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Evaluation of errors in national energy forecasts

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EVALUATION OF ERRORS IN NATIONAL ENERGY FORECASTS

by

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Abstract

Energy forecasts are widely used by the U.S. government, politicians, think tanks, and utility companies. While short-term forecasts were reasonably accurate, medium and long-range forecasts have almost always been highly erroneous. In the U.S. many energy policy decisions are driven by Annual Energy Outlook (AEO) forecasts prepared by Energy Information Association (EIA). This thesis evaluates accuracy of AEO reports from 1982 to 2003. Parameters evaluated are: total energy consumption, energy consumption by sector, sector specific parameters, and major model assumptions. Error decomposition and regression analysis are used to appraise accuracy of forecasts. I found that often underlying parameters used to calculate more aggregate parameters suffer from errors that are higher by amplitude than forecasted parameter itself. Positive and negative errors cancel each other and conceal higher error in the underlying parameters. Total energy consumption was predicted with higher accuracy than energy consumption by sector. Energy prices were predicted with very low accuracy and errors reach 250%. Almost all parameters suffer from systemic errors and were consistently overestimated or underestimated. I also determined numerical estimates for expected increase in accuracy because of increase in assumptions accuracy.

1. Introduction

Rapid progress in computing power has transformed energy modeling and forecasting into a popular and important business tool. The results of energy modeling and forecasting are widely used by the U.S. government to develop a national energy policy, by politicians and think tanks to advocate for or against various political decisions, by utility companies to make investment decisions, and by many others. As energy models become more complex and sophisticated, they may give a false sense of accuracy and precision. Modelers and those who use the results of modeling are often separate groups of people with different areas of expertise. Forecasts' users often have limited understanding of modeling principles and limitations; on the other hand modelers may not understand what decision makers need (Munson, 2004). All of these factors may lead to wrong decisions and overall disappointment in forecasting; as well as attract attention to non-existent problems while ignoring most important issues.

Energy forecasts have a long history. While short-term forecasts were reasonably accurate, medium- and long-range forecasts have almost always been wrong (Smil, 2003). Studying the accuracy of past projections will help to understand limitations and ranges of applicability more fully, and to improve future predictions by avoiding past mistakes.

In the U.S., many energy policy decisions and discussions are driven by information and insights derived from energy forecasts. If measured by use in the profession, the "gold standard" for such forecasts are those from the U.S. Department of Energy's (DOE) Energy Information Administration (EIA). The EIA has been making long-range energy forecasts using Intermediate Future Forecasting System (IFFS) and

National Energy Modeling System (NEMS) for over two decades through its Annual Energy Outlook reports (1982-2004). The importance of these forecasts in defining the energy debate cannot be understated.

Previous studies (Smil, 2003, O'Neill & Desaib, 2005) of the accuracy of energy forecasts for the U.S. have indicated limited success in our ability to predict what the energy landscape would look like 5,10 or 20 years hence. But these evaluations have tended to analyze aggregate energy production and consumption. With this thesis, I examine forecast errors within each major U.S. energy sector (transportation, buildings, commercial, residential). I identify which sectors experience the greatest forecast errors and whether these errors imply consistent over- or under-estimation of forecasts. I explore each sector individually to find what parameters are most/least accurate and how they contribute to sector error. I also examine the contribution of sectors to total energy error. Finally, I explore whether these forecasts are improving over time. The results presented in this thesis might help forecasters to improve their forecasts by determining which sectors are most important in terms of influence on total error, and pointing out problematic parts of EIA models that can be improved in the future.

2. Literature review

Because of the importance of the accuracy of energy projections, many researchers paid attention to how earlier energy forecasts predicted the future – our present. Several attempts to analyze the accuracy of medium- and long-term energy forecasts have been made. Some authors (Smil, 2003) argue the usefulness of energy forecasts while others (Craig, Gadgil, & Koomey, 2002) think that energy forecasts are still usable and useful.

William Ascher was one of the pioneers of comprehensive analysis of forecasting errors. In his book, "Forecasting: An appraisal for policymakers and planners" (Ascher, 1978) he studied the accuracy of numerous population, economic, energy, transportation and technological forecasts. Ascher sees accuracy as a best method for forecast appraisal. He looked for similarities between forecasts and general trends in forecasting and drew four major conclusions. First, time horizon is the most important factor that determines accuracy. The longer the forecasting horizon is the less accurate forecasts are. Second, forecasts produced during the same period of time appear to suffer from similar biases. For example high oil prices forecasts published between 1997 and 2001 were under the influence of relatively stable oil prices of 1990s (Smil, 2003). Third is that the choice of methodology is having little influence on forecasting accuracy, and is much less a factor than the choice of core assumptions. And finally the least accurate forecasts were often based on outdated information or the forecaster missed some major changes in trends. Ascher did not find any signs of improvement in forecasting of energy demand over time (Ascher, 1978, p.125), he also found that no methodology offers substantially more accurate results.

Vaclav Smil is one of the most active critics of current trends in energy forecasting. In his book *Energy At Crossroads: Global Perspectives And Uncertainties* Smil (2003) analyzed numerous forecasts of total energy consumption, prices and energy intensities, energy consumption structure, and electricity demand and concluded "long-range forecasters of energy affairs have missed every important shift of the past two generations" (p.176) and "with rare exceptions, medium- and long- range forecasts become largely worthless in a matter of years" (p.124). His analysis shows that almost all U.S. and world energy consumption long-range forecasts for the year 2000 were greatly overestimated. Apart from one forecast, all other analyzed forecasts were overestimating world primary energy consumption by 10% to 200% and US primary energy consumption by 20% to more than 200% (Smil, 2003). Even those projections that were close had very different fuel consumption structures, and, thus, if used to forecast emissions, fuel consumption by type, etc. would substantially offset derived forecasts. World oil prices are another example of forecasters' failure. Wild random fluctuations of world oil prices over the last 30 years have made almost all forecasts rather useless.

Smil (2003) concludes that no model, no matter how complex it is, is able to reflect and predict system behavior when extensive social, economic, technical, and environmental interactions and change exist. Such interactions lead to unexpected events that change the environment dramatically and are impossible to predict with any reasonable certainty. He is against the use of complex computer models and quantitative forecasting because they both need multiple numerical estimates and assumptions that, in case they are inaccurate, propagate errors throughout the model. Smil(2003) proposes using normative scenarios instead of numerical forecasting. With normative scenarios the forecaster is "outlining what should happen rather than what is likely to happen" (Smil, 2003, p179).

A different approach to analyze the accuracy of energy forecasts was used by Craig, Gadgil, & Koomey (2002). They did not argue about the usefulness of energy forecasts. Quite the contrary, they advocate forecasting as an instrument with many purposes, such as "bookkeeping devices" that show a lack of good data; aids in selling political ideas, which may be viewed as a form of normative scenarios proposed by Smil; as training, educational and communicational aids that help to better understand a system and communicate ideas between stakeholders; as aids to hypothesizing and what-if analysis. Craig et al. (2002) analyzed several forecasting techniques by strengths and weaknesses. EIA uses econometric models for its forecasts. The authors (2002) point out that econometric models give reasonable projections when there are no structural changes in a modeled system and perform best when used for short-term forecasting. Often they produce results that are not better than much simpler models. (I want to point out here that simpler models may not give enough information to solve problems that they were designed to solve, such as effects of alternative energy policies.) Craig et al. (2002) summarize their findings by the following recommendations to improve forecasts: document assumptions as completely and as clearly as possible; define the range of decisions this model will help to make; use a model that is simple enough for your tasks, pay more attention to assumptions than to sophistication; do not underestimate changes in human behavior in response to a changing environment; develop different scenarios; use a combined approach by averaging several forecasts; assess risks and uncertainties; and explain the results of forecasting carefully and effectively. The AEO represent a classic example of how forecasts should be created and communicated. They have extensive and very detailed assumptions, they are explained and discussed at the annual conference, they have several scenarios, and all information is publicly available since 1982 in libraries or from the EIA web page.

Attempts to analyze AEO projections have been made before. The EIA has been using a similar forecasting methodology and model structure for the last 20 years, which greatly simplifies analysis of the model accuracy and accuracy progress over time. EIA does such analyses by itself as in Sanchez (2002), Holte (2001). These are called the Annual Energy Outlook Evaluations. The most recent evaluation available when this thesis was written is for year 2002. In this paper EIA analyzes errors of most important variables by calculating "average absolute forecast error … of all absolute values of percent errors, expressed as the percentage difference between the Reference Case projection and actual historic value, shown for each AEO, for each year in the forecast" (Sanchez, 2002, para. 8). This type of analysis is appropriate to find years with highest errors that may be a sign of something unexpected that happened in that particular year, like oil price shocks. To analyze how forecasts' accuracy is changing over time other methods, such as decomposition (O'Neill & Desaib 2005) may be more appropriate.

O'Neill & Desaib (2005) applied a decomposition technique to analyze errors in GDP, energy intensity and energy consumption for all AEO available. Their analysis consists of calculations of the percentage error, absolute percentage error, mean percentage error and mean average percentage error for the baseline error, trend error and variability error. Analysis was made for total consumption and energy intensity without dividing the errors by sector, by fuel or by anything else. Their analysis shows that energy consumption errors were low, while GDP and energy intensity errors were much higher and had opposite signs, which introduced cancellation of errors. They find no evidence of improvements from earlier projections to recent ones along with the increase in the errors for longer projections. O’Neill & Desaib suggest paying more attention to predicting GDP and energy intensity.

Linderoth (2000) studies forecast errors in International Energy Agency countries by calculating forecast errors, average forecast errors and root mean square of forecast errors for total primary energy consumption, oil consumption, delivered energy (total energy minus losses) by sector and by country. He concludes that forecast errors are caused by inaccurate growth rate expectations. In addition, energy consumption in the transportation sector is generally underestimated. Similar to O'Neill & Desaib (2005) he also finds cancellation of errors in total energy consumption.

3. Methodology

3.1. Overview

The thesis compare actual values with forecasted values to calculate percentage error and then use an error decomposition technique to study errors of medium-range forecasts for U.S. total energy consumption and consumption by sector. Decomposition helps to identify the least/most accurate parts of the model, systemic underestimation/overestimation of model components, and how forecasts' accuracy changes over time (are forecasts become more precise over time).

Armstrong (2001) gives the following definition of decomposition: "The process of breaking a problem into subproblems, solving them, and then combining the solutions to get an overall solution." This thesis breaks total energy consumption error into errors by sector. Then sectoral errors are broken into sector specific errors.

Most energy forecast error analyses in the past have focused on errors in projected total energy production or consumption. One of the questions that remains unanswered in such analyses is: How do each of the major energy sectors contribute to this overall error? Oftentimes what looks like small errors in total energy forecasts actually hides more significant (but offsetting) errors in specific energy sectors.

An error decomposition technique was applied to study errors in energy forecasts by various energy sectors (commercial, industrial, transportation, residential) for the US. In the US, total energy consumption projections (through NEMS) are determined through an additive function across energy sectors. Thus, forecast errors within each sector will contribute to the overall total forecast error. By breaking down total forecast errors into its disaggregate parts, it is possible to determine what sectors within the NEMS model are more/less accurate and whether a systemic underestimation/overestimation exists within sectoral model components.

I also explore how forecast accuracy changes over time across each of the major energy sectors. That is, I address the question: "have US energy forecasters become better or worse with respect to accurately capturing energy production and consumption in the mid-term?"

I apply a methodology similar to that found in O'Neill & Desaib (2005). However, unlike O'Neill & Desaib (2005), I focus on the "visible error" defined as "the difference between the projected energy consumption and actual energy consumption" O'Neill & Desaib (2005).

In this work I use two metrics to determine forecast error: *mean percentage error* and *mean absolute percentage error*. Mean percentage error (MPE) is an average error of all forecasts of a given forecast horizon and is given by the function,

$$MPE_{\tau} = \frac{\sum_{t} \frac{(\hat{Y}_{t,\tau} - Y_{t,\tau})}{Y_{t,\tau}}}{\mathrm{n}_{\tau}} \tag{1}$$

where,

τ – forecast horizon (1 year,2 years,3 years...)
t - year in which AEO was published (1982,1983,...)
$\hat{Y}_{t,\tau}$ – forecasted value for period τ in AEO published for year t
$\mathrm{Y}_{\mathrm{t},\tau}$ – actual value for τ period of t - th AEO
n_{τ} – number of forecasts with time horizon τ

MPE calculations for a single forecast horizon (τ) and a single year (t) (i.e., where $n_\tau = 1$) could take on a positive or negative value. If MPE > 0, then the forecast value was higher than the actual value, and the forecast represents an overestimate. If MPE < 0, then the forecast value was less than the actual value, and the forecast is an underestimate. The reader should note that an average MPE near zero does *not* imply a near perfect forecast. The average may be close to zero, but may represent a combination of highly overestimated and underestimated forecasts that cancel each other out on average.

To more clearly explore the accuracy of forecasts, without concern over whether forecasts are underestimated or overestimated, I can apply the mean absolute percentage error (MAPE), given by the following function:

$$MAPE_\tau = \frac{\left| \sum_t \frac{(\hat{Y}_{t,\tau} - Y_{t,\tau})}{Y_{t,\tau}} \right|}{\mathrm{n}_\tau} \tag{2}$$

where the variables and indices remain the same as in (1). Here, however, the absolute value of the error for each forecast is used, so that the metric is not subject to misinterpretation from cancellation of under- and over-estimated forecasts. I apply both the MPE and the MAPE on a sector-by-sector basis below.

Both MPE and MAPE identify sector-by-sector forecast errors, but they do not allow for easy consideration of the contribution of these sectoral errors to total error. Because the US delivered energy can be derived as an additive function of energy consumption in all sectors, there is a clear connection between the forecast errors for each sector and the forecast error for energy consumption overall. To determine the contribution of sectoral forecast errors to total forecast error, I introduce the following.

Let the total forecast percent error ($TFPE_{t,\tau}$) for a given time horizon τ made at time period *t* be:

$$TFPE_{t,\tau} = \frac{\sum_j \hat{Y}_{t,\tau,j} - \sum_j Y_{t,\tau,j}}{\sum_j Y_{t,\tau,j}} = \frac{\sum_j \left(\hat{Y}_{t,\tau,j} - Y_{t,\tau,j}\right)}{\sum_j Y_{t,\tau,j}} \tag{3}$$

where *j* represents the set of sectors (commercial, industrial, residential, transportation). Given equation (3) it is possible to determine that the contribution of TFPE from a given sector (which is called the sectoral forecast percentage error for sector *j*, or $SFPE_j$) is given by:

$$SFPE_{t,\tau,j} = \frac{\hat{Y}_{t,\tau,j} - Y_{t,\tau,j}}{\sum_j Y_{t,\tau,j}} \tag{4}$$

The $SFPE_j$ can also be derived into a mean sectoral percentage forecast error ($MSFPE_{j,\tau}$) for a given time horizon τ by modifying (4) as follows:

$$MSFPE_{\tau,j} = \frac{\sum_t \left(\frac{\hat{Y}_{t,\tau,j} - Y_{t,\tau,j}}{\sum_j Y_{t,\tau,j}} \right)}{\mathrm{n}_\tau} \tag{5}$$

After decomposing errors by components I used regression analysis to study relationships between errors in model assumptions and errors in energy consumption, energy prices, etc.

"Regression analysis is a statistical methodology that utilizes the relation between two or more quantitative variables so that one variable can be predicted from the other or others" (Neter, Kutner, Nachtsheim, Wasserman, 1996, p3).

A simple linear regression model can be presented in a following way (6):

$$y = \alpha + \beta x \qquad (6),$$

where α is the intercept of regression curve with y axis and β is a slope of the regression line. To estimate parameters α and β the method of least squares was used.

To measure the strength of relationship a coefficient of determination r^2 (7) was used.

$$r^2 = \frac{\text{Sum of squares of regression}}{\text{Total sum of squares}} \qquad (7)$$

Coefficient of determination shows how much of total variability was explained by using regression model. The closer the value of r^2 to 1 the tighter the relationship is.

I expected that world oil price errors have most influence on transportation sector energy price errors, and GDP errors have most influence on industrial sector consumption errors. Oil is a major fuel and world oil price greatly influences average energy price and prices of the other types of fuel. Real GDP was chosen because it is a good overall indicator of economy development. Higher GDP levels mean that more products and services are sold. Most of them require energy for production. I analyzed these hypotheses using regression analysis methods. With the help of regression analysis I was also able to find how strong the relationship between errors in assumptions and errors in predicted variables are and how forecasts can be improved by using more accurate assumptions.

Numerous factors may negatively influence accuracy of any forecast. Among them are: incorrect core assumptions, unexpected random events that change behavior of predicted parameters, inadequate methodology or internal model structure. Random events are almost impossible to predict, after all no one proved the opposite (Smil, 2003, p.176). And as Ascher (1978) points out that choice of methodology is playing secondary role in determining forecasts' accuracy after the choice of core assumptions.

EIA uses extremely complex models to forecast all major parameters of energy markets in the U.S. and the whole world. These models use numerous assumptions and feedback loops. Table 1 shows selected assumptions for residential, commercial, industrial and transportation sector models.

Using wrong core assumptions will negatively influence accuracy of the whole model and negate all positive effects of correct methodology. Some model assumptions (GDP) behave in a very predictable way, still they often suffer from systemic errors. I will try to use simple models to forecast main assumptions and variables to check if it is possible to achieve better accuracy.

Table 1 - EIA models assumptions

Model	Input	Output
Residential	Delivered energy prices Number of households Housing starts by type and Census Division Projections of available equipment and their installed costs	Consumption by housing type Consumption by end-use
Commercial	Delivered energy prices Availability of renewable sources Interest rates Floorspace construction	Consumption by building type Consumption by nonbuilding uses Consumption by end use
Industrial	Delivered energy prices Employement Value of shipments for each industry Vintage of the capital stock that produces the output	Consumption of energy for heat and power Consumption of energy for feed stocks and raw materials by each of 16 industry groups
Transportation	Delivered energy prices GDP Disposable personal income Population Driving age population Total value of imports and export Interest rates The value of output for industries in the freight sector Industrial output by Standard Industrial Classification code New car and light truck sales	Energy consumption by fuel Energy consumption by model Energy consumption by vehicle vintage Energy consumption by size class

	The military budge	

3.2. NEMS description

The NEMS is a computer-based, energy-economy modeling system of U.S. energy markets for the midterm period through 2025. NEMS projects the production, imports, conversion, consumption, and prices of energy, subject to assumptions on macroeconomic and financial factors, world energy markets, resource availability and costs, behavioral and technological choice criteria, cost and performance characteristics of energy technologies, and demographics. NEMS was designed and implemented by the Energy EIA of the DOE (The National Energy Modeling System: An Overview, 2003).

The NEMS model breaks U.S. energy market up on smaller parts depending on energy usage. These smaller parts are modeled separately by NEMS modules. Additionally to U.S. energy market modules the NEMS model also includes Macroeconomic Activity, International Energy and Integrating modules. Currently EIA uses the following modules:

- Integrating Module
- Macroeconomic Activity Module
- International Energy Module
- Supply Modules
  - Oil and Gas Supply Module
  - Natural Gas Transmission and Distribution Module
  - Coal Market Module
  - Renewable Fuels Module
- Conversion Modules
  - Electricity Market Module
  - Petroleum Market Module
- Demand Modules
  - Residential Demand Module

- Commercial Demand Module
- Industrial Demand Module
- Transportation Demand Module

Each module includes extensive regional information divided geographically. These regions include:

- Nine Census divisions for residential, commercial, and transportation consumption
- Four Census regions, shared to nine Census divisions for industrial consumption
- Fifteen electricity supply regions (including Alaska and Hawaii) based on the North American Electric Reliability Council regions and subregions for electricity supply and nine Census divisions for electricity demand
- Fifteen electricity supply regions for renewables
- Six lower 48 onshore regions, three lower 48 offshore regions, three Alaska regions for oil supply
- Six lower 48 onshore regions, three lower 48 offshore regions, three Alaska regions, eight liquefied natural gas import regions for natural gas supply
- Twelve lower 48 regions and ten pipeline border points for Natural gas transmission and distribution
- Three refinery regions aggregated from Petroleum Administration for Defense Districts for refining
- Eleven supply regions, sixteen demand regions, sixteen export regions, twenty import regions for coal supply

The Integrating Module of NEMS is the main controlling module responsible for iteratively executing separate modules, data exchanges between modules and data updating until equilibrium between supply and consumption sectors is reached. To avoid unnecessary executions modules are executed until subsequent changes in prices and quantities are smaller then user defined value.

The main purpose of NEMS model is to produce data necessary for analyses of results of political decisions. It is also used for special analyses on request by Congress, White House, and other government offices. EIA gives several examples of such reports (The National Energy Modeling System: An Overview 2003):

- *Analysis of Corporate Average Fuel Economy (CAFE) Standards for Light Trucks and Increased Alternative Fuel Use*, requested by Senator Murkowski to analyze the effects of proposed provisions in S. 1766 and H.R. 4 calling for more stringent corporate average fuel economy standards on energy supply, demand, and prices, import dependence, and emissions.
- *Analysis of Efficiency Standards for Air Conditioners, Heat Pumps, and Other Products*, requested by Senator Murkowski to evaluate the effects of the provisions in H.R. 4 and S. 1766 that pertain to efficiency in the residential, commercial and industrial sectors.
- *Analysis of Strategies for Reducing Multiple Emissions from Electric Power Plants With Advanced Technology Scenarios,* requested by Senators Jeffords and Lieberman to analyze the impacts of technology improvements and other market–based opportunities on the costs of emissions reductions.
- *Impact of Renewable Fuels Standard/MTBE Provisions of S. 1766*, requested by Senator Murkowski to evaluate the Renewable Fuels Standard and methyl tertiary butyl ether provisions of S. 1766.

