How much flexibility is available for justice in the energy transition? - A global sensitivity analysis of national CO_2 targets

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Abstract

The transition of the European energy supply towards a zero-emission future should be efficient, fair, and preferably fast. The efficiency of the transition is ensured by the European Emissions Trading System, where emission allowances are traded, allowing market forces to operate. The free market forces are moderated to account for fairness by national targets on emission reductions determined by the Effort Sharing Regulation. These two pieces of legislation are the backbone of the transition of the European energy supply, attempting to balance the trade-off between efficiency and fairness. In this work, 30.000 Monte Carlo simulations of national emission targets dispositions has been performed and evaluated using an advanced energy system optimization model of the European electricity supply for the model year 2030. Results reveal a group of countries where emission reductions beyond the national targets are economically favorable in most scenarios. On the other side, there are countries where large abatement costs are unavoidable. An efficient transition may be achieved by allowing large emissions where abatement costs are high and reducing emissions to almost zero in countries with good renewable resources.

Main text

Introduction

The European Green Deal raises the ambition level for decarbonization of the European energy sector, in combination with goals of ensuring a just transition [1]. The quality of a just transition is, however, not easily measured and has in recent years become a topic of much debate [2, 3]. Emissions from the energy sector are currently governed by the EU Emission Trading System (EU ETS) [4], operating on the cap-and-trade principle, requiring that all power generators in Europe buy emission allowances. The Just Transition Mechanism combined with the Just Transition Fund is introduced to ensure equity in the transition [5]. Since 2013, a fixed amount of emission allowances has been auctioned off to power plants each year, thereby putting a price on CO_2 emission encouraging a reduction of emissions [6]. By controlling the number of quotas on auction every year, the EU ETS is capable of controlling the overall rate of emission reductions of the EU member states. The rate of emission reductions is governed by the recently accepted 2030 Climate Target plan, where the European Union commits to reducing emission by 55% by 2030 [7]. The burden of reducing emissions is shared among EU member states by setting national reduction targets. The Effort Sharing Regulation [8] translates the combined 55% reduction target into national targets for the member states. The national targets are based on Member States' relative wealth, measured by gross domestic product (GDP) per capita, and are put in place to ensure a just transition [8].

The European power sector is on the verge of a major transition from a fossil-based system to reliance primarily on renewable resources [9]. However, the starting line is far from straight, with some countries already relying heavily on carbon-neutral energy sources, and other countries still heavily reliant on fossil fuels [10]. The transition of the national energy supply can be encumbered by several factors of a technical, economic or political character. The availability of renewable resources [11], currently installed plants, and strengths of international transmission connections [12] are a few of the technical challenges. Figure 1 a) shows the capacity of plants installed today that are expected to be in operation in 2030. It is clear, that the starting point for rapid decarbonization of the energy supply is very diverse, with some countries relying heavily on coal and oil, and other countries having already installed some extend of renewable energy generators. Figure 1 b) shows the effective renewable potentials, calculated as the geographical potential times the average capacity factor (reference for geographical potentials). The figure clearly shows how the distribution of renewable potentials far from follow neither country sizes nor energy demands. The vastly different starting points of the member states should be capture by the EU ETS in the Effort Sharing Regulation [8] if a just transition is to be achieved.

The use of a single global CO_2 price is argued by economists to be the most effective way of achieving emission reductions [13]. Relying solely on a global CO_2 price, justice of the transition can not be ensured. Sovacool [14] argues that there is a need to move towards human-centered exploration of the energy transition if fairness is to be ensured. Distributing the global carbon budget to ensure equity is however a difficult task with many outcomes. In a review by P. Zhou [15] a range of allocation schemes based on different philosophies is identified. Some of the principal considerations in the allocation schemes are sovereignty, egalitarianism, efficiency, horizontal equity, vertical equity and polluter pays. Other studies combine these philosophies to create more complex allocation schemes, such as the Model of

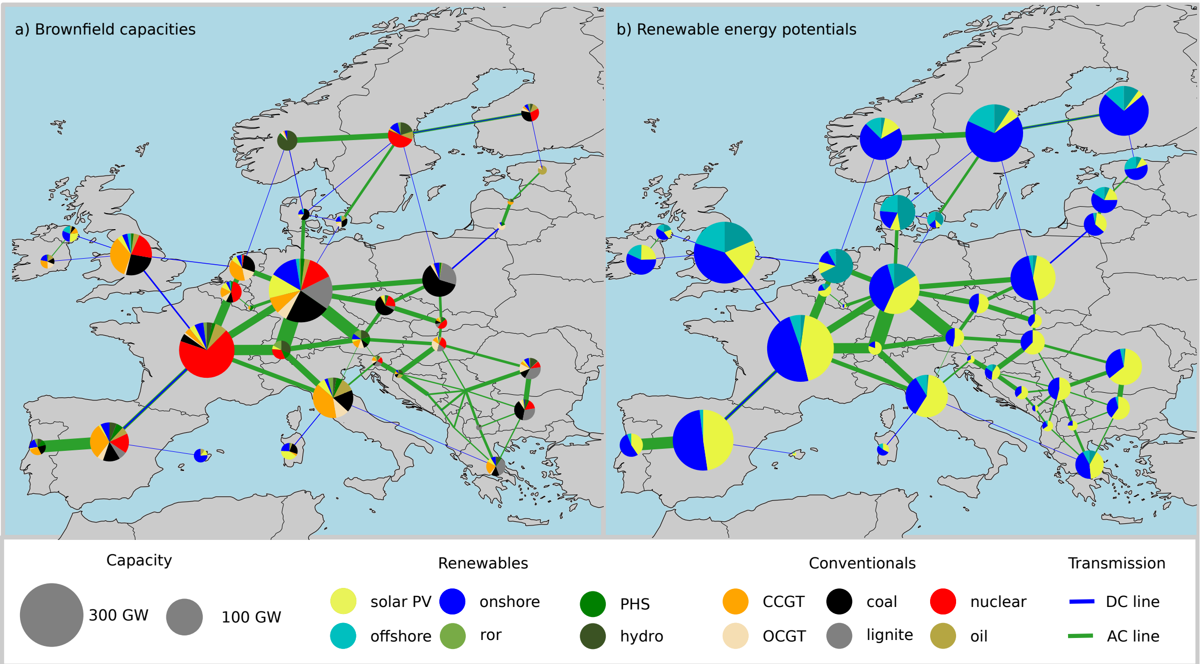

Figure 1: a) The currently installed technology capacity that will be in service in 2030. b) Effective renewable energy potentials. Calculated as the maximum geographical potential times the local capacity factor for the given technology. Wind turbine capacity is specified as offshore and onshore. Hydroelectric power is separated as either run-of-river (ROR), pumped-hydro-storage (PHS), and hydro. ROR has no storage capability, whereas PHS and hydro has a reservoir and PHS further has the capability of filling the reservoir. Two types of gas-turbines are included. These closed-cycle-gas-turbines (CCGT) and open-cycle-gas-turbines (OCGT). Transmission capacities are indicated either as high voltage AC or DC transmissions lines.

