explains that all dynamic econometrics are not based on auto-regressions. Additionally, Hunt et al. (2003) explain how the methodologies can be proved helpful which allow their coefficients to vary stochastically over time.

Historically, the macroeconomic models have been applied in different fields and a great deal of work has been done in which the economic systems are modelled with special featured models as: energy-environment-economy models. Two major approaches are adopted in these models 1) to combine the aggregated models of energy systems, climate change, economic activity and emissions, 2) to take the energy sector and technology models and focus on the climate change policy as well as the energy sector policy. It is worth clarifying why some studies have been using the exogenous technical progress model and others have been using induced technical change model[31]. There is no real answer for this question but one of the reasons could be because path dependence is introduced and non-linearity is implemented immediately after the

[29] They discussed some of the issues such as technological characteristics (uncertainty, heterogeneity and path dependence) which are under estimated while the impact and the lags in the effectiveness of policy options of the model are also underestimated.

[30] Hogan and Jorgenson find the inconclusive results by measuring the autonomous energy efficiency improvement and similarly some other studies are also done to measure AEEI but they also find the same inconclusive results.

[31] Induced technical change model is incorporated in few major economic models

incorporation of the induced technological change in the model and the model is solved with qualitative steps.

Constant return to scale is assumed for aggregate economy to make production modelling and energy demand equations consistent. All the models are estimated by using energy intensity (energy use/GDP) instead of estimating the gross energy consumption and output. Apparently, all changes (reactions in change in price, technology, structure of the economy) in consumption and production patterns could be observed and energy intensity could be estimated for policy implications by implementing this restriction. If this restriction is not applied then energy intensity is to be determined by output levels which may or may not provide policy implications and their influences.

2.2.2 Model I (An Exogenous Trend Model)

In the empirical literature (Romer, 1986) of energy economics, it is plausible to form a long run theoretical relationship between energy use, GDP and fuel prices where the exogenous trend also exists in energy intensity (energy use/real GDP). So, by using the methodology of Mabey *et al.* (1997) the models are described below and the long run model is given as:

$$Ln\left(\frac{C_t}{Y_t}\right) = \alpha + \beta\big(Ln(FP_t)\big) + \gamma(T_t) + \mathcal{E}_t \qquad (1)$$

Where C_t = fossil fuel consumption, Y_t = Real Gross Domestic Product (GDP), FP_t = weighted average real fuel prices, T_t = time, $\mathcal{E}_t$ =error term, and $\frac{C_t}{Y_t}$ = energy intensity

Firstly, we check the stationarity and find the order of integration of the variables by using the conventional unit root tests (Augmented Dickey-Fuller (ADF) Test and Phillips-Perron (PP) Test). Secondly, by using the Johansen procedure (Johansen 1991), long run cointegration vectors can be identified between logs of endogenous variables (fossil fuel intensity demand per unit GDP), exogenous variables (time trend as a proxy for technical progress) and, weighted average real fuel price. Johansen Cointegration test is utilized to find the existence of the long run relationship among the variables presented in equation (1). After confirming the cointegration from the long run model and the number of cointegrating relationships, the short run dynamics of the variables are modelled by using the Vector Error Correction Model (ECM). The short run dynamic for equation (1) could be found by regressing the residuals and difference between the lags of other variables (weighted average fuel price, GDP and energy consumption) against the change in energy consumption. So, the short run model is presented as:

$$\Delta Ln(C_t) = \alpha_0 + \alpha_1(ECT)_{t-1} + \sum_{i=1} \alpha_2 \Delta Ln(C)_{t-i} + \sum_{i=0} \alpha_3 \Delta Ln(FP_{t-i}) + \sum_{i=0} \alpha_4 \Delta Ln(Y_{t-i}) \qquad (2)$$

and also,

$$(ECT)_{t-1} = Ln\left(\frac{C_t}{Y_t}\right)_{t-1} - \alpha - \beta Ln(FP)_{t-1} - \gamma(T)_{t-1} \qquad (3)$$

In equation (2), to determine the change in fossil fuel energy consumption in the short run, residual ε_t is added into the analysis to have the effect of deviation from the long run equilibrium as well. The correction of any disequilibrium or the speed of adjustment towards the equilibrium is captured by the error correction term (ECT) as shown by equation (3), which is investigated by using the error correction model (ECM).

The sign "Δ" shows the first difference operator, while the Akaike information criteria (AIC) could be used to determine the optimum lag lengths for the variables of the equations. The error terms are shown by ε_t, which are serially uncorrelated. In equation (2), the parameter (α_1) is considered as the speed of adjustment coefficients. These coefficients are interpreted as, when any of the variables between $Ln(FP)_t$ *and* $Ln\left(\frac{C_t}{Y_t}\right)$ violates the long run relationship, the coefficient values of parameters inform the speed at which the values of respective variables come back to long run equilibrium level. The negative sign is expected for the coefficient values of parameters as it shows the convergence towards the long run equilibrium.

2.2.3 Model II - An Endogenous Technical Progress Model and Kalman Filter

To deal with the endogenous TC model we should discuss the Kalman Filter (KF) technique. All of the above requirements can be availed ideally by using Kalman filter methodology, which also gives the opportunity to deal with the variables affected by time (or the variables whose impact cannot be checked) during the estimation of regression (Slade, 1989). We can use both techniques (Kalman filter or Least Square

Approach) in case where there are no any variables varying over time, then results for both techniques are expected to be similar. However, to verify the instability of the parameters, Kalman filter is a better technique as compared to the least square model (Morisson and Pike, 1977). Kalman filter is expected to be the most appropriate technique in the presence of time varying variables in the model (Lotz, 2011). Athans (1974) suggests taking the Kalman filter technique as a supplement not as a replacement of the traditional econometric methods.

Additionally, sometimes the Kalman filter is also named a predictive and adaptive technique, as one step in the future is observed during the estimation of mean and covariance of the time series estimation. In the case of noisy measurements, the recursive filter proposed to be efficient because the internal state of the linear dynamic system is estimated. Masreliez and Martin (1977) suggest that KF could be seen as a simple dynamic Bayesian network. The true values of the model can be estimated recursively over time by using Kalman filter technique. A Gaussian distribution is assumed to find the stochastically varying parameters in the state-space model (Lotz, 2011).

According to Cuthbertson et al. (1992), predominantly two types of models can be represented via Kalman Filter (KF) as, time varying parameter models and unobservable component models. The simple definition of the term filtering is "to update the information inside the system once the new data becomes available". Filtering is totally different from forecasting because it takes the estimates of unobservable for as an information set in the same time, while forecasting is made for the future. The Kalman filter is also said to be the recursive linear filter which was developed in engineering applications and, later on, adopted by econometricians. The key function of filtering is to obtain the predicted values of unobservable of the next time period by using the current observations and then forecast for the next period.

In this section, we explain the general form of KF technique and then write the first model (time varying parameter model) from equation (2) in this specific form of KF technique by following its assumptions. It is observed that most of the models can be used in state space form by having little imagination with linearity restriction. Kalman filter can also be used for non-linear models in its extended form (Harvey, 1989). He also discussed that extended form of Kalman filter provides the approximation results rather than the exact results by using likelihood functions.

Firstly, we should describe the suitable representation of Kalman Filter[32] within the dynamic system with the help of state space model and make the system of the equations. We show the formal derivation of the Kalman Filter (KF). Our aim is to find out and show the gain from Kalman filter technique in equation form. The general approach of Kalman filter technique is nested in this section with a great variety of interpolating setups. All the workings of the Kalman filter are based on the equations (4) and (5) as shown below.

Measurement (or observation) equation: $y_t = x_t \beta_t + w_t \qquad by \qquad (4)$

Transition (or state space) equation: $\beta_t = F\beta_{t-1} + v_t \qquad by \qquad (5)$

Where F and x_t are the matrices and the dimensions of these matrices of parameters is represented[33] as $(r \times r)$ and $(n \times r)$ respectively, the unobserved state variable or state vector is represented by β_t which has the dimension $(r \times 1)$ vector. In equations (4) and (5) w_t, v_t represent the disturbance vectors or shocks and the assumptions are:

$$\left.\begin{array}{c} w_t \sim iid.N(0,R) \\ v_t \sim iid.N(0,Q) \\ E(w_t, v_t) = 0 \end{array}\right\} \qquad (6)$$

Where both Q and R are the matrices as: $(r \times r)$ and $(n \times n)$ respectively.

We can see that disturbances w_t and v_t are uncorrelated for all lags and the exogenous or predetermined factor is represented by x_t in our measurement (or observation) equation. It is clearly seen that we cannot obtain any extra information on β_{t+s} or w_{t+s} for s = 0,1,2,3 .... by having x_t factor in the model except the information given by the sequence y_{t-1}, y_{t-2}, y_t. This shows that with the presence of x_t factor any lagged values of y or other variables could be included in the model but those should also be uncorrelated with w_t and β_t. We need some assumptions for the initial value of the state vector β_t while explaining the series of observations $y_1, y_2, \ldots, y_t$ and this series is explained by the overall system of the equations. In Kalman filter $\beta_{t/t}$ and $\beta_{t/t-1}$ are estimated as optimally conditional on the information set up to time t and (t-1) respectively as it is a recursive algorithm while the KF assumes the knowledge of the parameters (x_t, Q, R, F) of state space. If we assume that some of the parameters

[32] The first section of this derivation is just the general form of KF for basic understanding.

[33] The matrices dimensions r is 2.

(x_t, Q, R, F) are known, then initially three steps are followed by the Kalman filter recursion as: The covariance of β_t can be taken as $P_{t/t-1}$and $P_{t/t}$ in case of time (t-1) and t respectively. So the forecasted value of (y) can be represented by $(y_{t/t-1})$ if the information is given up to time (t-1).

By equation (4)

Prediction Error = $\varepsilon_{t/t-1}$

where $$\varepsilon_{t/t-1} = y_t - y_{t/t-1} = y_t - x_t\beta_{t/(t-1)} \tag{7}$$

Variance of Predicted Error = $\delta_{t/t-1}$

where $\delta_{t/t-1} = Var(y_t - y_{t/t-1}) = Var[(x_t\beta_t + w_t) - x_t\beta_{t/t-1}]$

$$= E[(x_t(\beta_t - \beta_{t/t-1}) + w_t]^2$$
$$= E(x_t(\beta_t - \beta_{t/t-1})^2 + E(2w_t x_t(\beta_t - \beta_{t/t-1})) + E(w_t{}^2)$$

where $E(x_t(\beta_t - \beta_{t/t-1})^2 = x_t P_{t/t-1} x'_t$,

$E(2w_t x_t(\beta_t - \beta_{t/t-1}) = 0, \qquad E(w_t{}^2) = R$

So

$$\delta_{t/t-1} = x_t P_{t/t-1} x'_t + R \tag{8}$$

By equation (5)

$E(\beta_t) = E(F\beta_{t-1} + v_t)\,, \qquad where\ E(v_t) = 0$

So $\quad E(\beta_t) = F \times E(\beta_{t-1})$

Here we assume that for state vector an initial estimate is available as $E(\beta_0) = \beta_0$ and also $E(\beta_{t/t}) = \beta_{t/t}$

then $$\beta_t = F\beta_{t-1} or\ \beta_{t/t-1} = F\beta_{t-1/t-1} or\ \beta_{t/t} = F\beta_{t/t-1} \tag{9}$$

$Var(\beta_t) = Var(F\beta_{t-1} + v_t) = F \times Var(\beta_{t-1}) \times F' + Var(v_t)$

$where\ Var(\beta_{t-1}) = P_{t-1/t-1}\ and \qquad Var(v_t) = Q$

So $$Var(\beta_t) = FP_{t-1/t-1}F' + Q \tag{10}$$

So we can write the updating equations as:

$$\beta_{t/t} = \beta_{t/t-1} + K_t\varepsilon_{t/(t-1)} \tag{11}$$

$$P_{t/t} = P_{t/(t-1)} - K_t w_t P_{t/(t-1)} \tag{12}$$

where $P_{t/t}$ is the variance of $\beta_{t/t}$as mentioned above

where K_t shows the Kalman gain, which are given in the form of weights assigned to the new information.

Firstly, we guess the time 0 for state as $\beta_{0/0}$ *and* $P_{0/0}$. Secondly, we predict the optimal values of y at time 1 as $y_{1/0}$ by using the estimated value of $\beta_{1/0}$ as shown below:

$$\varepsilon_{1/0} = y_1 - y_{1/0} \tag{13}$$

$$\beta_{1/1} = \beta_{1/0} + K_t\varepsilon_{1/0} \tag{14}$$

Once we receive the new information on ε_t then we update the forecast of β_t by using this information and we also update the linear projection with an updated forecast.

$$F(y_3/y_2, y_1) = F(y_3/y_1) + H_{32}H_{22}^{-1}[y_2 - F(y_2/y_1)] \tag{15}$$

$F(y_3/y_2, y_1)$=updated forecast based on y_2

$F(y_3/y_1)$=old forecast based on y_1

$H_{32}H_{22}^{-1}$=variance

$F(y_2/y_1)]$=error in forecasting $y_2$using information y_1

So $y_3 = \beta_t$, $y_2 = y_t$, $y_1 = x_t$ and

$$\beta_{t/t} = \beta_{t/t-1} + [cov(\beta_t, y_t)var(y_t)][y_t - y_{t/(t-1)}] \tag{16}$$

And if we get $P_{t/t}$, which is the variance of the forecast error then:

$$VAR(y_3 - F(y_3/y_2, y_1)) = H_{33} - H_{32}H_{22}^{-1}H_{23} \tag{17}$$

And also $H_{33} - H_{32}H_{22}^{-1}H_{23} = P_{t/(t-1)} - K_t x_t P_{t/(t-1)}$ (18)

That's how we derive the gain from the Kalman as given below again:

$$\mathrm{K}_t = \mathrm{P}_{t/t-1}\, x'_t \delta^{-1}{}_{t/t-1} \quad or \mathrm{K}_t = \mathrm{P}_{t/t-1}\, x'_t (x_t \mathrm{P}_{t/t-1}\, x'_t + R)^{-1} \quad as\ \delta_{t/t-1}$$
$$= x_t \mathrm{P}_{t/t-1} x'_t + R \qquad (19)$$

If ($\mathrm{P}_{t/t-1}\, x'_t$) term is higher in positive uncertainty, we use the higher weights for the prediction errors and we use low weights if the value of R is high.
So we can write the final updating equations as:

$$\beta_{t/t} = \beta_{t/t-1} + \mathrm{K}_t \varepsilon_{t/t-1} \qquad (20)$$

$$\mathrm{P}_{t/t} = \mathrm{P}_{t/t-1} - \mathrm{K}_t w_t \mathrm{P}_{t/t-1} \qquad (21)$$

$$\mathrm{K}_t = \mathrm{P}_{t/t-1}\, x'_t \delta^{-1}{}_{t/t-1} \qquad (22)$$

The final equation is showing the Kalman gain. It can be seen in the final Kalman gain equation (19) that R (variance of measurement error) is inversely related with Kalman gain value. This confirms that the larger the R value, the lower the weights given to the measurement, in making the forecast for the next period by having todays information set.
In model (I), autonomous technical progress could be one of the reasons for the reduction of energy intensity. But this decline in energy intensity could also be due to several other factors (non-fossil fuel sources are improved, change in the structural of economy, non-price policy and innovation in price).
By following the general concept and methodology of Kalman Filter technique, we use equation (2) and write and solve the model in the same form. We find the error correction term with the presence of exogenous trend then we find the error correction term with the presence of endogenous trend and some further determinants as; stochastic trend, price of energy, investment, non-fossil fuel supply, trade, manufacturing components of GDP. In this model, the autonomous improvement in technology is represented by the stochastic trend. With Cuthbertson et al. (1992), the model for endogenous trend in energy consumption by following the Kalman Filter technique is represented as:

$$\Delta Ln(C_t) = \beta_0 + T_t + \beta_1 Ln\left(\frac{C}{Y}\right)_{t-1} + \beta_2 Ln(FP)_{t-1} + \sum_{i,k} \beta_{ik} \Delta Ln\left(V_{i,t-k}\right) \quad (23)$$

All the above variables are same as in equation (2). Additionally, the lags of differences in price, real GDP and consumption are represented by $\Delta Ln(V)$. We get T (the endogenous trend) from the transition equation as:

$$T_t = T_{t-1} + \pi_{t-1} + \gamma Ln(FP)_{t-1} + \sum_i \eta_i X_i + u_t \quad (24)$$

$$\pi_t = \pi_{t-1} + \nu_t \quad (25)$$

Where π = exogenous trend with stochastic component (ν_t). The structural determinants (investment, non-fossil fuel supply, trade, and manufacturing components of GDP) of the endogenous trend are represented by X_i, the lag of weighted average fuel prices is represented by FP_{t-1}, error term is represented by $\mathcal{E}_t$ and time lag is represented by T_{t-1}. In equation (1), energy intensity is treated as a dependent variable and it is described as the ratio of fossil fuel consumption and GDP. While, in most cases, total energy intensity is taken as the ratio of total fossil fuel consumption (the replacement value of hydro energy and nuclear energy could also be added), with GDP as a dependent variable.

According to definition, increase in fossil fuel was always accompanied by decrease in non-fossil fuel for a given energy demand while the change in non-fossil fuel consumption was not estimated in the endogenous trend during the analysis of total energy intensity. Hence, to get the estimated value of fossil fuel consumption, the total energy consumption could be estimated and the value of fossil fuel consumption could be attained by simply subtracting the forecasted values of exogenous trends of non-fossil fuel production from total energy consumption.

The combination of elasticity of the variables and trend is provided in Model II as shown in equation (23). While in transition equation (24), weighted average fuel price (FP_t) is also included because whenever the FP_t increases, energy efficiency irreversibly improves for the long term. Alternatively, in the simple elasticity of demand model, if the prices are increased or decreased then the original level of consumption is attained. The same does not happen in the case of endogenous technical progress model. The significant difference between the two models could be observed by simulation policies to check the stabilised levels of carbon emission in the future. To find the value of $\left(\frac{\partial C}{\partial t}\right)$, we take the first order derivative of equation (1) with respect to time (t).

Hence, in this model, there could only be two reasons for having continued stabilisation of energy use. Firstly, the existence of the stabilisation of energy use $\left(\frac{\partial C}{\partial t} = 0\right)$ occurs if there is a constant rise in the fuel price $\left(\frac{\partial FP}{\partial t} > 0\right)$ or $\beta < 0$. Secondly, aggregate growth in the economy matches exogenous increase in energy efficiency $\left(\frac{\partial Y}{\partial t} = -c\right)$. In the long run fuel prices do not make any difference. Mainly because of this property[34], it is necessary to apply energy tax for the stabilisation and elimination of CO_2 emissions. In exogenous technical model, we can only have a certain level of economic growth and our policy should have to work through controlling the economic growth. However, this trend imposes an inability to pick any thing for economic growth. While in the endogenous trend we have got other instruments which can manipulate or affect control of CO_2 emissions.

To find the value of $\left(\frac{\partial C}{\partial t}\right)$ for endogenous change model, we take the first order derivative of model II (equations, *23&24*) with respect to time (t). The presence of both (differential of energy price and just energy price) show the long run stabilisation equilibrium by having non-growing real energy prices and the equilibrium is represented as $(\gamma . FP_t = \beta_1 . \frac{\partial Y}{\partial t} - \pi^* - \sum_i \eta_i X_i)$. As per verification of simulation property, the values of X_i and π^* do not depend on time (t) and moreover a single energy price is found which is used to stabilise emissions for any constant rate of economic growth. Globally, fossil fuel is dealt with in dollar price. So, the process of devaluation of the currency is very common in most countries (especially in developing countries) and the price of fossil fuel become expensive in local currency, Mabey et al. (1997). Almost all countries try to substitute oil to gas, oil to coal etc., and we can find out this substitution by estimating the share equations which are explained in the next model.

[34] We need to acquire about this property that either it is realistic or unrealistic.

2.2.4 Model III (Estimating fossil Fuel Share Equations)

It is compulsory to calculate the total fossil fuel energy demand and the fuel mix of an economy in order to assess the values of carbon dioxide emissions. To find the consumption of fossil fuel energy variables (oil, gas and coal), the share of fossil fuel energy demand is taken by their primary energy values. It is expected in share equations to have the change in relative prices, total energy demand of fossil fuels, GDP and also the change in non-fossil fuel supplies as the additional variables. It is not commendable to say that all the fossil fuel energy variables (oil, gas and coal) are perfect substitutes for each other because there are many influences on the complex fuel market. These influences will be in the form of different factors as technological changes, strikes, price shocks, industrial mix and regulatory changes etc. and each of these will have a different impact on each fuel.

So, we find the inter fuel substitutions by using Almost Ideal Demand System (AIDS)[35] model introduced by Deaton and Muellbauer, (1980) and estimate the fuel share equations. Three share equations are estimated for Oil, Coal and Gas to find out the estimating substitution possibilities between them and also to find the policy implication for CO_2 emissions. Mostly, it is aimed to predict the energy needs under policy scenarios by using the econometric model. These models are also used to find the results from the estimated elasticities around change in prices, taxes, income, weather, demand for energy resources etc. We estimate the share equations by using the AIDS model. The aggregate analysis is divided into two parts as long run (Cointegration analysis) and short run (Error correction Model) dynamics to estimate the share equations. The general form of fuel share equation for all three fossil fuels (Gas, Oil and Coal) can be written as:

$$s_{i,t} = a_i + \sum_{j=1}^{2} b_{ij}\left(Ln\left(\frac{p_{jt}}{p_{3t}}\right)\right) + c_i\big(Ln(C_t)\big) + \sum_{k=1}^{n} d_{ik}V_{kt} \qquad (26)$$

[35] Almost Ideal Demand System (AIDS) was developed by Deaton and Muellbauer in (1980). AIDS model is used extensively in different fields of economics and consumer demand systems and it also describes the underlying equilibrium structure of interrelated consumer demand (Akmal, 2002). The most appropriate and slightly better functional form between Almost Ideal Demand System (AIDS), linear, log-linear and translog functional is said to be AIDS forms when the relationship between energy consumption and energy prices or other explanatory variables is estimated (Xiao et al., 2007).

While shares of gas, oil and coal are represented by s_1, s_2, s_3 respectively. Long run dynamics are estimated for fuel shares by using equation (26). As $(j = 1,2,3)$ so, the price of each fuel is $p_{j,t}$, total fossil fuel demand at time t is C_t and a set of n exogenous variables of interest are represented by V_{kt}. The variable of interest could be, the dummy variables (which represents different scenarios of government policies, oil price shocks, strikes, foreign investments in the energy system etc.), GDP and the Consumption of hydroelectricity, solar energy or nuclear energy.

By equation (26), we only take the prices of two fossil fuels (Gas and oil) relative to the price of coal to ensure the restriction of homogeneity in the system. According to this restriction, when the price of gas rises then the result is a fall in prices of other shares (oil and coal), when considering the effect on aggregate fuel consumption constant.

We can write the addition of fuel shares (Gas, Oil and Coal) equal to one as,

$$s_{1t} + s_{2t} + s_{3t} = 1 \tag{27}$$

Or $\quad share\ of\ gas + share\ of\ oil + share\ of\ coal = 1$ Or $\quad \sum s_{it} = 1$

We can also say for consistency on the other side of the share equations as:

$$\sum_i a_i = 1, \sum_i b_{ij} = 0, \qquad \sum_i c_i = 0$$

We estimate only two equations independently as the system is singular. Above equations (26) are estimated for gas and oil by using the OLS technique. In this context, the share of coal is obtained as the residual and the share of all three (gas, oil and coal) add up to one ($\sum s_{it} = 1$) as defined earlier. In this case, because we carry out mathematical calculation to find the values of the share of coal, the significance of the coefficients are not affected by the procedure and generally this is applied for the residual fossil fuel estimation from equation (26).

Our aim is to find the long run relationship for equation (26) using the cointegration technique and test the stationarity of the residuals by applying a number of diagnostics. In the estimation of the share equations, it is plausible and compulsory to have negative coefficient values for own prices, and the relationship is said to be better for having this relationship. In some cases, there occur some problems in the energy market because of market distortions which are considered dummy variables as per the earlier discussion. Furthermore, we find out three short run dynamic equations for each share (gas, oil and coal) and apply the error correction model (ECM) by using the same residuals from equation (26). To estimate these equations, we treat them as a system which has singularity and adding up constraints. Because of singularity and adding up constraints in the system, each fuel share equation is not considered independently by estimating error correction equations, and the identification of dynamic or adjustment of the coefficients system is also not possible (Anderson and Blundell (1984), Barr and Cuthbertson (1991)). The addition of the residuals and change in fuel shares for all "t" can be written as.

$$\Delta s1_t + \Delta s2_t + \Delta s3_t = 0 \tag{28}$$

$$res1_t + res2_t + res3_t = 0 \tag{29}$$

Where $res1_t, res2_t \; and \; res3_t$ are employed after the estimation of the long run dynamic model. The explanation of equation (28) and (29) is given as, the estimated values of the same set of exogenous variables and their coefficient values in the system, and the sum of the residuals should be equal to zero. Also the same sum of the adjustment coefficients ($\gamma_{i1}, \gamma_{i2} \; and \; \gamma_{i3}$) should be equal to each other as shown below in equation (30).

$$\sum_{i=1}^{3} \gamma_{i1} = \sum_{i=1}^{3} \gamma_{i2} = \sum_{i=1}^{3} \gamma_{i3} \tag{30}$$

In this case, we only take two residuals (res1 and res2) to estimate the equation and get the value of the third residual (res3) by using equation (29). However, we always try not to have a linearly dependent set of independent variables. Hence, we get the (3x2) matrix for the adjustment coefficients (γ_{i3}). There could also be one more possibility to get the adjusted value of the shares towards equilibrium by only choosing one residual from each equation, and choose just res1 for the equation of Δs_1 or res2 for the equation of Δs_2 and so on. But in this approach, the negative values of the coefficients of diagonal matrix show that each share adjusts towards the equilibrium at the same time because of equal elements $\gamma_{11} = \gamma_{22} = \gamma_{33}$ as shown in equation (30). Thus, we stick to the general approach of two residuals (res1 and res2) in each equation by having the adjustment at different rates. Hence the negative eigenvalues of (2x2) matrix are needed for stability in the estimation of dynamic system and this could only be possible if one of these two properties is satisfied as given below,

1) $\gamma_{11} + \gamma_{22} < 0$ (31)

And

2) $\gamma_{11}\gamma_{12} - \gamma_{21}\gamma_{22} > 0$ (32)

Hence, to estimate the equation for $\Delta s1_t$, we take two lag residuals ($res1_{t-1}$ and $res1_{t-2}$) and lag share of itself as ($\Delta s1_{t-i}$) and also the coefficients should be the same to verify the adding up.

Finally, we can write the system of three equations in the resulting form as:

$$\Delta s_{j,t} = \alpha_1 + \gamma_{j,1} res1_{t-1} + \gamma_{j,2} res2_{t-1} + \sum_{i=1}^{m} \mu_i \Delta s_{j,t-1} + \sum_{i=0}^{m} \beta 2_{j,i} \Delta FP2_{t-i} + \sum_{i=0}^{m} \beta 3_{j,i} \Delta FP3_{t-i} + \sum_{k=1}^{n} \sum_{i=1}^{m} \delta_{j,k,i} \Delta V_{k,t-i} \tag{33}$$

While the dynamic structure and set of variables ΔV_k remain the same in each equation of the above system we also get zero by adding up the residuals coefficients, independent variables and the relative prices. So, non-linear 3-Stage Least Square (3-SLS) is used to estimate the system.

2.3 Data sources and Construction of Variables

The key variables considered in this analysis are Natural Gas, Oil and Coal. Annual data is employed from 1971 to 2013 for the consumption of fossil fuel, which is available in the Pakistan Hydrocarbon Development Institute of Pakistan/Energy Year Book (Various Issues). In this study, we have taken the world price data of fossil fuel (Gas, Oil and Coal) from Bloomberg and in order to get the domestic prices of fossil fuel, exchange rate of the domestic currency in terms of dollar is multiplied with the world price of fossil fuels. Data for rest of the variables (GDP, GDP Deflator, Exchange Rate, etc.) could be obtained from the International Financial Statistics (IFS), International Monetary Fund (IMF), World Development Index (WDI), Bloomberg and Economic Surveys of South Asian Countries (Various Issues). Real GDP is taken at a constant price of base year (2000) US dollars. Energy consumption is taken in kilo tons of oil equivalent. Finally, all the data is converted into natural logarithm for modelling purposes and empirical analysis.

2.4 Empirical Findings

Annual data from 1971-2013 is used to perform the Johansen cointegrating tests on the long run relationship presented in equation (1) and it is also used to test the cointegration relationship between energy intensity (energy consumption/real GDP) and weighted average fuel prices (FP). Two different unit root tests are applied; ADF and PP tests, to check the time series properties of the variables. The results for both tests find that all the series have a unit root/non-stationary at level. All the series become stationary in their first differences, which indicates the first order integration or *I(1)*. The results of integration tests for all the series at level and first differences are shown in table 2.1.

Table 2.1: Results of unit root test

	ADF		PP	
	Level	1st diff.	level	1st diff.
Ln(Ct/Yt)	-1.249	-13.588*	-1.2973	-10.000*
LnFP	-2.331	-5.208*	-1.5964	-8.5732*

Because all the series are integrated at *I(1),* we can move to the next step to find whether the series are co integrated or not. We use the Johansen Co Integration test to find the CI relationship among the variables. The results of the Johansen CI tests are shown in table 2.2. There are two further tests in the Johansen CI test; Trace and Max-eigenvalue test. Both these tests reject the null hypothesis of no CI equation at 5% level of significance for equation (1).

Table 2.2: Results of Johansen's Co-integration test

Equation (1) Variables: Ln(Ct/Yt), LnFP							
Eigenvalue	Trace Statistic	5% Critical Value	Prob.	Max-Eigen Statistic	5% Critical Value	Prob.	No of cointegrating Vectors
0.4633	33.94*	25.8721	0.0040	24.90*	19.3870	0.0071	None
0.2022	9.040	12.5180	0.1779	9.040	12.5180	0.1779	At most 1

The results in table 2.2 suggest that there is at least one CI equation of $Ln(C_t/Y_t)$ and $LnFP$. In table 2.2, trace test suggests one cointegrating equation at 5% level of significance with probabilities 0.0040 and 0.1779 respectively. Alternatively, Max-eigenvalue test also suggests just one cointegrating equation at 5% level of significance with probabilities 0.0071 and 0.1779 respectively as shown in the same table. Therefore, we have taken the one cointegrating equation as indicated by both tests.
The results of the long run Co integration equation for first model are given as:

$$Ln\left(\frac{C_t}{Y_t}\right) = 0.2354 + 0.49^*\left(Ln(FP_t)\right) - 0.016^*(T_t) \qquad (34)$$

$$(2.9312) \qquad (-1.9332)$$

All the variables are statistically significant but have no expected signs in the long run relationship as shown in equation (34). The trend is showing the right signs for energy intensity but weighted average real fuel prices are not giving the right signs according to theory. The results for the above equation indicate positive price elasticity, and further describe that a 1% increase in weighted average real fuel prices $\left(Ln(FP_t)\right)$ increases energy intensity $\left\{Ln\left(\frac{C_t}{Y_t}\right)\right\}$ by 0.49% while time trend (T_t) is decreasing in energy intensity in the case of Pakistan. The positive relationship between $\left(Ln(FP_t)\right)$ and $\left\{Ln\left(\frac{C_t}{Y_t}\right)\right\}$ is not according to theory though it could be because of the nature of the data for energy intensity. It is shown in figure 2.2 that energy intensity has been increasing for a long time from 1971 to 2000 and then started to decrease after year 2000. This continuous increase in intensity may have captured all the effect of prices and, shows here a positive relationship between energy intensity and weighted average real fuel prices. The (*) Symbol shows that the variable is significant in the above equation, and t-values are mentioned in the parenthesis for further description.

