An exploration of MGA methods for use in strategic energy planning

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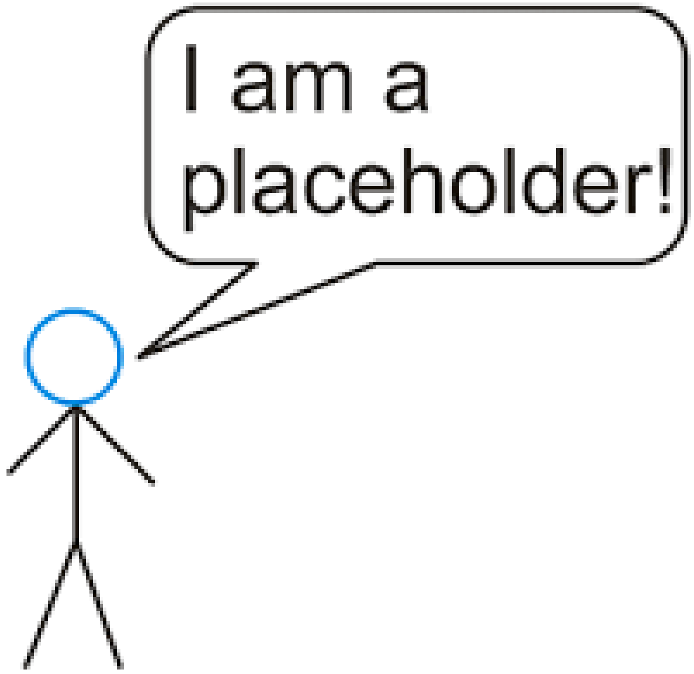

Contents

1 Introduction

High global ambitions for decreased CO2 emission and the resulting increase in 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 analysis tools providing insights in the constraints and possibilities decision makers must deal with, has never been more present.

A frequently used tool to gain insight in the future energy grid compositions, is energy-economic models on either regional, national or international scale. These models do however suffer from large uncertainties and the lack of validation possibilities, resulting in unreliable and therefore less informative results.
Model uncertainty can be categorized as either parametric uncertainty, arising from uncertainty in input parameters and data, or as structural uncertainty introduced by an incomplete or faulty mathematical description of the problem at hand[1]. Structural uncertainty is however not caused by the modelers lack of mathematical talent, but is the result of dealing with a very complex problem, influenced by multiple actors such as policymakers and private company's in the energy sector.

Recently an approach for extracting more relevant and less uncertain data from energy-economic models was proposes by DeCarolis, where a technique called Modeling to Generate Alternatives MGA, from the field of management research/planning science[2], is applied to the field of energy planning. MGA allows the modeler to explore the feasible near optimal decision space of the energy-economic model and hereby exploring possible optimal solutions otherwise not found due to structural and parametric uncertainty.
The MGA technique introduced by[2] and implemented on an energy-economic model by[1], is referred to as the Hop Skip Jump (HSJ) MGA algorithm, will produce a small number of alternative solutions from the feasible near optimal decision space. These alternative solutions do provide some insights in the characteristics of the feasible near optimal decision space, but a complete picture is not given. In this project the MGA approach will be further explored in an attempt to map the entire volume of the feasible near optimal solution space, and hereby providing a detailed description of possible outcomes of an energy-economic model.
The working model of the European energy grid build in PyPsa[3], presented in:[4], 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.

2 Theory

2.1 Modeling 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[1].
The MGA approach was first introduced in 1982 by Brill et al.[2], 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.
Following the naming convention from[4], indexing the notes in the network with the variable n, the power generating technologies by s, the hours in the year by t and the possible connecting power lines by l, the contributing variables to the objective function describing the total annualized system cost is the following:

- Hourly dispatch of energy from the given plants in the given countries $g_{n,s,t}$ with the marginal cost $o_{n,s}$.
- Total installed capacity of the given technologies in the given countries $G_{n,s}$ with the capital cost $c_{n,s}$.

- Total installed transmission capacity for all lines F_l with the fixed annualized cost c_l.

