An exploration of MGA methods for use in strategic energy planning

Tim T. Pedersen

January 2020

Part I

Main Report

List of Corrections

1 Introduction

High global ambitions for decreased CO2 emission and the resulting increase in implementation of renewable energy sources, introduce higher demands to the energy grid than ever. The volatile nature of renewable energy sources, implemented to reach ambitious CO2 emission goals, drives the need for collaboration/coupling between countries, energy sectors, and energy sources, to handle peak loads and hours of energy scarcity. This complicates the already complex task of energy system synthesis even further, hereby requiring decision makers to have greater in depth knowledge, in a world where rapid decisions and superficial political decisions are becoming more widespread. 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 can be used to study the behavior and composition of existing and future energy networks, together with the impact of new technologies or structural changes in the networks [26] !!CITE OTHEER WORKS USING energy-economic models!!. However, these models do 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 [7] . 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 has been proposes by DeCarolis, where a technique called Modeling to Generate Alternatives (MGA), from the field of management research/planning science [8], is applied to the field of energy planning. MGA allows the modeler to explore the near optimal feasible decision space of the energy-economic model and hereby exploring possible optimal solutions otherwise not found due to structural and parametric uncertainty. The concept of using MGA algorithms on energy planning problems have been further studied and the result presented in a range of articles and papers; [6], [16], [3], [9], [24].

The MGA technique introduced by [8] and implemented on an energy-economic model by [7], 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. Furthermore, the solutions found when using the HSJ MGA algorithm are somewhat randomly located in the feasible near optimal decision space, and the found solutions are highly dependent on the starting point.

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 all possible outcomes of an energy-economic model. This will provide greater insights, as knowing the shape of the feasible near optimal space provides the opportunity to create histograms and probability density functions highlighting capacity ranges most likely to be feasible amongst other information.

Maybe something about how to map the feasible near optimal space

In this project the model presented in: [21] of the European electricity grid, will serve as the base model. The model is build in [5], and formulates as a techno-economic linear optimization problem, with the objective of minimizing total annual system cost, while satisfying a range of constraints ensuring feasible operation. The model groups the European electricity network into 30 nodes, each one representing a single country. Countries are linked with power lines approximating the current layout of the European transmission grid. Each node in the network, will in this project, only be granted access to three electricity generating technologies and no storage technologies, simplifying the network drastically compared to the configuration used in [21]. The energy generating technologies chosen are open cycle gas turbines (OCGT), wind and solar power.

The goal of this project is to develop a method capable of exploring the volume of the feasible near optimal decision space from such linear techno-economic model, in order to extract probability data regarding installed capacities, technology combinations etc.

- Approach for developing method

- Very explicit explanation of how energy system optimization is performed now - Explain what is new about this method

2 Theory

The purpose of this chapter is to explain the mathematical concepts behind the numerical models used in this project, and to provide useful insight in the working concepts of the algorithms developed.

In this project the following formulations will be used. Scalar values will be non bold characters such as d. Vectors will be represented by bold characters $\mathbf{x}$. Single values in a vector may be indexed using a subscript $\mathbf{x}_i$, as in this example where the i'th element of $\mathbf{x}$ is represented. Vectors of higher dimension will be indexed with as many variables as dimensions. By example a single value from a three dimensional vector may accessed as $\mathbf{g}_{n,s,t}$.

[1]

2.1 Mathematical formulation

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 [21], 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 $\mathbf{g}_{n,s,t}$ with the marginal cost $\mathbf{o}_{n,s}$.
- Total installed capacity of the given technologies in the given countries $\mathbf{G}_{n,s}$ with the capital cost $\mathbf{c}_{n,s}$.
- Total installed transmission capacity for all lines $\mathbf{F}_l$ with the fixed annualized cost $\mathbf{c}_l$.

The objective function for the optimization problem then becomes:

$$min\ p(\mathbf{x}) = \left(\sum_{n,s} \mathbf{c}_{n,s}\mathbf{G}_{n,s} + \sum_{l} \mathbf{c}_l \mathbf{F}_l + \sum_{n,s,t} \mathbf{o}_{n,s}\mathbf{g}_{n,s,t} \right) \tag{2.1}$$

This objective function is subject to a range of constraints ensuring realistic behavior of the system. As described in [21] 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 $\mathbf{d}_{n,t}$, the incidence matrix describing the line connections is given by $\mathbf{K}_{n,l}$ and the hourly transmission in each line is described as $\mathbf{f}_{l,t}$. Then the power balance constraint becomes:

[1] FiXme Note: Write how the math is formulated

$$\sum_s \mathbf{g}_{n,s,t} - \mathbf{d}_{n,t} = \sum_l \mathbf{K}_{n,l}\mathbf{f}_{l,t} \; \forall n, t \tag{2.2}$$

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.

$$0 \leq \mathbf{g}_{n,s,t} \leq \mathbf{G}_{n,s} \; \forall n, s, t \tag{2.3}$$

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:

$$0 \leq \mathbf{g}_{n,s,t} \leq \overline{\mathbf{g}}_{n,s,t}\mathbf{G}_{n,s} \; \forall n, s, t \tag{2.4}$$

Where $\overline{\mathbf{g}}_{\mathbf{n,s,t}}$ represents the normalized availability per unit capacity.

The installed capacity is constrained by the geographical potential calculated in [21].

$$0 \leq \mathbf{G}_{n,s} \leq \mathbf{G}_{n,s}^{max} \; \forall n, s \tag{2.5}$$

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.

$$|\mathbf{f}_{l,t}| \leq \mathbf{F}_l \; \forall l, t \tag{2.6}$$

In the model it is possible to activate a CO2 constraint, limiting the allowed CO2 emissions for the entire energy network. As in [21] the constraint is implemented using the specific emissions $\mathbf{e}_s$ 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}.

$$\sum_{n,s,t} \frac{1}{\eta_s}\mathbf{g}_{n,s,t}\mathbf{e}_s \leq CAP_{CO_2} \tag{2.7}$$

The model is implemented in the open source software PyPSA [5], using much of the software presented in [21]. Optimization of the model is performed with the optimization software Gurobi [10].

In broader terms the problem can be formulated as

$$\begin{aligned} &\mathit{minimize} && f_0(\mathbf{x}) \\ &\mathit{subject\ to} && \mathbf{f}_i(\mathbf{x}) \leq 0 \;\; i = 1..m \\ & && \mathbf{h}_i(\mathbf{x}) = 0 \;\; i = 1..p \end{aligned} \tag{2.8}$$

Where all constraints are collected in the vector functions $\mathbf{f}_i$ and $\mathbf{h}_i$, and are rewritten to be either less than or equal to 0.

2.2 Properties of the near optimal feasible space

Analyzing the original optimization problem one can deduct that the set including all feasible solutions W, given by equation 2.10, must be convex, as all constraints f_i and the objective function f_0, are linear and therefore satisfy equation 2.9, thus ensuring convexity [23].

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \; \forall \; x, y \in \mathbb{R}^d and \; \alpha, \beta \in \mathbb{R} \tag{2.9}$$

Furthermore, when all variables are bounded; hourly production by the power balance constraint and installed capacity by geographical potential and CO2 emission constraints, the feasible decision space is not only convex but also closed. If the geographical potential constraint, or the CO2 emission limit is excluded the feasible decision space becomes an open convex space as illustrated on 2.1, this does however not have any immediate consequences, as the objective function increases as one moves in the open direction of the space.

