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Characterization of input uncertainties in strategic energy planning models

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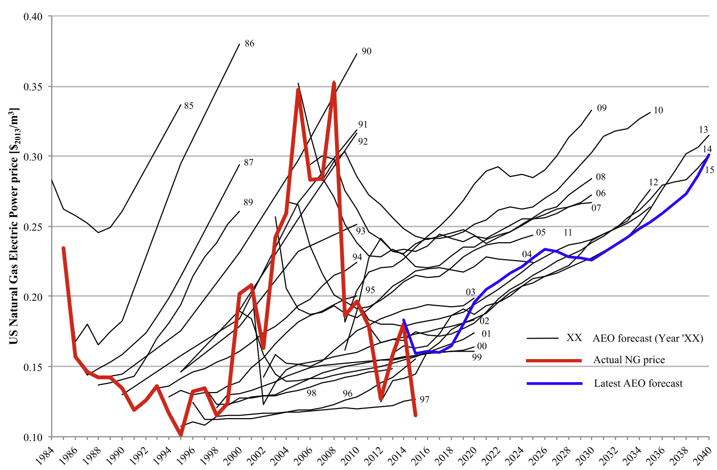
HIGHLIGHTS

- Novel method to characterize input uncertainties in energy planning models.
- Application: sensitivity analysis on national energy planning optimization model.
- Results: uncertainty ranges for typical parameters in energy models.
- Results: economic parameters have the highest impact on energy strategy.
- Full documentation of data sources for reproducibility and use in similar studies.

GRAPHICAL ABSTRACT



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ABSTRACT

Various countries and communities are defining strategic energy plans driven by concerns for climate change and security of energy supply. Energy models can support this decision-making process. The long-term planning horizon requires uncertainty to be accounted for. To do this, the uncertainty of input parameters needs to be quantified. Classical approaches are based on the calculation of probability distributions for the inputs. In the context of strategic energy planning, this is often limited by the scarce quantity and quality of available data. To overcome this limitation, we propose an application-driven method for uncertainty characterization, allowing the definition of ranges of variation for the uncertain parameters. To obtain a proof of concept, the method is applied to a representative mixed-integer linear programming national energy planning model in the context of a global sensitivity analysis (GSA) study. To deal with the large number of inputs, parameters are organized into different categories and uncertainty is characterized for one representative parameter per category. The obtained ranges serve as input to the GSA, which is performed in two stages to deal with the large problem size. The application of the method generates uncertainty ranges for typical parameters in energy planning models. Uncertainty ranges vary significantly for different parameters, from $[-2\%, 2\%]$ for electricity grid losses to $[-47.3\%, 89.9\%]$ for the price of imported resources. The GSA results indicate that only few parameters are influential, that economic parameters (interest rates and price of imported resources) have the highest impact, and that it is crucial to avoid an arbitrary *a priori* exclusion of parameters from the analysis. Finally, we demonstrate that the obtained uncertainty characterization is relevant by comparing it with

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Nomenclature

Acronyms and abbreviations

AEO	Annual Energy Outlook
DHN	district heating network
DM	decision-maker
EE	elementary effect
EIA	Energy Information Administration
EO	expert opinion
EU	European Union
FC	fuel cell
GHG	greenhouse gas
GSA	global sensitivity analysis
HH	households
HW	hot water
I	industry
IEA	International Energy Agency
MILP	mixed-integer linear programming
MPG	miles-per-gallon
NG	natural gas
O&M	operation and maintenance
PDF	probability density function
pkm	passenger-kilometer
PV	photovoltaic
S	services
SH	space heating
T	transportation

List of symbols

α	aleatory uncertainty
E	expected value
ε	epistemic uncertainty
e	error factor
η	efficiency
θ	parameter
μ^*	sensitivity index of the EE method
R	range of variation
R_0	nominal value
Y	output of interest
R_{min}	lower bound of the range
R_{max}	upper bound of the range
$R_{\%}$	relative range
$R_{\%,min}$	lower bound of the range (in relative values)
$R_{\%,max}$	upper bound of the range (in relative values)
S	first-order effect sensitivity index
S_T	total effect sensitivity index
V	variance
Y	output of interest

the assumption of equal levels of uncertainty for all input parameters, which results in a fundamentally different parameter ranking.