The objective function for the optimization problem then becomes:

$$min \left(\sum_{n,s} c_{n,s} G_{n,s} + \sum_{l} c_l F_l + \sum_{n,s,t} o_{n,s} g_{n,s,t} \right) \tag{1}$$

This objective function is subject to a range of constraints ensuring realistic behavior of the system. As described in[4] a power balance constraint is issued to ensure stable operation of the network. These constraints force the sum of energy produced and consumed in every hour to equal zero. The hourly electricity demand at each node is described by $d_{n,t}$, the incidence matrix describing the line connections is given by $K_{n,l}$ and the hourly transmission in each line is described as $f_{l,t}$. Then the power balance constraint becomes:

$$\sum_{s} g_{n,s,t} - d_{n,t} = \sum_{l} K_{n,l} f_{l,t} \forall n, t \tag{2}$$

For all conventional generators the maximum hourly dispatch of energy is limited by the installed capacity. It is important to node that for all simulations performed in this project the installed capacity is a variable.

$$0 \leq g_{n,s,t} \leq G_{n,s} \forall n, s, t \tag{3}$$

The dispatch of variable renewable energy sources (wind and solar) is not only limited by the installed capacity, as availability, hence the name, is variable. Therefore the constraint for dispatch of variable renewable energy sources become:

$$0 \leq g_{n,s,t} \leq \overline{g_{n,s,t}} G_{n,s} \forall n, s, t \tag{4}$$

Where $g_{n,s,t}$ represents the normalized availability per unit capacity.
The installed capacity is constrained by the geographical potential calculated in[4].

$$0 \leq G_{n,s} \leq G_{n,s}^{max} \forall n, s \tag{5}$$

All transmission lines in the model modelled with a controllable dispatch constrained by the fact that there must be energy conservation at each node the line is connected to. !! Something here about which lines is included !!!! . Furthermore the transmission in each line is limited by the installed transmission capacity in each line.

$$|f_{l,t}| \leq F_l \forall l, t \tag{6}$$

In the model it is possible to activate a CO2 constraint, limiting the allowed CO2 emissions for the entire energy network. As in[4] the constraint is implemented using the specific emissions e_s in CO2-tonne-per-MWh of the fuel for each generator type s, with the efficiency η_s and the CO2 limit CAP_{CO_2}.

$$\sum_{n,s,t} \frac{1}{\eta_s} g_{n,s,t} e_s \leq CAP_{CO_2} \tag{7}$$

The model is implemented in the open source software PyPSA[3], using much of the software presented in[4]. Optimization of the model is performed with the optimization software Gurobi[**Gurobi**].

2.1.3 Technical explanation of MGA HSJ

The MGA technique was first introduced in 1982 by Brill et. al in the article[2] and later rediscovered by DeCarolis in[1] for use in energy system optimization. The tecnique lets the user search the near optimal feasible decision space for an optimization problem such as the one addressed in this project described in 2.1.2.
In section 2.1.2 a series of constraints bounding the network model is listed. Together these constraints form a feasible region that can be described as a convex set in a d dimensional space. Where d is the number of variables in the model. The feasible set is convex as all bounding constraints are linear. The fact that linear constraints form a convex set is shown in[ConvexOpimization]. The MGA technique introduces yet another constraint limiting the size of this convex set even further by limiting the objective function value of all feasible points to be within a certain range of the optimal solution. The goal of the MGA technique is to explore a finite set of alternative solutions located within this convex set.
In the orginal articel by Brill et. al[2] the HSJ MGA technique is descrbed with the following steps.
(1) obtain an initial optimal solution for the problem at hand; (2) define a target value for the objective function by adding a user specified amount of slack to the value of the objective function in the initial solution (3) introduce the constraint limiting the objective function to surpass this target value, to the model (4) formulate a new objective function that seeks to minimize the sum of decision variables that had non zero values in the previous solution of the problem (5) iterate the reformulated problem, updating the objective function every time (6) terminate the optimization when the new solution is similar to or close to any previously found solution. Step 3 and 4 was described mathematically in[2] as follows:

$$\begin{aligned} Minimize :& p = \sum_{k \in K} x_k \\ Subjectto :& f_j(\vec{x}) \leq T_j \forall j \vec{x} \in X \end{aligned} \tag{8}$$