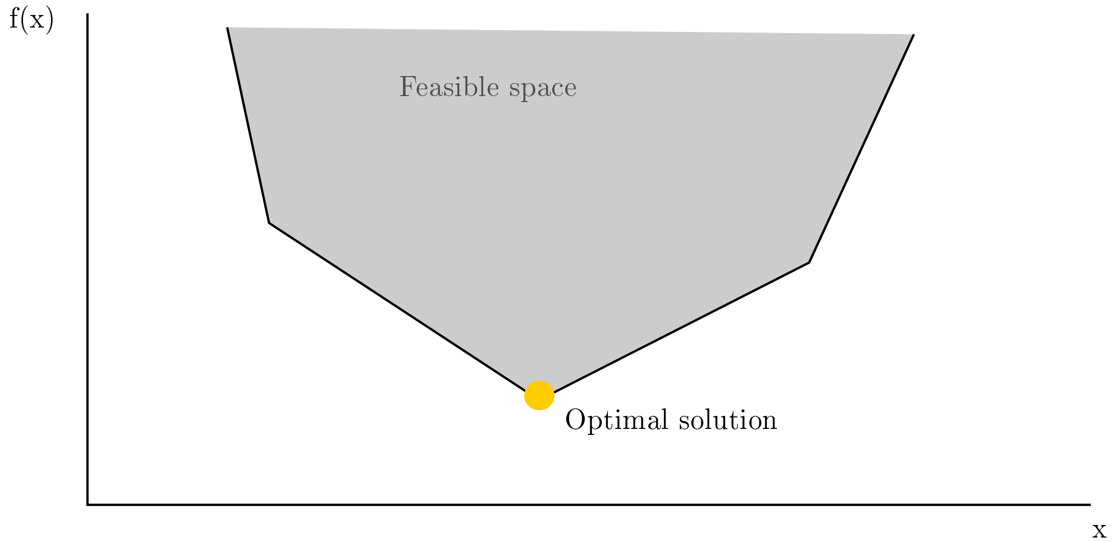

Figure 2.1. A sketch of a one dimensional feasible space with MGA constraint

The set containing the feasible decision space can be described with equation 2.10.

$$W = \{\vec{x} \in \mathbb{R}^d | f_i(\vec{x}) \geq 0\} \tag{2.10}$$

!!! Im not 100% on this !!!

Where the vector $\vec{x}$ is containing all variables in the model, and $f_i(x) \geq 0$ denotes that all constraints must be satisfied.

It is important to note that the variables $\vec{x}$ that defines the decision space variables in the original problem include all hourly technology dispatches g, all installed technology capacities G and all installed line capacities F.

$$\vec{x} = \{g_{n,s,t} \wedge G_{n,s} \wedge F_l \; \forall \; n, s, t, l\} \tag{2.11}$$

Therefore, the dimensionality of the decision space must be given by the number of individual dispatch decisions given by $n \cdot s \cdot t$ plus the number of capacities to optimize, given by $n \cdot s$ plus the number of line capacities to optimize l. The dimensionality of the full problem is therefore given by equation 2.12.

$$d = n \cdot s \cdot t + n \cdot s + l \tag{2.12}$$

In the case of the reference model used in this project that gives $30 \cdot 3 \cdot 8765 + 30 \cdot 3 + 52 = 788992$

The true dimensionality might be lower, as some variables do have strong corelations.

2.2.1 Dimensionality reduction

As the dimensionality of the decision space is very large, and therefore becomes very unhandy to work with, it makes sense to look at a subspace of lower dimensionality. One could choose to ignore the hourly dispatch of energy from the individual generators, hereby reducing the dimensionaly by a substantial amount.

$$d^* = n \cdot s + l \tag{2.13}$$

In that case the dimensionality would only be $d^* = 30 \cdot 3 + 52 = 142$.

Therefore, we design a new set $W^* \subseteq \mathbb{R}^{d^*}$, as a subset of W, but with reduced dimensionality, as it is only including all installed capacities as variables.

$$W^* = \{x^* \in x | x \in W\} \tag{2.14}$$

Because the set W^* is a subset of W, any solution $\vec{x^*}$ found to be inside W^*, must also lie inside the original feasible set W. But not necessarily vice versa.

By decreasing the dimensionality in this manner all information about hourly plant operation is lost, but as the focus of this project is to analyze the distribution of capacities, this is not a major loss. The loss in information is greatly overcome by the ease of computation.

Further reduction by grouping of variables

If desired it is possible to further reduce dimensionality, by grouping variables, on behalf of further loss of information. An example would be to group all individual technologies in groups containing all installed capacity of that given technology across the entire network. This new set would then have a dimentionality of:

$$d^{**} = s \tag{2.15}$$

Which in this project is only 3. This is now a very manageable dimension size. The new set $W^{**} \subseteq \mathbb{R}^{d^{**}}$ including only summed capacity sizes for all technologies can be designed as:

$$W^{**} = \{x^{**} | \sum_n G_{n,s} \; \forall \; s\} \tag{2.16}$$

Any solution x^{**} found in W^{**}, must satisfy the constraints $f_{\vec{x}} \leq 0$ and therefore the set W^{**} is a subset of W. This means that a solution found in W^{**} lies inside W.

2.3 Numeric optimization

2.4 Modeling to Generate Alternatives (MGA)

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

2.4.1 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 [7].

The MGA approach was first introduced in 1982 by Brill et al. [8], in the field of operations research/management science. This is a field where unmodeled objectives and structural uncertainty, are highly influential.

!! CITATION !! 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. !!!

2.4.2 Technical explanation of MGA HSJ

The MGA technique was first introduced in 1982 by Brill et. al in the article [8] and later rediscovered by DeCarolis in [7] 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.

In section 2.1 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 [23]. 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 [8] 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 [8] as follows:

$$Minimize\ p = \sum_{k \in K} x_k \tag{2.17}$$

$$Subjectto\ f_j(\vec{x}) \leq T_j \ \forall\ \vec{x} \in X \tag{2.18}$$

$$T_j = f(\vec{x}^*) \cdot (1 + \epsilon) \tag{2.19}$$

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 [6], 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

2.4.3 Other MGA approaches

2.5 Novel MGA approach

In this section a novel approach towards MGA optimization of energy networks will be presented. Building on the concepts presented in 2.4 this method seeks to explore not only a few alternative solutions from the decision space, but instead seeks to define the entire near optimal feasible space, and hereby provide useful statistical data through strategic sampling of this space.

The method developed can be divided into two phases. In the first phase, the shape of the feasible near optimal decision space is found, and in the second phase relevant data is extracted from the found space.

2.5.1 Feasible space mapping

As explained in section 2.2 on page 8, the near optimal is convex, and can either be closed or not before the MGA constraint is applied. The space will however always be closed when the MGA constraint from equation 2.18 on the preceding page is introduced.

Knowing that all constraints used including the MGA constraint is linear, the convex set defining the near optimal feasible space, must be a polyhedral and therefore it is possible to define the shape of this set with a finite number of vertexes. The goal of the first phase of this MGA approach is to find enough of these vertices in order to approximate the shape of the near optimal feasible space.

Due to the fact that the optimization problem is closed, any choice of objective function will provide a solution lying within the feasible region. Using this, it is possible to search in any desired direction in the decision space by altering the objective function of the numerical optimization problem. Using a unit vector pointing in the desired direction $\vec{n}$, multiplied with the variables to be optimized $\vec{x}$, as objective function (equation 2.20), provides full control over direction of search.

$$Minimize\ p = \vec{n}_i\vec{x} \tag{2.20}$$

In order to use this tool to map the feasible region, a framework is needed to select search directions $\vec{n}_i$ that will lead to the discovery of all vertices defining the feasible region. There are several ways to solve this problem, and the simplest choice would be to search in random directions until no new solutions are found. This is however not very efficient, and as dimensionality and model evaluation time increases, this method becomes unfeasible.