1. Introduction

In 2014, fossil fuels accounted for 81.1% of the world primary energy supply [1]. Combustion of such fuels is the primary source of anthropogenic greenhouse gas (GHG) emissions [2]. Thus, various countries and communities are defining long-term plans to increase the share of renewables and efficient technologies. Strategic energy plans define investment roadmaps for energy conversion technologies. Due to the lifetime of these technologies, these plans have a time horizon of 20 to 50 years.

Energy models, often based on optimization [3], can support strategic energy planning. In particular, mixed-integer linear programming (MILP) formulations are commonly used for this purpose, as in [4]. Most long-term energy planning optimization models, such as the NEMS [5], MARKAL [6], MESSAGE [7] and META∗Net [8] models, are in origin deterministic [9]. Therefore, they rely on long-term forecasts for important parameters.

Koomey et al. [10], analyzing available retrospectives on long-term energy models, argue that forecasting models are inevitably inaccurate as they fail to account for pivotal events. Based on the classification by Hodges and Dewar [11], Craig et al. [12] define energy forecasting models as “nonvalidatable”, i.e. likely to yield low accuracy and low precision. Forecasting models are usually made to estimate future energy demand and prices. Sohn [13] analyzes the consumption projections of fossil fuels over a 19 year time horizon based on a global economic model. Linderoth [14] assesses the International Energy Agency (IEA)’s errors in estimating future energy consumption of member countries. Bezdek and Wendling [15] analyze major US energy forecast errors in the years 1950–2000. O’Neill and Desai [16] evaluate the accuracy of the US Energy Information Administration (EIA) energy consumption forecasts in the years 1982–2000. These various studies highlight relevant errors in energy demand forecasts. Furthermore, Winebrake and Savka [17] performing similar analyses found no evidence that energy forecasts for the studied time period were becoming more accurate over time. The same conclusion can be drawn from the latest annual retrospective report by the EIA, which analyzes errors in its own past predictions [18].

Forecasts on energy prices suffer even higher volatility, as shown by Bezdek and Wendling [15], who find error factors[1] as high as five in long-term oil price forecasts. Oil price fluctuations remain, to date, extremely difficult to predict [20]. Wiser and Bolinger [21] show errors in the EIA predictions for wellhead US natural gas (NG) prices up to the year 2003. Siddiqui and Marnay [22] updated the analysis of Wiser and Bolinger in 2006. In Fig. 1, the analysis is extended by comparing the yearly EIA Annual Energy Outlook (AEO) forecasts for the US NG electric power price[2] with the actual prices for the years 1985–2015. Up to the analysis by Siddiqui and Marnay [22] forecasts were heavily overestimating fuel prices. The figure shows that the trend was opposite in the following years, as predictions failed to capture the increase in NG prices. Errors range from the maximum overestimation by a factor of 3.32 in 1995, to the maximum underestimation by a factor of 2.95 in 2005. Furthermore, there is no strong evidence that forecasts perform better in the short term compared to the long term.

[1] If $\hat{y}(t)$ is the predicted value at time t and $y(t)$ is the actual value, the “error factor” $e(t)$ of a forecast is defined as $e(t) = \hat{y}(t)/y(t)$ if $\hat{y}(t) \geqslant y(t)$, and $e(t) = y(t)/\hat{y}(t)$ if $\hat{y}(t) < y(t)$.

[2] The natural gas price to the electric power sector is taken instead of the wellhead price, since starting from 2013 the wellhead price of natural gas is no longer reported by the EIA.