An exploration of MGA methods for use in strategic energy planning

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Part I

Main Report

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 [18] !!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 [5] . 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 [6], 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 concept of using MGA algorithms on energy planning problems have been further studied and the result presented in a range of articles and papers; [4], [12], [1], [7], [16].

The MGA technique introduced by [6] and implemented on an energy-economic model by [5], 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: [14] of the European electricity grid, will serve as the base model. The model is build in [3], 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 [14]. 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
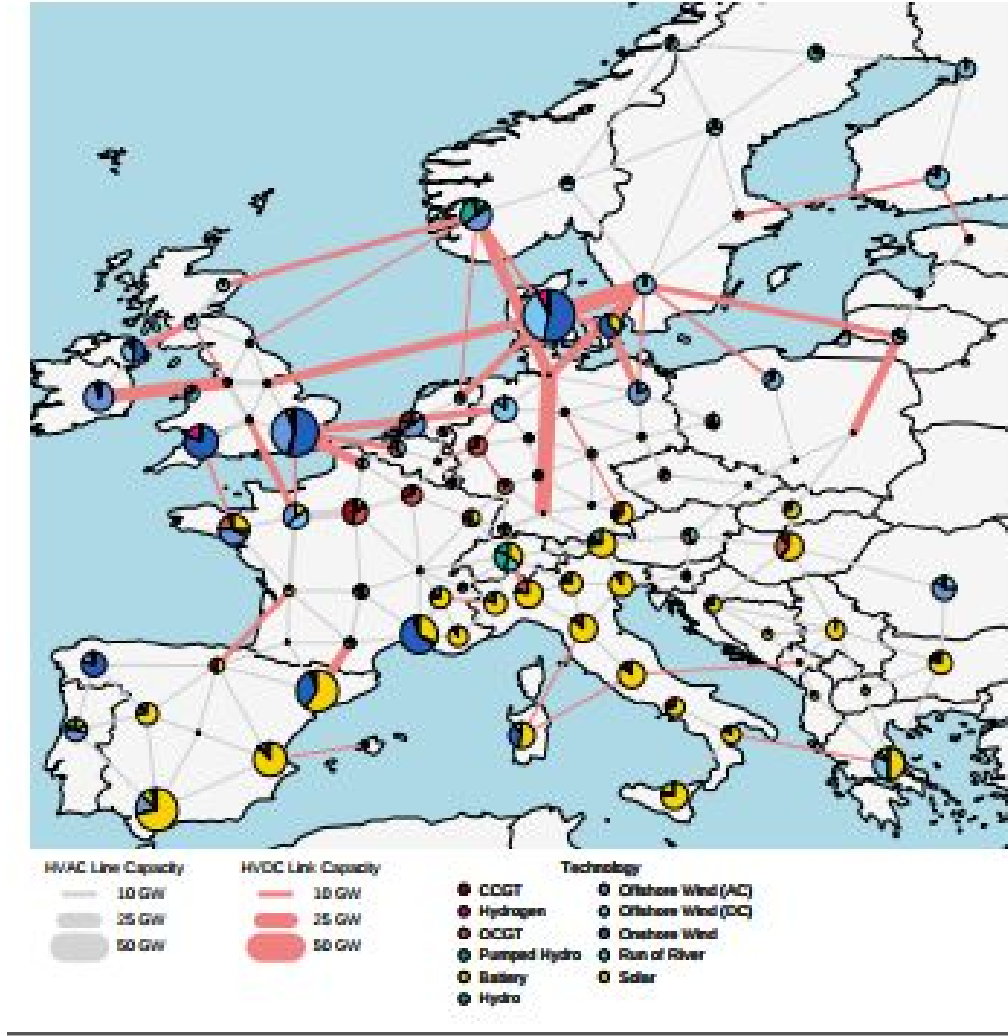
2 Theory

2.1 Model

- Network layout

Figure 2.1. Network layout

2.2 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 [14], 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:

$$min \left(\sum_{n,s} c_{n,s} G_{n,s} + \sum_l c_l F_l + \sum_{n,s,t} o_{n,s} g_{n,s,t} \right) \tag{2.1}$$

This objective function is subject to a range of constraints ensuring realistic behavior of the system. As described in [14] 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:

$$\sum_s g_{n,s,t} - d_{n,t} = \sum_l K_{n,l} f_{l,t} \ \forall n, t \tag{2.2}$$

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.