Not only governmental agencies use NEMS model. The model or its parts are installed on computers in Lawrence Berkeley National Laboratory (LBNL), Oak Ridge National Laboratory (ORNL), the Electric Power Research Institute, the National Energy Technology Laboratory, the National Renewable Energy Laboratory, and several private consulting firms. Some uses of NEMS modeling by aforementioned organizations are:

- Market Assessment Group at Lawrence Berkeley National Laboratory. To provide analyses on renewable energy sources, projected penetration of photovoltaics in residences under net metering, tax credits promoting the purchase of energy-efficient equipment, impacts of efficiency standards for residential appliances on utilities and the environment, and the costs of reducing carbon emissions in the U.S. (Use of the National Energy Modeling System at LBNL)

- ORNL used a modified version of NEMS to predict future U.S. energy consumption accounting for global climate change for the period of 2000-2025 (Hadley, Erickson III, Hernandez,Thompson. Future U.S. Energy Use for 2000-2025 as Computed with Temperatures from a Global Climate Prediction Model and Energy Demand Model)
- ORNL used a NEMS model to calculate potential savings from energy efficiency programs in North Carolina (Hadley, The potential for energy efficiency and renewable Energy in North Carolina, 2003)

3.3. Data

For this analysis I used energy forecasts from the *Supplemental Tables to the Annual Energy Outlook* for 1982-2003. All AEOs contain several scenarios. I focused my analysis on the "Reference Case" forecasts in these AEOs with the following caveats:

(1) Before 1990 AEO did not include information about dispersed (not connected to the grid) renewable energy consumption (Issues in Midterm Analysis and Forecasting, 1998). To determine dispersed renewable energy consumption forecasts for forecasts made before 1990, I followed the approach discussed in O'Neill & Desaib (2005). I think that this approach is reasonable because dispersed energy consumption is not rapidly changing from year to year.

(2) Before 1996 the AEO did not include electricity related losses by sector, and sector energy consumption was equivalent to delivered energy in later AEO versions. In this analysis, to make sector consumption comparable, I used total energy consumption by sector for pre 1996 AEOs and delivered energy for post 1996 AEO. I decided to analyze delivered energy (total energy consumption minus electricity related losses) instead of total energy consumption because delivered energy serves as a critical input for all other calculations.

(3) Originally, real GDP, world oil price and energy price were expressed in constant dollars for different years. To be able to analyze them I made them comparable and expressed them in constant dollars 1996. To make energy prices and GDP from year to year and across AEOs comparable I converted them to nominal dollars using Implicit Price Deflator from Macroeconomic Indicators table for each AEO and then converted them to real 1996 dollars using Implicit Price Deflator from Table D1 (AER, 2002).

(4) Actual values for energy consumption by sector, sector specific variables for years 1982-2002 were taken from Annual Energy Review (AER) 2002. It should be noted that actual data for 2003 were taken from AEO (2004) and are considered preliminary data.

The following table represents the EIA data used in this thesis:

Table 2 - Forecasted parameters used in analysis

Aggregate parameter	First level of disaggregation	Second level of disaggregation
Total Energy Consumption	Residential Sector Energy Consumption	• Number of Households • Energy Consumption Per Household • Energy price
	Commercial Sector Energy Consumption	• Total Floorspace • Energy Intensity • Energy Prices
	Industrial Sector Energy Consumption	• Energy Consumption • Energy Price
	Transportation Sector Energy Consumption	• Total Vehicle Stock • Fleet Average Stock Car Mileage Per Gallon • Energy Price
Real GDP in 1996 dollars		
World Oil Price in 1996 dollars		

For my analysis I built spreadsheets that contain data points for each sector, each AEO and each year available, conversions needed for comparison and calculations of percentage errors, absolute percentage errors, MPE, MAPE, and MSFPE.

Separate spreadsheets contain regression analyses with analysis of correlation between errors in world oil prices and errors in prices of energy by sector, GDP errors and energy consumption. I expect that errors in world oil price are having major impact on accuracy of energy prices for transportation sector. Because higher levels of production lead to higher energy consumption (given constant energy intensity) and higher real GDP levels it is interesting to study how errors in real GDP influence errors in energy consumption by sector.

Potential problems.

There are several potential problems with the data I used in my analysis. The first problem is that there are only few data points to analyze for most recent AEO. For example, for AEO 2003 actual data exists for only one year, two years for AEO 2002, etc. This may introduce potential problems when analyzing if forecasts are getting better over time.

Another problem appears with the analysis of forecasts with the longest forecasting horizon. Both MPE and MAPE have a few data points, thus negating smoothing properties of averaging. For example, for the forecasting horizon of 13-15 years there are only one or two data points available for averaging.

4. Total energy consumption decomposition

Analysis of MAPE by Sector

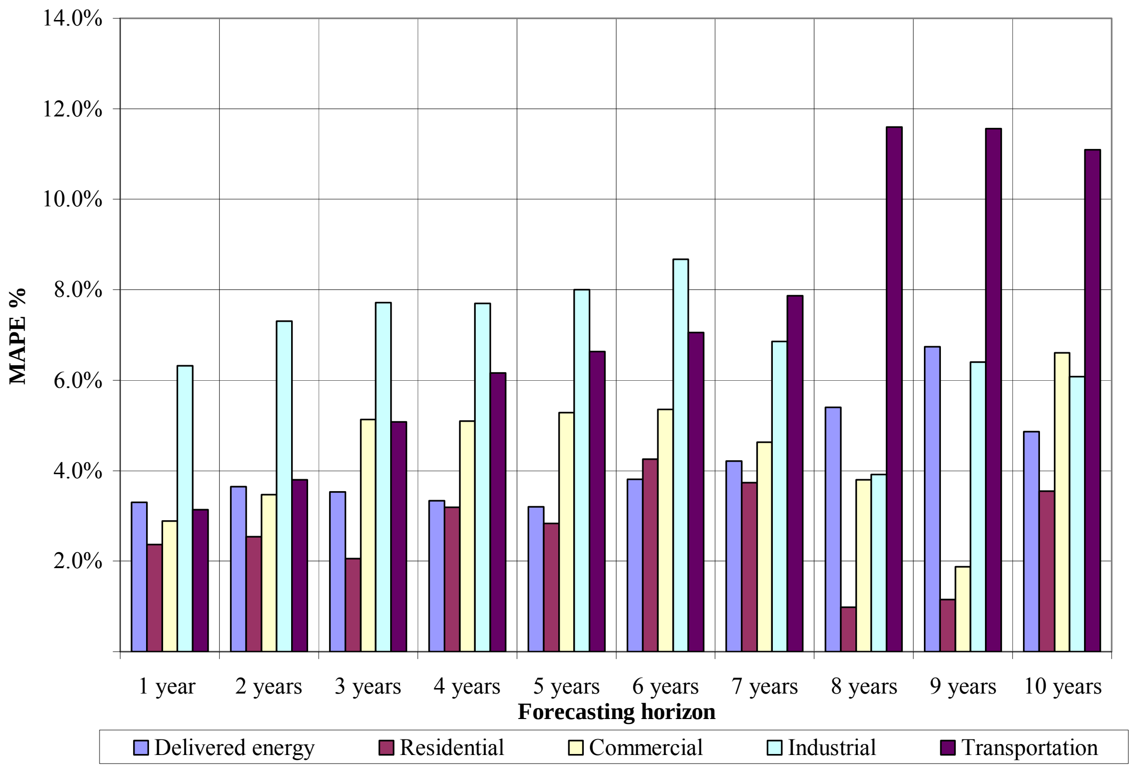
This analysis offers a closer look at the general accuracy of forecasts, by sector, for time horizons ranging from one to ten years. This analysis can be used to determine if: (a) forecasts exhibit increased uncertainty when time horizons are lengthened; and (b) certain sectors demonstrate a more accurate level of forecasting than others.

Table 3 presents both MAPE and MPE calculations by sector and in total. The results from the MAPE analysis are shown in Figure 1. Figure 1 demonstrates that while total energy consumption forecasts have relatively small errors for the time horizons analyzed (ranging from 1.7% to 4.8%), the sectoral errors are much higher. In particular, the transportation sector errors range from a low of 3.0% as an average for 1-year forecasts, to over 11% for 8-, 9-, and 10-year forecasts. The most accurate forecasts seem to be those associated with the residential sector.

Table 3 - Energy Consumption Errors by Sector

	Forecast horizon (years)									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Number of observations	14	14	12	11	11	8	6	4	2	3
MPE										
Delivered energy	1.66%	1.58%	1.28%	0.77%	0.10%	-0.94%	-2.53%	-5.40%	-6.74%	-4.86%
Residential	0.79%	0.11%	-0.30%	-1.47%	-0.90%	-3.27%	-2.99%	-0.72%	0.12%	-1.71%
Commercial	-0.44%	-0.50%	-0.69%	-0.88%	-2.31%	-2.47%	-2.07%	-2.40%	-1.87%	-6.61%
Industrial	3.81%	4.84%	5.55%	6.00%	5.88%	5.51%	2.92%	-2.30%	-6.40%	0.41%
Transportation	0.57%	-0.35%	-1.66%	-2.93%	-4.50%	-5.89%	-7.87%	-11.60%	-11.56%	-11.09%
MAPE										
Delivered energy	3.30%	3.64%	3.53%	3.34%	3.20%	3.81%	4.21%	5.40%	6.74%	4.86%
Residential	2.37%	2.54%	2.06%	3.19%	2.83%	4.26%	3.74%	0.98%	1.15%	3.55%
Commercial	2.89%	3.47%	5.13%	5.09%	5.28%	5.35%	4.63%	3.80%	1.87%	6.61%
Industrial	6.32%	7.31%	7.71%	7.70%	8.00%	8.67%	6.86%	3.91%	6.40%	6.08%
Transportation	3.14%	3.80%	5.08%	6.16%	6.63%	7.05%	7.87%	11.60%	11.56%	11.09%
MSPFE										
Delivered energy	1.66%	1.58%	1.28%	0.77%	0.10%	-0.94%	-2.53%	-5.40%	-6.74%	-4.86%
Residential	0.11%	0.00%	-0.06%	-0.25%	-0.15%	-0.53%	-0.49%	-0.11%	0.02%	-0.26%
Commercial	-0.05%	-0.06%	-0.09%	-0.12%	-0.27%	-0.30%	-0.25%	-0.27%	-0.20%	-0.73%
Industrial	1.35%	1.72%	1.97%	2.13%	2.09%	1.95%	0.98%	-0.90%	-2.46%	0.11%
Transportation	0.24%	-0.09%	-0.55%	-1.00%	-1.56%	-2.06%	-2.77%	-4.11%	-4.10%	-3.98%

Figure 1 - MAPE for Energy Consumption by Forecast Length

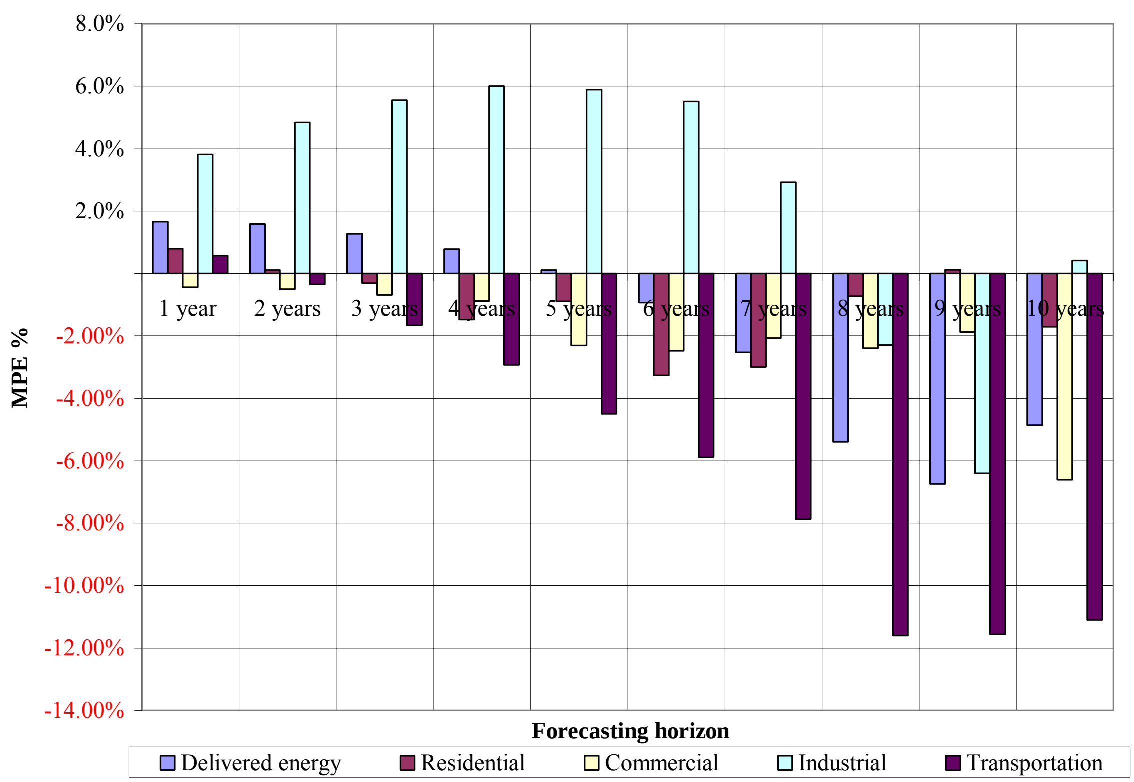


Analysis of MPE by Sector

This analysis expands on the MAPE analysis by identifying the directionality of forecast error. That is, this analysis can be used to determine if certain sectors tend to under-estimate or over-estimate forecast errors consistently for a certain time horizon. This analysis might point to a systemic problem with the forecast models being used for a given time horizon. The fact that the MAPE for total energy consumption is lower than errors for individual sectors means that there is a cancellation of errors across energy sectors. As previously mentioned, the use of MPE can shed light on the directional aspects of each sector's energy forecasts. MPE calculations are shown in Table 3 and Figure 2.

For forecasts of five years or less, total energy consumption errors are small on average (around 1%) and are positive (representing overestimation). However, for forecasts between 6-10 years in length, the errors are larger (about 4%) and are negative (representing underestimation). The transportation sector is observed to be highly and systematically underestimated, while the industrial sector tends to be overestimated, particularly for shorter forecast horizons.

Figure 2 - MPE for Energy Consumption by Forecast Length

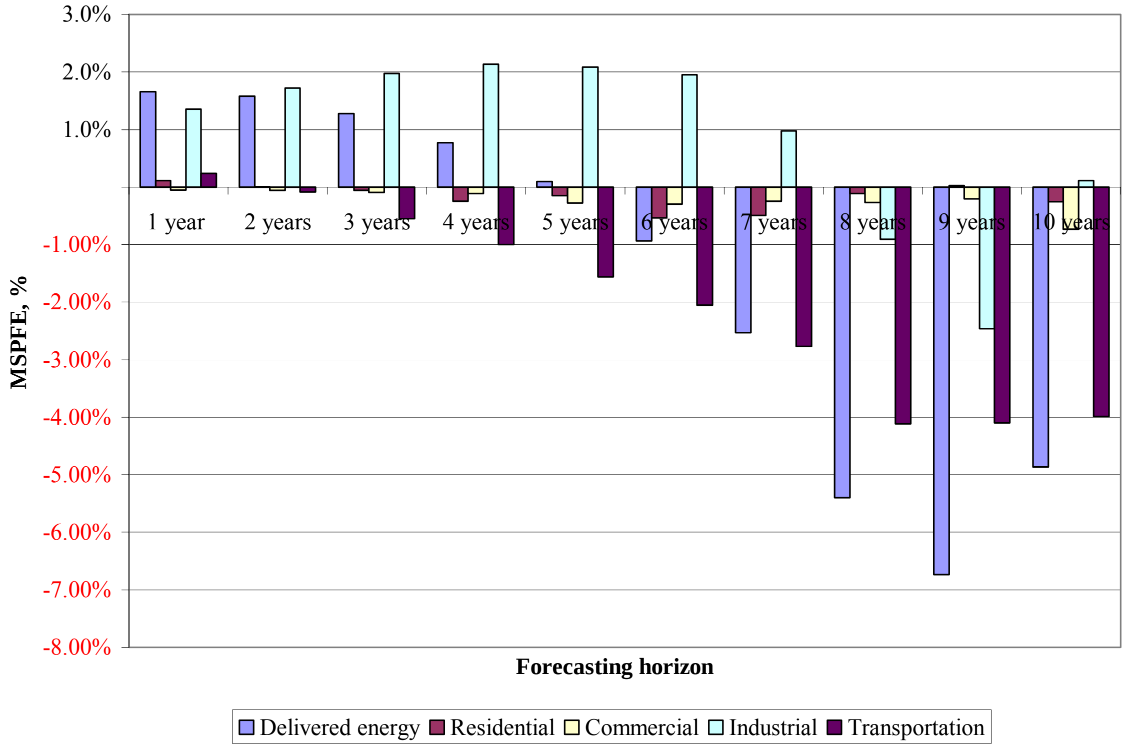


Analysis of MSFPE by Sector

I apply the MSFPE discussed earlier to help partition out the sectoral contributions of each sector on the total forecast error. Determination of sector error as a function of total forecast error is important. Such analysis demonstrates sectoral contributions to total error and helps us to determine if there are sectors in particular that have "high leverage" with respect to total error.

Table 3 shows MSFPE for each sector. Recall that MSFPE demonstrates a sector's average, real contribution to the total energy forecast error for a given forecast length. As shown in Figure 3, the transportation sector is a major contributor to total energy forecast error, particularly for forecasts with longer time horizons. In some cases, transportation underestimation by itself exceeds the total forecast underestimation, since the error is reduced by overestimation in other sectors. For forecasts with time horizons less than five years, the industrial sector is the largest contributor to this error.

Figure 3 - MSPFE for Energy Consumption by Forecast Length



Analysis of Total Energy Consumption Forecast Improvements

For a given forecast horizon, error trends can be analyzed to determine if forecasts are improving over time. For example, one may ask: Have 7-year forecasts improved in accuracy from 1982 to 1996? I conduct this analysis for several forecast time horizons (3-year, 5-year, and 7-year) across sectors.

Figures 4 through 6 present the results of this analysis. Each graph shows the absolute error based on the year in which the forecast was made. So, for example, Figure 4 evaluates whether three-year forecasts improved over time (from 1982-2000). Similarly, using Figures 5 and 6, it can be determined whether five-year and seven-year forecasts have improved.

The figures show that there is a general randomness, but it is interesting to note that all graphs are bowl shaped with a minimum around AEO 1987 – AEO 1989. Errors for this period look smaller. I see several reasons of such behavior. First is that period of 1987-1994 was relatively stable in terms of world oil prices (except for short period of instability in 1990) thus making it easier to predict them. It can also be just a random coincidence.

Figure 4 - Absolute Errors in Energy Consumption by Sector for Three-Year Forecasts by Year of Forecast.

