A MODEL FOR OPTIMIZING ENERGY INVESTMENTS AND POLICY UNDER UNCERTAINTY WITH APPLICATION TO SAUDI ARABIA

A Dissertation

by

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ABSTRACT

An energy producer must determine optimal energy investment strategies in order to maximize the value of its energy portfolio. Determining optimal investment strategies is challenging. One of the main challenges is the large uncertainty in many of the parameters involved in the optimization process. Existing large-scale energy models are mostly deterministic and thus have limited capability for assessing uncertainty. Modelers usually use scenario analysis to address model input uncertainty.

In this research, I developed a probabilistic model for optimizing energy investments and policies from an energy producer's perspective. The model uses a top-down approach to probabilistically forecast primary energy demand. Distributions rather than static values are used to model uncertainty in the input variables. The model can be applied to a country-level energy system. It maximizes the portfolio expected net present value (ENPV) while ensuring energy sustainability. The model was built in MSExcel® using the @RISK Palisade add-in, which is capable of modeling uncertain parameters and performing stochastic simulation optimization.

The model was applied to Saudi Arabia to determine its optimum energy investment strategy, determine the value of investing in alternative energy sources, and compare deterministic and probabilistic modeling approaches. The model, given its assumptions and limitations, suggests that Saudi Arabia should keep its oil production capacity at 12.5 million barrels per day, especially in the short term. It also suggests that most of the future power-generation (electricity) demand in Saudi Arabia should be met

using alternative-energy sources (nuclear, solar, and wind). Otherwise, large gas production is required to meet such demand. In addition, comparing probabilistic to deterministic model results shows that deterministic models may overestimate total portfolio ENPV and underestimate future investments needed to meet projected power demand.

A primary contribution of this work is rigorously addressing uncertainty quantification in energy modeling. Building probabilistic energy models is one of the challenges facing the industry today. The model is also the first, to the best of my knowledge, that attempts to optimize Saudi Arabia’s energy portfolio using a probabilistic approach and addressing the value of investing in alternative energy sources.

DEDICATION

To my parents for their love, sacrifices and prayers.

To my beloved wife, Asmaa, for her love, patience and support throughout my study.

To our adorable sons, Hatem and Thamer, for the joy and happiness they have brought to our life.

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Disclaimer: Analysis, opinions, and points of view expressed in this dissertation are those of the author and do not represent the official positions or policies of either Saudi Arabia or Saudi Aramco.

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1. INTRODUCTION AND LITERATURE REVIEW

1.1 Background and Problem Statement

Energy is critical to world social and economic development. Since the start of the industrial revolution in the nineteenth century, we have seen a tremendous growth in energy consumption. Along the way, the energy-consumption fuel mix has changed from primarily biomass to an increasing share of fossil fuels (Dahl 2004). The world total energy consumption is about 540 quadrillion British thermal units (Btu) or 97 billion barrels oil equivalent (boe) per year, with fossil fuels representing more than 85% of the total energy consumption (EIA 2013). **Fig. 1.1** shows the trend and changes in the fuel mix of the world energy consumption since 1965.The world total energy consumption has increased by almost 2.5 folds since 1970. **Fig. 1.2** shows selected total energy consumption and fuel-shares data for 1970, 1990 and 2010.

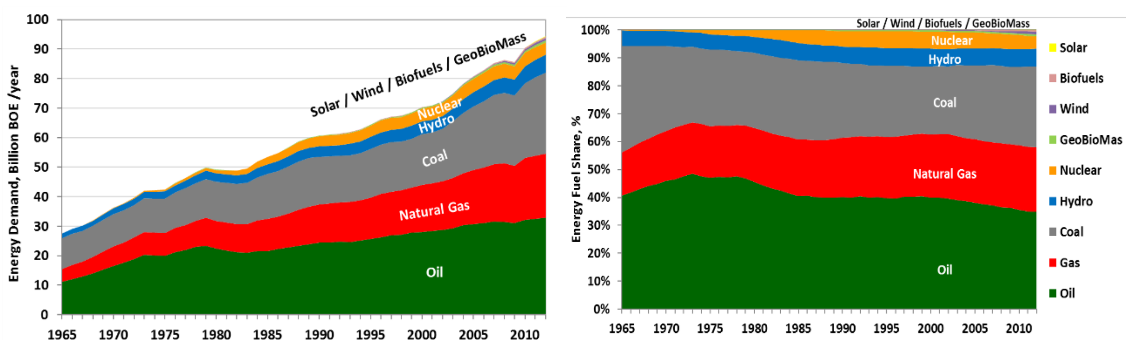
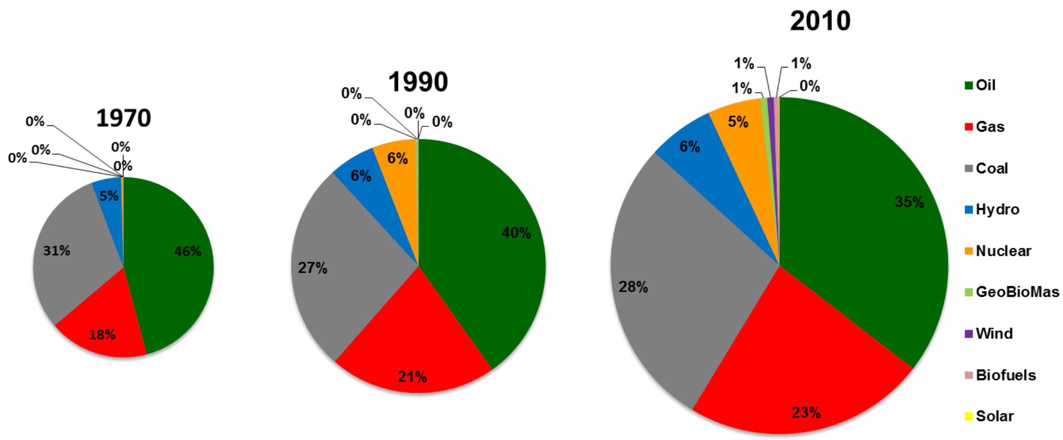


Fig. 1.1—World energy consumption by fuel (left) and fuel-mix changes (right) since 1965. Data from BP (2015).



1970	1990	2010
36.2 Billion boe	60.7 Billion boe	90.4 Billion boe
94.2% Fossil	88.2% Fossil	86.7% Fossil

Fig. 1.2—Snapshots of the world total-energy demand and fuel-share changes for the years 1970, 1990 and 2010. The total-energy demand has been increasing while the share of fossil fuels has been decreasing since 1970. Data from BP (2015).

From the two figures above, the following are observed:

1. Oil share started to decline since the first oil crisis (oil embargo) in 1973 from a maximum of 47% to as low as 35% in 2010.
2. Natural gas increased from about 15% in 1965 to 23% in 2010.
3. Coal, however, shows a rather interesting trend. Coal consumption share used to be as high as 38% in 1965 but decreased to the lowest point of 24% in 2000. In 2011, coal represented 30% of the world total energy demand. This shift in the trend is mainly due to increasing energy demand from China and India. Coal consumption in both countries has increased by 2 to 3 folds since 2002 (BP 2015).

4. Nuclear energy demand increased noticeably after the first oil crisis but its share has been within 5–6% for the past 25 years mostly due to public safety concerns and large capital costs compared to other power generation alternatives (e.g., natural gas and coal).
5. Hydropower's share was consistent at about 5–6% after 1965 with a small increase over time. This is mainly due to the limited availability of suitable locations and the fact that most candidate locations have already been developed.
6. Other renewable energy demand (including solar, wind, biofuels, geothermal and biomass) has a very small share of the overall energy demand. However, its rate of increase is remarkable. The contribution of these fuels increased at an average annual rate of about 23% over the past 5 years (BP 2015).

With these remarkable changes in energy demand, the energy markets' dynamics have also seen major fluctuations triggered by the first oil crisis of the early 1970s. **Fig. 1.3** shows historical trends for oil, U.S. coal and U.S. gas wellhead prices. A notable change is the volatility in prices just after the first oil crisis (1973 oil embargo).[1] This volatility in prices is a source of uncertainty that should be considered when planning future investments for a country or a company involved in the energy sector.

[1] The U.S. gas wellhead prices were under price regulation until January 1, 1993, following The Natural Gas Wellhead Decontrol Act of 1989 (EIA 2016).

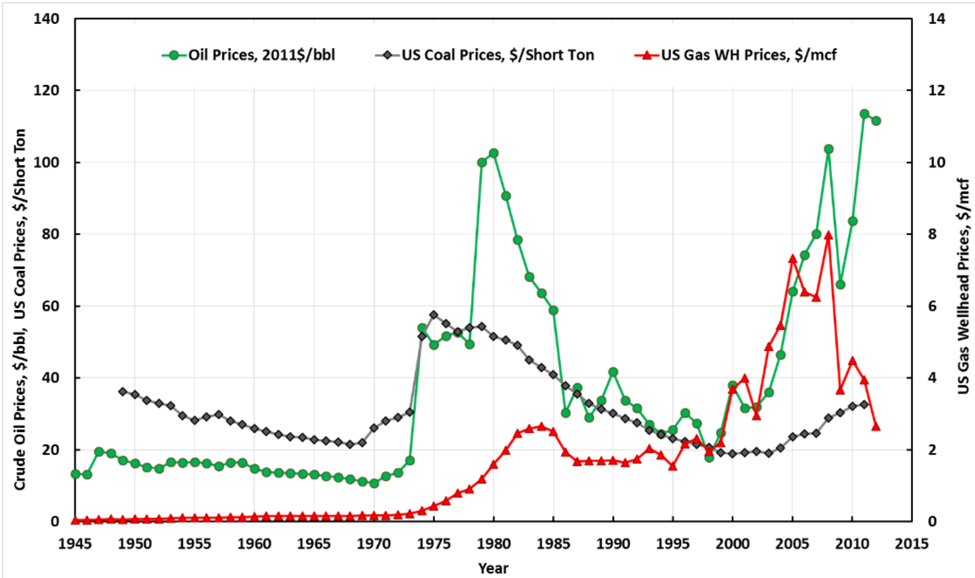


Fig. 1.3—Selected historical prices for oil, gas and coal indicating major volatility just after the early 1970s oil crisis. Note that U.S. gas wellhead prices were under price regulations until January 1, 1993. Data from EIA (2013).

In addition, recent economic crises, geopolitical unrest, and potential environmental regulations increase the uncertainty associated with the energy industry. Until the recent downturn, the energy industry faced a challenge in meeting growing energy demand (Eidt 2012), and this challenge is expected to continue in the long term.

These factors pose an economic challenge to countries and companies with large existing or planned investments in the energy industry in general, and in the oil and gas business in particular, as many developed countries try to be less dependent on fossil fuels and move to other alternative, "cleaner" sources of energy. However, forecasting future alternative energy supply also has huge uncertainty, as suggested by the National Petroleum Council Hard Truths 2007 Report (NPC 2007). Because of all these factors, determining optimal energy investment strategies to maximize the value of an energy producer's energy portfolio is quite challenging.

1.2 Status of the Problem and Research Gaps

The problem addressed in this work is a constrained optimization problem that can be solved by modeling energy supply and demand and factors that affect them as a dynamic system, while addressing the uncertainty inherent in the energy industry. Prior to reviewing previous work, an overview of energy models is provided.

According to Weijermars et al. (2012), the first oil crisis in the early 1970s and the advancement of computer power and programming capability led to the creation of models that relate energy supply, demand, and economic performance. Early models focused on the impact of the oil crisis on the economy and possible adaptation options. Recently, the objectives of energy models have expanded to energy supply security and cost in addition to environmental impact.

An energy model typically consists of several modules, including modules for supply, demand and conversion technologies (**Fig. 1.4**). Energy resources availability and control of greenhouse gas emissions are often considered as constraints to the model. Each module may be treated as a model by itself, e.g., energy demand model and energy supply model. The combination of all these modules in one model is referred to as an energy system model.

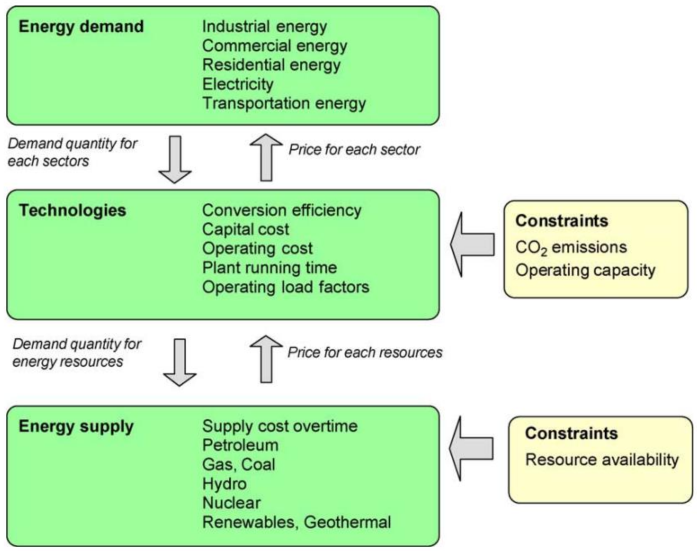


Fig. 1.4—Components of an energy system model (Nakata 2004)

Several models have been developed for analyzing energy systems for different objectives. These models can be classified based on several alternative criteria. One classification method uses the modeling techniques: linear programming-based method, input-output approach, econometric method, process method, system dynamics and game theory. Other classification methods use modeling approach or paradigm (bottom-up or top-down), methodology (partial or general equilibrium), modeling technology (optimization, econometric or accounting) and spatial dimension (national, regional or global) (Bhattacharyya and Timilsina 2010). The classification approach used by the World Bank is shown in **Fig. 1.5** (Timilsina 2011). Classifying the models streamlines the review process. Furthermore, the model objective usually dictates which type of model to be built.

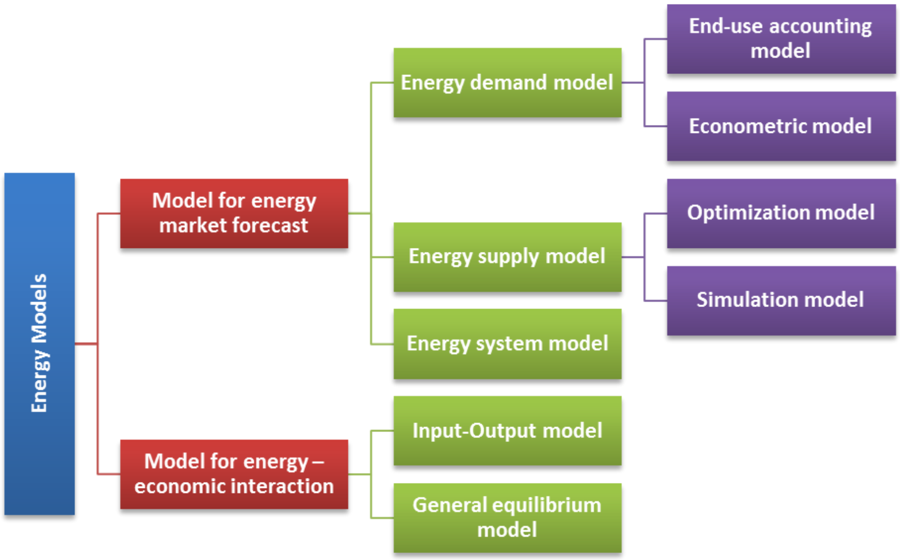


Fig. 1.5—Energy models classification used by the World Bank (Timilsina 2011).

For energy demand models, the top-down models focus on an aggregated level of analysis while bottom-up models identify end-uses for which demand is forecasted. The end-use accounting approach disaggregates the demand into homogenous modules and sectors and links the demand of each module to technical and economic indicators; hence, the name bottom-up or end-use. This approach emphasizes the role of technology, behavior of consumers and economic environment and their effects on demand (Bhattacharyya 2011). The econometric demand models analyze demand at aggregate levels and relate that to economic indicators that are used as independent variables.

Energy supply models can be used as standalone or as a module in an energy system model. These models take demand forecasts, energy resources, technology, and costs as key driving variables. Energy supply models can be classified as optimization or simulation models (Fig. 1.5). Optimization models minimize the cost of meeting specific demand while meeting all constraints, such as resources availability and emission constraints, among others. They are more appropriate when a large number of supply sources are available. Simulation models, on the other hand, simulate the behaviors of consumers and producers under different signals such as prices and income levels and can be sensitive to the starting conditions (Timilsina 2011).

Energy system models combine both supply and demand and can be used for energy market projections, policy analysis and impact on the environment. Bhattacharyya and Timilsina (2009, 2010) commented that existing energy system models have intensive data requirements and may inadequately capture developing countries energy features. This problem is more pronounced with econometric and optimization models.

Examples of the most commonly used energy models are shown in **Table 1.1**, along with their classification and a brief description for each model. Most of the models reviewed in Table 1.1 have an energy consumer perspective and thus try to minimize the cost of supply for a certain demand. My focus is to maximize the portfolio value of energy supply for a country or company. Unfortunately, none of these models for this purpose are in the public domain. In addition, potentially applicable models such as WEM, SAGE and NEMS are proprietary and likely not available for my use, even for a fee. Other models (MARKAL and TIMES) are expensive ($3,000 to $15,000) to acquire and are likely not customizable for my purposes. I would like to modify the models to include maximizing energy investments profits instead of minimizing the cost of meeting forecasted demand. Furthermore, to the best of my knowledge, only two models consider uncertainty quantification. MARKAL quantifies uncertainty in its forecasts using what-if analyses and NEMS uses distributions to quantify uncertainty in power generation investments.

The models listed in Table 1.1 are large energy-systems models that can handle the whole energy market, but there are also small-scale models that deal with specific issues such as global warming. Edmonds and Reilly (1985), for example, developed a model for estimating future carbon-dioxide (CO_2) emissions based on different energy supply and demand forecasts. They projected future supply and demand, solved for prices, computed the equilibrium quantities of energy produced and calculated the CO_2 emissions. Their model considered solar energy as the backstop technology (i.e., energy source with inexhaustible supply). They recognized the effects of uncertainty on their projections but their projections were based on a scenario-analysis approach.

Chakravorty et al. (1997) also built a model to assess the effect of carbon dioxide on global warming. They modeled the supply and demand of three fossil fuels (oil, coal and natural gas) and solar energy while considering four demand sectors (power generation, residential & commercial heating, industrial heating and transportation). They also modeled the substitution effects of meeting different sectors demand by different fuels. In their model, solar energy is considered as the backstop fuel. Their model, however, neglects to consider uncertainty in both the supply and demand forecasts.

Model Type	**Model Name**	**Model Characteristics**
Bottom-up, Optimization-based	**RESGEN** (**R**egional **E**nergy **S**cenario **Gen**erator)	Used for energy planning in developing countries for demand only.
	EFOM (**E**nergy **F**low **O**ptimization **M**odel)	Multi-period system optimization based on linear programming that minimizes the total discounted costs to meet a country specified demand and allows for marginal costs identification.
	MARKAL (**Mark**et **Al**location Model)	The most widely used model. It uses linear optimization to generate the least-cost supply system to meet a given demand, given energy system configuration and energy resources.
	TIMES (**T**he **I**ntegrated **M**ARKAL-**E**FOM **S**ystem)	Integration of EFOM and MARKAL and thus produces the least-cost solution considering the investment and operation decisions.
	MESAP (**M**odular **E**nergy **S**ystem **A**nalysis and **P**lanning)	The model is used for energy system analysis and environmental planning with emphasis on power generation.
Bottom-up, Accounting	**LEAP** (**L**ong-range **E**nergy **A**lternative **P**lanning Model)	Integrated energy planning model for both supply and demand. The model answers what-if types of analysis on supply and forecasts demand. It does not optimize market share but rather analyzes the implications of possible alternative market shares on demand.
Top-down, Econometric	**DTI** (**D**epartment of **T**rade & **I**ndustry Energy Model)	The model forecasts energy and future carbon emission estimations from power generation. Mostly used in power generation modeling.
Hybrid (Econometric and bottom-up)	**NEMS** (**N**ational **E**nergy **M**odeling **S**ystem)	A hybrid model for energy-economy interaction used by USDOE-EIA for USA only. The demand is divided into four components: residential, commercial, industrial and transport. The supply side contains four modules for oil and gas supply, gas transportation, coal supply and renewable fuels. The model is not widely used outside EIA due to reliance on costly proprietary software packages and complex model design.
	POLES (**P**rospective **O**utlook on **L**ong-term **E**nergy **S**ystems)	This model is used by European Union for energy policy analysis. It has four modules: final energy demand, new and renewable energy technologies, conventional energy transformation system and fossil fuel supply. It uses a disaggregated approach for demand and a detailed production model for main producers for supply considering resources, cumulative production and depletion.
	WEM (**W**orld **E**nergy **M**odel)	WEM is the global energy market model used by IEA. It provides the long-term supply and demand forecast. The model consists of six main modules: final energy demand (with sub-models covering residential, services, agriculture, industry, transport and non-energy use); power generation and heat; refinery/petrochemicals and other transformation; fossil-fuel supply; CO_2 emissions and investment. The demand part follows a hybrid approach where econometrics is combined with end-use methodology. It uses activity variables (GDP or per capita GDP) and structural variables for specific features of demand. It also uses price variables for energy end-use by linking them to international prices and energy taxes. It uses GDP, population, technological changes and international prices as exogenous to the model while using the scenario approach to define ranges of possibilities.
	SAGE (**S**ystem for the **A**nalysis of **G**lobal **E**nergy Markets)	Used by USDOE-EIA for global energy situation. The demand forecasts are based on demand trends, economic and demographic drivers, energy equipment stocks and technological changes. The supply module considers world oil market, gas market and other energy resources.