Climate Justice per capita [16], where historical emissions along with population growth are considered. Choosing a single ”right” allocation scheme is inherently difficult as it isn't a question about costs but rather one of morality [17]. A study by psychologist E Markowitz [18] even states that the human moral is ill-equipped to make this decision given the complexity of the problem, and our own complicity in causing it. In a conceptual review, Jenkins et. al. [2] identified three core tenants of energy justice: Distributional, recognition, and procedural. Distributional justice recognizes the unequal distribution of environmental benefits and will be the core focus of this work.

In a study by Schwenk-Nebbe et. al. [19], three effort sharing schemes for selecting national CO_2 targets are studied in a European context. In the paper, emissions are allocated based on cost efficiency, sovereignty (local-load), and grandfathering (local-1990). The efficiency scenario utilizes a global CO_2 price, the sovereignty scenario allocates emissions proportional to national electricity demand, and the grandfathering scenario allocates emissions proportional to historical emissions. These three scenarios will also be referenced throughout this work. In the paper Schwenk-Nebbe, et. al. finds that the ”Efficiency” solution leads to the placement of emissions in a small selection of countries where the cost of decarbonization is highest. Allocating emissions after the "Sovereignty" or "Grandfathering" principle will distribute emissions more uniformly, but lead to uneven CO_2 abatement costs and higher total system cost. Bauer et. al. [20] have studied the trade-off to be made between economic efficiency and sovereignty in a global context using a multi-objective approach. Their findings indicate a highly non-linear trade-off between efficiency and sovereignty, indicating that choosing an intermediate scenario will lead to an increased sum of total benefits. The studies by Schwenk-Nebbe and Bauer [19, 20] do, however, only analyze a fraction of the possible ways national CO_2 reduction targets can be distributed. As found in [15], there are numerous philosophies that can be applied towards effort sharing resulting in a vast number of emission distribution schemes.

In this work, a Markov Chain Monte Carlo (MCMC) method [21] will be employed in combination with a techno-economic optimization model of the European power supply to study a broad range of CO_2 target dispositions. The allocation dispositions come in the form of a set of national emission reduction targets for the model countries. Two criteria are required of the CO_2 target dispositions. First, a combined CO_2 reduction of at least 55% must be achieved by the model countries according to the EU 2030 Climate Target Plan [7]. Second, the total system cost of enforcing the CO_2 target disposition must not increase by more than 18% relative to the cost-optimal allocation of national targets. This constraint is based on the principles from Modeling to Generate Alternatives (MGA) where economically near-optimal model solutions are studied [22]. Applying MGA methods to energy system optimization models has gained a lot of attention. The method is, however, mainly used to study technical flexibility among the near-optimal solutions [23]. The method employed in this work consists of two steps. First, using an MCMC method to draw a random set of national CO_2 reduction targets for the model countries. Second, the total system cost and combined CO_2 reductions of the CO_2 target disposition are then evaluated using an energy system optimization model. If the CO_2 target disposition satisfies the two above-mentioned criteria, it is accepted and stored. If not, the CO_2 target disposition is rejected. This process is iterated until a sufficient sample size is obtained. The result is a set of CO_2 target dispositions that resembles all possible CO_2 target dispositions that will satisfy the two criteria.

The novelty of this work lies in the combination of an energy system optimization model and MCMC methods to study possible CO_2 target dispositions in a European context. Where previous studies have used scenario-based modeling or multi-objective optimization to study a small range of possible solutions, the method applied in this work is capable of identifying a much larger range of possible scenarios. Furthermore, detailed information about each CO_2 target disposition is obtained as the energy system optimization model is solved for each allocation scheme.

Method

The aim of this paper is to analyze the impact of changing national CO_2 targets and their effect on the European power system. Feasibility of the CO_2 target dispositions is accomplished if a disposition satisfies the criteria listen in Table 1. In addition to the two previously mentioned criteria, it is further required the energy system optimization model is solvable under the target disposition and national emission must not surpass the equivalent emissions of covering 150% of national energy demand with coal power. These additional criteria prevent very unrealistic scenarios from being found feasible.

To draw possible CO_2 target dispositions a modified version of the Adaptive Metropolis-Hastings (AMH) sampler is used [21]. The sampler falls under the broad umbrella of MCMC samplers. Using the AMH sampler to efficiently sample possible CO_2 target dispositions, and rejecting the dispositions considered infeasible, it is possible to approximate the distribution of feasible CO_2 target dispositions. The sampled variables are the national CO_2 reduction targets for the model countries. Using the AMH sampler, distributions approximating the distributions of all feasible CO_2 target dispositions are obtained. A detailed description of the sampler is available in the appendix.

The sampled CO_2 target dispositions are evaluated using an energy system optimization model of the European power sector. The model uses the PyPSA-Eur-sec framework [24] to define a model spanning 33 ENTSO-E member countries. A 2030 brownfield scenario is modeled, where all installed generator capacities as of 2019 that are expected to be in operation in 2030 are included. To cover energy demands the model will install new generation capacity, where it is economically optimal. Model countries are the EU-27 excluding Cyprus and Malta, but including Great Britain, Norway, Switzerland, Serbia, and Bosnia and Herzegovina. The model uses a one node pr. power trading region setup, with the nodes connected by high voltage AC and DC lines. Using one year of energy demand and weather data resolved in hourly time-steps, the model determines the cost-optimal power flows and investment in new generator capacity. Transmission line capacities included in the model are the currently installed capacities, plus the planned capacities from the Ten Year Network Development Plan (TYNDP) [25]. The energy-generating technologies included are run-off-river, onshore wind, offshore wind, solar PV, CCGT, OCGT, coal, lignite, nuclear, and oil. Furthermore, two storage technologies are included. These are hydrogen and battery storage. The technology parameters are found in Table 4. A brownfield scenario is used where existing technology capacities still in operation in 2030 are included. Brownfield capacities are seen in Figure 1 and in Table 5. The national CO_2 reduction targets given by the AMH sampler are included in the model, limiting the CO_2 emissions from energy generation in the model countries. Model countries are free to overperform on the national CO_2 reduction target if it is economically favorable.

Technology cost predictions for 2030 are used for all expandable generator types. All technology costs can be found in Table 3. Hourly energy demand and weather data from 2013 are used. 2013 is chosen as the reference year, as the demand and weather profile is a good representation of an average year. Weather and demand patterns are expected to change as a result of global warming and general electrification of energy use. Investigating these effects is, however, beyond the scope of this paper. A single model evaluation can be completed in approximately 15 minutes on a 4 core machine with sufficient memory.

By evaluating the result of the energy system optimization model for a given CO_2 target disposition it is possible to determine if the target disposition fulfills the criterion's in Table 1. The CO_2 target dispositions can then be accepted or rejected bases on the result.