The results of the short run dynamics for equation (2) are given as:

$$\Delta Ln(C_t) = 0.0261 - 0.0820^{*}ECT_{t-1} + 0.3540^{*}\Delta Ln(C_{t-2}) - 0.0002(trend) -$$

(1.01) (-1.90) (2.54) (-0.27)

$$0.095581^{*}\text{Dummies} \quad (35)$$

(-4.393)

$$(ECT)_{t-1} = Ln\left(\frac{C_t}{Y_t}\right)_{t-1} - 0.2354 - 0.49\big(Ln(FP_t)\big) + 0.016(T_t) \quad (36)$$

The speed of adjustment to restore the long run equilibrium in the case of any shock is significant and equal to -0.082. As we have estimated the exogenous trend model and have not found results according to theory, this may mean there is some flaw in the estimation or the methodology we have used. As we have estimated the exogenous trend model and have not found results according to theory, this may mean there is some flaw in the estimation or the methodology we have used. To fix the problem, we use the advanced technique Kalman Filter and apply this technique as discussed in detailed manner in section 2.2.3.

We estimated an endogenous technical progress model by Kalman filter by using the annual data of Pakistan from 1971-2013 and the results for Model II are employed as,

$$\Delta Ln(C_t) = 1.1197 + T_t - 0.50^{*}\, Ln\left(\frac{C}{Y}\right)_{t-1} - 0.0049Ln(FP)_{t-1} - 0.4614^{*}\Delta Ln(C_{t-1}) + 0.1509\Delta Ln(C_{t-2}) - 0.0075\Delta Ln(FP)_{t-1} + 0.6925^{*}\Delta Ln(y_{t-1}) - 0.05^{*}Dummies + e(-7.61) \quad (37)$$

$$T_t = T_{t-1} + \pi_{t-1} - 0.0116Ln(FP)_{t-1} - 0.0053^{*}ips + 0.013^{*}dummies + e(-51.39) \quad (38)$$

$$\pi_t = \pi_{t-1} + \ [\text{var} \ = \ \exp(-67.25)] \quad (39)$$

In equation (39), the exogenous technical progress average future rate is shown by π, constant growth is assumed in X_i variables while both differential of energy price and energy price are included. The presence of both (differential of energy price and energy price) show the long run stabilisation equilibrium by having non-growing real energy prices and the equilibrium is represented as ($\gamma . FP_t = \beta_1 . \frac{\partial Y}{\partial t} - \pi^* - \sum_i \eta_i X_i$). As per verification of simulation property, the values of $ips = X_i$ and π^* do not depend on time (t) and moreover single energy price is found which is used to stabilise emissions for a constant rate of economic growth. According to the simulation property, this shows an implicit backstop technology which can be estimated and the observed results of the transition dynamics of the economy will become consistent. There is negative relationship between trend and weighted average real fuel prices as shown in equation (38) and it verifies the exact and true relationship between both the variables.

According to the results of equations (37-39), we find a negative relationship between energy consumption (C_t) and industrial production (ips) which could be because of the arrival/import of efficient technology. If technology is going to be efficient then we get a negative relationship between energy (C_t) and (ips) . We also know that "ips" or "X" is the main variable in this Model II though the results for this relationship turn out to be insignificant.

As discussed earlier, the same results are depicted by equation (34) by using the exogenous change model. Our aim is to find the stabilisation for C_t.

$$Ln\left(\frac{C_t}{Y_t}\right) = 0.2354 + 0.49^*\big(Ln(FP_t)\big) - 0.016^*(T_t) \qquad by \;\; (34)$$

Simplify and by opening the LHS of the above equation as:

$$Ln(C_t) - Ln(Y_t) = 0.2354 + 0.49\big(Ln(FP_t)\big) - 0.016(T_t)$$

By taking lags of this equation as:

$$Ln(C_{t-1}) - Ln(Y_{t-1}) = 0.2354 + 0.49\big(Ln(FP_{t-1})\big) - 0.016(T_{t-1}) \qquad (40)$$

Finally take the difference

$$\Delta Ln(C_t) - \Delta Ln(Y_t) = 0.49\Delta\big(Ln(FP_t)\big) - 0.016\Delta(T_t) \qquad (41)$$

To stabilise Ct, we can equate $\Delta Ln(C_t)$ to zero and according to the assumption of exogenous trend it will solely depend on growth of GDP, so by taking the rest of the variables equal to zero as:

$\Delta Ln(C_t) = 0$ and $\Delta\big(Ln(FP_t)\big) = 0$ and $\Delta(T_t) = 1\ (= 2014 - 2013)$

$-\Delta Ln(Y_t) = -0.016\Delta(T_t)$

So

$$\Delta Ln(Y_t) = 0.016 \qquad (42)$$

So approximately 2% or 1.6% growth is required for stabilising the CO_2 emissions according to exogenous trend model.

We can also find the final equation for stabilisation for $\Delta Ln(C_t)$ for equation (37) by using the Endogenous Technical Progress with Kalman Filter technique as:

$$\Delta Ln(C_t) = 1.11968 + T_t - 0.50^* \; Ln\left(\frac{C}{Y}\right)_{t-1} - 0.0049Ln(FP)_{t-1} - 0.4614\Delta Ln(C_{t-1}) + 0.1509\Delta Ln(C_{t-2}) - 0.0075\Delta Ln(FP)_{t-1} + 0.6925\Delta Ln(y_{t-1}) - 0.05^* Dummies + e(-7.61) \qquad by\ (37)$$

$$T_t = T_{t-1} + \pi_{t-1} - 0.0116Ln(FP)_{t-1} - 0.0053^* ips + 0.013^* dummies + e(-51.39) \qquad by\ (38)$$

By putting the value of $(T_t)$from equation (38) in equation (37) as:

$$\Delta Ln(C_t) = 1.12 + T_{t-1} + \pi_{t-1} - 0.0116^* Ln(FP)_{t-1} - 0.0053ips + 0.013dummies + e(-51.39) \; - 0.50^* \; Ln\left(\frac{C}{Y}\right)_{t-1} - 0.0049Ln(FP)_{t-1} - 0.4614\Delta Ln(C_{t-1}) + 0.1509\Delta Ln(C_{t-2}) - 0.0075\Delta Ln(FP)_{t-1} + 0.6925\Delta Ln(y_{t-1}) - 0.05^* Dummies + e(-7.61) \qquad (43)$$

Putting the value of (T_t) (short run deviations assumes zero) and considering the ips and π_t constant growth as per simulation property.

$$0 = 1.12 - 0.0116^* Ln(FP)_{t-1} \; - 0.50^* Ln(C_t) + 0.50^* Ln(Y_t) - 0.0049Ln(FP)_{t-1}$$

Take difference so $0 = -0.0165^* \Delta Ln(FP)_{t-1} \; + 0.50^* \Delta Ln(Y_t)$

$$\Delta Ln(Y_t) = \frac{0.0165^*}{0.50} \; \Delta Ln(FP) \; or \; \Delta Ln(Y_t) = 0.033^* \Delta Ln(FP) \qquad (44)$$

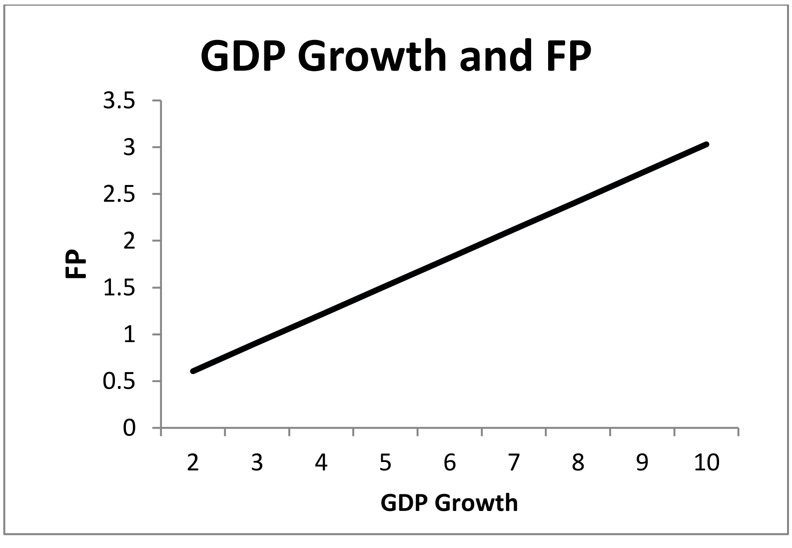

Figure 2.1: Trade-off b/w GDP growth and weighted average real fuel prices

According to the resulting form of the equation (37) shows, to stabilise (C_t) by using Kalman Filter both variables GDP and FP there is a trade-off between them. It also shows the true relationship between trend and FP which is estimated in exogenous model. Again, the results are not according to theory in exogenous model. It verifies that Kalman Filter has done a much better job in filtering out the true relationship of the variables and show exactly what is going on in Pakistan. Although exogenous trend model is showing the wrong sign for Pakistan's data, KF technique rectifies it. Figure (2.1) shows the trade-off between GDP and weighted average real fuel prices, which means, if fuel prices rises by 1% then GDP growth can be 3% higher. In exogenous trend the GDP growth just depends on trend.

We have also found the projected fossil fuel intensities for both (exogenous and endogenous) models as shown in figures 2.2&2.3.

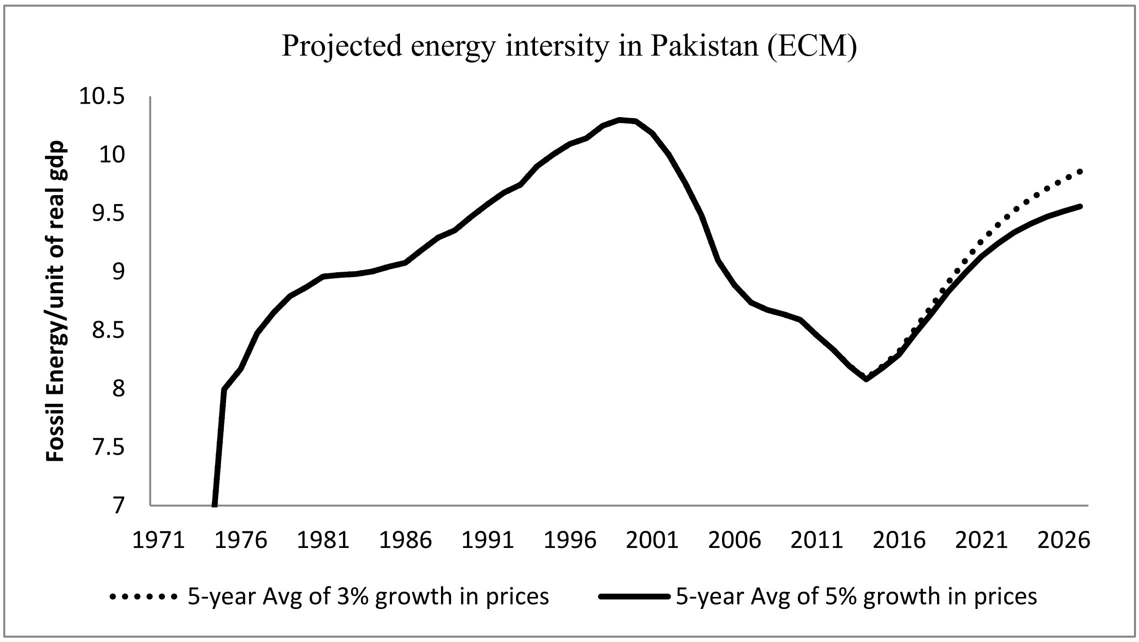

Figure 2.2: Fossil Fuel use (toe) per unit of real GDP, 1971-2030

We estimated the fossil fuel intensity for Pakistan for the period of (1971-2013) by using the above model (endogenous technical progress model) as shown in equations (37-39). The coefficient of fossil fuel energy use and weighted average fuel price is -0.80 and 0.024 respectively. So, according to the estimated results of endogenous technical progress, there is an increase in the prices of the fuel coefficient because the demand of fuel increases globally, and fossil fuel energy use decreases in Pakistan over time. According to the estimated results, because of the higher use of energy there is a higher rate of decline in it, which shows a symptom of energy efficiency convergence in the long run. Because there are traditional/different types of taxes levied on fuels in Pakistan, the estimation is not entertained in the cost share of GDP.

We also find the projected energy intensity by applying the same endogenous technical progress model over the simulation period as shown in figure 2.3. To find the projected energy intensity for the simulation period from 1971-2030 (which is also used for policy analysis), we apply three percent and five percent tax on the change in consumption and fixed GDP growth rate. According to figure 2.3, the energy intensity falls over time and the implied elasticities continue to increase if the prices are kept high.

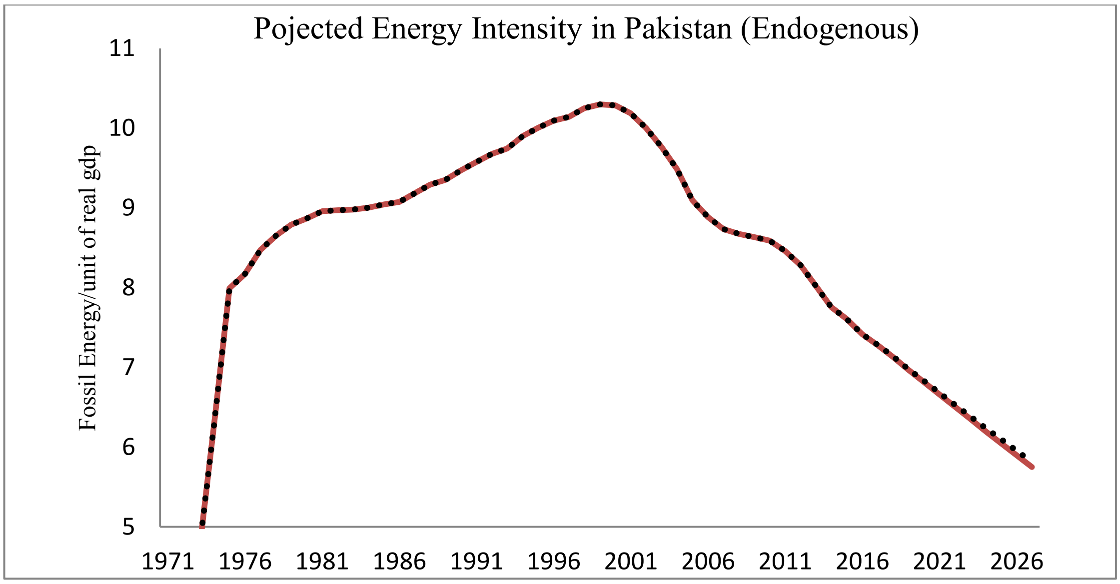

Figure 2.3: Fossil Fuel use (toe) per unit of GDP, 1971-2030

According to figure 2.2, the energy intensity increases over time as is the case for Pakistan. Globally, fossil fuel is dealt within dollar price. So, the process of devaluation of the currency is very common in most countries (especially in developing countries) and the price of fossil fuel become expensive in local currency, Mabey et al. (1997). Almost every country tries to substitute oil to gas, gas to coal etc., and we can find out this substitution by estimating the share equations which are explained in the next model.

We have found the projected energy intensity by applying exogenous technical progress model over the simulation period as shown in the figure 2.4. To find the projected energy intensity for the simulation period from 1971-2030 (which is also used for policy analysis), we apply three percent and five percent GDP growth on the change in consumption. According to figure 2.4, the energy intensity falls over time with this increase in GDP growth.

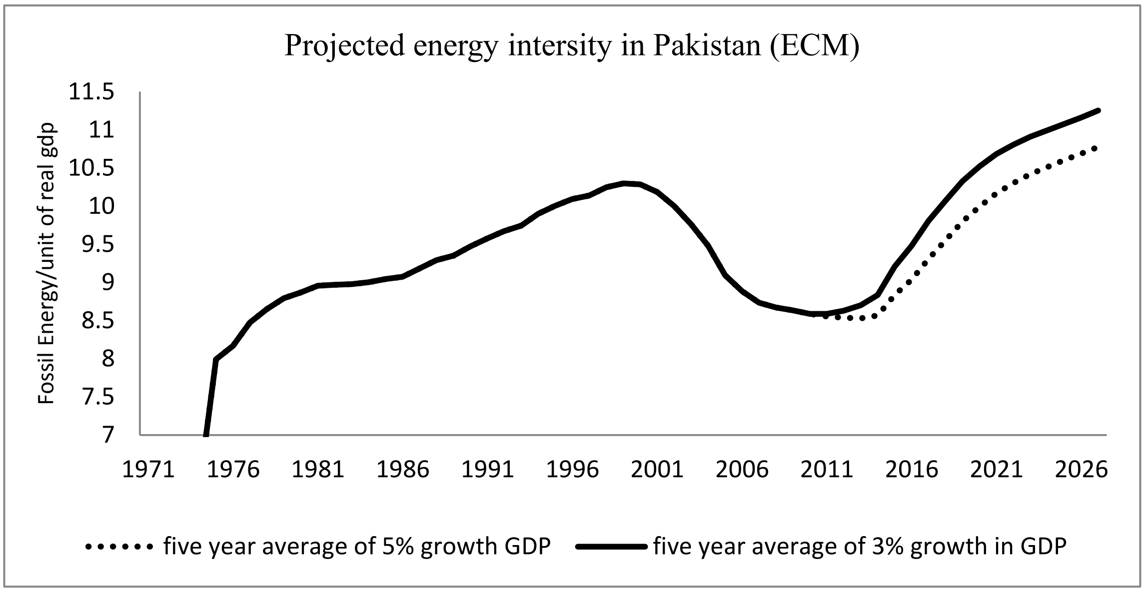

Figure 2.4: Fossil Fuel use (toe) per unit of real GDP, 1971-2030

We have also found the projected energy intensity by applying endogenous technical progress model over the simulation period as shown in the figure 2.5. To find the projected energy intensity for the simulation period from 1971-2030, we apply three percent and five percent GDP growth on the change in consumption. According to figure 2.5, the energy intensity falls over time with this increase in GDP growth.

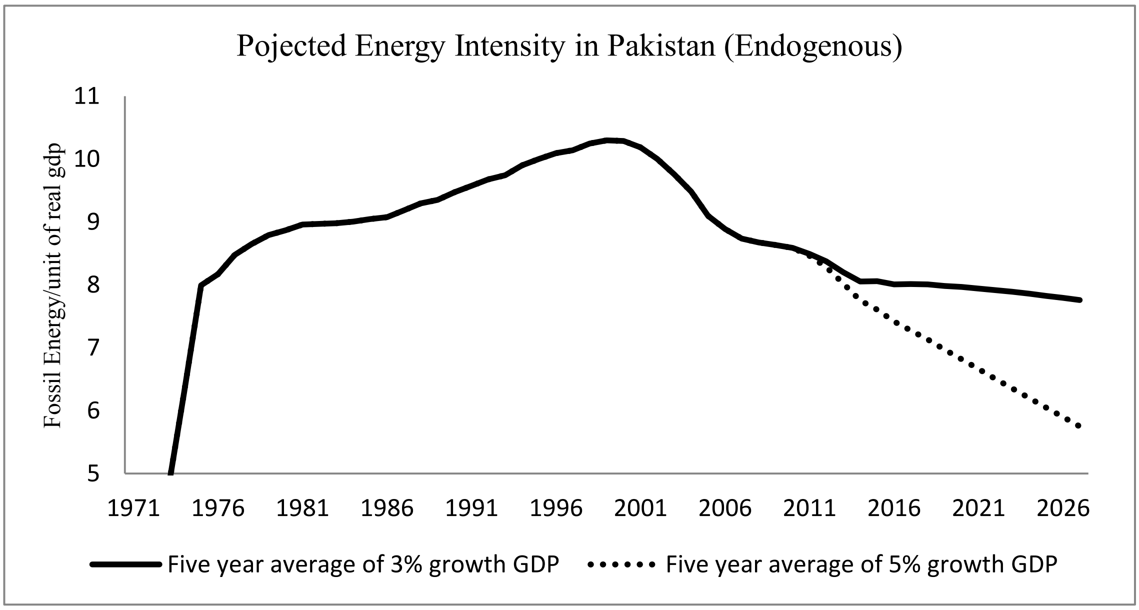

Figure 2.5: Fossil Fuel use (toe) per unit of GDP, 1971-2030

Generally, there is a decline in cost share of fossil fuel as compared to energy volume with a lower rate. This could be because of an increase in the international prices of energy over time and the exogenous technical progress shows that the elasticity of energy price increases in the long run but always remains less than one. In some cases, because of devaluation in the local currency, the oil price becomes expensive and the cost of energy rises in their local currency. There could be one other reason for the increase in energy cost, which is the substitution of oil with coal or gas with oil.

We have estimated the fuel share equations from Model III to find the substitution effects of fossil fuels (gas, oil and coal). As discussed earlier, we estimate just two shares (oil and gas or coal and gas or etc.) to remain singularity. Two equations are estimated to obtain the shares of gas and oil by using Model III and estimated results are shown in equation (45) and (46), while the share of coal is obtained as a residual which is shown in equation (47). In the estimated equation of coal share (equation 47), the significance level of the coefficients are not given any importance as the addition of three shares by definition is one. The same calculation is done for the remaining share after estimating two equations no matter which two shares are estimated first.

By using equation (26), we find the residuals and check their stationarity. We apply two different unit root tests (ADF and DF-GLS) to check the time series properties of the residuals and to find the stable long run relationship. The estimated results are reported in table 2.3 which show that all three residuals are stationary and null hypothesis of no cointegration does not hold by following the critical value given in the table of MacKinnon (1991). The residuals of share of gas, oil and coal reject the null hypothesis (no cointegration) and fail to reject the alternative hypothesis (cointegration exists). So, the comparison of critical values and estimated values suggest that residuals are stationary at I(0). According to the results, all three shares show a clear indication of stationarity and also cointegration as per ADF and DF-GLS but the share of oil has a lower value as compared to the other two shares which are close to the critical value.

Table 2.3. Results Cointegration test of Residuals

Equation of	Cointegration test	ADF test	DF-GLS test
Share of Gas	-2.7832*	-2.7832*	-2.0061*
Share of Oil	-2.3344*	-2.3344*	-1.7000*
Share of Coal	-4.2579*	-4.2579*	-1.612**

* and ** indicate the significance at 5% and 10%

In fact, negative own price coefficients are as a general rule, although it could be positive because of the dummy variables effect which could be in response to the distortions in the energy markets. While cross price coefficients are expected to be smaller than own-price coefficients, these are generally positive values. According to the estimated results of equation (45), there is positive relationship between the share of gas (s_g) and price of oil relative to the price of gas. Alternatively, the estimated results show that with a 1% increase in the price of oil relative to gas, share of gas increases by 0.0003%. When the price of oil increases people substitute oil for gas and as a result gas becomes more attractive because it is cheaper, and vice versa.

A positive sign also indicates that gas is a substitute for oil in this equation. Similarly in the same equation, with a 1% increase in the price of coal relative to the price of gas, the share of gas reduces by 0.0005%. When the price of coal increases then the price of gas also increases because the negative sign of the coefficient indicates that they complement each other, and as a result as gas become expensive so the coal does. Hence, because of an increase in the price of oil and a decrease in the price of coal, the share of gas increases and the energy consumption has negative relationship with the gas share. This shows that by a 1% increase in energy consumption, share of gas reduces to 0.00007%. All the variables in this equation show a significant effect except energy consumption.

The results of the long run analysis for each fuel share is estimated as,

$$s_g = 0.55^* + 0.03^*\left(Ln\left(\frac{p_o}{p_g}\right)\right) - 0.046^*\left(Ln\left(\frac{p_c}{p_g}\right)\right) - 0.007Ln(C_t) + 0.065^* d2003 \qquad (45)$$

$$s_o = 0.11 + 0.027^*\left(Ln\left(\frac{p_g}{p_o}\right)\right) + 0.0188\left(Ln\left(\frac{p_c}{p_o}\right)\right) + 0.023^* Ln(C_t) - 0.086^* d2003 - 0.067^* d04 + 0.065^* d99 \qquad (46)$$

$$s_c = 0.337 + 0.01875\left(Ln\left(\frac{p_g}{p_c}\right)\right) - 0.0458\left(Ln\left(\frac{p_o}{p_c}\right)\right) - 0.01518Ln(C_t) + 0.02130(d2003) + 0.067005(d04) - 0.0652(d99) \qquad (47)$$

According to the estimated results of equation (46), there is a positive relationship between the share of oil (s_o) and the price of gas relative to the price of oil and also the

price of coal relative to the price of oil. The estimated results show that by 1% increase in the price of gas relative to the price of oil and the price of coal relative to the price of oil, the share of oil increases by 0.00027% and 0.00019% respectively. A positive sign also indicates that oil is a substitute of gas and coal in this equation. So, because of an increase in price of both, the share of oil increases while the energy consumption has a positive relationship with oil share. This shows that by a 1% increase in energy consumption, share of oil increases by 0.00023%. All the variables in this equation show a significant effect (except the coefficient of price of coal relative to price of oil).
We can estimate equation (47) by following equation (27) and for consistency we can write the share equations on the right hand side as:

$$\sum_i a_i = 1, \qquad \sum_i b_{ij} = 0, \qquad \sum_i c_i = 0$$

According to the estimated results of equation (47), there is positive relationship between the share of coal (s_c) and price of gas relative to the price of coal and a negative relationship between (s_c) and the price of oil relative to the price of coal. The estimated results show that with a 1% increase in the price of gas relative to the price of coal, share of coal increases by 0.00019% and with a 1% increase in the price of oil relative to price of coal, share of coal decreases by 0.00046%. The energy consumption has got negative relationship with the coal share. This shows that with a 1% increase in energy consumption, share of coal reduces by 0.000151%. We do not check the level of significance in equation (47) as it is induced from equations (45) & (46).
As per earlier discussion for the short run dynamic equations for each share (gas, oil and coal) are treated as a system and the estimated results of the system using non-linear Three Stage Least Square (3-SLS) are given as:

$$\begin{aligned}\Delta s_g = \ & 0.0071 - 0.4151^{*} res1_{(t-1)} - 0.1890^{*} res2_{(t-1)} - 0.08358 \Delta s_{g(t-1)} \\ & - 0.0061 \Delta Ln\left(\frac{p_o}{p_g}\right)_{(t-1)} + 0.0092 \Delta Ln\left(\frac{p_c}{p_g}\right)_{(t-1)} + 0.0855^{*} \Delta LnC_{(t-1)} \\ & - 0.1566^{*} \Delta LnY_{(t-1)} + 0.0641^{*} dummies \qquad (48)\end{aligned}$$

$$\Delta s_o = -0.0049 + 0.2107^{*}res1_{(t-1)} - 0.0132res2_{(t-1)} + 0.0088\Delta s_{o(t-1)} - 0.0031\Delta Ln\left(\frac{p_c}{p_o}\right)_{(t-1)} - 0.0062\Delta Ln\left(\frac{p_g}{p_o}\right)_{(t-1)} - 0.0297\Delta LnC_{(t-1)} + 0.1209\Delta LnY_{(t-1)} - 0.0665^{*}dummies \quad (49)$$

$$\Delta s_c = -0.0020 + 0.2045res1_{(t-1)} + 0.2022res2_{(t-1)} + 0.0748\Delta s_{c(t-1)} + 0.0091\Delta Ln\left(\frac{p_c}{p_o}\right)_{(t-1)} - 0.0030\Delta Ln\left(\frac{p_g}{p_o}\right)_{(t-1)} - 0.05626\Delta LnC_{(t-1)} + 0.0356\Delta LnY_{(t-1)} + 0.0023dummies \quad (50)$$

According to the estimated results, it can be noted that the estimated dynamic system is stable as per eigenvalues results. The results for the eigenvalues of the 2x2 matrix are given as:

1) $\gamma_{11} + \gamma_{22} = (-0.4152 - 0.0132) = -0.4284 < 0$ (51)

and

2) $\gamma_{11}\gamma_{12} - \gamma_{21}\gamma_{22}$

$$= \{(-0.4151 * -0.1890) - (-0.2107 * -0.0132)\}$$
$$= \{(0.07845 + 0.0027)\} = 0.0812 > 0 \quad (52)$$

Hence, the estimated dynamic system is stable and also the sum of the change in share of coal, gas and oil approaches zero. The results of equation (51) and (52) imply that the shares adjust towards the equilibrium. Similarly, the sum of the coefficients of relative prices, independent variables and residuals add up to zero.

2.4.1 Simulation Properties

We can use all developed model in order to check the impact of different types of tax on carbon dioxide emissions and fuel mix. In exogenous model, change in aggregate energy consumption because of change in price could result in product substitution, pure substitution of other factors, non-fossil fuel substitution and price induced technical innovation. However, we cannot model the changes in supply and demand separately because the process undergoes exogenous trend. Fuel share model (Model III) can be used to get an exact idea of inter-fuel substitution and overall energy conservation could be compared with it. We can also compare the results of energy consumption after applying different types of taxes (e.g. carbon tax, energy tax, etc.).

As carbon tax accurately internalises the externalities, so, it is expected that carbon emissions are reduced by applying this tax as compared to any other energy tax. Elasticity of energy also depends on many factors such as income levels of the population. It varies from country to country what sort of tax could be best used. More likely, whenever energy prices are high then tax is charged less and vice versa. In Pakistan energy is used in an inefficient way although use of energy is very high. Due to government interventions, taxation is low, as people try to find low cost opportunities. It is very difficult to make improvements to those countries that face low energy intensity.

Hoeller and Coppel (1992) discuss how the price responses of different countries can be explained by existing taxation and difference in prices. Another scenario could be introduced with an equal percentage of energy and carbon taxes with the same amount of revenue in the form of ad valorem tax. By applying these three different taxes the outcomes will arise as: Firstly, if energy prices are already very high, energy tax will cause people to start finding low cost opportunities. Secondly, if carbon tax will be levied, consumption may go down, but there will be a shift in fuel mix and people will start moving from coal to gas or coal to oil. The coal market may start going down however, we may not find expected signs for the substitution of fuel because of difference in price levels. Thirdly, if both taxes are applied with equal percentage, then the areas that use gas and oil will be at an advantage. Whilst areas that use coal will pay a huge amount of tax.

Neither tax (energy tax and carbon tax) could be very helpful in the reduction of carbon emissions nor in the collection of revenue. All three scenarios (carbon tax, energy tax and ad valorem tax) will not be very helpful either. Because the fossil fuel intensity is reflected in energy tax rates, if the area of the country or the country itself uses less coal and more gas then revenue will show as a reduction in carbon tax. When fuel prices are low then ad valorem tax will also be a lesser charge.

The endogenous trend is not included or discussed in the above three scenarios. By estimating the model with growing endogenous trend and increasing prices, a huge reduction in carbon emission could be expected in the long run. Figure 2.3 shows that there is a continued reduction in energy intensity with the increase in prices and growing endogenous trend. Hoel (1993) discusses flat-rate tax and reduction in emissions. He states that an efficient way to reduce emissions is to implement flat-rate tax as compared to implementing an equivalent uniform target in the uniform world. Pakistan is a developing country and its energy market is oil-based. Pakistan has reservoirs of coal and gas but lack the technology to extract. To reduce emissions the cost will be minimised internationally. Therefore, flat-rate tax will not be a good idea for the country. Internationally, if such a type of tax is introduced then may be carbon emissions will reduce, but not all countries may follow it. On the other hand, some countries will just pay (afford) the tax and increase the use of energy, and emissions may also increase. The second best solution could be taken as the continued increase in energy price. In this case, many things will be ignored as physical and consumer differences although market distortions will be removed. As increase in price only will also not be the best solution to reduce emissions. At this point, the best, efficient and practical solution could be to set the individual county targets or different tax rates or tradable permits could be introduced. The relationship and forecasting of energy consumption and CO_2 emissions are discussed in detail in the third chapter.