Table 1.1—Summary of the most commonly used energy models and their characteristics.

Finally, several models are available that consider only one energy fuel (e.g., oil) and find the optimum production level that maximizes the producer profit function. Al-Qahtani (2008), for example, developed a static model for the global oil market that finds the optimum oil production levels for Saudi Arabia. Bukhari and Jablonowski (2012) studied the effect of oil prices uncertainty on the optimum allocation of oil production from multiple fields with different crude oil types. Mohaddes (2012) estimated the oil terminal price (price of oil at time of depletion) in addition to its cost and used these data to estimate future oil price and optimum extraction rate. However, these models, even with uncertainty quantification, lack completeness due to ignoring the fuel switching and substitution effects on the oil demand.

In his PhD. dissertation, McGlade (2013) identified uncertainties affecting oil and gas outlooks. These uncertainties include epistemic, communication, random macroscopic and uncertainties arising from simplifying assumptions. His main contributions were constructing supply cost curves for different oil and gas categories and building a bottom-up economic and geologic model for oil (BUEGO) that has up to 7000 oil fields. He used the TIAM-UCL (TIMES Integrated Assessment Model – University College London) model to test different scenarios for oil and gas outlooks. However, a deterministic approach was used when testing different scenarios instead of a Monte-Carlo (MC) simulation approach due to computational limitations (long running time) and the belief that relatively few additional insights would be gained if a fully probabilistic approach were used.

Another model that UCL (University College London) is currently developing is the Energy System Modeling Environment (ESME). ESME is a cost optimization model with a fully probabilistic approach to uncertainty and is built especially for the United Kingdom energy system. The model is used to test alternative pathways to a low carbon energy system for the UK (Pye et al. 2014). Unfortunately, access to TIAM-UCL and ESME models are not available outside UCL, as per e-mail correspondence with the UCL faculty members responsible for these models.

Therefore, there is a need for models that consider all energy sources from a supplier perspective and address the uncertainties associated with their supply. According to Kann and Weyant (2000), limitations of computing resources is the major obstacle to performing all-inclusive uncertainty analysis in energy models since large models face an important trade-off between level of details and run time. Extending existing large-scale energy models to perform extensive uncertainty analysis is a difficult task (Pfenninger et al. 2014).

1.3 Uncertainty Quantification in the Energy Industry

Uncertainty is present in most aspects of the energy industry. Throughout the review of energy models, uncertainty quantification was an important criterion for deciding on model suitability to this work. Brashear et al. (1999) distinguished two types of uncertainties affecting oil and gas portfolio optimizations as above-ground (e.g., environmental and operating regulations, changes in end-use demand) and underground uncertainties (e.g., geologic uncertainties). The Organization of Petroleum Exporting Countries (OPEC) identified four major sources of uncertainty that surround the energy future: the world economy, policies, technology and consumer choices (OPEC 2013). According to Tschang and Dowlatabadi (1995), energy models are subject to two types of uncertainties: uncertainty in the model structure and uncertainty in the input parameters.

1.3.1 Evidence for Uncertainty Underestimation in Energy Models' Forecasts

According to McVay (2015), all the biases affecting project evaluations can be boiled down to two fundamental biases—overconfidence (underestimation of uncertainty) and directional bias (optimism or pessimism). Overconfidence is due to not considering all possible outcomes, leading to too-narrow estimated distributions of uncertain quantities. Directional bias, e.g., optimism, results when failing to consider some possible negative outcomes or when giving greater weight to possible positive outcomes than possible negative outcomes.

Shlyakhter et al. (1994) analyzed the United States Energy Information Administration (EIA) forecasts credibility by comparing previous forecasts to actual energy demand data and found that the forecasts usually have too narrow ranges. They concluded that the assumption of normal error distribution is not valid and they had to fit the error data with an exponential distribution, which resulted in increasing the forecasts range (difference between low and high case). This is a clear indication of overconfidence and underestimation of uncertainty.

Probabilistic forecasts reliability can be analyzed graphically using calibration charts or numerically using calibration scores such as the Brier (1950) scoring method. Fondren (2013), for example, used the Brier score and calibration chart to calibrate different forecasts including drilling costs, shale gas reserves and football game scores. Calibration charts plot the frequency of an outcome (percent correct) against the assessed probability of that outcome (probability assigned). Perfectly calibrated forecasts will fall on the unit-slope line. Overconfident forecasts have a slope less than unity while underconfident forecasts have a slope greater than unity. **Figs. 1.6** and **1.7** show calibration charts for EIA oil prices and total energy demand forecasts, respectively. The analyses are based on multiple EIA International Energy Outlook (IEO) reports since 1995. The figures show these forecasts are overconfident, exhibiting narrow ranges between high and low estimates.

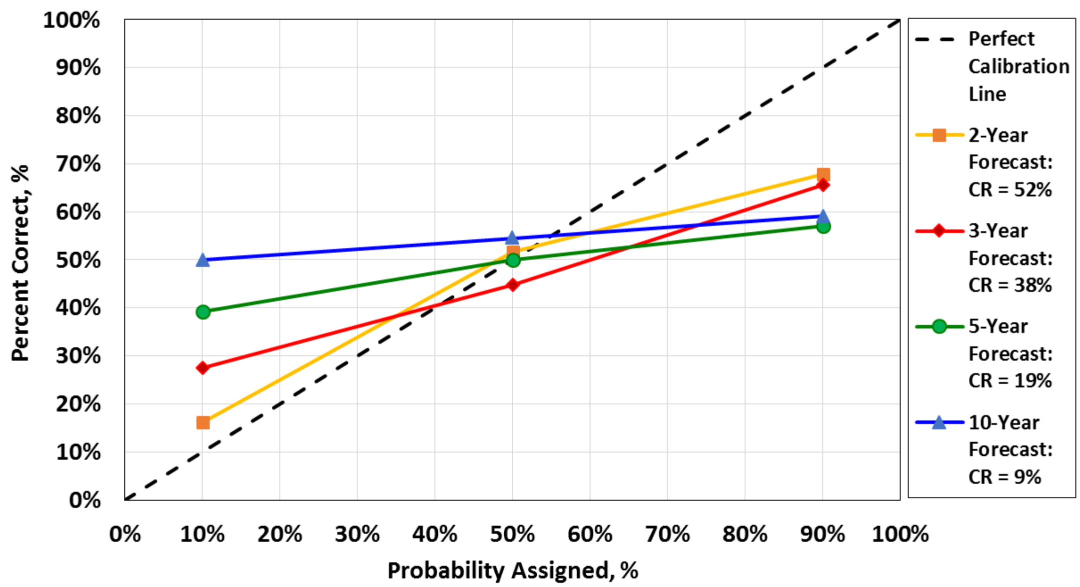


Fig. 1.6—EIA oil prices forecasts calibration check for multiple forecast intervals shows clear signs of overconfidence. (CR = coverage rate indicating percentage of forecasts actually within the 80% confidence interval).

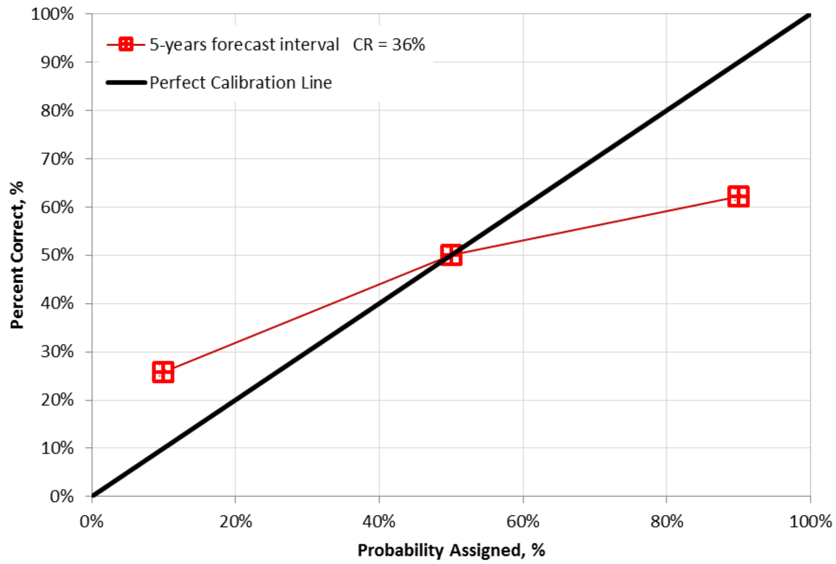


Fig. 1.7—EIA total energy demand forecast calibration check for 5-year forecast intervals demonstrates overconfidence.

1.4 Value of Assessing Uncertainty

One might question why we need to assess uncertainty. Capen (1976) suggested that a better understanding of uncertainty would have a significant effect on risk assessment and profits. Brashear et al. (2001) noted that return on net assets by the largest U.S.-based companies in the oil and gas upstream sector in the 1990s was 7% on average for projects that were selected with a hurdle rate of 15% and financed with capital that cost 9-12% percent on average. They partially attributed this underperformance of the oil and gas industry to the use of deterministic methods to estimate project value.

McVay and Dossary (2014) performed a quantitative study to measure the value of assessing uncertainty on the performance of portfolio optimization. They concluded that moderate overconfidence and optimism could result in a 30 to 35% expected portfolio disappointment (the difference between estimated and realized portfolio NPV as a percentage of the estimated NPV). Thus, reducing overconfidence and optimism should result in improved decision making, reduced disappointment, and greater portfolio value.

In summary, uncertainty is present in many aspects of the energy industry. Underestimation of uncertainty results in underperformance and reduced value. Thus, assessing uncertainty is a necessity for an energy producer trying to optimize its energy portfolio and maximize its value.

1.5 Research Objectives

This research has two main objectives:

1. Develop a coarse, fully-probabilistic model for energy portfolio optimization that considers all energy sources from a supplier perspective and can be used to determine the optimum mix of energy investments for individual countries or companies.
2. Use the model to assess and determine the optimum energy investments and strategies for Saudi Arabia, including the value of investing in alternative energy sources.

1.6 Overview of Methodology

To achieve the project objectives, this research included the following tasks:

1. Conducted extensive literature review of previous modeling efforts and identified research gaps.
2. Constructed a model architecture that addresses the research objectives and allows for uncertainty quantification.
3. Compiled energy supply and demand data for the target country to be analyzed with the model.
4. Identified and modeled factors that may affect both supply and demand.
5. Identified and modeled the impact of primary alternative fuels on fossil fuels energy production within the target country.
6. Developed a coarse probabilistic energy model that maximizes the country energy portfolio value while ensuring energy sustainability. The model was built in MS Excel® to capitalize on stochastic modeling capabilities of the @RISK (Palisade 2015a) add-in.
7. Used the model to determine the optimal energy investment strategies for Saudi Arabia.
8. Developed an equivalent deterministic model using mean and mode of distributions and compared the results of deterministic and probabilistic models with and without alternative energy sources as it applied to Saudi Arabia.

2. MODEL DESCRIPTION

This section describes the model architecture and its major components. A more detailed mathematical formulation is shown in Section 3 with the model application to Saudi Arabia.

2.1 The Ideal Energy Model

As explained in the Section 1, there are numerous models built for different purposes. Each model has its own benefits and shortcomings. However, an ideal model is the one that combines microeconomic realism, macro-economic completeness, and technological explicitness as shown in **Fig. 2.1**. I would add that an ideal model should also be fully probabilistic to properly account for uncertainty present in almost every aspect of the energy industry. Although many energy models use scenario analysis to account for input uncertainties, the models are deterministic in nature and may not capture the full effect of uncertainty on their final output.

Building such an ideal model at once is not practical due to huge data and intensive computational power requirements. Limitations of computing resources is a major obstacle to performing all-inclusive uncertainty analysis in energy models. Thus, large energy models face a trade-off between level of details and run-time (Kann and Weyant 2000). Therefore, taking any one of the existing detailed large-scale models and converting it to a stochastic model is not practical as well (Pfenninger et al. 2014). As a result, in this work I start by building a coarse model but with explicit characterization of uncertainty that can be built upon in a later work to be more detailed and complex. Thus, the intended model will lie in the bottom face of the cube but it has an uncertainty component that is not shown in Fig. 2.1.

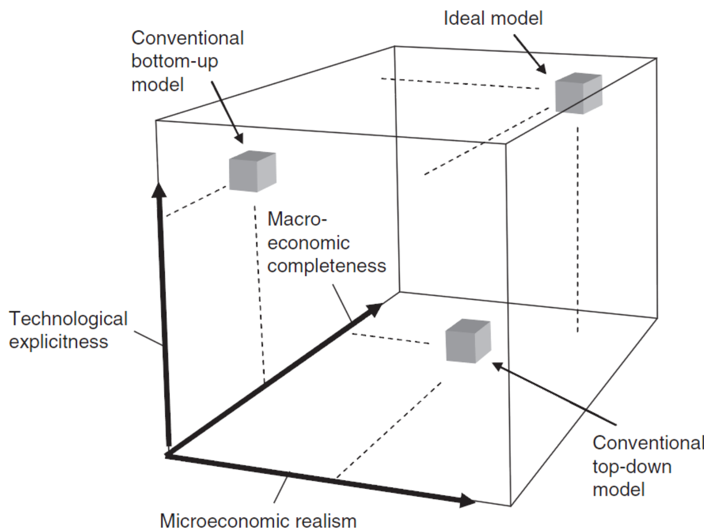


Fig. 2.1—Three-dimensional assessment of energy models (Evans and Hunt 2009).

2.2 Model Architecture

Fig. 2.2 shows the model architecture. The model has three major components: energy supply, energy demand and optimization modules. The optimization module is where the target country/company energy portfolio is specified (e.g., Saudi Arabia).

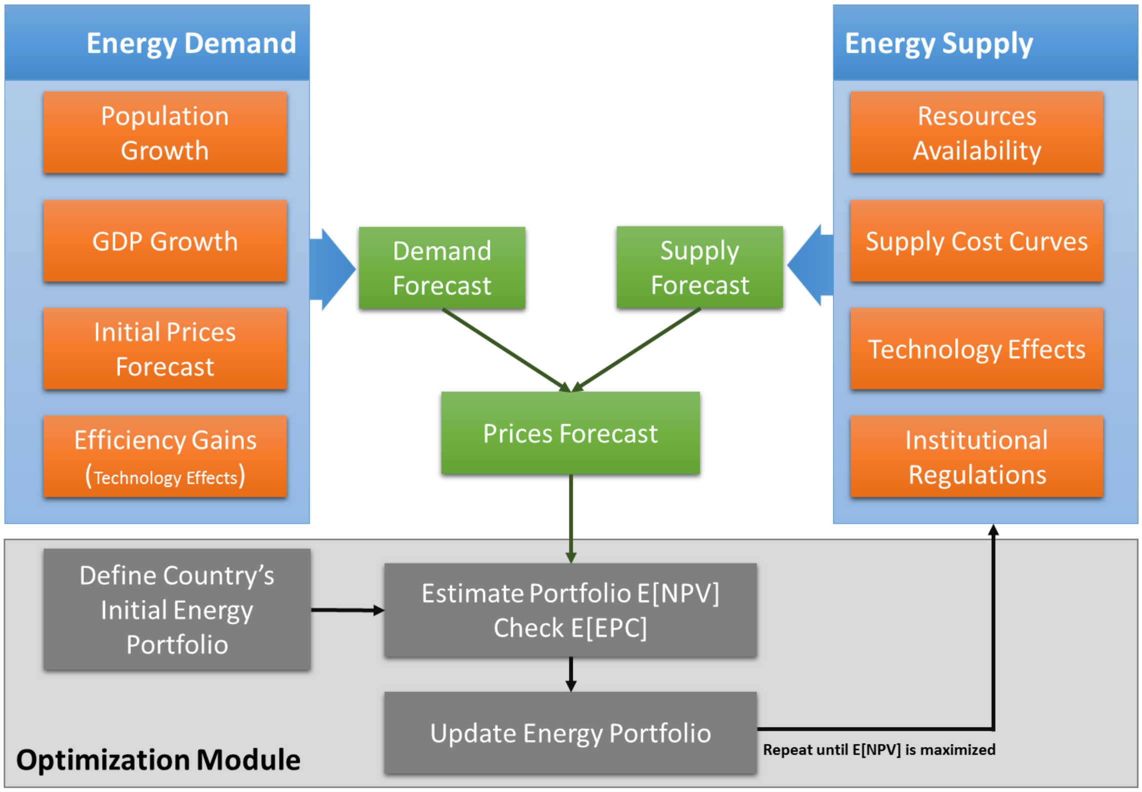


Fig. 2.2—General architecture of the model.

The demand module can be a detailed bottom-up, technology-rich model that forecasts demand for each energy fuel by region and/or sector or it can be an aggregated a top-down model. In this work, top-down approach is followed using demand equations such as Cobb-Douglas (Eq. 2.1**,** or Eq. 2.2 in logarithmic form).

$$D_t = f(p_t, Y_t, Z_t) = a\, p_t^b Y_t^c Z_t^d \quad \text{(2.1)}$$

$$\ln D_t = a + b \ln p_t + c \ln Y_t + d \ln Z_t \quad \text{(2.2)}$$

where *D* is the demand and *p*, *Y* and *Z* are parameters that drive demand—prices, income, and population growth, respectively. The constants *b*, *c* and *d* are the elasticities defined as the percentage change in demand due to 1% change in the corresponding parameter.

The supply module forecasts the supply of each energy fuel based on resources availability (in case of non-renewables) and costs of production. Technological advancement affects the supply forecast by either expanding the resources base and/or by reducing production costs. Institutional regulations such as limits on emissions of greenhouse gases impose an upper bound on production of fossil fuels. As in the demand modeling, the model can be aggregated by fuel or it can be detailed at the regional level. An aggregated approach will be used in this model.

The optimization module is where the target country energy portfolio is defined and optimized. In this module, the followings are specified:

1. Energy resources available (oil, gas, coal, wind, solar, and nuclear)
2. Current portfolio choices and production levels from each fuel
3. Production cost curves
4. Planned investments

The optimization module takes the prices forecasts from the supply and demand modules as input and it also updates them with the new production rates during each iteration until the optimum portfolio choices and production rates are reached.

2.3 Model Objective Function

The model objective function has two components: maximizing expected net present value (ENPV) and ensuring energy sustainability. The expected per capita energy production capacity (EEPC) is used as a proxy for energy sustainability. In mathematical form:

$$\underset{q_{j,t}}{\text{maximize}} \quad E[NPV] \quad \text{...} (2.3)$$

$$\text{Subject to} \qquad E[EPC] = E\left[\frac{Total\ Energy\ Production\ Capacity}{Population_t}\right] \geq X \qquad \forall\ t \text{.....} (2.4)$$

where X is the minimum desired per-capita energy production capacity in boe/year and $q_{j,t}$ is the energy production from energy source j during time t.

The objective function above is subject to other constraints that are specific to the target country to which the model is applied as detailed in the application section.

2.3.1 Energy Sustainability

Maximizing the net present value (NPV) is as short-term objective. NPV is indifferent to cash flow in the far future. The higher the discount rate the more shortsighted NPV becomes. Therefore, I added energy sustainability as a long-term objective.

In the context of this work, energy sustainability refers to the use of energy in such a way that meets the needs of the present generations without compromising future generations ability to meet their own needs (Greene 2010). Then since fossil fuels are exhaustible or non-renewable, ensuring energy sustainability will eventually necessitate the need to tap into renewable energy sources to meet future energy demand.

Greene (2010) attempted to quantify energy sustainability mathematically. He defined it as the per-capita energy services for next generations being at least equal or greater than that of current generation. However, modeling energy services (e.g., cooling, heating, etc.) is beyond the scope of this coarse energy model. Therefore, per capita energy production capacity (EPC) is used as a proxy for energy sustainability as shown in Eq. 2.4. Per capita energy production capacity should not be confused with the per-capita energy consumption. EPC includes both domestic consumption and exported energy.

2.4 Solution Method

The model is built in MS Excel® and uses Palisade's @RISK software. @RISK is an Excel add-in that has uncertainty analysis capability. The RISKOptimizer tool within @RISK is used to perform the optimization. RISKOptimizer combines Monte Carlo (MC) simulation and optimization to find optimal solutions to models that contain uncertainty. It uses genetic algorithm (GA) and OptQuest as optimization methods.

GA is an optimization algorithm developed based on evolutionary biological method where the fittest survive. The algorithm seeks to find global optima within the specified range. The algorithm works by randomly generating a population of chromosomes, which can be called solutions, to solve the optimization problem. Each chromosome contains number of genes equals to the number of variables in the solution. From this initial population of chromosomes, the breeding process starts by either crossover or mutation. Crossover is a combination of two chromosomes whereas mutation is replacement of one of the genes with another. The probability of crossover and mutation are usually specified as 0.5 and 0.05, respectively. **Fig. 2.3** shows a flowchart of how GA works.