Instead, the method proposed here suggest a seven step approach that reduces the number of model evaluation by a clever choice of search direction. Initially, the optimization problem is solved using the original objective function in order to define the MGA constraint (equation 2.18). This provides a single point $\vec{x}_0$ located within the feasible region. By selecting search directions that seek to maximize and minimize every single variable in $\vec{x}$ one by one, an additional $2 \cdot d$ solutions are found. Knowing that the feasible region is defined by a polyhedron, it makes sense to imitate this shape by computing the hull containing all points found so far. Using the face normal vectors of this hull to define the next set of search directions ensures that if one of the faces in the hull is not part of the polyhedron defining the feasible region, then a new point will be found when searching in the normal direction of that particular face. Using the newly found points combined with all previously found points, to repeat the process of defining a hull and searching in the face normal directions, will as long as the hull computed isn't the full solution to the problem, continue finding new points within the feasible region, until all points defining the feasible region are found.

If the feasible region was to have a very complex shape being defined by a high number of vertexes, or if a non-linear constraint was introduced, and thereby preventing that the entire region from being represented by a finite number of vertices, it would be necessary to have a termination criteria that does not require that the complete solution is found. The volume of the hull estimating the feasible region will converge towards the size of the feasible region and implementing a convergence criteria on the hull volume provides a good termination criteria. The entire process of searcing the feasible region is listed in bullet form in table 2.1 and visualized on figure 2.2.

Table 2.1. MGA method step by step

1	Find initial solution and add MGA constraint
2	Maximize and minimize all variables
3	Based on these points define a convex hull
4	Compute all face normals of the hull
5	Iterate over each face normal, discard any previously searched direction, and change objective funct
6	Add the newly found points to list of points and define a new hull
7	Check if the hull volume satisfies the convergence tolerance. If yes then termite, else return to step

[2]

[3]

2.5.2 Hull fill

In order to extract meaningful statistical data about the model from the found feasible region, a method for sampling the feasible space is needed. Assuming that all solutions to this particular problem are evenly distributed across the entire feasible region, sampling randomly evenly across the region will provide a good dataset representing the true data if enough points are sampled. For know hold to the assumptions that the true solutions are evenly distributed throughout the region, but this assumption will be further investigated. [4]