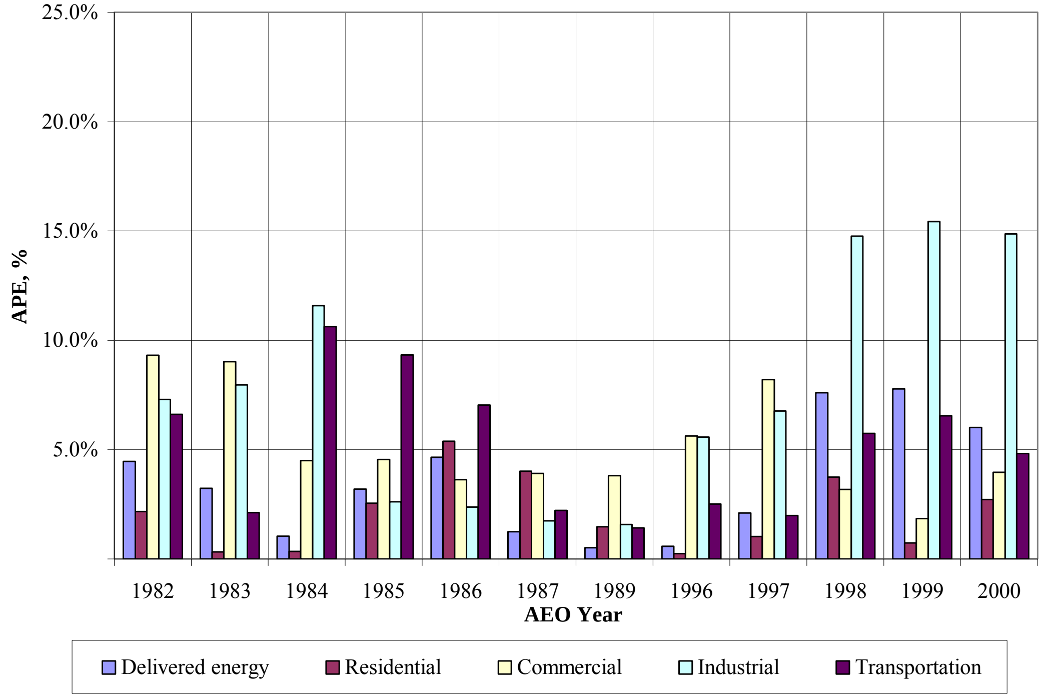


Figure 5 - Absolute Errors in Energy Consumption by Sector for Five-Year Forecasts by Year of Forecast

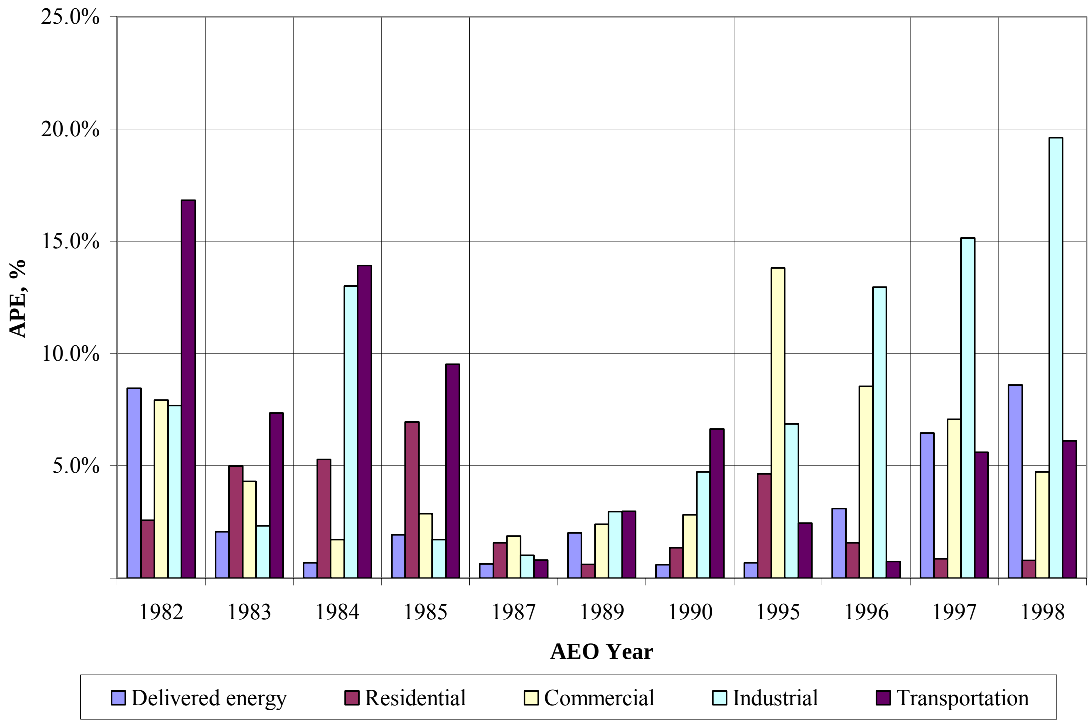


Figure 6 - Absolute Errors in Energy Consumption by Sector for Seven-Year Forecasts by Year of Forecast

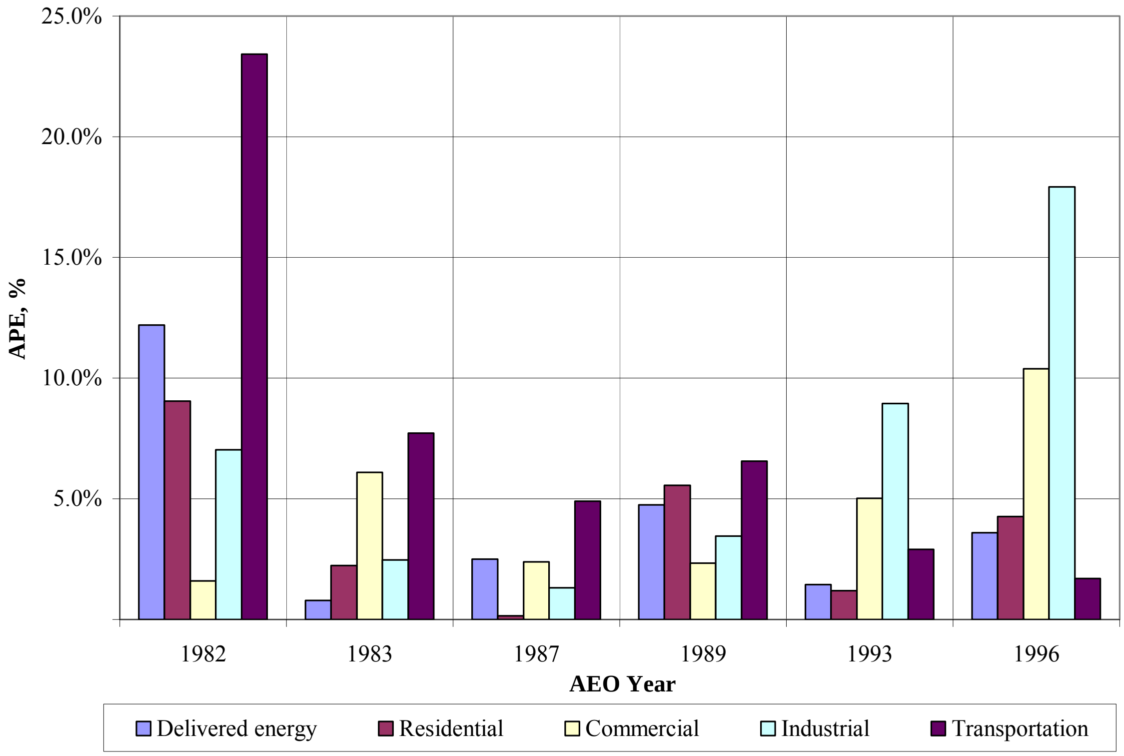
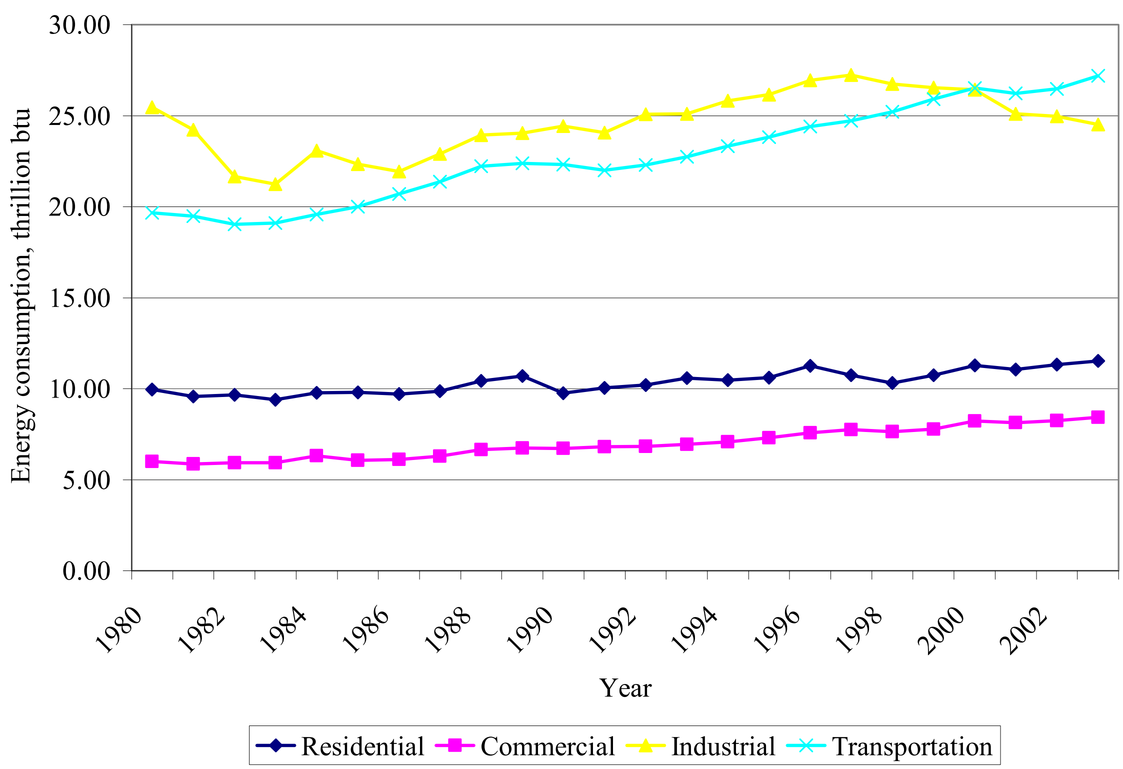


Figure 7 shows actual energy consumption by sector for the period between 1980 and 2003. It is easy to notice that transportation, commercial and residential energy consumption grew in a much more predictable way than industrial sector energy consumption. Residential and commercial sectors energy consumption were growing linearly without sudden boom and busts. Variability around the linear trend is small. In case of the transportation sector the trend looks more like quadratic or exponential equation. But still variability is small. The industrial sector energy consumption does not show any strongly pronounced trend. Energy consumption has periods of growth and decline.

Consistent growth of energy consumption in the residential, commercial and transportation sector may suggest that it is easier to predict energy consumption for thsese sectors. And indeed commercial and residential sectors energy consumption MPEs are the lowest of the four. Transportation and industrial sector energy consumption MPE are the highest and close to each other. It is not clear why predicting transportation sector energy consumption is more difficult if compared to residential and commercial sectors. I'll study this problem in transportation sector analysis.

Figure 7 - Energy consumption by sector



5. Transportation sector analysis

As previous analysis showed, the transportation sector along with the industrial sector are the most important sectors in terms of influence on total error. The transportation sector is responsible for up to 82% of total error (Table 3). Unfortunately before 1996 transportation sector data in AEO consisted of only transportation sector energy consumption and energy price. After 1996 it also includes total vehicle-miles traveled (VMT), average gas consumption in miles per gallon (MPG), and total fleet stock. I used only data only for Light Duty Vehicles as they represent the largest portion of transportation sector energy consumption. Data for air, rail and marine transportation were not analyzed because of different representation that made comparison between different types of transports impossible.

Analysis of Transportation Sector MPE and MAPE

To find how accurate U.S. transportation sector energy forecasts are I analyzed MAPE and MPE for total energy consumption, total vehicle stock, total vehicle miles traveled and transportation sector average energy price. As Table 3 shows, transportation energy sector consumption error (MAPE) gradually grew from 3.14% for 1 year forecasts to more than 11% for 8 and more years forecast. Another type of question to ask about forecasts is how forecasts' accuracy changing as one predict more and more distant events. Given the unstable nature of the economy and complexity of societal interactions we can intuitively assume that it is harder to predict further events.

Figure 8 and Figure 9 show how transportation sector energy consumption, total vehicle stock, and total vehicle miles traveled (VMT) errors from forecasts made with

NEMS behave over time. Transportation sector energy consumption and total vehicle stock predictions were the least accurate and errors were growing fast, transportation sector energy consumption and average MPG projections were the most accurate of all projections. Because of very limited sample I was not able to explain why errors for fleet average stock car MPG and total VMT average become smaller for longer projections.

It is easy to see that relatively small errors in sector energy consumption hide larger errors in predicting sector specific parameters. In case of the transportation sector, the total number of vehicles error is much greater than energy consumption error. Errors in predicting energy price for transportation sectors, which will be analyzed separately later, are even larger.

Figure 8 – Transportation sector MAPE for NEMS model

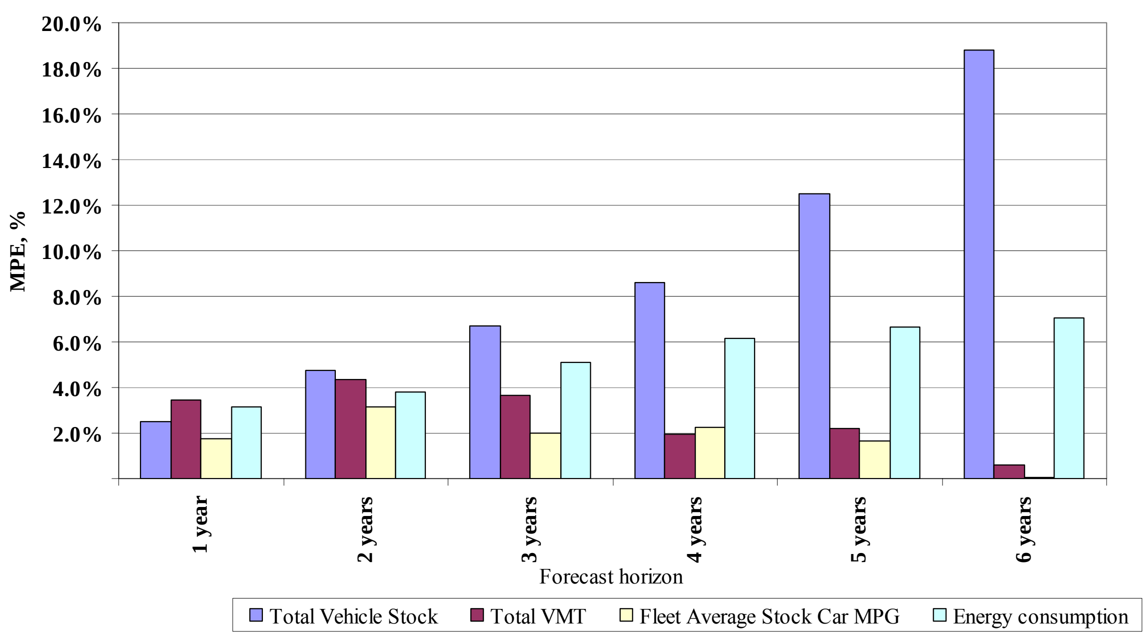
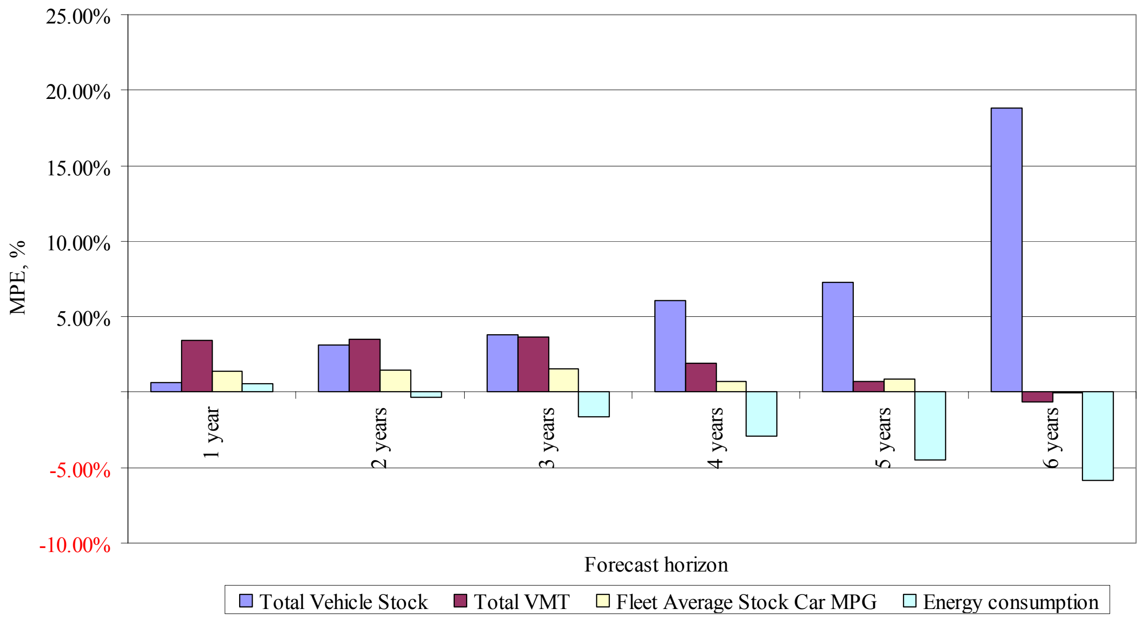


Figure 9 – Transportation sector MPE for NEMS model



Analysis of the MPE graph (Figure 9) shows that total vehicle stock was consistently overestimated, energy consumption underestimated, total VMT and Fleet average MPG were predicted with good accuracy and errors do not tend to grow as forecast horizon becomes longer.

Analysis of Transportation Energy Sector Forecast Improvements

To analyze how forecasts' accuracy is changing over time I built graphs with errors of 1 year forecasts, 2 year forecast, etc. Figure 10 and Figure 11 show a very typical view for that sort of graph. Errors in energy prices dwarf all other errors; they behave erratically. On the other hand errors in energy consumption show underestimation for AEO published before 1996 and overestimation after that. In 1996 EIA switched from using IFFS to NEMS. Change in model used by forecasters makes analysis of reasons of change in errors behavior before 1996 and after troublesome. It is unclear if such changes were mainly because of changes in the model or changes in assumptions. Overall I did not find any accuracy improvement over time.

Figure 10 – Percentage error for 1-year forecast for transportation sector by AEO

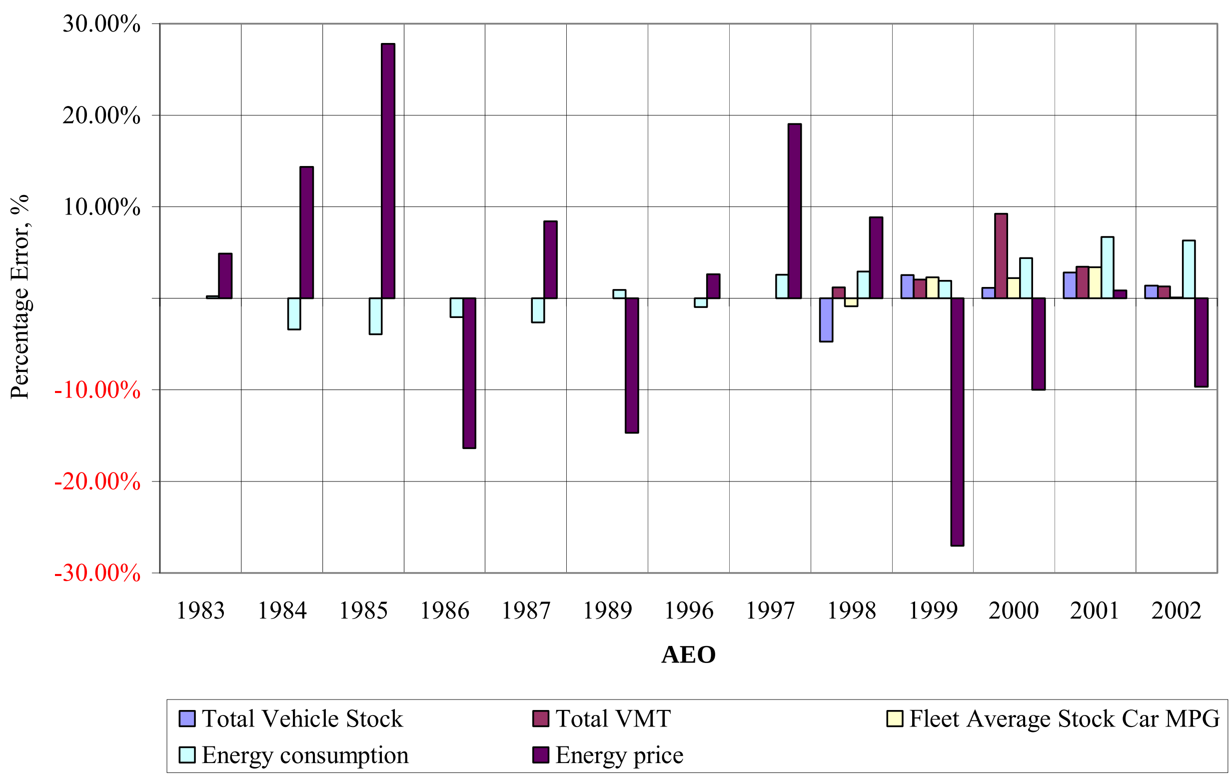
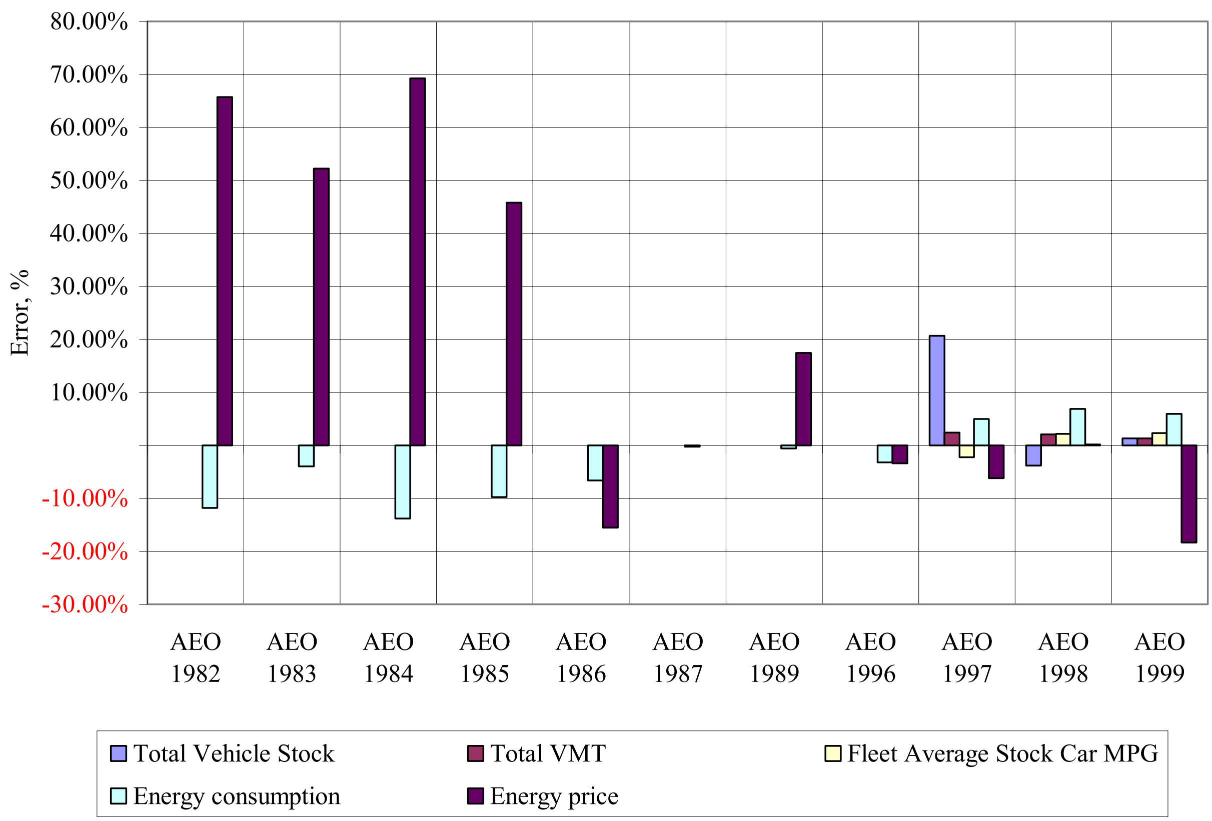


Figure 11 - Percentage error for 4-year forecast for transportation sector by AEO



Analysis of Assumptions' Influence on Transportation Energy Sector Forecast Accuracy

Assumptions are important factors influencing every model. They "represent the forecaster's basic outlook on the context within which the specific forecasted trend develops" (Ascher, p. 199). Ascher thinks that assumptions are the most important determinants of a forecast's accuracy. The transportation sector uses numerous input values (The Transportation Sector Model of the National Energy Modeling System, 2004, p. 8). Among them are fuel prices, new vehicle sales, economic and demographic indicators, etc. I picked two the most important (in my opinion) input variables: *world oil* *price* – which is a good encompassing indicator of fuel prices that are used in the transportation sector; and *GDP* which is an indicator of economic performance and thus influences many related variables.

