Energy System Design in Europe: A Multi-Objective Approach

INF569 Decision Theory

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Contents

1 Introduction

The aim of this project is to design a comprehensive way to model renewable energy systems so as to achieve a renewable energy production that meets all the energy needs of selected European countries. There is no doubt that the objective is to remain realistic from a budgetary optimization perspective, but also to avoid opposition from the population. As the share of renewable energies in the energy system will rise and renewable technologies will become more salient to the public, including public opinion in system design decisions will be of increasing importance in the upcoming years. Moreover, to examine interactions with a third objective dimension, another objective is to generate as many employment opportunities as possible in the area of the production of green energy.

This report proceeds as follows. In Section 2, we give an overview of the related literature and outline our unique contribution in such research. In Section 3, we describe the problem at hand in detail through a mathematical interpretation. While Section 4 presents the data used and certain choices that are made namely to assert the opposition of the population, Section 5 sheds light on our methodology through theory-based explanations based on the lectures. We present our results as well as our selected solution in Section 6, Section 7 concludes.

2 Related literature

Our research project is closely linked to four strands of the literature. The first strand investigates the optimal design of renewable energy systems minimizing the system costs (see e.g., [1], [2], [3], and [4]). The second strand developed methodological tools for solving multi-objective optimization problems (see e.g., [5], [6], [7]). [8] provides a survey on the evolution of that research field. Recently, a third strand evolved that combines both by applying multi-objective optimization methods to energy system design problems. Several studies have already been carried out to locate plants of a specific technology in a given region with respect to multiple criteria, e.g. for wind ([9], [10]) and solar farms ([11], [12]). A few studies accommodated a broader set of technologies or a wider geographical space. For instance, [13] optimized the distribution of wind and photovoltaic plants across Italy in order to achieve a good trade-off between the total energy output and its fluctuations. Meanwhile, [14] present pathways for an optimal European power system accounting for environmental and economic goals. A fourth strand provides research on the public opinion of energy production technologies (see, e.g. [15], [16], [17], and [18]). This research is highly relevant for policymakers to facilitate the process of energy transition. For instance, the European Commission itself conducts research in this field to adapt policies accordingly [19], [20].

All in all, we remark steadily growing streams of literature concerning multi-objective energy system design and public opinion on energy sources. However, to the best of our knowledge, there is no study that links both with each other by incorporating public opposition as a system objective itself. Yet, we see the need for such a comprehensive system development in order to reach high shares of renewable technologies. We therefore develop a model that may serve as a starting point for a new strand of literature filling this research gap.

3 Problem definition

We aim at identifying an optimal expansion strategy of the future European energy system with respect to energy costs and public technology opposition.[1] As this is a fairly new approach, we restrict the problem to a few basic features. Namely, the energy system configuration must account for the demand in each country, the losses that arise from energy transportation between countries and for the capacities already installed in each country. This simple setup allows us to keep track of the mechanisms at work. Nevertheless, our framework is easily extendable to more sophisticated features.

In the following, we present the mathematical formulation of our problem. Table 1 contains information on the symbols used for notation.

The objective functions are

$$f_1(x) = \sum_{i \in \mathcal{C}} \sum_{t \in \mathcal{T}} c_{i,t} \cdot x_{i,t} \tag{1}$$

$$f_2(x) = \sum_{i \in \mathcal{C}} pop_i \sum_{t \in \mathcal{T}} opp_{i,t} \cdot x_{i,t} \tag{2}$$

$$f_3(x) = \sum_{i \in \mathcal{C}} \sum_{t \in \mathcal{T}} v_t \cdot x_{i,t} \tag{3}$$

where (1) describes the yearly costs of energy production from newly built sites, (2) reflects the weighted public opposition against energy policy x, and (3) includes the vacancies created. Note that we search for a minimum of f_1 and f_2 while maximizing f_3. The

[1] Note that we will only include technologies that are commonly described as *carbon-free*. Therefore, the goal of zero-carbon emissions is implicitly guaranteed.

Table 1: Symbols used for the mathematical problem

Symbol	Description
Sets	
$\mathcal{C}$	Countries
$\mathcal{T}$	Technologies
Parameters	
$c_{i,t}$	LCOE[a] of energy produced in country $i \in \mathcal{C}$ by technology $t \in \mathcal{T}$
$opp_{i,t}$	Opposition against newly built plants of technology $t \in \mathcal{T}$ in country $i \in \mathcal{C}$
v_t	Jobs created (vacancies) by technology $t \in \mathcal{T}$
D_i	Yearly electrictity energy demand in country $i \in \mathcal{C}$
$S_{i,t}^{initial}$	Currently, yearly produced energy in country $i \in \mathcal{C}$ using technology $t \in \mathcal{T}$
$dist_{i,j}$	Distance between country i and j, with $i, j \in \mathcal{C}$
ρ	Energy losses per distance transported
pop_i	Relative population size of country $i \in \mathcal{C}$
M[b]	Big-M for deactivating *no export* restriction if $z_{i,j} = 1$
Decision variables	
$x_{i,t}$	Added yearly energy production in country $c \in \mathcal{C}$ by technology $t \in \mathcal{T}$
$y_{i,j}$[c]	Yearly energy transportation from country i to j, with $i, j \in \mathcal{C}$
$z_{i,j}$	Indicates whether country i exports energy to country j, with $i, j \in \mathcal{C}$

[a] LCOE: Levelized cost of energy.