2.5 Conclusion

Simple theoretical frame work may not provide the best solution and econometric estimation of the economic variables with interaction terms may also introduce large errors, while the econometric modelling for the energy sector measure such relationship with accuracy. Fuel mix/fuel substitution is the response of distortion in the energy markets within the country in local markets and also between two countries. Three types of taxes are discussed in the simulation period (1971-2030) as, carbon tax, flat-rate tax and ad valorem tax. According to results, these taxes could not reduce the carbon emissions because the complexities in the fuel markets are very high. The variation in the energy elasticities occur because of functional form, estimation period, fuel, sector, and time series data or cross sectional data (Atkinson and Manning, 1995). In the analysis, they estimated the overall energy elasticities (specifically for fossil fuel intensity) and found very low values as compared to other commonly used techniques.

In olden times, the concept was to reduce the GDP of oil importing countries during the price shocks of oil to make for balanced trade. It was also presumed that because of decrease in GDP, the energy consumption of the country might also decrease and the energy consumption was wrongly associated with the change in energy prices. These models assumed that to reduce GDP the energy demand was to be controlled (reduced). In this case, the carbon tax did not have any huge effect on GDP, energy consumption and external prices. Neuburger (1992) found low elasticity by using the model as the energy intensity a function of price produced.

The functional form of the endogenous technical progress model shows how energy intensity goes down with the increase in prices and also irreversible improvements are achieved in energy efficiency. In this model, increase in prices is taken as the improvement in technology and it is also decayed into a conventional demand response. The conventional energy models were used to find the elasticity and dynamics of the model to check the short and long run effect. The endogenous model is also used to find the same but with innovation of continuous decline in energy intensity with continuous high prices. This model has attempted to endogenise the technical progress or the "Autonomous Energy Efficiency Improvement" (AEEI). There is no authentic solution to find the stabilised level of carbon emissions in the long run unless the continuous increase in energy prices is always greater than the economic growth forever. But this cannot be true, because fossil energy consumption will achieve stabilisation levels at a certain price level due to the increase in the use of non-polluting alternatives. This limitation has been tried to overcome in Global Econometric (GE) models but no empirical evidence is provided for this assumption. However, in the endogenous trend model the non-growing energy prices with steady growth are found stable from energy use.

Some of the points for the reduction in carbon emissions are discussed with the help of estimation results and simulation properties. Firstly, according to the results of model I, the elasticity turns up 0.49 which means tax will be ineffective in making a huge reduction in energy intensity to achieve the stabilised level of emissions. Secondly, inter-fuel substitution could provide the required stabilisation level just in the short run. In the long run, improved technology or innovation will be in a position to achieve the required level but it needs too much time to start working on the long run plans. Thirdly, imposing carbon tax will provide room for the private sector to invest in speculative R & D, but the investment will become sub-optimal because of regulatory uncertainty. Lastly, one possible policy option is to start investing some portion of gained revenue from carbon tax into different projects of energy saving investments via private or public sectors to control these small energy elasticities. This investment could be used in institutional changes and in several fields by public sector as energy labelling, building regulations and energy efficiency research which is not encouraged by the private sector. Some problems arise in the energy elasticity estimates as; when low income house hold start investing through finances in the energy sector or energy related sector, and when people get unexpected incentives while living in rented or public (subsidised) houses. Then the above policy implications give the advantage of overcoming market failure which is caused by these elasticity estimates.

The best policy option could be the inter fuel substitution but the required stabilization level could be achieved just in the short run. In the long run, improved technology or innovation will be in a position to achieve the required level but it needs too much time to start working on the long run plans. According to the results of model I (exogenous trend), the elasticity turns up 0.49 which means tax will be ineffective in making a huge reduction in energy intensity to achieve the stabilised level of emissions. While model II (KF model, endogenous trend) shows, to stabilise (C_t), there is a trade-off between GDP and fuel prices, which means, if fuel prices rises by 1% then GDP growth can be 3% higher. The coefficient of fossil fuel energy use and weighted average fuel price is -0.80 and 0.0078 respectively. So, according to the estimated results of endogenous technical progress, there is an increase in the prices of the fuel coefficient because the demand of fuel increases globally, and fossil fuel energy use decreases in Pakistan over time. According to the estimated results, because of the higher use of energy there is a higher rate of decline in it, which shows a symptom of energy efficiency convergence in the long run. Model II is definitely the best policy option for Pakistan.

Chapter 3

Energy Demand and Energy Efficiency in the Asian Developing Countries: A Stochastic Demand Frontier Approach

3.1 Introduction

The present era is an era of environmental awareness which needs to find ways to fulfil the energy demand requirements for the whole world. Energy is considered the most important concern inspect of environmental issues which is one of the reasons for the increment/rise in Green House Gases emissions (GHGs) especially Carbon Dioxide (CO_2) emissions. The world's surface temperature has increased by 0.74 degree Celsius (°C) and the sea level has increased up to 0.17m during the twentieth century (IPCC, 2007). The Paris Agreement[36], 2015 has also suggested to the parties[37] that to maintain a 1.5°C temperature reduction and to achieve this target sometimes zero emissions will have to be maintained (John and Joshua, 2015). After the wold oil crisis of 1970, energy demand has become the attraction and concern for the whole world's researchers especially in the developing countries. Presently, developing countries do not contribute much to energy consumption and CO_2 emissions but soon they will be consuming a significant part of the world's energy (Dahl, 1994). It is predicted that the share of developing countries oil consumption will rise by up to 35.8% in 2020 as compared to the rest of the world (IEA, 2002) and if the same pattern of energy use continues then global energy consumption will increase up to 50% before 2030 (CSIRO and The Natural Edge Project, 2007).

Obviously, the more energy used, the more environmental degradation will increase. As the main source of CO_2 emissions are energy resources, so the adoption of efficient ways to use energy can reduce the problems in an attempt to make the environment better. Here it is needed to review the energy systems in order to control this threat to the environment. Improvement in the efficiency of energy utilization may help in

[36] United Nations Climate Change Conference was conducted in Paris in December, 2015 with the aim of environmental concerns but the discussed concerns are yet to be adopted by the world (those were agreed though).

[37] Here parties mean 196 countries from the whole world, who attended this United Nations Climate Change Conference in December, 2015. The main aim of the conference was how to spread the vigilance in the whole world to reduce GHGs emissions.

reducing the greenhouse effects, pollutions and CO_2 emissions. Further, the study of efficiency of energy utilization provides a framework that improves the effectiveness of ecological tax reforms. Therefore, this chapter focuses on the estimation of income and energy demand price elasticities and energy efficiency for developing economies.[38]

Energy intensity, energy use to GDP ratio or energy consumption to GDP ratio, is a key indicator widely used in energy policy analysis. IEA (2009) shows that energy efficiency has improved in many countries since 1970. Energy intensity is measured as the amount of energy used per unit of activity (GDP). It is also observed that energy efficiency is assessed as a response of energy intensity which is not an accurate way to observe energy efficiency all the time because change in energy intensity is not only a function of energy efficiency, but it is also the function of change in several factors (structure of the economy). In this case, energy intensity is not just considered as a proxy of energy efficiency.

We investigate about this relationship that either energy intensity is a proxy of energy efficiency or not. Hence, it is not wise to measure and assess any country's energy efficiency level with a simple estimation (weak method) which is based on energy intensity (aggregate energy consumption to GDP ratio). It may measure the energy efficiency for a fixed time period but to measure the level of "underlying energy efficiency" that characterizes the whole economy of a country, this simple measure could not provide accurate enough results and conclusion for energy policy over the time period.

Since the oil price shock of the early 1970s, the analysis of energy has become important. The Index Decomposition Analysis (IDA) is used by a large number of studies.[39] With the objective to improve the estimation procedure, Aigner et al. (1977) use the stochastic frontier approach. This method constructs the frontier from best practices and distance from best practise is considered as inefficiency. These methods suggested in energy economics literature overcome the problems in measurement of energy efficiency and these approaches have been followed by simple monetary based energy efficiency indicators.[40] Economic-wide energy efficiency could be found by

[38] The relevant variables could be the Indicators (monetary or physical) of energy efficiency which relate with energy use in positive or negative manners and measure the economics activity. Patterson (1996) discusses about the further indicators which define the economic activity in aggregation at different levels as sector, economy wide, firms, sub-sectors etc.

[39] For detail on the empirical studies that used IDA see Ang and Zhang (2000)

[40] These indicators are suggested as the Index Decomposition Analysis (IDA), Energy Demand Frontier Analysis or simply Frontier Analysis and energy use to GDP ratio.

using one of the indicators called IDA[41] which is a bottom-up framework. Whereas the estimation of parametric and non-parametric approaches could be found by using the frontier analysis (production frontier analysis is exchanged with energy frontier analysis as an example) and the level of energy efficiency is availed by using the difference approach (difference between the actual energy use and predicted energy use). Ferrier and Hirschberg (1992) discussed and implemented the frontier approach for first time. Huntington (1994) discusses the relationship between productive efficiency and energy efficiency by using the production theory analysis.

Parametric approach (parametric frontier analysis) is used at sectoral level by Buck and Young (2007). A stochastic energy use frontier function is estimated by using this approach (parametric approach). They take the data of energy use per square foot from Canadian commercial buildings as well as taking the data of some variables on physical characteristics and activities of the building. Boyd (2008) also uses the parametric frontier analysis approach to estimate the energy use frontier function. He takes the energy use as a function of four output variables and also the capacity utilization for a sample of wet corn milling plants. Stochastic frontier function approach is utilized in both[42] of these studies as initially introduced by Aigner et al. (1977). Zhou and Ang (2008) use the non-parametric approach in his analysis for 21 OECD countries for the time period from (1997-2001). Data Envelopment Analysis (DEA) [43] is used to measure energy efficiency performance for these countries and the model is built on the basis of two non-energy inputs, four energy inputs, GDP, a desirable output, CO_2 emissions and an undesirable output.[44] The parametric frontier approach is followed in this paper to estimate the energy demand frontier function. In general, the frontier approach provides the maximum attainable output by using the given inputs. However, in the case of energy demand model, this approach provides the minimum level of energy needed to attain a given level of output. Therefore, this frontier approach helps in identifying the countries that produce a specific output by utilizing the best technology. Once the most efficient country is identified the frontier is constructed and the distance from this

[41] All the workings, methods, applications and discussion regarding IDA could be found in Ang (2006).

[42] These both studies by Buck and Young (2007) and Boyd (2008) are some examples about the use of parametric frontier analysis approach.

[43] Relative efficiency is measured by using the DEA method (which is based on the multiple inputs and outputs) and peer decision making units (DMUs) are achieved. Different weights are given to multiple inputs and outputs to make it best practice frontier.

[44] Zofio and Prieto (2001) & Zhou, et al. (2008) measure the environmental performance of OECD countries and an environmental DEA approach is used. In this approach, with in the production process the energy is considered as an input.

frontier is considered as the level of inefficiency. By using the energy demand frontier function approach, some variables (price effect, income effects, country specific effects, a common Underlying Energy Demand Trend (UEDT), exogenous technical progress and some other exogenous factors) are controlled explicitly to isolate the "underlying energy efficiency". Hence, the impact of endogenous technical progress can be checked by price effect and the impact of exogenous technical progress can be observed by UEDT. Economy wide energy demand is provided by the demand of energy services. These services are categorised as transport services, cooked food, heat, hot water, manufacturing process, illumination etc. The capital equipment[45] and energy fuels are combined in order to get the desired services. Therefore, it shows that demand for energy is influenced by the production process or by the level of energy efficiency of the equipment. So, by upgrading the equipment from old to new, there is the possibility to get the same level of production and services by using less energy.

Of course, there are many other important factors in reality apart from economic and technological factors to explain the level of energy consumption such as, exogenous regulatory and institutional factors. Furthermore, the impact of these exogenous changes may or may not be consistent over time. Most importantly, UEDT should be specified in a non-linear way and it should also be flexible in increasing and decreasing over the estimation period (Hunt et al. (2003a, b)). Griffin and Schulman (2005) and Adeyemi and Hunt (2007) suggest to use time dummies to capture the impact of these unobserved exogenous factors particularly in panel data. Kumbhakar and Lovell (2000) discuss that there could occur some estimation problems by using a large number of time dummies in the parametric frontier framework. They suggest an alternative approach of including time trend[46] instead of time dummies for the specification of the UEDT.

In order to get the results for these different influences, we aim to find and estimate the relationship between energy consumption of economic activities with energy prices by using a general energy demand approach with the help of standard literature on energy demand modelling. Furthermore, an aggregate energy demand function is estimated for a panel of ASIAN developing countries by using this relationship. Moreover, to control the effect of other factors on energy demand across the country, some additional

[45] The capital equipment could be cars, machinery, household appliances, insulated walls etc.

[46] In our present study, time trend model instead of time dummies is used which is suggested by Kumbhakar and Lovell (2000).

variables are introduced and added to the model as; structure of the economy, area size, population and variables of interest which have an effect on economic conditions.

Hence, the framework adopted in this study is an attempt to isolate the "underlying energy efficiency" by using control variables such as; energy price[47], income, population, effects due to different structures of the economies, exogenous factors (technical progress & other exogenous factors) and the effects because of difference in area sizes. Therefore, the level of underlying energy efficiency is isolated by using this technique, and we can also confirm that an economy is said to be a best practice economy if they use energy efficiently, or the common energy demand (efficient use of energy) is estimated by considering the homogenous income elasticity, price elasticity, homogenous UEDT and other factor responses.

This is also important to find the underlying energy efficiencies and isolate them separately for different countries.[48] As a results, once we find out the effects of these factors and control them, then the underlying energy efficiency is estimated for each country. This estimated underlying energy efficiency verifies two important things as; firstly, it shows how the estimated efficiency has changed over the estimation period, and secondly, it shows the differences in efficiency across the panel of countries.

The rest of the paper is organized as follows: Section 2 presents the methodological issues and empirical analysis. Data is introduced in Section 3. Empirical findings are discussed in section 4. Conclusion is presented in section 5.

3.2 Methodological Issues & Empirical Analysis

3.2.1 An Aggregate Frontier Energy Demand Model

In the present study, by considering the above discussion, we assume that energy consumption is affected by some variables[49] and there exists a relationship (an aggregate energy demand relationship) between them for a panel of Asian developing

[47] Buck and Young (2007) & Boyd (2008) find the energy efficiency and energy intensity by using the stochastic frontier but they do not use the energy demand and ignore and omit a very important control variable (energy price). But in this present study energy price is used as a control variable.

[48] As exogenous technical progress is included in UEDT, therefore, it could be argued that different countries may use the technologies in different ways (poor way to install the technology or efficient way to install the technology). So as a result, there will be difference between the behaviour of the countries and it will reflect the inefficiency across the countries. So, different (in)efficiency terms are taken for all countries.

[49] The other variables could be the Indicators (monetary or physical) of energy efficiency which relate with energy use in positive or negative manners and measure the economics activity. Patterson (1996) discusses about the further indicators which define the economic activity in aggregation at different levels as sector, economy wide, firms, sub-sectors etc.

countries. By following the methodology, which was initially proposed by Aigner et al. (1977) [50], our model is presented as:

$$CE_{it} = E(RP_{it}, Y_{it}, POP_{it}, A_i, IS_{it}, SS_{it}, FDI_{it}, UPOP_{it}, COd_{it}, Agry_{it}, D_t, UEF_{it}) \qquad (1)$$

Where aggregate energy consumption is represented by CE_{it} while RP_{it} is the real prices of energy, Y_{it} is GDP, POP_{it} is the population, A_i is the area size, IS_{it} is the share of value added of the industrial sector and the share of value added for the service sector is represented by SS_{it} for country i in year t. FDI_{it} is foreign direct investment, $UPOP_{it}$ is urban population, COd_{it} is CO_2 damage, $Agry_{it}$ is agricultural value added, and Underlying Energy Demand Trend (UEDT) is represented by D_t which captures the common impact of important unmeasured exogenous factors that influence all countries. Finally, the unobserved level of "underlying energy efficiency" of an economy is represented by UEF_{it}which could incorporate a number of factors that will differ across countries, including different social behaviours as well as government regulations, life style, values and norms. So we could say that a low level of underlying energy efficiency postulates an inefficient use of energy (i.e. "waste energy"). In this situation one possibility is to increase the awareness for energy conservation in order to attain "optimal energy demand function". Despite this, from an optimal perspective when using Asian developing countries data, the aggregate levels of energy efficiency of production process and of capital equipment are not entertained directly.

The economics performance (CE_{it}) of production process is measured by using the production theory. A stochastic frontier function has generally been used to perform this task in the production theory. A maximum and minimum level of a function of an economic indicator is attained in the central concept of the frontier approach which is achieved by an economic agent. A minimum level of cost is attained by a firm for any given level of output for a cost function in frontier approach and this minimum level of input is used by the firm for any given level of output for an input demand function

[50] Aigner et al. (1977) introduced the frontier function approach which was developed within the neo-classical production theory. This approach has been used to estimate the level of inefficiency (allocative and technical inefficiency) by using the production and cost frontier. In the present study, a stochastic frontier approach is used within the empirical approach traditionally and just the concept of neo-classical production theory is used in the estimation of economy wide energy demand function while the neo-classical production theory is discarded. Of course the, the underlying energy inefficiency concept which is developed here still follows a production process.

which is also utilized in this approach. So, technically the inefficiency[51] can be represented by differencing the observed input and the cost minimizing input demand. A frontier approach which is used in our present study for an aggregate energy demand function gives us the minimum level of energy which is necessary for an economy to produce any given level of energy services. In fact, our aim is to estimate the baseline energy demand by applying the frontier function concept and that is the frontier by which the demand of the countries is reflected by utilizing highly efficient equipment and production process is also managed efficiently. In this case, it is possible to find out whether the county is on frontier or not by using this frontier approach. Moreover, if we find that a country is not on the frontier, then the level of consumption is measured by the distance above the baseline demand, which is the level of energy inefficiency.

3.2.2 An Aggregate Frontier Energy Demand Model Log-Log Functional Form

In our study we use the assumption for this approach that one-sided non-negative term approximates the level of the economy-wide energy efficiency. So, we can specify equation (1) in panel log-log functional form by using the stochastic frontier function approach as:

$$\begin{aligned} ce_{it} = \alpha + \alpha^{rp} rp_{it} + \alpha^{y} y_{it} + \alpha^{pop} pop_{it} + \alpha^{a} a_{i} + \alpha^{Is} Is_{it} + \alpha^{ss} ss_{it} + \alpha^{fdi} fdi_{it} \\ + \alpha^{upop} upop_{it} + \alpha^{cod} cod_{it} + \alpha^{agry} agry_{it} + \delta_t D_t + v_{it} + u_{it} \qquad (2) \end{aligned}$$

The relationship mentioned in (1) is represented in equation (2) by applying functional form and adding constant and two error terms. Small letters indicate the natural log of the variable. For instance, the natural log of aggregate energy consumption (CE_{it}) is represented by ce_{it}. We have specified D_t in three ways, i.e. using a series without a time trend, with time trend and time-decay.[52] The error term in equation (2) is also

[51] The discussion for the interpretation of the efficiency in an input demand function can be seen by Kumbhakar and Lovell (2000, p. 148).

[52] As per discussion of Kumbhakar and Lovell (2000), time trend could cause the problems during the estimation of the frontier model among the rest of the explanatory variables as a proxy of technical progress. One of the reasons for this problem could be that, when we try to find out the separate effects of productive efficiency change and technical change then it becomes difficult to see this effect while both of them depend on time trend. In the present study, it will also be seen that some of the models will not be estimated for time trend as TFE model etc.

specified in two independent parts. Firstly, the effect of noise is captured by the symmetric disturbance (v_{it}). Secondly, inefficient use of energy is indicated by u_{it} e.g. the "wastage energy", which also represents the underlying energy level of efficiency UEF_{it} in equation (1).[53]

The level of energy efficiency of a country could be increased by improving the equipment of energy efficiency or by using a new production process on the use of energy. Therefore, the influence of a new production process (organizational, technological and social innovation) in the production and consumption of energy services on energy demand could be explained by time trend and time decay models. Underlying energy efficiency is estimated for each country in the sample by using equation (2). The data is discussed in the next section.

3.3 Data

In this study, an unbalanced panel data set for a sample of 19 ASIAN developing countries[54] is used from 1980 to 2013. The key variables considered in this analysis are Aggregate Energy Consumption (CE), Real GDP (Y), Index of Real Energy Prices (RP), Area Size (A), Value added of the Industrial and Service Sectors as percentage of GDP (ISH and SSH). In this study area size is taken in square kilometres and data is employed from WDI and RP data is employed from Bloomberg for all the countries. Data for rest of the variables (CE, GDP, ISH and SSH, etc.) could be employed from the International Financial Statistics (IFS), International Monetary Fund (IMF), World Development Index (WDI), Bloomberg and Economic Surveys of Asian Countries (Various Issues). Real GDP is taken at constant prices of 2000 US dollars. Energy consumption is taken in kilo tons of oil equivalent. ISH and SSH are measured as percentage of GDP. Finally, all the data is converted into natural logarithm for modelling purposes and empirical analysis.

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[53] In this paper, we have estimated the energy demand function which could be considered as an input demand function. In fact, this function is derived from a cost minimization process with the help of an aggregate production function. As we know by following the theory, the price of other inputs could also affect the energy demand, but to include those other variables is not wise as the data limitation does not allow us to add them (by following the previous studies on energy demand). That is why, equation (02) in our study is specified and it is tried to follow the general energy demand literature model. So it is attempted to follow the production theory indirectly in *ad hoc* way.

[54] The choice of 19 Asian developing countries is done on the basis of availability of data. The analysis could have been done for all Asian developing countries but unavailability of data was the main hurdle in front of this effort.

The results of descriptive statistics for key variables and their description could be found in Table 3.1. It is needed from the econometric specification prospective to consider the literature on the estimation of stochastic frontier models by using the panel data.[55]

The first approach is introduced for the panel data version which could be used for the estimation of equation 2. The error term is the addition of two uncorrelated parts (u_{it} and v_{it}) in this pooled model specification, where u_{it} is a one sided non negative disturbance term reflecting the effect of inefficiency which also includes both allocative and technical inefficiencies and assumes to follow an exponential distribution.[56] While v_{it} is a symmetric disturbance which captures the effect of noise and it is assumed to be normally distributed. But a possible drawback by using this model is that we cannot directly consider the unobserved, time invariant, country specific heterogeneity in the estimation.

Table 3.1: Descriptive Statistics

Variable Description	Name	Mean	Std. Dev.	Min	Max
Energy consumption (Ktoe)	CE	115177	292883	0.02	2727728
Real price of Energy	RP	83	48	5.03	481
GDP (Billion US ($))	Y	193	438	4.6	4520
Population in millions	POP	14	31	0.022	135
Area size in km^2	A	1174502	1978994	11610	9327490
Share of industrial sector in % of GDP	IS	37	11	11.89	75
Share of services sector in % of GDP	SS	47	9	16.56	80
FDI net inflows % of GDP	FDI	2.28	2.90	0.00	23.54
urban population in million	Upop	4.70	10.30	0.02	69.90
Carbon dioxide damage in millions	COd	245	842	0.26	9230
Agriculture value added % of GDP	Agry	16	10	0.18	46

A Second approach is proposed by Pitt and Lee (1981), which assumes u_{it} (inefficiency effects) constant over time. However, a possible drawback to using this model is that the unobserved, time invariant, country specific heterogeneity is considered as inefficiency in the estimation.[57] In order to resolve this problem, an extension of

[55] To see different approaches in energy sector for the estimation of frontier model see Farsi and Filippini (2009).

[56] Half normal and truncated normal distributions have also been used as an extension of the model for the inefficiency term.

[57] A model is proposed by Battese and Coelli (1992) in which the variation of efficiency with time is considered as a deterministic function, and it is commonly defined for all firms.

fundamental panel data version approach is introduced with the name of Stochastic Frontier model Approach (SFA) and fixed or random individual effect are added by Greene (2005a and 2005b).[58] By using these models, we get the efficiency estimates although the persistent inefficiencies are not found which may more or less remain constant over time. Fixed effect or individual random effect models are used to find the time invariant and country specific energy inefficiencies. Therefore, certain sources of energy inefficiencies are found which result in time invariant excess energy consumption.

Apparently, to get the relatively high and imprecise levels of energy efficiency these models could be estimated. One advantage of panel data version approach could be the reduction of the potential unobservable variable bias. As in a situation when coefficients of explanatory variables could be biased because of the correlation between observable and unobservable. This problem could be reduced by introducing some explanatory variables as population, area size and some variables on the structure of the economy.

Considering the above discussion, the pooled model, the True Fixed Effects (TFE) model and the True Random Effects (TRE) model are used to estimate equation (2). Furthermore, the pooled models are estimated in three different ways as, simple (without any time trend), by using time trend and by using time-decay models. TFE and TRE models are also estimated by using two different techniques as, TFE and TRE models by following exponential distribution and TFE and TRE models with heteroscedasticity.

In this study, to estimate the efficiency of a country, we use the conditional mean of the efficiency term approach $\mathrm{E}[u_{it} \,|\, v_{it} + u_{it}]$ which is introduced by Jondrow et al. (1982).[59] Finally, we can express the level of energy efficiency as:

$$E_{it} = \frac{{E_{it}}^F}{E_{it}} = \exp(-\hat{u}_{it}) \qquad (3)$$

Where E_{it} is defined as the observed energy consumption per capita and ${E_{it}}^F$ is defined as the frontier or minimum demand of the ith country in time t. A country is considered efficient if it is on the frontier or the energy efficiency score is one, while the country

[58] Farsi, et al. (2005) & (2006) have applied these models in the network industries and found successful applications.

[59] Battese and Coelli (1992) and Kumbhakar and Lovell (2000) can also be seen to find out the estimation of country's efficiency.

will not be 100% efficient if the score is less than one and it is also non-frontier. The measure of underlying energy efficiency could be found by using the approach of energy efficiency.[60] Due to the estimation of dual cost function instead of production function, exponential of negative term is used to compute inefficiency. In summary, equation (2) is used to estimate the Stochastic Frontier model Approach (SFA) and equation (3) is used to find the efficiency scores of each country for each year. The results are discussed in the next section.

3.4 Empirical findings

The frontier energy demand model is estimated by using the same technique but with three different models as discussed earlier. The results for Pooled models (simple, with time trend and time decay-model) are shown in table 3.2 where the expected signs of some variables do not present according to theory.

Firstly, we estimate the simple pool model with exponential property. According to the results from table 3.2, the own price elasticity show a positive sign for a simple pool model but the variables are significant. This might be due to the missing variable bias or omitted variable bias. Secondly, we introduce the time trend in the model but still find a positive signs for own price elasticity and time trend. Lastly, time-decay is introduced to get better results. We find a positive sign for own price elasticity and negative sign for eta (-0.000017), where eta is the characteristic of time, which means inconsistent results. To resolve the problem, to capture the impact of unobserved time invariant factors and to get the expected signs, TFE and TRE models are estimated. By using the equation 3.2, the frontier energy demand models are estimated and the results are given in table 3.3 for TRE (exponential distribution & exponential distribution with heteroscedasticity) models and in table 3.4 for TFE (exponential distribution & exponential distribution with heteroscedasticity) models.

There is a possibility of heteroscedasticity in the estimates due to varying structures of the countries. In order to consider this issue, the variances of both the variables are explained by the inflow of FDI to GDP ratio. The estimated results show the expected

[60] Similarly we could find the energy inefficiency given by the exponential of u_{it}. This contrast approach for inefficiency work in the same manner e.g. a value of .5 indicates that level of energy inefficiency is 50%.

signs for coefficients and lambda, and also the results are statistically significant.[61] According to the variables property in log form, the elasticities are directly reported as the estimated coefficients results of the variables.

Table 3.2: Estimated coefficients for pooled model

Coefficients	Pooled Model Simple	Pooled Model with Time Trend	Pooled Model Time-decay
Observations	550	550	550
Countries	19	19	19
log-likelihood	-394.82908	-384.81948	-384.90609
Wald chi2	506.23	551.12	28.1
α^{rp}	0.21 (4.16)	0.19 (4.01)	0.19 (4.01)
α^{y}	0.98 (13.25)	0.46 (3.36)	0.47 (3.40)
α^{ss}	-0.02 (-2.07)	-0.01 (-1.76)	-0.01 (-1.77)
α^{Is}	-0.02 (-2.86)	-0.02 (-2.31)	-0.02 (-2.34)
trend		0.03 (4.51)	
Constant (α)	-13.96 (-4.86)	-2.37 (-0.81)	-1641.42 (-1.26)
/mu	6.74 (2.58)	7.39 (8.90)	1647.16 (1.27)
/eta			-0.000017 (-1.27)
/lnsigma2	1.21 (3.89)	1.64 (4.83)	1.62 (4.87)
/ilgtgamma	2.76 (8.20)	3.27 (9.10)	3.25 (9.20)
sigma2	3.35	5.17	5.07
gamma	0.94	0.96	0.96
sigma_u2	3.15	4.98	4.89
sigma_v2	0.20	0.19	0.19
t-values are given in parentheses			

The estimated results of TRE model (exponential) suggest that the estimated income elasticity is approximately 0.16 and estimated own price elasticity is -0.08, while the estimated foreign direct investment elasticity is approximately 0.01 which shows that energy consumption will increase by 0.1 percent if there will be a 10 percent increase in the foreign direct investment. If there is a 10 percent increase in carbon dioxide damage then energy consumption is to increase by 5.6 percent.

[61] The relative contribution of u_{it} and v_{it}, which is also called Lambda (λ) provided the information on the decomposed error term ε_{it}. It shows the information that either the one sided error component is relatively large or not.

Table 3.3: Estimated coefficients for True RE model (t-values in parentheses)

Coefficients	True Random Effect Model Exponential	TRE Model Exponential with Heteroscedasticity	TRE Battesse and Collie (1995)
Observations	541	547	585
Countries	19	19	19
log-likelihood	-339.4818	-316.0015	-461.329
Wald chi2	1210000	12586.06	1016.31
Base for Randomized Halton Sequences	7	7	7
α^{rp}	-0.08 (-3.73)	-0.22 (-8.72)	-0.19 (-3.35)
α^{y}	0.16 (11.06)	1.17 (40.77)	0.96 (22.30)
α^{fdi}	0.01 (1.94)		
α^{cod}	0.53 (-)		
α^{a}		0.45 (18.40)	0.81 (16.24)
α^{agry}		0.02 (5.85)	
_cons	-0.08 (29.89)	-19.22 (-31.55)	-17.66 (-17.49)
Usigma			
_cons	-1.18 (-12.40)	-2.55 (5.24)	-1.38 (-9.72)
upops		2.34 (-11.72)	
Vsigma			
_cons	-6.83 (-7.63)	-8.83 (-10.97)	-3.01 (-13.36)
upops		8.14 (7.18)	
Theta			
_cons	2.16 (186.90)	2.37 (106.39)	1.44 (63.70)
sigma_u	0.55 (21)		0.50 (14.08)
sigma_v	0.03 (2.23)		0.22 (8.87)
Lambda (λ)	16.90 (493.78)		2.26 (41.12)
E(sigma_u)		0.50	
E(sigma_v)		0.12	

All the models are estimated by using the exponential distribution property.