Energy price errors for transportation sector are quite distinct among other errors that I analyzed before. Figure 12 show MAPE for transportation sector energy consumption and energy prices along with U.S. GDP and world oil prices for later analysis. Because world oil price errors and energy price errors were much larger than all other errors I plotted them on secondary axis. It is important to mention that last three average values were obtained from only one observation. Errors in predicting energy prices are so large that they cast doubt over the usefulness of such predictions. MAPE for energy price goes as high as 232% for 12 years. Figure 13 show MPE for the same parameters. Transportation sector energy price MPE shows that on average energy prices were underestimated for up to 5 years forecasts and greatly overestimated after that.

As Figure 12 and Figure 13 show, world oil price MPE and transportation sector energy price MPE are moving synchronously. They have very similar patterns and behavior over time.

Figure 12 shows that transportation sector energy prices MPE reaches 232%, and world oil prices MPE reaches more that 400% error in 12 years.

Figure 12 – Transportation sector energy price and energy consumption MPE, world oil price and GDP MAPE

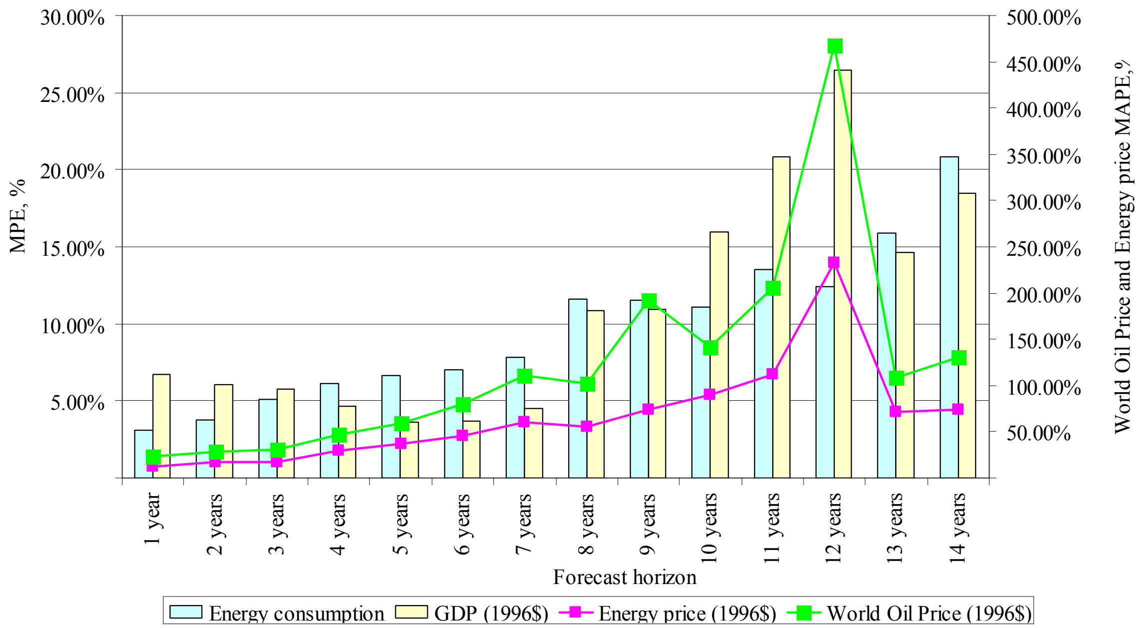
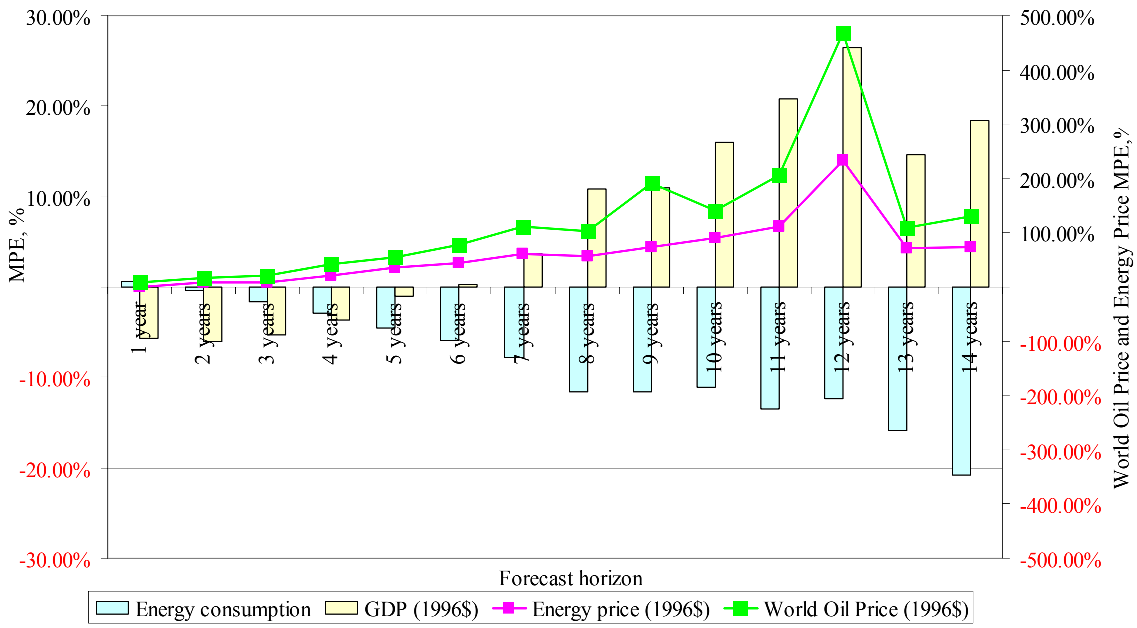


Figure 12 shows that transportation sector energy consumption, GDP, world oil price and transportation sector energy price suffer from severe systemic errors. Both world oil price and energy price were consistently overestimated, while energy consumption underestimated. GDP projections tend to be underestimated for the first few years and then overestimated. Amplitude of MAPE is smaller than MPE which means that some cancellation of errors exists. If we consider the assumption that growing energy prices decrease energy consumption by a certain degree (short and long term elasticity), underestimation of the energy consumption can be partially explained by the overestimation of world oil prices.

Figure 13 - Transportation sector energy price and energy consumption MAPE, world oil price and GDP MPE



To find if there is any relationship between world oil prices MPE and transportation energy sector price MPE I used regression analysis. Figure 14 shows distribution of energy price errors vs. world oil price errors and a linear trend line. The regression equation is

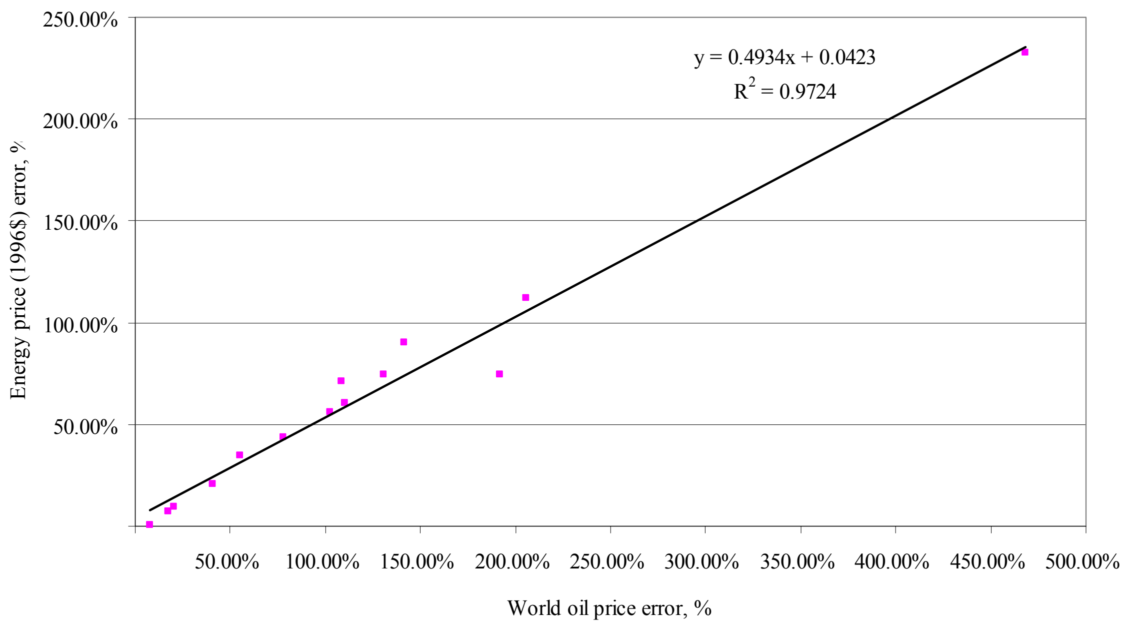
Y=0.4844X+0.0788, where

Y – energy price MPE

X - world oil price MPE

R square is 0.97 which means that 97% of total variability of energy price MPE was explained by using linear regression. Visually errors lie very close to the regression line. Line slope of 0.4844 means that for approximately every two percent reduction in world oil price MPE we can expect one percent reduction in energy price MPE.

Figure 14 – Transportation sector energy price errors vs. world oil price (1996$) errors for forecasting horizon from 1 to 14 years



To analyze the possibility of reduction in world oil price errors I built a graph that shows actual values of world oil price and forecasted with IFFS and NEMS. Figure 15 shows how world oil prices were predicted in different AEO in comparison with actual values. All forecasts show gradual smooth increase in oil prices, while actual values show very different behavior.

Figure 16 shows how world oil prices were changing over the period between 1974 and 2003. Smil (2003, p. 155) points that year to year price shifts have been random and

Figure 16 is a good confirmation of his words “nothing appears to be more incorrect where the future of oil prices is concerned than charting largely horizontal lines”. Figure 15 shows typical, what William Ascher (Ascher, 1978) calls it, “assumption drag”, when changing trends are not captured in forecasts and forecasters continue using outdated and incorrect assumptions. AEO produced in 1982, 1983, 1984, 1987, and 1989 are greatly overestimating world oil prices and forecasting rapid growth of oil prices over time even when prices started to fall.

During periods of high and growing oil prices both models forecasted rapid, almost exponential growth in the future. Periods of stable world oil prices tend to flatten forecasts to a gradual growth.

For periods of relatively stable oil prices linear trends appear to be the best estimate of future oil prices and NEMS forecasts made in 1996-2003 are more precise than earlier projections. This precision is attributed only to stable prices and any random shocks in the nearest future will reduce accuracy. Taking into account random nature of world oil prices it is unrealistically to expect world oil price forecasts along with transportation sector energy prices to be much more precise than they are now.

Figure 15 – Comparison of actual and forecasted world oil prices (AEO 1982-2004)

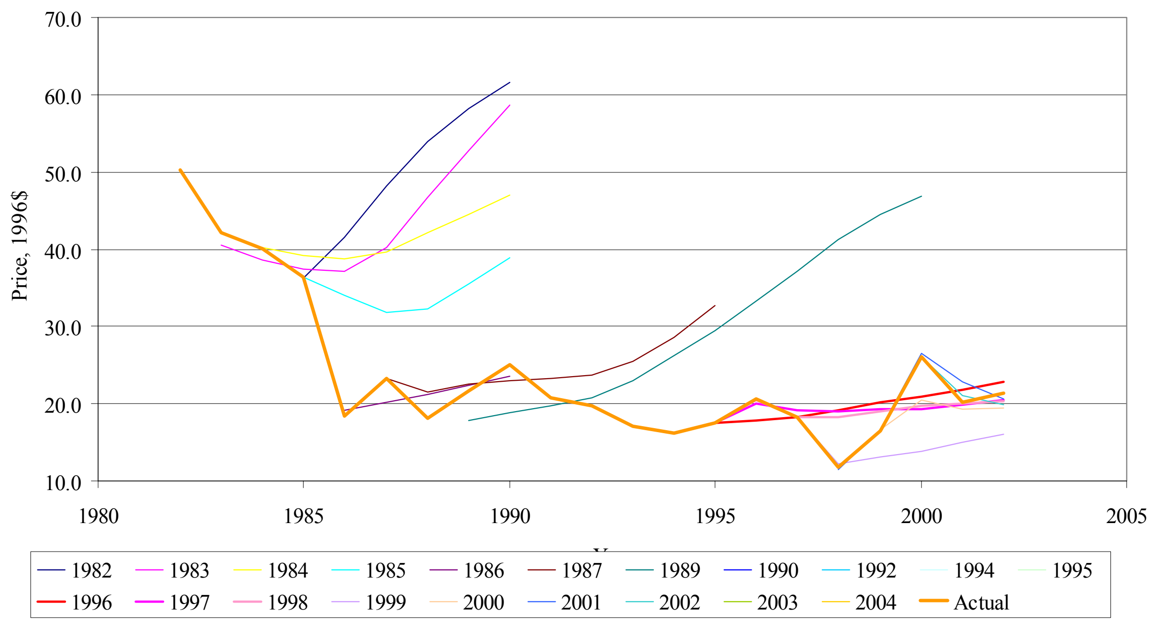
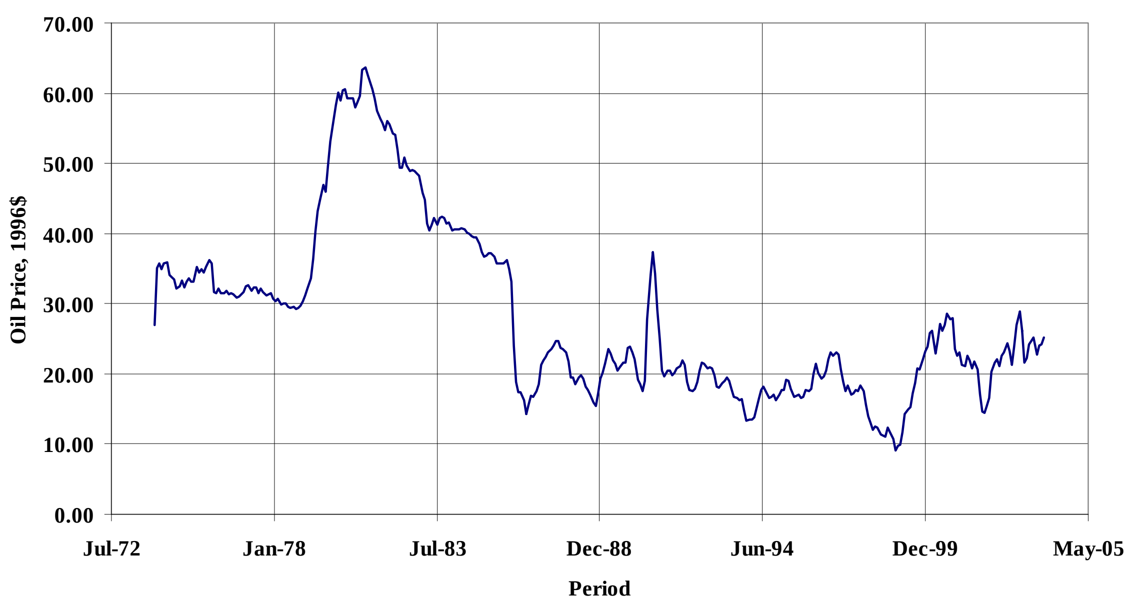


Figure 16 – World oil prices chronology (World Oil Market and Oil Price Chronologies: 1970 – 2004)



Another important assumption for both IFFS and NEMS is GDP. In contrast to world oil prices, GDP grows in a quite predictable manner without sudden booms and busts over time (Figure 17). But even for such forecasting is not particularly accurate and errors go as high as 25% (Figure 12). Because GDP is behaving in such predictable way I decided to do forecasting using regression analysis techniques. Table 4 shows the results of such analysis. I used historical real GDP in billions of 2000 dollars from 1970 to 1994 to build an exponential growth model. Then I forecasted real GDP for 1995-2003 using this model and compared these forecasts with actual data. Column (6) percent error shows that for period of 9 years error didn't exceed 4% which is better than results received with much more complex IFFS and NEMS models shown in Figure 18.

Figure 17 - Real GDP chronology and forecasting results

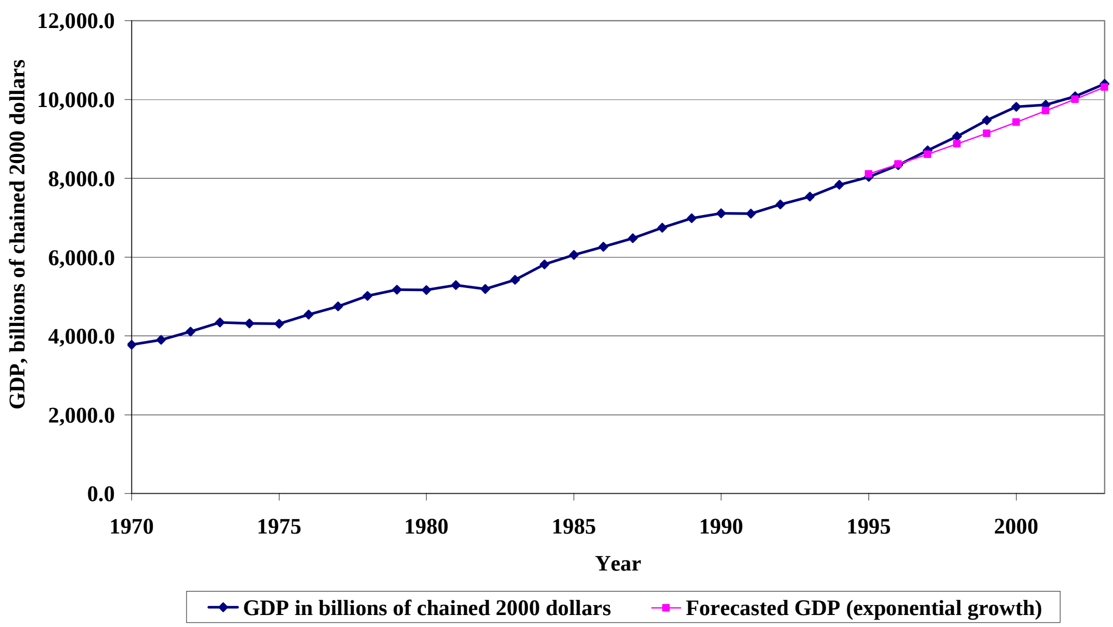


Table 4 - GDP exponential trend calculation

Year	GDP in billions of chained 2000 dollars	Linearized GDP	Forecasted linearized GDP	Forecasted GDP (exponential growth)	Percent Error
(1)	(2)	(3)	(4)	(5)	(6)
1970	3,771.9	8.2353	8.250	3827.5	1.47%
1971	3,898.6	8.2684	8.280	3944.2	1.17%
1972	4,105.0	8.3200	8.310	4064.4	-0.99%
1973	4,341.5	8.3760	8.340	4188.3	-3.53%
1974	4,319.6	8.3709	8.370	4316.0	-0.08%
1975	4,311.2	8.3690	8.400	4447.6	3.16%
1976	4,540.9	8.4209	8.430	4583.1	0.93%
1977	4,750.5	8.4660	8.460	4722.8	-0.58%
1978	5,015.0	8.5202	8.490	4866.8	-2.96%
1979	5,173.4	8.5513	8.520	5015.2	-3.06%
1980	5,161.7	8.5490	8.550	5168.0	0.12%
1981	5,291.7	8.5739	8.580	5325.6	0.64%
1982	5,189.3	8.5543	8.610	5487.9	5.76%
1983	5,423.8	8.5985	8.640	5655.2	4.27%
1984	5,813.6	8.6680	8.670	5827.6	0.24%
1985	6,053.7	8.7084	8.700	6005.2	-0.80%
1986	6,263.6	8.7425	8.730	6188.3	-1.20%
1987	6,475.1	8.7757	8.760	6376.9	-1.52%
1988	6,742.7	8.8162	8.790	6571.3	-2.54%
1989	6,981.4	8.8510	8.820	6771.6	-3.00%
1990	7,112.5	8.8696	8.851	6978.1	-1.89%
1991	7,100.5	8.8679	8.881	7190.8	1.27%
1992	7,336.6	8.9006	8.911	7410.0	1.00%
1993	7,532.7	8.9270	8.941	7635.9	1.37%
1994	7,835.5	8.9664	8.971	7868.6	0.42%
1995	8,031.7	8.9911	9.001	8108.5	0.96%
1996	8,328.9	9.0275	9.031	8355.7	0.32%
1997	8,703.5	9.0715	9.061	8610.4	-1.07%
1998	9,066.9	9.1124	9.091	8872.8	-2.14%
1999	9,470.3	9.1559	9.121	9143.3	-3.45%
2000	9,817.0	9.1919	9.151	9422.0	-4.02%
2001	9,866.6	9.1969	9.181	9709.2	-1.60%
2002	10,083.0	9.2186	9.211	10005.2	-0.77%
2003	10,398.0	9.2494	9.241	10310.2	-0.84%