[b] We generously set $M = \sum_{i \in \mathcal{C}} D_i$. One could also think of tighter, country-specific choices of M to account for cross-country line capacities.

[c] Note that if $i = j$, $y_{i,j}$ captures the energy produced in country $i \in \mathcal{C}$ for domestic use.

constraints can be written as

$$\sum_{t\in\mathcal{T}} \left(x_{i,t} + S_{i,t}^{initial}\right) = \sum_{j\in\mathcal{C}} y_{i,j} \qquad \forall i \in \mathcal{C} \tag{4}$$

$$\sum_{i\in\mathcal{C}} y_{i,j} \cdot \left(\frac{1}{1+\rho}\right)^{dist_{i,j}} = D_j \qquad \forall j \in \mathcal{C} \tag{5}$$

$$y_{i,j} \leq M \cdot z_{i,j} \qquad \forall i,j \in \mathcal{C} \tag{6}$$

$$z_{i,j} + z_{j,i} \leq 1 \qquad \forall i,j \in \mathcal{C}, i \neq j \tag{7}$$

$$x_{i,t} \geq 0 \qquad \forall i \in \mathcal{C}, t \in \mathcal{T} \tag{8}$$

$$y_{i,j} \geq 0 \qquad \forall i,j \in \mathcal{C} \tag{9}$$

$$z_{i,j} \in \{0,1\} \qquad \forall i,j \in \mathcal{C} \tag{10}$$

where (4) ensures that a country distributes exactly as much energy among all countries as it produces, (5) guarantees a sufficient production given the demand[2], (6) forces energy transportation from country i to j to be zero if the export in this direction is not activated, and (7) guarantees that energy exchange between two countries follow only one sense. The non-negativity constraints in (8) prevent us from ignoring existing production capacities whereas (9) prohibits negative energy transportation. (10) is the binary constraint on z.

4 Data

The main issue for the data retrieval was to identify an optimal measure for public opposition on energy technologies. Yet, there is not much literature on it, especially for a cross-country and cross-technology comparison. Trade-offs had to be made, the limitation being to use as few different scientific papers as possible to ensure uniform and consistent measurement. Finally, we relied on a paper [16] establishing the preferences of the Portuguese on biomass, wind, solar and hydro energy which we assumed to be the average for all European countries.[3] Nevertheless, nuclear energy enabled us to have a difference between countries, as we found the opposition to nuclear energy for all EU countries [17].[4]

Data on the other variables has been easier to find. An effort has been made to narrow down the number of different resources and ensure consistency in terms of timeline. For the most part, our data is from the year 2018. We show data for objective function parameters in Table 2 (cost), Table 3 (opposition), and Table 4 (Jobs). Other data can be found in the Appendix to prevent overcrowding the report.

[2]This restriction is noted as strict equality to keep the single-objective problems max $f_3(x)$ bounded.

[3]Hence, we could not include cross-country differences for the public opinion on biomass, wind, solar and hydro yet. Conducting a similar research as [16] for all European countries would enable us to include country differences and to improve the results of our model.

[4]For Switzerland, we took the average of the opposition in the other countries considered.

Table 2: Levelized cost of energy in mio. $/GWh

	PV	Wind	Biomass	Hydro	Nuclear
France	0.03394	0.05608	0.07000	0.05400	0.03065
Italy	0.05809	0.05287	0.07596	0.06141	0.05000
Switzerland	0.09000	0.08000	0.07000	0.05000	0.029600
Austria	0.10800	0.07635	0.07000	0.05433	0.05000
Germany	0.09000	0.07000	0.07000	0.05700	0.05000

LCOE was obtained from the sources [21], [22], and [23]. When a value wasn't available we approximated it by choosing the EU average.

Table 3: Opposition in % of total population

	PV	Wind	Biomass	Hydro	Nuclear
France	2	4	6	12	38.8
Italy	2	4	6	12	32.4
Switzerland	2	4	6	12	47.9
Austria	2	4	6	12	67.8
Germany	2	4	6	12	52.9

Source: [16], [17]

Table 4: Job-creation estimation

Technology	Yearly jobs per GWh
PV	0.87
Wind	0.17
Biomass	0.21
Hydro	0.27
Nuclear	0.14

Source: [24]

5 Methodology

Solving the problem characterized in Section 3 poses challenges to the mathematical optimizer and the decision maker because it involves multiple and potentially contradicting objectives. For instance, the cheapest energy technology is likely not to be the least opposed one in each country. Therefore, in general there is no unique solution to multi-objective optimization problems. Instead, one might find several solutions that do not dominate each other along all objective dimensions. This complicates both the search for optimal solutions and the process of picking one of them. To address this issue, the literature has developed a rich set of techniques, from which we present and apply those introduced in [25].