Drawing random samples inside the feasible space

2.5.3 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.
```

[2]FiXme Note: Something about this method being independant of dimension
[3]FiXme Note: Maybe something about the fact that more complex shapes appear in lower dimensional spaces
[4]FiXme Note: Look at this again

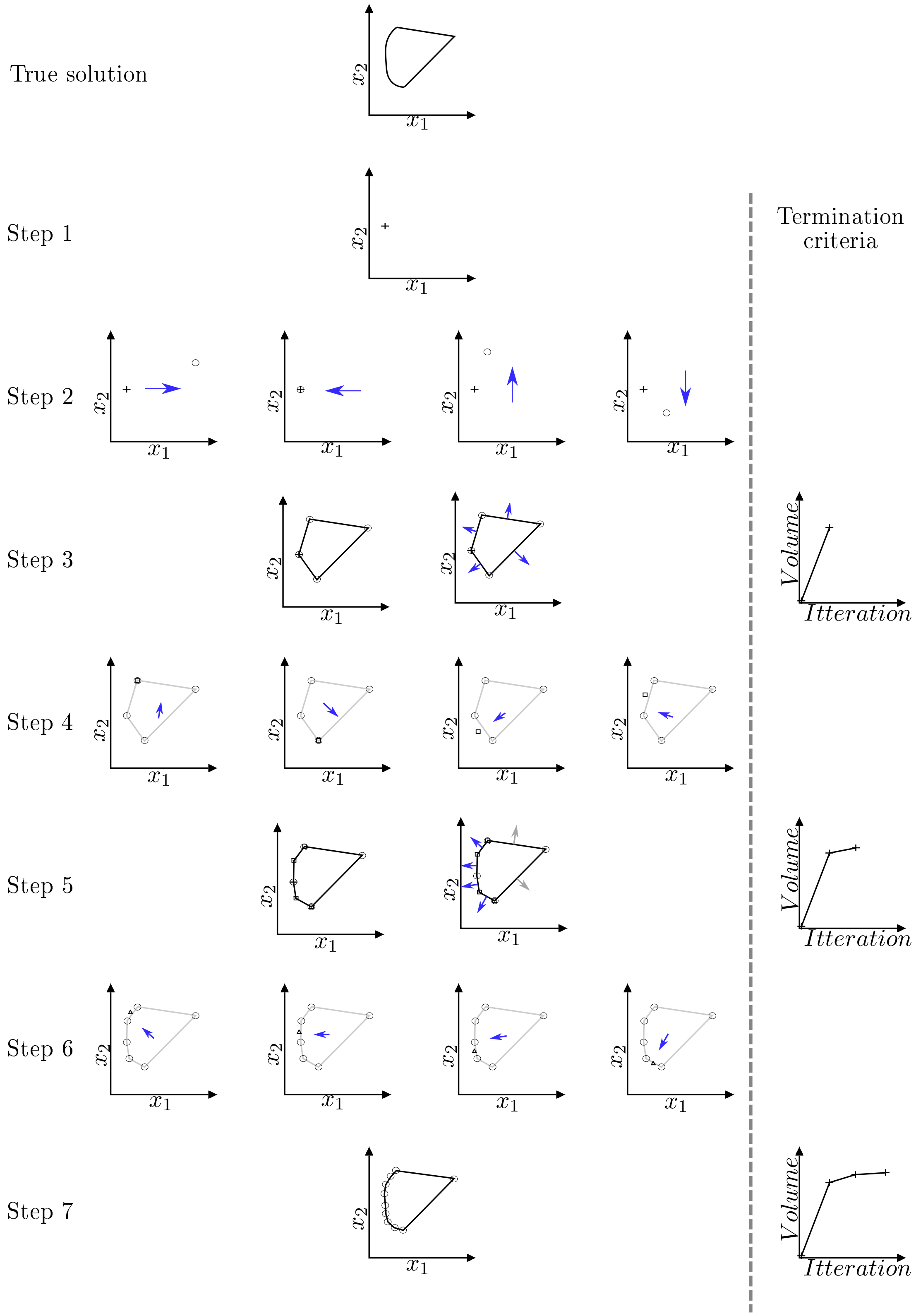

Figure 2.2. A sketch of a one dimensional feasible space with MGA constraint

2.6 Gini coefficient

In this project, the gini coefficient is used to express the equality in the distribution of energy generation versus consumption. The gini coeficient is calculated as the relationship between the area under the total equality line and the area between the equality line and the Lorentz curve. [5]

Therefore, a scenario where every country over the duration of an entire year, produces as much energy as it consumes, would have a gini coefficient of 0, and represent the equality line on figure 2.3. A scenario where one country is producing all energy and consuming none, would on the other hand have a gini coefficient of 1, and represent total inequality.

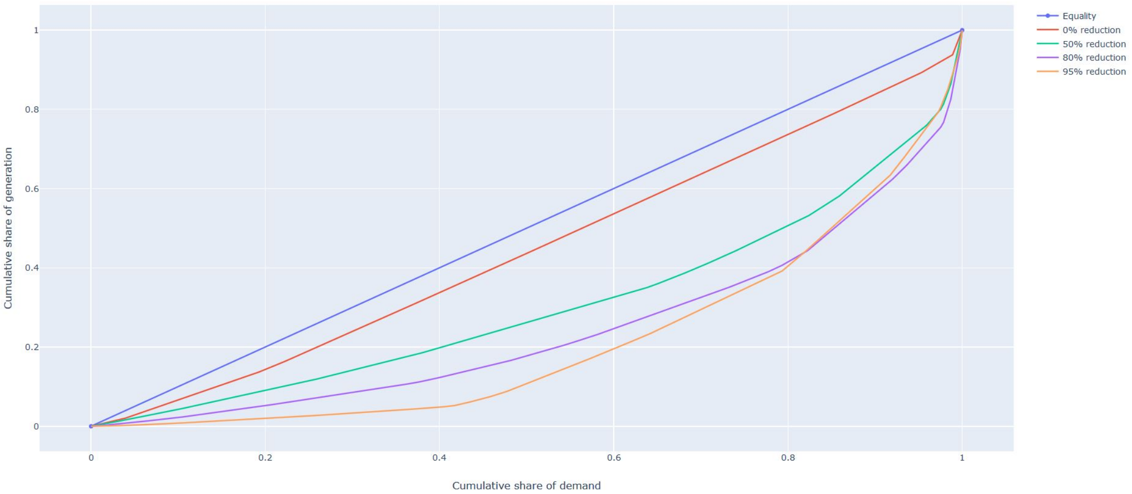

Figure 2.3. Lorentz curves for the four optimal solutions [6]

2.7 Implementation and utilization of parallel programming

As the MGA approach described in section 2.5 requires a high number of similar optimizations to be performed only with slighly changed objective functions, it is possible to achieve a great performance boost, by utilizing parallel programming.

[5] FiXme Note: Reformulate this about the gini coefficient

3 Model

3.1 Energy Economic model of Europe

In this section the composition of the energy-economic model used in this project will be described.

3.1.1 Topology

The model used in this project is based on the work presented in [21], where a model spanning the electricity grid of 30 European countries is formulated as a techno-economic linear optimization problem. Countries included in the model are the EU-28 countries not including Cyprus and Malta, instead including Norway, Switzerland, Serbia and Bosnia and Herzegovina.

The topology of the network, presented on 3.1, is such that each node represents a country and the links represent international HVDC or HVAC links. The links included are based on currently installed international transmission lines.

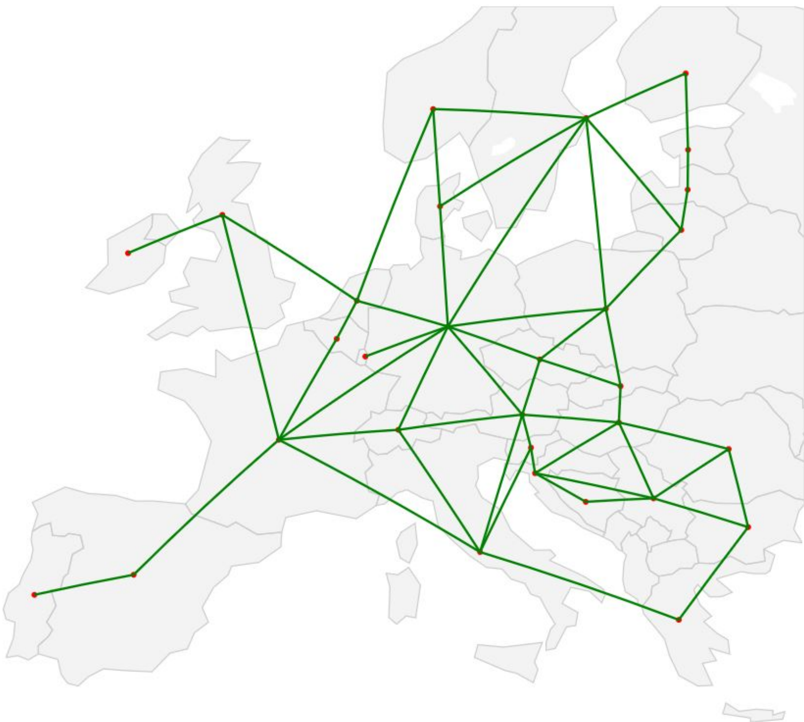

Figure 3.1. Network layout

All model input parameters are based on 2011 values as this is the earliest year with all data available. The temporal resolution of the model is hourly, with all simulations spanning a full year. Technology costs are all valued in 2011 Euros. Should also be included: <

3.1.2 Energy production

Each node in the network, has energy producing technologies available, with initial capacities being zero. The available energy producing technologies used in this project is:

Onshore wind, offshore wind, Solar PV and OCGT. In the model all technology capacities are expandable limited only be the geographical potential.

The geographical potentials used are calculated following the work of [21]. In the calculation of geographical potential, the potential available area suited for either onshore wind, offshore wind and solar PV, must first be defined. These areas was found by allowing certain technologies to be installed only in areas with certain land use types. Hereby restricting onshore wind farms from being installed in cities and solar PV plants to be installed in forests etc. The placement of offshore wind farms was restricted to areas with a water depth of less than 50m. Furthermore, all nature reserves was excluded from the potential areas. As competing land use and likely public acceptance issues will occur, the found potential areas are set to bee only 20% of the found area for onshore and offshore wind and only 1% for solar PV. Assuming a maximum nominal installation density of 10 MW/km^2 for offshore and onshore wind power, and 145 MW/km^2 for solar PV, it is possible to calculate the geographical potential for the three technologies all across Europe. Geographical potential for the three technologies are presented on figure 3.2.

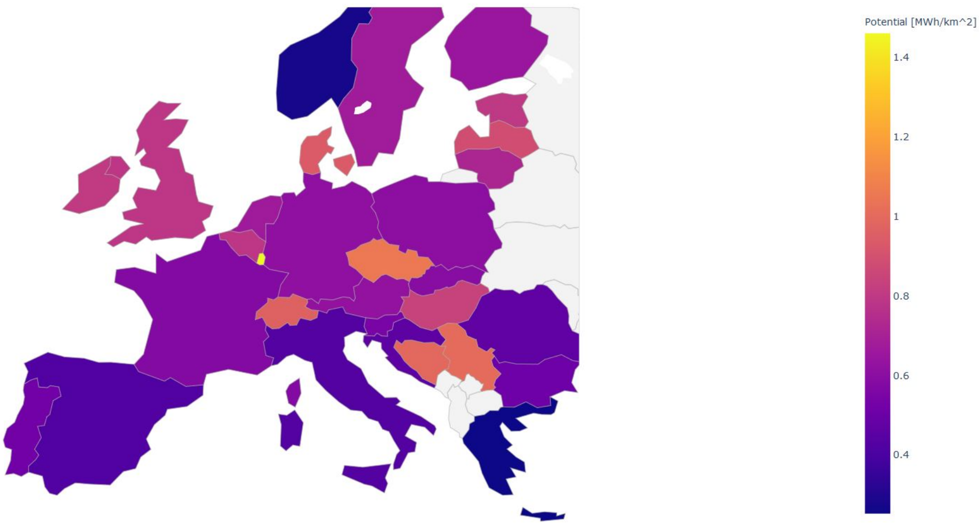

Figure 3.2. !!! PLACE HOLDER !!! Geographical potential GW/km2

The hourly energy production of all variable renewable energy sources is limited by the production potential given by the weather. Following [21], the availability was calculated using historic weather data for 2011 from [20] with a spatial resolution of 40x40 km and hourly temporal resolution. The weather data is first converted to generation potentials for each 40x40 km cell using the REatlas software [2], and then the national means are found.

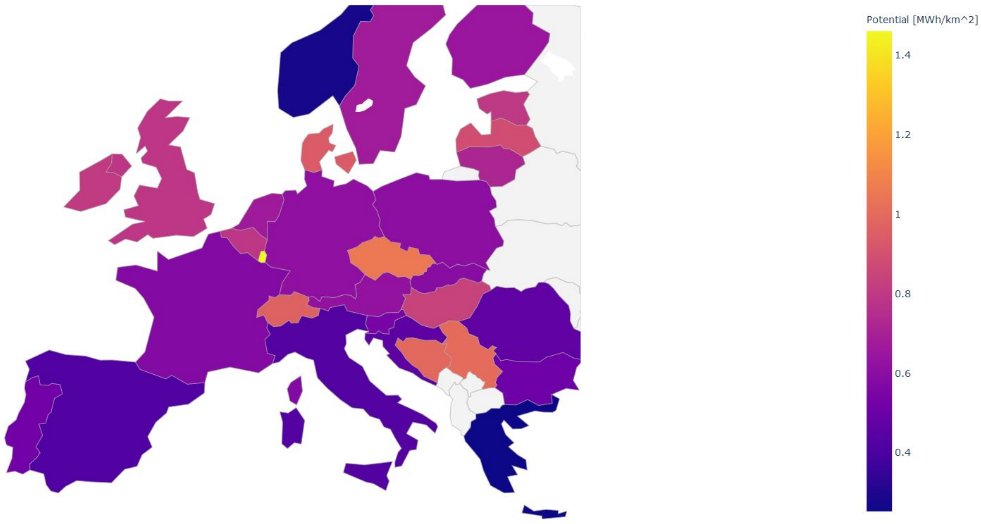

Figure 3.3. !!! PLACE HOLDER !!! Mean wind generation potential