The estimated results of TRE models (exponential with heteroscedasticity and Battesse and Collie (1995)) suggest that the estimated income elasticity is around 1.17, 0.96 respectively and estimated own price elasticity is -0.22, -0.19, while the estimated land elasticity is approximately 0.45 and 0.81. The estimated results show that the price elasticity is -0.48 and income elasticity is 0.36 for true fixed effect model (exponential) while the elasticities for both variable decrease from -0.48 to -0.32 and 0.36 to 0.28 respectively once the model is estimated as TFE model (exponential with heteroscedasticity).

Table 3.4: Estimated coefficients for True FE model (t-values in parentheses)

Coefficients	True Fixed Effect Model exponential	TFE Model Exponential with heteroscedasticity
Observations	550	508
Countries	19	19
log-likelihood	-368.7614	-282.0181
Wald chi2	285893.28	98811.41
α^{rp}	-0.48 (-4.60)	-0.32 (-4.69)
α^{y}	0.36 (8.54)	0.28 (7.84)
α^{ss}	-0.05 (-3.50)	-0.05 (-4.56)
α^{cod}	0.70 (11.61)	0.71 (12.46)
Usigma		
FDI		0.05 (1.63)
_cons	-0.97 (-5.54)	-1.24 (-6.18)
Usigma		
α^{fdi}		-0.19 (-0.92)
_cons	-4.50 (-5.86)	-4.73 (-9.11)
sigma_u	0.62 (11.46)	
sigma_v	0.11 (2.60)	
Lambda (λ)	5.86 (102.02)	
E(sigma_u)		0.57
E(sigma_v)		0.08

The service sector provides the elasticity -0.5 and the elasticity of CO_2 are found 0.70 and 0.71 for both TFE models (Exponential and exponential with heteroscedasticity) as shown in table 3.4. The estimated results for the inflow of FDI to GDP ratio also indicate significant results in the variance.

We use the conditional mean of the efficiency term to find each country's efficiency by using equation (3). Pooled model is not used to find energy efficiency at all as the coefficients results are inconclusive. We apply equation (3) to find the efficiency score for TRE model for exponential distribution, for TRE model exponential with heteroscedasticity and also TRE model proposed by Battesse and Collie (1995), but in vain, as most of the countries show an efficiency score equal to 1 and 0.999. Finally, we find the average energy efficiency score for each country with their ranking for the whole sample by using the true fixed effect model exponential distribution and TFE model exponential distribution with heteroscedasticity. The average energy efficiency score results are reported in table 3.5.

Table 3.5: Average Energy Efficiency Score and Ranking

	TFE Model (Exponential distri.)		TFE model (Exponential disti.) with heteroscedasticity	
Country	Score	Rank	Score	Rank
Afghanistan	0.5122	15	0.4819	15
Bangladesh	0.7348	6	0.7861	6
China	0.7990	1	0.8362	1
India	0.7914	2	0.8299	2
Indonesia	0.4569	16	0.4314	17
Iran	0.4296	17	0.4799	16
Jordan	0.3575	18	0.3540	18
Kazakhstan	0.6545	12	0.6747	12
Kuwait	0.7092	8	0.7225	9
Malaysia	0.7201	7	0.7581	7
Oman	0.2385	19	0.2489	19
Pakistan	0.7587	3	0.8042	3
Philippines	0.7456	5	0.7989	4
Saudi Arab	0.5895	13	0.6078	13
Sri Lanka	0.6983	9	0.7375	8
Thailand	0.7542	4	0.7883	5
Turkey	0.6572	11	0.7077	11
UAE	0.5653	14	0.5432	14
Vietnam	0.6901	10	0.7199	10

Comparing the results of TFE model and TFE with heteroscedasticity model, it can be seen from table 3.5 that both models provide almost the same results for ranking. Kuwait is also another good example regarding the use of energy. Kuwait is an oil based economy but still it stays in the middle regarding the efficient use of energy among the all 19 countries. Most of time the countries who are blessed with abundant oil resources, they do not care about the cost of energy utilization as Oman, Jordan, Iran, Indonesia, Afghanistan, UAE, Saudi Arab and Kazakhstan. Indonesia and Afghanistan have some issues related to law & order and governance so are not using energy so efficiently. By having the rich resources of oil, Kuwait is stays in the middle regarding the use of energy in our study. Table 3.7 also explains that Kuwait is on number 13th regarding the efficient use of energy, and also, it stands on number 10 regarding the energy intensity from year (2000-2013). This result also give very good indication of energy use and efficient use of energy. But in our study, it is still suggested that without conducting this analysis for underlying energy efficiency it may not be possible to tell which country's energy intensity is a good proxy for its energy efficiency. As the ranking of Kuwait is very close regarding energy efficiency and energy intensity (13th and 10th rank respectively), so it could be misinterpreted wrongly.

But the energy efficiency is different in both models even with almost the same ranking. It is also the focus of this paper to find the different levels of underlying energy efficiency across countries and all further analysis is solely based on the TFE model as mentioned in table 3.4. The estimated underlying energy efficiency score is compared with energy intensity (energy consumption/GDP) for each country over the estimation period as shown in figure 3.1 which is also explained in next paragraphs. However, it is worth to note that figure 3.1 should not be considered as the exact position of the energy efficiency of each country. But the best explanation is to get an idea of each country's efficiency which changes over time and the relative position of the countries could be compared.

Going back to table 3.5 for the estimated results of efficiency score and ranking, it can be seen that China, India, Pakistan, Thailand and Philippines are the top five counties using energy efficiently. By using the TFE with heteroscedasticity, there is only a small change in the ranking analysis as the rank of Thailand improves by 1 point and the rank of the Philippines decreases by one point. Oman, Jordan, Iran, Indonesia, Afghanistan, UAE, Saudi Arab and Kazakhstan are relatively less efficient countries in term of energy usage. Most of these countries are blessed with abundant oil resources. Therefore, these economies do not bother about the cost of energy utilization. Indonesia and Afghanistan have some issues related to law & order and governance so are not using energy so efficiently.

We can also compare the ranking of energy efficiency (by estimating the underlying energy efficiency for each country) with the ranking of energy intensity[62] (by estimating the ranks of energy intensity) as shown in table 3.5. According to the estimated results of underlying energy efficiency and ranking, we can see China, India, Pakistan,

[62] Here the energy intensity means log (energy use)/log (GDP). After finding the energy intensity of all countries for time period 1980-2013 the average of energy intensity is found for every country. After finding the average of energy intensity the ranking is assigned.

Thailand and the Philippines are the top five countries that use energy efficiently. These results seem reasonable as these economies are net importer of energy input. Further, these economies have to maintain export competiveness in international markets.

To check the efficient use of energy, different time periods are observed for estimated average underlying energy efficiency. According to table 3.6, results show that compared to the present time span (2000-2013), Bangladesh used to be more efficient in (1990-1999) as compared to the remaining 17 economies[63]. Similarly, China, India, Jordan, Kuwait, Malaysia, Pakistan, the Philippines, Thailand, and Turkey have become less efficient as compared to previous time periods (1990-1999) when compared to the rest of the economies. However, during the present decade, the rest of the countries energy efficiency has improved from (1990-1999) to (2000-2013).

Table 3.6: Average Energy efficiency score over time for the TFE model (Exponential distribution)

Country	Average Energy Efficiency		
	1980-1989	1990-1999	2000-2013
Afghanistan	n/a	n/a	0.512
Bangladesh	0.674	0.881	0.670
China	0.766	0.823	0.806
India	0.752	0.881	0.753
Indonesia	0.122	0.387	0.768
Iran	0.094	0.417	0.865
Jordan	0.737	0.275	0.129
Kazakhstan	n/a	0.411	0.767
Kuwait	n/a	0.726	0.677
Malaysia	0.592	0.828	0.735
Oman	0.031	0.157	0.815
Pakistan	0.639	0.870	0.765
Philippines	0.768	0.873	0.631
Saudi Arab	0.451	0.520	0.750
Sri Lanka	0.468	0.788	0.815
Thailand	0.553	0.853	0.833
Turkey	0.654	0.871	0.495
UAE	0.677	0.362	0.635
Vietnam	0.683	0.573	0.782

[63] The remaining seventeen economies are shown in the table 3.6. Because, data for Afghanistan is not available during time period (1990-1999), that is why, analysis was not done for her during this specific time.

It can be seen in figure 3.1 that both energy intensity and underlying energy efficiency are negatively correlated with each other in most cases. The energy intensity is shown on the right hand axis (dotted line) and average underlying energy efficiency is shown on left hand axis (solid line). It shows that when the level of energy efficiency increases then the level of energy intensity decreases. It means that there are some countries which have a positive relationship between energy intensity and energy efficiency which is not a good proxy for them. It is also impossible to tell for each country whether the energy intensity is a good proxy or not. Energy intensity is measured by taking the ratio of energy use to GDP. The energy efficiency is computed by using the frontier approach mentioned in equation (3).

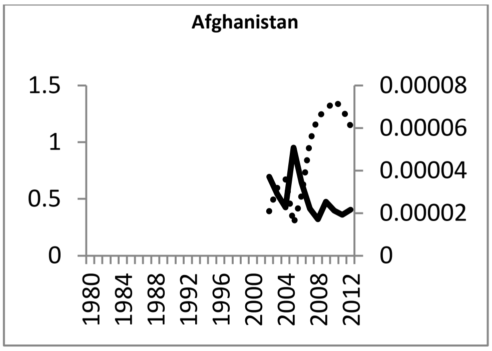
Technically, all these countries have not become less efficient but they have become less efficient as compared to other countries, of course, regarding the use of energy every country has become efficient more or less. But relatively some of the economies have become less efficient when compared to others. Iran and Oman have become more efficient as compare to the other economies and also, if we see the use of energy according to time span as shown in table 3.6. The possible reasons for the efficient use of these both countries could be the innovation in technology or import of technology, change of infrastructure of energy system, shift from non-renewable energy to renewable energy, inter fuel substitution, vigilance regarding the use of energy, foreign direct investments in energy sector, government policies etc. While, in Pakistan, the energy is not used efficiently from (2000-2013) as compare to (1990-1999) by using the analysis based on stochastic frontier approach as shown in table 3.6. Pakistan should find out the ways to improve the energy system for the better usage. In comparison with Iran, the efficient use of energy in Pakistan is very week. Iran has improved their use of energy efficiently more than double while the case is different in Pakistan as discussed earlier. Pakistan should adopt such policies through which they can become more efficient in the use of energy.

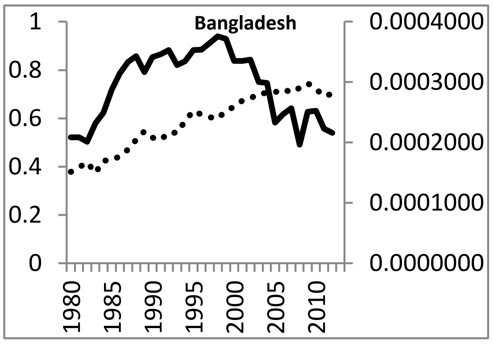
Figure 3.2 shows the estimated average energy efficiency according to rank of the country from 1980-2013. Most efficient countries are shown from left to right in the said figure. Figure 3.3 shows the energy intensity for the period 2000-2013 which reports high energy intensive from right to left and figure 3.4 simply shows the estimated average underlying energy efficiency for the latest time period (2000-2013).

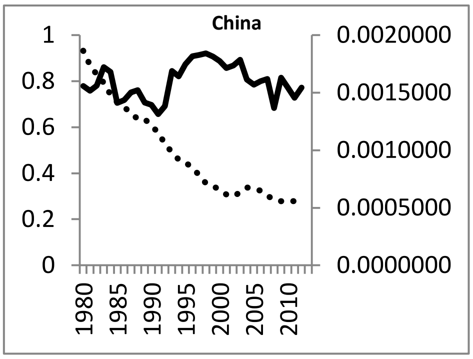
Legend

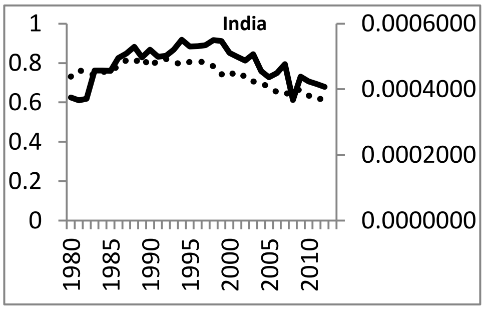
____Estimated Energy Efficiency TFE Model (LH axis)

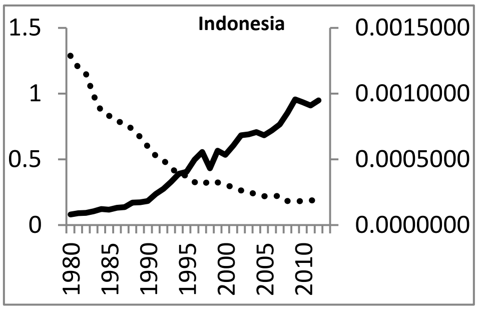
---- Energy Intensity toe per thousand (RH axis)

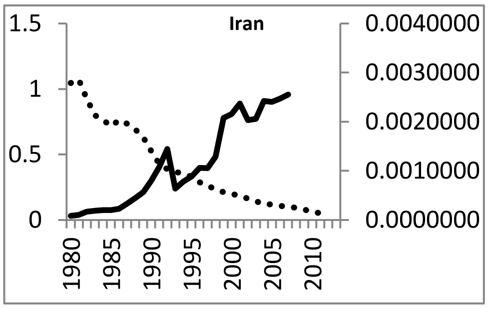


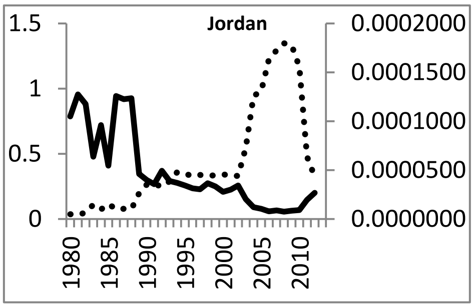


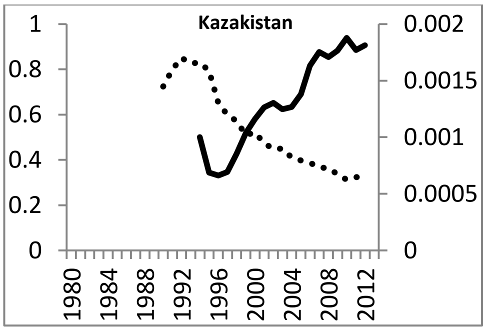


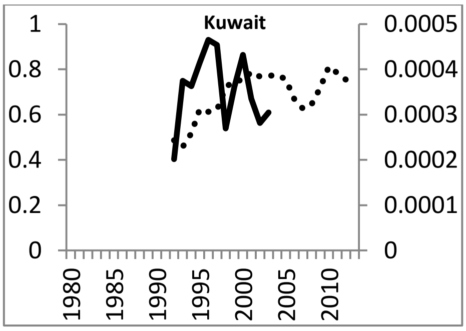


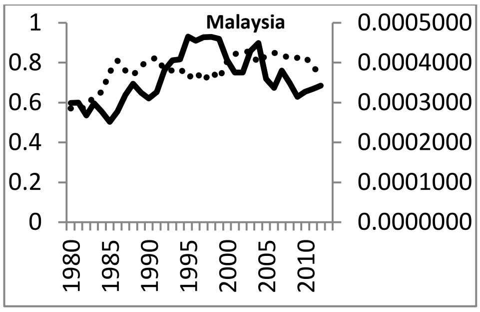








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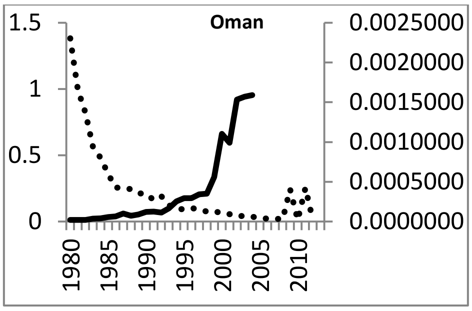
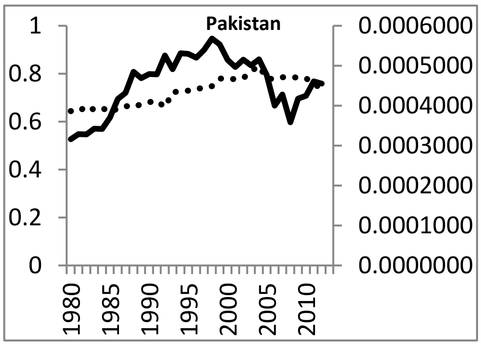

Oman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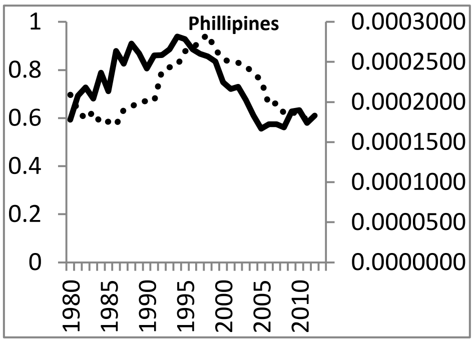
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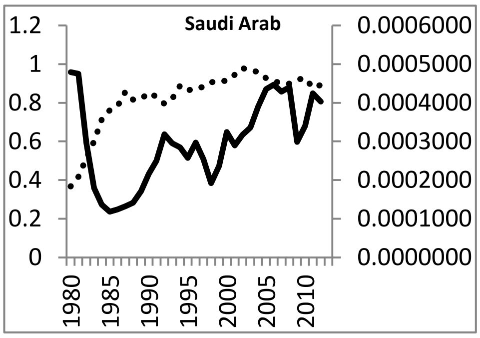
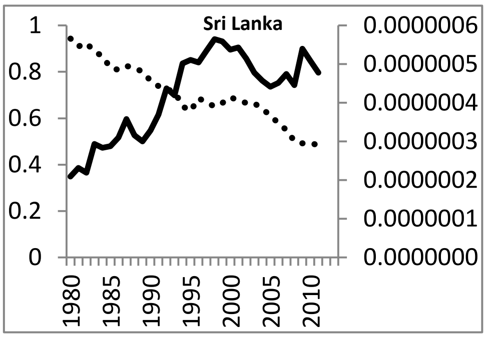
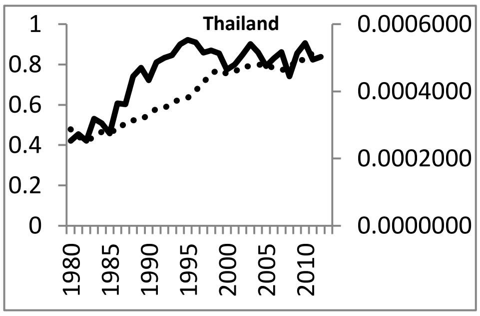
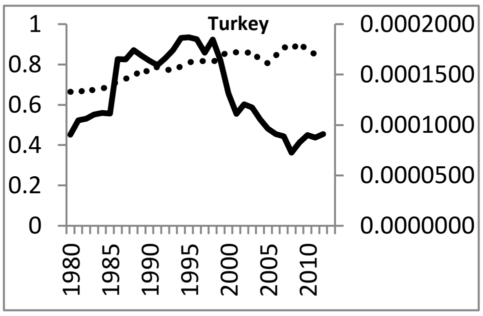

Saudi Arab


Sri Lanka


Thailand


Turkey

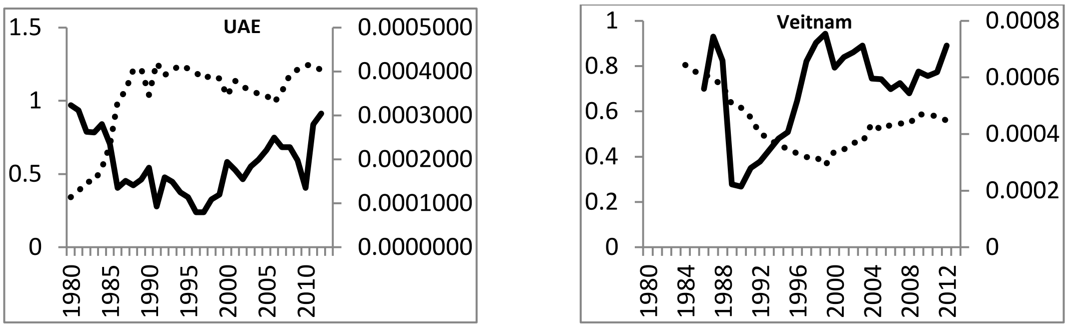


Figure 3.1: Comparison of Energy Intensity with Estimated Underlying Energy Efficiency

Finally the energy intensity and the estimated average underlying energy efficiency for the time period (2000-2013) is reported in table 3.7. By using table 3.7 we can see the exact picture of the ranking of the countries by using estimated underlying energy efficiency and energy intensity. According to the said table, we can see that energy intensity for Thailand appears at rank 17[64] for the time period (2000-2013). On the other hand, Thailand is on rank 2 by using the estimated average underlying energy efficiency for the time period (2000-2013).

This means that according to energy intensity measure Thailand is a less efficient energy intensive country whilst being the second most energy efficient country according to the estimated average underlying energy estimate. Similarly, according to energy intensity China is ranked 18th whilst by using the estimated average underlying energy technique it appears as the 5th energy efficient country.

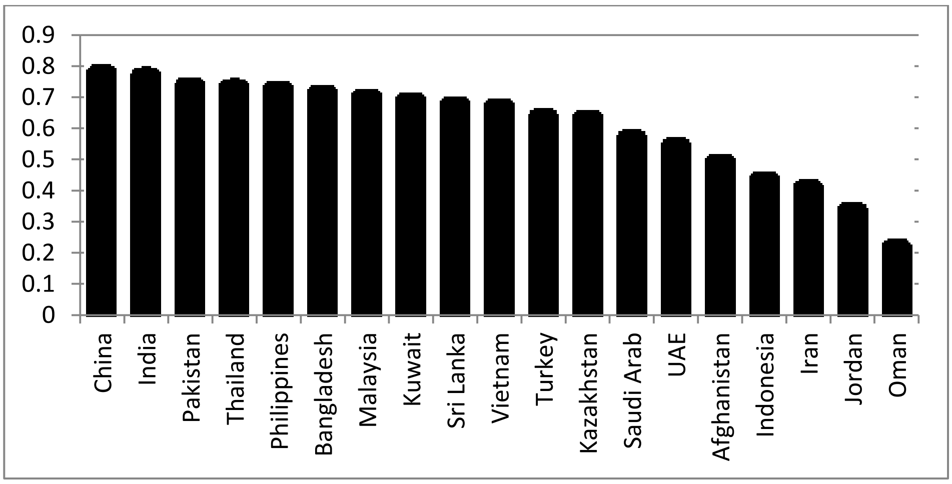


Figure 3.2: Estimated Average Underlying Energy Efficiency (1980-2013)

64 Rank 1 means that energy intensity is high or the country is highly energy intensive and the country is on top among all the other countries with said rank.

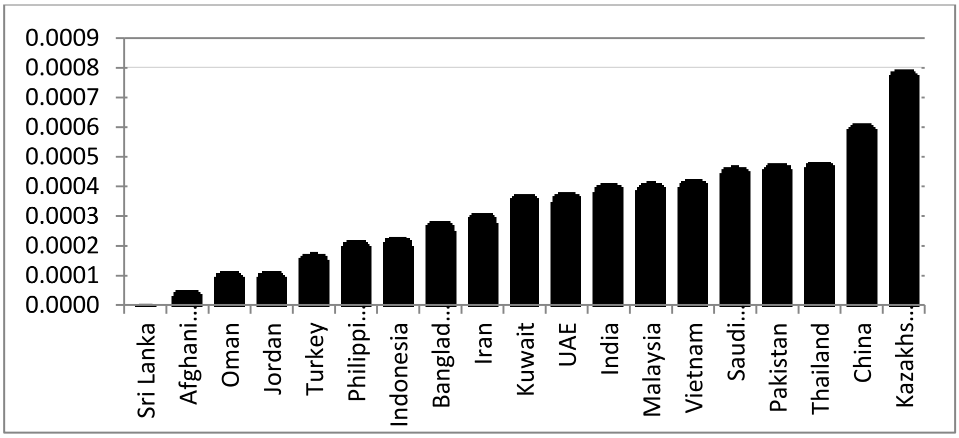


Figure 3.3: Energy Intensity (2000-2013)

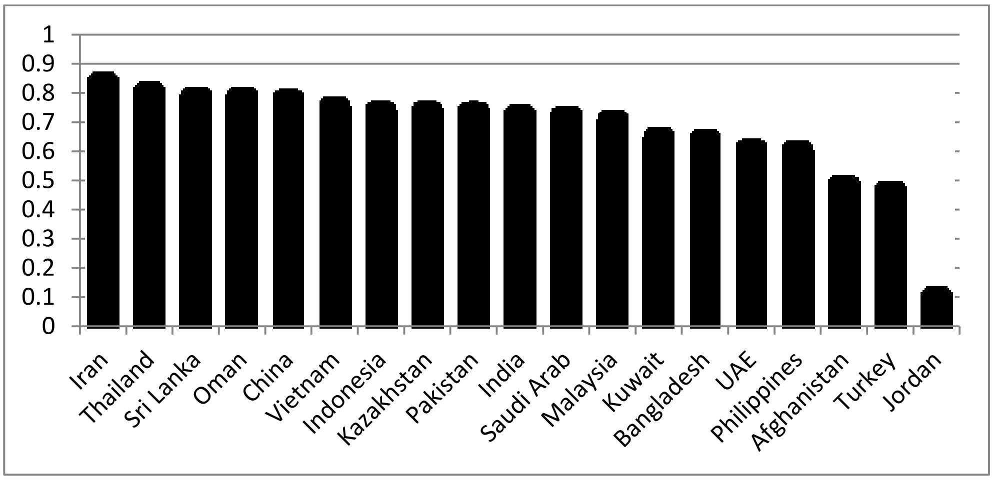


Figure 3.4: Estimated Average Underlying Energy Efficiency (2000-2013)

We can also see that Kazakhstan is ranked as the 19th energy intensive country but it is ranked 8th energy efficient country by using estimated average energy efficiency technique for the time period (2000-2013). All the remaining country's results are reported in table 3.7.

3.5 Conclusion

This research is aimed to isolate the energy efficiency from simple energy intensity (energy use to GDP ratio) for 19 Asian developing countries for the period of (1980-2013). Underlying energy efficiency is estimated for each country by combining the two approaches which are used in energy demand modelling and stochastic frontier analysis. This method was first adopted, as far as is known, to model energy demand and efficiency for the Asian developing countries. In the model, some variables (energy price, income, population, FDI, urban population, industrial structure, area, agriculture, services etc.) are controlled by energy demand to find the measure of energy efficiency by using the stochastic demand frontier (as previously the work was done to estimate cost and production) thus underlying energy efficiency (which reflects the relative use of inefficient use of energy or "waste energy") is found in present work.

Table 3.7: Comparison between Underlying energy efficiency and energy intensity

Country	Energy Efficiency (2000-2013)		Energy Intensity (2000-2013)	
	level	Rank	level	Rank
Afghanistan	0.5121699	17	0.000048	2
Bangladesh	0.6695879	14	0.000281	8
China	0.8058003	5	0.000607	18
India	0.7531803	10	0.000406	12
Indonesia	0.7679339	7	0.000224	7
Iran	0.8653193	1	0.000304	9
Jordan	0.1290106	19	0.000109	4
Kazakhstan	0.7667325	8	0.000787	19
Kuwait	0.6765757	13	0.00037	10
Malaysia	0.7352808	12	0.000411	13
Oman	0.8149302	4	0.000109	3
Pakistan	0.7652551	9	0.00047	16
Philippines	0.6309252	16	0.000213	6
Saudi Arab	0.7497807	11	0.000462	15
Sri Lanka	0.8151651	3	0.0000004	1
Thailand	0.8331162	2	0.00048	17
Turkey	0.4946905	18	0.000171	5
UAE	0.6353547	15	0.000373	11
Vietnam	0.782407	6	0.000418	14

To estimate energy efficiency by using a full frontier model some time suggests that energy intensity for a number of countries may give an indication of efficiency improvement, but this is not always the case for all countries over time. Pakistan is the 16^{th} most energy intensive country by estimating the simple energy intensity method while it is ranked 9^{th} efficient country by using the estimation method of average underlying energy efficiency among all Asian developing countries which are considered in the analysis for year (2000-2013). The use of energy in Pakistan is high, which also means that CO_2 emissions should also be controlled. According to the results from chapter 2, to stabilise CO_2 emissions, we should have correct methodology (either exogenous TC or endogenous TC). As per correct use of methodology, the estimated results say, because of the higher use of energy there is a higher rate of decline in it, which shows a symptom of energy efficiency convergence in the long run. It means either we can use the right methodology to find out the efficient use of energy, alternatively, we can use the mentioned approach in chapter 3 to find out the exact picture of efficient use of energy. It means to use the energy efficiently the CO_2 emissions could be stabilised by increasing the prices or in the form of taxes as discussed in chapter 2. In fact, to stabilise CO_2 emissions the efficient ways of energy use should be adopted. So, the second chapter finds the right methodology for the stabilisation of CO_2 emissions, while it is attempted to find either energy intensity is right proxy for energy efficiency or not in third chapter. The possible recommendations could be as, to change the infrastructure of energy system (non-renewable energy to renewable) on domestic and national level and also innovation in the technology, which could also help any economy to keep the environment clean. A prime example of Afghanistan can be undertaken for better understanding. According to table 3.7 and figure 3.3, it can be seen that Afghanistan is the 2nd most energy intensive country while it is the third last energy efficient country or 17th energy efficient country (least energy efficient country) among the 19 countries as per results of the estimated average underlying energy for time period 2000-2013 shown in figure 3.4. Similarly, Jordan is the 4th most energy intensive country by estimating the simple energy intensity method while it is the least efficient country ranked 19th by using the estimation method of average underlying energy efficiency among all Asian developing countries which are considered in the analysis from 2000-2013. It means on one side Jordan is a high energy intensive country and on the other hand it is a least energy efficient country. So, it is suggested that without conducting this analysis for underlying energy efficiency it may not be possible to tell which country's energy intensity is a good proxy for its energy efficiency. The main finding of this paper is to give some additional indicators to the policy makers with reference to table 3.7. According to table 3.7, it is shown that underlying energy efficiency should be estimated to find out the exact picture of a country's situation rather than just carrying out an analysis of energy intensity. To follow the energy intensity for the country's energy conditions, it could be misleading for the policy makers.

Finally, it is not claimed that energy efficiency can only be measured by using stochastic demand frontier approach. The purpose of this study is not to give a definite answer on how to measure the level of energy efficiency by using stochastic demand frontier approach. This attempt is to give further room to improve the models and methods for analysis of measuring the aggregate energy efficiency for future research.

Chapter 4

Modelling and Forecasting CO_2 emissions in Pakistan

4.1 Introduction

Concerns about global warming and climatic changes have raised the importance of research on energy systems. We have many challenges for global warming and Green House Gases (GHGs) emissions when discussing the energy system in present era. For over two decades, energy system analysis has become a worldwide concern to deal with the threats of global warming and climate changes. Due to this concern, the developed economies of the world have introduced various methods of controlling emissions. These measures include Kyoto Protocol and various control programs. The objectives of the Kyoto Protocol (1997) are to concentrate on the reduction of GHGs, which are responsible for changes in climate. The aim of the Kyoto Protocol is to set the specific target in the reduction of GHGs and achieve it. Reducing Carbon Dioxide (CO_2) emissions is always given more importance among all GHGs (Beer 2000). The share of Carbon Dioxide (CO_2) emissions is 58.8 percent among all the GHGs (World Bank report (2007)). It is a fact that developed economies have shown more concerns about environmental issues. Although developing economies do not formulate plans in line with developed economies, these developing economies have not ignored the problem. Instrument of accession to the Kyoto Protocol is deposited by Pakistan to the United Nations (UN) Secretariat on 11th Jan, 2005. The Clean Development Mechanism (CDM) project is also filled by Pakistan to become a part of it. The purpose of adopting this strategy is to fulfil the requirements of establishing a Designated National Authority (DNA). It also attempts to have transparent, participatory and effective management of CDM processes in the country. The details of the functions and powers of the DNA are described in the strategy that is based on preliminary studies which include the initial project, namely Asia Least Cost Greenhouse Gases Abatement Strategy (ALGAS), 1998. The establishment of DNA is being implemented by the government of Pakistan within the Ministry of Environment to manage CDM.