Throughout the results, there will be referred to five national CO_2 target strategies. Based on the strategies described in [15], these are grandfathering, sovereignty, efficiency, egalitarianism, and ability to pay. The interpretation and rule for the distribution of emissions for the strategies are found in Table 2

Table 1: CO_2 disposition scheme feasibility criterion's

a)	Combined CO_2 reductions must be equal or grater than 55%.
b)	Total system cost of the scenario does not surpass the cost of the cost optimal scenario + 18%
c)	A technically feasible solution to the model exists.
d)	National emissions must be less than the equivalent emissions of covering 150% of national energy demand with coal power

Table 2: Strategies for CO_2 target disposition

Name	Interpretation	Rule
Grandfathering	All nations have equal right to pollute	Distribute emissions proportional to historic emissions
Sovereignty	All nations have equal right to pollute	Distribute emissions proportional to energy production
Efficiency	Maximize global welfare	Distribute emissions to reduce total socio-economic costs
Egalitarianism	All people have equal right to pollute	Distribute emissions proportional to population size
Ability to pay	Nations with higher welfare should take on a larger part of the task	Distribute emissions inversely to GPD per population

Results

Applying the described MCMC method, a total of 30.000 random dispositions were drawn, with an acceptance rate of 80%. All samples were saved allowing for analysis of emitted CO_2, technology investments, power prices, etc. Solving the optimization problem 30.000 times, requiring 15 minutes each, was performed using 10 parallel threads, resulting in roughly 30 days of computation.

In Figure 2, the global CO_2 emission from all samples is shown, plotted against the total system cost of the samples. The reference scenario (Efficiency) with the lowest total system cost is indicated with the red cross. The Pareto optimal front was calculated by continuously decreasing the allowed global CO_2 emissions, and is indicated by the blue line.

In the figure, a gap between the Pareto optimal front and the samples can be observed. There is nothing preventing the sampler from drawing samples on the Pareto optimal front, it is, however, very unlikely. Because probability of the sampler drawing the exact combination of the 33 variables that will lead to a Pareto optimal solution is very low. This also shows that the optimal solution is an extreme scenario that is very hard to obtain without extensive collaboration and agreement between model countries. This is, however, not the case as countries have individual national targets and agendas. Therefore, we argue that solutions located in the dark blue regions of Figure 2 can be considered as significantly more probable outcomes, because they can be realized with many different national dispositions.

All CO_2 disposition strategies except the "Efficiency" strategy are seen having a higher CO_2 reduction than what is required. This over-performance on emissions reduction is a result of several countries finding it cost-optimal to reduce emissions beyond their assigned national target. The "Grandfather-

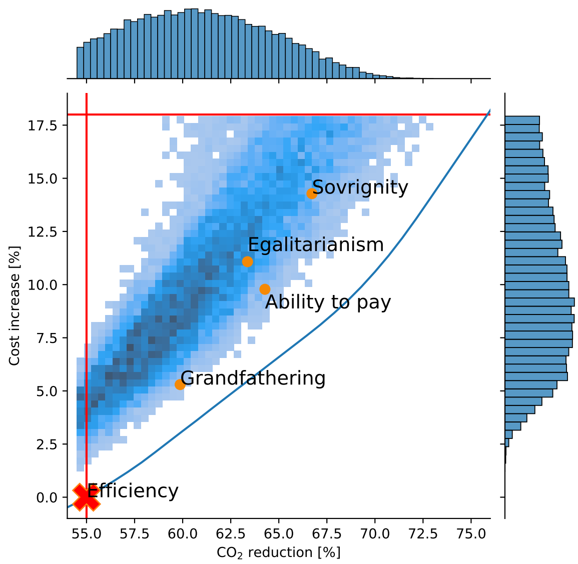

Figure 2: Histogram showing the CO_2 reduction and cost increase of all feasible CO_2 target dispositions. The minimum required CO_2 reduction and maximum allowable cost increase is marked with red lines. The blue line marks the Pareto-optimal front of a dual objective optimization problem using total system cost and CO_2 reduction as the two objective functions. The cost-optimal solution is marked with a red X, and the CO_2 target scenarios Grandfathering, Ability-to-pay, Egalitarianism, and Sovereignty are marked with orange.

ing" and "Ability to pay" schemes are located close to the Pareto-optimal front, whereas the "Sovereignty" and "Egalitarianism" are found to deviate significantly from the Pareto-optimal front.

Looking at the marginal distribution of the global CO_2 reduction, it is clear that the probability of achieving reductions close to the global target (marked by the red line) is more probable than overachieving. The marginal distribution of the system cost reveals that an increase in the total system cost of a minimum 5% relative to the optimal scenario is almost unavoidable, since, to obtain the lowest possible total system cost, the burden of transitioning must be shared in a very exact way. It is, nevertheless, very unlikely that this will happen as countries have different national ambitions. Therefore a cost increase of the entire system is expected. What Figure 2 tells us is that this cost increase with a 75% chance will be above 4.6% and has a 50% chance of being between 4.6% and 12.2%.

Figure 3 shows the emitted CO_2 from the model countries relative to 1990 values and weighted by national energy production. In the figure, emissions from the CO_2 target dispositions are also plotted. As seen in the figure, all countries have zero emissions in one or more scenarios. Countries such as Norway and Sweden have zero emissions in all scenarios. This is not because they are given a very low CO_2 reduction target, but simply because it is cost-optimal to rely fully on renewable or nuclear energy. On the other end, there are countries such as Poland and Macedonia with large emissions pr MWh energy produced. By analyzing the CO_2 target disposition in the "Efficiency" scheme, it is seen that higher than average shares are allocated to countries that generally have high emissions and fewer than average shares to the countries with low emissions. In other words, the "Efficiency" scheme favors assigning low CO_2 reduction targets to countries that have a hard time reducing emissions and cuts emissions drastically in countries where CO_2 reduction is easier. In the "Sovereignty" scenario, CO_2 reduction targets are distributed equally based on the national energy demand. Naturally, a much more even emission pr. unit of produced energy is seen for this scenario. In the "Ability to pay" scenario emissions are distributed inversely to national GDP. This redistribution of emissions in the "Ability to pay" scheme is clearly seen in Figure 3, where wealthy countries such as Germany and the Netherlands have low emissions and countries such as Romania, Macedonia, and Bulgaria have higher emissions.