Figure 18 – Comparison of actual and forecasted real GDP values

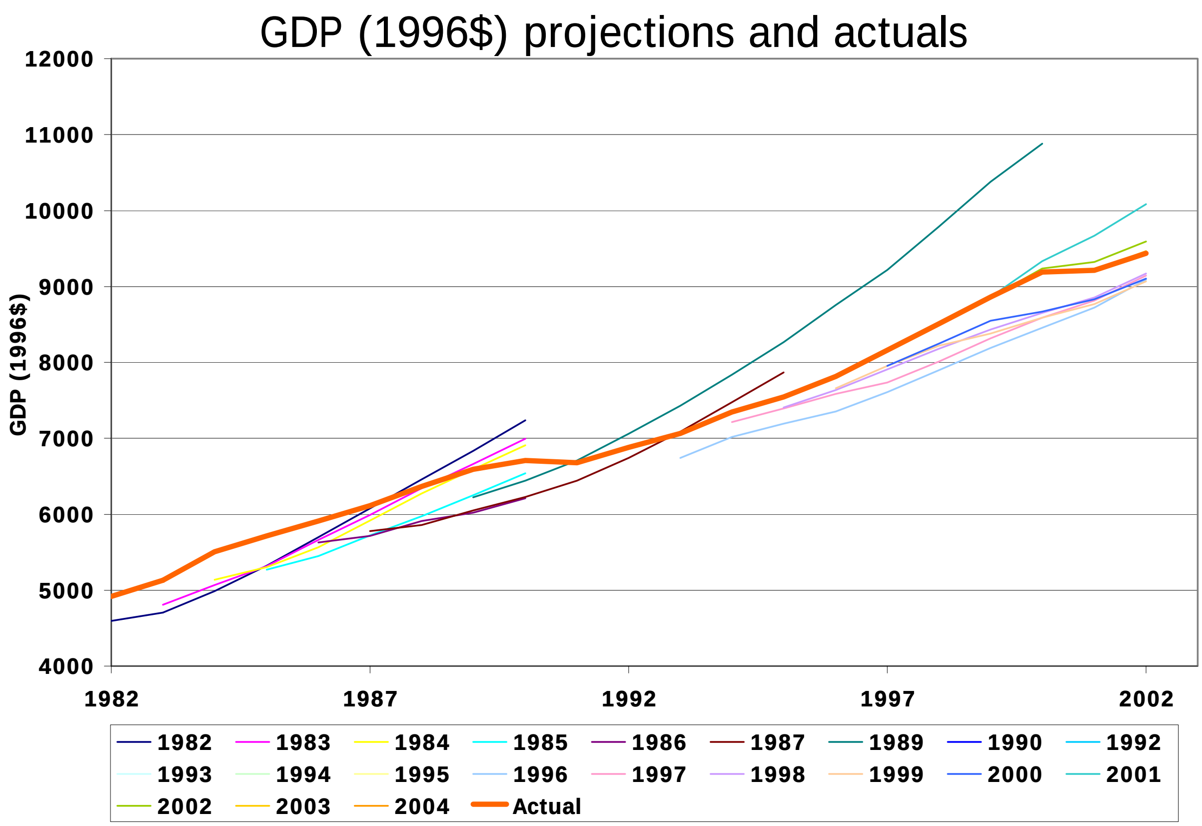
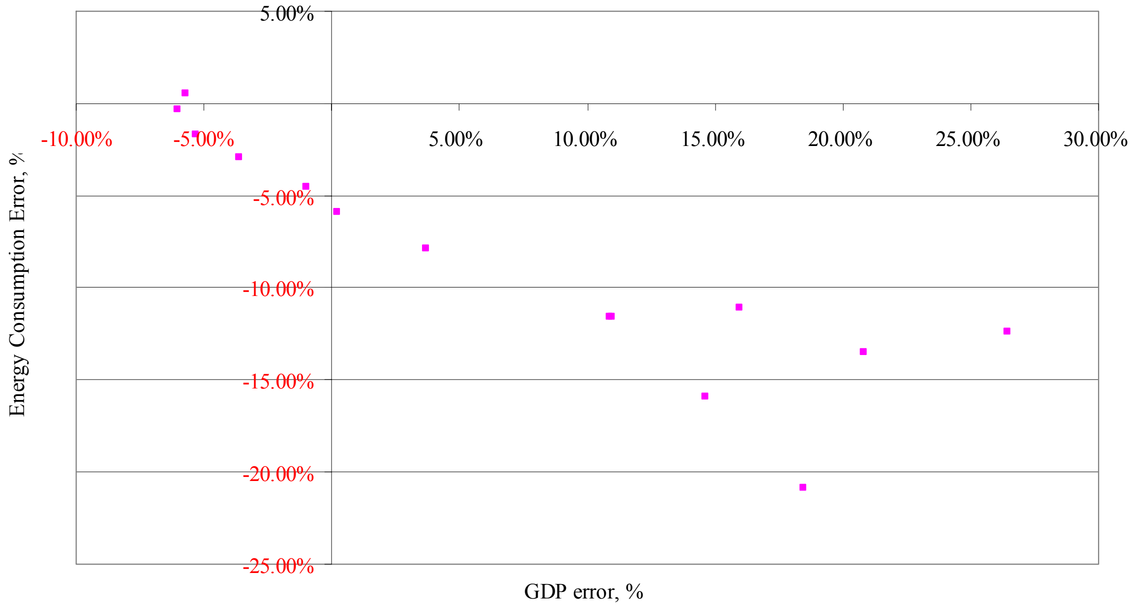


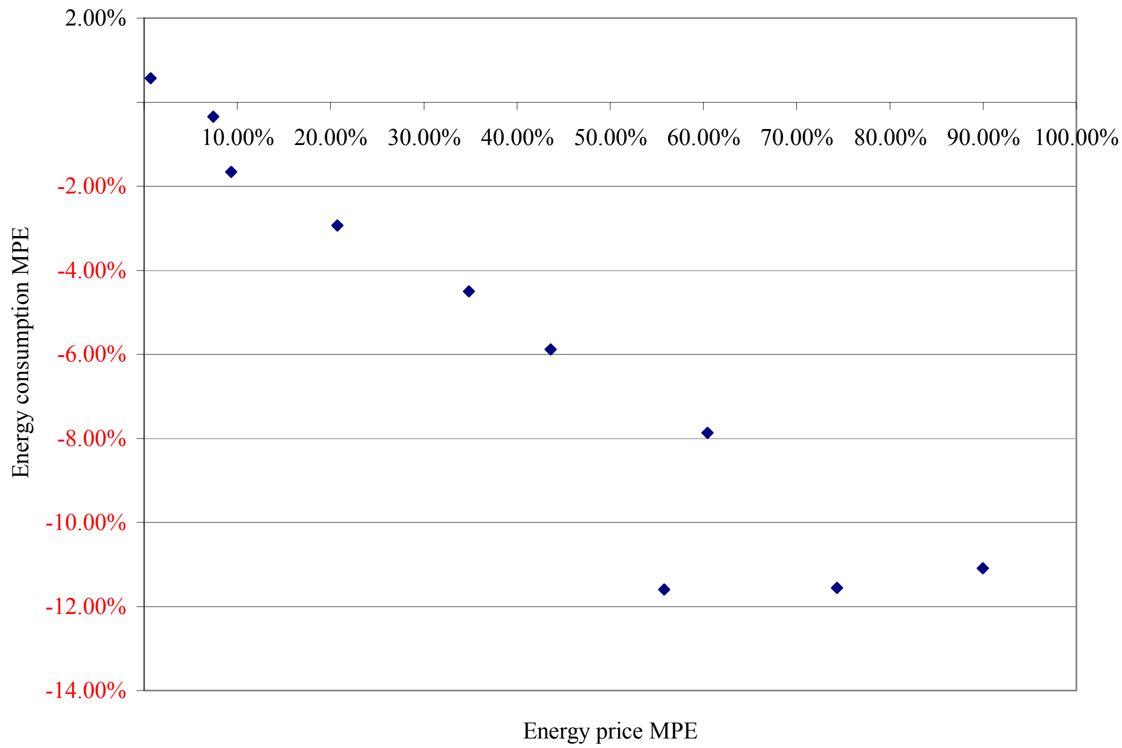
Figure 19 shows that GDP and energy consumption errors are somehow related, and improvement of GDP accuracy will influence energy consumption accuracy. The graph shape is not exactly linear as in case of world oil prices and transportation sector energy prices but it shows that higher by absolute value errors in GDP lead to higher by absolute value errors in energy consumption.

Figure 19 – Transportation sector energy consumption errors VS GDP errors for 1 to 14 years forecast



NEMS documentation states: "Four end-use demand modules represent fuel consumption in the residential, commercial, transportation, and industrial sectors, subject to delivered fuel prices, macroeconomic influences, and technology characteristics." (The National Energy Modeling System: An Overview 2003). Fuels that are used in the transportation sector are mainly petroleum based. Because of this, fuel prices depend very much on world oil prices. So, high error in predicting transportation sector energy price may introduce additional error in predicting energy consumption. Figure 20 presents a graph of transportation sector energy consumption MPE vs energy price MPE. The graph shows that generally high overestimation of world oil prices lead to underestimation of energy consumption. The link between energy consumption and energy price in IFFS/NEMS maybe stronger than it is in reality.

Figure 20 - Transportation sector energy consumption MPE vs energy price MPE

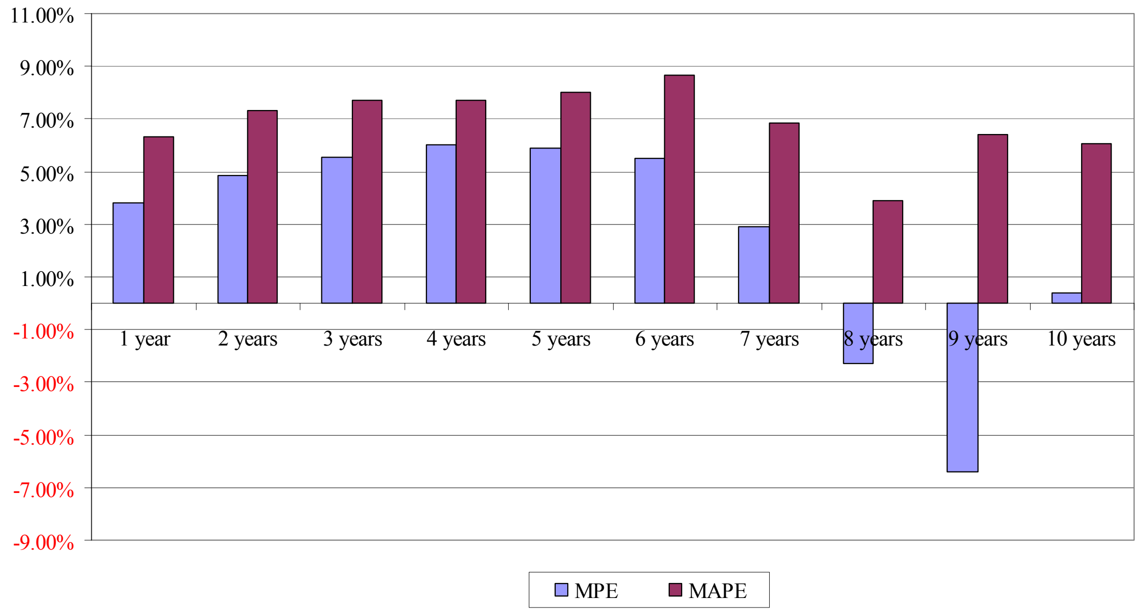


6. Industrial sector analysis

The manufacturing sector consists of all manufacturing establishments in the 50 States and the District of Columbia (Energy Use in Manufacturing, 2005).

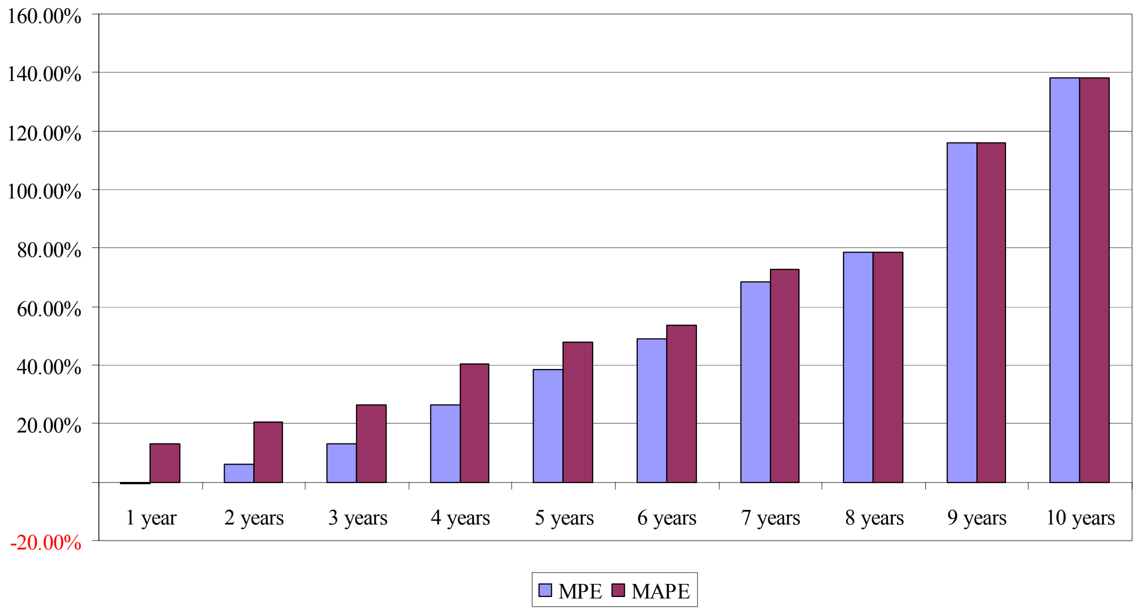
The industrial sector is similar to the transportation sector by the impact it has on error in total energy consumption (Table 3). While errors in energy consumption in the transportation sector are slowly growing over time, errors in the industrial sector energy consumption (MPE) have a wavy form that show slow growth in the beginning and slow decay at the end (Figure 21). This form can be explained by initial positive bias and underestimated growth rate. The similarity of MPE and MAPE for the first six years shows that energy consumption for industrial sector was generally overestimated, and after that both overestimation and underestimation exist. It is also interesting to note that for up to 10 years there is no visible growth in the amplitude of MPE or MAPE which means that forecasts' accuracy is not declining over the 10 year period.

Figure 21 - MPE and MAPE for industrial sector energy consumption



Errors in predictions of energy prices are very similar in behavior to those of the transportation sector. Industrial sector energy prices are overestimated and the degree of overestimation is rapidly growing over time. MPE and MAPE are very close to each other which means that there is no cancellation of errors and energy price accuracy suffer from incorrect growth rate.

Figure 22 - MPE and MAPE for industrial sector energy price



Analysis of Industrial Energy Sector Forecast Improvements

Figure 23, Figure 24, and Figure 25 show errors in forecasting industrial sector energy consumption and energy prices for 3, 5 and 7 years forecasts respectively. These figures help to analyze how forecasts' accuracy was changing between AEOs. Analysis of energy consumption shows that there are no signs of improving accuracy over time. Switching from IFFS to NEMS in 1996 did not improve accuracy. At the same time energy prices accuracy improved to some degree. This improvement in accuracy can be attributed to relatively more stable prices over the period of 1990-2003 if compared to pre 1990 period. But because improvements in accuracy are mainly attributed to a stable environment I do not expect it to improve further. The next random shock can reverse positive trends and decrease the accuracy of current forecasts.

Figure 23 - Errors in 3 years forecasts of industrial sector energy consumption and energy price

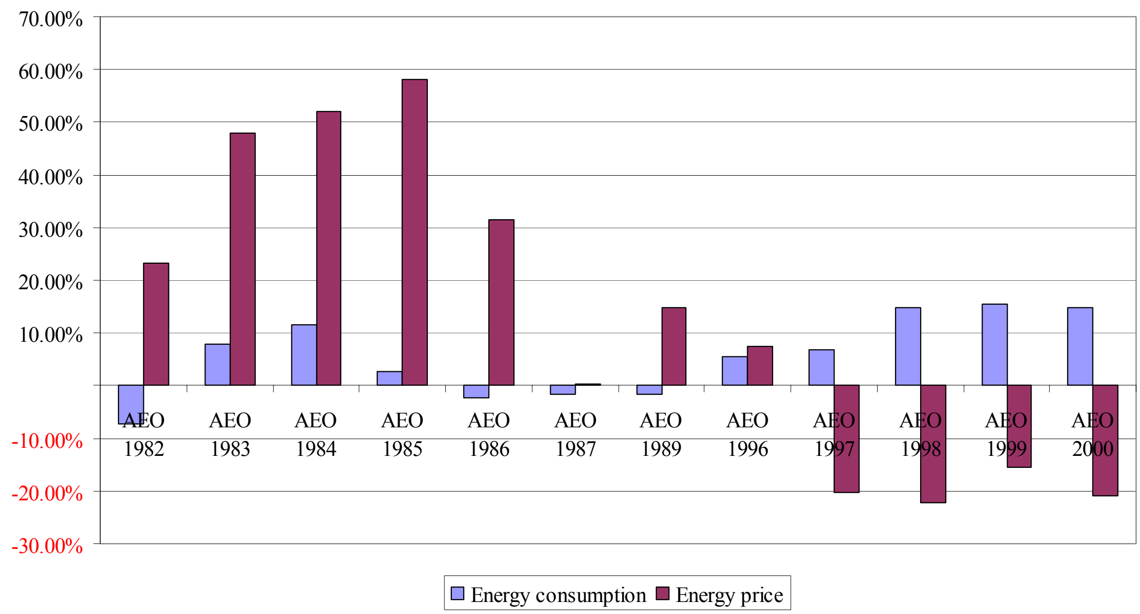


Figure 24 - Errors in 5 years forecasts of industrial sector energy consumption and energy price

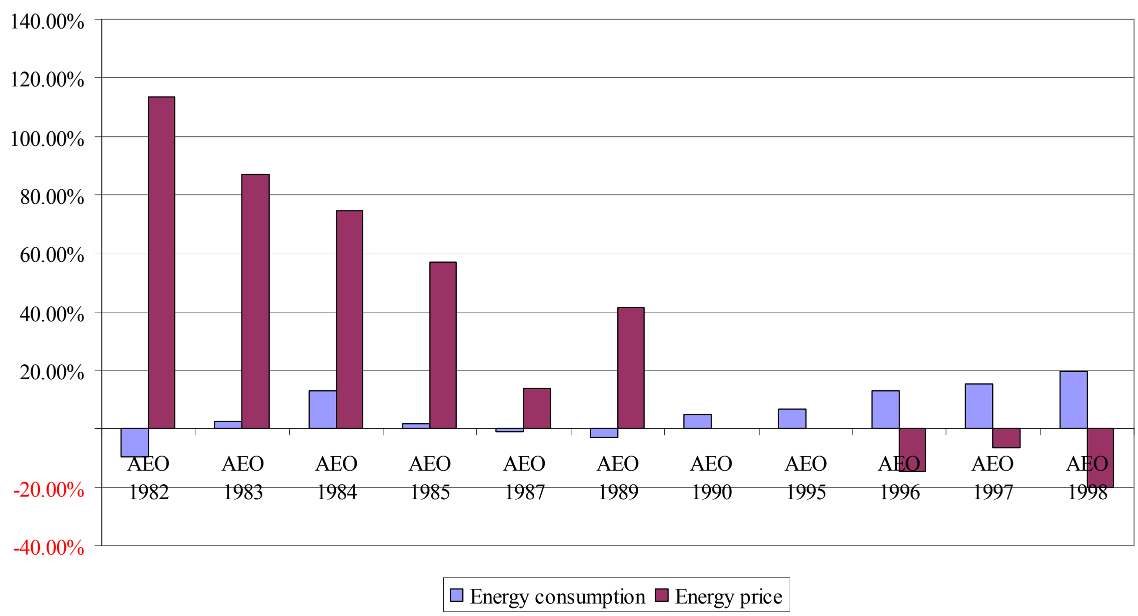
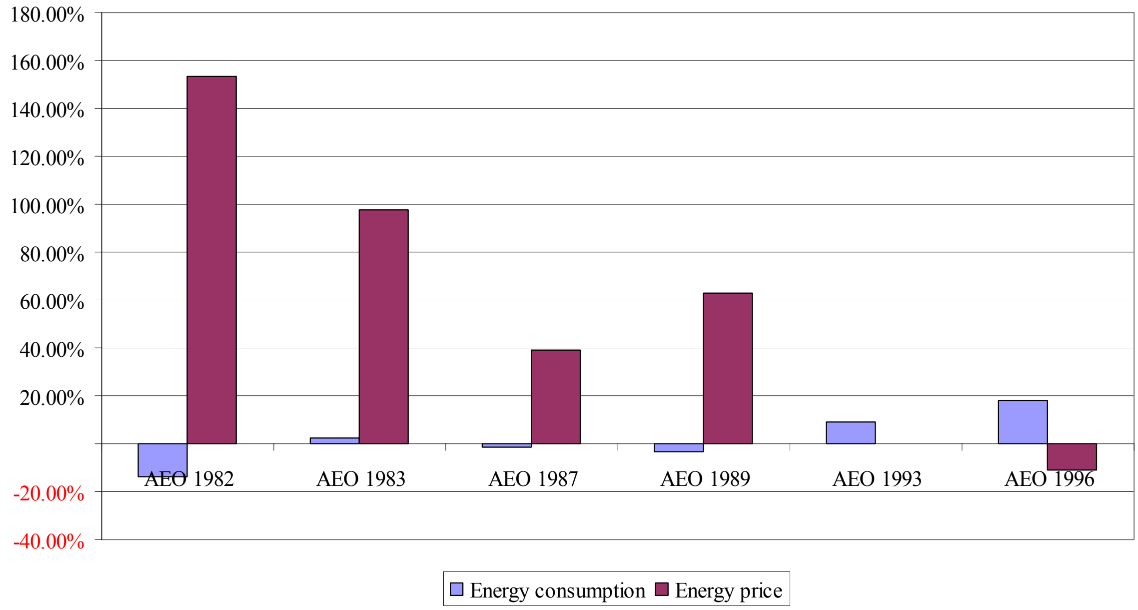


Figure 25 - Errors in 7 years forecasts of industrial sector energy consumption and energy price



Analysis of Assumptions' Influence on Industrial Energy Sector Forecast Accuracy

Figure 26 and Figure 27 show results of an analysis of the influence of errors in core assumptions on accuracy of industrial sector energy consumption and energy price. These figures are very similar to the figures presented for the transportation sector. Higher MPE in predicting world oil prices leads to higher MPE in predicting industrial sector energy prices. The relationship is quite linear and line slope suggests that for each percent improvement in world oil price MPE we can expect 0.65% improvement in industrial sector energy price.