The dispatchable energy sources available in all countries are chosen to be open cycle gas turbines (OCGT), as they have a high flexibility and good load following capabilities, therefore making them suitable as a backup generator in a highly decarbonized scenario. They do however not necessarily produce realistic results, when used in scenarios with low decarbonization. The capacities and energy generation of the gas turbines are contrary to the variable renewable energy sources, not limited by geographical or generation potentials. They are however, limited by the maximum allowable CO2 emission. The CO2 emission intensity of the open cycle gas turbine is 0.19 t/MW.

In all simulations the capacities of all energy generators are initially set to be zero, with the capability to be expanded until geographical potentials or CO2 limits further expansion. The cost of expanding capacities is calculated as annualized cost, given as the annualized investment cost plus fixed annual operations and maintenance cost. Annualized investment cost is calculated by multiplying the annuity factor 3.1 by the investment cost.

$$a = \frac{r}{1 - \frac{1}{(1+r)^n}} \tag{3.1}$$

Where r is the discount rate, and n is the expected lifetime of the given technology. In this project a discount rate of 7% is used. The lifetime of the individual technologies are listed in table 3.1. All cost data are based on the 2030 values presented in [22].

3.1.3 Energy demand

The data for the hourly electricity demand found in the European Network of Transmission System Operators data portal is used as energy demand [15]. The data has a resolution of one hour, and is provided for all countries included in the model.

3.1.4 Energy transmission

In the model used in this project, all transmission lines are treated as transport models with a coupled source and sink, only constrained by energy conservation at each connecting

Technology	Investement [€/MW]	Fixed O&M [€/kW/year]	Marginal cost [€/MWh]	lifetime [years]
Onshore Wind	1182	35	0.015	25
Offshore Wind	2506	80	0.02	25
Solar PV	600	25	0.01	25
OCGT	400	15	58.4	30
Transmission	400 €/MW km +150000 pr line	2%	0	40

Table 3.1. Generator parameters are based on the values from [22], and transmission parameters are based on the work presented in [11].

node. Transmission loss is thereby not considered. This approximation is assumed to be acceptable as most international transmission lines already are, or probably will be in the near future, controllable point-to-point high voltage direct current (HVDC) lines.

Line capacities initially start as zero, and can then be expanded if found feasible in the optimization, with no constraint on the maximum allowable capacity. The investment cost of line capacity is calculated as a cost pr MWkm plus an additional cost for a high voltage AC to DC converter pair. The price of a high voltage AC to DC converter pair is set to be 150000€ regardless of line capacity [11].

The length of each line is set as the distance between the centroids of each connecting country plus an additional 25%. The extra 25% is added to the line length as competitve land use and public acceptance issues will prohibit lines from being placed in optimal positions.

Furthermore, to satisfy n-1 security the price is adjusted with a factor of 1.5, to account for the extra installed capacity needed, as shown in [21].

$$c_l = (L * I_s * 1.25 + 150000) * 1.5 * 1.02 * a \tag{3.2}$$

1.25 = 25% extra length due to land use competition 150000 = Price of DC converter pair 1.5 = n-1 security 1.02 = 2% FOM (fixed operations and maintanance cost) a = annuity

[1]

3.2 Experiment design

3.2.1 4D experiment

In this study a four dimensional sub space of the decision space is utilized to explore the characteristics of the model. The four variables in this new space is the total amount of installed gas turbine (ocgt) capacity, wind turbine capacity, solar pv capacity and the total installed transmission capacity. Using a low dimensional space allows for a thorough exploration of the feasible space as the relative fast computation time allows for several studies to be performed using different parameters.

For every single MGA explorations there are two parameters that can be altered. These are the amount of reduction in CO_2 emission compared to the base model, and the amount of MGA slack used. For this experiment it was chosen to iterate over both of these variables

[1] FiXme Note: Consider showing some time series for demand etc

exploring CO2 reductions og 0, 50, 80 and 95%, and MGA slacks of 1, 2, 5, and 10%. This means that a total of 16 MGA studies is to be performed.

3.2.2 CO2 experiment

3.2.3 Multiplicity experiment

3.2.4 Spatial grouping experiment

4 Results

4.1 The optimal solution

Before starting any MGA studies, it is important to investigate and understand the optimal solution of the problem at hand. In this section, the found optimal solutions of the model will be presented. A range of CO2 constraints have been investigated, and as the CO2 constraint is altered a new optimal solution is found, therefore four optimal solutions representing a business as usual scenario, a 50% CO2 reduction, a 80% CO2 reduction and a 95% CO2 reduction scenario will be presented.