By analyzing correlations between actual national CO_2 emissions from all the samples, Figure 4 is generated. On Figure 4 a) it is very evident that neighboring countries have a great effect on each other. The strong positive correlation between Sweden and Norway's emissions is however an artifact as these two countries have zero-emission in almost all scenarios. Germany is found to play a central role in the emissions of many central European countries. Strong negative correlations are seen between Germany and the neighbors France, Austria, Denmark, Luxembourg, and the Netherlands. This indicates that in scenarios where Germany has low emissions, the neighboring countries are likely to have higher than average emissions. A likely explanation is that the neighboring countries are providing dispatchable energy when Germany is capable of providing this itself due to tight national CO_2 reduction targets. A cluster of tightly correlated countries is, furthermore, found among the northeastern countries Poland, Estonia, Lithuania, and Latvia. Here Poland appears to be dominating, with strong negative correlations to the three other countries. This reveals a dynamic

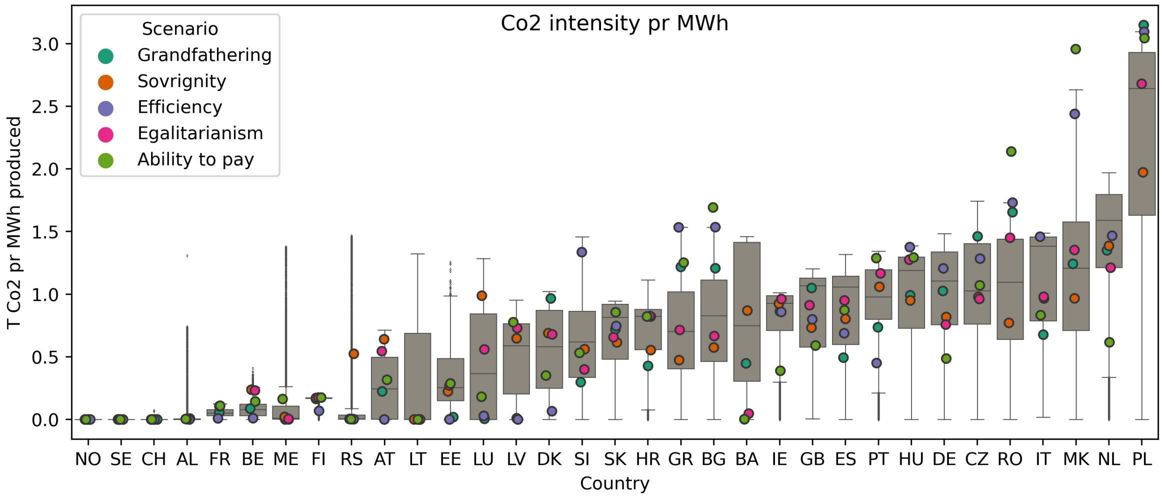

Figure 3: a) National CO2 emissions relative to 1990 values. b) The box-plot displays the emitted CO_2 pr. produced MWh of electricity for all model countries. The two scenarios local-load and local-1990 have been included along with the cost-optimal solution.

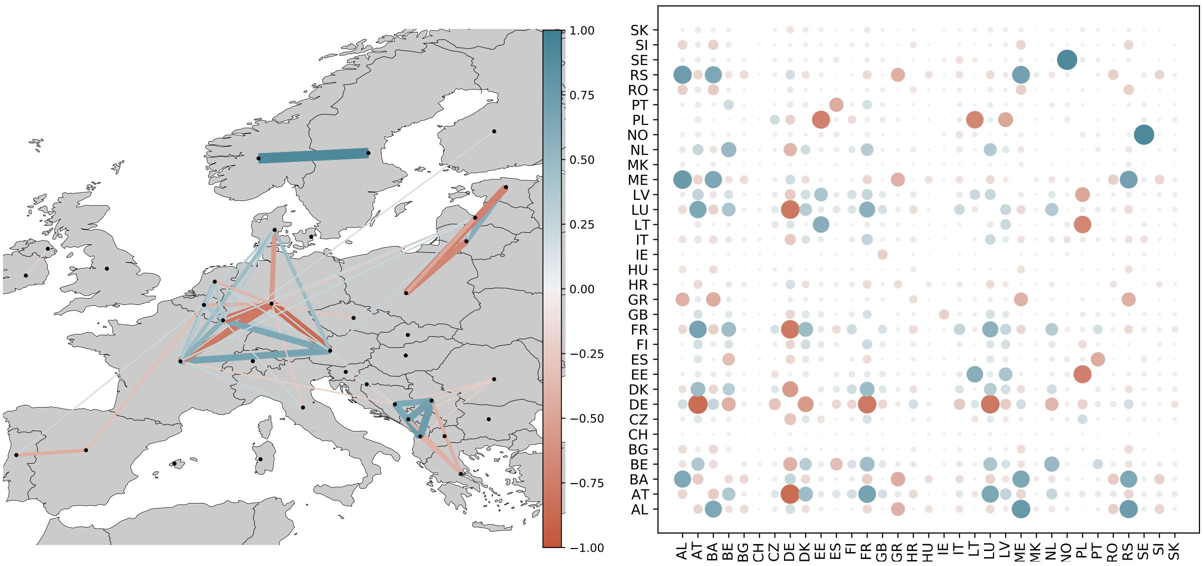

Figure 4: The data used to create this figure is the Pearson correlation of the national CO_2 emission across all samples. a) CO_2 emission correlations shown on a map of the model countries. Correlation strength and direction is indicated by the link color and size. Correlations below 0.2 has been removed for clarity. b) A matrix plot of CO_2 emission correlation for all model countries.

where CO_2 emitting dispatchable energy is moved between these countries depending on where national emission reduction targets are tightened. In this region of Europe renewable, resources are less favorable, and this strong correlation could indicate that the countries located here are strongly dependent on energy from dispatchable resources from each other. Another cluster with similar dynamics is found in southeastern Europe between the countries Greece, Bosnia and Herzegovina, Albania, Montenegro, and Serbia.

In this study, CO_2 reduction targets were assigned to countries giving the countries the option to either use all allowable emission or simply leave them unused if it is found economically optimal. The top panel of Figure 5 shows a box plot of the utilization of the national reduction targets for the individual couturiers across all scenarios. Here, a value of 100% means that the country is emitting as much CO_2 as their reduction target allows, whereas 0% indicates that the country has no emissions although the CO_2 reduction target is not 0. Below the box plot, the reduction target utilization has been plotted against the total amount of target emissions for five example countries. The top panel of Figure 5 clearly shows three distinct behavioral patterns for the countries. The countries either a) emit as much as the national target allows no matter what, b) sometimes overperform on the target or c) never have any emission. These different patterns are clearly highlighted in the lower panels. Where Poland is seen always emitting as much as the national target allows. The Netherlands, Austria, and Finland can be seen over-performing as when they have higher allowable emissions. The curved lines appearing in these figures correspond to the countries "capping-out" at a certain emission level. Finland can be seen having a clear upper bound to how much CO_2 they prefer to emit, whereas Austria appears to have several preferable levels. This behavior is very likely a result of the strong correlation between Austria's emissions with the emission from Germany and France found in Figure 4. In scenarios where Germany is assigned less than their preferred amount of emissions, Austria can provide dispatchable power resources and therefore have higher emissions. In scenarios where Germany and its neighbors have high allowable emissions, the demand for dispatchable resources from Austria drops, and it becomes cost-optimal for Austria not to use all allowable emissions.

Studying how the five CO_2 disposition schemes from Table 2 are distributed on Figure 5 reveals that the "Efficiency" scheme ensures that all national targets are utilized 100%. In the "Efficiency" scheme no country is allocated more emissions than needed, whereas the other disposition schemes result in inefficient allocations increasing total system cost. Especially the "Grandfathering" scheme leads to a large share of allocated emissions being unused. It is important to note that as only the electricity sector is considered in this work, the 55% emission reduction target applied is a bit conservative, considering that the electricity sector is expected to be the first to be decarbonized. As several countries already have decarbonized their electricity sector to a high extend, they will find it economically optimal not to use all the emissions they are allocated. Norway, Sweden, and Switzerland are seen not using any of their allocated emissions in most scenarios. This is compliant with the findings from Figure 3.