GHGs emissions were not considered an important issue in Pakistan before the establishment of CDM project. Global warming can be controlled by managing GHGs emissions. Sheikh (2010) argues that Pakistan fulfils more than 99 percent of its energy requirements with fossil fuels. CO_2 emissions and total GHGs emissions increase due to the combustion of fossil fuels. It is the largest single contributor to CO_2 emissions and the impact of this has grown more rapidly since 1970. Therefore, Pakistan's environmental energy policy requires an accurate forecast of CO_2 emissions.

To make future decisions clearer, we can use energy-economic models to point out which way we can go and which perspectives we have. During the last twenty years, the empirical relationship has been analysed between energy consumption and economic growth; environmental pollution and economic growth intensively. The empirical analysis is performed to investigate the relationship between environmental pollution and economic growth, which checks the validity of Environment Kuznets Curve (EKC) hypothesis. Kuznets (1955) analyses that there is an inverted U shaped curve between the changing relationship of per capita income and income inequality. The inverted U shaped curve is explained as; when the per capita income increases, income inequality also increases at the start. Later, it reaches a maximum level or turning point, and then it starts to reduce due to the trickledown effect. This phenomenon is called Kuznets Curve (KC). According to EKC hypothesis, it is postulated that an inverted U shaped curve occurs between economic development and environmental pollution. In this case, the environmental pollution level increases, and only starts to decrease when increase in income passes a turning point. Initially, Grossman and Kruger (1991) tested and proposed this hypothesis. The detailed review surveys of the studies are provided by Stern (2004) and Dinda (2004). Further examples of the hypothesis are provided by Mangi and Jena (2008), Martinez and Bengochea (2004), and Dinda and Coondoo (2006). However, it is not necessary that increase in national income always reduces the emission of pollutants. To check the relationship between income and emissions, a time series dynamic model can be overviewed, which is used by Coondoo and Dina (2008), Lee and Lee (2009) and Akbostanci et al. (2009). They find the empirical results inconclusive.

In addition, the empirical relationship is analysed between energy consumption and real output. It is suggested that there is a positive relationship between output and economic development. However, energy consumption is closely related to economic growth. Hence, higher economic development needs more energy consumption and we can use energy more efficiently if there is a higher level of economic development.

According to recent literature, the dynamic relationship is examined by Ang JB (2008), Haliciogla F. (2009), Zhang and Cheng (2009), Soytas and Sari (2010), and Aqeel and

Butt (2001) between energy consumption, economic growth and environmental pollutants. However, it is not attempted to conduct a systematic time series investigation to analyse the relationship between CO_2 emissions, energy consumption and output for Pakistan's economy.

In 2015, China's president signs an agreement to invest approximately 30.7 billion pounds in Pakistan in the next two decades. The aim of the spending is to build a network of roads, railways, pipelines and electricity generation in Pakistan. This investment (Murshid Hussain Sayed, chairman of the Pakistani parliament's defence committee) will strengthen the struggling economy and help end chronic power shortages in Pakistan. In fact, this investment is not just a symbol of help in the way to build infrastructure, but also the Chinese want to make Pakistan a key partner in its grand economic and strategic ambitions. Further, the investment in the energy sector of Pakistan will have better returns for the Chinese investment as well. Pakistan is growing economically strong and it will continue to improve with this investment. Pakistan has focused on CO_2 emissions in the past years on a very low level. It is necessary to concentrate on GHGs, especially the CO_2 emissions. With the new investment in the energy sector of Pakistan, there is a need to revise the estimates of the CO_2 emissions that can only be done if the baseline forecasts are available.

Therefore, this paper is an attempt to explore the dynamic relationship between energy consumption, economic growth and CO_2 emissions. Due to the nature of the data, the theoretically justified long run models are estimated. Deviation from long run equilibrium is used as a determinant to model the short run behaviour of the concerned variables. To forecast the energy system and environmental protection a sound technique is required. Forecasting models are categorised in two ways as multivariate analysis and univariate time-series analysis. Energy consumption is forecasted using the multivariate model techniques in several studies (Amarawickrama (2008), Pao (2006) and Bianco, Manca and Nardini (2009)). The future values of variables of interest can be forecasted by using the historical time series data of the same variables by using the univariate models. Further, the multivariate modelling is compared with the forecasts of univariate models. Univariate Grey prediction (GP), Exponential Smoothing (ES) modelling and multivariate model solving techniques (one step ahead forecast/static solution) are used to perform this task. These techniques are widely used in almost every type of research to forecast.

Many univariate or projection methods are used to forecast, where only the current and past values of the variables are provided. Among these methods, a broadly sensible approach, Exponential Smoothing (ES) is well known and was proposed in the late 1950s by (Holt 1957, Brown 1959, Winter 1960, Chatfield 1978, Montgomery and Johnson 1976, Granger and Newbold 1977). It has introduced some of the most successful forecasting methods by using weighted averages of past observations.

Another univariate model is used for single variable forecasting. This is called Grey Prediction (GP) model. It is claimed in the literature that univariate time series Grey Prediction model can be estimated by using a limited amount of data. The behaviour of the grey system can be found (Deng, 1989). Much of the literature in forecasting energy demand has used this technique. We believe that this technique is fundamentally wrong because it is evaluating itself on an in sample forecasting by using the future values. This is not the correct way to forecast. Many researchers have been attracted by GP theory due to the rapid development and popularity of it by following the same methodology. Apparently, GP model has become popular in the Far East and developing countries. In most of the GP studies, it is observed that when GP system-based approaches are applied to real time systems, they achieve good performance characteristics because it is simply an extension of trend forecasting. This is the only reason that when GP method is compared with conventional methods, the results for GP model turn out to be more robust.

GP theory has been used in many disciplines such as economics, geological, military, metrological, transportation, scientific and technology, medical, hydrological, mechanical, industrial, ecological, agriculture, social and finance etc. GP model has been used as a predictive model in a number of fields, also research has been carried out to explain the phenomenon in different fields such as geography, geology, earthquake and agriculture (Lee (1986); Song (1992)). Some researchers have tried to explain the social phenomenon including supply and demand for electronic power, stock markets and financial operating performances (Morita et al. 1996), management decisions (Mon et al. 1995) and air travel markets (Hsu et al. 1998) with the help of GP model. Alternatively, more research work has been done on the textile industry (Lu et al. 1995), military weapons (Wu 1994), and medicines (Chew 1995) by using the GP model as GM (1, 1) or GM (1, N). The basic and simple model GM (1, 1) is applied to predict future values by using recent data, while GM (1, N) is applied to the applications of the systems, data processing, prediction, analysis, modelling control and decision making. Poor results of forecasting could happen when random data with central symmetry occurs.

GP model has also been used in the field of business by Tamura et al. (1992), Lin and Yang (2003), Chang et al. (2003) and Wu and Chen (2005) and in the field of transportation by Hsu and Wen (1998). Hsu and Chen (2003) apply GP model to electric power. Lee et al. (1997) argue that it is not necessary to assume any particular relationship between dependent and independent variables in GP model. Ong et al. (2005) say that GP model gives better performance on a small data set.

Grey Prediction model has become popular in the past decade to forecast, especially with energy demand. There are a few factors which influence energy demand, such as Gross Domestic Products (GDP), Energy Consumption (EC), Income (Y), and Population, etc. It is not clear exactly how these factors affect the energy demand. Several forecasting models are introduced by Grey forecasting, although GM (1, 1) is the most commonly used method.

Lin et al. (2008) use grey relation analysis to predict motor vehicle energy consumption in Taiwan. The number of motor vehicles, GDP and the relative influence of fuel prices are also estimated. They evaluate the travel per kilometre of a vehicle as per increase in energy. Lee and Tong (2011) forecast energy consumption in China by using GP model. Pao and Tsai (2011) follow grey prediction model to forecast CO_2 emissions, energy consumption and GDP in Brazil. They compare forecasted results of GP model with Auto Regressive Integrated Moving Average (ARIMA) model. They find the results of GP model more reliable with minimal errors. Lee and Shih (2011) use grey model with the interaction of cost efficiency, and forecast power generation cost of renewable energy technologies. Lu et al. (2009) forecast the vehicular energy consumption and CO_2 emissions in Taiwan by using the GP model. Hsu and Chen (2003), Yao et al. (2003) and Zhou et al. (2006) use GP model to forecast the demand for electricity.

Yao and Chi (2004) use Taguchi-Grey based prediction to forecast the electricity demand, which is outlined in conjunction with a PC based electricity demand control system. After running an experiment, they found the system very cost effective and efficient. Akay and Atak (2007) argue that GP model turns up with highly accurate forecasting results, when it is compared with other forecasting techniques. They predict the total and industrial electricity consumption of Turkey by using the Grey Prediction Rolling Mechanism (GPRM) approach. They compare the forecasting results of GPRM approach with Model of Analysis of Energy Demand (MAED) and found the prediction results better for GPRM approach. Yao et al. (2005), Zhon et al. (2006) and Yao and Chi (2004) use GP to forecast energy and have found GP a reliable and practical tool. Bianco et al. (2010) use Trigonometric Grey Model with Rolling Mechanism (TGMRM) to predict electricity consumption up to 2020 for non-residential Romania. They compare the results of TGMRM with a Holt-Winter exponential smooth method and find the TGMRM result with minimal errors. Mu et al. (2004) use GP model to predict renewable energy sources. They also predict consumption of biofuels of rural households in China by using Grey Relative Analysis (GRA). All these studies demonstrate that GP model is used to get the most effective results with incomplete and uncertain information by using a few data points.

There are certain reasons behind the spread of GP theory. In early 1990s, grey system theory courses had been offered by some universities located in China, Australia, USA, Taiwan and Japan but it was initiated in 1982 by Deng Julong. In 1996, a Chinese Grey System Association (CGSA) had also been established and a yearly conference is conducted on grey system theory and applications. There has also been a journal (The Journal of Grey System) established in England for the dissemination of research results. The Journal of Grey System encourages and focuses on the development of methods, models, techniques and applications of grey system said by Professor Sifeng Liu, the editor in chief of the journal. Professor Sifeng Liu is not just appointed as a research Professor at De Montfort University, Leicester but he has also been awarded the Marie Curie International Incoming Fellowships by Europe Commission in Grey System research. Some of the conferences are being conducted for Grey System establishment as; IEEE International Conference on Grey System and Intelligent Service, GSSC Annual Conference on Grey System in Mainland China, Annual Conference on Grey System in Taiwan of China, Annual IEEE International Conference on System, Man and Cybernetics, WOSC International Congress of Cybernetics and System and International Conference on Industrial Management.

The focus of the Journal of Grey System is not on any specific field and not limited to any topic, but their research work is being offered in the field of Grey mathematics, Generator of Grey Sequences, Grey Indices Analysis Models, Grey Clustering Evaluation Models, Grey Prediction Models, Grey Decision Making Models, Grey Programming Models, Grey Input and Output Models, Grey Control, Grey Game and Practical Applications. Above all, more than 300 articles about GP model are published every year in different fields throughout the world. It can be seen that grey prediction system is not given much attention in the Western world as most of the research work is done by scientists in the far Eastern. Almost, all the papers that are presented in conferences and are published in journals are by Eastern Scientists.

Grey Prediction (GP) has become very popular in the past decade to forecast energy demand, especially, in the Far East and developing countries. This grey prediction technique is used in many papers[65]. It is claimed in these papers that it is a very simple technique and is able to characterize unknown systems by using just a few data points and forecast the time-series data. However, I argue that this claim is wrong in section 4.2.3 and 4.4.4 with the help of numerical examples and tables. In fact, GP model is used in many fields but with the wrong concept and methodology. According to methodology of GP model, future values of time series data is used to forecast present and future values. For example, time series data of 2010-2013 is used to forecast 2010 values. The first forecasted value always turns up exactly the same as actual value after the GP model estimation process which is unacceptable. It shows clearly that the forecast is done on the basis of future information. In fact, a local trend is built in GP model by using the past and future information.

So, GP model is just an example of trend forecasting and it is related to Exponential Smoothing (ES) forecasting techniques. In GP model, future values are used to forecast the current trend, which is why it is an in sample forecast but out of sample forecast is not used. So it is pretty much clear that GP model is based on an in sample forecasting technique (not an out of sample forecasting techniqe). To properly evaluate the GP model a new model is introduced as “Out Of Sample Grey Prediction (OOSGP) model” after criticizing the GP model. In OOSGP model only the lag values are used to forecast. Criticism on GP model and working of OOSGP model is shown in detail in section 4.4 and 4.5 respectively.

The rest of this paper is organized as follows: Section 2 presents the research methodology. Data is discussed in Section 3. Empirical findings and criticism is given in Section 4. The conclusion is presented in section 5.

[65] GP model technique is introduced by J. L. Deng (1989) and followed by Huang, Lin and Liou (2011), Wang X, Chen Z, Yang C and Chen Y (1999), Tseng FM, Yu HC and Tzeng GH (2003), Lin CT and Yang SY (2003), Hsu LC (2003), Mao M and Chirwa EC(2006) etc.

4.2 Research Methodology

Two multivariate and two univariate models are constructed to study the behaviour and forecast of CO_2 emissions. The first multivariate model explores the long run relationship between CO_2 emissions, energy consumption and economic growth. After confirming the prerequisites of the cointegration, the short run dynamics are estimated and the desired variables are forecasted. The second multivariate model introduces prices in the long run model to see the impact of the cost of energy on the energy consumption relative to GDP and CO_2 emissions. The univariate models use Exponential Smoothing (ES) and Grey Prediction (GP) techniques to forecast the CO_2 emissions in Pakistan. Finally, the forecasts of all the models are compared and discussed in detail.

4.2.1 Model I

In the empirical literature of energy economics, it is plausible to form a long run theoretical relationship between CO_2 emissions, economic growth and energy consumption in linear logarithm quadratic form, with a view to testing the validity of the Environment Kuznets Curve (EKC) hypothesis as shown below:

$$Ln(CO_2) = \delta_0 + \delta_1 Ln(Y_t) + \delta_2 (LnY_t)^2 + \delta_3 \big(Ln(EC_t)\big) + \delta_4 (T_t) + \mathcal{E}_t \qquad (1)$$

Where $\mathrm{Ln}(\mathrm{CO_2})$, $\mathrm{Ln}(\mathrm{EC_t})$ and $\mathrm{Ln}(Y_t)$ represent natural logarithms of CO_2 emissions, energy consumption and real GDP, respectively, $\mathrm{T_t}$ is the exogenous trend representing the technological progress, and $\mathcal{E}_t$ is the error term. The expectation is to have positive signs of energy consumption because a higher level of energy consumption may result in greater economic activity and stimulate CO_2 emissions. Under the Environment Kuznets Curve hypothesis, the expectation is to have positive signs for δ_1 and δ_3 and a negative sign for δ_2, which reflects the inverted U-shape pattern. Here $\frac{\delta_2}{2\delta_1}\,(\overline{Yr}) = 0$ shows the turning point at a given income level. A monotonic increase between real GDP and CO_2 emissions can be indicated by the result, when maximum value of real GDP is less than the turning point $(\frac{\delta_2}{2\delta_1})$ value (Halicioglu F. (2009)). Finally, the stationarity of $\mathcal{E}_t$ indicate the existence of valid long run relationship. The long run relationship can be shown among CO_2 emissions, real GDP and energy consumption with the imposition of EKC hypothesis. The presence of EKC hypothesis is verified with significant results of δ_2.

The long run relationship is given as:

$$Ln(CO_2) = \delta_0 + \delta_1 Ln(Y_t) + \delta_2 (LnY_t)^2 + \delta_3\big(Ln(EC_t)\big) + \delta_4(T_t) + \mathcal{E}_t \qquad by\ (1)$$

The value of $(LnY)^2$ is found to be totally insignificant, which is why it is not needed to estimate $(LnY)^2$ in short run. So, the short run dynamics for equation (1) are given as:

$$\Delta Ln(CO_2) = \alpha_0 + \alpha_1 ECT_{t-1} + \textstyle\sum_{i=1} \alpha_2 \Delta Ln(CO_2)_{t-i} + \sum_{i=1} \alpha_{3_i} \Delta Ln(Y)_{t-i} + \sum_{i=1} \alpha_{4_i} \Delta (LnY)^2{}_{t-i} + \sum_{i=1} \alpha_5 \Delta Ln(EC)_{t-i} + \varepsilon_{1t} \qquad (2)$$

$$\Delta Ln(Y_t) = \beta_0 + \beta_1 ECT_{t-1} + \sum_{i=1} \beta_2 \Delta Ln(CO_2)_{t-i} + \sum_{i=1} \beta_3 \Delta Ln(Y)_{t-i} + \sum_{i=1} \beta_4 \Delta (LnY)^2{}_{t-i} + \sum_{i=1} \beta_5 \Delta Ln(EC)_{t-i} + \varepsilon_{2t} \qquad (3)$$

$$\Delta Ln(EC_t) = \gamma_0 + \gamma_1 ECT_{t-1} + \sum_{i=1} \gamma_2 \Delta Ln(CO_2)_{t-i} + \sum_{i=0} \gamma_{3_i} \Delta Ln(Y)_{t-i} + \sum_{i=1} \gamma_4 \Delta (LnY)^2{}_{t-i} + \sum_{i=1} \gamma_5 \Delta Ln(EC)_{t-i} + \varepsilon_{3t} \qquad (4)$$

Where

$$(ECT)_{t-1} = Ln(CO_2)_{t-1} - \delta_0 - \delta_1 Ln(Y)_{t-1} - \delta_2 (LnY)^2{}_{t-1} - \delta_3 Ln(EC)_{t-1} - \delta_4 (T)_{t-1} \qquad (5)$$

4.2.2 Model II

The long run model that incorporates the cost element of energy is developed for the aggregate energy consumption, where the exogenous trend also exists in energy intensity (energy use /real GDP), Mabey et al. (1997).

The long run equation is given as:

$$Ln\left(\frac{EC_t}{Y_t}\right) = a + b\big(Ln(FPIW_t)\big) + c(T_t) + \mathcal{E}_t \qquad (6)$$

Where EC_t = Energy consumption, Y_t = real GDP, $FPIW_t$= weighted average real fuel price, T_t is the exogenous trend and $\mathcal{E}_t$ =error term

The short run dynamics for equation (6) are given as:

$$\Delta Ln(EC_t) = \psi_0 + \psi_1 ECT_{t-1} + \sum_{i=1} \psi_2 \Delta Ln(EC)_{t-i} + \sum_{i=1} \psi_3 \Delta Ln(FPIW_{t-i}) + \sum_{i=0} \psi_4 \Delta Ln(Y_{t-i}) + \varepsilon_{5t} \quad (7)$$

Where,

$$(ECT)_{t-1} = Ln\left(\frac{EC_t}{Y_t}\right)_{t-1} - \mathrm{a} - bLn(FPIW)_{t-1} - c(T)_{t-1} \quad (8)$$

Equation (8) is derived from equation (6) which shows the long term cointegration relationship. In equation (8), ψ_1 shows the speed of adjustment towards the long run equilibrium.

We can find out the short and long run relationship between energy intensity and weighted average fuel prices by using the equation (6) and (8) respectively. We know that EC_t is also affected by CO_2emissions. It is assumed that the optimal decision of energy consumption is carried out with the consideration of CO_2emissions by industry/firms. Firstly, the model is constructed by ignoring CO_2emissions as shown in equation (6). Afterwards, the CO_2emissions are generated by the equilibrium level of energy consumption. Therefore CO_2emissions are added into this model separately. We can derive the equation to find out the level of CO_2emissions as:

$$\Delta Ln(CO_2) = \eta_0 + \eta_1 \Delta Ln(Y_t) + \eta_2 \Delta Ln(EC_t) + \sum_{i=1} \eta_3 \Delta Ln(CO2)_{t-i} + \sum_{i=1} \eta_4 \Delta Ln(Y)_{t-i} + \sum_{i=1} \eta_4 \Delta Ln(EC)_{t-i} + \varepsilon_{6t} \quad (9)$$

Where $\mathrm{Ln(CO_2)}$, $\mathrm{Ln(EC_t)}$ and $\mathrm{Ln}(Y_t)$ represent natural logarithms of CO_2 emissions, energy consumption and real GDP, respectively. In fact equation (9) is simply OLS equation to find out the value of CO_2emissions.

4.2.3 Model III (Standard account of Grey prediction theory)

We begin by giving a standard account of Grey Prediction (GP) theory as usually found in the literature. The GP theory due to J. L. Deng (1982) is used to predict the series by using the original data of the concerned variable. This theory is based on the Grey Prediction Model (GM). In general, if we know all the information about any system it is called "white", and "black" for the opposite. However, grey system is called the partially known system. GM is a stochastic process whose amplitude varies with time. GM is a time series forecasting model. It is not just based on the first order differential equation but it also encompasses a group of differential equations adapted for parameter variance. We can predict the future values by using the GM in the presence of limited available data of any series. All the steps and operations on the data to use the GP model are illustrated in the flow chart, which is presented in figure 4.1.

The standard account of GM has three basic operations to predict the values and these are Accumulating Generating Operation (AGO), Inverse Accumulated Generating Operation (IAGO) and grey modelling. The most commonly use model, GM (1, 1) is explained for values (1, 1) as, the first "1" shows the existence of one variable and the next "1" shows the existence of first order grey differential equation. We construct our model on the basis of GM (1, 1) property. Generally, at least four observations are required to predict the series for GM (1, 1). We can predict the series using the GM (1, 1) by following these necessary steps.

The following is the standard derivation of the GM from the literature.

$$b = \frac{dx_1}{\mathrm{dt}} + ax_1 \tag{10}$$

Where "a" denotes the developed coefficient, t represents the independent variable in the system and b is the driving coefficient, or grey input, or grey controlled variable. The solution for "a" and "b" is needed as per model requirement.

We construct the original data series X_0 on the basis of available data, and the primitive sequence is as follows:

$$X_0 = x_0(t) \ \ and \ X_0 = x_0(1), x_0(2), x_0(3), x_0(4), x_0(5), \dots \dots, x_0(n)\,, t = 1,2, \dots, n \tag{11}$$

In the above equation (n ≥ 4) means the number of time series values while X_0 is time sequence with n samples or time points. X_0 is a notation to show a time series value. We take non-negative data series in consecutive order with equal time intervals.

Firstly, we take one-order Accumulating Generating Operation (AGO) to the primitive sequence (X_0) by adding the initial values with the lag value to construct a model. The Accumulating Generating Operation of primitive sequence is defined by $x_1(t)$ as shown below.

$$x_1(t) = AGO\big(x_0(t)\big) = \sum_{t=0}^{k} x_0(t) \tag{12}$$

Where

$x_1(0) = x_0(0),\ \ x_1(1) = x_0(1)\ while\ x_1(2) \neq x_0(2)\ because\ x_1(2)$
$= x_0(2) + x_0(1)$

Secondly, we find out the values for Z_1 as[66],

$$Z_1(t) = 0.5\big(x_1(t) + x_1(t-1)\big) \tag{13}$$

The value of $Z_1$is showing the average value for the present and the lag term in equation (13).

Then the GM (1, 1) is written as,

$$x_0(t) +\ aZ_1(t) = b, \qquad t = 1,2, \dots, n \tag{14}$$

In the above GM (1, 1) "a" is called the develop parameter or development coefficient and "b" is called the grey input or driving coefficient. Initially, our aim is to find out the value of "a" and "b" by solving the least square equation.

Thirdly, we can estimate the coefficients "a" and "b" from equations (10) and (14) by using the least square method as:

$$[a\ b]^{\,T} =\ [B^{\,T}B\,]^{-1}B^{\,T}Y_n \tag{15}$$

So, we can write the values of B and Y in the matrix form with the help of Z_1, X_0 as:

$$B = \begin{pmatrix} -Z_1(2) & 1 \\ -Z_1(3) & 1 \\ -Z_1(4) & 1 \\ \cdots & \cdots \\ -Z_1(n) & 1 \end{pmatrix}\ or\ B = \begin{pmatrix} -0.5[(x_1(2)+x_1(1)] & 1 \\ -0.5[(x_1(3)+x_1(2)] & 1 \\ -0.5[(x_1(4)+x_1(3)] & 1 \\ \cdots & \cdots \\ -0.5[(x_1(t)+x_1(t-1)] & 1 \end{pmatrix}, Y_n = \begin{pmatrix} x_0(2) \\ x_0(3) \\ x_0(4) \\ \cdots \\ x_0(n) \end{pmatrix} \tag{16}$$

The Confirm model and the time response equations are given as:

$$b = \frac{dx_1}{\mathrm{dt}} + ax_1 \qquad or\ \ x_0(t) + aZ_1(t) = b, t = 1,2, \dots, n \tag{17}$$

Equation (17) can be used to find out the response equation as:

$$b = \frac{dx_1}{dt} + ax_1\quad or\quad b - ax_1 = \frac{dx_1}{dt} \qquad by\ (17)$$

$$dt = \frac{dx_1}{b - ax_1}$$

By taking the integration on both sides of the above equation as:

$$\int (dt) = \int \left(\frac{dx_1}{b - ax_1}\right)$$

$$t + c_1 = -\frac{\ln(ax + b)}{a}, \qquad where\ c_1\ is\ constant$$

$$-at + c_2 = ln(ax + b)\ , \qquad where\ c_2 is\ second\ constant\ value\ as\ c_2 = -ac_1$$

[66] It is not compulsory to add the equation (13) for$Z_1(t)$. We can also put the average values of $x_1(t), x_1(t-1)$directly in the matrix form.

By taking the exponential on both sides we get,

$ax + b = e^{-at}.c_3$, $if\ t = 0\ then\ we\ can\ say\ that\ c_3 = ax_0 + b$

By putting the value of $c_3 = ax_0 + b$ in the above equation we are given,

$$ax + b = e^{-at}\ (ax_0 + b)$$

$$ax = e^{-at}\ (ax_0 + b) - b$$

So

$$x = e^{-at}\ \left(\frac{ax_0}{a} + \frac{b}{a}\right) - \frac{b}{a}$$

And

$$x = e^{-at}\ \left(x_0 + \frac{b}{a}\right) - \frac{b}{a}$$

Finally we get,

$$x(t) = e^{-at}\ \left(x_0(1) + \frac{b}{a}\right) - \frac{b}{a} \tag{18}$$

So we can say that the response equation is:

$$\widehat{x_1}(t) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} + \frac{b}{\mathrm{a}} \tag{19}$$

Where the analogue value of $\hat{X}_1$ is evaluated as,

$$\hat{X}_1 = (\widehat{x_1}(1), \widehat{x_1}(2), \dots \dots \dots, \widehat{x_1}(n)) \tag{20}$$

Fourthly, we perform the One-Order Inverse Accumulating Generating Operation $(IAGO)_1$ on $\widehat{x_1}(t+1)$ and we get the predicted values of $\widehat{x_0}(t+1)$ as,

$$\widehat{x_0}(t+1) = (IAGO)_1\left(\widehat{x_1}(t+1)\right) = \widehat{x_1}(t+1) - \widehat{x_1}(t) \tag{21}$$

OR

$$\widehat{x_0}(t+1) = \widehat{x_1}(t+1) - \widehat{x_1}(t)$$

$$= \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-a(t+1)} + \frac{b}{\mathrm{a}}\right] - \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} + \frac{b}{\mathrm{a}}\right]$$

$$\widehat{x_0}(t+1) = \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at-a} + \frac{b}{\mathrm{a}}\right] - \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} + \frac{b}{\mathrm{a}}\right]$$

$$\widehat{x_0}(t+1) = \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at}.\mathrm{e}^{-a} + \frac{b}{\mathrm{a}}\right] - \left[\left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} + \frac{b}{\mathrm{a}}\right]$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at}.\mathrm{e}^{-a} + \frac{b}{\mathrm{a}} - \left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} - \frac{b}{\mathrm{a}}$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at}.\mathrm{e}^{-a} - \left(x_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at}$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-at}. [\mathrm{e}^{-a} - 1]$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-at} \left[\frac{1}{\mathrm{e}^{a}} - 1\right]$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-at} \left[\frac{1 - \mathrm{e}^{a}}{\mathrm{e}^{a}}\right]$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-at}. \mathrm{e}^{-a}. (1 - \mathrm{e}^{a})$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-at-a}. (1 - \mathrm{e}^{a})$$

$$\widehat{x_0}(t+1) = \left(x_0(1) - \frac{b}{\mathrm{a}}\right) \mathrm{e}^{-a(t+1)}. (1 - \mathrm{e}^{a})$$

So the final equation to predict the series is given as:

$$\widehat{x_0}(t+1) = (1 - e^{a}) \left(x_0(1) - \frac{b}{\mathrm{a}}\right) e^{-a(t+1)} \quad , t = 0,1, \dots, \dots, n \tag{22}$$

The above equation (22) is the expanded form of equation (21). So, we can find the predicted values by using both equations.

When *t=0* then the above equation is written as:

$$\widehat{x_0}(0+1) = (1 - e^{a}) \left(x_0(1) - \frac{b}{\mathrm{a}}\right) e^{-a(0+1)}$$

OR

$$\widehat{x_0}(1) = (1 - e^{a}) \left(x_0(1) - \frac{b}{\mathrm{a}}\right) e^{-a} \tag{23}$$

Finally, we get the required series for $\hat{X}_0$ as,

$$\hat{X}_0 = \left(\widehat{x_0}(n)\right) \quad or \quad \hat{X}_0 = (\widehat{x_0}(1), \widehat{x_0}(2), \dots \dots \dots, \widehat{x_0}(k) \quad where\ n = 1,2,3, \dots, k \tag{24}$$

Which is called the GM (1, 1) fitted sequence for the series and the forecast values are shown by the series $\widehat{x_0}(k+1), \widehat{x_0}(k+2), \dots \dots, \dots$.