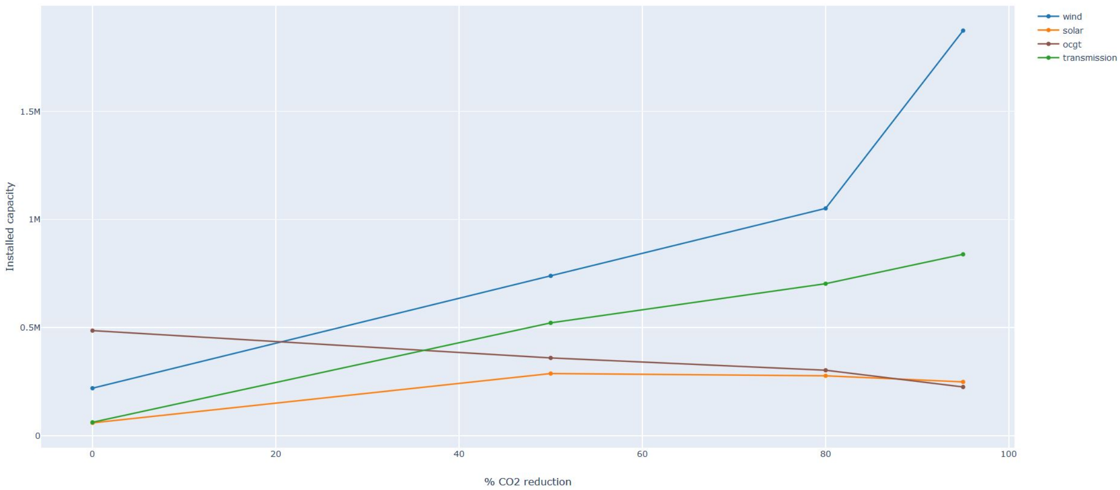

Figure 4.1. Optimal solutions

On figure 4.1, the summarized technology capacities are presented, showing how the two CO2 neutral energy sources increase as the CO2 constraint is tightened. It is important to note how the installed wind capacity increases rapidly compared to solar PV that levels out, as the CO2 reduction reaches the higher percentages. This could indicate that any further solar PV capacity would primarily generate surplus energy, as long as no storage technologies are implemented. Studies have previously shown that solar PV is highly dependandt on short term storage if it is to be utilized in higher scale [18] [1]. This is due to the high daily fluctuations in energy production from solar PV and therefore solar PV has a great synergy with short term storage technologies.

Figure 4.1 further shows that a wind solar mix of approximately 80% wind and 20% solar PV is desirable, when no storage solutions are, if +90% CO2 reduction should be achieved. This complies very well with the results presented in [18].

Analyzing the gini coefficients presented in table 4.1 and on figure 2.3 it becomes evident that, in order to reach a high degree of CO2 reduction, the energy generation will have to be moved towards countries where production of energy with variable renewable energy sources are the most favorable. As expected the amount of transmission in the network and the gini coefficient are highly related as seen in the data presented in table 4.1.

[1] FiXme Note: other references on this

Table 4.1. Optimal solutions

Technology	Buisiness as usual	50% CO2	80% CO2	95% CO2
Wind GW	219.1			
Solar	58.6			
OCGT	485.6			
Transmission GW	61.4	521.4	702.6	838.7
Gini coefficient	0.11	0.39	0.51	0.57
CO2 emission 1e+06 Ton	1151.9	301.2	120.46	30.1
Cost 1e+9€	200.7	265.6	329.4	458.8

4.1.1 Business as usual

In the business as usual scenario, figure 4.2, where no constraint on the CO2 emission is implemented, energy is primarily supplied by gas turbines as expected. Any significant capacities of variable renewable energy sources is only implemented in countries where such technologies are readily available. Analyzing figure 4.2 it is found that wind energy is favorable in the northern countries and solar energy only becomes favorable in the most southern countries, in this case Spain and Portugal. Furthermore, the energy generation is spread, fairly even across the network, thereby requiring less transmission capacities, and thereby also resulting in a fairly low gini coefficient of 0.11.

The CO2 emission in the base scenario without CO2 constraints was found to be 1151.9 MT CO2/year, which complies reasonably well with the 2011 CO2 emission for the EU-28 countries energy sector, found by the European Environment Agency (EEA) to be 1517.3 MT CI2/year [1]. Although the numbers are off by some hundred MT CO2/year, and the numbers from EEA only represent the EU-28 countries, this comparison can conclude that the model used in this project, despite its course spatial resolution and small number of included technologies, is capable of producing results with an acceptable accuracy.

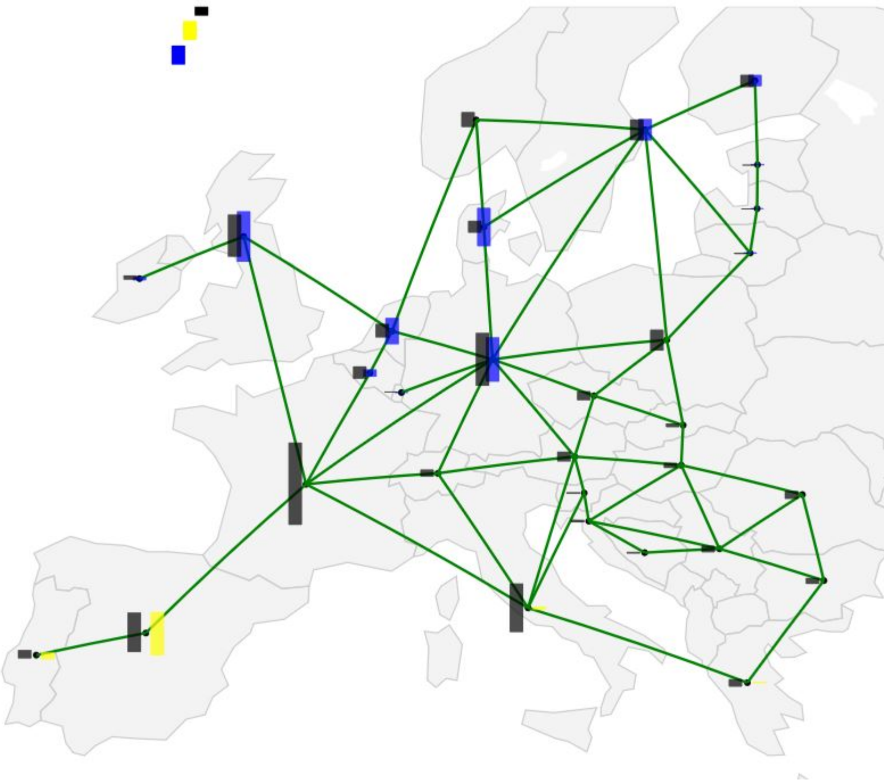

Figure 4.2. Optimal solution for a business as usual scenario

2

[2] FiXme Note: include demand on these plots

4.1.2 Reduced CO2 emission scenarios

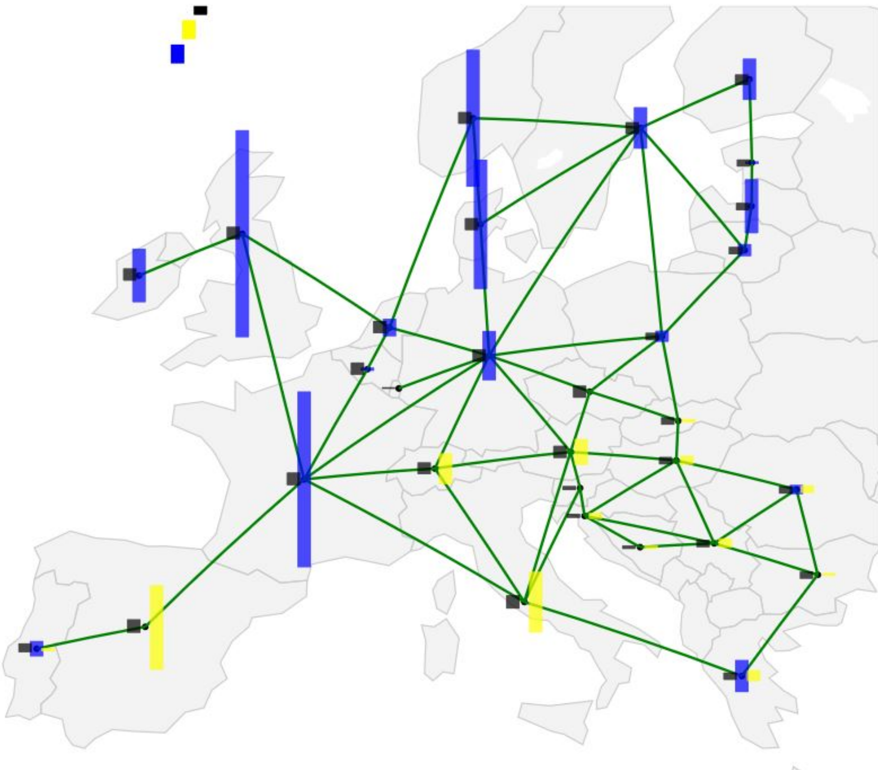

Figure 4.3. Optimal solution for a scenario with 80% CO2 reduction

4.2 MGA study of grouped technologies

In the first MGA study performed it was chosen to explore a four dimensional near optimal feasible space, with the four dimensions being total installed ocgt capacity, total installed wind capacity, total installed solar PV capacity and total installed transmission capacity.

In the study it was found that wind energy is a key resources if CO2 emission is to be reduced by a significant amount. Analyzing figure 4.4, showing the technology capacity distributions, it goes to show that scenarios without either wind or solar is possible in the business as usual scenario, but as soon as a CO2 constraint is implemented it is no longer possible to supply the network with electricity without a significant amount of that energy being produced by wind power. However, solar PV can in all cases of CO2 constraints be omitted. The mean solar PV capacity doeas however increase as the CO2 constraint is tightened.

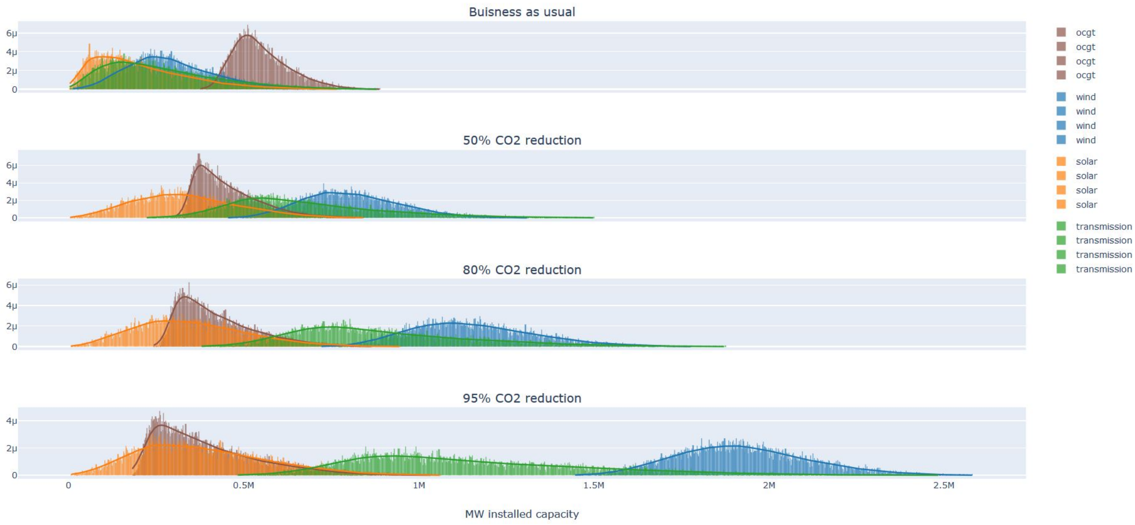

Figure 4.4. Study of capacities with 10% MGA slack

Looking at the ocgt capacities on figure 4.4, it is clear that the distribution has a steep side towards the minimum. This indicates that there is a sharp lower limit to the amount of ocgt capacity needed in all scenarios. This minimum represents the capacity needed to supply the network with electricity, when the variable renewable energy resources are scarce.