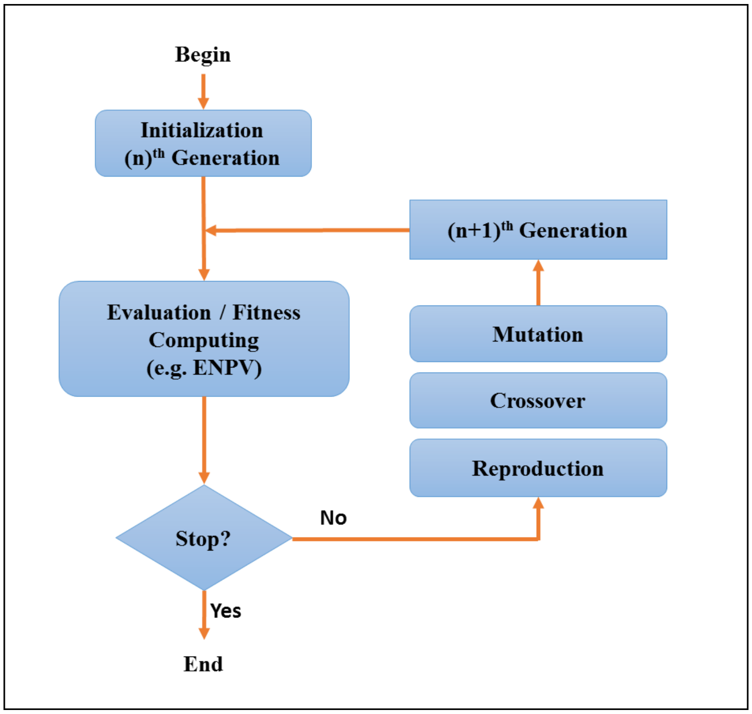


Fig. 2.3—A flowchart for genetic algorithm.

The OptQuest engine uses metaheuristics, mathematical optimization, and neural network components to guide the search for optimal solutions. The OptQuest engine combines Tabu search, scatter search, integer programming, and neural networks into a single, composite search algorithm that provides maximum efficiency in identifying new scenarios (Palisade 2015b).

When running the model, RISKOptimizer was set to automatically choose the optimization engine. OptQuest was chosen in most cases, as the GA method requires that all constraints must be met at the beginning of the optimization.

Since the optimization has two objectives, I used the efficient frontier method to represent the optimal solution curve. Thus, the model is set to maximize the ENPV while

EEPC is considered one of the constraints that must be met. I then run the optimization multiple times by varying the minimum required EEPC until I get the desired efficient frontier curve. The following section has more details about the model structure along with model application to Saudi Arabia.

3. MODEL APPLICATION TO SAUDI ARABIA

Saudi Arabia is an example of an energy producer that has a relatively simple energy system. The current fuel mix consists of only oil and gas. Thus, I will apply the model to Saudi Arabia to find the optimum mix of energy investments, optimum energy strategy, and the value of investing in alternative energy sources.

Several authors have addressed optimizing Saudi Arabia's oil and gas reserves development. For example, Al-Qahtani (2008) developed a static, deterministic model for the global oil market and studied different scenarios to find the optimum oil production for Saudi Arabia. Husni (2008) developed a multi-period deterministic optimization algorithm for scheduling large-scale petroleum development projects subject to several resources constraints. Bukhari (2011) studied the effects of uncertainty in oil prices, using deterministic and stochastic oil prices models, on the optimum allocation of oil production from multiple fields with different crude grades. However, to the best of my knowledge, this is the first attempt to probabilistically optimize Saudi Arabia's oil and gas reserves development while considering alternative energy sources and their impact on the overall Saudi energy portfolio.

3.1 Saudi Arabia Energy Challenge

Saudi Arabia's economy is highly dependent on revenue from oil and gas production. The oil sector represents about 42.1% of the country gross domestic product (GDP) and more than 87% of the government revenue (SAMA 2015).

While Saudi Arabia enjoys vast oil resources, growing domestic energy demand driven by increasing population and economic growth represents a major challenge. The domestic demand has been increasing at an annual rate of about 5%, risking diminishing oil export volumes. **Fig. 3.1** shows Saudi Arabia total domestic energy consumption with the share of each fuel source. In 2013, crude oil and oil products represented about 55% of the total demand and the rest was met by natural gas.

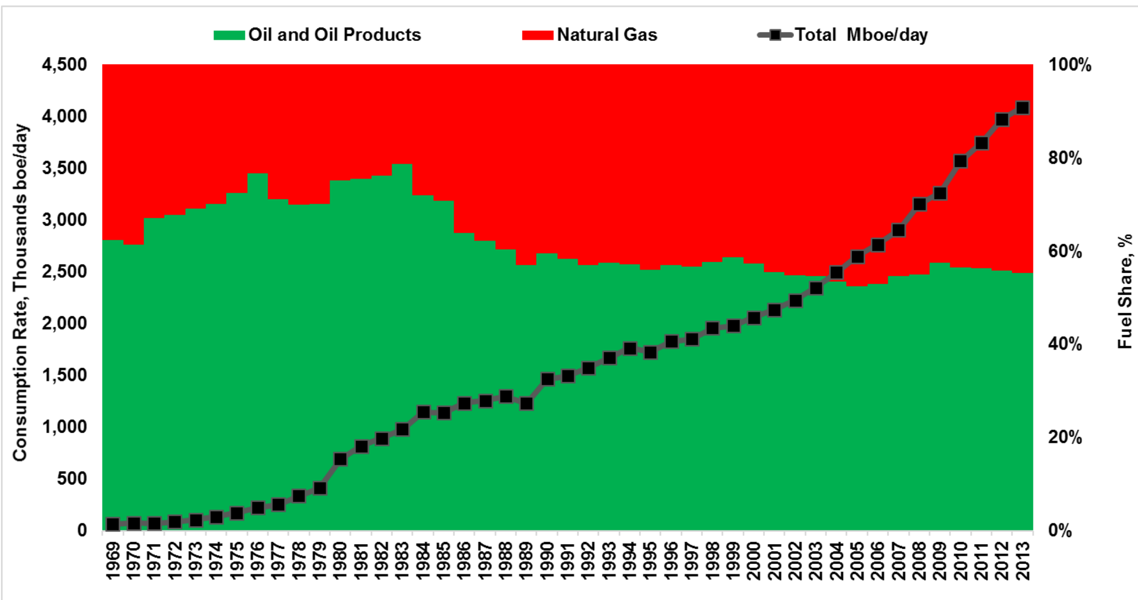


Fig. 3.1—Saudi Arabia total oil and gas demand with the share of each fuel source.

There are efforts underway trying to moderate this domestic energy demand growth by establishing energy efficiency standards and spreading awareness among the public led by the Saudi Energy Efficiency Center (SEEC). Current program initiatives are target three main sectors that are consuming more than 90% of the total domestic energy consumption—construction, industry and land transportation.

Saudi Arabia also introduced the Saudi CAFÉ (Corporate Average Fuel Economy) Standards, which were enforced in early 2016. This new policy is expected to increase light-duty vehicles from current fuel economy of 33 miles per gallon to 40 miles per gallon in 2020, a 4% increase per year.

On another front, the Kingdom established King Abdullah City for Atomic and Renewable Energy (K.A.CARE) in 2010 by a Royal Decree. K.A.CARE's objective is to help diversify Saudi Arabia domestic energy supply and alleviate some of the pressure on non-renewable resources. The main target for K.A.CARE efforts are targeting the power generation sector. Power demand is expected to double by 2030 to 110 GW (gigawatt). This increase is expected to be supplied by nuclear and renewable energy sources. **Table 3.1** shows K.A.CARE planned power generation capacity additions by 2032. In this work, power from waste and geothermal will not be considered and solar will be combined in one technology.

Another challenge facing the Kingdom is the low administered energy prices. Energy prices are fixed by the government and set much lower than market prices as a way of distributing wealth among the public. Natural gas prices are fixed at $0.75 per million Btu and oil at about $4 per bbl (Matar et al. 2015). This may be one reason for the high domestic energy demand. During late 2015, however, the government increased domestic energy prices by an average of 50-75%. The prices are still less than market prices.

Technology	Planned Capacity Additions, GW
Nuclear	17.6
Solar PV	16
Solar CSP	25
Wind	9
Waste	3
Geothermal	1
Total	**71.6**

Table 3.1—K.A.CARE planned power generation capacity additions by 2032.

Another challenge facing the Kingdom is the low administered energy prices. Energy prices are fixed by the government and set much lower than market prices as a way of distributing wealth among the public. Natural gas prices are fixed at $0.75 per million Btu and oil at about $4 per bbl (Matar et al. 2015). This may be one reason for the high domestic energy demand. During late 2015, however, the government increased domestic energy prices by an average of 50-75%. The prices are still less than market prices.

Therefore, Saudi Arabia's main challenge is the increase in its domestic energy demand which will eventually affect its oil exports capacity and the government revenue. This work will address investment in alternative energy sources to meet domestic power demand and its effect on the overall Saudi energy portfolio.

3.2 Saudi Arabia's Energy Portfolio

Saudi Arabia's current energy portfolio has only oil and gas as the main sources of energy. The Kingdom proved oil reserves stand at 268 billion barrels (EIA 2015). The Kingdom has played a vital role in stabilizing the oil markets due to having the largest total petroleum liquids export capacity and the largest crude oil spare production capacity. Saudi Arabia also has huge natural gas resources. The proved total natural gas reserves amounts to 291 trillion cubic feet (Tcf) (EIA 2015). All Saudi Arabia's gas production is directed to domestic consumption, such as power generation and feedstock to the petrochemical industry. **Figs. 3.2**, **3.3** and **3.4** summarize historical production data for oil, gas and power generation, respectively. In addition to oil and gas, nuclear, solar, and wind will be added to the portfolio.

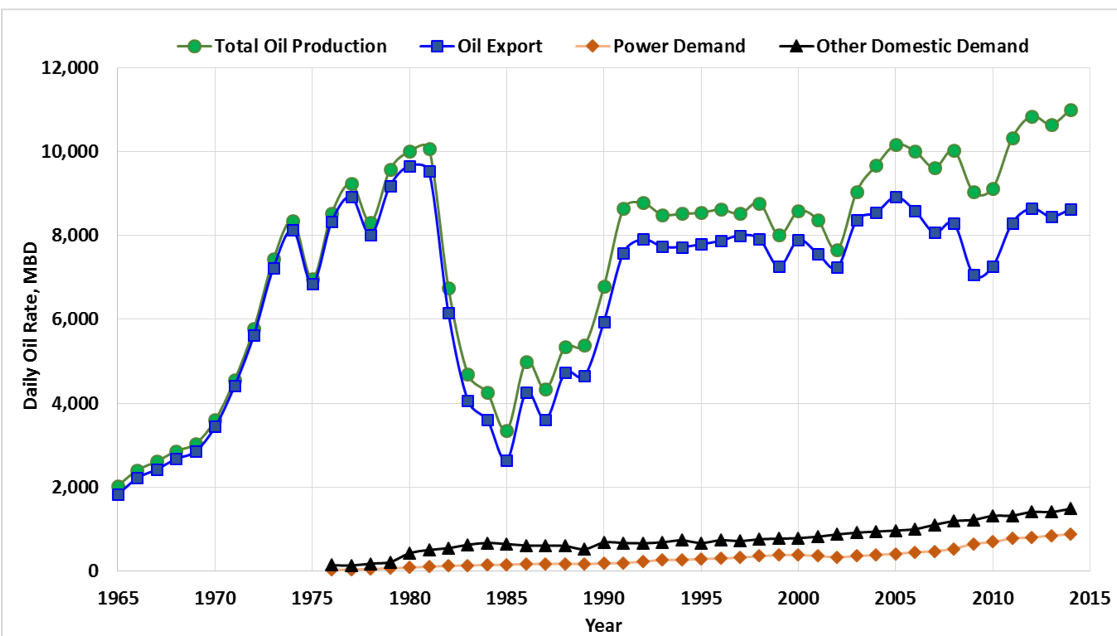


Fig. 3.2—Saudi Arabia historical total oil production, export, oil for power demand, and oil demand from other sectors.

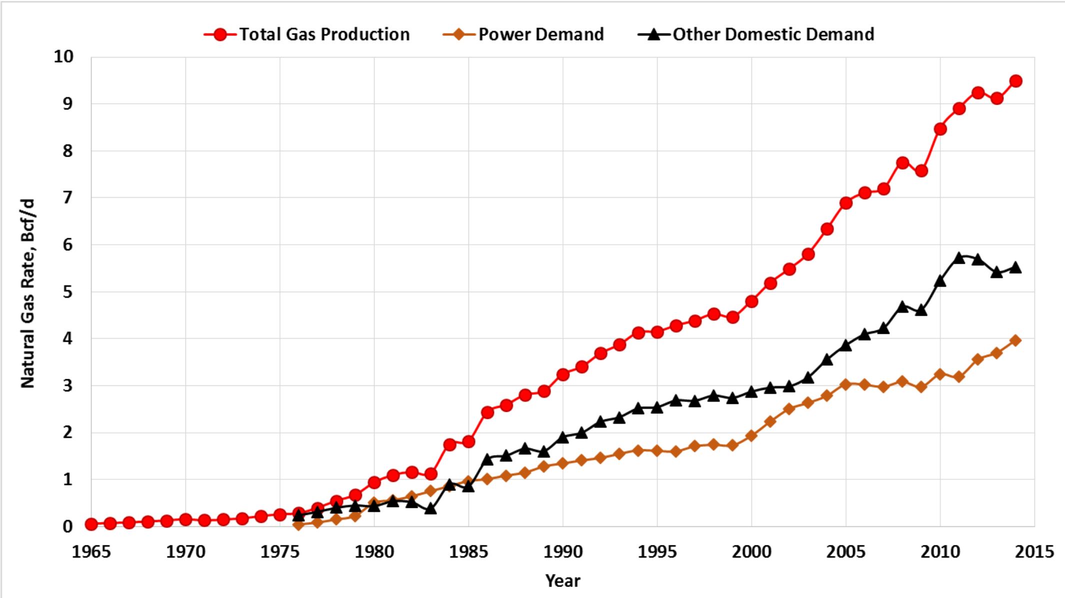


Fig. 3.3— Saudi Arabia historical total gas production, gas for power demand, and gas demand from other sectors.

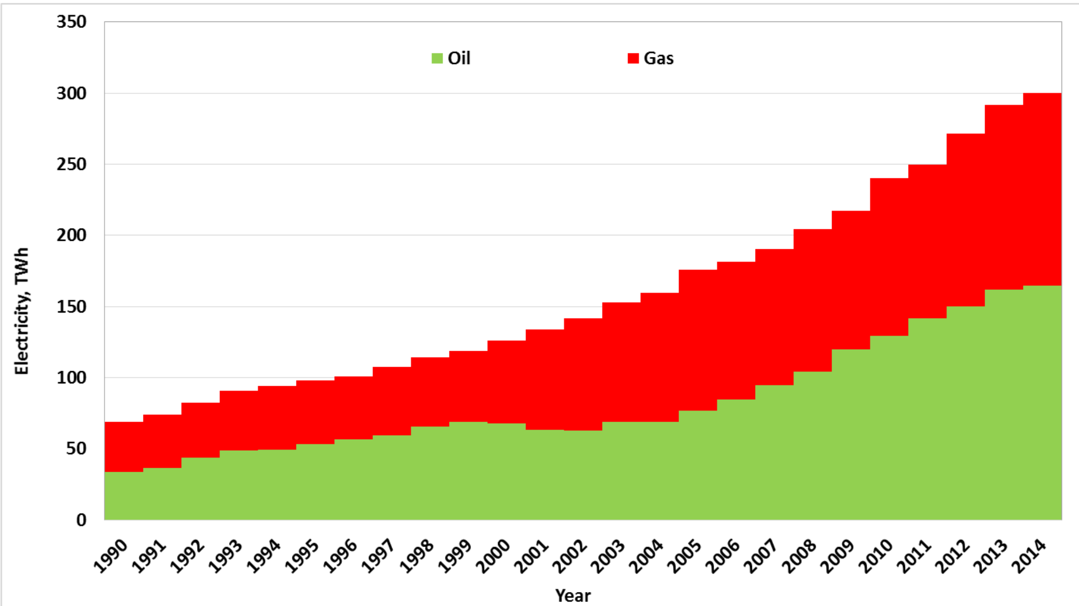


Fig. 3.4—Saudi Arabia annual power (electricity) consumption with the share of oil and gas.

3.3 Mathematical Formulation

As shown in Eqs. 2.3 and 2.4, the model maximizes the energy portfolio expected net present value (ENPV) while ensuring per capita expected energy production capacity (EEPC) is greater than a set minimum value as a measure of energy sustainability. EEPC is used for probabilistic models. **Fig. 3.5** below shows a simplified chart for primary energy flow for Saudi Arabia used in the model.

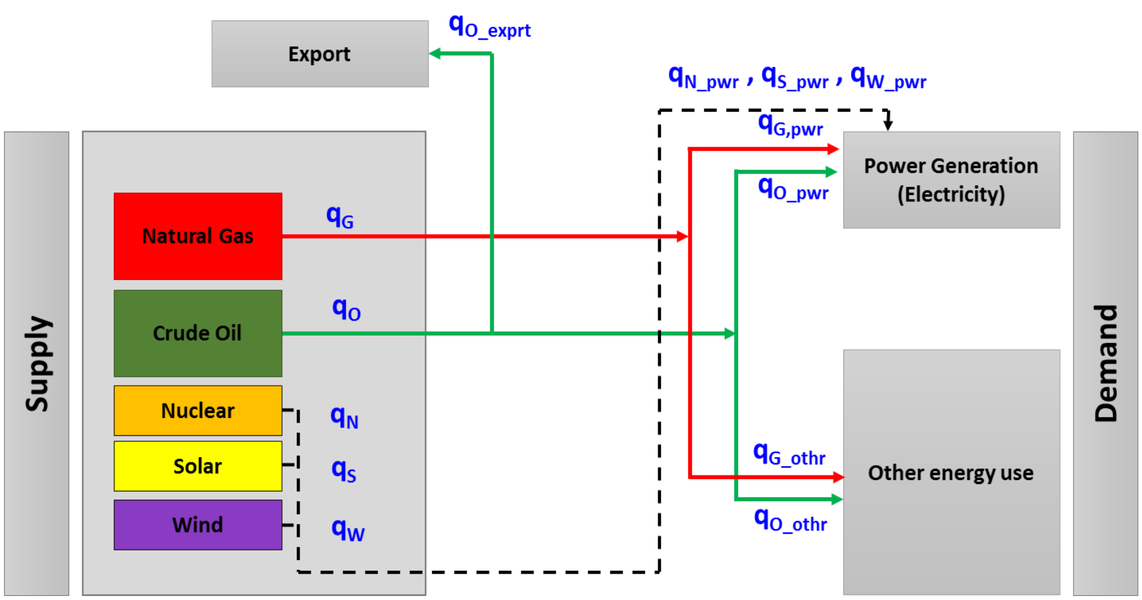


Fig. 3.5—A chart for primary energy flow for Saudi Arabia energy system as used in the model.

The Saudi demand side has many sectors including power generation, industrial, residential, commercial, and transportation. In this work, however, the Saudi demand side is assumed to have only two sectors: power generation and all other sectors are combined as one. Since the model considers only primary energy flow at this stage (not secondary energy such as refinery products and petrochemicals), a simplified demand sector is acceptable and will simplify the modeling as well. In addition, no reliable data were found that show by-sector demand for Saudi Arabia except for the power generation sector.

The supply side shows five energy sources (oil, gas, nuclear, solar, and wind). Oil prices and thus oil revenue through oil exports is the only link of the Saudi energy sector to the outside world in the model. More details are shown in the oil price model section below.

Based on the above discussion, the Saudi energy sector objective function is given by (bold face variables are stochastic, i.e., uncertain)

$$\underset{q_{j,t}}{\text{maximize}} \quad E\left[\sum_{t=1}^{T}\sum_{j=1}^{J}\beta^{t} \times q_{j,t}\left(\boldsymbol{p_{j,t}} - \boldsymbol{c_{j,t}}\right)\right] \qquad (3.1)$$

$$\text{Subject to} \quad E[\boldsymbol{EPC}] = E\left[\frac{\sum_{j=1}^{J}\bar{q}_{j,t}}{\boldsymbol{Population_t}}\right] \geq X \qquad \forall\, t \qquad (3.2)$$

where

$j =$ fuel source index (oil, gas, nuclear, solar, and wind)

$t =$ time step index (one-year time intervals)

$\bar{q}_{j,t} =$ production capacity from energy source *j* at time *t*

$X =$ desired minimum per-capita energy production capacity

$\beta = \frac{1}{1+i}$ = discount factor, where *i* is the discount rate

$c_{j,t} =$ production cost in \$ per energy unit

The cost function in Eq. 3.1 has multiple components including capital, fixed, and operating costs.