A numerical example of GM (1, 1) is solved for better understanding of the model.

$$b = \frac{dx_1}{\mathrm{dt}} + ax_1 \text{OR} \quad b = \frac{d(co2)_1}{\mathrm{dt}} + a(co2)_1 \tag{25}$$

We construct the original data series $(CO2)_0$ on the basis of available data as:

$$(CO2)_0 = (co2)_0(t) \quad where\ t = 1,2, \dots \dots.. \quad and\ (\mathrm{n} \geq 4)$$

OR

$$(CO2)_0 = (co2)_0(1), (co2)_0(2), (co2)_0(3), (co2)_0(4), \dots \dots, (co2)_0(n) \tag{26}$$

Construct the original data series $(co2)_0(t)$ from the available data as given below:

Year	2010	2011	2012	2013
CO_2 emission(kt) $(CO2)_0$	161395.671 $(co2)_0(1)$	160591.732 $(co2)_0(2)$	162140.785 $(co2)_0(3)$	163151.611 $(co2)_0(4)$

$(CO2)_0 = (161395.67, 160591.73, 162140.78, 163151.61), \quad n \geq 4$

Now we can go through the procedure as:

Firstly, we take one-order Accumulating Generating Operation (AGO) on $(co2)_0(t)$ by adding the initial values with the lag value as shown in the formula below.

$$(co2)_1(t) = AGO\big((co2)_0(t)\big) = \sum_{t=0}^{k}(co2)_0(t) \tag{27}$$

Accumulate $(co2)_0(t)$ once and get the results as:

$$(co2)_1(t) = [\{(co2)_0(1)\}, \{(co2)_0(2) + (co2)_0(1)\}, \{(co2)_0(3) + (co2)_0(2) + (co2)_0(1)\}, \{(co2)_0(4) + (co2)_0(3) + (co2)_0(2) + (co2)_0(1)\}]$$

$\boldsymbol{(co2)_1(t)} = (\mathbf{161395.7}, \quad \mathbf{321987.4}, \quad \mathbf{484128.2}, \quad \mathbf{647279.8})$

Where

$$(co2)_1(1) = (co2)_0(1) \text{ as } \mathbf{161395.67 = 161395.67} \ while\ (co2)_1(2) \neq (co2)_0(2)\ as\ \mathbf{321987.4 \neq 160591.73}$$

$(CO2)_1 = (co2)_1(1), (co2)_1(2), (co2)_1(3), \ldots \ldots \ldots \ldots, (co2)_1(n)$

Secondly, we find out the values for Z_1 as,

$$Z_1(t) = 0.5\big((co2)_1(t) + (co2)_1(t-1)\big) \tag{28}$$

$Z_1(2) = 0.5 * (321987.4 + 161395.7) = \mathbf{241691.5}$

So

$Z_1(2,3,4) = \mathbf{241691.5}, \quad 403057.8, \quad 565704.0)$

Then the GM (1, 1) is written as,

$$(co2)_0(t) + aZ_1(t) = b, \quad t = 1,2, \ldots, n \tag{29}$$

Smooth test is applied on $(CO2)_0$ to find *ρ(t)* ,

$$\text{Where } \rho(n) = \frac{(CO2)_0(n)}{(CO2)_1(n-1)}, n = 1, 2, 3, 4 \tag{30}$$

So

$\rho(2) \approx 0.50$, $\rho(3) \approx 0.33 < 0.5$, $\rho(4) \approx 0.25 < 0.5$

When $t > 3$, then the quasi smooth condition is satisfied

It can also be determined whether $(CO2)_1$ satisfies the quasi exponential rule or not.

So

$$\sigma_1(t) = \frac{(co2)_1(n)}{(co2)_1(n-1)} = 1 + \rho(t) \tag{31}$$

$\sigma_1(2) \approx 1.50$, $\sigma_1(3) \approx 1.33$, $\sigma_1(4) \approx 1.25$, $where\ t > 3$

$\sigma_1(t) \in [1, 1.5]$, $\delta < 0.5$, the quasi exponential rule is satisfied, therefore Grey Prediction GM(1,1) can be constructed for $(CO2)_1$.

In the above GM (1, 1) *"a"* is called the develop parameter and *"b"* is called the grey input.

Thirdly, we can estimate the parameters $[a \ \ b]^T$ from equation (42) and (46) by using the least square method as mentioned below.

$$[a \ \ b]^T = [B^T B]^{-1} B^T Y_n \tag{32}$$

So, we can write the values of B and Y in matrix form with the help of $Z_1, (CO2)_0$ as:

$$B = \begin{pmatrix} -Z_1(2) & 1 \\ -Z_1(3) & 1 \\ -Z_1(4) & 1 \\ \cdots & \cdots \\ -Z_1(n) & 1 \end{pmatrix} \ or \ B = \begin{pmatrix} -0.5[(co2)_1(1)+(co2)_1(2)] & 1 \\ -0.5[((co2)_1(2)+(co2)_1(3)] & 1 \\ -0.5[((co2)_1(3)+(co2)_1(4)] & 1 \\ \cdots & \cdots \\ -0.5[((co2)_1(t-1)+(co2)_1(t)] & 1 \end{pmatrix}, Y_n = \begin{pmatrix} (CO2)_0(2) \\ (CO2)_0(3) \\ (CO2)_0(4) \\ \cdots \\ (CO2)_0(n) \end{pmatrix} \tag{33}$$

$$B = \begin{pmatrix} -241691.5 & 1 \\ -403057.8 & 1 \\ -565704 & 1 \end{pmatrix}, Y_n = \begin{pmatrix} 160591.731 \\ 162140.785 \\ 163151.611 \end{pmatrix}$$

Solve $[a \ \ b]^T = [B^T B]^{-1} B^T Y_n$

$$[a \ \ b] = [-0.0079 \qquad 158774.523]$$

The Confirm model and the time response equations are given as:

$$b = \frac{d(co2)_1}{\mathrm{dt}} + a(co2)_1 \quad or \qquad (co2)_0(t) + aZ_1(t) = b, \tag{34}$$

The response equation is,

$$\widehat{(co2)}_1(t) = \left((co2)_0(1) - \frac{b}{\mathrm{a}}\right)\mathrm{e}^{-at} + \frac{b}{\mathrm{a}} \ , \quad t = 0,1, \ldots. \tag{35}$$

$$\widehat{(co2)}_1(0) = \left(\mathbf{161395.67} - \frac{158774.523}{-0.0079}\right)\mathrm{e}^{-(-0.0079*0)} + \frac{158774.523}{-0.0079}$$

$$\widehat{(co2)}_1(0) = 20263686.301 * (1) * 20102290.63 = 161395.671$$

$$\widehat{(co2)}_1(0) = (\mathbf{161395.670}) \ \boldsymbol{as \ t = 0}$$

So,

$$\widehat{(co2)}_1(t+1) = \widehat{(co2)}_1(0+1) = (\widehat{\boldsymbol{co2}})_{\mathbf{1}}(\mathbf{1}) = (\mathbf{322112.788}), \boldsymbol{when \ t = 0}$$

$$\widehat{(co2)}_1(1+1) = (\widehat{\boldsymbol{co2}})_{\mathbf{1}}(\mathbf{2}) = (\mathbf{484104.601}), \boldsymbol{when \ t = 1} \tag{36}$$

$$\widehat{(co2)}_1(2+1) = (\widehat{\boldsymbol{co2}})_{\mathbf{1}}(\mathbf{3}) = (\mathbf{647381.2165}), \boldsymbol{when \ t = 2} \tag{37}$$

Fourthly, we perform the one-order Inverse Accumulating Generating Operation (IAGO) on $\widehat{(co2)}_1(t+1)$; we get the predicted values of $\widehat{(co2)}_0(t+1)$ as,

$$\widehat{(co2)}_0(t+1) = ((IAGO)_1\widehat{(co2)}_1(t+1) = \widehat{(co2)}_1(t+1) - \widehat{(co2)}_1\big((t+1)-1\big)$$

$$= \widehat{(co2)}_1(t+1) - \widehat{(co2)}_1(t) \tag{38}$$

And

$$(\widehat{co2})_0(t+1) = (\widehat{co2})_1(1) - (\widehat{co2})_1(0) \quad if\ t = 0$$

$$(\widehat{co2})_0(t+1) = 322112.788 - \mathbf{161395.670} = \mathbf{161395.671}$$

OR

$$(\widehat{co2})_0(t+1) = (1 - e^{a})\left((co2)_0 - \frac{b}{\mathrm{a}}\right)e^{-a(t+1)} \quad , t = 0,1, \ldots.$$

GP model (GP-4) can be shown in the resulting equation form as:

$$(\widehat{co2})_0(t+1) = (1 - e^{-0.0079})\left((CO2)_0 + \frac{158774.52}{0.0079}\right)e^{0.0079(t+1)} \tag{39}$$

Where the analogue value of $(\widehat{CO2})_1$ is evaluated as,

$$(\widehat{CO2})_1 = ((\widehat{co2})_1(t) \text{ or } (\widehat{CO2})_1 = ((\widehat{co2})_1(1), (\widehat{co2})_1(2), \ldots \ldots \ldots, (\widehat{co2})_1(n) \quad where\ t = 1,2,3, \ldots., n \tag{40}$$

Finally, we get the required series for $(\widehat{CO2})_0$ as,

$$(\widehat{CO2})_0 = ((\widehat{co2})_0(n)\ or\ (\widehat{CO2})_0 = ((\widehat{co2})_0(1), (\widehat{co2})_0(2), \ldots \ldots \ldots, (\widehat{co2})_0(k) \quad where\ n = 1,2,3, \ldots., k \tag{41}$$

This is called the GM (1, 1) fitted sequence for the series and the forecast values are shown by the series$(\widehat{co2})_0(k+1), (\widehat{co2})_0(k+2), \ldots \ldots, \ldots$

The methodology of the standard account of GP theory is followed in the numerical example from equation (25) to (41). We found the same methodology in the literature where future values are used to forecast the present value. Data from 2010-2013 is used to forecast 2010 value by using the standard GM (1,1) methodology. According to the forecast results, the first value of the actual value turns up exactly the same as the forecasted value. Despite the popularity of GP model, it may not provide satisfactory results and prediction accuracy in an out of sample real application. Unfortunately, GP model is used in many fields but with the wrong concept and methodology. By using the grey model methodology the first forecasted value always turns up exactly the same as actual value. To make it clear we have taken some print outs from the literature to show the exact same actual and forecasted values as:

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Table 3
Forecasted values and errors among models (unit: 10^4 tons of SCE).

Year	Original value	GM(1, 1)		Hsu and Chen [5]		GPGM(1, 1)		Linear regression	
		Model value	Error[a]	Model value	Error[a]	Model value	Error[a]	Model value	Error[a]
1990	98,703	98703.00	0.00	98703.00	0.00	98,703	0.00	101756.57	3.09
1991	103,783	108706.11	4.74	103783.00	0.00	103,783	0.00	106243.38	2.37
1992	109,170	112335.53	2.90	116225.80	6.46	108445.2	−0.66	110730.19	1.43
1993	115,993	116086.14	0.08	111804.10	−3.61	111804.1	−3.61	115217.01	−0.67
1994	122,737	119961.97	−2.26	115248.80	−6.10	124675.1	1.58	119703.82	−2.47
1995	131,176	123967.21	−5.50	129154.80	−1.54	129154.8	−1.54	124190.63	−5.33
1996	138,948	128106.16	−7.80	133816.10	−3.69	133816.1	−3.69	128677.45	−7.39
1997	137,798	132383.31	−3.93	138668.20	0.63	138668.2	0.63	133164.26	−3.36
1998	132,214	136803.27	3.47	143721.00	8.70	129885.5	−1.76	137651.07	4.11
1999	133,831	141370.79	5.63	133756.50	−0.06	133756.5	−0.06	142137.89	6.21
2000	138,553	146090.81	5.44	137709.80	−0.61	137709.8	−0.61	146624.70	5.83
2001	143,199	150968.42	5.43	141743.60	−1.02	141743.6	−1.02	151111.51	5.53
2002	151,797	156008.89	2.77	145855.20	−3.91	145855.2	−3.91	155598.32	2.50
2003	174,990	161217.64	−7.87	150041.60	−14.26	172393.5	−1.48	160085.14	−8.52
MAPE (%) (1990–2003)			4.13		3.61		2.59		4.20
2004	203,227	166600.20	−18.02	178901.50	−11.97	178901.5	−11.97	164571.95	−19.02
2005	224,682	172162.60	−23.37	185702.40	−17.35	185702.4	−17.35	169058.76	−24.76
2006	264,270	177910.70	−32.68	192813.80	−27.04	192813.8	−27.04	173545.58	−34.33
2007	265,583	183850.70	−30.77	200254.30	−24.60	200254.3	−24.60	178032.39	−32.97
MAPE (%) (2004–2007)			26.21		20.23		20.23		27.76

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Table 8
Forecasts of CO_2 emissions (million metric tons) for Brazil, 2004–2013.

Year	Actual	GM (1,1)	ARIMA
2004	356.17	356.17	352.32
2005	370.41	370.29	363.44
2006	383.51	383.63	379.69
2007	397.56	397.44	393.24
2008		411.76	407.11
2009		426.59	416.29
2010		441.95	424.66
2011		457.87	432.82
2012		474.37	440.78
2013		491.45	448.63

Table 9
Forecasts of energy consumption (billion BTU) for Brazil, 2002–2013.

Year	Actual	GM (1,1)	ARIMA
2002	8547.03	8547.03	8702.65
2003	8657.56	8646.09	8819.51
2004	8991.29	8989.05	8932.61
2005	9345.64	9345.61	9274.11
2006	9680.55	9716.31	9636.71
2007	10130.44	10101.72	9979.41
2008		10502.42	10439.78
2009		10919.01	10756.31
2010		11352.12	11080.21
2011		11802.42	11411.65
2012		12270.58	11750.81
2013		12757.30	12097.86

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Table 5
Grey prediction of vehicle fleet, traffic energy consumption and CO_2 emission.

Year	Number of motor vehicles (thousand vehicles)			Energy consumption (thousand kiloliters)			CO_2 emission (thousand metric tons)		
	Actual values	Predicted values	Residual value (%)	Actual values	Predicted values	Residual value (%)	Actual value	Predicted values	Residual value (%)
1990	9194	9194	–	7688	7688	–	18,352	18,352	–
1991	9722	10,574	8.76	8206	9553	16.41	19,554	22,701	16.09
1992	10,350	10,959	5.88	9415	9864	4.77	22,455	23,434	4.36
1993	10,912	11,359	4.09	10,175	10,185	0.10	24,257	24,192	0.27
1994	11,413	11,773	3.15	10,753	10,517	2.20	25,595	24,974	2.43
1995	12,179	12,202	0.18	11,225	10,859	3.26	26,653	25,781	3.27
1996	13,159	12,647	3.90	11,546	11,212	2.89	27,326	26,614	2.60
1997	14,089	13,108	6.97	11,829	11,577	2.13	27,994	27,474	1.86
1998	14,643	13,585	7.22	12,369	11,954	3.36	29,260	28,362	3.07
1999	14,345	14,080	1.85	12,881	12,343	4.18	30,491	29,279	3.97
2000	14,967	14,594	2.49	13,124	12,744	2.89	31,084	30,225	2.76
2001	15,236	15,126	0.72	13,128	13,159	0.24	31,063	31,202	0.45
2002	15,630	15,677	0.30	13,733	13,587	1.06	32,616	32,211	1.24
2003	16,027	16,248	1.38	13,907	14,030	0.88	32,922	33,252	1.00
2004	16,624	16,841	1.30	14,423	14,486	0.44	34,185	34,327	0.41
2005	17,224	17,454	1.34	14,829	14,958	0.86	35,153	35,436	0.81
2006	17,596	18,091	2.81	14,782	15,444	4.48	35,121	36,581	4.16

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Table 1
Observed and forecasted electricity demands in China, 1981–2002, for three different approaches (unit: 100 million kWh)

Year	Observed value	GM(1,1)		ARIMA		TGM[a]	
		Forecasted value	RE (%)	Forecasted value	RE (%)	Forecasted value	RE (%)
Model building stage: 1981–1998							
1981	3096	3096	0.00	3096	0.00	3096	0.00
1982	3280	3327.7	1.45	3368.7	2.70	3422.9	4.36
1983	3519	3611.5	2.63	3662.2	4.07	3552.1	0.94
1984	3778	3919.5	3.75	3977.8	5.29	3756.1	−0.58
1985	4118	4253.9	3.30	4316.8	4.83	4037.5	−1.96
1986	4507	4616.7	2.43	4680.8	3.86	4395.1	−2.48
1987	4985	5010.5	0.51	5071.1	1.73	4824.4	−3.22
1988	5467	5437.9	−0.53	5489.3	0.41	5318.3	−2.72
1989	5865	5901.7	0.63	5937.1	1.23	5867.3	0.04
1990	6230	6405.1	2.81	6416.1	2.99	6461.1	3.71
1991	6775	6951.4	2.60	6928.1	2.26	7089.0	4.63
1992	7542	7544.3	0.03	7475.0	−0.89	7741.4	2.64
1993	8426.5	8187.8	−2.83	8058.7	−4.36	8410.5	−0.19
1994	9260.4	8886.2	−4.04	8681.1	−6.26	9091.6	−1.82
1995	10,023.4	9644.1	−3.78	9344.2	−6.78	9783.3	−2.40
1996	10,764.3	10,466.7	−2.76	10,050.3	−6.63	10,488.4	−2.56
1997	11,284.4	11,359.5	0.67	10,801.4	−4.28	11,213.7	−0.63
1998	11,598.4	12,328.4	6.29	11,599.9	0.01	11,970.6	3.21
Ex post testing stage: 1999–2002							
1999	12,305.2	13,379.9	8.73	12,448.1	1.16	12,773.9	3.81
2000	13,471.4	14,521.2	7.79	13,348.5	−0.91	13,641.8	1.26
2001	14,633.5	15,759.8	7.70	14,303.6	−2.25	14,594.9	−0.26
2002	16,331.5	17,104.0	4.73	15,315.8	−6.22	15,655.6	−4.14

[a]The proposed trigonometric grey prediction approach.

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Table 1
Model values and forecast errors (unit: 10^3 W h)

Year	Real value	GM(1,1)		Improved GM(1,1)		ARIMA	
		Model value	Error (%)	Model value	Error (%)	Model value	Error (%)
1985	47,919,102	47,919,102	0.00	47,919,102	0.00	47,919,102	0.00
1986	53,812,862	56,318,092	4.66	53,812,862	0.00	52,307,500	−2.80
1987	59,174,751	60,319,829	1.94	59,630,904	0.77	53,957,006	−8.82
1988	65,227,727	64,605,914	−0.95	65,310,510	0.13	60,243,936	−7.64
1989	69,251,809	69,196,550	−0.08	69,917,174	0.96	65,958,706	−4.76
1990	74,344,947	74,113,379	−0.31	74,850,394	0.68	72,405,080	−2.61
1991	80,977,405	79,379,577	−1.97	80,133,358	−1.04	76,688,020	−5.30
1992	85,290,354	85,019,971	−0.32	85,790,897	0.59	82,105,943	−3.73
1993	92,084,684	91,061,148	−1.11	91,849,611	−0.26	89,156,925	−3.18
1994	98,561,004	97,531,587	−1.04	98,337,985	−0.23	93,739,526	−4.89
1995	105,368,193	104,461,790	−0.86	105,286,530	−0.08	100,954,923	−4.19
1996	111,139,816	111,884,424	0.67	111,040,924	−0.09	107,828,630	−2.98
1997	118,299,046	119,834,482	1.30	118,971,794	0.57	115,049,615	−2.75
1998	128,129,801	128,349,438	0.17	127,467,127	−0.52	121,169,150	−5.43
MAPE[a] (1986–1998)			1.54		0.57		4.24
1999	131,725,892	137,469,433	4.36	133,459,644	1.32	128,756,418	−2.25
2000	142,412,887	147,237,458	3.39	144,204,700	1.26	139,168,992	−2.28
MAPE (1999–2000)			3.88		1.29		2.27

Grey model technique (GP model) is used in literature and future values of time series data is used to forecast present and future values. To produce the forecast for 2010 we need to use figures from the future. The way this technique is being evaluated in the literature is simply not the correct out of sample forecast. For example, time series data for 2010-2013 is used to forecast 2010 values. The first forecasted value always turns up same as actual value after GP model estimation process which is unacceptable and wrong. It shows clearly that the forecast is done on the basis of future information. The accumulation process of GP model is to add actual and one lag value but, $(co2)_1(t)$'s from equation (27) are the accumulation from the future. Thus, they are basing their forecast on the future.

In fact, little trend is built in GP model by using the past and future information. So, GP model is just an example of trend forecasting and is related to Exponential Smoothing (ES) forecasting techniques. It does not predict but shows a little trend. To properly evaluate the GP model a new model is introduced as "Out Of Sample Grey Prediction (OOSGP) model". Critical analysis of the GP model is explained in detail in section 4.4.5.

GP model is an example of trend forecast and nothing else. There are many flaws in the GP model. Future data is used to forecast or predict in GP model. A small amount of data gives the best results in it as the same trend can be built up by using data this way. If a large amount of data is used then the trend will not be built up accordingly or in perfect historical format. These flaws could be reduced by the extension of GP model but cannot be removed completely. Therefore, the OOSGP approach is followed which utilizes full/complete data information of any data series, and can provide an accurate and reasonable prediction.

4.2.4 Model IV (Exponential Smoothing)

Many univariate or projection methods are used to forecast, where only the current and past values of the variables are provided. Among these methods, a broadly sensible approach (exponential smoothing) to forecast is widely used which was proposed in the late 1950s by (Holt 1957, Brown 1959, Winter 1960, Chatfield 1978, Montgomery and Johnson 1976, Granger and Newbold 1977). It has introduced some of the most successful forecasting methods by using weighted averages of past observations.

4.2.4.1 Simple Exponential Smoothing

It is important to discuss some basic concepts of Simple Exponential Smoothing (SES) or Exponentially Weighed Moving Average (EWMA) methods. EWMA procedures are simply based on the weighted averages. The term smoothing is used to indicate that irregularities in the data are smoothed with the weighted averages. EWMA is only used for data having no seasonal components or systematic trends. Having such a time series, an approach can be used by taking a weighted average of past values. As for a series $(X_1, X_2, X_3, \dots \dots .., X_T)$ the estimated valued X_k can be written in one of two ways.

$$X_k = w_1 X_{t-1} + w_2 X_{t-2} + \dots \dots \dots \dots .., + w_{k-1} X_{t-k-1}$$

Or

$$X_k = \sum_{j=1}^{k-1} w_j X_{t-j} \quad Or \; X_k = \sum_{j=1}^{k-1} w_j^* X_{t-j} + \sum_{j=1}^{T-k} w_j^* X_{t+j}\, , where\; j = 1,2,3 \qquad (42)$$

Where w_j are the weights given to the past values and sum to unity as:

$$w_j = \alpha(1-\alpha)^{t-j} \qquad where\; j = 1,2,3 \dots \dots$$

While α is a smoothing constant as $0 < \alpha < 1$.

We can also write the forecasted value of X_t as:

$$X_k = \alpha(\text{previous actual } X_t) + (1-\alpha)(\text{previous forecast})$$

X_{k-j} is the previous forecast on estimate. To measure the previous forecast for the first period, the average of all the actual data of X_t could be taken or the average of the first six actual values of X_t could be taken, or the same actual value for the same time period could be written as the previous forecasted value. The final equation to find out the forecast by using EWMA can be written as:

$$X_k = \alpha X_{t-j} + (1-\alpha) X_{k-j} \;\; where\; j = 1,2,3 \dots \dots \qquad (43)$$

$$X_k = \alpha X_{t-j} + X_{k-j} - \alpha X_{k-j}$$

$$X_k = \alpha(X_{t-j} - X_{k-j}) + X_{k-j}$$

$$X_k = \alpha \varepsilon_n + X_{k-j}, \qquad where\; \varepsilon_n = X_{t-j} - X_{k-j} \qquad (44)$$

α is the smoothing constant. It will depend on the irregularity and characteristics of time series data. α can be estimated by minimising the sum of squared prediction errors by $\sum \varepsilon_n^2$.

4.2.4.2 Holt's Method

In the Holt (1957) and winter (1960) procedure the forecasting function is not just the latest estimate of the level, but also some form of trend is taken in to account, whether constant or non-constant. Holt's method is the extended form of the simple exponential smoothing method. If f_t is defined as the forecast of X_t where $X_t = (X_1, X_2, X_3, \dots \dots .., X_T)$ then the forecast of X_{t+1} can be named as $(f_{t+1}\ or\ X_{k+1})$ and the function can be written as:

$$f_{t+1} = m_t + g_t \qquad or \qquad X_{k+1} = m_t + g_t \tag{45}$$

m_t is called our best estimate of the underlying value of the series and g_t is called the expected rate of increase of the series. A recursion can be developed to obtain a set of estimations for m_t & g_t through time "t" as:

$$m_{t+1} = \alpha_0 X_{t+1} + (1 - \alpha_0)(m_t + g_t) \tag{46}$$

Or

$$m_t = \alpha_0 X_t + (1 - \alpha_0)(m_{t-1} + g_{t-1})$$

The above equation is given on level at time "t" and estimate of the slope could be obtained once we know the value of level as:

$$g_{t+1} = \alpha_1(m_{t+1} - m_t) + (1 - \alpha_1)\, g_t \tag{47}$$

Or

$$g_t = \alpha_1(m_t - m_{t-1}) + (1 - \alpha_1)\, g_{t-1}$$

We can also write these equations in error correction form as:

$$m_t = m_{t-1} + g_{t-1} + \alpha_0 \varepsilon_t \tag{48}$$

$$g_t = g_{t-1} + \alpha_0 \alpha_1 \varepsilon_t \tag{49}$$

This is called the Holt's method. The value of α_0 and α_1 can be found/estimated by minimising the sum of squared errors as they are found in single exponential smoothing procedure. It is also noted that $m_t = X_1 \; and \; g_1 = X_2 - X_1$.

In the case of seasonal data being include in the trend values, Holt's method could be extended to the new methodology known as the Holt-Winters (HW) method. The HW method deals with the trend and seasonality in two further versions called Additive and Multiplicative methods.

The equation for multiplicative Holt-Winters method can be written as:

$$X_k = (m_t + g_t)c_{t-s} \tag{50}$$

Having three components, we will have three smoothing constants as $\alpha_0, \alpha_1 and \; \alpha_2$. In this case the further equations for $m_t, g_t \; and \; c_t$ can be written as:

$$m_t = \alpha_0 \left(\frac{X_t}{c_{t-s}}\right) + (1 - \alpha_0)(m_{t-1} + g_{t-1}) \tag{51}$$

$$g_t = \alpha_1(m_t - m_{t-1}) + (1 - \alpha_1) \, g_{t-1} \tag{52}$$

$$c_t = \alpha_2 \left(\frac{X_t}{m_t}\right) + (1 - \alpha_2) \, c_{t-s} \tag{53}$$

Where $\alpha_0, \alpha_1 and \; \alpha_2$ lie between 0 and 1. The equation for additive HW method can be written as:

$$X_k = m_t + g_t + c_{t-s} \tag{54}$$

$$m_t = \alpha_0(X_t - c_{t-s}) + (1 - \alpha_0)(m_{t-1} + g_{t-1}) \tag{55}$$

$$c_t = \alpha_2(X_t - m_t) + (1 - \alpha_2) \, c_{t-s} \tag{56}$$

The equation for g_t will remain the same as with the HW multiplicative method. The values for $\alpha_0, \alpha_1 and \; \alpha_2$ could be estimated by minimizing the sum of squared one-step-ahead errors. It is also important to know that Holt's method is only used for the trend and irregular components, while HW method is used for trend and seasonality.

No universal preferred measure is used for estimation and forecasting accuracy. In sample forecast performance, five different evaluation statistics are used to find out the accuracy in out of sample forecast as: Relative deviation (RD), the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and the Theil Index (TI). These are expressed as follow:

$$RD = \sum_{i=1}^{n} \frac{|P_i - A_i|}{A_i} \tag{57}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} (P_i - A_i)^2 / n} \tag{58}$$

$$MAE = \sum_{i=1}^{n} \frac{|P_i - A_i|}{\mathrm{n}} \tag{59}$$

$$MAPE = \sum_{i=1}^{n} \frac{|(P_i - A_i)/A_i|}{\mathrm{n}} \; X\, 100 \tag{60}$$

$$TI = \frac{\sqrt{\sum_{i=1}^{n} (P_i - A_i)^2 / n}}{\sqrt{\sum_{i=1}^{n} (P_i)^2 / n} + \sqrt{\sum_{i=1}^{n} (A_i)^2 / n}} \tag{61}$$

Table 4.1. MAPE criteria for model evaluation
Source: Lewis (1982)

MAPE (%)	Forecasting ability
<10	Highly accurate Predictability/forecast
10-20	Good Predictability/forecast
20-50	Reasonable Predictability /forecast
>50	Weak and Inaccurate Predictability/ forecast

In the above equations (57-61), P_i shows the i^{th} forecasting values, A_i shows the actual values of the original series and n is the total number of predictions in the out of sample forecast. The performance of the forecast can be assessed with the help of the Table 4.1, which is introduced by Lewis (1982).

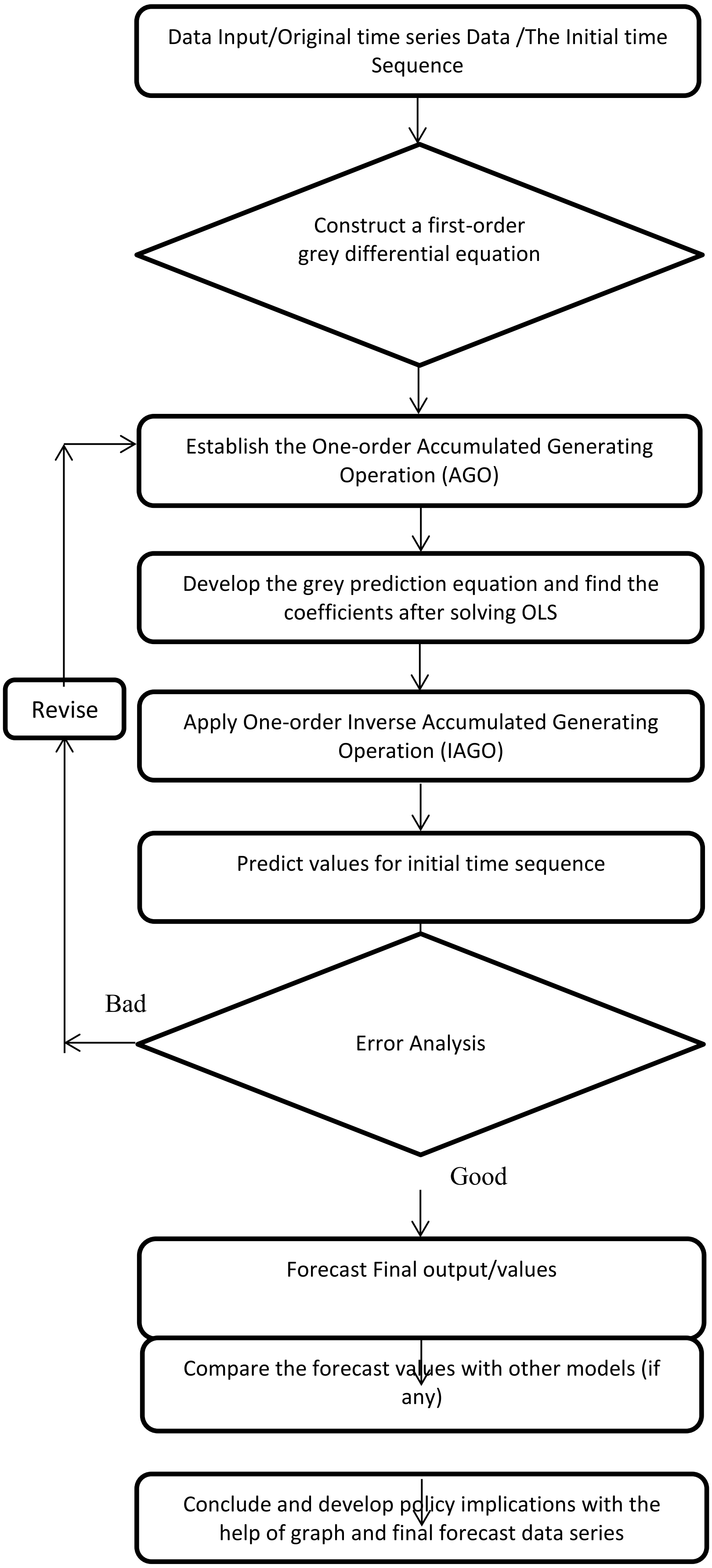

Figure 4.1: Scheme of Grey-based prediction

4.2.5 Econometric methodology

The Johansen Cointegration test is utilized to find out the existence of the long run relationship among the variables presented in equation 1 and 6. After confirming the cointegration from the long run model and the number of cointegrating relationships, the short run dynamics of the variables are modelled by using the Vector Error Correction Model (ECM). The analysis is based on the steps as follows.