$$0 \leq g_{n,s,t} \leq G_{n,s} \ \forall n, s, t \tag{2.3}$$

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:

$$0 \leq g_{n,s,t} \leq \overline{g}_{n,s,t} G_{n,s} \ \forall n, s, t \tag{2.4}$$

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

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

$$0 \leq G_{n,s} \leq G_{n,s}^{max} \ \forall n, s \tag{2.5}$$

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.

$$|f_{l,t}| \leq F_l \ \forall l, t \tag{2.6}$$

In the model it is possible to activate a CO2 constraint, limiting the allowed CO2 emissions for the entire energy network. As in [**?**] 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}.

$$\sum_{n,s,t} \frac{1}{\eta_s} g_{n,s,t} e_s \leq CAP_{CO_2} \tag{2.7}$$

The model is implemented in the open source software PyPSA [3], using much of the software presented in [**?**]. Optimization of the model is performed with the optimization software Gurobi [8].

2.3 Properties of the near optimal feasible space

Analyzing the original optimization problem one can deduct that the feasible decision space, must be convex, as all constraints f_i and the objective function f_0 satisfy equation 2.8, and therefore must be convex [15].

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \ \forall \ x, y \in \mathbb{R}^n and \ \alpha, \beta \in \mathbb{R} \tag{2.8}$$

Furthermore, when all variables are bounded; hourly production by the power balance constraint and installed capacity by geographical potential, the feasible decision space is not only convex but also closed. If the geographical potential constraint is excluded the feasible decision space becomes an open convex space as illustrated on 2.2, this does however not have any immediate consequences, as the objective function increases as one moves in the open direction of the space.
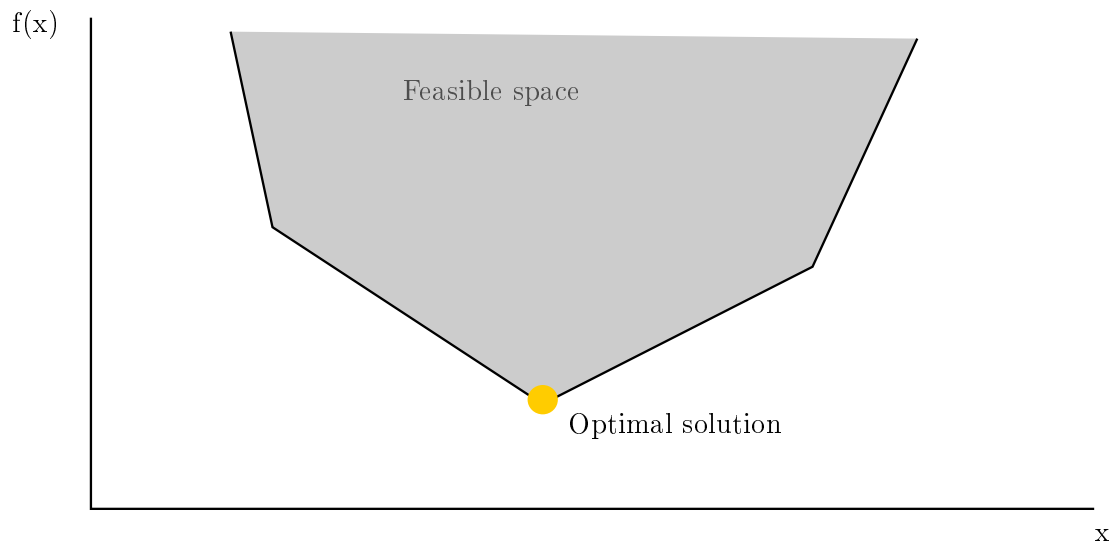

Figure 2.2. A sketch of a one dimensional feasible space with MGA constraint

$$W = \{\vec{x} \in \mathbb{R}^d | f_i(x) \geq 0\} \tag{2.9}$$

!!! This is not completely right !!!