5.1 Definitions

Following the notation of [25], a multi-objective, mixed-integer linear program can be written as

$$\min\{f_1, f_2, ..., f_n\} \tag{11}$$

$$x \in X \tag{12}$$

with the non-empty and bounded feasible set X and (contradicting) objectives $f_i(x)$. For multi-objective optimization, it is useful not only to consider the decision variable space but also the objective space $\mathbb{R}^n$. The objective vectors $(z_1\ z_2\ ...\ z_n)^\top$ with $z_i = f_i(x)$ and $x \in X$ are elements of this objective space. We can then define the feasible objective region $F = f(X)$ as the image of the feasible set X. Following [5] and [25], we define the Pareto optimal solution and the weak Pareto optimal solution as follows:

Definition 1 (Pareto optimality) *A decision vector $x^* \in X$ is Pareto optimal if there does not exist another vector $x \in X$ such that $f_i(x) \leq f_i(x^*)$ for all $i = 1, ..., n$ and $f_j(x) < f_j(x^*)$ for at least one index j.*

Definition 2 (Weak Pareto optimality) *A solution vector $x^* \in X$ is weakly Pareto optimal if there does not exist another vector $x \in X$ such that $f_i(x) < f_i(x^*)$ for all $i = 1, ..., n$.*

5.2 Preprocessing

In order to facilitate the calculations and the comparison of the results, we transform all objectives f_i to minimization problems where necessary[5] and adapt their ranges to values that are approximately in the interval $[1, 10]$. We do this by solving the single-objective

[5] That is, we multiply f_i by -1 if it is originally supposed to be maximized, i.e. f_3.

optimization problems to get lower bounds. The obtained optimal points of each problem can then be plugged into the other objective functions, respectively, to calculate their approximate upper bounds. Using the lower and the approximate upper bounds we are able to compute the constants C_i and K_i that normalize the objectives $f_i^{norm} = \frac{f_i + C_i}{K_i}$, $\forall i = 1, ..., n$.

5.3 A priori methods

A priori methods aim at reducing the complexity of the problem at hand by deciding in advance about the prioritization of the the objectives.

Value function method The value function method relies on the assumption that the decision maker is able to provide a utility function $U(f_1, ..., f_n)$ with respect to the different objectives f_i. Then, the problem translates into a single objective problem

$$\min_x U\left[f_1(x), f_2(x), ..., f_n(x)\right] \tag{13}$$

$$x \in X \tag{14}$$

However, the utility function u is often not available, as in our case. We therefore negclect the value function method for our project.

Lexicographic method The lexicographic method requires a less restrictive assumption on the abilities of the decision maker. We require them only to be able to order the objectives in a strictly decreasing way. Then, we can start by solving the single-objective problem for the most important objective. Subsequently, we solve for the optimal value of the second important objective, additionally requiring to meet the optimal value of the prior objective and so on and so forth. The lexicographic method is guaranteed to find a Pareto optimal solution. In Section 6, we provide results of the lexicographic method for all combinations of rankings.

5.4 A posteriori methods

In contrast to a priori methods, a posteriori methods try to find many non-dominated solutions, from which the decision maker may pick one afterwards. Ideally, the mathematical optimizer finds all Pareto optimal solutions, the so-called Pareto set, which is a challenging task.

Weighting method The weighting method assigns weights w_i to all respective objectives f_i, $w_i \geq 0$, $\sum_{i=1}^n w_i = 1$, and optimizes the weighted sum of objectives $\sum_{i=1}^n w_i f_i$. The theory assures Pareto optimality of solutions for $w_i > 0, i = 1, ..., n$. However, the weighting method does not guarantee to find *all* Pareto optimal solutions. In Section 6, we present the results of our weighting method approaches for both the bi-objective cases and for all objective functions.

ε-constraint method The ε-constraint method reduces the multi-objective problem to a single-objective problem by picking one function for optimization and including the others into the set of constraints, requiring them to meet a minimum quality ε. Mathematically, it can be written as

$$\min_x f_l \tag{15}$$

$$f_i(x) \leq \varepsilon_i \quad \forall i = 1, ...n, i \neq l \tag{16}$$

$$x \in X \tag{17}$$

In theory, using the ε-constraint method may yield every Pareto optimal solution. To be Pareto optimal, the solution $x^* \in X$ must either be unique, or, for every $l = 1, ..., n$, it must satisfy the constraints with $\varepsilon_i = f_i(x^*)$, for all $i = 1, ..., n$ and $i \neq l$. Since the uniqueness is difficult to prove, we pursue to meet the latter condition and provide detailed results in Section 6.

6 Results

In this section, we provide a rigorous analysis of the problem at hand. First, we present the single-objective results to get an idea of the objective values and the decision variables. Next, we show our results of three chosen solution methods, namely the lexicographic, the weighting and the ε-constraint method. Last, we pick one of the obtained solutions and interpret the corresponding decision variable values.

6.1 Single-objective optimizations

Considering each objective separately, we can begin to identify if we have conflicting objectives and also evaluate the optimal values of the objective functions and thereby infer if there is a need for normalization.