Enforcing a national limit on CO_2 emissions naturally entails a price on abating emissions for the given region. In a linear optimization model such as the one used in this paper, the Lagrange multiplier of the national CO_2 constraints serves as a proxy for the national CO_2

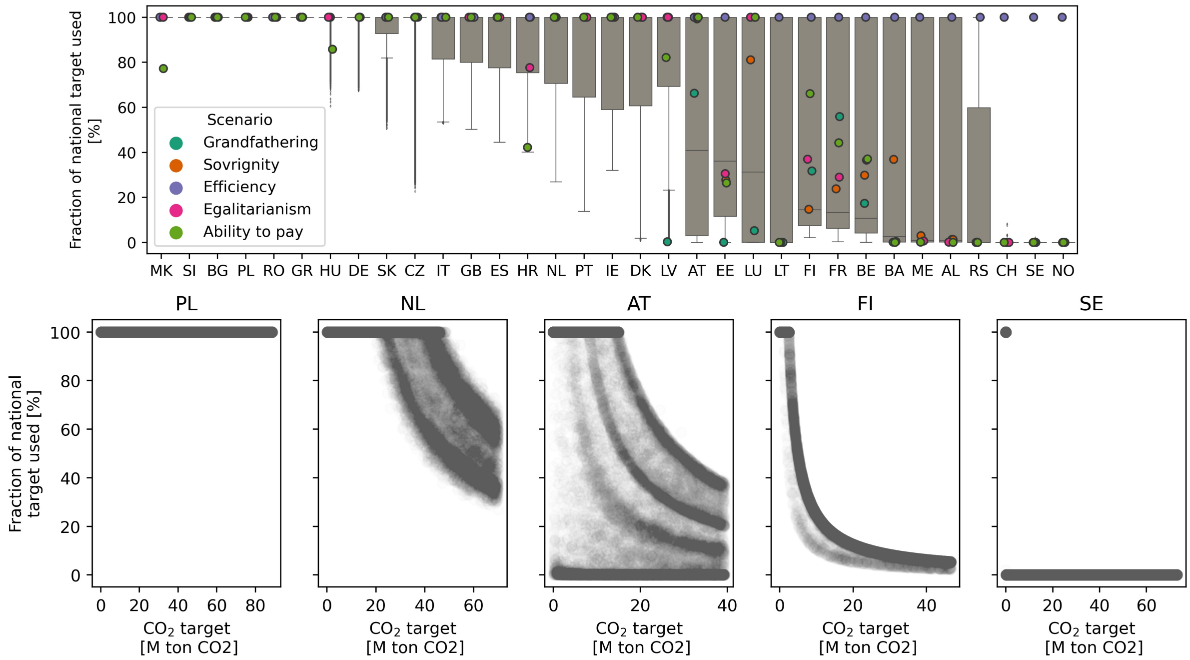

Figure 5: Data from all sample points. a) a box plot of the utilization of the national reduction targets for the individual couturiers across all scenarios. A value of 100% means that the country is emitting as much CO_2 as their reduction target allows, whereas 0% indicates that the country has no emissions although the CO_2 reduction target is not 0. b) Example countries. Reduction target utilization plotted against the total amount of target emissions.

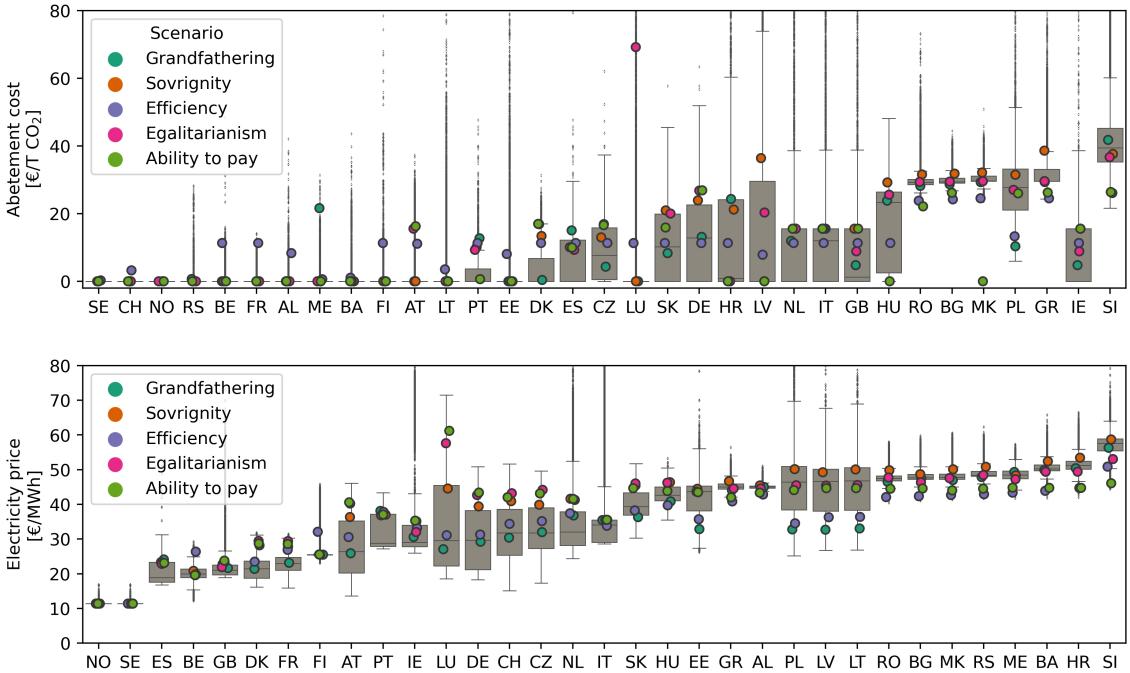

Figure 6: The lower panel shows the average electricity price for the individual countries across all scenarios. The top panel show the national CO_2 price for all countries across all scenarios. The countries are sorted after average emission pr. energy. produced.

abatement cost. The Lagrange multiplier measures the change in objective function value caused by a change in the given constraint. Thus, the Lagrange multiplier associated with the national emission limits measures the increase in total system cost when the given node is constrained on its emissions. CO_2 abatement costs for all modeled scenarios are seen in the top panel of Figure 6. Equivalently, the hourly national electricity price can be found as the Lagrange multiplier value of national energy balance constraints. Average electricity prices are seen on the lower panel of Figure 6. For the formulation of the linear optimization problem, including the national CO_2 constraint and the nodal energy balance constraint refer to the appendix.

CO_2 abatement costs are highly dependent on local CO_2 reduction targets and the availability of renewable resources. An abatement cost will only occur if the national emission reduction constraint is binding. Thus, in a scenario where a given country is only utilizing parts of the allocated CO_2 target, an abatement cost of 0 will be obtained. In Figure 5 it is seen that a large number of the model countries are not utilizing the entire share of allocated emissions. Therefore, CO_2 abatement costs of zero are seen for several countries in many of the scenarios in Figure 6. The group of countries observed to always utilize their allocated emissions on Figure 5, is similarly also seen always having a non-zero CO_2 abatement cost on Figure 6. The abatement cost for these countries are ranging from 30 to 40 €/Ton in most scenarios, but with outliers ranging much higher.