3.3.1 Optimization Constraints

In addition to the EEPC constraint, which is considered as the secondary objective, the optimization problem has additional constraints:

1. The total power generated each time step (year) from all energy sources must be at least equal to the forecasted power demand that year. Since the forecasted power demand is uncertain, chance constrained programming is used to model such constraint as explained in a later section.

$$\sum_{j=1}^{N} \left(q_{j\_pwr}\right)_t \geq \left(\boldsymbol{q_{prjctd\,pwr}}\right)_t \qquad \forall\, t \quad \text{.........} (3.3)$$

2. Additional capacity power projects are capital intensive and thus once a power project is ON it will stay ON

$$\left(q_{j\_pwr}\right)_t \geq \left(q_{j\_pwr}\right)_{t-1} \qquad \forall\, j, t \quad \text{.........} (3.4)$$

3. Low oil depletion rate:

   Oil production is constrained to be less than the maximum allowed rate which is equivalent to 5% annual reserves depletion. Low depletion rate is one of the reservoir management best practices in order to extend the life of an oil field, gaining more knowledge, and capitalizing on new technologies and thus maximizing oil recovery.

$$(q_O)_t \leq \left(q_{O,max}\right)_t = 5\% \times \frac{(\boldsymbol{Oil\ Reserves})_t}{365} \quad \forall\, t \quad \text{.........} (3.5)$$

4. Annual change in total oil production is kept within 15%.

   Limiting annual changes to 15% avoids unreasonable changes in total oil production and thus annual capacity changes.

5. Annual change in total power production is kept within 15% as well for the same reason above.

3.3.2 Other Mathematical Equations

Other mathematical equations included that describe energy flows in the model are

1. Oil equation:

$$q_O = q_{O\_pwr} + q_{O\_othr} + q_{O\_exprt} \quad \text{(3.6)}$$

   Total oil production is the sum of oil directed to power generation (as crude or oil products), oil directed to meet other sectors demand, and the exported oil.

2. Gas equation:

$$q_G = q_{G\_pwr} + q_{G\_othr} = q_{associated} + q_{nonassociated} = q_O \times GOR + q_{nonassociated} \quad \text{(3.7)}$$

3. Power generation equations—from alternative energy sources

$$q_k = q_{k\_pwr} \quad , k = \text{ Nuclear, Solar, and Wind} \quad \text{(3.8)}$$

4. Oil capital cost:

   Oil capital cost is assumed to range (with uniform distribution) from $2,500 to $17,500 per bbl/day of peak production of the added capacity. This cost is assumed to increase exponentially as more capacity is added within the same year.

5. Oil and gas production costs:

   The production cost of oil (gas) is assumed to increase as more oil (gas) is extracted. I assumed an exponential function form to represent production costs as a function of the cumulative production. Thus, oil production cost, c_o, is given by

   $$c_o = 1.4\, e^{0.0098 \times Cumlative\ Oil\ Produced} \quad (3.9)$$

   and gas production cost, c_g, is given by

   $$c_g = 0.15\, e^{0.005 \times Cumlative\ Gas\ Produced} \quad (3.10)$$

   The potential technological effect on reducing production costs was not considered as this is a long-term model. Production costs are expected to increase in the long-term as more hydrocarbon is produced and resources scarcity increases.

3.3.3 Oil Price Model

Ideally, oil prices should be estimated by probabilistically forecasting global oil supply and demand and solving for equilibrium prices. However, since the model is built for Saudi Arabia in this work, a simpler approach can be followed if we consider Saudi Arabia as a price maker in the oil market. This is in fact true not only due to its large production and spare capacity but also as the largest producer within OPEC. Therefore, I assume that the oil price is inversely related to total Saudi Arabia's oil production.

Gao et al. (2009) provided an easy to use model for oil prices in the context of the above assumptions. They used the Energy Information Administration's (EIA) Oil Market Simulation (OMS) model to simulate an equilibrium model of the world oil market. They simulated 25 different cases for the years 1986-2010 and solved for oil prices and oil production choices by OPEC countries. Then they fit the data with an inverse demand equation that relates average daily supply of OPEC and the resulting oil price.

The resulting model takes the form

$$\ln p_t = \alpha_0 + \alpha_1 y_t + \alpha_2 T + \epsilon \quad \text{(3.11)}$$

where

p_t = the equilibrium oil market price

y_t = OPEC production choices

T = the time trend index defined as $T = t/65$ (t =1 in year 1986)

ϵ = regression error

Using ordinary least square regression, their oil price (in 1986 U.S. dollars) model is given by

$$\ln p_t = 3.5323 - 0.0398\, y_t + 3.9656\, T + \epsilon \quad \text{(3.12)}$$

Then assuming that Saudi Arabia will continue to produce about 27% of the total OPEC production in the long run, the model becomes

$$\ln p_t = 3.5323 - 0.0398 \times 3.7 \left(q_{O_{KSA}}\right)_t + 3.9656\, T + \epsilon \quad \text{(3.13)}$$

where q_{O_KSA} is the total oil production by Saudi Arabia.

Eq. 3.13 may not be the perfect model for oil prices but it is a simple relationship that satisfies the need of this work by relating Saudi Arabia production to global oil market prices. This link is the only part of this model that connects Saudi Arabia's energy system to the outside world. Eq. 3.13 is converted to 2014 US dollar value by multiplying it by the appropriate US CPI (consumer price index) ratio. In addition, the price model is converted to a probabilistic equation by multiplying it by a normal distribution of $\mathcal{N}(1,0.4)$. A standard deviation of 0.4 gives a P10-P90 range that encompasses most of past oil price fluctuations (**Fig. 3.6**). The model seems reasonable given that the average model response follows the general oil prices trend and the range brackets most of the actual historical fluctuations since 1986.

Therefore, the total oil revenue, R_O, function for Saudi Arabia as is given by

$$(R_O)_t = 365 \times \left(q_{O_{KSA}}\right)_t e^{\left[\left(3.5323-0.0398\times3.7\left(q_{O_{KSA}}\right)_t+3.9656\,T\right)\times\mathcal{N}(1,0.4)\right]} \quad \text{......} \ (3.14)$$

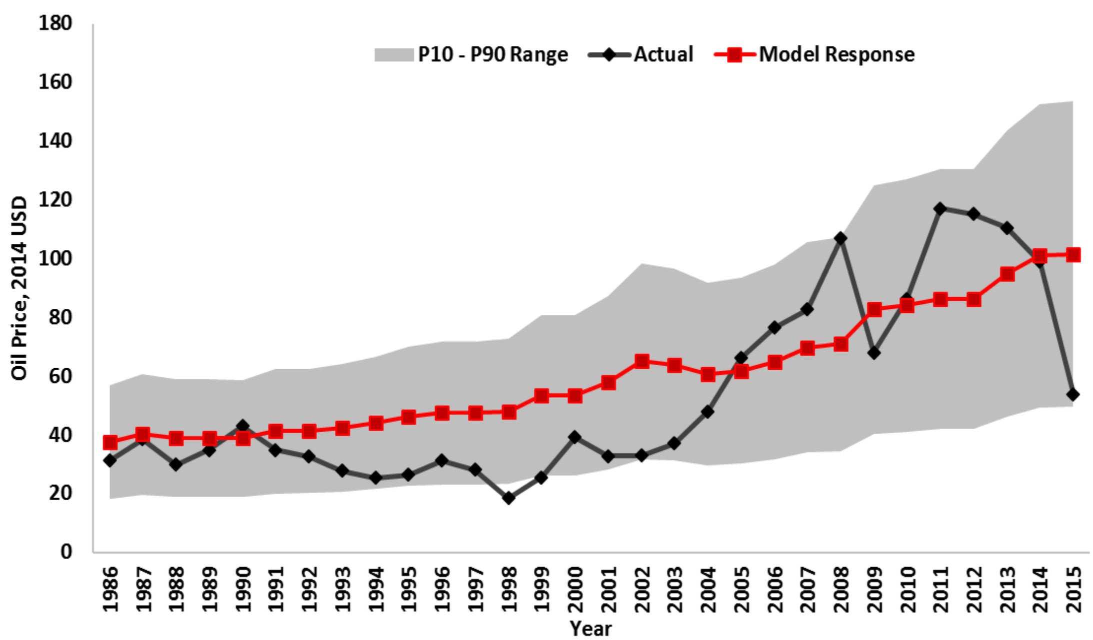


Fig. 3.6—Comparison between actual and model response for oil spot prices since 1986. The red line is the average model response and gray area is the 80% confidence interval (or P10-P90 range).

3.3.4 Modeling Uncertain Constraints

The model has many stochastic (uncertain) variables in the right-hand side of the constraints formula (Eq. 3.3, for example). If the left-hand side of the constraint is uncertain we can easily take certain percentiles that satisfy that constraint. However, it is difficult to deal with uncertain variable in the right-hand side of the constraint. There are several methods to account for such constraints including chance-constrained programming (CCP) and quadratic programming (McCarl and Spreen 2003). I use CCP in this work due to its simplicity and easy implementation in @RISK.

Chance constrained programming ensures that the stochastic (uncertain) constraint is met based on the level specified by the user. For example, the projected power demand is an uncertain variable in the model and, thus, if we specify that we need to meet the projected power demand with a 90% probability, the constraint becomes

$$\Pr\left[\sum_{j=1}^{N}\left(q_{j\_pwr}\right)_t \geq \left(\boldsymbol{q_{prjctd\,pwr}}\right)_t\right] \quad \geq 0.9 \qquad \forall t \text{........................} (3.15)$$

Then, we can replace the stochastic constraint in Eq. 3.15 with an equivalent constraint by specifying the 90th percentile of the projected power demand as

$$\sum_j\left(q_{j\_pwr}\right)_t \geq \left(\boldsymbol{q_{pwr,prjctd}}\right)_{t_{P90}} \qquad \forall t \quad \text{..} (3.16)$$

3.3.5 Forecasting Equations

Population and economic growth are considered the major factors deriving energy demand in Saudi Arabia. Energy prices and taxes play a major role in influencing demand as well. However, in Saudi Arabia, energy prices are administered by the government and are not often changed. Thus, their effect is negligible in driving demand, especially in the short term, unless prices are deregulated.

Therefore, I consider only GDP and population growth influencing energy demand in this work. In addition, the reported Saudi GDP in government reports or the World Bank statistics does not represent the actual economic activities in Saudi Arabia since about 42% of the GDP is due to oil revenue. Aldukheil (2013) used a modified GDP for forecasting Saudi Arabia future energy demand. He used the non-oil GDP (GDP_{NO}) plus only 10% of the oil GDP to get a representative GDP for Saudi Arabia. His assumption is that 10% of the oil GDP is the cost of extraction. Lahn and Stevens (2011) also used non-oil GDP as a driver for Saudi energy demand. Thus, in this work non-oil GDP (GDP_{NO}) is used to forecast future energy demand in addition to the population growth. **Fig. 3.7** shows how Saudi non-oil GDP compares to the total GDP.

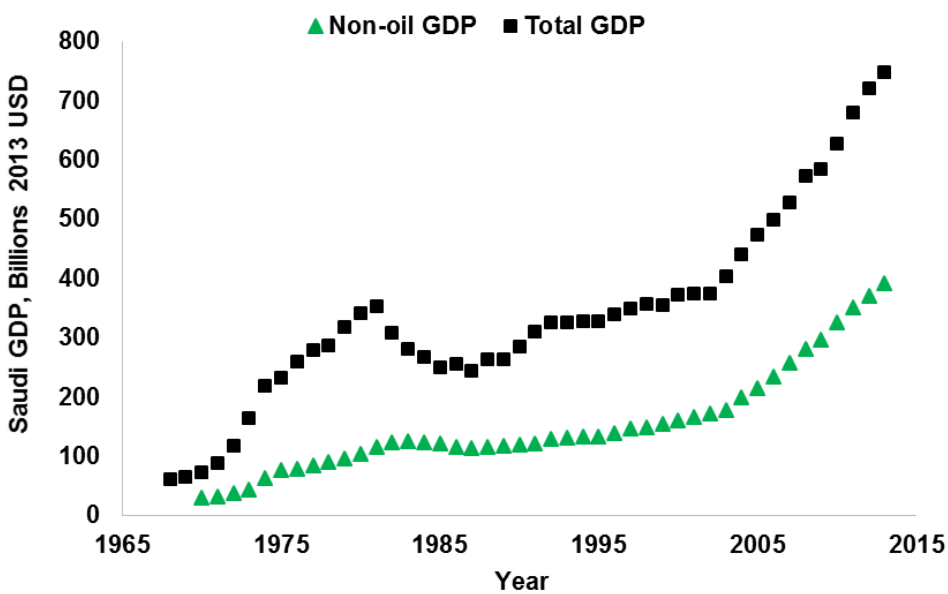


Fig. 3.7—Saudi total GDP and non-oil GDP in 2013 US dollars.

Therefore, using population growth and GDP_{NO}, we can estimate future energy fuels demand using Cobb-Douglas demand equation (Cooper 2003) as

$$D_t = a\, p_t^b\, Y_t^c\, e_t \quad \text{(3.17)}$$

In logarithmic form, Eq. 3.17 is written as

$$\ln D_t = \ln a + b \ln p_t + c \ln Y_t + \ln e_t \quad \text{(3.18)}$$

I assumed that since energy prices are set by the government in Saudi Arabia, their effect on energy demand is negligible. Thus, the price term is eliminated from Eq. 3.18. Then, using per-capita energy demand and per-capita GDP_{NO}, we can estimate future energy demand. For example, for power demand, D_{pwr}, we have

$$\ln\left(\frac{D_{pwr}}{Population}\right)_t = \ln a + c \ln\left(\frac{GDP_{NO}}{Population}\right)_t + \ln e_t \quad \text{(3.19)}$$

Eq. 3.19 can be written as

$$\ln\left(\frac{D_{pwr}}{Population}\right)_t = \alpha_0 + \alpha_1 \ln\left(\frac{GDP_{NO}}{Population}\right)_t + \epsilon_t \quad \text{(3.20)}$$

where α_0 is the intercept, α_1 is the income elasticity of demand, and ϵ_t is the regression error. Regression was made using Eq. 3.20 on Saudi Arabia historical demand data since 1995. The regression results are shown in **Table 3.2** while **Fig. 3.8** shows how well the regression model fits the actual data. Eq. 3.20 then uses input data from population and non-oil GDP forecasts (**Fig. 3.9**) to estimate future energy demand for power and oil and gas demand for other sectors (**Fig. 3.10**).

In Section 3.6, regulated domestic oil prices assumption will be relaxed and assumed to follow global oil market prices. Gas prices, however, will still be assumed constant due to the localized nature of gas markets.

Variable		α_0	α_1
Power Demand	Estimate	0.903	0.872
	Standard Error	0.444	0.049
	R^2	0.950	
Oil: Other Sectors Demand	Estimate	-0.351	0.448
	Standard Error	0.267	0.029
	R^2	0.933	
Gas: Other Sectors Demand	Estimate	-0.740	0.636
	Standard Error	0.312	0.034
	R^2	0.951	

Table 3.2—Regression results for estimating demand equations. "Other Sectors Demand" refers to the total demand of all energy sectors except power generation.

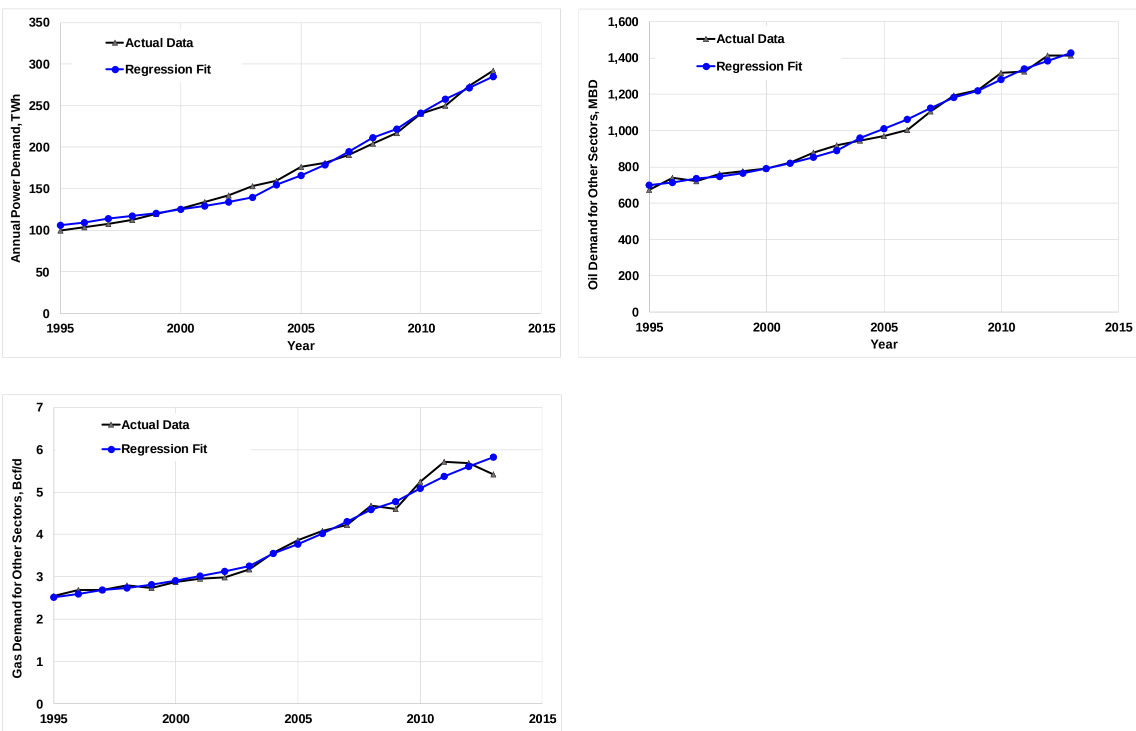
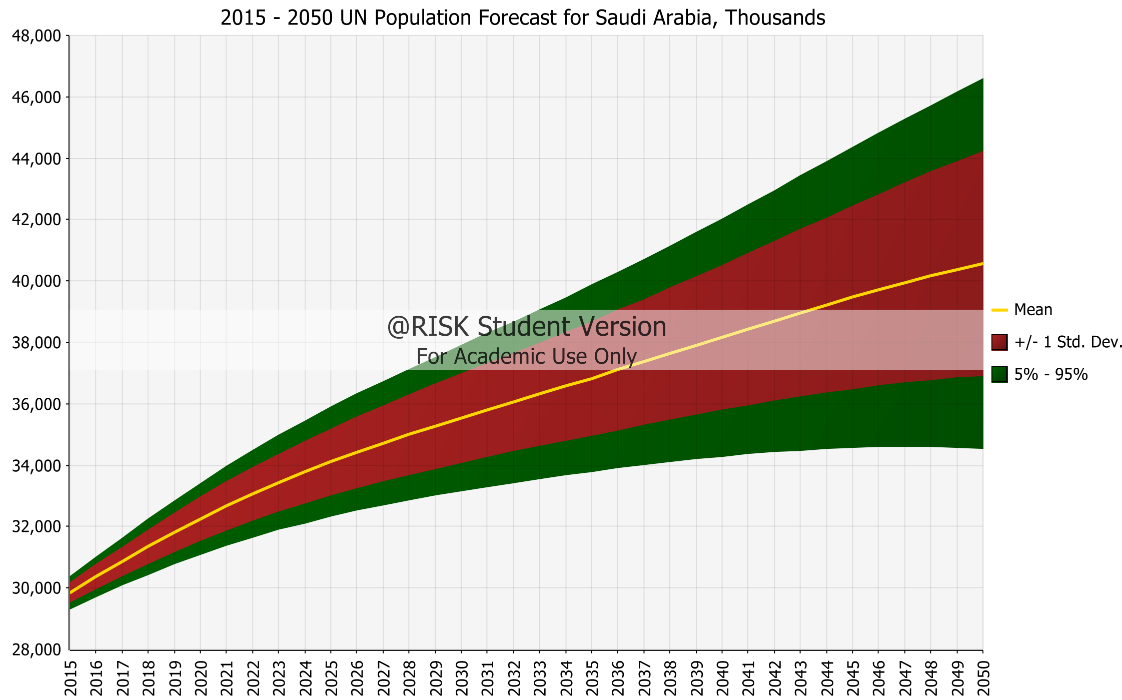


Fig. 3.8—Regression model fit in comparison with actual data for power demand (upper left), oil demand for other sectors (upper right), and gas demand for other sectors (lower left).