We notice that the solutions are very different between the methods and moreover the values of the objective functions are not in the same order of magnitude. We deduce that trying to satisfy these three objectives will not be trivial and will require the normalization of each objective function in order to give them equal importance.

```
x [*,*]
:            Biomass Hydro  Nuclear  PV  Wind    :=
Austria         0       0        0    0    0
France          0       0        0    0    0
Germany         0       0        0    0    0
Italy           0       0        0    0    0
Switzerland     0       0   552360    0    0
;

objf_cost = 16349.9
```

Figure 1: Solution with cost minimization as the objective

```
x [*,*]
:            Biomass Hydro Nuclear      PV    Wind    :=
Austria         0       0      0          0    0
France          0       0      0          0    0
Germany         0       0      0          0    0
Italy           0       0      0          0    0
Switzerland     0       0      0     552360    0
;

objf_opp = 412.273
```

Figure 2: Solution with opposition minimization as the objective

```
x [*,*]
:            Biomass Hydro Nuclear       PV     Wind    :=
Austria         0       0      0          0      0
France          0       0      0    47713.8      0
Germany         0       0      0    50416.4      0
Italy           0       0      0    506801       0
Switzerland     0       0      0          0      0
;

-objf_jobs = 526290
```

Figure 3: Solution with the employment maximization as the objective

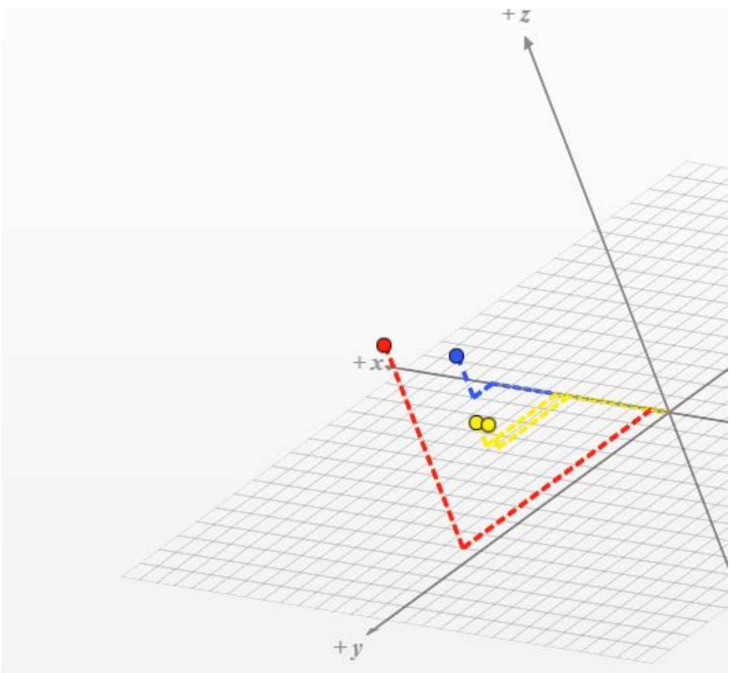


Figure 4: Lexicographic method results in the objective space, x= objf_cost, y= objf_opp and z= objf_jobs

6.2 Lexicographic method

Since we have 3 objective functions there are 3!=6 ways to define preferences. Yet, the 6 cases only provide 4 distinct solutions. In fact, if the priority is based on the cost or opposition of the inhabitants, the sequence in which the two remaining objectives are defined is irrelevant. Furthermore, we notice that if the priority is on cost (red dot), the value of opposition is 10 (the approximate maximum) and inversely if the priority is on opposition (blue dot), the value of cost is maximum, regardless of whether the latter is in second or third priority. The case of job creation is distinct, it does not clearly conflict with either of these objectives. We thus have two distinct solutions according to the different priorities (the two yellow dots). The exact objective values of the six problems an be found in Appendix B, Table 8.

6.3 Weighting method

We start our weighing method analysis with the bi-objective case. For all combinations of objectives (*Cost vs. Opposition*, *Cost vs. Jobs* and *Opposition vs. Jobs*), we iterated over the weights in 0.01 steps. Where required, we conducted an additional fine search to obtain a greater variety of solutions. In particular, this procedure was needed for *Cost vs. Opposition* and *Cost vs. Jobs*.[6] Figures 5a-5c illustrate the set of solutions found. In line with our findings from 6.2, we infer that opposition and jobs objectives don't conflict by much. The objectives of cost and the jobs seem also to be roughly compatible with each other, we find that solutions close to the ideal solution vector (1, 1) are feasible.

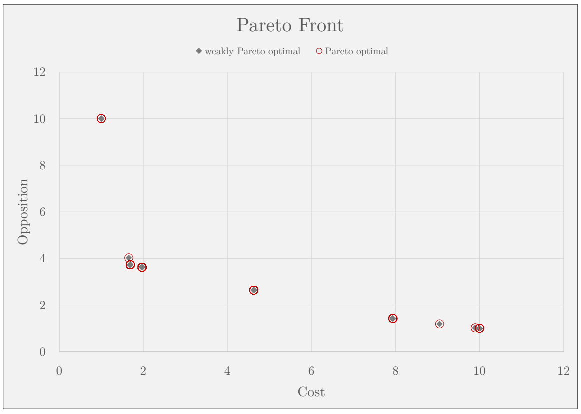
In Figure 5d we depict the results for the optimization of the multi-objective problem with three objectives. For facilitating the visualization, we represent the solutions on a two-dimensional plot between cost and opposition and provide the job objective values as labels of the data points. However, we conclude that conceiving all aspects of the three-objective problem from this plot is difficult and that decision makers might prefer bi-objective visualizations.