Furthermore, as the CO2 constraint is tightened, the deviation of all distributions increases.

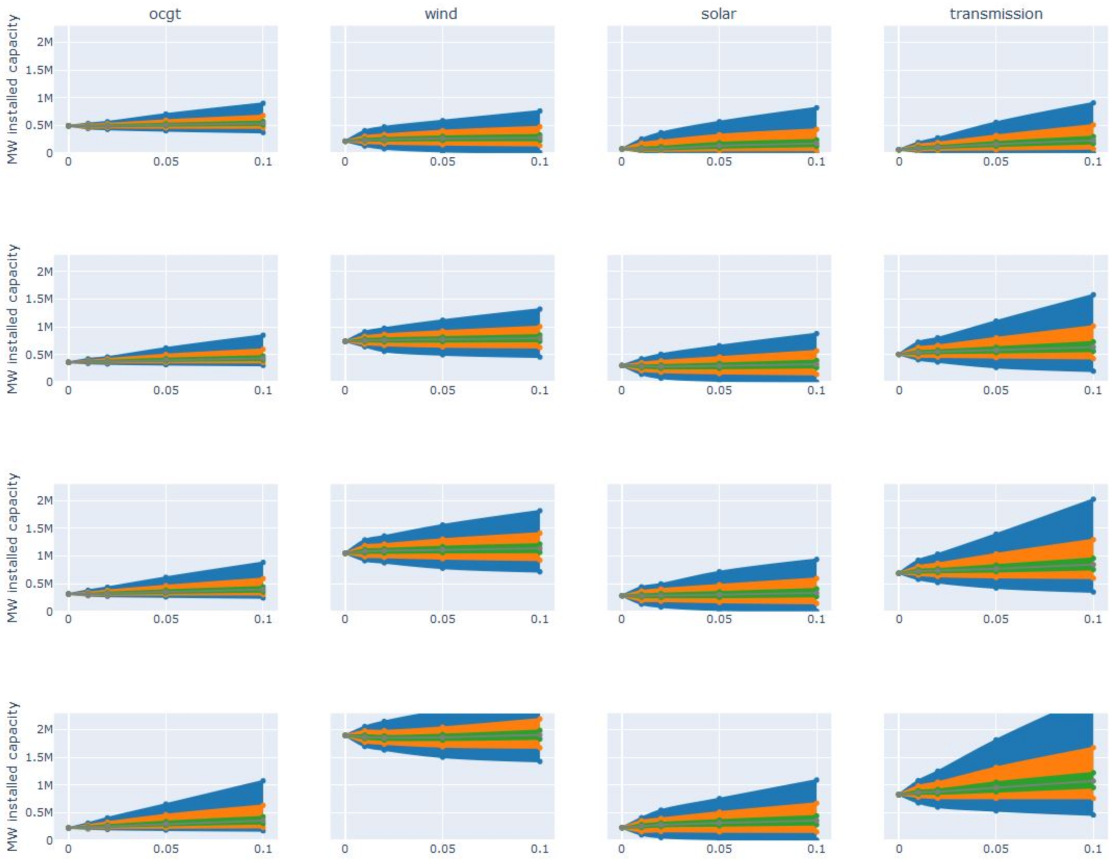

Figure 4.5.

4.3 HSJ compared to novel approach

5 Discussion

Why high dim are so hard to deal with.

6 Conclusion

Notes

Python Packages used

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

Notes on references

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

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.

MODELING TO GENERATE ALTERNATIVES: THE HSJ APPROACH AND AN ILLUSTRATION USING A PROBLEM IN LAND USE PLANNING [8]

This is the original article, [8], 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.

MGA: a decision support system for complex, incompletely defined problems[4]

Elaborating on the MGA approach presented in [8], and evaluating the performance of MGA as a whole.

Using modeling to generate alternatives (MGA) to expand our thinking on energy futures[7]

[7] is one of the first implementations of MGA on energy planning. Uses the HSJ method from [8].

Modeling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models [16]

In this article MGA is used to explore near optimal solutions in energy network optimization, much like [7]. 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.

Ensuring diversity of national energy scenarios: Bottom-up energy system model with Modeling to Generate Alternatives [3]

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.

Simulation-Optimization techniques formodelling to generate alternatives in waste management planning [9]

This article describes the MGA method used in [3]. Here a random population is created and is sorted through a number of itterations.

GENETIC ALGORITHM APPROACHES FOR ADDRESSING UNMODELED OBJECTIVES IN OPTIMIZATION PROBLEMS [14]

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.

A Co-evolutionary, Nature-Inspired Algorithm for the Concurrent Generation of Alternatives [17]

The article [17] describes an implementation of the genetic firefly algorithm used to perform MGA.

Swarm Intelligence and Bio-Inspired Computation : Theory and Applications - Chapter 14 [25]

The book [25] Chapter 14 describes the firefly algorithm in depth an has multiple examples of the firefly algorithm implemented. The book cites [17] .

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

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

Transmission needs across a fully renewable European power system

[19] Article exploring the effect of transmission across the EURO-30 model.

Validation of Danish wind time series from a new global renewable energy atlas for energy system analysis

[2] REAtlas software

The NCEP Climate Forecast System Version 2

[20] Weather data

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.

Modelling to generate alternatives with an energy system optimization model [6]

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

The optimum is not enough: A near-optimal solution paradigm for energy systems synthesis [24]

A different approach for exploring the near optimal feasable space, using a technique that is not quite MGA but very similar. The approach generates a finite set of alternative solutions.

Optimisation of regional energy supply chains utilising renewables: P-graph approach

Article : [13]

Current and prospective costs of electricity generation until 2050

[22] includes cost data for all energy technologies relevant for this study

Optimal Combination of Storage and Balancing in a 100% Renewable European Power System

[18] Article where the optimal mix between wind and solar energy is explored.

Bibliography

[1] E. E. Agency. Annual european union greenhouse gas inventory 1990 – 2015 and inventory report 2017. 2017. URL `https://www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2017#tab-data-visualisations`.

[2] G. B. Andresen, A. A. Sondergaard, and M. Greiner. Validation of danish wind time series from a new global renewable energy atlas for energy system analysis. *Energy*, 93:1074 – 1088, 2015. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2015.09.071.

[3] P. B. Berntsen and E. Trutnevyte. Ensuring diversity of national energy scenarios: Bottom-up energy system model with modeling to generate alternatives. *Energy*, 126: 886 – 898, 2017. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2017.03.043. URL `http://www.sciencedirect.com/science/article/pii/S0360544217304097`.

[4] E. D. Brill, J. M. Flach, L. D. Hopkins, and S. Ranjithan. Mga: a decision support system for complex, incompletely defined problems. *IEEE Transactions on Systems, Man, and Cybernetics*, July 1990. ISSN 0018-9472. doi: 10.1109/21.105076.

[5] T. Brown, J. Horsch, and D. Schlachtberger. Python for power system analysis (pypsa) version 0.14.1, may 2019. URL `https://doi.org/10.5281/zenodo.3233682`.