Figure 26 - Industrial sector energy price MPE vs. world oil price (1996$) MPE

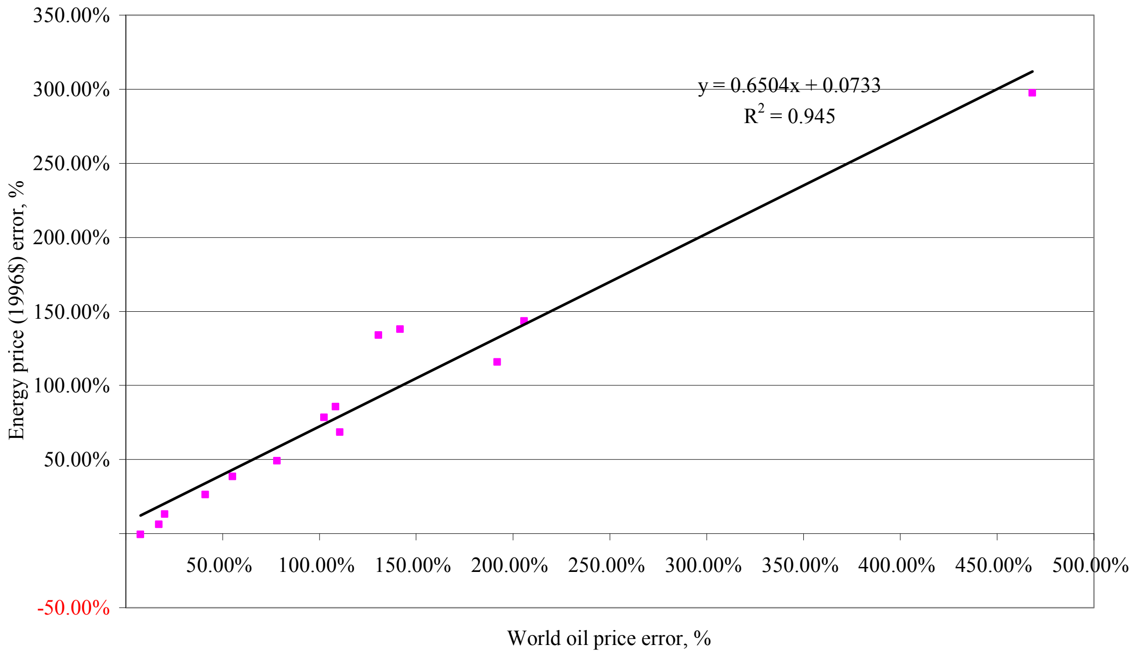
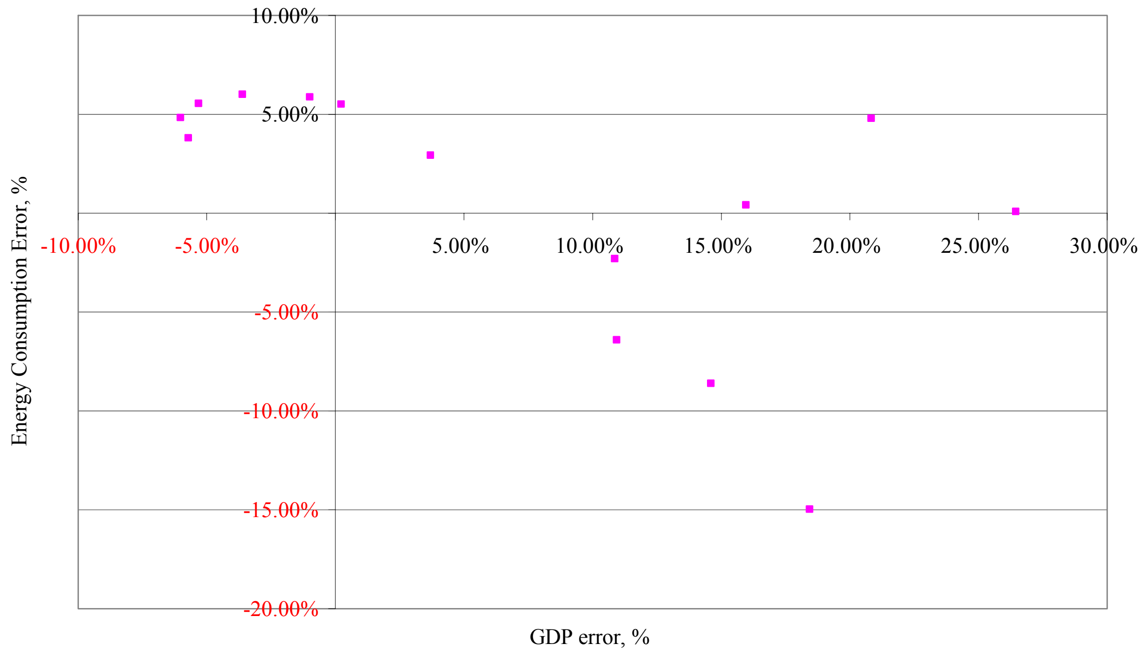


Figure 27 shows relationship between industrial sector energy consumption MPE and real GDP MPE. Relationship is not readily visible but we can assume that increased GDP MPE may lead to increased energy consumption MPE.

Figure 27 - Industrial sector energy consumption MPE vs. GDP MPE

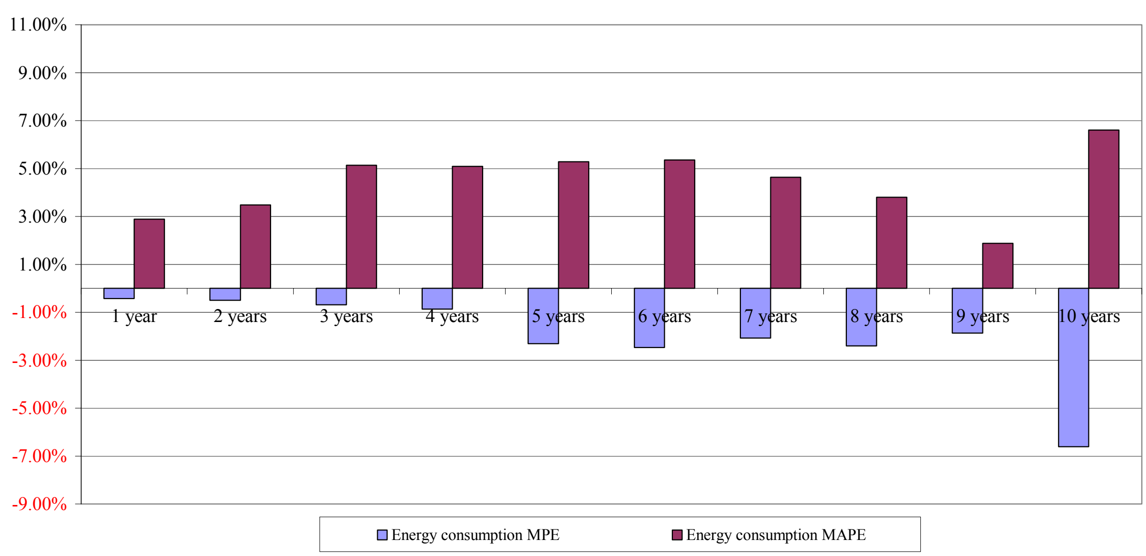


7. Commercial sector analysis

The commercial sector consists of business establishments and other organizations that provide services. The sector includes service businesses, such as retail and wholesale stores, hotels and motels, restaurants, and hospitals, as well as a wide range of buildings that would not be considered “commercial” in a traditional economic sense, such as public schools, correctional institutions, and religious and fraternal organizations. Excluded from the sector are the goods-producing industries: manufacturing, agriculture, mining, forestry and fisheries, and construction (Background Information on CBECS, 2001).

The commercial sector is number three by its influence on total energy consumption accuracy. The commercial sector energy consumption MAPE fluctuates between 3% and 7%. At the same time MPE is always negative and smaller by absolute value (Figure 28). This means that there is a slight negative bias in forecasting energy consumption for the commercial sector.

Figure 28 - Commercial sector energy consumption MPE and MAPE



The commercial sector energy prices were almost always overestimated and errors in predicting energy prices grow rapidly over time. MAPE grows from less then 10% for 1 year forecast to more than 70% in 10 years forecast (Figure 29). MPE is either slightly less than MAPE or equal to it which means that periods of underestimation exist but they are not reversing general overestimation trend.

Figure 29 - Commercial sector energy price MPE and MAPE

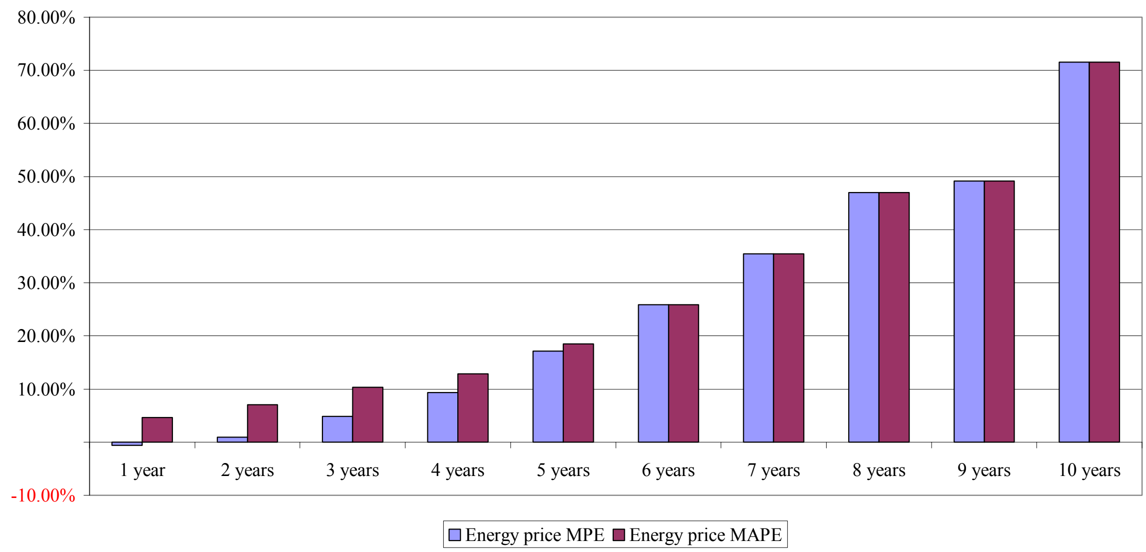


Figure 30 and Figure 31 show results of MAPE and MPE analysis respectively. MAPE for energy consumption is much lower than total floorspace, energy consumption per square feet (energy intensity) and energy price. The commercial sector energy consumption can be expressed as a function of total commercial floorspace, energy intensity and energy price. And error for aggregate energy consumption is lower that any single disaggregate parameter. While energy consumption MAPE is generally less than

5% for up to 7 years, energy intensity MAPA reaches almost 40%, total floor space fluctuates between 7% and 12%, and energy price MAPE reaches 36% in 7 years.

MPA analysis shows that energy intensity was underestimated with little or no cancellation between years; total floor space tends to be overestimated; energy price was mostly overestimated and energy consumption has no definite bias.

Figure 30 - Commercial sector NEMS model parameters MAPA

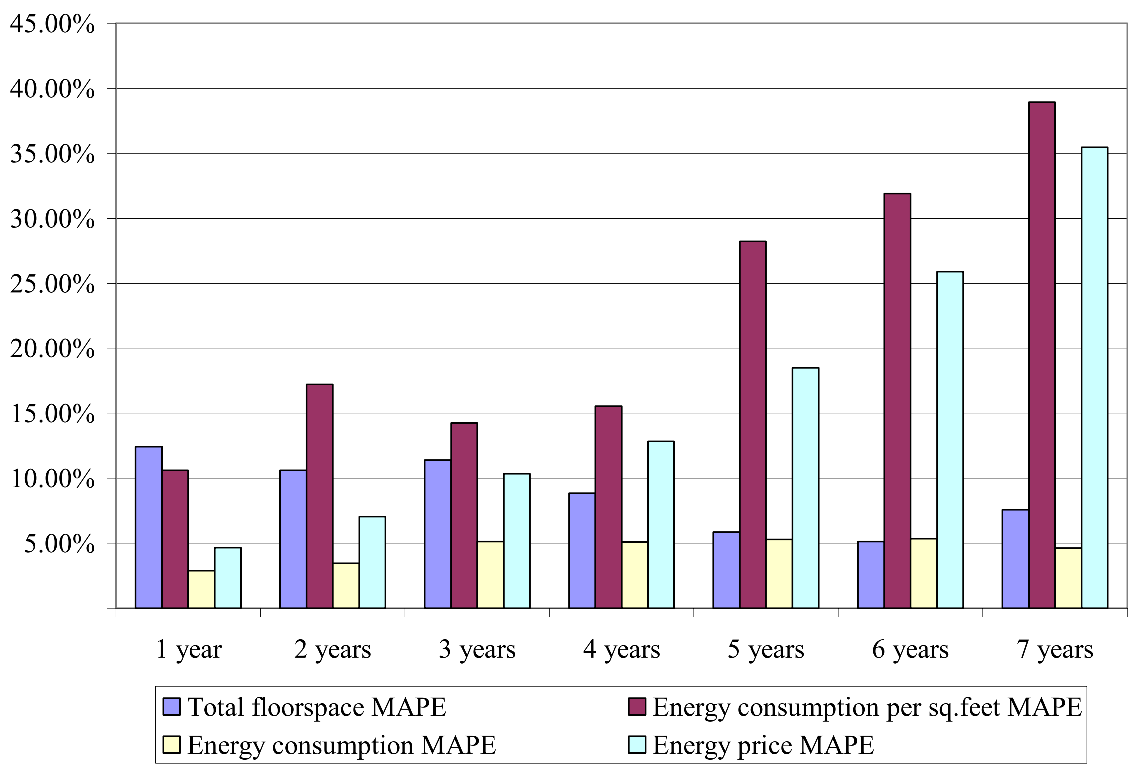
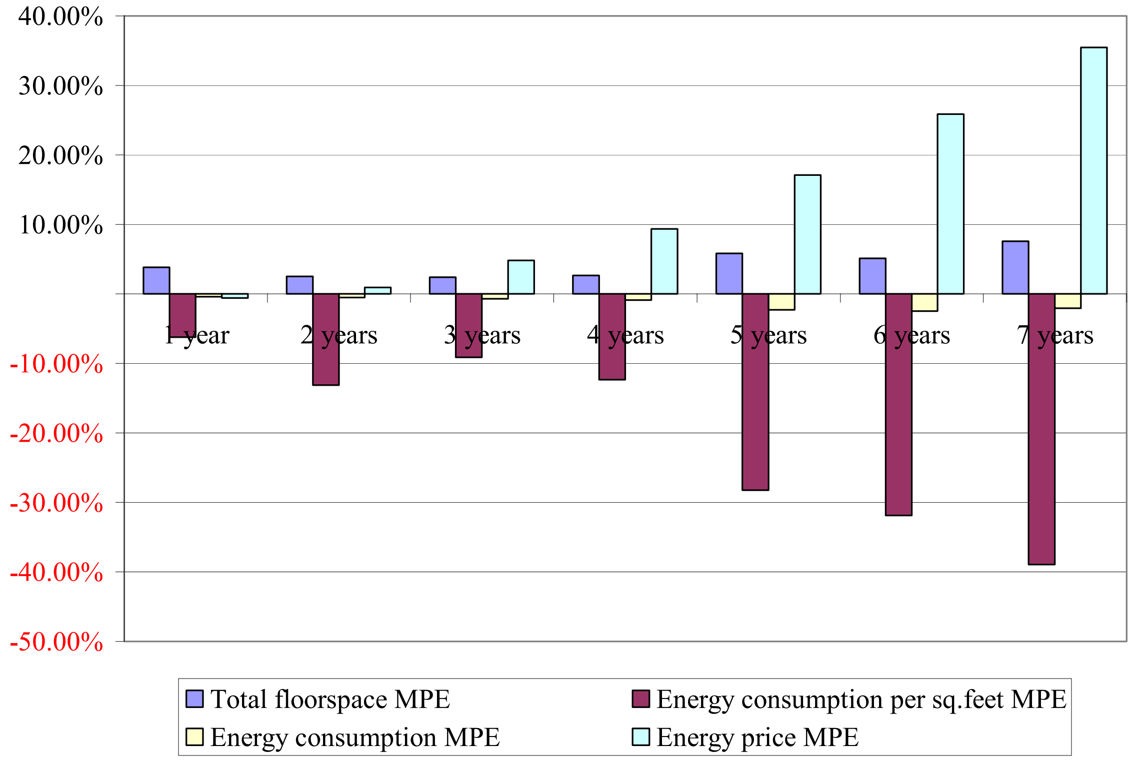


Figure 31 - Commercial sector NEMS model parameters MPA



Analysis of Commercial Energy Sector Forecast Improvements

Figure 32, Figure 33 and Figure 34 show percentage errors of energy consumption and energy price for forecasting horizons of 3,5 and 7 years respectively. All three graphs show no improvement of energy consumption accuracy over time. Later AEOs seem to have better accuracy in predicting energy prices then earlier ones. For example for three years forecasts energy price percentage error for AEO published between 1982 and 1989 stays between 10% and 35%; for AEO published after 1989 error is less than 10% This improved accuracy may be explained by relatively stable oil prices is mid-1990 and later.