6.4 ε-constraint method

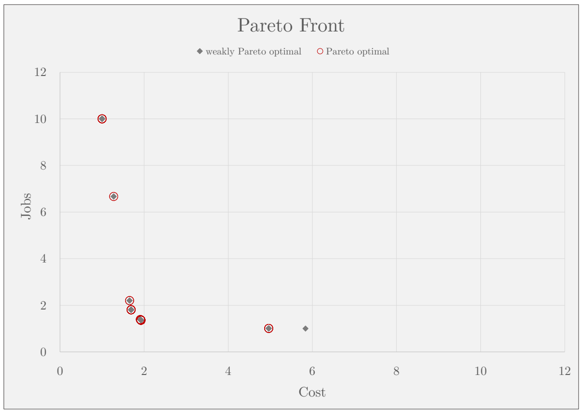
Figure 6 depicts the results from the ε-constraint method. Even though this method is theoretically able to find all Pareto-optimal solutions, in practice we might miss some of them because we can't conduct the method for all possible ε. For this reason, the obtained plots still might show sparse regions. However, they are much more complete than the solutions from the weighting method and hence we obtain already a good characterization of the problem at hand.

As an example, we examine the solution of the bi-objective problem *Cost vs. Jobs* from Figure 6b. The Pareto front starts at the cost-optimal point (1, 10) where it begins to fall steeply. That is, we can optimize the jobs easily while causing only a minor amount of additional costs. This steep decline is followed by a short period of moderate gradients. In this region, cost and jobs can be counterbalanced at similar scale. As we reach a job objective of roughly 1.4, the Pareto front shows a very flat tail, meaning that a further optimization of jobs comes with a stark increase in costs. The kinks typically reflect a significant change in the decision variables. The values of the x-variables at the four kink points documented in Figure 7 let us conclude that the characteristics of the Pareto Front for *Cost vs- Jobs* are induced by choosing between nuclear and solar power technologies.

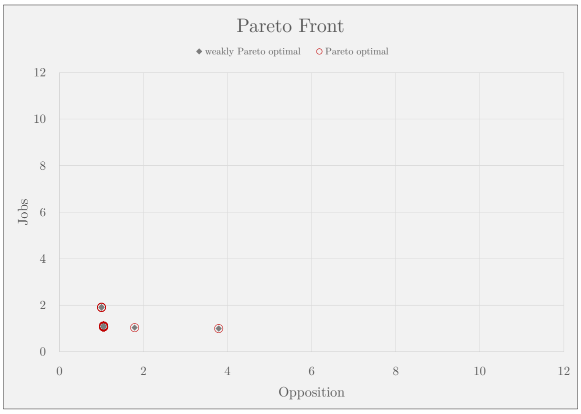
[6] See also the AMPL code provided.