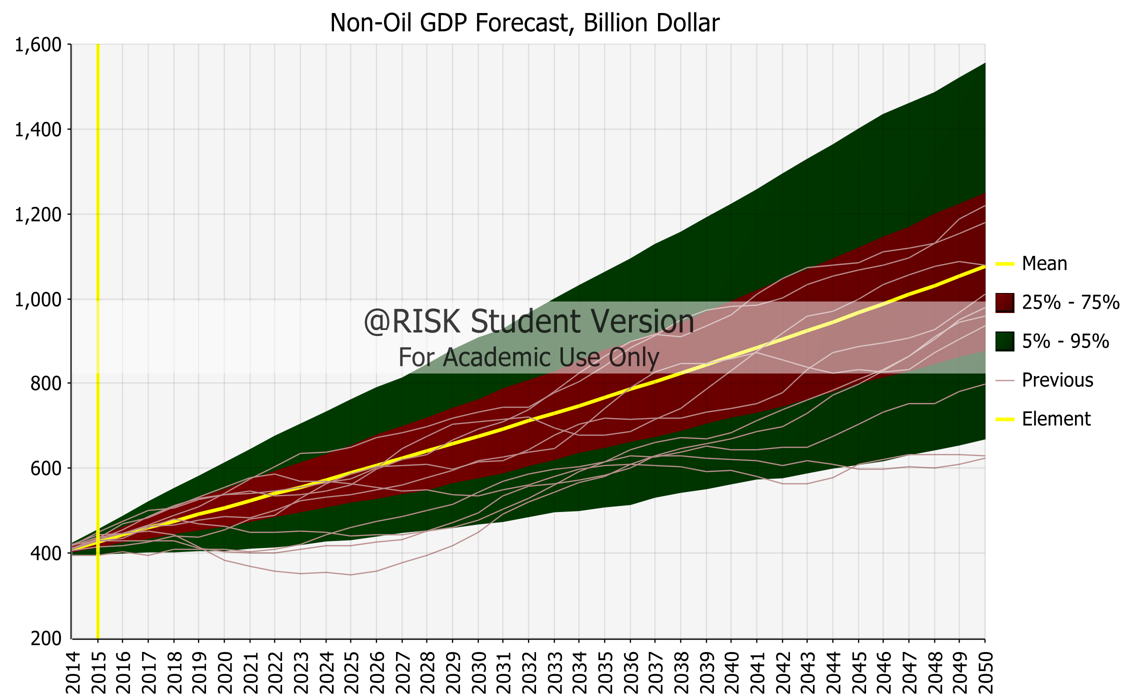


Fig. 3.9—Saudi Arabia population (top) and non-oil GDP (bottom) forecasts used as input to the model.

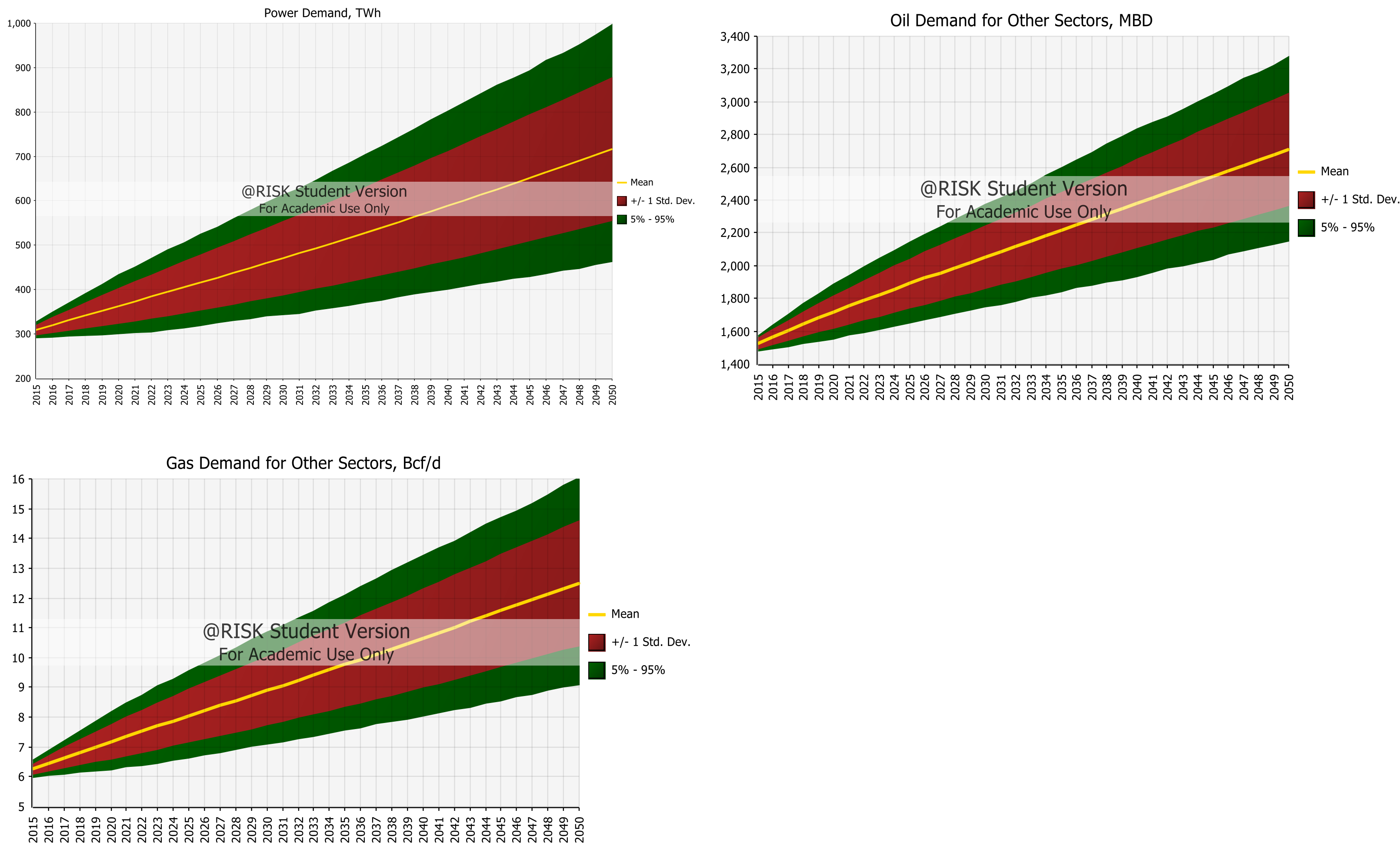


Fig. 3.10—Stochastic forecasts for Saudi Arabia power demand (upper left), oil demand for other than power sectors (upper right) and gas demand for other than power sectors (lower left).

3.4 Model Input and Assumptions

The model is run until 2050. A discount factor of 10% is used to calculate the NPV. **Table 3.3** shows in put variables along with their distributions and formulae.

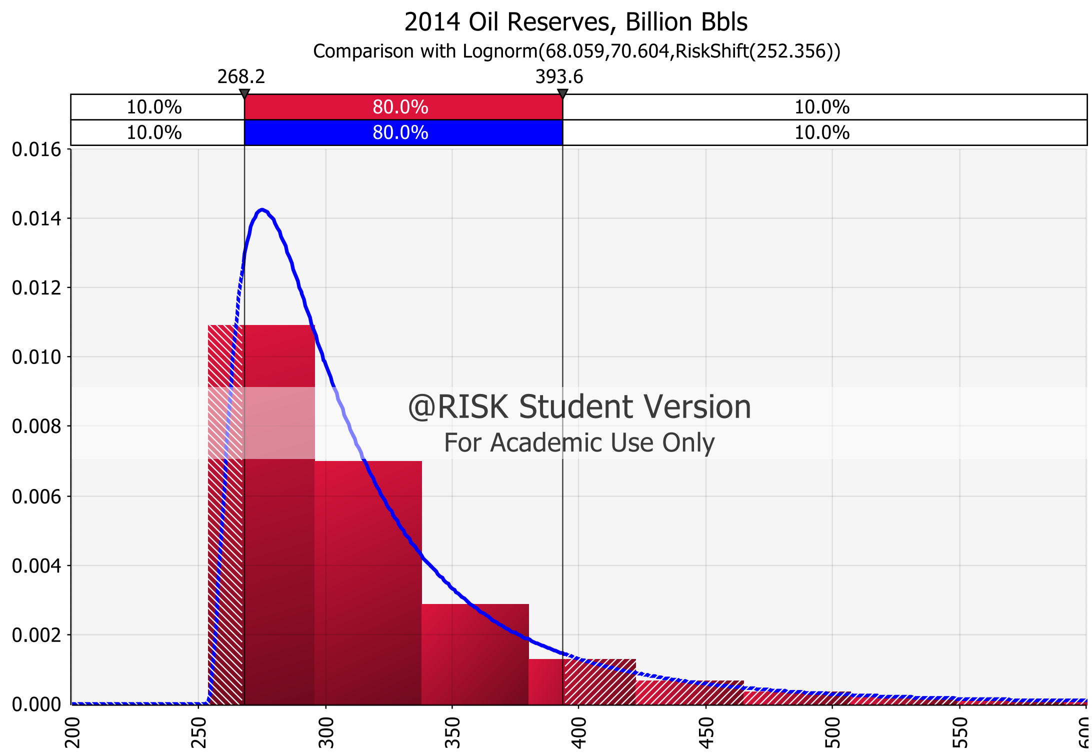
Variable	Function
Population (Thousands)	Normal ()*
Non-oil GDP (Billions $)	Autoregressive model (AR1)
Projected Power Demand (TWh)	Regression Formula: *f* (GDP per-capita)
Projected Oil Demand (Other sectors) (MBD)	Regression Formula: *f* (GDP per-capita)
Projected Gas Demand (Other sectors) (MBD)	Regression Formula: *f* (GDP per-capita)
Oil Reserves (Billion bbl)	Log-normal [68, 71, Shift(252)]
Gas Reserves (Tcf)	Log-normal [146, 97, Shift(235)]
Oil Annual Decline Rate (%)	Uniform (0.05, 0.10)
Gas Annual Decline Rate (%)	Uniform (0.03, 0.10)
Oil Prices ($/bbl)	p_O * Normal (1, 0.4)
Oil Projects Capital Cost ($/bbl of peak production)	Uniform (2500, 17500)

Notes:
1) * using 5th and 95th percentiles from the UN population forecasts for Saudi Arabia.
2) p_O is the oil price calculated using the oil price model.
3) MBD: thousands bbl/day

Table 3.3—Density functions and formulae of uncertain input variables.

3.4.1 Modeling Oil and Gas Reserves

Saudi Arabia oil and gas reserves are modeled using lognormal distributions (**Figs. 3.11** and **3.12**) along with their reserves replacement rates. With the assumed reserves replacement rates, the model is less sensitive to oil and gas resources availability. In other words, the oil production, for example, will not be forced to decline due to non-availability of oil reserves. Hence, the model is more sensitive to costs and value generated from each energy source.



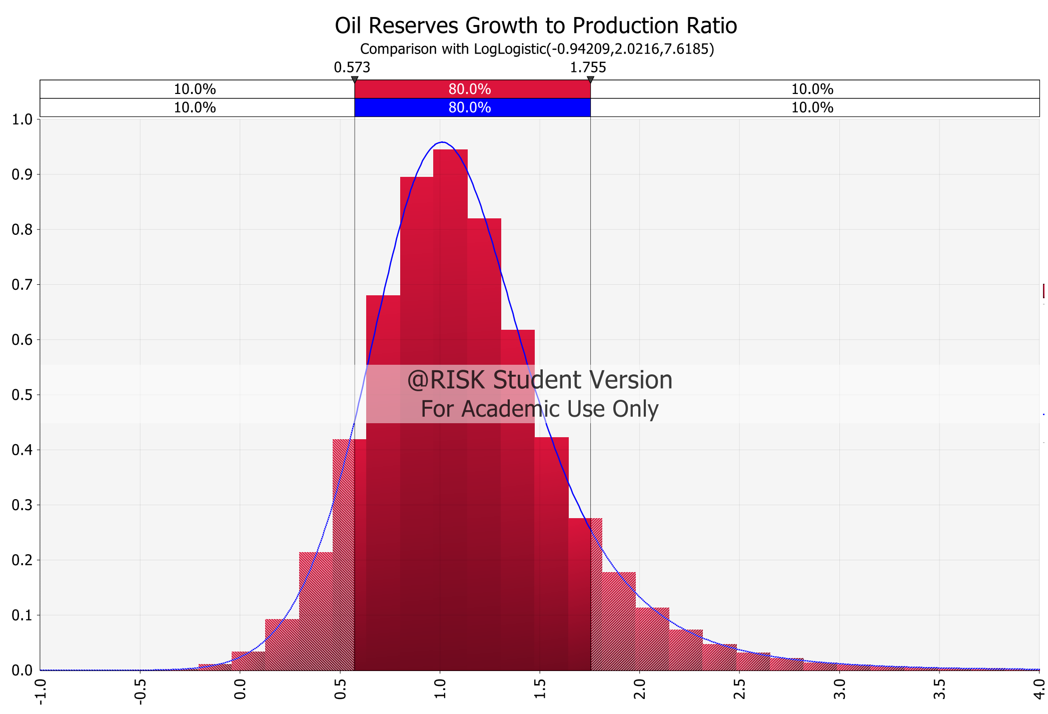


Fig. 3.11—Oil reserves distribution (top) and reserves growth to production ratio (bottom).

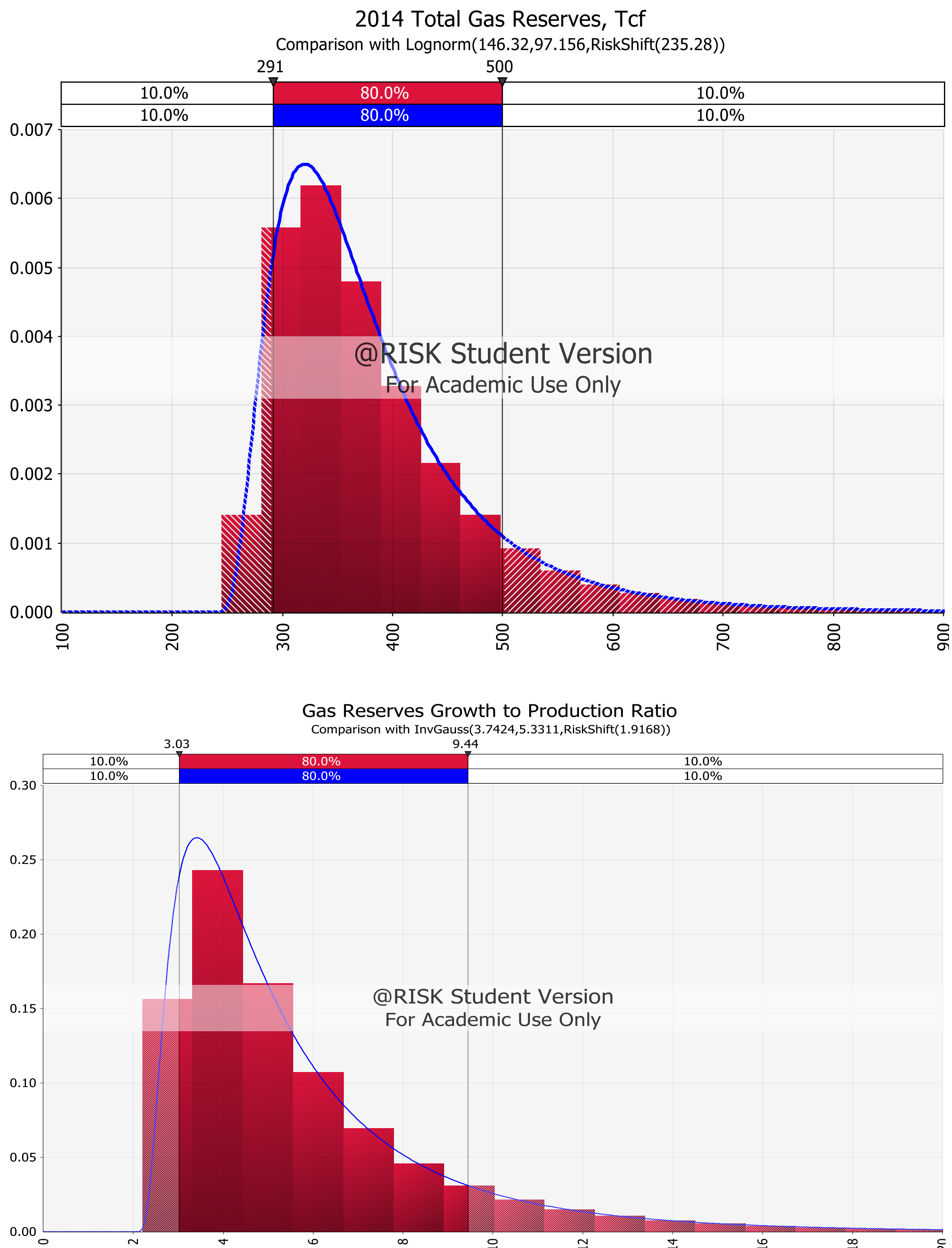


Fig. 3.12—Total gas reserves distribution (top) and reserves growth to production ratio (bottom).

3.4.2 Power Generation Technologies Assumptions

In this model, only five technologies are included for power generation—oil, gas, nuclear, wind, and solar. The choice of which energy technology to include is mainly location (country) specific. For example, in the case of Saudi Arabia coal and hydropower are not viable options due to non-availability of coal and lack of large hydropower locations.

Table 3.4 shows capital and non-fuel operating costs for each power generation technology. Lead time is also included which indicates the time needed to begin capital investments and build a project before it actually starts. I recognized there is potential for the cost of renewable energy projects to go down with time following the historical trends, but I chose to leave it constant over the forecast time period. This assumption will be relaxed in section 3.6.

Technology	**Capital Cost (USD/kW)**	**Fixed O&M Cost (USD/kW-year)**	**Non-fuel Variable O&M Cost (USD/MWh)**	**Lead Time (years)**	**Lifetime (years)**
Oil (Crude or Oil Products)	2,120	11.2	1.64	3 - 4	30
Natural Gas	1,500	11.2	4.00	3 - 4	35
Nuclear	4,500	100	2.14	5 - 10	35
Solar	2,100	30	0	2	25
Wind	2,100	40	0	3	25

Table 3.4—Capital and non-fuel operation costs for new installed capacity in the power sector (IRENA 2015; Matar et al. 2015)

Appendix A shows conversion factors that can be used to convert from one energy unit to another. It is especially needed for power generation calculations to have a consistent energy measure unit (e.g., boe).

3.5 Model Results

The model was built to be run two different ways: probabilistic and deterministic (**Table 3.5**). The model is run assuming different values of EEPC ranging from 130 to 180 boe/year per capita. Any value of EEPC below 130 would result in the same ENPV since the model will reach its minimum energy production. On the other hand, the model will not reach a solution for EEPC values above 180 due to model constraints—it requires additional energy production more than the allowed rate of increase per year. A special case was also run for each model type called the business-as-usual (BAU) case considering only Saudi legacy energy sources, i.e., oil and gas. Each of the model types will give a different perspective on the energy strategy for Saudi Arabia.

Model Type	Description
Probabilistic	A probabilistic model with uncertain variables modeled using distributions. Uncertain constraints are modeled using chance constrained programming.
Deterministic – Mode	Replacing each distribution in the probabilistic model with its **mode**.
Deterministic – Mean	Replacing each distribution in the probabilistic model with its **mean**.

Table 3.5—Description of model types run in this work.

3.5.1 Probabilistic Model Results

The probabilistic model was run for five different values of EEPC as its secondary objective in addition to maximizing the ENPV. The ENPV efficient frontier for this optimization is shown in **Fig. 3.13**.

The efficient frontier shows the maximum possible portfolio expected net present value (ENPV) that can be reached for each specified level of minimum expected energy production capacity (EEPC). Any combinations of ENPV and EEPC below the efficient

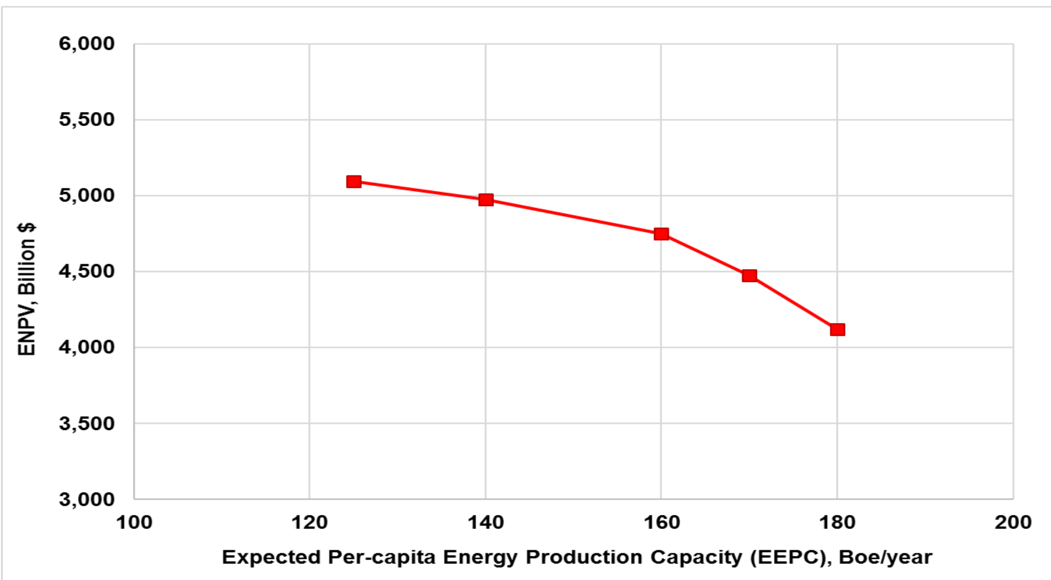


Fig. 3.13—Efficient frontier for the probabilistic model optimization.

frontier curve are not optimum and combinations above the efficient frontier are not possible.

From this efficient frontier curve we can see that ENPV declines as the required energy production capacity increases since more investments are needed to add new capacity. In addition, high EEPC values require higher oil production which exerts downward pressure on oil prices resulting in lower revenue and total ENPV (Eq. 3.14).

