An exploration of MGA methods for use in strategic energy planning

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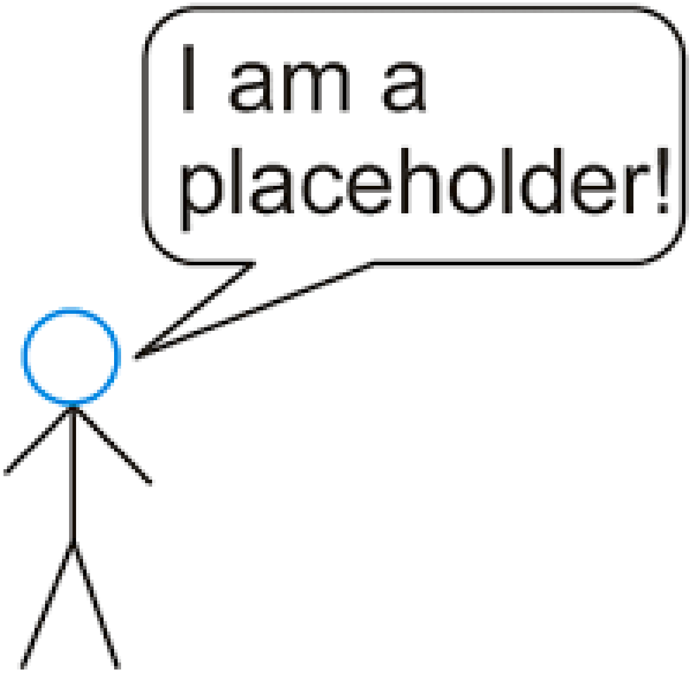

Contents

1 Introduction

1.1 Problem definition

High global ambitions for decreased CO2 emission and the implementation of renewable energy sources, introduce higher demands on the energy grid than ever. The volatile nature of renewable energy sources, drives the need for collaboration between countries, energy sectors, and energy sources, to handle peak loads and hours of energy scarcity. Therefore, the need for good analysis tools providing insights in the constraints and possibilities decision makers must deal with, has never been more present.

Developing the future energy supply of Europe is a process highly influenced by political decision makers, and as the theoretical optimal power supply for Europe, might not be complying with politics, it is valuable to explore alternative near-optimal solutions.

- Fundamental change is needed (policy wise) - Energy-economy models is an important tool - Modelers should focus on robust insights rather than point estimates

1.2 Project description

This project will explore the use of the so-called Modeling to Generate Alternatives(MGA)[1] formulation, to find a range of alternative near cost optimal configurations of the European power supply. The working model of the European energy grid build in PyPsa[2], presented in:[3], will serve as the foundation of this project. The MGA approach will build on top of this model, however, only including major technologies available in the energy sector, such as solar, wind, and fossil fuel power plants.
- MGA[5] - Feasible near optimal decision space - Uncertainty in the models (Structural and parametric) - Structural uncertainty is addressed with higher comlexity - Parametric uncertainty is addressed with running multiple scenarios or sensitivity analysis - Little to none possibility to validate models
Alternative solutions generated with energy-economy optimization models also provide valuable insight that can be used to challenge preconceptions and suggest creative alternatives to decision makers.

1.3 project boundary's

2 Theory

2.1 Modelling to Generate Alternative (MGA)

In this section the basic principles of MGA will be explained together with the benefits and challenges this technique introduces.

2.1.1 Motivation for using MGA

In the field of mathematical modeling, the scientist aim to produce models representing physical systems as realistically as possible. However, some degree of uncertainty in the models is inevitable as model fidelity is limited by a range of factors including: numeric precision, uncertainty of data, model resolution etc. Modeling of energy systems is a field especially prone to large model uncertainties, deriving not only from lack of fidelity, but from factors such as unmodeled objectives and structural uncertainty[4].
The MGA approach was first introduced in 1982 by Brill et al.[5], in the field of operations research/management science. This is a field where unmodeled objectives and structural uncertainty.
The basic insight can be summarized as follows: Because it is not possible to develop a complete mathematical representation of complex public planning problems, structural uncertainty in optimization models will always exist. As a result, the ideal solution is more likely to be located within the model's inferior region rather than at a single optimal point or along the noninferior frontier (Brill, 1979)
Policy makers often have strong concerns outside the scope of most models (e.g., political feasibility, permitting and regulation, and timing of action), which implies that feasible, suboptimal solutions may be preferable for reasons that are difficult to quantify in energy economy optimization models.
The purpose of MGA is to efficiently search the feasible region surrounding the optimal solution to generate alternative solutions that are maximally different.