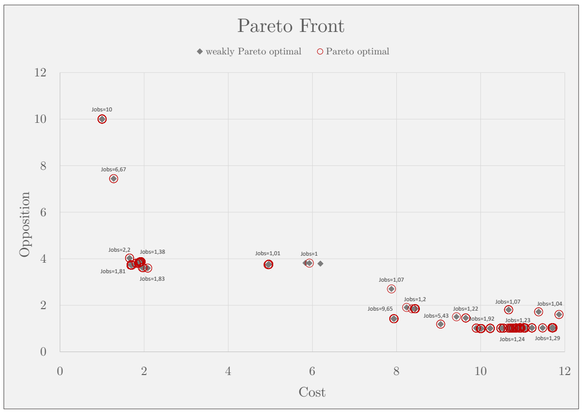
(a) Bi-objective Cost vs. Opposition



(b) Bi-objective Cost vs. Jobs

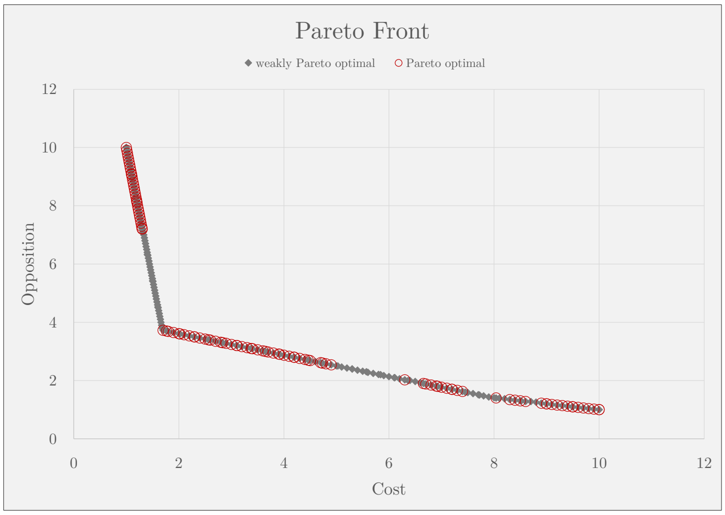


(c) Bi-objective Opposition vs. Jobs

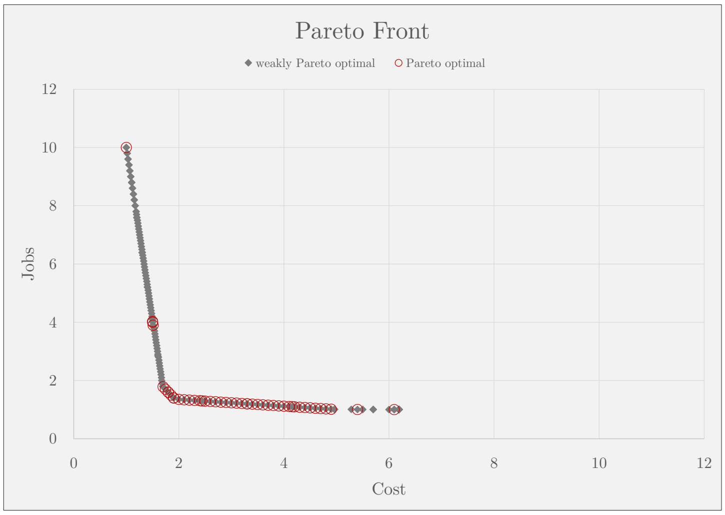


(d) All objectives

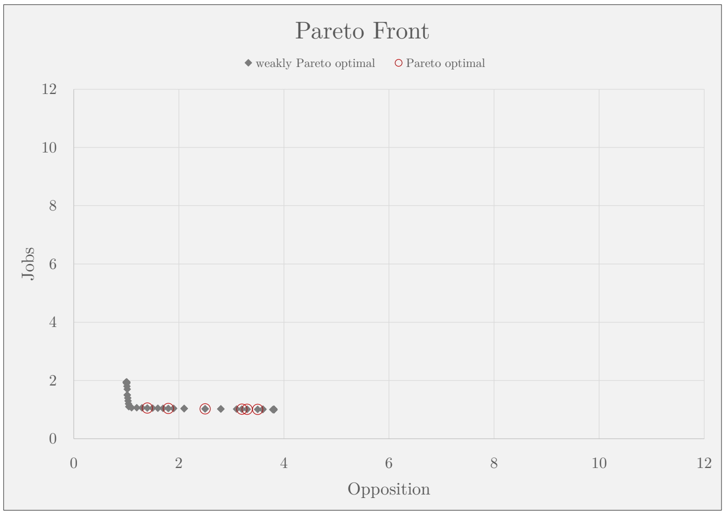
Figure 5: Pareto optimal points obtained by the weighting method.



(a) Bi-objective Cost vs. Opposition



(b) Bi-objective Cost vs. Jobs



(c) Bi-objective Opposition vs. Jobs

Figure 6: Pareto optimal points obtained by the ε-constraint method.

```
Decision Variables
x [*,*]
:             Biomass Hydro Nuclear      PV    Wind    :=
Austria          0      0      0          0     0
France           0      0      0          0     0
Germany          0      0      0          0     0
Italy            0      0      0          0     0
Switzerland      0      0      0     552360     0
;
```

(a) Point (6.1, 1.0)

```
Decision Variables
x [*,*]
:             Biomass Hydro Nuclear      PV     Wind    :=
Austria          0      0      0          0      0
France           0      0      0     560017      0
Germany          0      0      0          0      0
Italy            0      0      0    25418.6      0
Switzerland      0      0      0          0      0
;
```

(b) Point (2.1, 1.34)

```
Decision Variables
x [*,*]
:             Biomass Hydro   Nuclear      PV    Wind    :=
Austria          0      0       0           0     0
France           0      0       0      564677     0
Germany          0      0       0           0     0
Italy            0      0       0           0     0
Switzerland      0      0    724.051        0     0
;
```

(c) Point (1.75, 1.7)

```
Decision Variables
x [*,*]
:             Biomass Hydro  Nuclear  PV Wind    :=
Austria          0      0         0    0   0
France           0      0         0    0   0
Germany          0      0         0    0   0
Italy            0      0         0    0   0
Switzerland      0      0    552361    0   0
;
```

(d) Point (1.0, 10.0)

Figure 7: Decision variables x at the kinks of the Pareto Front from Figure 6b (*Cost vs. Jobs*). The minimal costs are achieved by building solely nuclear power plants in Switzerland, whereas the optimal jobs requires the full deployment of solar power. The region of moderate gradients is characterized by a mixture of technologies and countries.

6.5 Solution selection

Now, we take the perspective of the decision maker. Being equipped with the analysis above, we have to pick a policy assuming that no other factors play a role on optimal energy system expansion and that we have full control on the future development.

From Section 6.1, we get a first idea of the magnitudes of the distinct objectives and how they translate into the normalized scale. Section 6.2 suggests that the cost and opposition minimization are the most conflicting objectives which is in line with our prior expectations. In fact the jobs criterion seems to be partially linked to the other two objectives. This rationale is also supported by the results from the weighting method in Section 6.3. Additionally, we see that trying to conceive three objectives at once is a challenging task for the decision maker, even with visual support. For these reasons, we select a solution based on the bi-objective optimization problem between costs and opposition. We stick with the solutions from the ε-constraint method because they offer the most complete picture.

Since we can deal with moderate levels of opposition and rather want to minimize costs at first place, we decide for the solution at the kink of the Pareto-Front in Figure 6a with normalized values of 1.70 (Cost) and 3.725 (Opposition). We finally calculate the detailed characterization of the solution, see Figure 8. From this, we can see that the optimal policy x would consist of an enormous expansion of PV capacity in France, supported by some biomass and nuclear power in Switzerland. This would also require massive energy exports y from France to all other countries.