In this formulation k represents the variable indices for the variables with nonzero values in the previous solution, j is the objective function indices if multiple objective functions exists, $f_j(\vec{x})$ is the evaluation of the j'th objective function and T_j is the target value specified for the particular objective function. In the formulation of the constraint $\vec{x} \in X$ specifies that all previously defined constraints still applies as all new solutions $\vec{x}$ must be a part of the set of feasible solution vectors from the original formulation X. How the new objective function precisely is formulated and which variables to include is discussed in[13], where two alternative approaches of defining the new objective function is presented. One approach suggest giving all nonzero variables from the last iteration a weight of 1 in the new objective function. This approach does not consider weight from previous iterations. However, the second approach suggests adding on to the coefficient with a factor of +1 for every time one variable has appeared with nonzero in a row, hereby further increasing the intended to reduce the use of that specific technology. This

2.1.4 Other MGA approaches

2.2 Novel MGA approach

In this section a novel approach towards MGA optimization of energy networks will be presented. Based on the same concepts as presented in 2.1 this method seeks to explore not only a few alternative solutions from the decision space, but the entire decision space. Hereby an in depth knowledge of the possible solution is obtained providing insight in the distribution of alternative solutions.
Analyzing the original energy network optimization problem it is clear that this the constraints in the system defines an open convex set, as nothing prevents to model from installing excessive amounts of energy sources, however the objective function will seek to minimize installed capacities end hereby cost. However, a lower bound for installed capacities is present as energy demand must be met for every hour. Introducing the MGA constraint from equation 9 this open set is closed, as the installed capacities is limited in size by the limited maximum cost of the system.

$$f(\vec{x}) \leqslant f(\vec{x^*}) \cdot (1+\epsilon) \tag{9}$$

As we now have a closet set that must be convex since only linear constraints is used to define it, it now is possible to explore the shape of this convex set. Assuming that all constraints used including the MGA constraint is linear, the convex set must be a polyhedral and therefore it is possible to define the shape of this set with a finite number of vertexes.

However, finding these vertices is no trivial task. The method proposed here will use the following steps to approximately find all vertices. 1) maximize and minimize all variables. 2) Based on these points define a convex hull. 3) change objective function to search in the direction of the normal of each face on the hull. 4) Update hull with new points and repeat 3 and 4 until hull volume stops increasing.

Pseudo code:

```
Solve network subject to regular constraints and with original objective function
Add MGA constraint !Equation number
while ϵ > tol
    If first loop
        directions = max and min all variables
    Else
        directions = normals to hull faces
    for direction in directions
        objective function = direction[i] * variable[i]
        point on convex hull += solve problem subject to objective function
    hull = ConvexHull ( points on convex hull)
    epsilon = new hull volume - old hull volume / hull volume
```

Evenly distribute points in hull

Plot histogram using evenly distributed points.

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
- ——
-

4 Notes on references

4.0.1 Impact of CO2 prices on the design of a highly decarbonized coupled electricity and heating system in Europe[4]

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[2]

This is the original article,[2], 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[5]

Elaborating on the MGA approach presented in[2], 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[1]

[1] is one of the first implementations of MGA on energy planning. Uses the HSJ method from[2].

4.0.5 Modeling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models[6]

In this article MGA is used to explore near optimal solutions in energy network optimization, much like[1]. 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] .

4.0.11 The benefits of cooperation in a highly renewable European electricity network[4]

Article describing simulations using the PyPSA-EUR-30 model. There is a great explanation of the math behind PyPSA

4.0.12 The role of spatial scale in joint optimisations of generation and transmission for European highly renewable scenarios[12]

An article exploring the influence of spatial simplification on energy models. An exapmle using k-means to perform spatial simplification is shown.

4.0.13 Modelling to generate alternatives with an energy system optimization model[13]

Another article by DeCariolis exploring the HSJ MGA methodology on energy system optimization

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