Fig. 3.14 shows the probabilistic model results for EEPC $\geq$ 180 boe/year per capita. For such a high energy sustainability requirement, the model suggested increasing oil production from the current rate of about 11 million bbl/day to about 16.3 million bbl/day by 2050, doubling natural gas production rate (mainly due to increase in other sectors demand), and meeting almost all new power demand from alternative sources of energy (nuclear, solar, and wind).

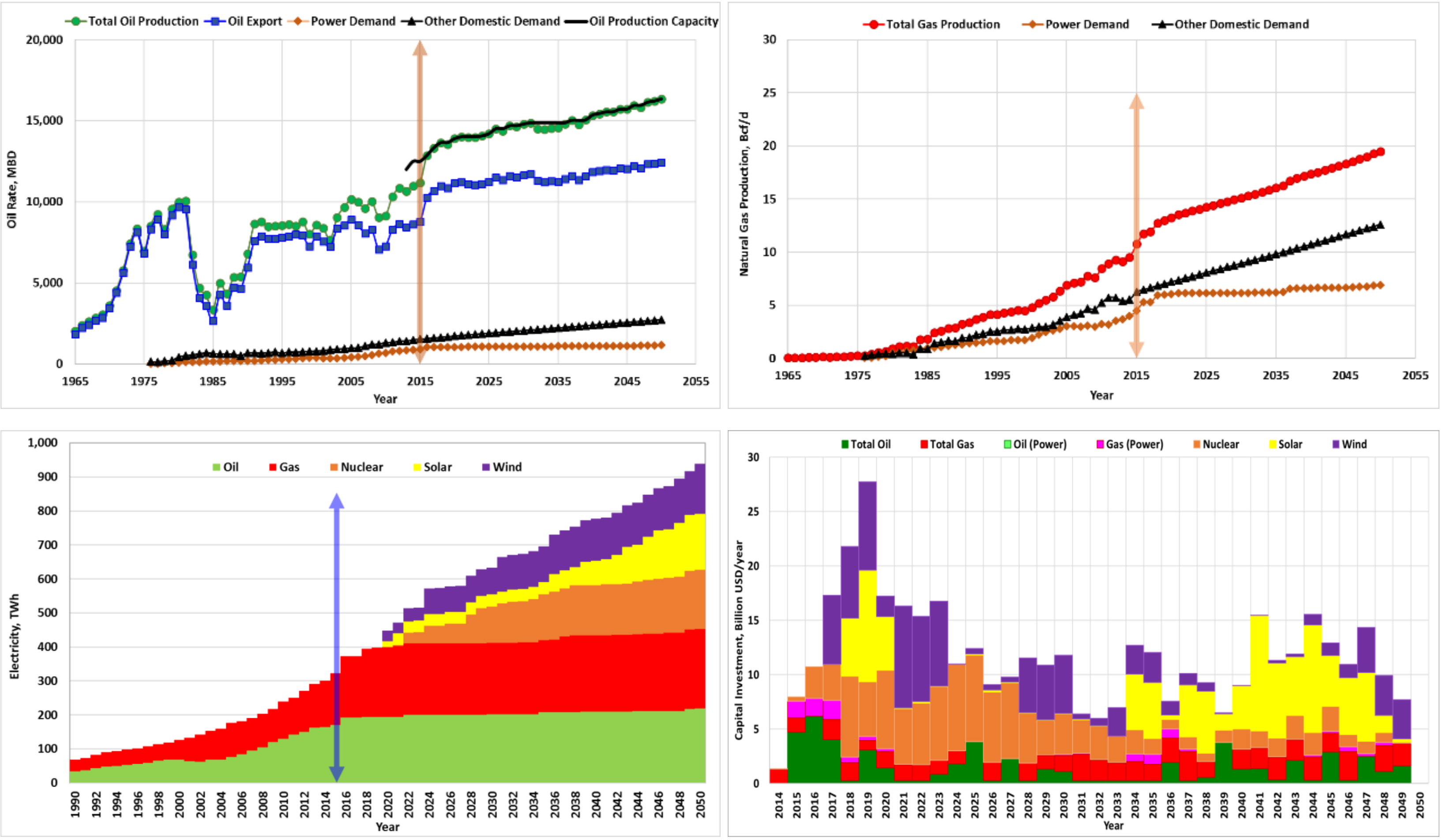


Fig. 3.14—Probabilistic model results for EEPC ≥ 180 boe/year per capita. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

Results for minimum EEPC of 160 boe/year per capita are shown in **Fig. 3.15**. In fact, EEPC of 160 boe/year per capita is about the average EEPC for the past 10 years for Saudi Arabia. Therefore, we can consider this value a good measure sustainability. This case resulted in higher ENPV than the previous one (EEPC $\geq$ 180 boe/year) since it requires less energy production. Recommended optimal total oil production is about 12.5 million bbl/day until 2035 and about 13.8 million bbl/day beyond 2035. Natural gas production should be doubled to 20 Bcf/d by 2050 where most of additional gas is directed to meet demand from other sectors and only small portion to power generation. In addition, almost all future power demand requirements should be met using alternative energy sources.

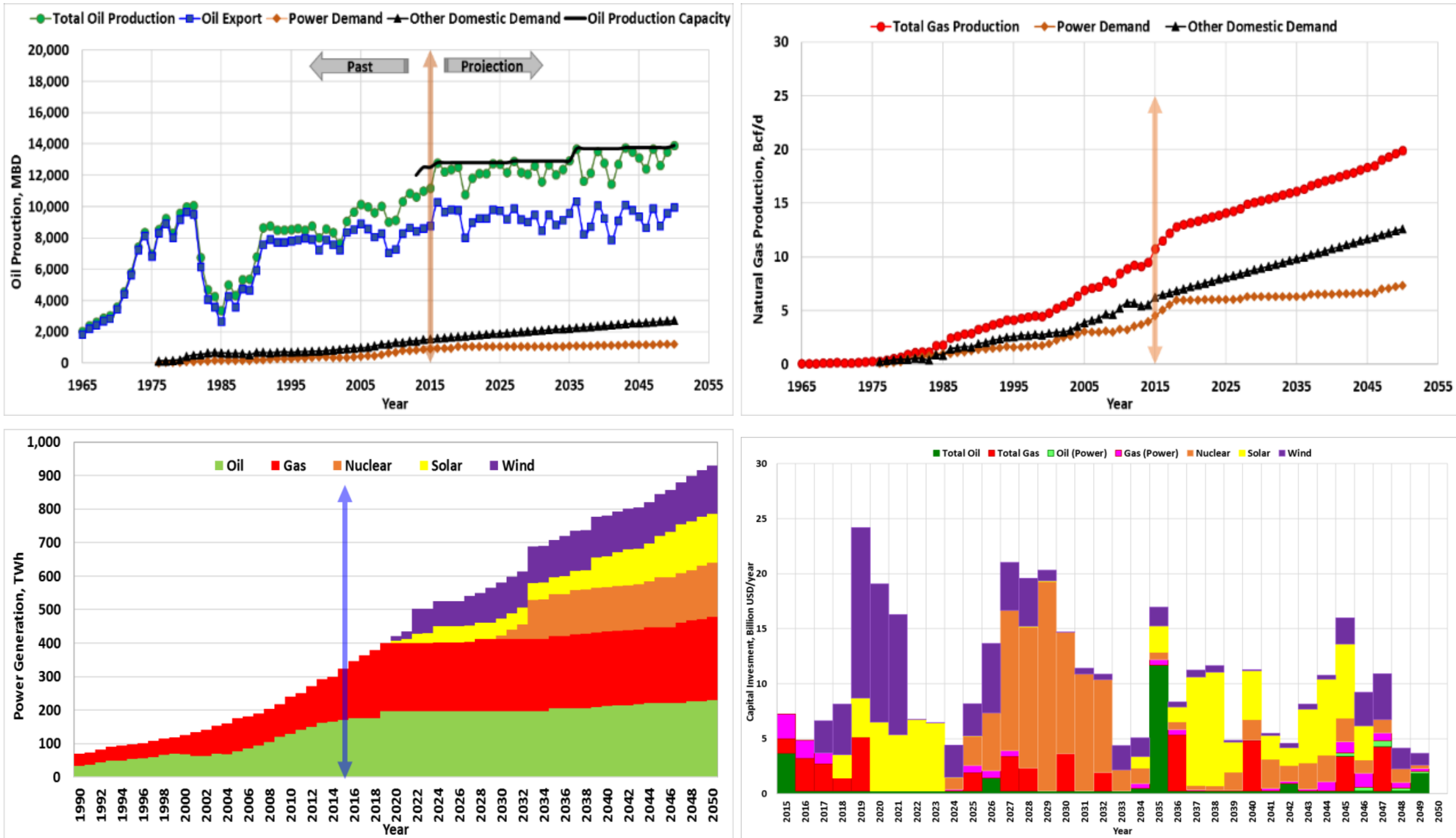


Fig. 3.15—Probabilistic model results for EEPC ≥ 160 boe/year per capita. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

3.5.2 Deterministic Model Results

Efficient frontier curves for the deterministic optimization models are similar in shape to those of the probabilistic model (**Fig. 3.16**). However, efficient frontier curve for the Deterministic-Mode model is slightly higher than the Deterministic-Mean curve except for very high values of EEPC. One reason for this difference is the Deterministic-Mean model suggested higher oil production than the Deterministic-Mode model (**Figs. 3.17** and **3.18** for EEPC ≥ 160 boe/year per capita). Thus, with higher oil production, the required investments will be higher and oil prices would be lower, resulting in overall lower ENPV. In addition, the mode of the projected power demand is slightly lower than its mean (**Fig. 3.19**), affecting the value used in Eq. 3.3. Therefore, the Deterministic-Mode model suggests lower investment in building power capacity (see capital investment distribution in Fig. 3.17) and hence higher ENPV.

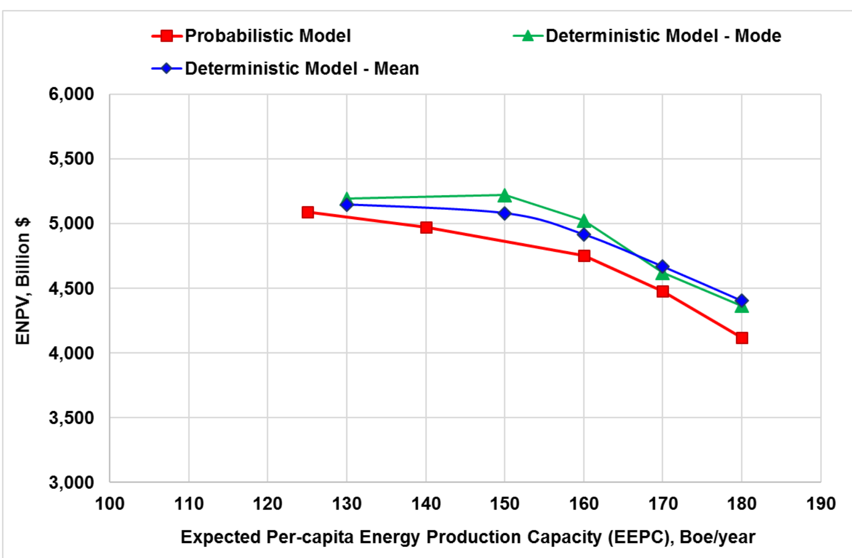


Fig. 3.16—Efficient frontier for Deterministic-Mode and Mean models optimization and how they compare to the probabilistic model curve.

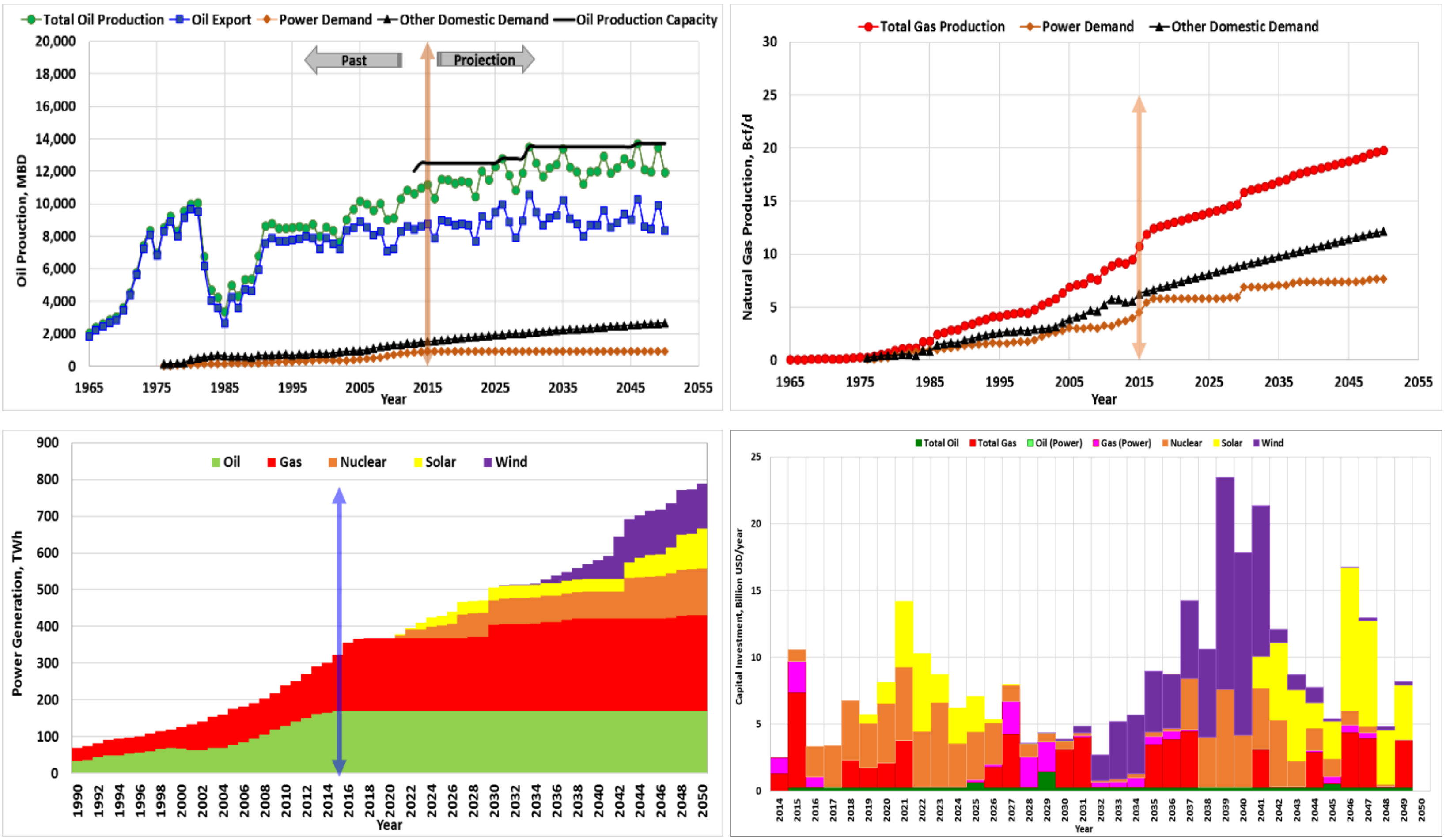


Fig. 3.17—Deterministic-Mode model results for EEPC ≥ 160 boe/year per capita. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

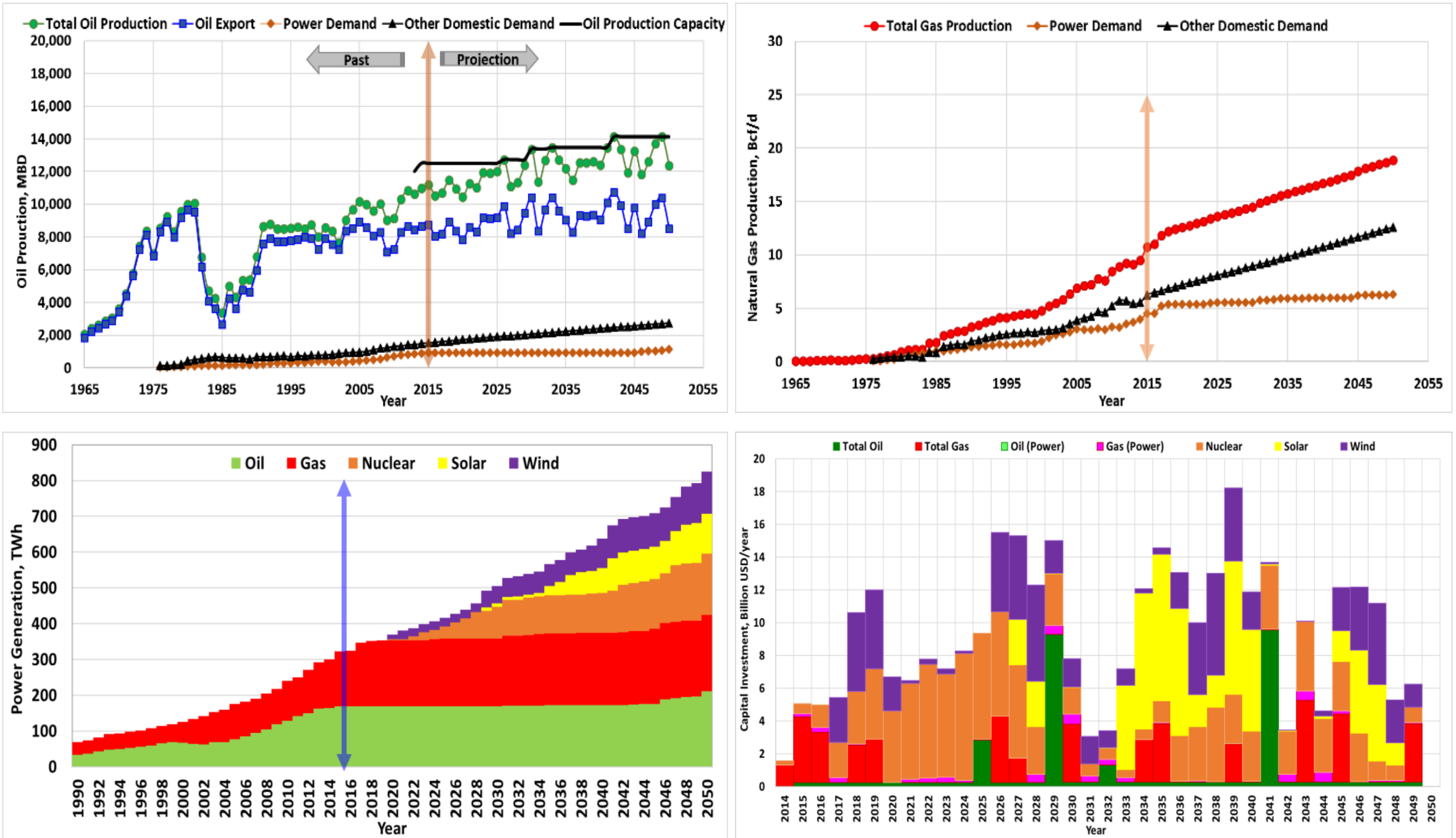


Fig. 3.18—Deterministic-Mean model results for EEPC ≥ 160 boe/year per capita. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

3.5.3 The Value of Probabilistic Modeling Approach

Fig. 3.16 showed efficient frontier curves for all three models. We observe that the probabilistic model efficient frontier curve is consistently below those of the deterministic models. Thus, the probabilistic model shows lower ENPV for all possible values of EEPC.

The main reason for such difference is how the constraints are set up in the probabilistic model using the CCP approach. For example, the projected power demand is met with a probability of 90% and thus requires that the total generated power is at least equal to the P90 of the projected annual power demand. The Deterministic models are required to meet much smaller (mean and mode) demand (Fig. 3.19). However, since the projected power demand is uncertain, it is prudent to use a probabilistic approach with a probability of 90%. Thus, depending on deterministic models may result in underestimation of the required investments needed to meet future power demand. We can see that by comparing the investments distribution chart in Fig. 3.15 with Figs. 3.17 and 3.18.

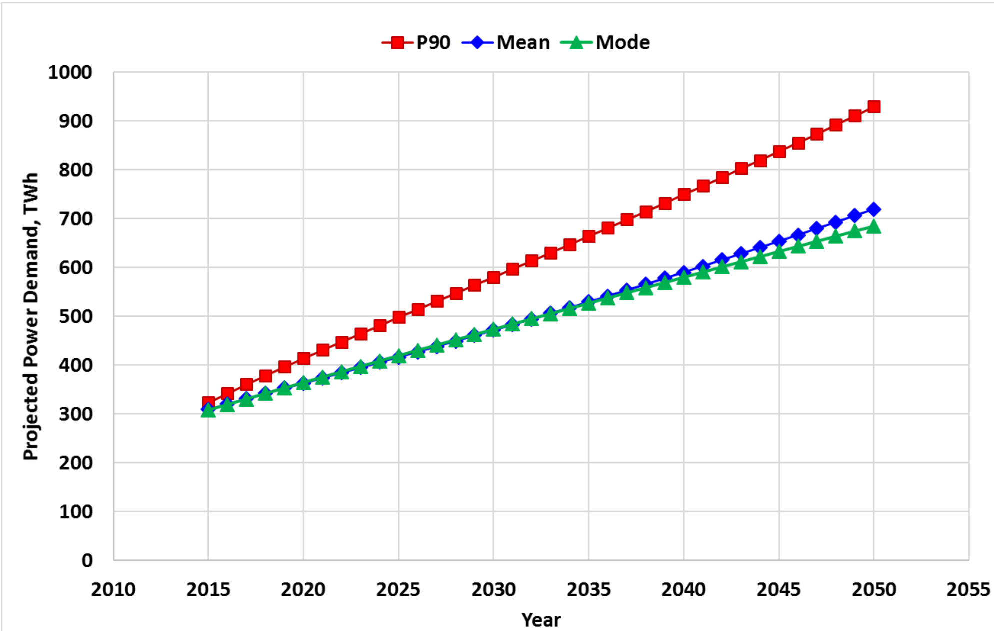


Fig. 3.19—Projected power demand constraint used in each model. P90 in probabilistic model (CCP), Mean in Deterministic-Mean model and Mode in Deterministic-Mode model.