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

$$\vec{x} = \{g_{n,s,t} \wedge G_{n,s} \wedge F_l \ \forall \ n, s, t, l\} \tag{2.10}$$

Therefore, the dimensionality, of the decision space must be given by the number of nodes in network n for every technology s for every hour t, plus the number of nodes n times technologies s and finally the number of lines l 2.11.

$$d = n \cdot s \cdot t + n \cdot s + l \tag{2.11}$$

In the case of the reference model used in this project that gives $30 \cdot 3 \cdot 8765 + 30 \cdot 3 + 90 = 789030$!!! number of lines is a guestimate!!

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

2.3.1 Sub space

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.

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

In that case the dimensionality would only be $d^* = 30 \cdot 3 + 90 = 180$.

The subspace would then be given by:

$$W^* = \{\vec{x}^* \in \mathbb{R}^{d^*} |\} \tag{2.13}$$

The set W^* therefore includes information about installed capacities of all technologies and transmission lines. Since plant operation, is not the focus of this project, but rather distribution of capacities, the subspace W^* still provides the information of interest, despite its much lower dimensionality.

Further reduction

If desired it is possible to further reduce dimensionality, by sacrificing all spatial information.

$$x^{**} = \{\sum_n G_{n,s} \forall n, s\} \tag{2.14}$$

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

$$W^{**} = \{\vec{x}^{**} \in \mathbb{R}^{d^{**}} | \} \tag{2.16}$$

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 [5].

The MGA approach was first introduced in 1982 by Brill et al. [6], 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 [6] and later rediscovered by DeCarolis in [5] 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 2.2.

In section 2.2 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 [15]. 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 [6] 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 [6] as follows:

$$Minimize : p = \sum_{k \in K} x_k$$
$$Subject to : f_j(\vec{x}) \leq T_j \forall j \vec{x} \in X$$

(2.17)

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 [4], 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. Based on the same concepts as presented in 2.4 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.

An important feature about the method developed is that it can be used for any dimensional decision 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 Decision space mapping

As explained in section 2.3 on page 7, the near optimal feasible space will always be convex, and can either be closed or not. However, when the MGA constraint from equation 2.18 is introduced the space will be closed.

$$f(\vec{x}) \leqslant f(\vec{x}^*) \cdot (1 + \epsilon) \tag{2.18}$$

As we now have a closed convex space, 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. !!! This might not be the case for CO2 constraint!!!!

However, finding these vertices is no trivial task. In the method developed, all solutions found, that lie within the near optimal feasible space is treated as a point in that space. Furthermore, the possibility of letting the objective function search in a given direction in the decision space is utilized, by replacing the original objective function to an objective function on the from presented in 2.19.

$$Minimize \; p = \vec{n}_i \vec{x} \tag{2.19}$$

Where $\vec{n}_i$ is the i'th normal vector.

The method proposed here will use the following steps to approximately find all vertices.

1. Find initial solution
2. Add MGA constraint
3. Maximize and minimize all variables
4. Based on these points define a convex hull, and define all face normals
5. Iterate over each face normal and change objective function to 2.19
6. Add the newly found points to list of points and define new hull and its face normals
7. Repeat step 5 and 6 until the size of the convex hull converges

2.5.2 Hull fill

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.
```

2.6   Implementation and utilization of parallel programming

3 Results

3.1 HSJ compared to novel approach

4   Discussion

5   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 [6]

This is the original article, [6], 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[2]

Elaborating on the MGA approach presented in [6], and evaluating the performance of MGA as a whole.

Using modeling to generate alternatives (MGA) to expand our thinking on energy futures[5]

[5] is one of the first implementations of MGA on energy planning. Uses the HSJ method from [6].

Modeling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models [12]

In this article MGA is used to explore near optimal solutions in energy network optimization, much like [5]. 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 [1]

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 [7]

This article describes the MGA method used in [1]. Here a random population is created and is sorted through a number of itterations.

GENETIC ALGORITHM APPROACHES FOR ADDRESSING UNMODELED OBJECTIVES IN OPTIMIZATION PROBLEMS [11]

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 [13]

The article [13] describes an implementation of the genetic firefly algorithm used to perform MGA.

Swarm Intelligence and Bio-Inspired Computation : Theory and Applications - Chapter 14 [17]

The book [17] Chapter 14 describes the firefly algorithm in depth an has multiple examples of the firefly algorithm implemented. The book cites [13] .

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

The role of spatial scale in joint optimisations of generation and transmission for European highly renewable scenarios[9]

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 [4]

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 [16]

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 : [10]

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