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Cost and impact of weak medium term policies in the electricity system in Western North America

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ABSTRACT

We study the cost and lock in of carbon intensive technologies due to weak medium-term policies. We use SWITCH WECC—a power system capacity expansion optimization model with high temporal and geographical resolution. We test three carbon cap scenarios. For each scenario, we optimize the power system for a medium timeframe (2030) and a long timeframe (2050). In the medium timeframe optimizations, by 2030 coal replaces gas power. This occurs because the long optimization foresees the stronger carbon cap in 2050. Therefore, it is optimal to transition towards cleaner technologies as early as 2030. The medium-term optimization has higher costs in 2040 and 2050 compared to the long optimization. Therefore, to minimize total costs to reduce emissions by 80 % in 2050, we should optimize until 2050 or have stronger carbon cap policies by 2030 (such as 26 % carbon emissions reductions from 1990 levels by 2030 across the WECC).

1. Introduction

For over 20 years we have been negotiating agreements that try to reduce greenhouse gas emissions to stabilize their concentration (Center for Climate and Energy Solutions, 2018). A recent iconic international meeting was the 21st Session of the Conference of the Parties to the United Nations Framework Convention on Climate Change in 2015. Its main outcome was the reaffirmation of the goal of limiting global temperature increase below 2 °C, while urging efforts to limit the increase to 1.5 °C (United Nations, 2015). In 2007, the Intergovernmental Panel on Climate Change (IPCC) had stated that the 2 °C goal could be achieved if different sectors of the economy in industrialized countries would reduce their emissions to specific targets. The electricity sector would have to reduce its emissions to 80 % below 1990 levels by 2050 (Intergovernmental Panel on Climate Change et al., 2007). In an attempt to achieve this long-term goal, the U.S. proposed the Clean Power Plan (CPP)—which was repealed by the U.S. Environmental Protection Agency in 2019 (Federal Register, 2019). The target stated that the power system would need to reduce its emissions to 32 % below 2005 levels by 2030 (Environmental Protection Agency, 2015). Additionally, California set its state-wide carbon cap target to reduce emissions 40 % below 1990 levels by 2030 (Office of the Governor and Brown, 2021). More recently, the IPCC stated that if global warming would be limited to 1.5 °C, the avoided climate change impacts on sustainable development, eradication of poverty and reducing inequality would be greater compared to the impacts from 2 °C (IPCC, 2018).

These different emissions reductions goals with different timeframes present a challenge for power system regulators. What is the most economically efficient way to plan and operate the power system? Should we optimize investments on new power plants to reach 2030 emissions targets (e.g. CPP's intent) and from there optimize until 2050 to achieve the long-term emission targets (e.g. IPCC)? Or should we plan and optimize the power system capacity expansion from today until 2050?

This question has been studied for the entire economic sector using different global integrated assessment models. It has been shown (Luderer et al., 2013; Riahi et al., 2013; Kriegler et al., 2014; Bertram et al., 2013; Schaeffer et al., 2015; Riahi et al., 2015; Weyant, 2017; Bertram et al., 2015) that weak climate near-term targets delay the transition towards a cleaner economy, which will require aggressive subsequent action to achieve climate stabilization goals. These studies also show that, due to the lack of foresight, unproductive near-term investments take place, which results in fossil fuels lock-ins and higher long-term mitigation costs. Therefore, it is relevant to study the impacts

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of short or medium-term policy for the electric power system. Additionally, the electricity and heat sector is particularly important because it is the greatest emitter in the world, accounting for 30.4 % of total greenhouse gas emissions as of 2016 (World Resources Institute, 2020). To the best of our knowledge, this type of analysis has not been applied to the electric power sector, and this study fills that gap. This publication expands the work done by the authors for the California Energy Commission (Wei et al., 2019).

The main contribution of this work is to show the cost effectiveness of having stronger medium term (2030) policies that would promote an earlier transition towards lower carbon intensive technologies in the power system.