On the top panel of Figure 6 the "Efficiency" scheme is seen having almost similar CO_2 abatement costs for all model countries. The significantly higher abatement costs in the "Efficiency" scheme of the five countries RO, BG, MK, GR, and SI, is caused by the constraint on maximum emissions relative to using only coal power seen in Table 1 (d).

Electricity prices are found to have a smaller spread for the individual countries as seen on the lower panel of Figure 6. The robustness of the power price does, however, depend on the country observed with countries at each end of the figure having more robust prices, and countries towards the center having larger deviations. The countries observed to have constantly high prices are to a large extent the same countries that had high abatement costs. The countries observed to have high fluctuations in the electricity price are also the countries observed having strong correlations in national CO_2 emissions on Figure 4. The observed electricity prices on the lower panel of Figure 6 span from 10 €/MWh all the way to above 70 €/MWh for some outlier scenarios. This span in power prices is rather large compared to current power prices which are around 50 €/MWh for most European countries.

Discussion (Policy implications)

- Only the electricity sector has been modeled in this work where a 2030 scenario is modeled. The effects of sector coupling are only expected to be moderate by 2030, thus this simplification is believed to give a minor source of error. If sector coupling were implemented, the electricity sector is expected to achieve higher decarbonization levels then the 55% target, as the electricity sector is considered as easier to decarbonize than other sectors. Emissions from northern countries, that have achieved a high decarbonization in the electricity sector (Norway, Sweden, Finland) will rise, as they are still relying on oil and gas for heating, industry and transportation.

- 55% target is not very ambitious when only considering the electricity sector. Several studies show that the electricity sector will be the first to decarbonize. Therefore, the electricity sector should have reached higher decarbonization levels by 2030.

- The entire cost of electricity is not captured in the electricity price plots, as brownfield costs are not included in model cost

- Perspective to PRIMES model

- EU ETS/effort sharing scenarios.

Conclusion

In this study a Markov Chain Monte Carlo simulation of 30.000 emission allocation schemes of the European power supply has been performed for the model year of 2030. Results reveal that a cost increase of 5% from the cost-optimal solution is almost inevitable. Furthermore, strong correlation between emissions from three groups of countries located in central, North Eastern, and South-Eastern Europe was identified. These correlation reveal that enforcing a tight CO_2 limit on one cluster country will move emissions to the other countries in the cluster. Analyzing the utilization of allocated emissions reveal a group of countries where it will be economically favorable to decorbonize the power-sector, thus having zero emissions although emissions are allocated to the given country. A large group of countries do however favor some level of emissions from the power sector, but the level of favored emissions do in many cases depend on emissions from neighboring countries. The national CO_2 abatement cost associated with the sampled emission allocation schemes reveal large inequality with some countries being likely to have significantly higher abatement costs. A similar picture is found when studying power prices. The key take-away from this study is the fact that the burden of transitioning our power supply is inequitably distributed, and actions must be taken to compensate.

Appendix

Sampling method

To draw possible CO_2 target dispositions the Adaptive Metropolis-Hastings (AMH) sampler is implemented [21]. The AMH sampler is based around a Markov Chain process where samples are continuously drawn from a proposal distribution centered around the previous sample point. By controlling the width of the proposal distribution continuously the AMH sampler ensures efficient sampling.

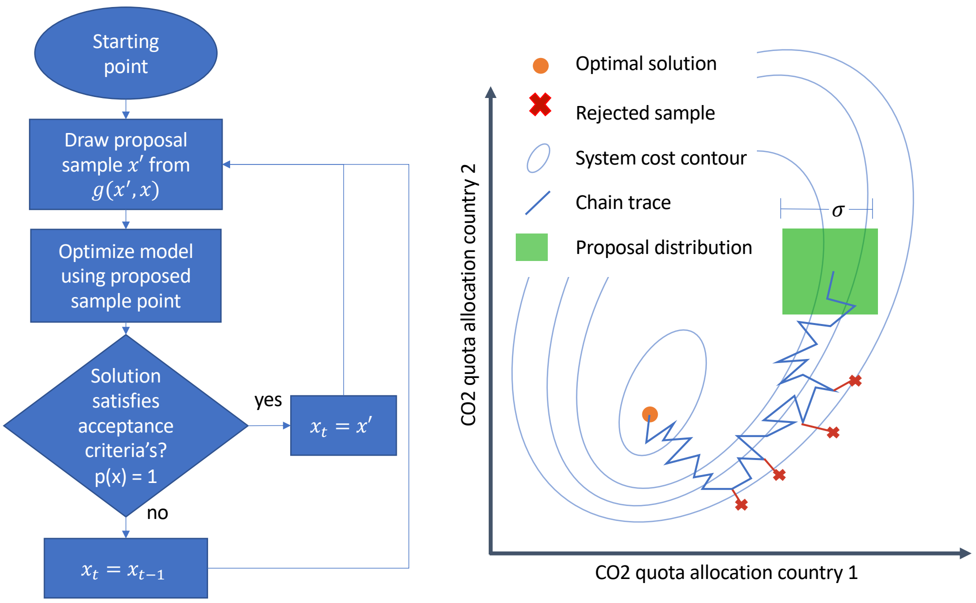

Figure 7: Sampling method schematic

An arbitrary CO_2 target disposition can be denoted as the vector $\mathbf{x}$, with each component of this vector x_i representing the national CO_2 emission target of the i'th country relative to the total CO_2 emission target. The allowed emission for a given country can be determined as $x_i \cdot CO2_{CAP}$, where the $CO2_{CAP}$ is the total global amount of CO_2 emissions allowed in tonnes of CO_2. Realizations of the variables are denoted with subscript $\mathbf{x}_t$.

Given a starting point $\mathbf{x}_0$ the AMH sampler will continuously generate new sample proposals $\mathbf{x}'$. New samples are drawn from the proposal distribution centered around the previous sample. The proposal distribution is defined as a uniform distribution around the previous sample point with the width σ. Thus the maximal change in each variable x_i pr. iteration is $\sigma/2$. There are however a few caveats. As the variables considered $\mathbf{x}$ are fractions of a total CO_2 budget, they are constrained to be between 0 and 1. Therefore, the uniform distribution is bounded not to exceed this area.

$$\mathbf{x}' \sim \mathcal{U}[\max(\mathbf{x}_i - \frac{\sigma}{2}, 0), \min(\mathbf{x}_i + \frac{\sigma}{2}, 1)] \tag{1}$$

The distribution width σ can be tuned continuously as more information about the solutions space i obtained. By setting σ too low, the sampler will need an excessive amount of samples to explore the entire solution space. On the other hand, setting σ too high will result in the rejection of too many samples. By continuously monitoring the acceptance rate, it is possible to determine if the chain is taking either too short or long steps. If the acceptance rate is very high σ should be increased, and if the acceptance rate is low σ should be decreased. In practice, this is implemented by letting the sampler run for a number of iterations and evaluating the acceptance rate in that batch of samples. In this work, an ideal acceptance rate of 75% is chosen. If the realized acceptance rate is higher, σ is decreased and if the acceptance rate is lower than the ideal σ sigma is increased by a fixed amount ϵ. An ϵ value of 0.05 was used throughout this work.