3.5.4 The Value of Investing in Alternative Energy Sources in Saudi Arabia

All three models (probabilistic and deterministic) were run for business-as-usual (BAU) cases where no investment in alternative energy sources is considered and EEPC is kept at 160 boe/year per capita. As shown **Fig. 3.20**, BAU ENPV values were within the range of other cases with alternative energy sources and minimum EEPC of 160 boe/year. However, comparing the models results in **Figs. 3.21**, **3.22**, and **3.23** with their counterparts in Figs. 3.15, 3.17, and 3.18, respectively, all BAU cases require much higher gas production, reaching 25 Bcf/day by 2050, in addition to directing more oil to power generation. In addition, BAU cases result in a less diversified and riskier energy portfolio, especially since oil and gas are exhaustible resources.

Investing in alternative energy sources will reduce the required gas production to less than 20 Bcf/day by 2050. It will also direct more oil toward export, maximizing oil revenue.

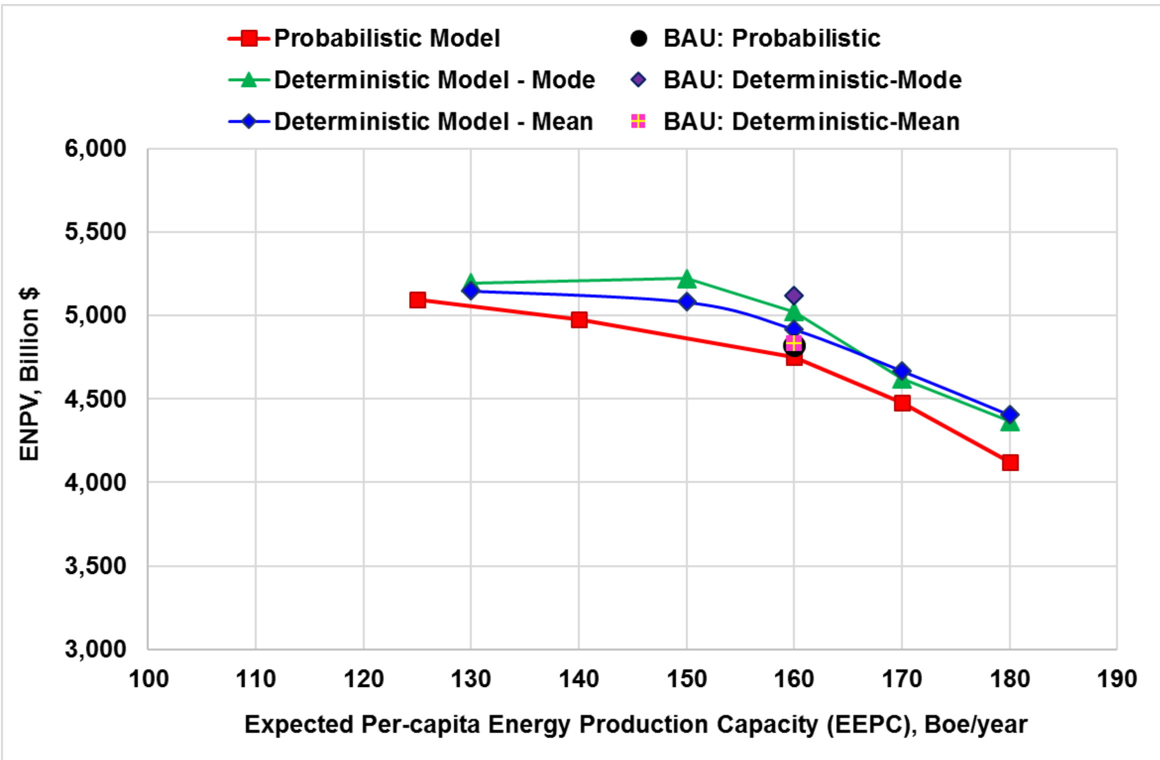


Fig. 3.20—BAU cases compared to probabilistic and deterministic model efficient frontiers.

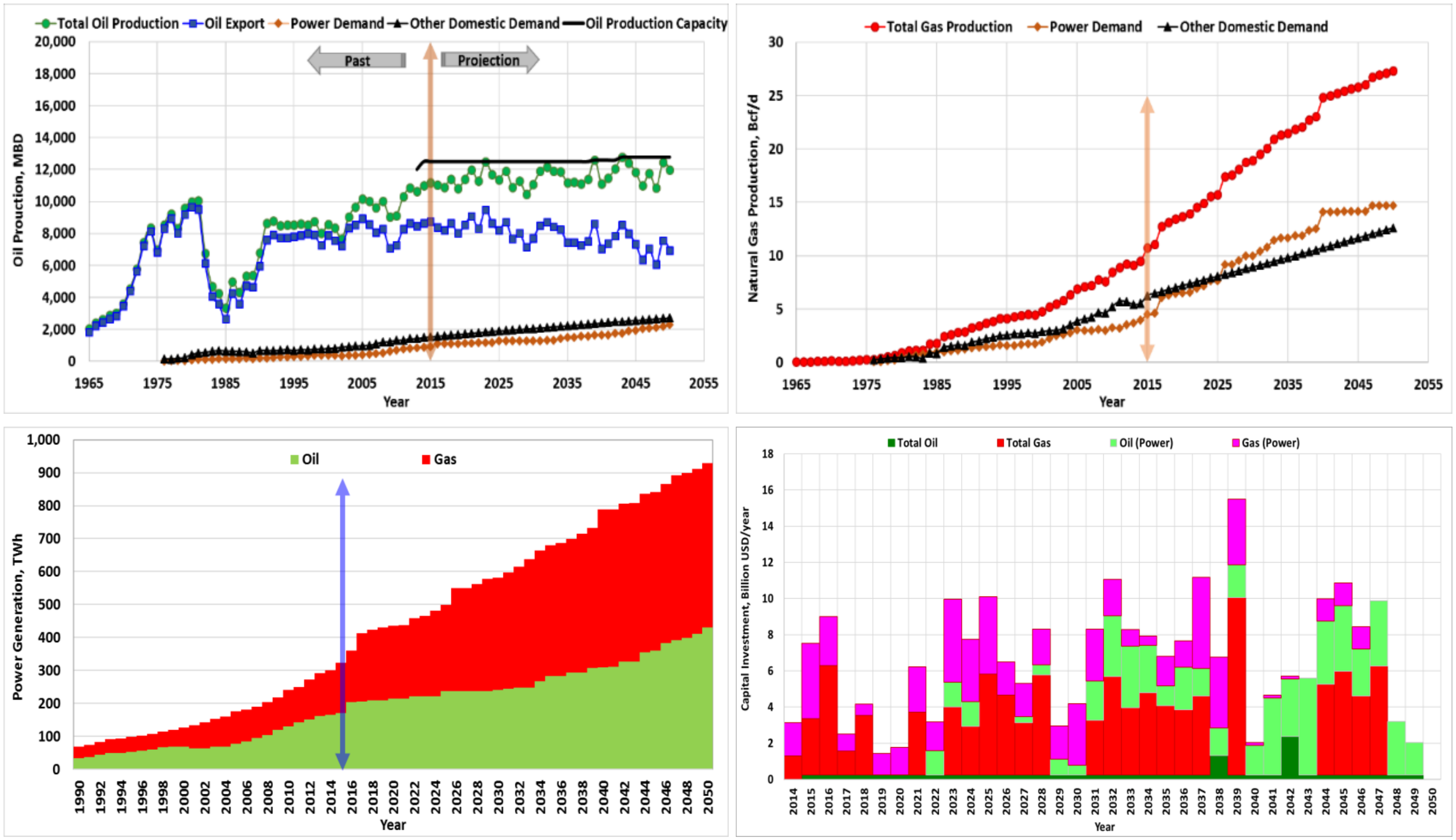


Fig. 3.21—Probabilistic model results for BAU case (EEPC ≥ 160 boe/year per capita). The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

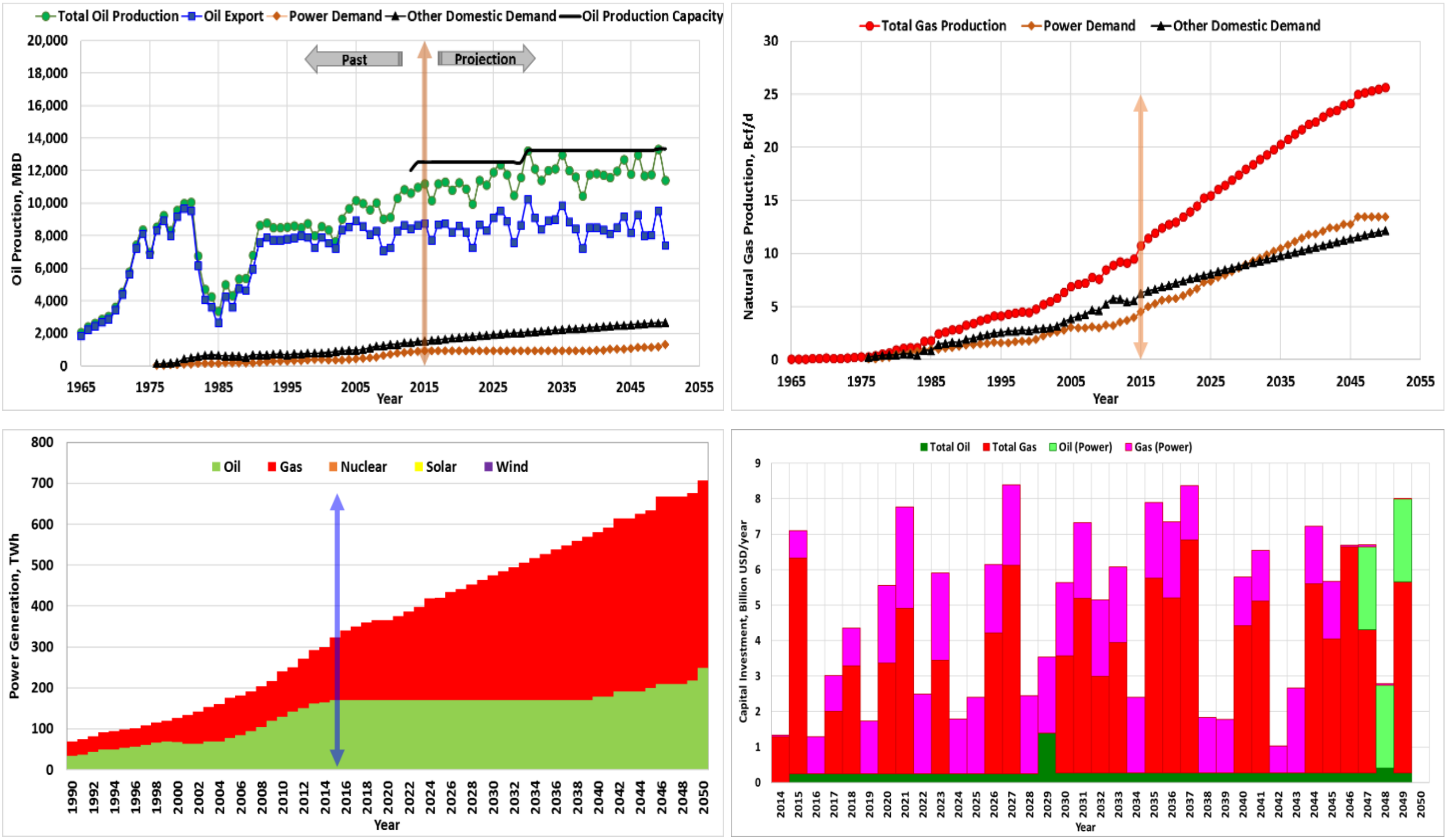


Fig. 3.22—Deterministic-Mode model results for BAU case (EPC ≥ 160 boe/year per capita). The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

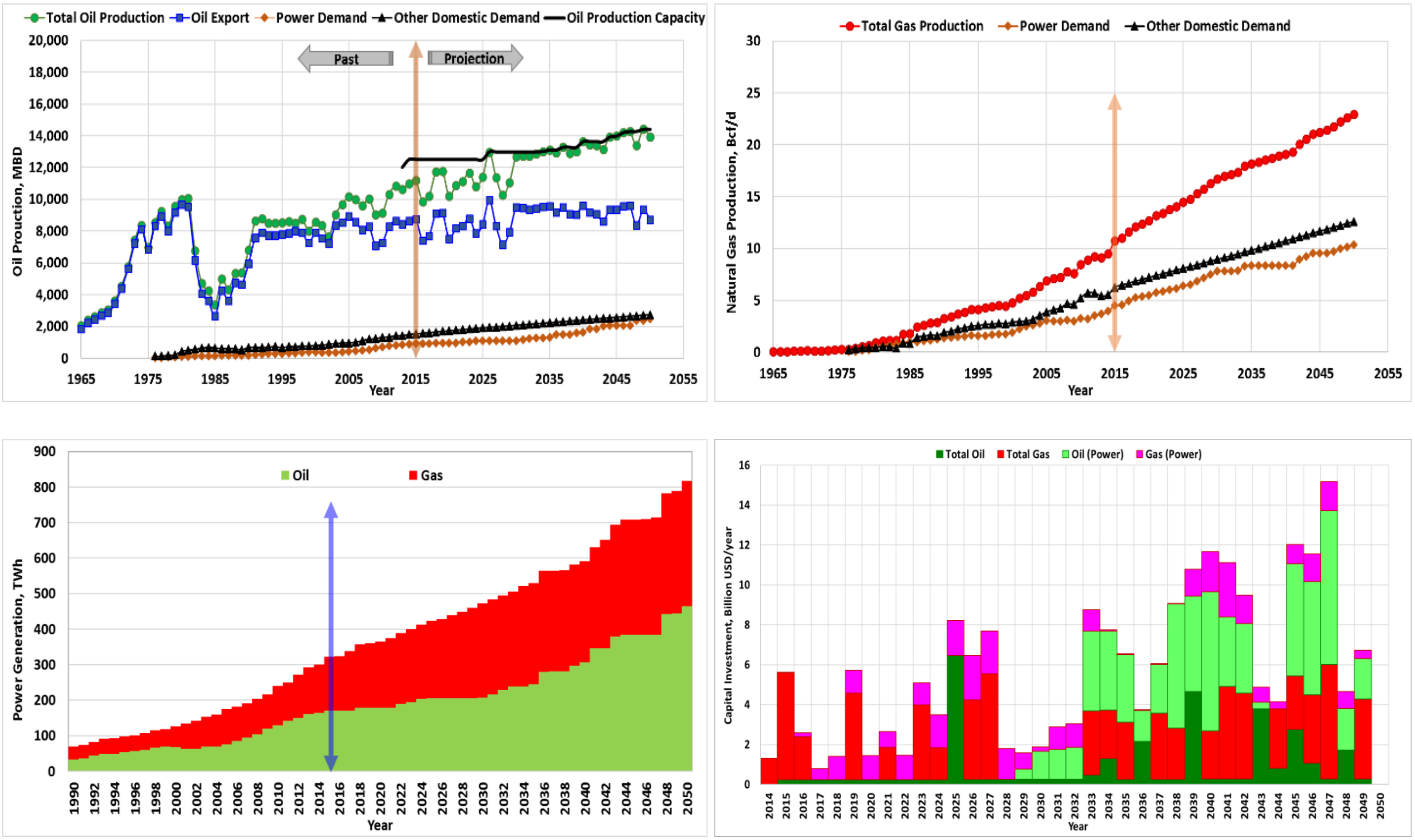


Fig. 3.23—Deterministic-Mean model results for BAU case (EPC ≥ 160 boe/year per capita). The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

3.6 Model Extensions and Policy Changes Effects

In this section, I relaxed some of the assumptions in the previous sections to explore different scenarios and effects of policy changes. The model was run for three cases: domestic oil prices deregulation, potentially lower alternative energy costs, and low-income elasticity of domestic energy demand.

I ran the new cases for EEPC of 160 boe/year per capita since this value ensures energy sustainability for Saudi Arabia and thus results for each case are compared to the probabilistic model results in Section 3.5.1.

3.6.1 Saudi Arabia Domestic Energy Prices Reform

Although domestic energy prices are administered by the Saudi government and are rarely changed, increase in domestic oil prices by the government or complete price deregulation is likely to occur in the future. The extreme case is when domestic oil prices are allowed to change with global oil market prices. Thus, the model is run assuming domestic oil prices are equal to the global oil prices and accounting for their effect on domestic oil demand. The forecasting equation (Eq. 3.20) will take the form

$$\ln\left(\frac{D_O}{Population}\right)_t = \alpha_0 + \alpha_1 \ln(p_t) + \alpha_2 \ln\left(\frac{GDP_{NO}}{Population}\right)_t + \epsilon_t \quad (3.21)$$

where D_O is the Saudi domestic oil demand for other sectors and p_t is the global oil prices. **Table 3.6** the regression of domestic oil demand for other sectors results using oil price and non-oil GDP per capita as factors influencing oil demand in Saudi Arabia. The price elasticity of demand (α_1) magnitude is small compared to income elasticity of demand (α_2), indicating that oil demand is influenced more by income rather than by prices. It also indicates that domestic oil demand in Saudi Arabia is inelastic with respect to prices change.

Variable		α_0	α_1	α_2
Oil: Other Sectors Demand	Estimate	-1.187	-0.052	0.562
	Standard Error	0.565	0.026	0.072
	R^2	0.927		

Table 3.6—Regression results for estimating Saudi Arabia's oil demand equation accounting for prices and non-oil GDP per capita effects. "Other Sectors Demand" refers to the total demand of all energy sectors except power generation.

The results for EEPC of 160 boe/year per capita (**Fig. 3.24**) show that oil production capacity need not be increased more than its current level and the oil production required is much less compared to the case when price effects were assumed negligible (Fig. 3.15). In addition, the ENPV (**Fig. 3.25**) is much larger now showing $6,200 Billion compared to $4,750 Billion when oil prices were regulated. This increase is due to additional income that was foregone by the government when domestic oil prices were subsidized and due to less capital investment in the oil sector. Thus, deregulating domestic oil prices should result in higher revenue without the need to increase oil production capacity.

The effects described here are only the economic effects of prices deregulation. The social impacts are beyond the scope of this research and were not addressed.