2. Problem formulation

To study the consequences of weak short-sighted electricity policy we use the SWITCH model (AMPL version). SWITCH is a long-term power system capacity expansion model with high temporal and geographical resolution. The objective function minimizes the total power system cost: investment and operation costs of electricity generation and transmission. In addition to operational (reserves, ramping, etc.), technological and resource potential constraints, different policy constraints can be modeled (e.g. carbon cap, carbon tax, Renewable Portfolio Standard (RPS), etc.). To the best of our knowledge, SWITCH's high time and geographical resolution makes it a power system capacity expansion model without precedent. For example, Western North America is divided in 50 geographical zones (refer to Fig. 6), and the time resolution can vary from hourly to sampled hours that represent typical days during the years being optimized. This allows a more realistic study of the expansion and operation of the electrical grid with presence of renewable intermittent resources such as wind and solar power. For a detailed description of the model refer to the Supplementary Information.

So far, the SWITCH model has been developed for different regions and used for several studies (Fripp, 2012; Wei et al., 2013; Mileva et al., 2013; Nelson et al., 2012; Wei et al., 2019; He et al., 2016; Carvallo et al., 2014; Ponce de Leon Barido et al., 2015). This study uses SWITCH WECC (Western Electricity Coordinating Council) because the electricity system is the second highest-emitting economic sector in the U.S. with a 32 % share as of 2018 (Environmental Protection Agency, 2020).

We use two optimization methods: "long optimization" and "medium optimization". In the long optimization, the timeframe optimized is from 2016 until 2055, taking into account carbon cap constraints for all the years. The medium optimization optimizes in a shortsighted manner by solving the problem in two consecutive stages: 1) optimizing the grid in 2016–2030 (without any information after 2030), 2) using the optimal buildout in 2030 from stage 1 optimizes from 2031 until 2055. For more details on the problem formulation refer to the Methodology section. The medium and long optimization are run for each of the three scenarios modeled (i.e. solutions from six optimization problems are studied in this work).

3. Methodology

SWITCH is a long-term power system capacity expansion model with high temporal and geographical resolution. As an optimization problem, it is classified as a deterministic linear or mixed integer program. The objective function minimizes the total power system cost: investment and operation costs of generation and transmission. The decision variables of the optimization problem can be summarized in the following sets: capacity investment decisions for each potential new project in each period, capacity investment decisions for each potential new transmission line between any load areas in each period, hourly dispatch decisions for each existing and new generator installed in each period, decisions on hourly transmitted energy through the existing and new transmission lines. The main constraints in the optimization problem are: hourly demand in each load area has to be met by the generation and transmitted energy, capacity limits must be respected for generators and transmission lines, wind and solar generators are limited by their hourly geolocated capacity factors, generation from each hydropower plant is limited by historical monthly availability (minimum, average and maximum generation), biomass and geothermal deployment is limited by the resource availability in the WECC, hourly ramping restrictions for generators depending on their technology, respect yearly maintenance time for each generation technology, lifetime of different technologies must be respected, policy constraints as carbon cap, carbon tax, RPS, among others. For a complete list and description refer to the Supplementary Information.

Geographically, the SWITCH WECC model divides the WECC in 50 zones or load areas. The transmission system was obtained from Ventyx geolocated transmission line data (Ventyx Corporation, 2009) also using data on the thermal limits from the Federal Energy Regulatory Commission (FERC) (Federal Energy Regulatory Commission, 2009). In total, there are 105 existing transmission lines connecting load zones in SWITCH. SWITCH can decide to build more transmission lines if it is optimal. De-rating of lines and transmission losses are taken into account.

Electricity demand profiles come from historical hourly loads from 2006 (Federal Energy Regulatory Commission, 2006; Platts Corporation, 2009). These profiles are projected for future years. Hourly existing and potential new wind farm power output is derived from the 3TIER Western Wind and Solar Integration Study wind speed dataset (National Renewable Energy Laboratory, 2010a,b) using idealized turbine power output curves on interpolated wind speed values. For existing and potential new solar power plants, hourly capacity factors of each project over the course of the year 2006 are simulated using the System Advisor Model from the National Renewable Energy Laboratory (National Renewable Energy Laboratory 2013a). The optimization can choose from over 7,000 potential new geolocated generators in the WECC.

Fuel prices projections for each load area were obtained from the U.S. Energy Information Administration (U.S. Energy Information Administration, 2017). Capital costs and operation and maintenance costs were obtained from Black and Veatch (Black & Veatch, 2012). The historical pool of exiting power plants in the WECC was obtained from the US Energy Information Administration (EIA-860, EIA-923, 2007 data).