Firstly, we check the stationarity and find out the order of integration of the variables by using the conventional unit root tests (Augmented Dickey-Fuller (ADF) Test and Phillips-Perron (PP) Test). Secondly, after getting the same level of integration that is *I(1)* it shows that there exists long run relationship among the variables. The correction of any disequilibrium or the speed of adjustment towards the equilibrium is captured by the error correction term (ECT), which is investigated using the error correction model (ECM).

For simplicity, one long run relationship is presented here but the number of long run relationships is determined on the basis of significant cointegrating vectors in the Johansen test. Equation (5) is derived from equation (1) which shows the long term cointegration (CI) relationship. The sign "Δ" shows the first difference operator, while the Akaike information criteria (AIC) is used to determine the optimum lag lengths for the variables of equations (2)-(4). The error terms are shown by ε_{it}, which are serially uncorrelated. The parameters (α_1, β_1 and γ_1) are considered as the speed of adjustment coefficients. These coefficients are interpreted as, when any of the variables among ($Ln(CO_2)$, (Y_t) , $Ln(EC_t)$, $(LnY_t)^2$) violate the long run relationship, the coefficient value of parameters tells the speed at which the values of respective variables come back to long run equilibrium level. The negative sign is expected for the coefficient values of parameters as it shows the convergence towards the long run equilibrium. Finally, CO_2 emissions are forecasted from (2014-2030) by using the model solving techniques of one step ahead forecast in E views.

CO_2 emissions are forecasted by using final equation of GP model as:

$$(\widehat{co2})_0(t+1) = (1 - e^{a})\left((co2)_0 - \frac{b}{a}\right)e^{-a(t+1)} \qquad ,t = 0,1,\ldots. \qquad by\ (22)$$

Where the analogue value of $(\widehat{CO2})_1$ is evaluated as,

$$(\widehat{CO2})_1 = ((\widehat{co2})_1(1), (\widehat{co2})_1(2), \ldots\ldots\ldots, (\widehat{co2})_1(n) \qquad by\ (20)$$

Finally, we get the required series for $(\widehat{CO2})_0$ as,

$$(\widehat{CO2})_0 = ((\widehat{co2})_0(1), (\widehat{co2})_0(2), \dots \dots \dots, (\widehat{co2})_0(n) \qquad by\ (24)$$

This is called the GM (1, 1) fitted sequence for the series and the out of sample forecast values are shown by the series$(\widehat{co2})_0(n+1), (\widehat{co2})_0(n+2), \dots \dots,$.
While, CO_2 emissions are forecasted by using final equation of Exponential Weighted Moving Average (EWMA) technique as:

$$CO2_k = \alpha CO2_{t-j} + (1-\alpha)CO2_{k-j} \ \ where\ j = 1,2,3 \dots \dots. \qquad by\ (43)$$

$$CO2_k = \alpha\varepsilon_n + CO2_{k-j}, \qquad where\ \varepsilon_n = CO2_{t-j} - CO2_{k-j} \qquad by\ (44)$$

α is the smoothing constant, and will depend on the irregularity and characteristics of time series data.
According to Holt's method the final forecast equation can be written as:

$$CO2_{k+1} = \ m_t + \ g_t \qquad by\ (45)$$

$$m_{t+1} = \alpha_0 X_{t+1} + (1-\alpha_0)(m_t + \ g_t) \qquad by\ (46)$$

$$g_{t+1} = \alpha_1(m_{t+1} - m_t) + \ (1-\alpha_1)\ g_t \qquad by\ (47)$$

We can also write these equations in error correction form as:

$$m_t = m_{t-1} + \ \ g_{t-1} + \alpha_0\varepsilon_t \qquad by\ (48)$$

$$g_t = g_{t-1} + \alpha_0\alpha_1\varepsilon_t \qquad by\ (49)$$

After finding the predicted values, we use different evaluation statistics as: Relative deviation (RD), the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and the Theil Index (TI). Lewis (1982) finds the accuracy interval for MAPE. He interprets that it is called a highly accurate forecast if MAPE is less than 10 percent. Between 10 and 20 percent it is still a good forecast, and between 20 to 50 percent it is a reasonable forecast. More than 50 percent is called the inaccurate forecast.

4.3 Data

Annual data has been collected for CO_2 emissions, energy consumption and real GDP from 1971 to 2013 from World Development Indicators (WDI) and the Pakistan Energy Year book (various issues). We don't use per capita data as per the explanation of Friedl and Getzner (2006). They argue that the use of total emissions data is better than per capita emissions data in a single country study, because the Kyoto Protocol calls for a reduction in the percentage of emissions. They have also suggested that the use of total emissions is better than per capita emissions, specifically, when we study a single country and divide emissions by population. This population number only scales the variable down. That is why CO_2 emissions are used in kilo tons. Real GDP is taken at constant prices of 2005 US dollars. Energy consumption is taken in kilo tons of oil equivalent. The time trend is shown in figure 4.2 for all three series. All the data is converted into natural logarithm for modelling purposes and empirical analysis.

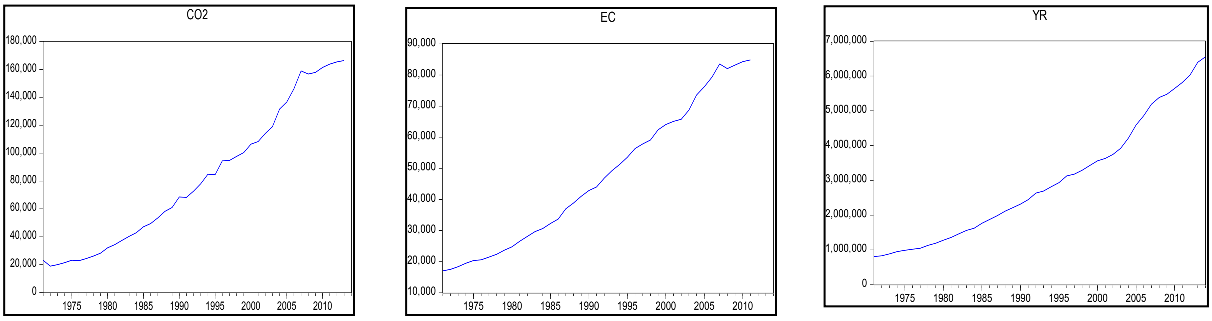

Figure 4.2: Time series plots of the CO_2 emissions (CO_2), energy consumption (EC) and real GDP (YR), 1971-2013

4.4 Empirical findings

Annual data from 1971-2013 is used to perform the Johansen cointegrating tests on the long run relationship presented in equations (1) and (6). Equation (1) is used to test the cointegration relationship among carbon emissions, energy consumption and real GDP, while equation (6) is used to check CI relationship between energy intensity and weighted average real fuel prices.

4.4.1 Results of Unit roots, Co integration and Error correction model test

Two different unit root tests are applied; ADF and PP tests, check the time series properties of the variables. The results for both tests find that all the series have a unit root/non-stationary at level. All the series become stationary in their first differences, which indicates the first order integration or *I(1).* The results of integration tests for all the series at level and first differences are shown in table 4.2.

Table 4.2: Results of Unit root test

	ADF		PP	
	Level	1^{st} diff.	level	1^{st} diff.
$LnCO_2$	-0.7466	-4.2153*	-0.7420	-8.1832*
LnEC	-2.4098	-4.1759*	-2.597	-4.2775*
LnY	-1.7360	-4.8486*	-1.3864	-4.9118*
LnY^2	-1.1767	-4.9501*	-0.8006	-4.9926*
LnFPIW	-2.3313	-5.2081*	-1.5964	-8.5732*

Because all the series are integrated at *I(1),* we can move to the next step to find out whether the series are co integrated or not. We use the Johansen Co Integration test to find out the CI relationship among the variables. The results of the Johansen CI tests are shown in table 4.3. There are two further tests in the Johansen CI test; Trace and Max-eigenvalue test. Both these tests reject the null hypothesis of no CI equation at 5% level of significance for equation 1 & 6.

The results in table 4.3 suggest that there is at least one CI equation of $Ln(CO_2)$, LnY_t, $LnY^2{}_t$and $Ln(EC_t)$. In table 4.3, trace test suggests two co integrating equations at 5% level of significance with probabilities 0.0002 and 0.0194 respectively. Alternatively, Max-eigenvalue test suggests just one co integrating equation at 5% level of significance with probabilities 0.0057 and 0.171 respectively as shown in table 4.3. Therefore, we have taken the one cointegrating equation as indicated by the Max-eigenvalue test.

Table 4.3: Results of Johansen's Co-integration test

Equation (1) Variables: LnCO2, LnEC, LY, LnY^2

Eigenvalue	Trace Statistic	5% Critical Value	Prob.	Max-Eigen Statistic	5% Critical Value	Prob.	No of cointegrating Vectors
0.6160	86.066*	63.876	0.0002	39.245*	32.118	0.0057	None
0.4042	46.821*	42.915	0.0194	21.237	25.823	0.1798	At most 1
0.3472	25.582	25.872	0.0543	17.488	19.387	0.0924	At most 2
0.1791	8.0944	12.517	0.2441	8.0944	12.517	0.2441	At most 3

The results of the long run co integration equation for first model are given as:

$$Ln(CO_2) = 20.62 + 2.34Ln(Y) - 0.058(LnY)^2 + 0.95\big(Ln(EC_t)\big) - 0.012(T_t) \quad (62)$$

(-3.539) (2.471) (-6.699) (1.794)

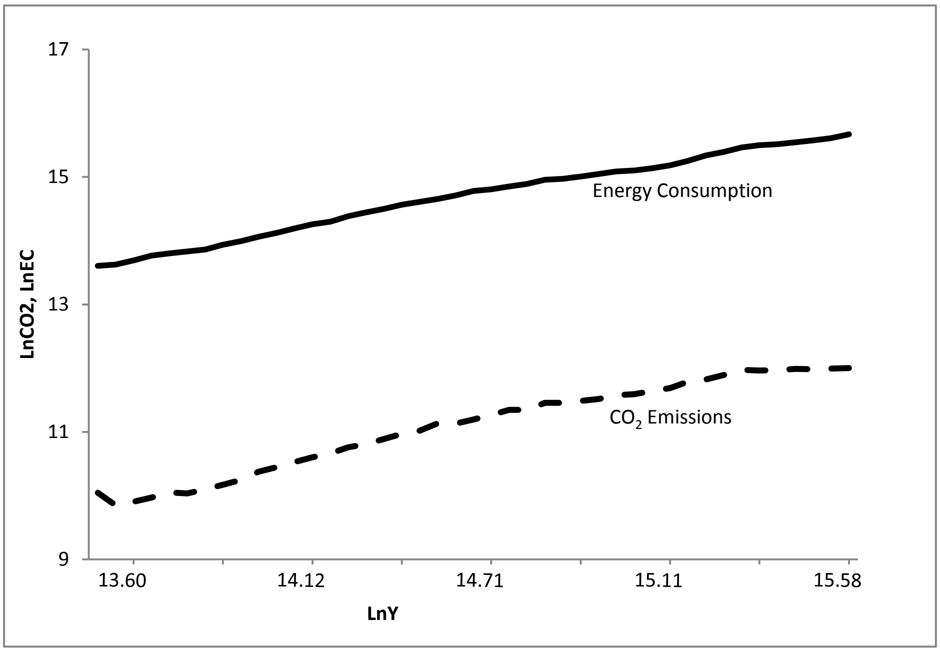

Figure 4.3: Relationship between GDP (Y) and CO_2 emissions and Energy consumption (EC)

The values in parenthesis show the t-values. All the variables are statistically significant and have expected signs in the long run relationship as shown in equation (62). There is monotonic increase between both (and real output and carbon emissions relationship, real output and energy consumption relationship) as the maximum value of real GDP (15.67) is less than the turning point value $\left[\frac{2.344}{2*0.058} = 20.02\right]$ (in logarithms). Carbon emissions and real output relationship from (1971 and 2013), and energy consumption and income relationship show a monotonic increase. The relationship of monotonic increase is shown in figure 4.3.

The results for equation (62) show that a 1% increase in real GDP increases the carbon emissions by 0.6% at mean data when energy consumption is kept unchanged. Similarly, a 1% increase in energy consumption increases the carbon emissions by 0.93% when real output is kept unchanged.

The results of short run dynamics for model 1 are given as:

$$\Delta Ln(CO_2) = 0.0171 - 0.352^{*}ECT_{t-1} - \ 0.265^{*}\Delta Ln(CO2)_{t-1} + 12.368^{*}\Delta Ln(Y)_{t-1}$$

(1.13) (-1.904) (-2.252) (2.670)

$$-0.413^{*}\Delta(LnY)^{2}{}_{t-1} + 0.844^{*}\Delta Ln(EC)_{t-1} \quad (63)$$

(-2.640) (2.571)

$$\Delta Ln(Y_t) = 0.0210^{*} - 0.130ECT_{t-1} + 3.3782\Delta Ln(Y)_{t-1} - 0.0972\Delta(LnY)^{2}{}_{t-1} +$$

(2.57) (-1.08) (1.32) (-1.142)

$$0.360^{*}\Delta Ln(EC)_{t-1} - 0.282^{*}\Delta Ln(EC)_{t-2} - 0.0019^{*}Dummies \quad (64)$$

(2.780) (2.416) (3.343)

$$\Delta Ln(EC_t) = 0.0031 - 0.217^{*}ECT_{t-1} - \ 0.200^{*}\Delta Ln(CO2)_{t-1} + 9.449^{*}\Delta Ln(Y)_{t-1}$$

(0.468) (-2.577) (-3.909) (4.512)

$$-0.303^{*}\Delta(LnY)^{2}{}_{t-1} + \ 0.034^{*}Dummies \quad (65)$$

(-4.309) (6.260)

The error correction term in equations (63) and (65) are statistically significant, whilst in equation (64) it is insignificant. The insignificant results of ECT in short run equation (64) indicate that real output is not impacted by the deviation from the long run equilibrium. Therefore, real GDP is weakly exogenous in short run to restore the long run equilibrium, whenever any shock occurs in the system. The behaviour of (LnY) is already estimated, hence, it is not needed to estimate $(LnY)^2$ in short run.

The results of long run Co integration equation for second model are given as:

$$Ln\left(\frac{C_t}{Y_t}\right) = 0.2354 + 0.49^{*}\left(Ln(FPIW_t)\right) - 0.016^{*}(T_t) \quad (66)$$

(2.9312) (-1.9332)

The results for the above equation indicate that a 1% increase in weighted average fuel prices increases energy intensity by 0.49%. The positive relationship between $\left(Ln(FPIW_t)\right)$ and $\left\{Ln\left(\frac{C_t}{Y_t}\right)\right\}$ is not according to theory though but it could be because of the nature of the data of energy intensity for Pakistan. Energy intensity has been increasing and going up for a long time from 1971 to 2000 and then it started decreasing after year 2000 for Pakistan. So, this continuous increase in intensity may have captured all the effect of prices and, that is why, here is positive relation between energy intensity and weighted average real fuel prices. The (*) Symbol shows that the variable is significant in the above equation, and t-values are mentioned in the parenthesis for further description.

The results of short run dynamics for equation (7) are given as:

$$\Delta Ln(EC_t) = \underset{(1.01)}{0.0261^*} - \underset{(-1.90)}{0.0820^*}ECT_{t-1} + \underset{(3.711)}{0.354^*}\Delta Ln(EC_{t-2}) - \underset{(-0.27)}{0.002^*}(trend) - \underset{(-4.393)}{0.095581^*}\text{Dummies} \qquad (67)$$

The speed of adjustment to restore the long run equilibrium in case of any shock is significant and equal to -0.082.

The results of derived equation for carbon emissions from equation (9) are given as:

$$\Delta Ln(CO_2) = \underset{(-0.602)}{-0.006} + \underset{(3.838)}{0.8439^*}\Delta Ln(Y_t) + \underset{(2.681)}{0.218^*}\Delta Ln(EC_t) - \underset{(-1.752)}{0.3445^*}\Delta Ln(Y_{t-1}) + \underset{(6.352)}{0.5385^*}\Delta Ln(EC_{t-1}) - \underset{(-2.02)}{0.0322^*}Dummies \qquad (68)$$

The CO_2emissions are generated by the equilibrium level of energy consumption. We find the results of equilibrium level of CO_2emissions in equation (68).

4.4.2 Constancy of Cointegration space

ECM equations (2) to (4) are based on Akaike Information Criterion (AIC), and face an important problem for the estimated parameters in that they may change over time. This change in parameters sometimes makes them unstable and the model is termed mis-specified. The constancy of the parameters is checked after the estimation of ECM. Brown et al. (1975) introduced the tests to check the constancy of the estimated parameters. These are called the cumulative of the recursive residuals CUSUM and the cumulative of the recursive residuals square CUSUMSQ tests. Figures 4.4-4.6 show the graphical results of these tests for the dependent variables ($Ln(CO_2)$, LnY_t and $Ln(EC_t)$). The graphical representation of both tests for said variables are within the critical bounds. Therefore, it is shown that the estimated parameters of ECM are stable as shown in figures 4.4-4.6. It can be concluded from (CUSUM) and (CUSUMSQ) tests that an uneven shock or major distortion in the level variables for the explanatory variables in ECM doesn't occur. All the parameters are showing a stable pattern in ECM at the time of the estimation process.

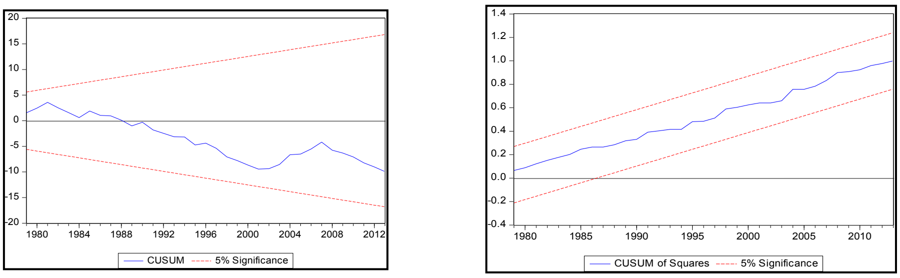

Figure 4.4: Plot of both CUSM and CUSMSQ for dependent variable LnCo2, 1971-2011

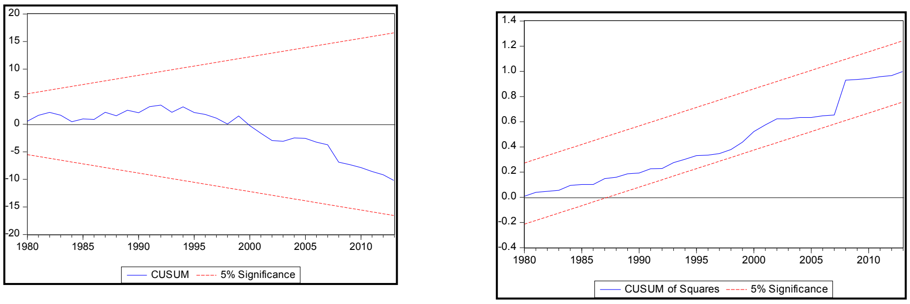

Figure 4.5: Plot of both CUSM and CUSMSQ for dependent variable LnEC, 1971-2011

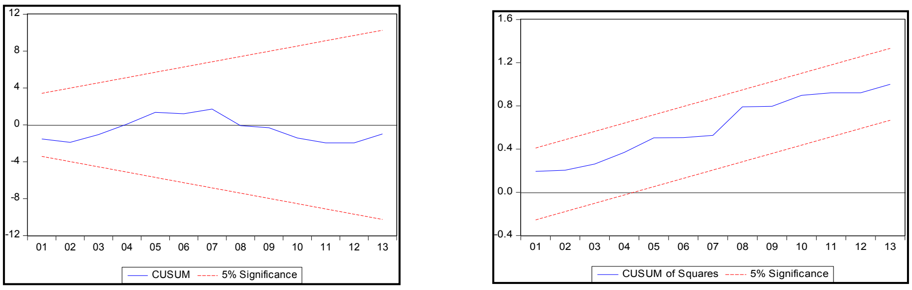

Figure 4.6: Plot of both CUSM and CUSMSQ for dependent variable LnY, 1971-2011

4.4.3 Forecasting of CO_2 *emissions*

Carbon emissions are forecasted using different techniques; Univariate (GP model and Exponential Smoothing technique) and multivariate (one step ahead forecast/static solution). Initially, one step ahead forecast technique is used for Models I&II then univariate model techniques are used to forecast CO_2 emissions for models III&IV (GP model is followed to forecast as introduced by J. L. Deng (1989) and others[67], while exponential smoothing techniques are used to forecast as introduced by Holt (1957) and winter (1960)).

Forecasting abilities of the one step ahead technique is used for Models I&II and these are compared with GP models and exponential smoothing techniques (Models III &IV)

[67] Many authors have followed the same technique introduced by J. L. Deng (1989) as: Huang, Lin and Liou (2011), Wang X, Chen Z, Yang C and Chen Y (1999), Tseng FM, Yu HC and Tzeng GH (2003), Lin CT and Yang SY (2003), Hsu LC (2003), Mao M and Chirwa EC(2006) etc

by using the actual data from 1971-2013 for carbon emissions. All available actual data (1971-2013) can be used by GP model to forecast the values from 2014-2030. However, we apply GP model in three groups as six years data (GP-6, 2008-2013), five years (GP-5, 2009-2013) and four years (GP-4, 2010-2013) in sample data to predict CO_2 emissions Because bigger values of "n" in GP model (e.g. GP-7, GP-10, GP-25, GP-43) give bigger errors after the estimation, smaller values of, GP-4, GP-5 and GP-6 are used to predict the value of CO_2 emissions. Data from 1971-2013 is used to predict the value of CO_2 emissions by using one step ahead forecast technique for Model I&II. Once the models are solved with the help of in sample data, predicted values can be found with the help of out of sample period.

By using the data from 1971-2013, EWMA method is used to forecast CO_2 emissions ($LnCO_2$) as shown in figure 4.7. This technique is good to forecast just one step ahead value.

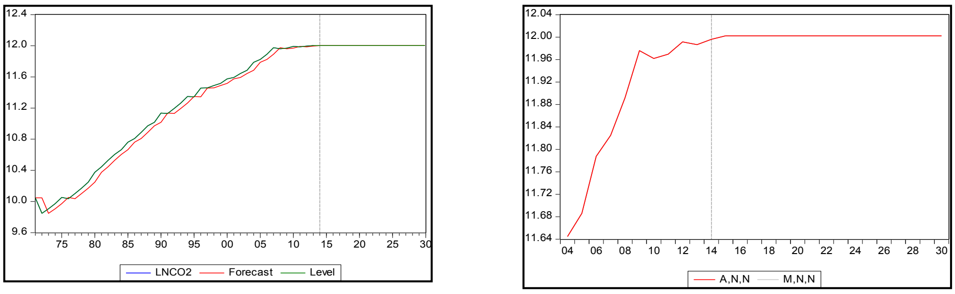

Figure 4.7: Forecasting CO_2 emissions ($LnCO_2$) performance by using EWMA

Holt's method is also used to forecast CO_2 emissions ($LnCO_2$) as shown in figure 4.8. The forecast results are shown in table 4.5. The best model is selected by using the Akaike Information Criteria (AIC).

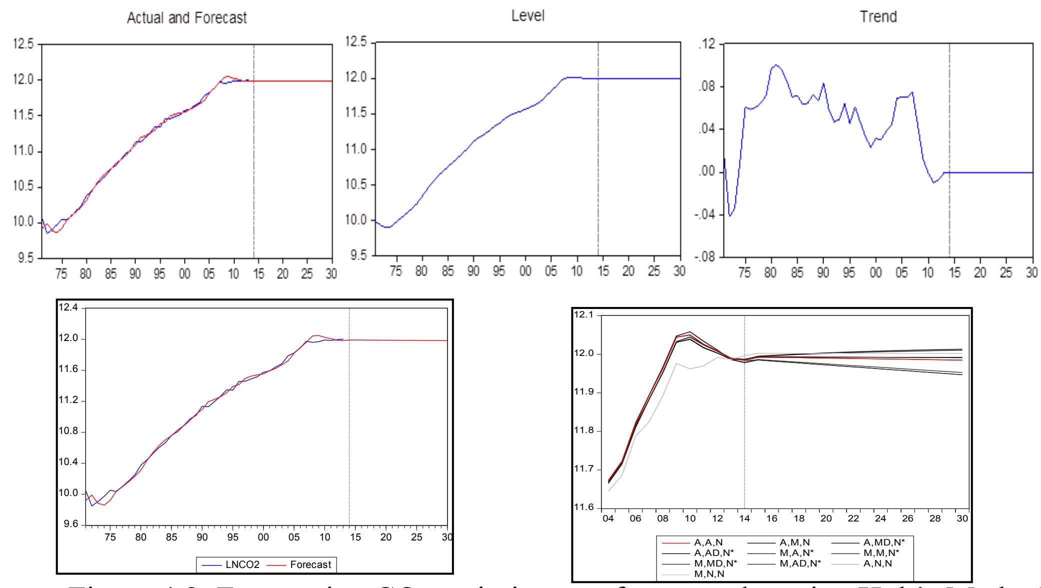

Figure 4.8: Forecasting CO_2 emissions performance by using Holt's Method

Table 4.4: Forecast Performance of Models

	Model I	Model II	GP-4	GP-5	GP-6	EWMA	Holt's
RD	0.0230	0.0094	0.0006	0.004	0.004	0.0106	0.0205
RMSE	3845.9	1809.0	115.7	858.2	794.3	2022.1	3701.4
MAE	3729.4	1518.9	99.81	668.3	662.9	1717.3	3318.3
MAPE	**2.30%**	**0.94%**	**0.06%**	**0.41%**	**0.41%**	**1.06%**	**2.05%**
Theil	0.0117	0.0056	0.0004	0.003	0.002	0.0063	0.0114

*GP-4, GP-5 and GP-6 show that the values of 2010-2013 (n=4), 2009-2013 (n=5) and 2008-2013 (n=6) are used respectively to forecast by using the methodology of GP model.

Prediction accuracy is checked by using five evaluation statistics as Relative deviation (RD), the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and the Theil index (TI).

Table 4.5: Forecast of CO_2 emissions

Years	t value	Actual	Model I	Model II	Model III (GP-4)	Model IV (Holt's)
2010	0	**161396**	163746	161891	**161396**	167057
2011	1	160592	165345	161571	160717	164302
2012	2	162141	165540	163636	161992	161018
2013	3	163152	167566	166258	163277	160373
2014	4		166687	158771	164572	161541
2015	5		172915	166017	165877	161457
2016	6		178257	171634	167192	161373
2017	7		183611	181636	168519	161289
2018	8		189389	189876	169855	161205
2019	9		195042	199527	171202	161121
2020	10		200575	207274	172560	161037
2021	11		206131	214937	173929	160953
2022	12		211628	220909	175308	160869
2023	13		217023	226346	176699	160785
2024	14		222342	230592	178100	160701
2025	15		227570	234405	179513	160617
2026	16		232679	237572	180936	160534
2027	17		237662	240562	182371	160450
2028	18		242512	243320	183818	160366
2029	19		247209	246109	185276	160283
2030	20		251741	248907	186745	160199

Seven models (Model I, Model II, GP-4, GP-5, GP-6, EWMA and Holt's)) are estimated to check the forecasting performance for CO_2 emissions as shown in table 4.4. A MAPE accuracy criterion is followed by Lewis (1982), and can state that results of all seven models are showing highly accurate forecast. GP, EWMA and Holt-Winters models are only forecasting the local trend and MAPE is less than 3 percent. In the grey prediction model four future values are taken to forecast the present value which is why the errors are very low. The MAPE value for GP-4 model is 0.06%, while MAPE value for GP-5 model is 0.412% and 0.413% for GP-6 model. As we need to opt just for one model among all three GP models, GP-4 model is used as the MAPE value of said model is less than the other two models (GP-5 and GP-6). Among the three GP models we need to select one to compare with Model I, Model II and Model IV (Holt's) forecasting performance. GP-4 model is chosen with minimum errors. The MAPE value for EWMA model is 1.06% and 2.05% for Holt's model, while the MAPE value for one step ahead forecast for Model I and Model II are 2.30% and 0.94%. Finally, CO_2 emissions for Pakistan is forecasted from 2014-2030 by using four different models (Model I, Model II, Model III (GP-4) and Model IV (Holt's method). The first forecasted value turns up exactly the same as actual value according to GP model as shown in table 4.5.

4.4.4 Criticism on Grey Prediction Model

Few (four, five or six) future years information is used to estimate GM (1, 1) to forecast present value. According to the results of table 4.5 and figure 4.9, it is analysed that the GM (1, 1) is forecasted by using (GP-4, or n=4) with an error of 0.06%. According to figure 4.2, it is also shown clearly that there are ups and downs in the CO_2 emissions graph from 2007 to 2013. To get an accurate forecast, it is not really helpful to use future values, when there is too much of a discrepancy in the data. It is claimed in the literature that GP model has become a popular tool for forecasting in comparison to other systems with a complex, uncertain and chaotic nature structure[68]. The GP model is used in forecasting studies due to small amounts of data being required and results are achieved with minimum errors. The reason for this is the extension of the trend and forecasting is done on the basis of future values. The standard account of grey prediction model is actually an example of in sample forecasting. GM (1, 1) is a univariate model to forecast the variables, and is used in the field of economics particularly in the field of energy.

In an earlier section of this chapter, CO_2 emissions are forecasted with the help of GM (1, 1). Time series data is used from 2010-2013 to forecast the value of CO_2 emissions from 2010-2030 by using standard GP model. All the steps of standard GM (1, 1) are followed and forecasts are carried out for 2010-2030. According to the property of grey

[68] Akay and Atak (2007), Yao et al. (2005), Zhon et al. (2006) and Yao and Chi (2004) use the GP model to forecast energy. They analyse that GP model provides better results as compare to other models.

model there should be time series data with at least four values of a variable. In the estimation, n=4 (GP-4), n=5 (GP-5) and n=6 (GP=6) are used to forecast. Some bigger values of n (e.g. n=20 or GP-20, n=30 or GP-30 and n=40 or GP-40) are also attempted to forecast, however the errors are very high for such n values. By following the rule of GM (1, 1) model, the errors among the actual and predicted values are calculated for different n's. According to the results for errors (GP-4) or n=4 is given with minimum errors of 0.06 as compared to the other values as shown in table 4.4. Therefore, the minimum errors series is selected with n=4 and a forecast is made from 2010-2030.

To enhance the effectiveness and accuracy in errors for GM (1, 1), some studies have been developed to improve GP model by Hsu and Chen (2003), Hsu (2003), Hsu and Wang (2007), Wang and Hsu (2008), Bianco et al. (2010), Tan and Chang (1996), Tan and Lu (1996), Guo, Song and Ye (2005), Yao and Chi (2004), Huang and Wang (2001), Lin, Su and Hsu (2001), Yao, Chi and Chen (2003), Yao and Chi (2004), Pao, Chang and Tsai (2008) and Fu and Tseng (2012) but they also used the future values to predict for the present. Modified grey prediction model has been introduced by them with some additional information but with the same methodology. The same GP system is followed by all of them and in all of the studies minimum data is used to forecast. Fewer errors are given by using minimum data thus, it is preferred and suggested by all researchers to use a small amount of data.