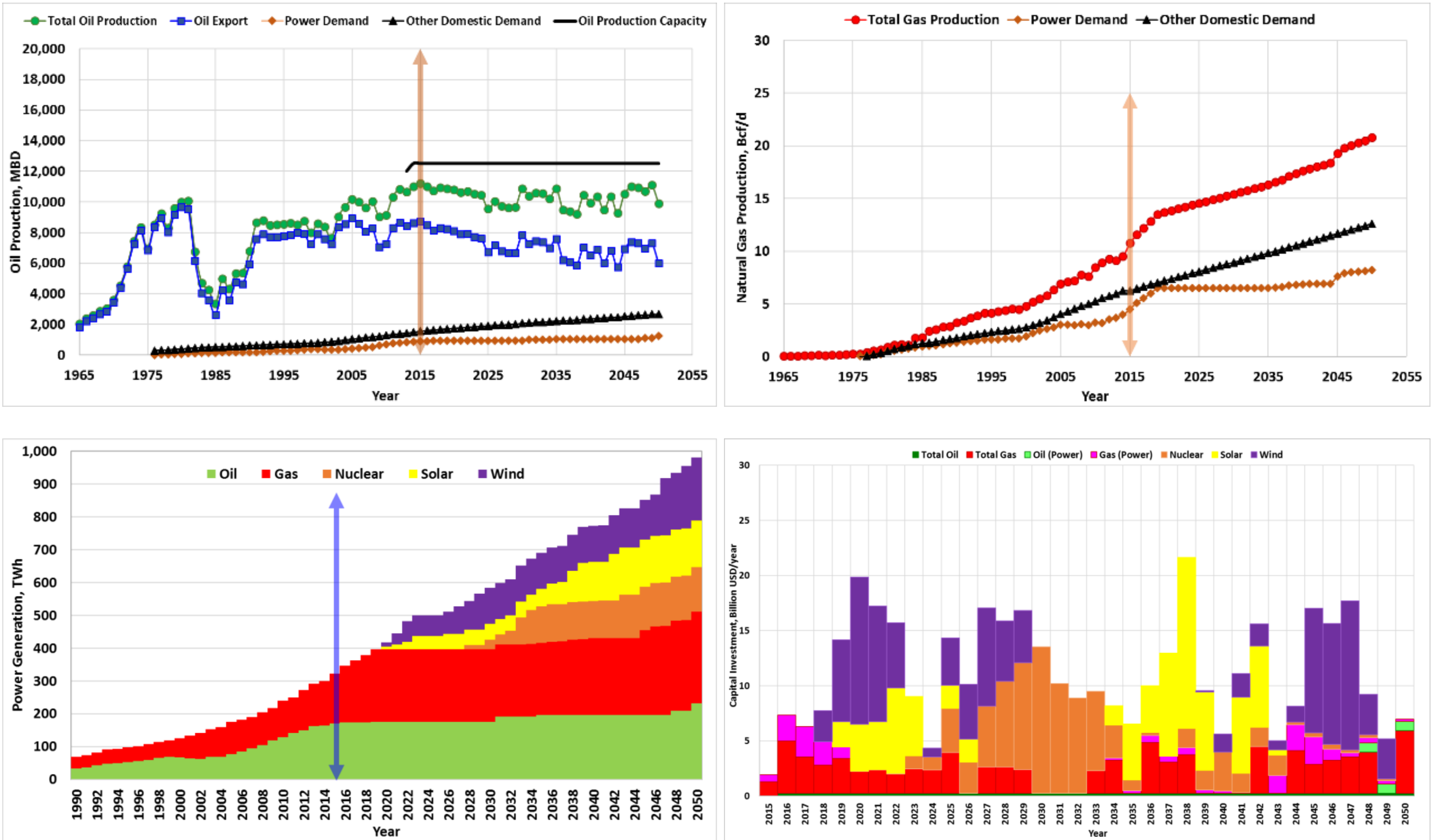


Fig. 3.24—Probabilistic model results for EEPC ≥ 160 boe/year per capita with oil prices deregulation and higher gas prices. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

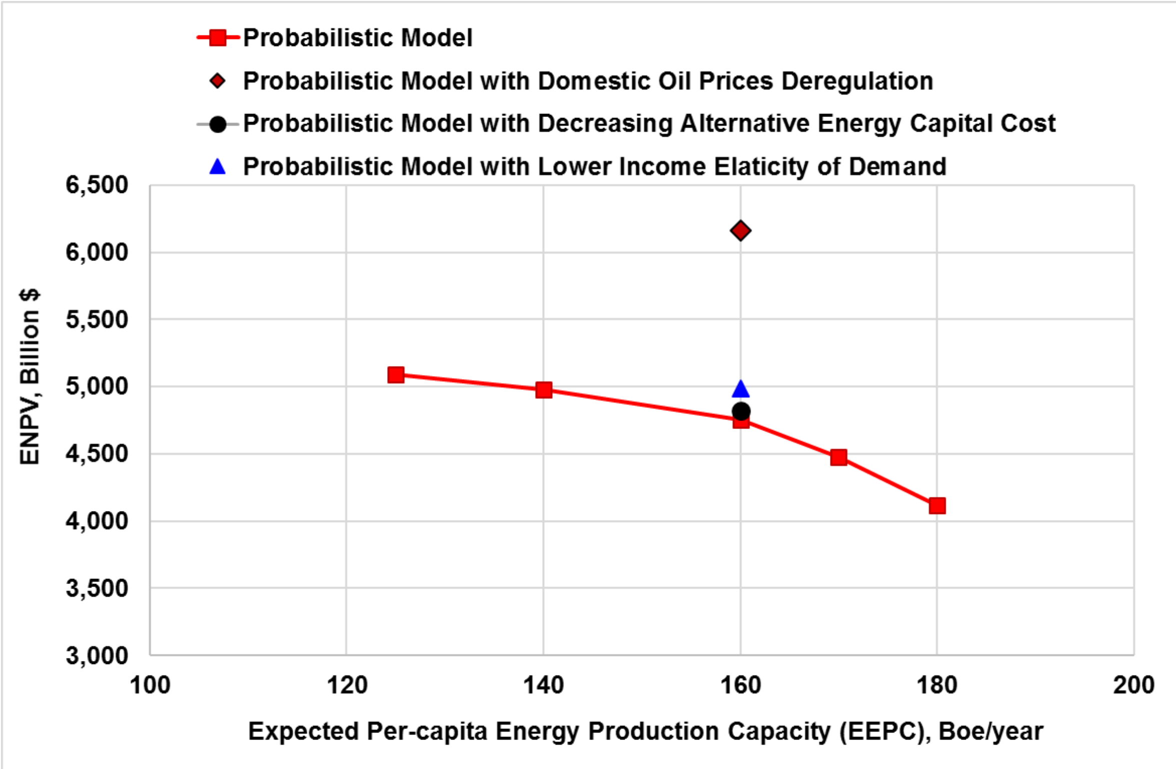


Fig. 3.25—Probabilistic model result with the changes proposed in this section compared to probabilistic model efficient frontier.

3.6.2 Reduction in Alternative Energy Capital Costs

Capital costs of alternative energy sources for power generation are expected to decline with time due to technological advancement and/or due to establishing a learning curve with more practice. In this case, the probabilistic model for EEPC of 160 boe/year per capita was run assuming potential reduction in alternative energy capital costs. Capital costs are assumed to decline at an average rate of 2% per year starting in 2016.

Fig. 3.26 shows that reduction in alternative energy costs have little effect on the overall energy production strategy mainly since investment in alternative energy sources to meet future power demand has been already established to be better than continue dependence on fossil fuels. The ENPV is slightly higher than the case with high alternative energy capital costs (Fig. 3.25) mainly due to lower investment costs in alternative energy sources.

3.6.3 Lower Income Elasticity of Demand

In developing countries, like Saudi Arabia, energy consumption is usually linked to economic growth and vice versa. This correlation is very large and reflected in high income elasticity of demand. However, as the economy developed and advanced (similar to developed nations), the correlation between domestic energy consumption and economic growth becomes weaker. For Saudi Arabia, this correlation is expected to be very strong especially in the short term but it is likely to get weaker in the long run. The model is run simulating this case by allowing the income elasticity of domestic demand to be lower than estimated values by multiplying it by a uniform distribution ~ Uniform(0.95, 1).

The results for EEPC of 160 boe/year per capita is shown in **Fig. 3.27**. The domestic energy demand is slightly less than the case with constant elasticity values (Fig. 3.15) especially for natural gas and total power demand. The ENPV is also higher mainly due to lower demand and thus lower investments and higher income from oil exports.

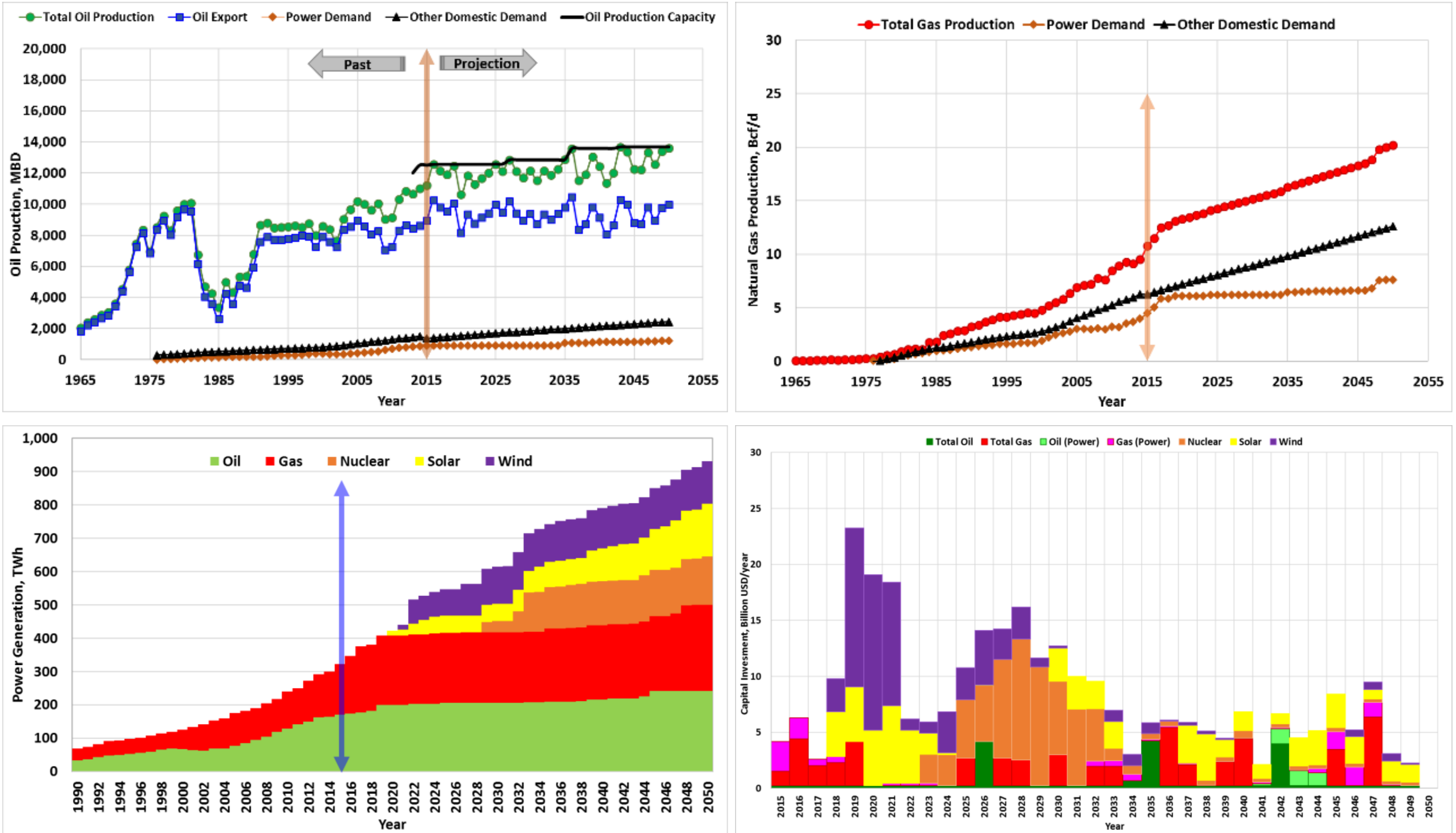


Fig. 3.26—Probabilistic model results for EEPC ≥ 160 boe/year per capita considering low alternative energy capital costs. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

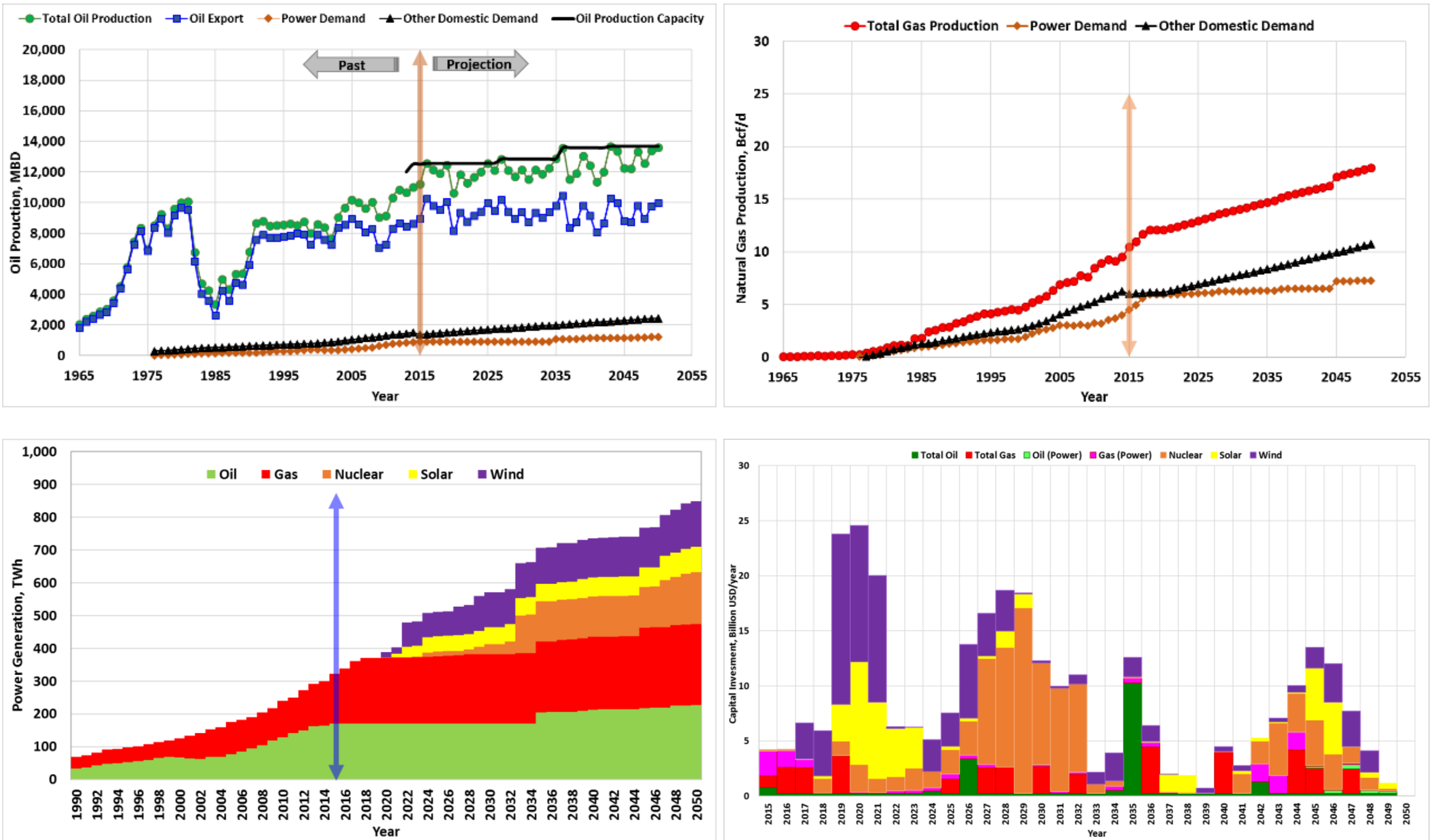


Fig. 3.27—Probabilistic model results for EEPC ≥ 160 boe/year per capita considering possibly lower income elasticity of demand. The figures are (clockwise from upper left): optimum oil production rates, optimum gas rates, capital investments distributions, and optimum share of power generation from each fuel source.

3.7 Optimum Energy Strategy for Saudi Arabia

Although the model developed in this work is coarse and models only primary energy flows, it can provide some insights into the optimum energy strategy for Saudi Arabia. These insights are based on model runs with EEPC of 160 boe/year per capita (especially Fig. 3.15) since this value ensures energy sustainability for Saudi Arabia, i.e., future generations will enjoy the same energy production capacity benefits as the current generation. Based on the model results and its assumptions, I conclude that Saudi Arabia should keep its oil production capacity at about 12.5 million bbl/day in the short term, suggested by the model for the EEPC of 160 boe/year per capita. In the long term, the model suggests increasing oil production capacity to about 14 million bbl/day.
Natural gas production should be increased to about 20 Bcf/d by 2050. Most of this gas should be directed to meet the demand for other energy sectors (petrochemical, industrial, etc.) while limiting increase in gas directed to power generation.

In addition, increases in future power demand should be met primarily by alternative energy sources. Not investing in alternative energy sources will require high gas production rates to meet future power demand. With increasing gas production, power generation cost will increase due to increasing gas production costs, i.e., higher fuel cost. Additionally, not considering alternative energy sources for power generation leads to a less diversified and riskier energy portfolio, especially since oil and gas are exhaustible resources. Therefore, in order to keep the energy sustainability measure (or EEPC) at its current level of 160 boe/year per capita, Saudi Arabia should invest in alternative energy sources—solar, wind, and nuclear—to meet its rising future power demand.

Finally, if domestic oil prices were to be deregulated, the model suggests increasing revenue and ENPV would be realized while no increase in the oil production capacity would be required.

3.8 Notes on Solutions Stability and Reproducibility

The model attempts to find the optimum solution of 6 variables by changing 216 (6 variables × 36 time steps) values. In all model runs, RISKOptimizer within @RISK was set to run for 15,000 trials and stop the optimization process whenever the objective function value (ENVP) did not change by more than 0.01% for the last 500 trials. Although RISKOptimizer engines (GA and OptQuest) are designed to find a global optimum, these optimization setting may not guarantee finding that solution. The probabilistic model takes a long time to reach a stable solution. According to the @RISK User's Manual, the optimization solution should improve if given more time to run. Thus, I expect the fluctuations in oil rate (e.g., Fig. 3.15) to decrease with longer run time, with little change in the overall results and conclusions.

4. SUMMARY AND RECOMMENDATIONS

4.1 Summary

In this work, I built a coarse, fully-probabilistic model for optimizing energy investments and policy that can be applied at a country or company level. The model considers all energy sources from a supplier perspective. It can handle primary energy flows at this stage. The model as presented in this work was specifically designed for Saudi Arabia's energy system. However, it can be easily modified and generalized for another country's application.

The model was applied to Saudi Arabia in order to determine its optimum energy strategy, determine the value of investing in alternative energy sources, and compare deterministic and probabilistic modeling approaches.

The model suggests that Saudi Arabia oil production capacity should remain at about 12.5 million bbl/d in the short term and increase to about 14 million bbl/d in the long term. It also suggests that most of the future power demand should be met using alternative energy sources. Otherwise, large gas production will be needed to meet such demand. With increasing gas production, power generation cost will increase due to increasing gas production costs, i.e., higher fuel cost. Comparing probabilistic to deterministic model results shows that deterministic models may underestimate future investments needed to meet projected power demand.

A primary contribution of this work is addressing uncertainty quantification in energy modeling. Building probabilistic energy models is one of the challenges facing the industry today. It is also the first model, to the best of my knowledge, that attempts to optimize Saudi Arabia's energy portfolio using a probabilistic approach and addressing the value of investing in alternative energy sources.

4.2 Recommendations for Future Work

This project started as a very ambitious research topic. The ultimate goal is to build a global, fully-probabilistic energy-system model. However, the time required to complete such task was underestimated. Nonetheless, this work is the first step to achieving that ultimate objective.

Therefore, I recommend the following possible extensions to the current model presented in this dissertation for future work:

1. Run the model for a very long time and check if solution changes and stability improves.
2. Improve the model running speed, especially the probabilistic version, by considering software that has similar capabilities as @RISK but runs much faster.
3. Expand the model to include more energy sectors such as transportation, residential, industrial and commercial.
4. Expand the model to include secondary energy flows. This requires adding modules for refinery and petrochemical processes.
5. Once secondary energy flows are included, improve the energy sustainability measure by modifying its definition to reflect energy services as proposed by Greene (2010).
6. Expand prices modeling to include all energy sources.

NOMENCLATURE

Bbl	Barrels (of oil)
Bcf	Billion Cubic Feet
Boe	Barrel oil equivalent
Btu	British thermal unit
CPI	Consumer Price Index
DOE	Department of Energy
EEPC	Expected Per-capita Annual Energy Production Capacity (Boe/year)
EF	Fixed expenses (cost)
EIA	U.S. Energy Information Administration
ENPV	Expected Net Present Value
EPC	Per-capita Annual Energy Production Capacity (Boe/year)
ESME	Energy System Modeling Environment
GDP	Gross Domestic Product
GOR	Gas Oil Ratio, cf/bbl
i	Discount rate, % [fraction]
IEA	International Energy Agency
MARKAL	Market Allocation Model
MBD	Thousands Barrels per Day (for oil rate)
NPV	Net Present Value
OPEC	Organization of the Petroleum Exporting Countries

p	Unit price
Pr [ ]	Probability function
R	Total revenue
t	time step index (years)
Tcf	Trillion Cubic Feet
TIAM	TIMES Integrated Assessment Model
TIMES	The Integrated MARKAL-EFOM System
TW·h	Terawatt-hour (10^{12} watt-hour)
UCL	University College London
U.S.	United States
USD	Unites States Dollar
USDOE	United States Department of Energy
β	Discount factor $=1/(1+i)$, where i is the discount rate
q_{G_othr}	Gas used for other demand, Bcf/d
q_{G_pwr}	Gas used for power generation, Bcf/d
q_G	Total gas production, Bcf/d
q_N	Total power generation from nuclear, TW·h
q_{O_exprt}	Exported oil rate, Bbl/d
q_{O_othr}	Oil used for other demand, Bbl/d
q_{O_pwr}	Oil used for power generation, Bbl/d
q_O	Total oil production, Bbl/d
q_S	Total power generation from solar, TW·h

q_W Total power generation from wind, TW·h

$q_{associated}$ Associated gas production, bcf/d

$q_{nonassociated}$ Nonassociated gas production, bcf/d

$q_{prjctd\ pwr}$ Projected total power demand, TW·h

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APPENDIX A

CONVERSION FACTORS

The following table shows approximate conversion factors used in this document.

Unit	**Multiplied by**	**Approximate Conversion Factor**	**Equals**	**Unit**
Barrel of Oil (bbl)	×	5,848,000	=	British Thermal Units (Btu)
Cubic Feet of Natural Gas (cuf)	×	1,025	=	British Thermal Units (Btu)
Kilowatt Hour (KWh)	×	3,412	=	British Thermal Units (Btu)
Tonnes (metric)	×	7.33	=	Barrels

Table A.1—Approximate conversion factors used in this dissertation.