The results from our basic model is likely not to be a realistic path to carbon-free energy autarky of the countries considered. For instance, France has probably neither

```
Denormalized objectives
Cost:           18944.719840    [million $]
Opposition:     0.005875        [percentage of total population opposing to this policy]
Jobs:           484958.318266   [Jobs per year assured by this policy]

Decision Variables
x [*,*]
:              Biomass Hydro   Nuclear     PV    Wind    :=
Austria           0       0      0           0    0
France            0       0      0       557076   0
Germany           0       0      0           0    0
Italy             0       0      0           0    0
Switzerland    1145.61    0    442.099       0    0
;

y [*,*]
:              Austria    France  Germany   Italy   Switzerland    :=
Austria        53278         0        0        0        0
France         25336.8    518970   304619   236971     11.5413
Germany          0           0    300600       0        0
Italy            0           0        0    107655       0
Switzerland      0           0        0        0    67509.7
;

z [*,*]
:            Austria France Germany Italy Switzerland    :=
Austria         1      0       1      1        1
France          1      1       1      1        1
Germany         0      0       1      1        0
Italy           0      0       0      1        0
Switzerland     0      0       1      1        1
;

Total yearly energy production added: 558663.392024 [GWh]
```

Figure 8: Final solution selected

the area nor the power lines available for the huge amount of PV power production and transportation. There are several reasons why our model fails to select a realistic solution in this basic version. First, we didn't include important determinants such as spacial availability and power line capacity. Second, due to limited data on opposition, we had to assume that the public opinion on solar, wind, biomass and hydro energy is equal in all countries. From that perspective, it is reasonable that the optimal solution locates nuclear power, the commonly most opposed but cheapest technology, in the smallest country Switzerland which accounts only for 3.37 % of the total population. More precise data could help by allowing for diversification according to country-specific preferences.

Nevertheless, we emphasize that, compared to the single-objective cost minimization, the solution has totally changed. This suggests that including public opinion measures into energy system decisions may be very important, opening new paths for a less opposed energy system transition.

7 Conclusion

In our research project, we included a new objective dimension to energy system design optimization, namely the public opinion measure *opposition*. This is important since public opposing movements may pose problems to the expansion of the European energy system, as already experienced by, e.g., the German wind energy sector [26]. As the share of renewable energies in the energy system rises, these technologies will become more salient to the public. This is likely to increase the need for including public opinion measures into system design decisions.

To this end, we pursued three approaches for multi-objective optimization from [25], namely the lexicographic, the weighting and the ε-constraint method. We explored the strengths and weaknesses of each approach and presented an exemplary solution selection procedure. Moreover, we showed that the inclusion of public opposition criteria has significant effects on the optimal energy system design which might be important to consider for speeding up the transition of the European energy system.

However, our results suffer from strong model assumptions and limited data availability on opposition. Hence there remain several challenges for future research. First, due to difficult data retrieval, we did not include important restrictions, for instance a restriction on the maximum production of each country. Second, we did not consider the stochastic effects of renewable energy supply. Since the system design should be robust to rare events, the integration of stochastic elements and an extensive robustness analysis would be interesting. And third, due to a lack of data we assumed public opposition on biomass, solar, wind and hydro technologies to be equal across countries. Gathering country- or region-specific data for all members of the European energy grid might be crucial to the reliability of the optimal solution.

References

[1] Gregor Czisch. “Szenarien zur zukünftigen Stromversorgung, kostenoptimierte Variationen zur Versorgung Europas und seiner Nachbarn mit Strom aus erneuerbaren Energien”. PhD thesis. 2006.

[2] Yvonne Scholz. “Renewable energy based electricity supply at low costs: development of the REMix model and application for Europe”. PhD thesis. 2012.

[3] David P Schlachtberger et al. “The benefits of cooperation in a highly renewable European electricity network”. In: *Energy* 134 (2017), pp. 469–481.

[4] David P Schlachtberger et al. “Cost optimal scenarios of a future highly renewable European electricity system: Exploring the influence of weather data, cost parameters and policy constraints”. In: *Energy* 163 (2018), pp. 100–114.

[5] Kaisa Miettinen. *Nonlinear Multiobjective Optimization.* Vol. 12. International Series in Operations Research & Management Science. Springer US, 1998.

[6] Arturo Alarcon-Rodriguez et al. “Multi-objective planning of distributed energy resources: A review of the state-of-the-art”. In: *Renewable and Sustainable Energy Reviews* 14.5 (2010), pp. 1353–1366.

[7] Tyler Perini et al. “A criterion space method for biobjective mixed integer programming: The boxed line method”. In: *INFORMS Journal on Computing* 32.1 (2020), pp. 16–39.

[8] Matthias Ehrgott and Xavier Gandibleux. “Multiple Criteria Optimization: State of the Art Annotated Bibliographic Surveys”. In: (2002).

[9] Rob Van Haaren and Vasilis Fthenakis. “GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): Evaluating the case for New York State”. In: *Renewable and sustainable energy reviews* 15.7 (2011), pp. 3332–3340.

[10] Sultan Al-Yahyai et al. “Wind farm land suitability indexing using multi-criteria analysis”. In: *Renewable Energy* 44 (2012), pp. 80–87.