Figure 32 -Percentage errors in three years forecasts of commercial sector energy consumption and energy price

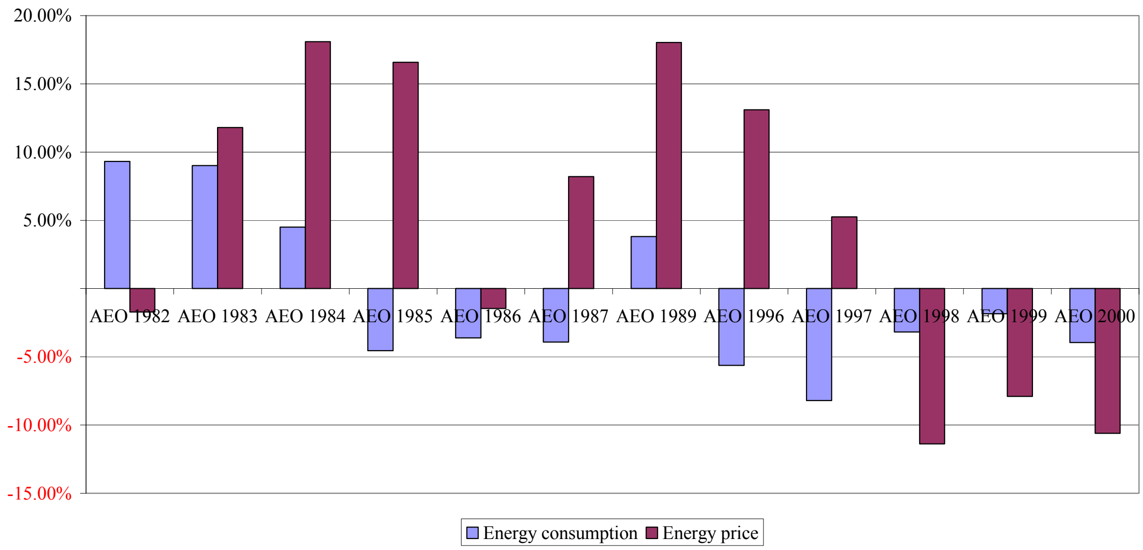


Figure 33 - Percentage errors in five years forecasts of commercial sector energy consumption and energy price

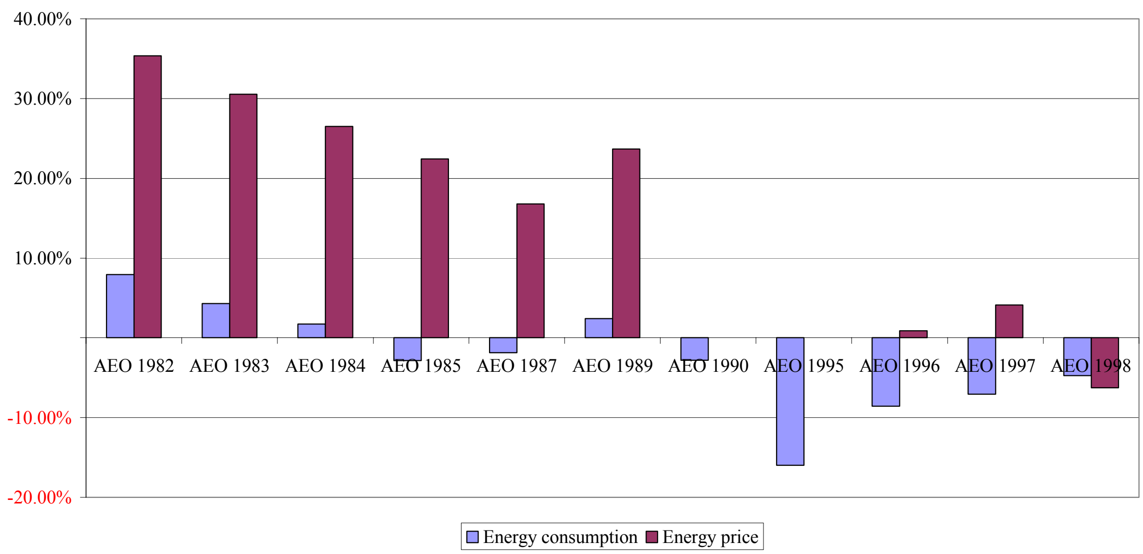
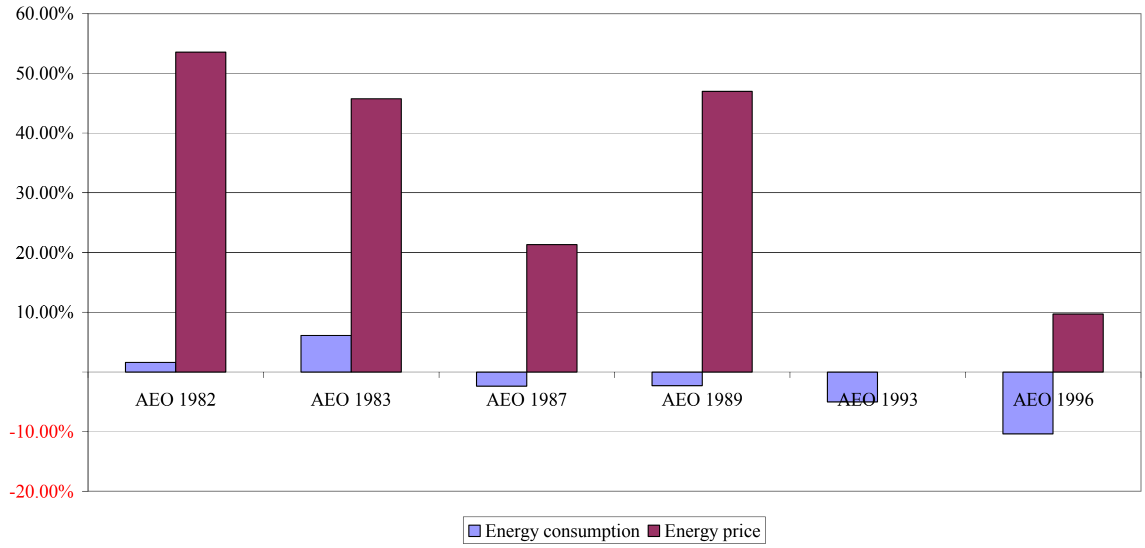


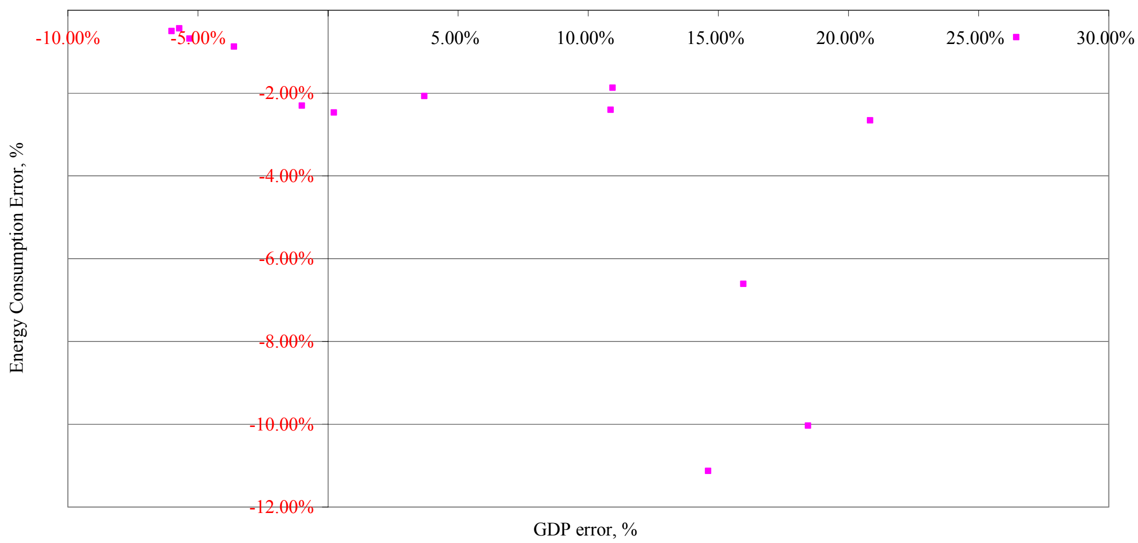
Figure 34 – Percentage errors in seven years forecasts of industrial sector energy consumption and energy price



Analysis of Assumptions' Influence on Commercial Energy Sector Forecast Accuracy

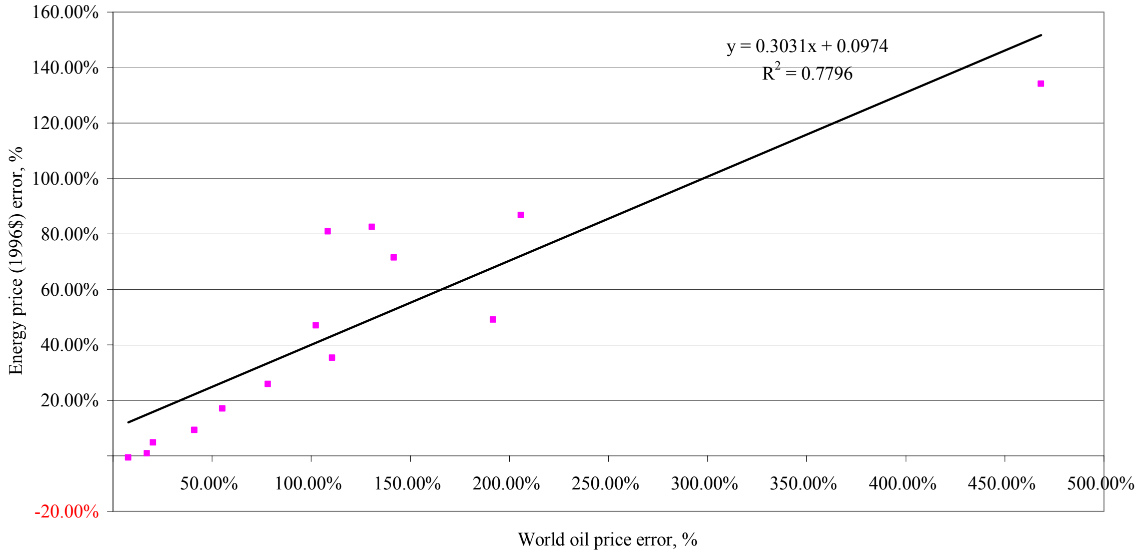
Figure 35 and Figure 36 show results of analysis of the influence of erroneous core assumptions on energy consumption and energy price accuracy. Visual comparison and regression analysis did not show any definite relationship between accuracy of commercial sector energy consumption and GDP. Dots on the graph are distributed quite randomly.

Figure 35 - Graph of commercial sector energy consumption MPE vs. GDP (1996$) MPE



On the other hand energy prices and world oil prices seem to be related to each other. Because world oil prices are one of the core assumptions we can say that accuracy in predicting world oil prices influences the accuracy of predicting commercial sector energy prices. Figure 36 shows that higher world oil prices MPE result in higher commercial sector energy price MPE. We can expect 0.3% decrease in the commercial sector MPE for each percent decrease in world oil prices MPE.

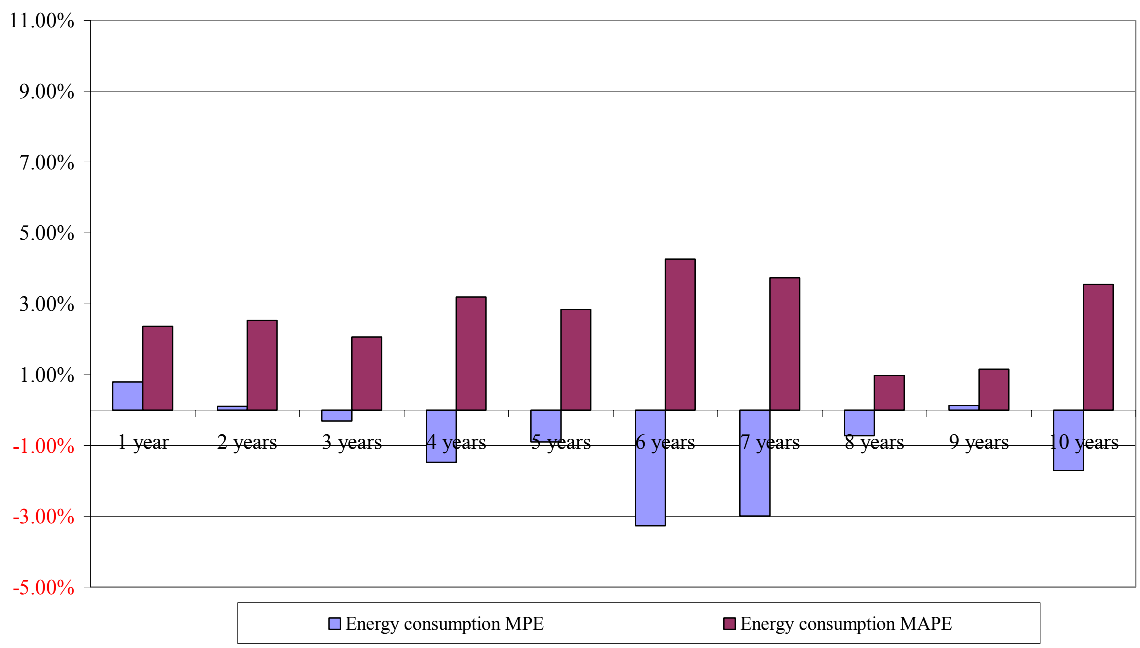
Figure 36 - Graph of commercial sector energy prices (1996$) MPE vs. world oil prices (1996$) MPE



8. Residential sector analysis

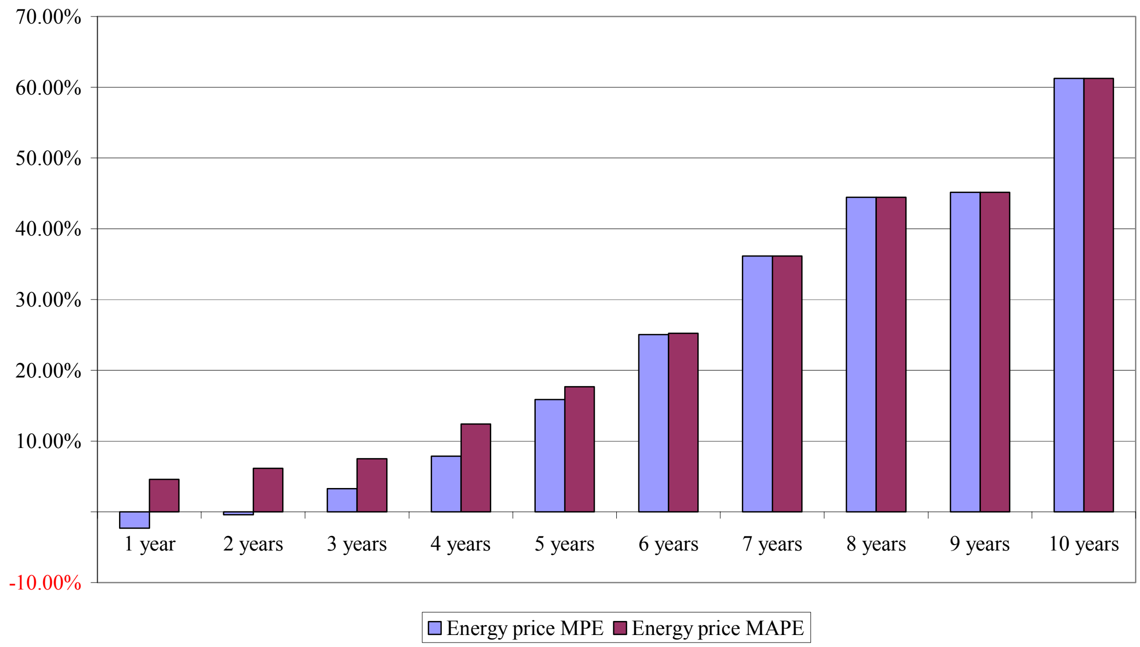
The residential sector was predicted with the highest accuracy among all four sectors. Figure 37 shows that the residential sector energy consumption MAPE for up to 10 years lies between 1% and 4%. MPE graph suggests that there is some cancellation of errors between years with some tendency to underestimation of energy consumption.

Figure 37 - Residential sector energy consumption MPE and MAPE



Residential sector energy prices as in case of other sectors suffer from much higher errors then energy consumption. MPE and MAPE suggest that energy prices were seriously overestimated. MAPE grows rapidly and reaches more than 60% in 10 years. Both graphs resemble very closely equivalent graphs for commercial sector.

Figure 38 - Residential sector energy price MPE and MAPE



Number of households and energy consumption per household were predicted only with NEMS model. Figure 39 and Figure 40 show results of MAPE and MPE analysis of these parameters. Number of households was generally underestimated with MAPE gradually growing from 2.48% in 1 year to 6.48% in 6 years. Energy consumption per household was overestimated and underestimated with MAPE fluctuating between 1.5% to 5.5%.

Figure 39 - Residential sector NEMS parameters MAPE

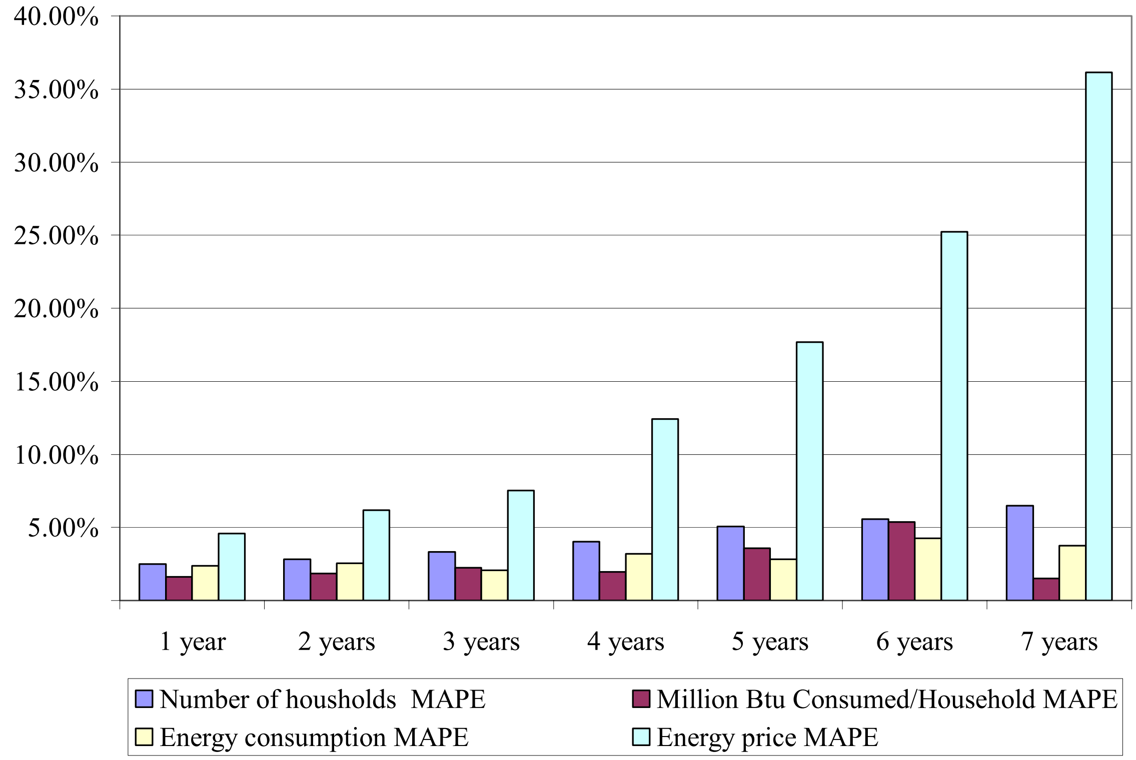
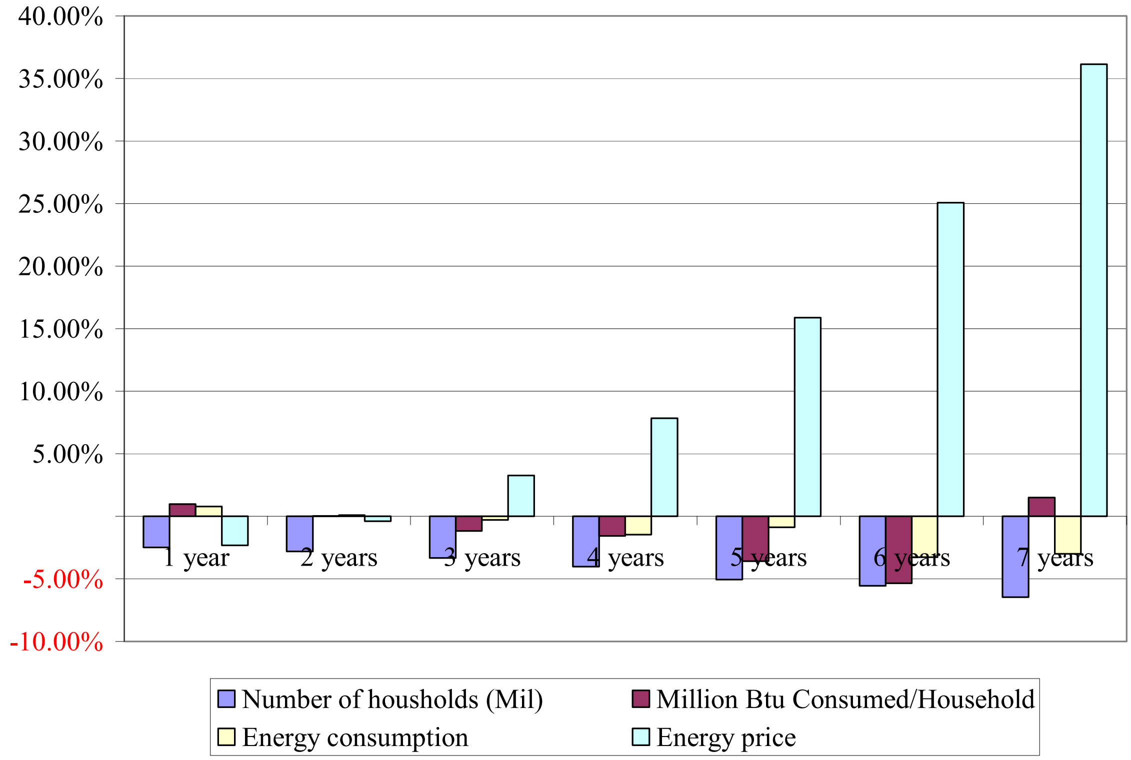


Figure 40 - Residential sector NEMS parameters MPE



Analysis of Residential Energy Sector Forecast Improvements

Figure 41, Figure 42 and Figure 43 show how percentage errors for energy price and energy consumption were changing between AEOs given forecast horizon length of three, five and seven years. All three figures suggest that energy consumption accuracy did not improve over time. Energy prices accuracy seems to improve for five and seven years forecasts.