In this implementation of the AMH sampler, σ is updated by continuously monitoring the acceptance ratio of the samples. When the acceptance ratio is below a user-specified value, σ is incremented by a small amount, and vice versa when the acceptance ratio is too high. In this work, a desired acceptance ratio of 80% has been used.

The feasibility of a proposed sample $\mathbf{x}'$ is evaluated using the energy system optimization model. If the solution to the energy system optimization model given $\mathbf{x}'$ as input satisfies all criteria from table 1 the sample is accepted. Otherwise, the sample is rejected and a new proposal sample is drawn. When a proposed sample is accepted it is assigned index i, such that $\mathbf{x}_i = \mathbf{x}'$. If a sample is rejected the previous sample point is stored instead $\mathbf{x}_i = \mathbf{x}_{i-1}$. The process of drawing samples from the proposal distribution and either accepting or rejecting them is repeated until sufficient sample size is reached. The process is illustrated in Figure 7.

The result is a set of realizations of $\mathbf{x}$ that can ensure feasible operation of the model, global emission reductions higher than the base scenario, and a total system cost that is no more than 18% higher than that of the base scenario. If enough samples are drawn the distribution of the set of realizations will approximate all solutions satisfying the above-mentioned criteria.

In practice, the above algorithm is implemented as a parallel process with multiple chains running simultaneously. The samples from the parallel chains can then be merged at the end of the sampling process.

The starting point for all chains is the optimal solutions $\mathbf{x}_1$ is the same. Therefore, the correlation between the chains and auto-correlation within the chains themselves is unavoidable at the start. As these starting samples would skew the result towards the starting scenario, a burn-in period is implemented. By discarding the first samples from the chains any bias towards the start solution is avoided.

Energy system optimization model

The energy system optimization model used in this work is based on the PyPSA-Eur-sec model [24]. The PyPSA-Eur-sec model to a high extend depends on data imports from the PyPSA-Eur model [26]. The model formulated in this work represents a 2030 scenario of the European electricity supply. The model spans the EU-27 countries excluding Cyprus and Malta, but including Great Britain, Norway, Switzerland, Serbia, and Bosnia and Herzegovina. The electricity transmission grid is represented by a one node pr. power trading region network, connected with links representing existing and planned international AC and DC transmission lines. All existing plus the planned transmission capacities in the Ten Year Network Development Plan (TYNDP) [25] is included. (!! Make a figure of transmission capacities !!)

A brown-field scenario is generated where existing capacities that are planned to be in operation by 2030 are included in the model. The included brown-field capacities are seen in Table 5. Existing conventional capacities are found from the power-plant matching database [27], while renewable capacities are found from the IRENA annual statistics [28].

Some technology capacities can be expanded to meet energy demand at a certain cost. Cost of the expandable technologies are given in Table 3. Efficiency and emission data are available in Table 4. Technology costs are primarily based on the 2030 cost prediction given by the Danish Energy Agency in their technology data catalog [29]. A discount rate of 7% has been used to calculate annualized costs using the annuity factor given in Equation 2. Here r is the discount rate and n is the technology lifetime.

$$a = \frac{1-(1+r)^{-n}}{r} \tag{2}$$

The model of the European power sector is formulated as a linear optimization problem, consisting of an objective function along with a set of constraints. Throughout this description of the model, the model variables are split in two vectors namely $\mathbf{x}$ and $\mathbf{y}$. Where $\mathbf{x}$ describes the national CO_2 reduction target given by the MCMC sampler $\mathbf{x} = r_n \ \forall \ n$. Here r_n is the national CO_2 target in ton CO_2 for all model countries n. The remaining variables $\mathbf{y}$ represent technology capacities and dispatch $\mathbf{y} = \{\mathbf{g}_{n,s,t}, \mathbf{G}_{n,s}, \mathbf{F}_l\}$. Here index s is indexing the technology for all technologies included in the model, index t is indexing the hour for all hours in the year, and l is the transmission line. The variables determined in the optimization process is thus:

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

The model is then formulated as a linear problem following the standard formulation given as:

$$\begin{aligned} \text{minimize} \quad & \mathbf{f}_0(\mathbf{y}) \\ \text{subject to} \quad & \mathbf{f}_i(\mathbf{x},\mathbf{y}) \leq 0 \quad i = 1..m \\ & \mathbf{h}_i(\mathbf{x},\mathbf{y}) = 0 \quad i = 1..p \end{aligned} \tag{3}$$

The national CO_2 targets $\mathbf{x}$ are given by the MCMC sampler and is thus not optimized in the model. Only the technical variables $\mathbf{y}$ are optimized in the optimization problem.

The objective function of the model is to minimize total system cost and can be formulated as follows:

$$\text{minimize } f_0(\mathbf{x}, \mathbf{y}) = \sum_{n,s} \mathbf{c}_{n,s} \mathbf{G}_{n,s} + \sum_{l} \mathbf{c}_l \mathbf{F}_l + \sum_{n,s,t} \mathbf{o}_{n,s} \mathbf{g}_{n,s,t} \tag{4}$$

For all model nodes and all hours in the year, a power balance constraint is enforced requiring that the energy demand $\mathbf{d}_{n,t}$ is fulfilled. Energy demand data is taken from the ENTSO-E data portal [30] and decomposed in industrial and residential demand following the method given in [26]. The incidence matrix describing the line connections is given by $\mathbf{K}_{n,l}$ and the hourly transmission in each line is described as $\mathbf{f}_{l,t}$. The nodal power balance constraint can then be formulated as:

$$\sum_{s} \mathbf{g}_{n,s,t} - \mathbf{d}_{n,t} - \sum_{l} \mathbf{K}_{n,l} \mathbf{f}_{l,t} = 0 \ \ \forall n, t \tag{5}$$

The dispatch of each technology $\mathbf{g}_{n,s,t}$ is limited by the installed technology capacity $\mathbf{G}_{n,s}$. The dispatch of renewable energy generators such as wind and solar are furthermore limited by the hourly capacity factor $\overline{\mathbf{g}}_{n,s,t}$. The capacity factor for conventional power plants is 1, whereas it is generated from weather data for the renewable generators. A detailed explanation of the derivation of renewable generation potentials is given in [26].

$$0 \leq \mathbf{g}_{n,s,t} \leq \overline{\mathbf{g}}_{n,s,t} \mathbf{G}_{n,s} \ \forall n, s, t \tag{6}$$

Similarly, transmission in transmission lines is also limited by the installed capacity. As the direction of the transmission is without significance it is the absolute transmission $|\mathbf{f}_{l,t}|$ that is limited.