[11] Juan M Sánchez-Lozano et al. “Geographical Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) methods for the evaluation of solar farms locations: Case study in south-eastern Spain”. In: *Renewable and sustainable energy reviews* 24 (2013), pp. 544–556.

[12] Meryem Tahri et al. “The evaluation of solar farm locations applying Geographic Information System and Multi-Criteria Decision-Making methods: Case study in southern Morocco”. In: *Renewable and Sustainable Energy Reviews* 51 (2015), pp. 1354–1362.

[13] Alexis Tantet et al. “e4clim 1.0: The Energy for a Climate Integrated Model: Description and Application to Italy”. In: *Energies* 12.22 (2019).

[14] Jean-Nicolas Louis et al. “A multi-objective approach to the prospective development of the European power system by 2050”. In: *Energy* 191 (2020), p. 116539.

[15] Jed J. Cohen et al. “Re-focussing research efforts on the public acceptance of energy infrastructure: A critical review”. In: *Energy* 76 (2014), pp. 4–9.

[16] Fernando Ribeiro et al. “Public opinion on renewable energy technologies in Portugal”. In: *Energy* 69 (2014), pp. 39–50.

[17] Jaesun Wang and Seoyong Kim. “Comparative analysis of public attitudes toward nuclear power energy across 27 European countries by applying the multilevel model”. In: *Sustainability* 10.5 (2018), p. 1518.

[18] Valeriya Azarova et al. “Designing local renewable energy communities to increase social acceptance: Evidence from a choice experiment in Austria, Germany, Italy, and Switzerland”. In: *Energy Policy* 132 (2019), pp. 1176–1183.

[19] European Commission. *Europeans’ attitudes on EU energy policy.* URL: `https://ec.europa.eu/commfrontoffice/publicopinion/index.cfm/survey/getsurveydetail/instruments/special/surveyky/2238`.

[20] Geraint Ellis and Gianluca Ferraro. “The social acceptance of wind energy”. In: *Where we stand and the path ahead. JRC Science for policy report. European Commission, Brussels* (2016).

[21] Our World In Data. *Levelized cost of energy by technology.* URL: `https://ourworldindata.org/grapher/levelized-cost-of-energy?tab=table&stackMode=absolute&time=earliest..latest&region=World`.

[22] IEA. *Levelised Cost of Electricity Calculator.* URL: `https://www.iea.org/articles/levelised-cost-of-electricity-calculator`.

[23] Paula Díaz et al. “Do We Need Gas as a Bridging Fuel? A Case Study of the Electricity System of Switzerland”. In: *Energies* 10.7 (June 2017), pp. 1–15.

[24] Daniel M. Kammen Max Wei and Shana Patadia. *Putting renewables and energy efficiency to work: how many jobs can the clean energy industry generate?*

[25] Claudia D’Ambrosio. *Decision Theory, with applications in energy systems.* Lecture notes. École Polytechnique, Département d’Informatique, 2021.

[26] Epoch Times. *Widerstand von den Anwohnern: Ausbau der Windkraft fast zum Erliegen gekommen.* URL: `https://www.epochtimes.de/politik/deutschland/`

widerstand-von-den-anwohnern-ausbau-der-windkraft-fast-zum-erliegen-gekommen-a2965126.html.

[27] IEA. *Explore energy data by category, indicator, country or region.* URL: https://www.iea.org/data-and-statistics/data-tables?country=GERMANY&energy=Electricity&year=2018.

[28] Eurostat. *Energy balance flow.* URL: https://ec.europa.eu/eurostat/cache/sankey/energy/sankey.html.

[29] IEA. *Switzerland.* URL: https://www.iea.org/countries/Switzerland.

Appendix A Supplementary data

Table 5: Distance between countries in 1000km

	France	Italy	Switzerland	Austria	Germany
France	0	1.214	0.552	1.101	0.92
Italy	1.214	0	0.984	0.879	1.297
Switzerland	0.552	0.984	0	0.605	0.602
Austria	1.101	0.879	0.605	0	0.608
Germany	0.92	1.297	0.602	0.608	0

Distances were approximated using Google Maps pedestrian navigation distances between two respective countries.

Table 6: Initial yearly production in GWh

	PV	Wind	Biomass	Hydro	Nuclear
France	10569	28599	6132	70590	412942
Austria	1438	6030	4594	41216	0
Switzerland	1944	0	663	37802	25513
Germany	45784	109951	44717	24143	76005
Italy	22654	17716	16782	50503	0

Source: [27]

Table 7: Country-specific electricity demand and population

Country	Electricity demand [GWh]	Population [million people]
France	518970	66,76
Austria	77544	8,822
Switzerland	67521	8,484
Germany	594423	82,79
Italy	333607	60,48

Source: [28], [29]. For the population measure, we relied on the respective official sources from each country.

Appendix B Supplementary results

Table 8: Detailed results for the lexicographic method

Priorities	1. Cost 2. Opp 3. Jobs	1. Cost 2. Jobs 3. Opp	1. Opp 2. Cost 3. Jobs	1. Opp 2. Jobs 3. Cost	1. Jobs 2. Cost 3. Opp	1. Jobs 2. Opp 3. Cost
Objective value *Cost*	1	1	10	10	5.67	6.36
Objective value *Opp*	10	10	1	1	3.74	3.73
Objective value *Jobs*	8.68	8.68	1.78	1.78	1	1