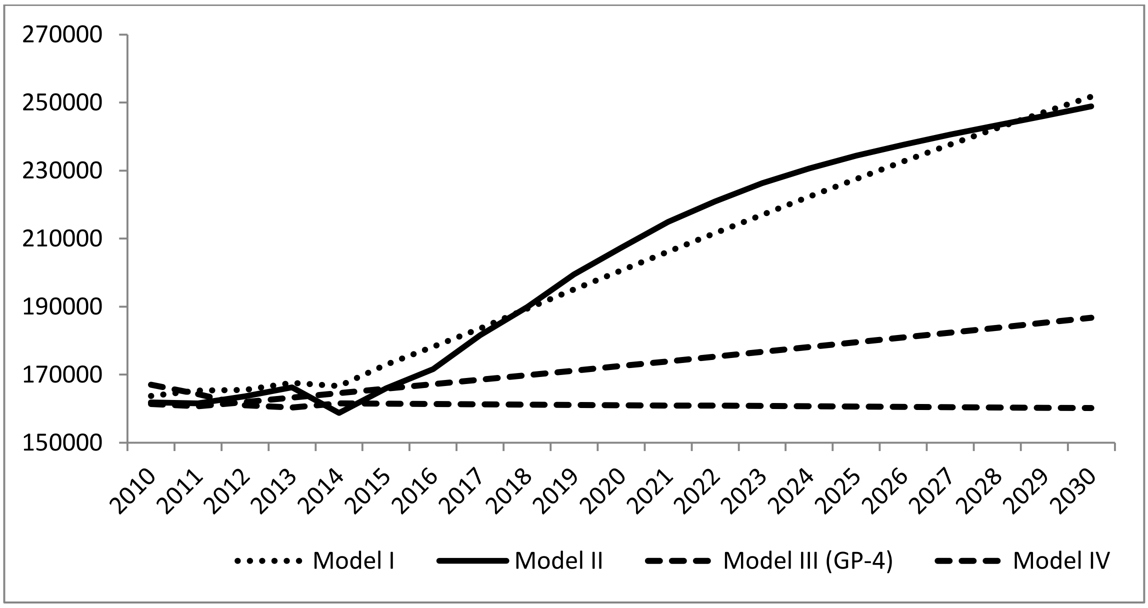

Figure 4.9: Forecasting CO_2 emissions performance results for four models

In GP model, the predicted values of a time series data are estimated by using the standard methodology of this model, which are only based on a set of the most recent

data. It also depends on the size of the predictor (n) and error accuracy. It is assumed that the sampling frequency of the time series in GP model is fixed. The requirement is to have at least four years data to get successful forecasting results in GP model, (Song (1992), Hsu and Wen (1998), Hsu (2003), and Lin and Yang (2003). But in reality they have been using four future values instead of lag values.
Motivated by the importance of forecasting the CO_2 emissions, this study proposes an Out Of Sample Grey Prediction model (OOSGP model) which criticizes the methodology of GP model. As GP model is being used in different fields but with wrong methodology. The aim is to attempt to provide a better way of using this technique (GP model) with out of sample forecasting. The new model could be established to improve the predictive accuracy of the GP model. An OOSGP model has been introduced to solve this problem which is explained in section 4.4.5.

Alternatively, one step ahead forecast (static solution) is used to estimate MAPE. The MAPE values turn up 2.30% and 0.94% for Models I&II. According to table 4.4, it is observed that the forecast for all models is accurate. The graphical representation is shown in figure 4.9 for all four models from 2010-2030. However, there are some significant problems in GP model which may need further attention. Forecast by GP model as compared to other models is completely different in nature, because the GP model has fewer errors it is extending the local trend and using future values to forecast present values. Because of this, it cannot be said to be an accurate forecast. While the one step ahead forecast has used all the available data in all the variables to forecast the CO_2 emissions, the GP model has used just a few future observations to forecast for the next twenty years and challenges to have the best forecast when we compare the errors. It is worth applying GP model as many researchers have applied it in different fields, but with correct methodology and concept.

4.4.5 Out Of Sample Grey Prediction (OOSGP) Theory

Motivated by fewer errors and accurate results in the forecast, we would suggest using out of sample grey prediction (OOSGP) modelling. The first objective of OOSGP model is to use the lag values instead of using future values. Also, to find better results, the model uses all the available data by applying the same univariate model (GP model) on lag values. Furthermore, OOSGP Modelling is attempting to change and modify GP model which has been used fundamentally incorrectly. Finally, the standard GP model technique is being estimated as an in sample forecast and the aim is to introduce proper out of sample forecast. OOSGP model forecasting technique is established by us to forecast the variable in GM (1, 1). By using data from 1971-1974, the value of 1975[69] is forecasted. This forecasting is done on the same procedure as earlier by following the same steps. Thus, the forecasted value of 1975 is considered as one step ahead forecast and the actual data is used from 1972-1975 (n=4) to forecast 1976. To find out the forecast for 1977 the lag values of 1973-1976 (n=4) are used by using the GM (1,1) methodology. Similarly, to find out the future one step ahead forecast, the four lag values are used every time to estimate GM(1,1) model. GP model is estimated thirty nine times by using the lag values as n=4 to find out the one step ahead forecast.

The lag values of n=4 are used to find out the forecast of next year's values as 1975, 1976,…., 2014. This OOSGP forecasting is shown in table 4.6. The OOSGP forecasting of CO_2 emissions commenced from 1975 by using the data from 1971-1974. The final values of CO_2 emissions are found for 2014 by using OOSGP forecasting. This time, GP models are estimated thirty nine times by using the four lag values (n=4) to estimate one step ahead forecast as GP-4. The values for 2014 are also forecasted by using the same procedure.

Finally, the forecasted value for 2014 is considered as actual value and values from original data are taken for 2011 to 2013 (n=4). By using the lag values of 2011-2014 the forecast for 2015 is estimated by using the same methodology (n=4). To forecast the values of CO_2 emissions from 2014-2030, the forecasted value of 2010-2013 are used for n=4 by following the same procedure[70]. The forecasted value of CO_2 emissions for one step ahead forecast are used as actual values and forecasted values are estimated for CO_2 emissions from 2014-2030. The forecasted value of CO_2 emissions is not equal to actual value by using OOSGP model, it can be seen in table 4.8.

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[69] The forecast of 1975 is found by using the same procedure as by J. L. Deng (1989) but with lag values. It is tried to avoid using future values to forecast for present. The addition in GP model is occurred.

[70] This forecasted value of CO_2 emissions for 2014 is shown in table 4.6. This is the same forecasted value of CO_2 emissions from 2010-2013, which is estimated by using the OOSGP forecasting in univariate model (GM (1, 1)). To find out the forecast for CO_2 emissions for 2015, this 2014's estimated value is treated as actual value with the actual values of 2011, 2012 and 2013 to fulfil the requirement of n=4. Once the forecast for 2015 is attained then this 2015's forecasted value is treated as actual value and 2012, 2013, 2014 values are also used to fulfil the requirement of n=4. Finally, the same procedure of n=4 is used to forecast CO_2 emission from 2014-2030.

Table 4.6: CO_2 emissions from (1975-2013) by using one step ahead forecast for grey prediction model

Years	Actual CO_2 emissions	Predicted values of CO_2 emissions by OOSGP	Years	Actual CO_2 emissions	Predicted values of CO_2 emissions by OOSGP
1971	23076.43	-	1993	78008.09	74243.33
1972	18929.05	-	1994	84839.71	83315.77
1973	20036.48	-	1995	84484.01	91378.42
1974	21418.94		1996	94447.25	89024.65
1975	23219.44	22746.91	1997	94711.27	98152.60
1976	22838.07	24939.94	1998	97663.21	101707.41
1977	24389.21	23923.32	1999	100384.15	98881.55
1978	26138.37	24691.86	2000	106449.33	103387.73
1979	28250.56	27937.93	2001	108282.83	110638.60
1980	32067.91	30356.94	2002	114084.07	113118.40
1981	34400.12	35302.04	2003	118895.11	117499.73
1982	37385.06	38147.85	2004	131601.26	124744.07
1983	40303.99	40279.01	2005	136636.07	140258.80
1984	42856.22	43637.37	2006	146074.95	147569.15
1985	47175.95	45941.01	2007	158894.77	153263.88
1986	49453.16	50802.35	2008	156676.24	170896.66
1987	53534.53	53413.33	2009	157890.01	164595.86
1988	58213.62	56776.37	2010	161395.67	156814.48
1989	60956.54	63082.20	2011	160591.73	163440.67
1990	68565.56	65327.09	2012	162140.78	162666.72
1991	68242.87	73762.74	2013	163151.61	162124.36
1992	72789.95	73375.34	2014		164535.00

The final forecast equation for CO_2 emissions can be written as[71] by using the GM (1, 1).

$$(CO2)_0(t+1) = (1 - e^{a})\left((CO2)_0 - \frac{b}{a}\right)e^{-a(t+1)} \qquad (7)$$

[71] The resultant equation is found for CO_2 emissions, when n=4 after the OOSGP forecast.

Table 4.8 shows the forecasting performance of all four models[72]. It is also shown in table 4.8 that the forecast results of CO_2 emissions are lying in the criteria of highly accurate forecast for three models (Model I, Model II and Model IV) as per criteria of Lewis (1982) while one model is just showing the good forecast accordingly. The MAPE value is 2.47% for model I, 1.36% for model II, 3.21% for model III and 2.93% for model IV as shown in table 4.7. The graphical representation of the actual and forecasting trend for all four models is shown in figure 4.10. Among all four models, the best forecasting results are provided by model II&I with mean absolute percentage error of 1.36% and 2.47%. It is observed in the data and in figure 4.10 that the GP model, Holt's model is using the little local trend. The last couple of year's trend is extended in the final forecast results of GP and Holt's model. By taking the trend for a long period of time GP model does not provide minimum errors.

Table 4.7: Forecasting performance of three models (1971-2013)

	Model I	Model II	Model III (OOSGP)	Model IV (Holt's)
RD	0.0247	0.0136	0.0321	0.0293
RMSE	2950.1	2000.4	3845.2	4003.2
MAE	2202.6	1270.1	2730.3	2605.1
MAPE	**2.47%**	**1.36%**	**3.21%**	**2.93%**
Theil	0.0148	0.010	0.0193	0.0201

The forecast results are highly accurate in table 4.8 by using the minimum error information of MAPE in table 4.1.

4.5 Conclusion

Many challenges have to be met nowadays within the energy system. Energy economic models can be a helpful tool to inform us of the right direction and to make future decisions clearer. Within the energy economic models, different approaches are used with both advantages and problems. Suitable energy economic models can be found and an adequate tool can be applied to consider economic parameters. In this case, the required data can be accessed to run the model. Five different models are used in this chapter to forecast CO_2 emissions in Pakistan to guide development policy.

[72] One step ahead forecast for Models I&II, IV remains the same. While the results for forecast of CO_2 emissions for Model III are taken from GM (1, 1) by using n=4 for OOSGP. The forecasted values of model I&II and IV remain same but the errors are checked from 1975-2013.

Table 4.8: Forecast of CO_2 emissions

Years	Actual	Model I	Model II	Model III (OOSGP)	Model IV (H-W)
2010	**161396**	163746	161891	**156814**	167057
2011	160592	165345	161571	163441	164302
2012	162141	165540	163636	162667	161018
2013	163152	167566	166258	162124	160373
2014	-	166687	158771	164536	161541
2015	-	172915	166017	165686	161457
2016	-	178257	171634	167007	161373
2017	-	183611	181636	168229	161289
2018	-	189389	189876	169532	161205
2019	-	195042	199527	170797	161121
2020	-	200575	207274	172102	161037
2021	-	206131	214937	173396	160953
2022	-	211628	220909	174713	160869
2023	-	217023	226346	176030	160785
2024	-	222342	230592	177363	160701
2025	-	227570	234405	178701	160617
2026	-	232679	237572	180051	160534
2027	-	237662	240562	181410	160450
2028	-	242512	243320	182779	160366
2029	-	247209	246109	184157	160283
2030	-	251741	248907	185546	160199

Six GHGs are addressed by Kyoto Protocol including CO_2 emissions. CO_2 is considered the most frequently blamed factor in climate change. According to the forecasting results of three models (Model I, Model II and Model III) in this chapter, it is clear that CO_2 emissions will be increasing in Pakistan in the next twenty years as shown in table 4.8. Because of limited natural resources, Pakistan does not fulfil its energy needs by itself and relies on energy imports. Pakistan is not bound by Kyoto Protocol, but this important issue of CO_2 emissions should be considered by Pakistan as they are a member of the global village. Forecasted values in Model IV are based on local trend, which is why CO_2 emissions are showing a decreasing trend from 2014-2030.

Firstly, the purpose of this study is to determine the long run relationship among CO_2 emissions, energy consumption and real output for Pakistan over the period from 1971 to 2013.

Secondly, the aim is to find out the predicted values for CO_2 emissions from 2014 to 2030 by using different models. According to results, CO_2 emissions are found to be elastic with both energy consumption and real output in Pakistan. EC is a very important determinant of CO_2 emissions as compared to real output. Unfortunately, there is very little contribution from the energy sector of Pakistan in the way of greenhouse gas (GHG) emissions. There is an inverse U shaped relationship between EC and real output, and also the EKC hypothesis is supported by the results. There is monotonic increase between both real output and CO_2 emissions and EC and CO_2 emissions, as the turning point value (20.02) is greater than the maximum value of real output (15.67) for the time period 1971-2013 in Pakistan as shown in figure 4.2. Once the threshold level of GDP is attained, then real output starts decreasing. At this point, the real output becomes negatively related with EC and CO_2 emissions. In response, the economies grow and the demands for environmental quality increase. The EKC hypothesis enriches the specification by introducing the squared term of the GDP in the long run model. It helps in deriving the optimal level of income after that the relationship between income and emission becomes negative. The optimal log level of real GDP value is 20.20 that has not been achieved yet.

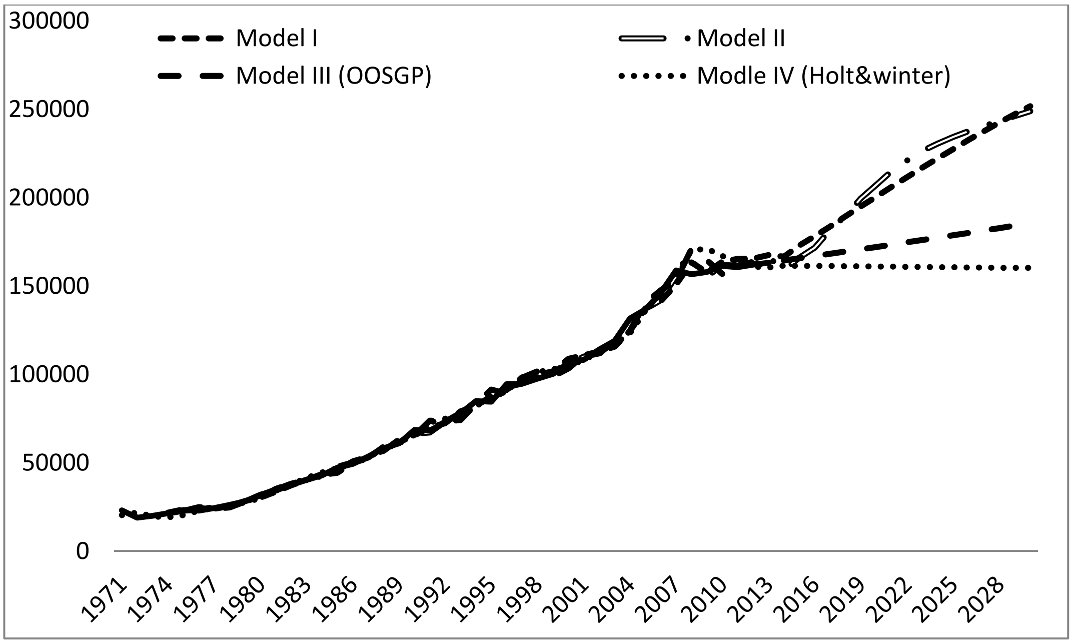

Figure 4.10: Actual and Forecasting results of all four models

Thirdly, the univariate models (GP, EWMA and Holt's models) are applied to predict $CO_2\ emissions$ from (2014-2030) by using the recent year's data and different techniques. The forecasting performance of GP models and Exponential smoothing models are compared with the one step ahead forecast for Model I&II for the time period from (2014-2030). GP-4 is chosen on the basis of lowest value of MAPE among

GP-4, GP-5 and GP-6. Furthermore, GP-4 forecasting performance is compared with the one step ahead forecast for CO_2 emissions. It is analysed that GP-4 (univariate model) provides a forecasting performance on the basis of future values and local trend is tried to build as compared to the other models. GP-4 provides the forecasting performance with MAPE as less than 3%, while the model I, model II (static solutions or one step ahead forecast) performance estimates the MAPE value as 2.30% and 0.94%. Although it looks GP-4 model has an accurate forecast after comparing the MAPE values of all models. But it shows at the end of section 4.2.3 that GP theory is used fundamentally incorrectly and future values are used to predict present values. The forecasting results for GP-4 in table 4.5 are not reliable as those are based on future values rather than lag values.

Fourthly, the out of sample grey prediction (OOSGP) model is introduced after criticizing the in sample GP model. New techniques are used to solve the OOSGP models and future values are avoided for use. Analysis shows the results of OOSGP model are better than the standard account of GP model as no future values are used in OOSGP model. One step ahead forecast is used to estimate Model I&II by using the data from 1971-2013 and they provide accurate results. The forecasting performance is verified by MAPE criteria in all four models. The MAPE for Model I is observed as 2.47%, errors for model II are observed as 1.36%, errors of model IV are observed as 2.93% and lastly errors for OOSGP model (Model III) are observed as 3.21%, As model III (OOSGP model) and Model IV (Holt-Winters model) is based on a local trend and forecasting is an extension of a small trend. The latest trend is always taken to build the forecasting performance as shown in figure 4.10. While Model I&II are forecasted by using all the available information in the model solving technique, it is not just the trend forecasting. The graph for actual and forecasted trends for all four models is also shown in figure 4.10 for better understanding.

Finally, through this study, the out of sample grey prediction model seems to provide an appropriate forecasting method to yield accurate results as compared to the standard account of in sample grey prediction model GM (1, 1). The general approach of OOSGP model can also be extended to other fields.

Pakistan should effectively conserve CO_2 emissions, respond actively to climate change and protect the environment. These findings provide a reference with which Pakistan's government could establish a measure to control CO_2 emissions with increase in GDP. The principle factor of continuous increase in the CO_2 emissions in Pakistan is the heavy reliance (99 percent) of Pakistan's energy consumption on fossil fuel energy (sheikh 2010). CO_2 emissions and energy consumptions increase with the increase in GDP as shown in figure 4.3. The increase in CO_2 emissions and energy consumption could be conserved by formulating an energy tax and the environment could also be protected. Non-carbon and low carbon renewable energy sources (such as solar energy, wind power and hydro power) could be used as a substitute to fossil fuel energy to conserve GHGs emissions (especially CO_2 emissions). The government should encourage their enterprises and citizens to use energy in an efficient way and also government should introduce the policies and promotions with which energy consumption could be controlled. Vigilance about the efficient use of energy could be promoted in all sectors. The government of Pakistan can use these results to adjust the environmental and energy policies, and Pakistan can also achieve the optimal level of economic development by considering those policies.

Chapter 5

Conclusion

To follow the objective to deal with energy, environment and economics, several approaches are used to look at the Green House Gases GHGs) emissions (specifically CO_2 emissions) and energy efficiency. It is attempted to show that a simple theoretical frame work does not provide the best solution. Econometric modelling for the energy sector of Pakistan measures such a relationship with accuracy by following Kalman Filter (KF) technique. Furthermore fuel mix/fuel substitution is discussed and three types of taxes are discussed in the simulation period (1971-2030) as, carbon tax, flat-rate tax and ad valorem tax which could not reduce the carbon emissions because of complexities in the fuel markets which are very high in Pakistan. It has been assumed in earlier times, that to reduce the GDP of oil importing countries would decrease energy consumption as a direct response to a decrease in energy prices. This was wrongly interpreted. In this case, carbon tax did not have any great effect on GDP, energy consumption or external prices. In the first analysis by following the methodology of KF in endogenous Technical Change (TC) model, it is shown how energy intensity decreases with the increase in prices and also that irreversible improvement are achieved in energy efficiency. Both exogenous TC model and endogenous TC model were used to find the elasticity and dynamics of the model to check the short and long run effect for stabilisation of CO_2 emissions.

Exogenous TC model does not provide any authentic solution to find the stabilised level of carbon emissions in the long run unless the continuous increase in energy prices is always greater than the economic growth forever. But this cannot be true because fossil energy consumption will achieve stabilisation level at that certain price level due to increasing use of non-polluting alternatives. We try to overcome this limitation in increasing Global Econometric (GE) models but no empirical evidence is provided for this assumption. On the other hand, in the endogenous trend model, non-growing energy prices with steady growth are found stable from energy use. The reduction in carbon emissions are discussed with the help of estimation results and simulation properties by following some key points. Firstly, exogenous TC model estimates the price elasticity 0.49 for Pakistan which means there is a positive relationship between energy intensity and fuel prices (which is not according to theory) while the endogenous TC model provide correct results by having negative elasticity. Secondly, stabilisation in CO_2 emissions can only be found in the short run by using the analysis of inter-fuel substitution while in the long run improved technology or innovation will be in a position to achieve the required level but too much time is needed to start working on the long run plans. Thirdly, imposing a carbon tax will provide opportunities for the private sector to invest in speculative R & D, but the investment will become sub-optimal because of regulatory uncertainty. Lastly, one possible policy option is to start investing a portion of gained revenue from carbon tax in different projects of energy saving investments via private or public sectors to control these small energy elasticities. This investment could be used in institutional changes and in several fields by the public sector as energy labelling, building regulations and energy efficiency research which is not encouraged by the private sector. Some problems arise in the energy elasticity estimates as; when low income house hold start investing through finances in the energy sector or energy related sector, and when people get unexpected incentives while living in rented or public (subsidised) houses, then the above policy implications give the advantage of overcoming market failure which is caused by these elasticity estimates.

After checking the stabilisation techniques for CO_2 emissions, energy efficiency is estimated for 19 Asian developing countries for the period of (1980-2013). Underlying energy efficiency is estimated for each country by combining the two approaches which are used in energy demand modelling and stochastic frontier analysis. In the model, some variables (energy price, income, population, FDI, urban population, industrial structure, area, agriculture, services etc.) are controlled by energy demand to find the measure of energy efficiency by using the stochastic demand frontier (as previously the work is done to estimate cost and production) thus underlying energy efficiency (which reflects the relative use of inefficient use of energy or “waste energy”) is found in this present work. To estimate energy efficiency by using a full frontier model some time suggests that energy intensity for a number of countries may give the indication of efficiency improvement, but this is not always the case for all countries over time. A prime example of Afghanistan is undertaken for better understanding. According to table 3.7 and figure 3.3, it can be seen that Afghanistan is the 2nd energy intensive country while it is the third last energy efficient country. Similarly, Jordan is the 4th energy intensive country by estimating the simple energy intensity method while it is the least efficient country with a rank of 19 by using the estimation method of average underlying energy efficiency among all Asian developing countries which are considered in the analysis from 2000-2013. It means on one side Jordan is a high energy intensive country and on the other hand it is the least energy efficient country. So, it is suggested that without conducting this analysis for underlying energy efficiency it may not be possible to tell which country's energy intensity is a good proxy for its energy efficiency. The main finding in this research is to give some additional indicators to the policy makers with reference to table 3.7. According to this table, it is shown that underlying energy efficiency should be estimated to find out the exact picture of the country's situation rather than just doing the analysis of energy intensity. To follow the energy intensity for the country's energy conditions, it could be misleading for the policy makers. It is not claimed that energy efficiency can only be measured by using stochastic demand frontier approach. The purpose of this study is also not to give a definite answer on how to measure the level of energy efficiency by using stochastic demand frontier approach. This attempt is to give further room to improve the models and methods for the analysis of measuring the aggregate energy efficiency for future research.

The long run relationship is determined among CO_2 emissions, energy consumption and real output for Pakistan over the period from 1971 to 2013 which verifies the Environment Kuznets Curve (EKC) hypothesis. There is monotonic increase between both real output and CO_2 emissions and Energy Consumption (EC) and CO_2 emissions, as the turning point value (20.02) is greater than the maximum value of real output (15.67) for the time period 1971-2013 in Pakistan as shown in figure 4.2. Once the threshold level of GDP is attained, then real output starts decreasing. At this point, the real output becomes negatively related with EC and CO_2 emissions. In response, the economies grow and the demands for environmental quality increase. The EKC hypothesis enriches the specification by introducing the squared term of the GDP in the long run model. It helps in deriving the optimal level of income which the relationship between income and emission becomes negative. The optimal log level of real GDP value is 20.20 which has not been achieved yet.

Energy economic models can be a helpful tool to inform us of the right directions and to make future decisions clearer. Within the energy economic models, different approaches are used with both advantages and disadvantages. To forecast the CO_2 emissions in Pakistan five different models are used in the fourth chapter to guide development policy. According to the forecasting results of three models (Model I, Model II and Model III) in that chapter, it is clear that CO_2 emissions will be increasing in Pakistan in the next twenty years as shown in table 4.8. Forecasted values in Model IV are based on local trend, which is why CO_2 emissions are showing a decreasing trend from 2014-2030.

The predicted values for CO_2 emissions are found from 2014 to 2030 by using different models (Grey Prediction (GP) model, Exponential Smoothing (ES), Holt-Winter (H-W), Out of Sample Grey Prediction (OOSGP) model and model solving technique. The forecasting performance of GP models and ES models are compared with the one step ahead forecast for Model I&II for the time period from (2014-2030). GP-4 (four lag values are taken to forecast) is chosen on the basis of lowest value of MAPE among GP-4, GP-5 (five lag values are taken to forecast) and GP-6. Furthermore, GP-4 forecasting performance is compared with the one step ahead forecast for CO_2 emissions. It is analysed that GP-4 (univariate model) provides a forecasting performance on the basis of future values and local trend is built as compared to the other models. GP-4 provides the forecasting performance with MAPE as less than 3%, while model I and model II (static solutions or one step ahead forecast) performance estimates the MAPE value as 2.30% and 0.94% respectively. Although it looks like GP-4 model has an accurate forecast after comparing the MAPE values of all models, it shows at the end of section 4.2.3 that GP theory is used fundamentally incorrectly and future values are used to predict present values. The forecasting results for GP-4 in table 4.5 are not reliable as those are based on future values rather than lag values.

Motivated from incorrect form of GP, it attempted to improve it by introducing Out Of Sample Grey Prediction (OOSGP) model after criticizing the in sample GP model. New techniques are used to solve the OOSGP models and future values are avoided. Analysis shows the results of OOSGP model are better than the standard account of GP model as no future values are used in OOSGP model. One step ahead forecast is used to estimate Model I&II by using the data from 1971-2013 and they provide accurate results. The forecasting performance is verified by MAPE criteria in all four models. The MAPE for Model I is observed as 2.47%, errors for model II are observed as 1.36%, errors of model IV are observed as 2.93% and lastly errors for OOSGP model (Model III) are observed as 3.21%, As model III (OOSGP model) and Model IV (Holt-Winters model) is based on a local trend and forecasting is an extension of a small trend, the latest trend is always taken to build the forecasting performance as shown in figure 4.10. While Model I&II are forecasted by using all the available information in the model solving technique, it is not just trend forecasting. The graph for actual and forecasted trends for all four models is also shown in figure 4.10 for better understanding. Through this study, the out of sample grey prediction model seems to provide an appropriate forecasting method to yield accurate results as compared to the standard account of in sample grey prediction model GM (1, 1). The general approach of OOSGP model can also be extended to other fields.

As per forecast, CO_2 emissions is going to increase in next 20 years in Pakistan, So some policy implication should be opted in Pakistan by considering the efficient use of energy. As aforementioned this issues that we should always use the right methodology to find out the correct effects. As, in our study, we used two models in the second chapter to find out the stabilisation of CO_2 emissions. According to endogenous technical change model the estimated results say, because of the higher use of energy there is a higher rate of decline in it, which shows a symptom of energy efficiency convergence in the long run. While the exogenous technical change model was just showing that GDP is linked with the time trend. It means either we can use the right methodology to find out the efficient use of energy, alternatively, we can use the mentioned approach in chapter 3 to find out the exact picture of efficient use of energy. It means to use the energy efficiently the CO_2 emissions could be stabilised by increasing the prices or in the form of taxes as discussed in chapter 2. In fact, to stabilise CO_2 emissions the efficient ways of energy use should be adopted. So, the second chapter finds the right methodology for the stabilisation of CO_2 emissions, while it is attempted to find either energy intensity is right proxy for energy efficiency or not in third chapter. Similarly, fourth chapter also contribute in the way of forecasting the CO_2 emissions. This is also very important that we use the right methodology to forecast any variables. In our study, we used five different techniques to forecast CO_2 emissions and also introduced one new technique as Out Of Sample Grey Prediction (OOSGP) technique. The forecasting results are also found by using this technique and, later on, these results are also compared with other techniques. According to the results, in comparison, the new technique does a good job as compare to Grey Prediction (GP) model. Here are some possible recommendations/points in the form of policy implications and the strategy of Pakistan to control CO_2 emissions as, research on climate change could be promoted, Infrastructure of any project should be designed in the energy efficient way, Shift of renewable energy from non-renewable energy (e.g. solar, wind, hydro, or any other energy) could be adopted, vigilance about energy conservation could also be spread, taxes on CO_2 emissions in different sectors (transport sector, industrial sector, etc.) could be implemented, Innovation in technology or import of advanced technology should be encouraged, environment policies should be designed in the way that all the industrial sector adopt the efficient use of energy to keep the environment clean and produce les environmental pollution, subsidies could be given on the renewable energy projects on domestic and national level to reduce pollution, the production of the outputs should also be controlled according to CO_2 emissions policies in Pakistan as some of the exporting outputs really become the reason for huge CO_2 emissions, lastly, the proper measurement of CO_2 emissions, energy efficiency and forecast of CO_2 emissions should be focused on country level which could also help any economy to keep the environment clean.

The purpose of this research is not just limited to Pakistan. Endogenous model could be used globally to find out the correct impact of the variables and the stabilisation of CO_2 emissions could be achieved. If the proper estimation methodology will be used then it will really be helpful for the policy maker to improve the weakness of economy. In our study, the suggestions about the correct methodologies are given. In Pakistan, as far as known, such methodological issues are not pointed out which are discussed in our study. It is assumed that by using these methodological issues the policy makers will get the right figures of forecasting, stabilisation of CO_2 emissions and also the difference between energy intensity and energy efficiency.

Pakistan should effectively conserve CO_2 emissions, respond actively to climate change and protect the environment. These findings provide a reference with which Pakistan's government could establish a measure to control CO_2 emissions with increase in GDP. The increase in CO_2 emissions and energy consumption could be conserved by formulating an energy tax and the environment could also be protected. Non-carbon and low carbon renewable energy sources (such as solar energy, wind power and hydro power) could be used as a substitute to fossil fuel energy to conserve GHGs emissions (especially CO_2 emissions). The government should encourage their enterprises and citizens to use energy in an efficient way and also government should introduce policies and promotions with which energy consumption could be controlled. Vigilance about the efficient use of energy could be promoted in all sectors. The government of Pakistan can use these results to adjust the environmental and energy policies, and Pakistan can also achieve the optimal level of economic development by considering those policies.

The inaccessibility of data is the main hurdle that restricts research for developing countries like Pakistan. Unfortunately, most of the energy data (e.g. electricity prices, solar energy consumption etc.) is not available. Some of the data is available but is not reliable. To use the time series model for rich dynamic, data for extra variables could be included and better results could be attained. KF could be applied to deal with the electricity issues in Pakistan. Some other environmental factors could be discussed with the empirical analysis to control the global warming for the implementation of Paris Agreement.

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