$$|\mathbf{f}_{l,t}| \leq \mathbf{F}_l \ \forall l, t \tag{7}$$

The maximum capacity allowed for each technology is determined by geographical potentials available $\mathbf{G}_{n,s}^{max}$ [REFERENCE].

$$0 \leq \mathbf{G}_{n,s} \leq \mathbf{G}_{n,s}^{max} \ \forall n, s \tag{8}$$

CO_2 emissions can be constrained in two ways. Either through a global constraint on emissions, or by national constraints on emissions. The global CO_2 reduction constraint is formulated as:

$$\sum_{n,s,t} \frac{1}{\eta_s} \mathbf{g}_{n,s,t} \mathbf{e}_s - CAP_{CO_2} \leq 0 \tag{9}$$

Here the CAP_{CO_2} is the global emissions limit given in ton CO_2. Note that only a single constraint is given here. Limiting emissions through national constraints can be done by defining a constraint for each country in the model. The national emissions targets $\mathbf{r}_n$ are given by the MCMC sampler.

$$\sum_{s,t} \frac{1}{\eta_s} \mathbf{g}_{n,s,t} \mathbf{e}_s - \mathbf{r}_n \leq 0 \; \forall \; n \tag{10}$$

The global CO_2 constraint (Equation 9) is only used in the ”Efficiency” scenario. In all other scenarios, the national CO_2 targets are explicitly given, either by the sampler or following a certain allocation scheme.

When the model is solved Lagrange multipliers associated with each constraint are introduced. The value of these Lagrange multipliers represents the cost increase/decrease associated with tightening/loosening the constraint by one unit. Thus be evaluating the Lagrange multipliers associated with the energy balance constraint (Equation 5) a proxy for the nodal hourly electricity price can be obtained. Similarly, the Lagrange multiplier of the national CO_2 target constraint (Equation 10) provides a proxy for the national CO_2 abatement cost.

THE FOLLOWING SHOULD BE ADDED HERE:
- Total CO2 budget
- Table over national CO2 targets in scenarios
- Renewable potential calculation
- 150% coal limit

Table 3: Technology costs of new technologies.

Technology	Capital cost Eur/kW	FOM %/year	VOM Eur/MWh	Lifetime years
OCGT	435.2	1.78	4.5	25
Offshore wind turbine	1573.2	2.29	2.67	30
Offshore wind AC connection submarine	2685.0*	0	0	30
Offshore wind AC connection underground	1342.0*	0	0	30
Offshore wind AC station	250.0	0	0	30
Offshore wind DC connection submarine	2000.0*	0	0	30
Offshore wind DC connection underground	1000.0*	0	0	30
Offshore wind DC connection underground	1000.0*	0	0	30
Offshore wind DC station	400	0	0	30
Onshore wind	1035.6	1.22	1.35	30
Utility scale solar PV	376.3	1.93	0	40
Electrolysis	550.0	5.0	0	25
Fuel Cell	1100.0	5.0	0	10
Hydrogen storage tank	44.0**	1.11	0	30
Hydrogen underground storage	2.0**	0	0	100
Battery inverter	160.0	0.34	0	25
Battery storage	142.0**	0	0	25

* Eur/MW/km

** Eur/kWh

Table 4: Technology data

Technology	Efficiency %	Emissions T CO_2/MWh
OCGT	41	0.49
CCGT	58	0.34
Coal	33	1.00
Lignite	33	1.24
Oil	35	0.77
Electrolysis	66	0
Fuel Cell	50	0
Battery inverter	96	0

Table 5: Existing generator technology capacities by 2030 in MW

	Offshore wind	Onshore wind	Run off river	Solar PV	CCGT	OCGT	Coal	Lignite	Nuclear	Oil
AT	0.0	3132.7	4478.5	1438.6	4278.7	3203.7	3004.7	0.0	0.0	0.0
BA	0.0	50.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BE	1185.9	2074.8	59.0	3984.5	6555.0	3562.5	4620.5	0.0	17957.0	0.0
BG	0.0	691.0	22.4	1029.0	0.0	1907.3	15041.5	12100.0	6060.6	0.0
CH	0.0	63.0	5280.0	2171.0	0.0	0.0	0.0	0.0	10393.9	0.0
CZ	0.0	316.2	40.2	2074.3	580.7	0.0	21772.0	2199.2	8060.6	0.0
DE	6396.0	52447.0	2997.0	45179.0	31242.9	19620.2	85058.7	63131.8	47843.8	10561.1
DK	1708.1	4431.2	0.0	991.0	172.4	3481.6	10999.8	0.0	0.0	1900.0
EE	0.0	329.8	0.0	25.4	298.3	609.8	0.0	0.0	0.0	6031.4
ES	0.0	23433.1	16.4	4753.5	41972.9	7177.0	19756.7	9336.8	22947.2	10095.5
FI	67.0	1971.3	1289.6	123.0	1117.2	1652.9	9211.2	0.0	8436.4	3501.1
FR	0.0	14898.1	5780.8	9604.0	9674.2	2600.0	13010.0	0.0	191303.0	20491.8
GB	8212.7	13553.9	685.2	13107.3	56593.6	2247.6	43863.6	0.0	34124.2	8005.4
GR	0.0	2877.5	103.1	2650.6	7727.6	1017.1	4697.0	11833.3	0.0	0.0
HR	0.0	580.3	278.7	67.4	637.3	201.2	922.0	0.0	0.0	1851.0
HU	0.0	335.0	19.7	724.0	2171.0	5777.3	128.2	3576.4	5717.6	1171.4
IE	25.2	3650.9	216.0	21.8	5079.3	3219.5	2590.9	0.0	0.0	2591.4
IT	0.0	10230.2	6563.7	20073.6	59376.1	15833.6	33110.5	0.0	0.0	17557.1
LT	0.0	532.0	0.0	81.9	0.0	3841.5	0.0	0.0	0.0	0.0
LU	0.0	114.2	30.9	124.7	604.3	0.0	0.0	0.0	0.0	0.0
LV	0.0	62.9	642.1	0.0	1767.2	0.0	0.0	0.0	0.0	0.0
ME	0.0	118.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MK	0.0	37.0	41.6	17.0	0.0	0.0	0.0	2497.0	0.0	0.0
NL	957.0	3491.0	0.0	4522.0	23417.2	9734.1	16942.4	0.0	1490.9	0.0
NO	0.0	1708.0	0.0	53.4	775.9	1885.6	0.0	0.0	0.0	0.0
PL	0.0	5762.1	14.4	562.0	562.1	2519.3	65419.7	28503.0	0.0	985.7
PT	0.0	5172.4	1615.5	665.4	6601.7	0.0	5321.2	0.0	0.0	0.0
RO	0.0	3243.0	870.4	1385.7	1862.1	5565.9	4563.6	14482.5	3933.3	250.1
RS	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SE	204.0	7097.0	1955.9	481.0	1220.7	0.0	393.9	0.0	28884.8	6100.0
SI	0.0	0.0	861.3	251.8	1434.5	1095.1	745.5	2860.6	2203.0	410.2
SK	0.0	0.0	641.3	533.0	1117.2	0.0	1333.3	1472.7	5878.8	0.0

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