[6] J. DeCarolis, S. Babaee, B. Li, and S. Kanungo. Modelling to generate alternatives with an energy system optimization model. *Environmental Modelling and Software*, 79, 2016. ISSN 1364-8152.

[7] J. F. DeCarolis. Using modeling to generate alternatives (mga) to expand our thinking on energy futures. *MEnergy Economics*, 33, 2010. doi: 10.1016/j.eneco.2010.05.002.

[8] L. D. H. E. DOWNEY BRILL JR., SHOOU-YUH CHANGt. Modeling to generate alternatives: The hsj approach and an illustration using aproblem in land use planning. *Management Science*, 28, 3 1982. doi: 185.45.22.249.

[9] Y. Gunalay and J. S. Yeomans. Simulation-optimization techniques for modelling to generate alternatives in waste management planning. *Applied Operational Research*, 2011.

[10] Gurobi. Gurobi. URL `https://www.gurobi.com`.

[11] S. Hagspiel, C. Jagemann, D. Lindenberger, T. Brown, S. Cherevatskiy, and E. Troster. Cost-optimal power system extension under flow-based market coupling. *Energy*, 66:654 – 666, 2014. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2014.01.025. URL `http://www.sciencedirect.com/science/article/pii/S0360544214000322`.

[12] J. Horsch and T. Brown. The role of spatial scale in joint optimisations of generation and transmission for european highly renewable scenarios. *arXiv e-prints*, May 2017.

[13] H. L. Lam, P. S. Varbanov, and J. J. Klemes. Optimisation of regional energy supply chains utilising renewables: P-graph approach. *Computers and Chemical Engineering*, 34(5):782 – 792, 2010. ISSN 0098-1354. doi: https://doi.org/10.1016/j.compchemeng.2009.11.020. URL `http://www.sciencedirect.com/science/article/pii/S0098135409003056`. Selected Paper of Symposium ESCAPE 19, June 14-17, 2009, Krakow, Poland.

[14] D. H. LOUGHLIN, S. R. RANJITHAN, E. D. B. JR., and J. W. B. JR. Genetic algorithm approaches for addressing unmodeled objectives in optimization problems. *Engineering Optimization*, 2001. doi: 10.1080/03052150108940933.

[15] E. N. of Transmission System Operators. Country-specific hourly load data, October 2019. URL `https://www.entsoe.eu/data/data-portal/`.

[16] J. Price and I. Keppo. Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models. *Applied Energy*, 195:356 – 369, 2017. ISSN 0306-2619. doi: https://doi.org/10.1016/j.apenergy.2017.03.065. URL `http://www.sciencedirect.com/science/article/pii/S0306261917302957`.

[17] J. S. Y. Raha Imanirad, Xin-She Yang. A co-evolutionary, nature-inspired algorithm for the concurrent generation of alternatives. *GSTF*, 2, 10 2012. doi: 10.5176/2010-3043_2.3.193.

[18] M. G. Rasmussen, G. Bruun Andresen, D. Heide, and M. Greiner. Optimal combination of storage and balancing in a 100% renewable european power system. *Proceedings of the 10th International Workshop on Large-scale Integration of Wind Power Into Power Systems As Well As on Transmission Networks for Offshore Wind Power Plants*, pages 682–684, 2011.

[19] R. A. Rodriguez, S. Becker, G. B. Andresen, D. Heide, and M. Greiner. Transmission needs across a fully renewable european power system. *Renewable Energy*, 63:467 – 476, 2014. ISSN 0960-1481. doi: https://doi.org/10.1016/j.renene.2013.10.005. URL `http://www.sciencedirect.com/science/article/pii/S0960148113005351`.

[20] S. Saha, S. Moorthi, X. Wu, J. Wang, S. Nadiga, P. Tripp, D. Behringer, Y.-T. Hou, H.-y. Chuang, M. Iredell, M. Ek, J. Meng, R. Yang, M. P. Mendez, H. van den Dool, Q. Zhang, W. Wang, M. Chen, and E. Becker. The ncep climate forecast system version 2. *Journal of Climate*, 27(6):2185–2208, 2014. doi: 10.1175/JCLI-D-12-00823.1. URL `https://doi.org/10.1175/JCLI-D-12-00823.1`.

[21] D. Schlachtberger, T. Brown, S. Schramm, and M. Greiner. The benefits of cooperation in a highly renewable european electricity network. *Energy*, 134:469 – 481, 2017. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2017.06.004. URL `http://www.sciencedirect.com/science/article/pii/S0360544217309969`.

[22] A. Schröder, F. Kunz, J. Meiss, R. Mendelevitch, and C. von Hirschhausen. Current and prospective costs of electricity generation until 2050. DIW Data Documentation 68, Berlin, 2013. URL `http://hdl.handle.net/10419/80348`.

[23] L. V. Stephen Boyd. *Convex Optimization*. Cambridge University Press, 2004.

[24] P. Voll, M. Jennings, M. Hennen, N. Shah, and A. Bardow. The optimum is not enough: A near-optimal solution paradigm for energy systems synthesis. *Energy*, 82: 446 – 456, 2015. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2015.01.055. URL `http://www.sciencedirect.com/science/article/pii/S0360544215000791`.

[25] A. H. G. M. K. R. X. Xin-She Yang, Zhihua Cui. *Swarm Intelligence and Bio-Inspired Computation*. Elsevier, 2013. ISBN 9781493301362.

[26] K. Zhu, M. Victoria, T. Brown, G. Andresen, and M. Greiner. Impact of co2 prices on the design of a highly decarbonised coupled electricity and heating system in europe. *Applied Energy*, 236:622 – 634, 2019. ISSN 0306-2619. doi: https:

//doi.org/10.1016/j.apenergy.2018.12.016. URL http://www.sciencedirect.com/science/article/pii/S030626191831835X.