Figure 41 - Residential sector three years forecasts percentage errors

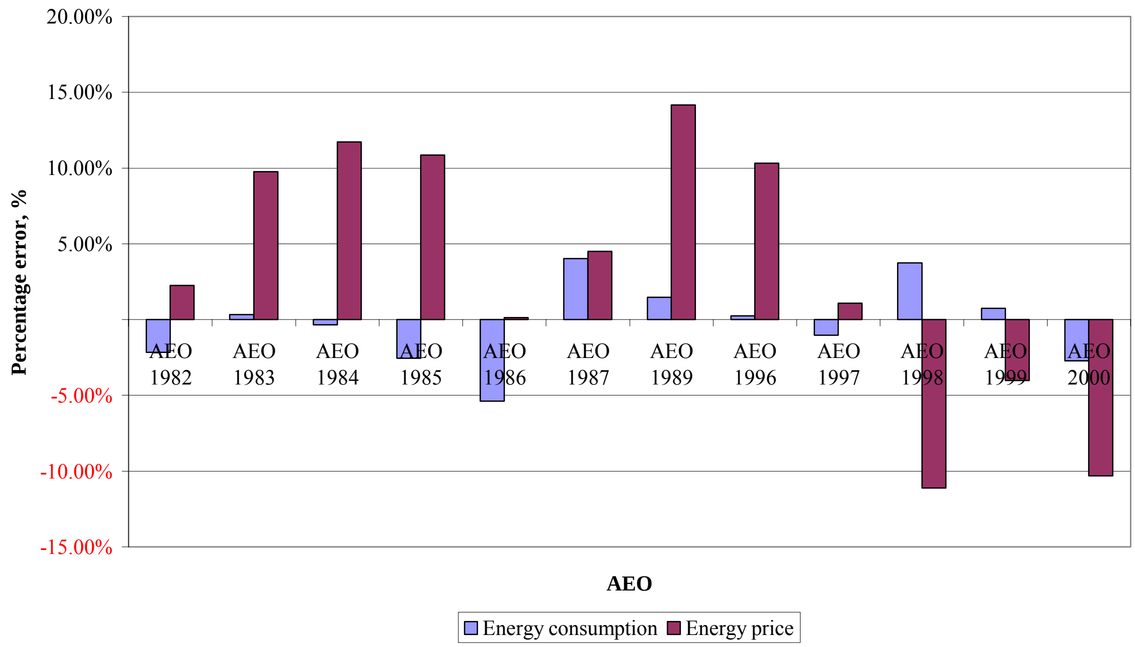


Figure 42 - Residential sector five years forecasts percentage errors

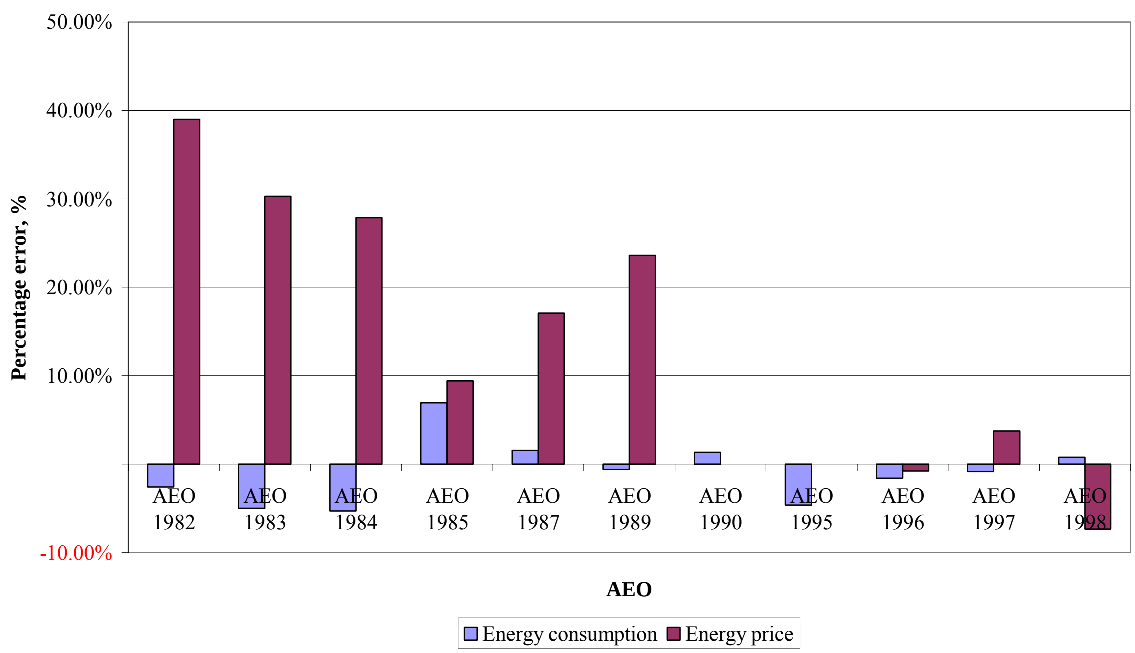
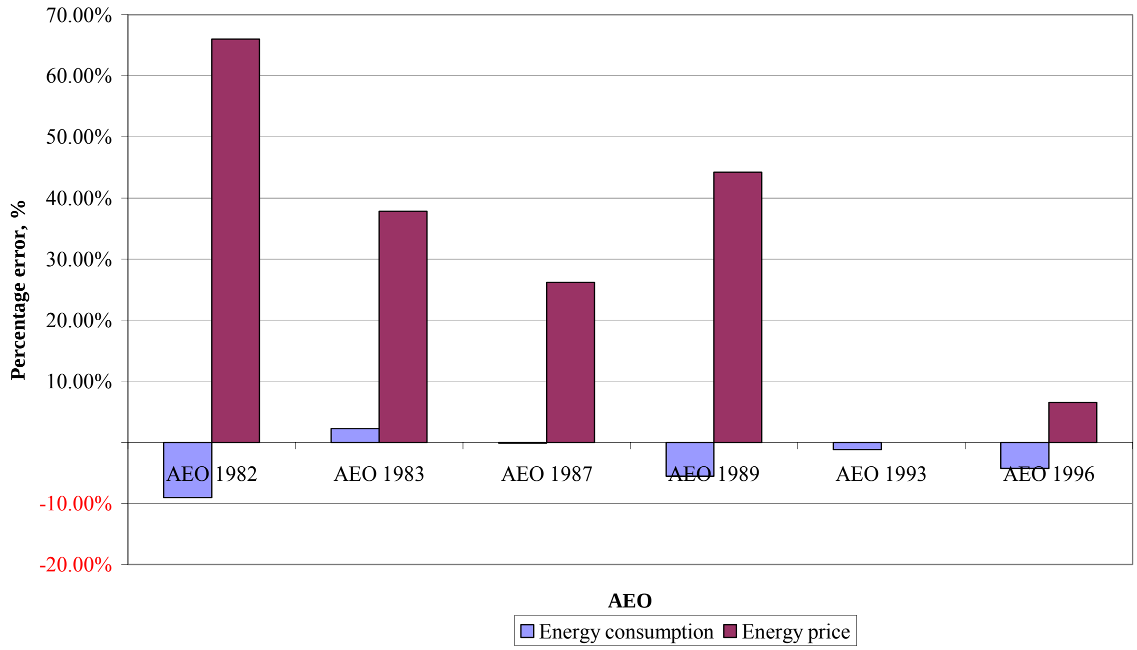


Figure 43 - Residential sector seven years forecasts percentage errors



Analysis of Assumptions' Influence on Residential Energy Sector Forecast Accuracy

Figure 44 and Figure 45 show results of analysis of influence of erroneous assumptions on accuracy of prediction of the residential sector energy consumption and energy price. Energy prices accuracy depends heavily on world oil prices accuracy. Each percent improvement is world oil price MPE gives approximately 0.29% decrease of residential sector energy price MPE. GDP accuracy has less influence on residential sector consumption accuracy. Mostly low GDP MPE result in low energy consumption MPE and high GDP MPE lead to high energy consumption MPE, but there are few points with high GDP MPE and low energy consumption MPE.

Figure 44 - Graph of residential sector energy prices (1996$) MPE vs. world oil prices (1996$) MPE

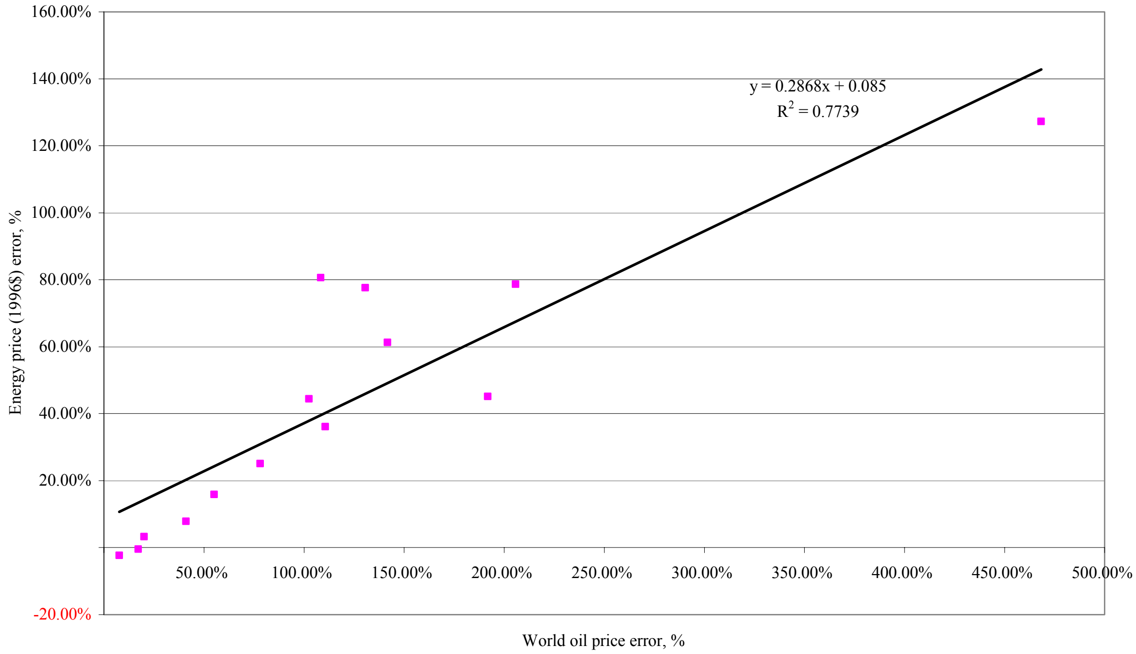
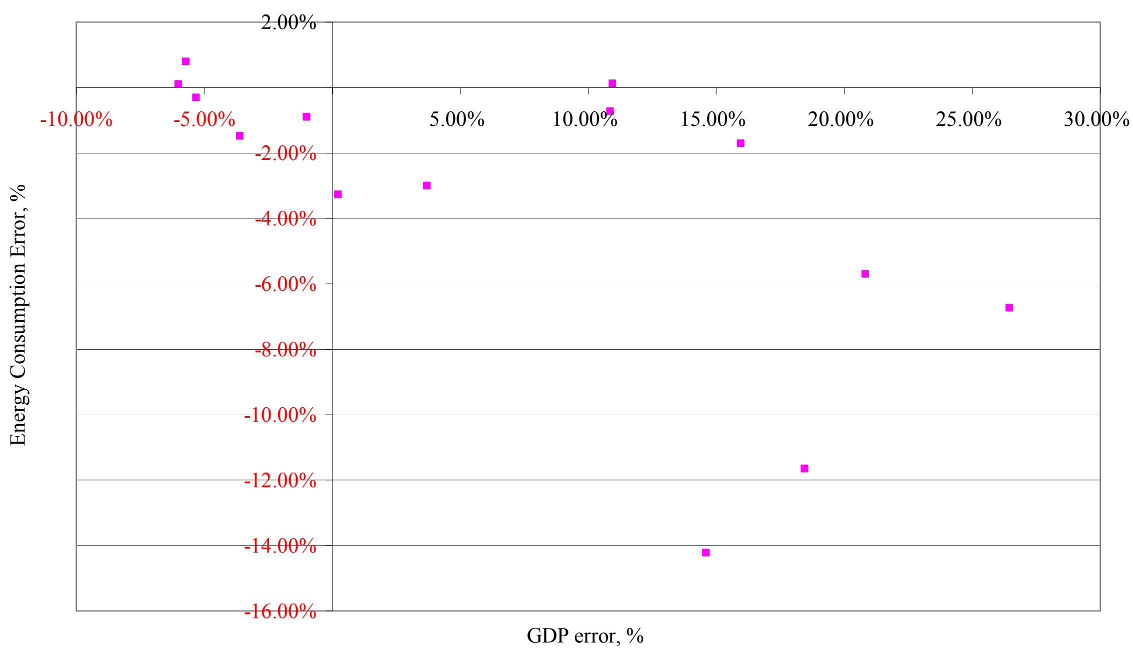


Figure 45 - Graph of residential sector energy consumption MPE vs. GDP (1996$) MPE



9. Conclusions

Forecasting is tricky business. This is particularly true in the energy field, where the highly random behavior of energy prices and technological change make forecasting difficult. However, because these forecasts are so integral to policy and business decisions, it is worth analyzing where these forecasts fail. These results indicate that all energy sectors (especially the industrial and transportation sectors) seem to exhibit systemic modeling problems that should be further explored. In my thesis I analyzed accuracy of United States national energy forecasts produced and published by EIA over the period from 1982 to 2003. AEOs have the longest history of publicly available forecasts with rather stable methodology. While this makes comparison of forecasts somewhat easier it is still insufficient to make statistically meaningful comparisons.

Results of total energy consumption decomposition

- Using total (aggregate) energy consumption forecast errors to judge the quality of U.S. energy forecasts is misleading. In fact, these relatively low, aggregate forecast errors conceal much higher errors at the sector (disaggregate) level. For example for the 11 five-year forecasts made between 1982 and 2002, the Mean Percent Error for total energy consumption was 0.1%. Yet, this hides the fact that the industrial was on average overestimated by 5.9% and the transportation sector was underestimated by 4.5%.
- The residential sector errors are the lowest among all sectors. Commercial sector errors are higher than residential sector but only influence total consumption error slightly (as shown by the low MSPFE). Meanwhile, the industrial and

transportation sectors errors are the highest and offer the largest contribution to total error.

- Both the commercial and transportation sector were consistently underestimated.
- I found no evidence that energy forecasts for the time period studied are becoming more accurate over time.
- Two most influential sectors are transportation and industrial. They have both high proportions in total energy consumption and high errors which makes them determinant when it comes to total energy consumption forecast accuracy.

Results of transportation sector analysis

Energy forecasts of the transportation sector are probably the least accurate in national energy forecasts prepared by EIA. While there are evidences that some parameters are predicted with higher accuracy, I did not find that forecasts are becoming substantially more precise over time. To some degree it is explained by highly random behavior of world oil prices which makes parameters such as fuel prices hard to predict with acceptable accuracy. Energy consumption for transportation sector was predicted with much higher accuracy than energy prices. Many predicted variables suffer from constant positive (Energy price, Total Vehicle Stock) or negative (Energy consumption) bias.

Industrial sector analysis results

Absolute percentage error for the industrial sector energy consumption forecasts with up to 10 years forecasting horizon is neither declining nor improving over time.

Energy consumption errors change sign and overestimation for up to 7 years forecasts is replaced with underestimation after that.

Energy prices absolute errors for industrial sector were very high and rapidly growing from -0.58% to 140% in 10 years. MPE is very close to MAPE which means that there is no cancellation of errors and energy prices are almost always have positive bias, growing error signals that growth rate were incorrect.

There are no signs of improvement in prediction accuracy of industrial sector energy consumption. The industrial sector energy price forecasts accuracy seem to improve over time. Later AEOs suffer from much smaller energy price errors. Partially this accuracy may be attributed to more stable energy prices, partially to less extreme assumptions about energy prices growth rates. This increase in accuracy doesn't seem to be long term. Next price hike will most probably decrease accuracy again.

Results of commercial sector analysis

The commercial sector forecasts accuracy suffers from the same set of problems that plagues all other sectors. Accuracy in predicting energy consumption is much higher than accuracy of underlying parameters such as commercial floorspace, energy consumption per square feet, energy price. Combination of positive and negative biases and cancellation of errors because of opposite signs produce visually more accurate forecast. The commercial sector energy consumption MAPE fluctuates between 2.5% and 7% without visible decrease in accuracy as forecasting horizon becomes longer. Energy consumption accuracy does not improve with new editions of AEO. Energy prices for the commercial sector were almost always overestimated and energy price MAPE grows gradually from approximately 5% for 1 year forecasts to more that 70% for 10 years forecast. Forecasting accuracy seems to improve with later AEO. Energy consumption per square foot which is a measure of energy intensity was predicted with least accuracy. It was almost always underestimated with MAPE that grows from 10% for 1 year forecast to almost 40% for 7 years forecast.

Errors in energy consumption of industrial and commercial sectors suggest that there is a possibility of unaccounted substitution of energy consumption between sectors as economy is getting more service oriented.

Results of residential sector analysis

The residential sector accuracy is the best among all sectors. Energy consumption and energy price MPA and MAPE behavior resembles those of the commercial sector. Energy consumption tends to be underestimated with MAPE between 1% and 4.5% The residential sector energy price was greatly overestimated with MAPE gradually growing to approximately 60%. Parameters predicted by NEMS were reasonably accurate. Both number of households and energy consumption per household MAPE were less then 7% for up to 7 years. Energy consumption accuracy did not improve over time. Energy price accuracy improved for three and five years forecasts. Higher errors in world oil price MPE and MAPE lead to higher errors in residential sector energy price. GDP accuracy seems to have only marginal effect on residential sector energy consumption.

Summary

Forecasts produced by EIA and published in AEO represent a remarkable piece of forecasting history. There hardly exist any other set of forecasts that are so extensive by amount of predicted parameters, so consistent over time and so influential and important. Unfortunately such consistency comes with a price. Many predicted parameters often (if not always) suffer from systematic errors. Consistent under or overestimation show up in AEO on a regular basis. Table 5 show a summary of parameters that I analyzed in my thesis.

Table 5 - Accuracy of energy forecasts summary

	Min MPE	Max MPE	Min MAPE	Max MAPE	Systemic Underestimation/Overestimation	Comments
Total energy consumption	-6.7%	1.7%	3.2%	6.7%	Overestimation for up to 7 year and underestimation after that	Low aggregate error
Residential sector						
Energy Consumption	-3.3%	0.8%	1.0%	4.3%	Mostly underestimation	Uniform growth
Energy Price	-5.4%	1.5%	1.5%	5.4%	Mostly underestimation	
Number of Households	-6.5%	-2.5%	2.5%	6.5%	Systemic underestimation	
Energy Consumption per Household	-5.4%	1.5%	1.5%	5.4%	Mostly underestimation	
Commercial Sector						
Energy Consumption	-0.4%	-6.6%	1.9%	6.6%	Systemic underestimation	Uniform growth
Energy Price	-2.3%	61.2%	4.7%	71.5%	Systemic overestimation	
Commercial Floorspace	2.4%	7.6%	5.1%	12.4%	Systemic overestimation	
Energy Consumption per Square Feet	-38.2%	-6.2%	10.6%	38.5%	Systemic underestimation	
Industrial Sector						
Energy Consumption	-6.4%	6.0%	3.9%	8.7%	Underestimation for up to 7 years, overestimation after that.	Non uniform growth/decline
Energy Price	-0.6%	138.0%	13.1%	138.0%	Systemic overestimation	
Transportation Sector						
Energy Consumption	-11.5%	0.6%	3.1%	11.6%	Systemic underestimation	Error grows rapidly
Energy Price	0.7%	90.0%	12.7%	89.9%	Systemic overestimation	
Total vehicle stock	0.6%	18.8%	2.5%	18.8%	Systemic overestimation	
Total VMT	-0.6%	3.7%	0.6%	4.4%	Underestimation for up to 5 years	
Fleet Average Stock Car MPG	-0.1%	1.6%	0.1%	3.1%		
World oil price	7.7%	191.8%	23.9%	191.8%	Systemic overestimation	Highly unpredictable
Real GDP	-6.0%	16.0%	3.6%	16.0%	Underestimation for up to 5 years overestimation after that	Highly predictable

My analysis show that often underlying parameters used to calculate more aggregate parameters suffer from errors that are higher by amplitude than forecasted parameter itself. This may give a false sense of accuracy, when high accuracy is nothing but a statistical phenomenon when positive and negative errors cancel each other and conceal higher error in underlying parameters. Two most important model assumptions GDP and world oil prices were predicted with insufficient accuracy. Errors from such erroneous assumptions propagate thought the model and trigger error chain reaction when incorrect assumptions produce incorrect prediction also known as “garbage in/garbage out” principle. For example overestimated world oil prices inflate fuel prices, which in their turn rise energy prices and finally lead to the underestimation of the energy consumption. Recent run up of world oil prices will most probably invalidate forecasts in most recent AEO which predicted relatively stable world oil prices.

And while it is hard to expect dramatic increase in prediction accuracy of world oil prices because of their high volatility, GDP behaves in much more predictable way. Other variables such as residential sector energy consumption, commercial sector energy consumption and to some degree transportation sector energy consumption are changing in very predictable manner. Increased accuracy can be easily achieved by using simpler models and integrating these simpler models into NEMS structure.

Because the NEMS model is designed to analyze the effects of various potential policies and policy decisions it is logical to assume that model accuracy depends on the fact of implementing or not implementing such policies and decisions. If proposed tax policy was not accepted then results of including of such policy in the NEMS model are skewing results of forecasting. This idea goes along with idea that model accuracy depends largely on accuracy of the model assumptions. Another interesting option to explore would be an analysis of accuracy of predictions when policies included in the model were adopted and not adopted or abolished.

My recommendations are:

- EIA should perform a comprehensive accuracy evaluation similar to one performed in preparation of this thesis to appraise previous forecasts and give forecast users an estimation of future accuracy;
- EIA should carry out AEO accuracy evaluations on a regular basis, at least once a year and publish results of such evaluation;
- Revise principles of core assumptions generation to achieve highest assumptions accuracy possible. Analyze the possibility of indirect influence of current political situation and government on results of assumption generation;
- Analyze the reasons of systematic errors and update internal model structure accordingly to previous underestimation/overestimation history. Pay special attention to equations that are responsible for energy price influence on energy consumption. Modeled influence of energy prices is higher than observed.

Finally, I want to emphasize that my analysis is far from being comprehensive. There are numerous aspects that are missing in this analysis and need further investigation. My analysis ignores all fuel consumption structure and prices except oil price, impacts of individual policies, supply and conversion modules. Additional analyses that encompass parts missing in my thesis may explain some of the reasons of discrepancy between forecasted and actual values.

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