2.1.2 Technical explanation of the optimization problem

The optimization problem at hand is a simplified energy economic model of Europe, build with focus on exploring the composition of VRES (variable renewable energy sources) on a global and national scale. In the model each country is represented as a note connected to the surrounding countries through a link. Each country has three energy producing technologies available, gas, wind and solar power. A data resolution of 1 hour is used, and simulations run over an entire year.
Analyzing this model one finds that the following variables are relevant for the optimization problem:

- Hourly dispatch of energy from the given plants in the given countries P_i.
- Total installed capacity of the given technologies in the given countries P_{nom_i}
- Hourly power flow in each line connecting two countries
- Total install line capacity for all lines S_{nom_i}

The objective function for the optimization problem then becomes:

$$p = \sum P_i \cdot m_{p_i} + \sum P_{nomi} c_i + \sum S_{nom} \cdot c_s \tag{1}$$

Subject to the constraints

2.1.3 Technical explanation of MGA HSJ

2.1.4 Other MGA approaches

3 Notes

3.1 TO DO

- MGA theory

3.2 Python Packages used

- import_ipynb
- $ pip install import_ipynb
- This package is used for importing other ipython (jupyter) notebooks in to a second notebook
- ——
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4 Notes on references

4.0.1 Impact of CO2 prices on the design of a highly decarbonised coupled electricity and heating system in Europe[3]

An investigation on the CO2 price levels needed to reduce CO2 emissions. In the article a PyPSA model of Europe is presented. The model could be used in this project.

4.0.2 MODELING TO GENERATE ALTERNATIVES: THE HSJ APPROACH AND AN ILLUSTRATION USING A PROBLEM IN LAND USE PLANNING[5]

This is the original article,[5], explaining the thoughts behind MGA. In this article the HSJ (Hop Skip Jump) approach is implemented. This article seams to be the mother of all other MGA articles.

4.0.3 MGA: a decision support system for complex, incompletely defined problems[6]

Elaborating on the MGA approach presented in[5], and evaluating the performance of MGA as a whole.

4.0.4 Using modeling to generate alternatives (MGA) to expand our thinking on energy futures[4]

[4] is one of the first implementations of MGA on energy planning. Uses the HSJ method from[5].

4.0.5 Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models[1]

In this article MGA is used to explore near optimal solutions in energy network optimization, much like[4]. However a slightly more advanced MGA objective function is used. The objective function to be maximized is the Manhattan distance between the current and all preveiously generated MGA solutions.

4.0.6 Ensuring diversity of national energy scenarios: Bottom-up energy system model with Modeling to Generate Alternatives[7]

A different approach towards implementing MGA on energy system planning. Here they use the EXPANSE software/model to implement MGA on. They use a sort of random search MGA approach.

4.0.7 Simulation-Optimization techniques for modelling to generate alternatives in waste management planning[8]

This article describes the MGA method used in[7]. Here a random population is created and is sorted through a number of itterations.

4.0.8 GENETIC ALGORITHM APPROACHES FOR ADDRESSING UNMODELED OBJECTIVES IN OPTIMIZATION PROBLEMS[9]

This article describes the basic theory of MGA very well, and introduces two new genetic algorithms, that could be used for MGA. The Algorithms are based on genetic nieching/sharing algorithms.

4.0.9 A Co-evolutionary, Nature-Inspired Algorithm for the Concurrent Generation of Alternatives[10]

The article[10] describes an implementation of the genetic firefly algorithm used to perform MGA.

4.0.10 Swarm Intelligence and Bio-Inspired Computation : Theory and Applications - Chapter 14[11]

The book[11] Chapter 14 describes the firefly algorithm in depth an has multiple examples of the firefly algorithm implemented. The book cites[10] .

5 Bibliography

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