In order to study the impact of insufficient planning horizons with weak near-term policies we use two optimization methods: "long optimization" and "medium optimization". The control case or long optimization is the traditional deterministic optimization from 2016 to 2055. The optimization horizon is divided in four investment periods of ten years each: 2016–2025 (which we call "2020"), 2026–2035 ("2030"), 2036–2045 ("2040"), and 2046–2055 ("2050"). Each period simulates 72 h of dispatch. For one year per period we sample every two months, two days per month (median and peak load days) and every four hours per day (6 months x 2 days/month x 6 hour/day = 72 h). The peak days have the weight of 1 and the median days of $n - 1$ where n is the number of days of that month, and this represents a full month.

The medium optimization was developed for this study to analyze the impacts of short term policy goals on the power system operations and capacity expansion. The basic idea behind the medium optimization is to break investment planning into two stages: present day until 2030, and 2030–2050. The first step minimizes the cost of the operation and investment of the power system from 2016 to 2030 taking into account all policy constraints (e.g. yearly carbon cap). The second step consists of optimizing investments and operations from 2031 to 2055 with stronger emission policies for 2050 (i.e. 80 % reductions). This medium optimization recreates the challenge of optimizing the expansion and operation of the power system in phases. First, only taking into account policies until 2030. Investment decisions made until 2030 become the initial state for the second step of the optimization. The second step optimizes decisions from 2031 to 2055 to comply with more stringent policies, specially by 2050. Therefore, the hypothesis is that the first step will expand and operate the system in a shortsighted way; having as a consequence carbon locks-in or a delayed transition towards technologies with lower CO_2 emissions. Thus, the second step will have to change the energy mix more aggressively to transition towards a cleaner electric grid by 2050 compared to the long optimization (which optimizes in only one step: 2016–2055, taking into account the more stringent 2050 carbon cap constraints).

The long and medium optimization use the same periods and hours sampled for consistency reasons and in order to isolate the impact and carbon locks-in produced by weak medium-term electricity policies. The medium and long optimization are run for each of the three carbon cap scenarios modeled (i.e. solutions from six optimization problems are studied in this work).

4. Scenarios

The scenarios that are used in this study are three different carbon cap scenarios shown in Fig. 1.

In Fig. 1, the scenario with the green line ("80 % by 2050") corresponds to a linear decrease in emissions from 2016 until 2020 where emissions are restricted to 1990 levels (Office of the Governor Arnold Schwarzenegger, 2006). Then a linear decrease from 2021 until 2050 where 80 % reductions from 1990 levels are enforced (Intergovernmental Panel on Climate Change et al., 2007). The blue line ("CPP") corresponds to a linear decrease in emissions from 2016 until 2020 where emissions are restricted to 1990 levels and then a linear decrease in emissions until 2030 where the CPP target is enforced (32 % reductions from 2005 levels, or analogously, 11 % reductions from 1990 levels). From 2031 until 2050 the cap has a linear decrease until 80 % reductions from 1990 levels are achieved by 2050. Finally, the red line ("40 % by 2030") corresponds to the same linear decrease in emissions from 2016 until 2020 where emissions are restricted to 1990 levels. Then a linear decrease until 2030 where 40 % of reductions are enforced according to a Californian executive order (Office of the Governor and Brown, 2021), simulating the case if this policy were to be expanded to the WECC. And from 2030 until 2050 a linear decrease until 2050 when 80 % reductions are mandated. Throughout this manuscript the three scenarios will be addressed as "80 % by 2050", "CPP", and "40 % by 2030" respectively.

The intuition behind the first step of the medium optimization is that it provides decisions that would be made until 2030 without considering the more stringent policy that will be enforced in 2050. Therefore, they reflect the signals that are currently given to the investors of the power system and to the grid's operators. On the other hand, the second step of the medium optimization faces the challenge of achieving the more stringent carbon caps from 2031 until 2050 having a grid already built by 2030 (from the first step) that did not take into account in its expansion carbon caps beyond 2030. Therefore, the medium optimization seeks to mimic the way we would expand the power system in the WECC if we keep imposing only near-term policies as we have done so far. The caveat of this study is that we assume we will have stringent carbon cap policies by 2050, whether they affect our 2030 decisions (long optimization) or not (medium optimization).

Consequently, the research question we study is: How to plan and implement policy in the power system efficiently? From today until 2030 and then until 2050? Or plan from today until 2050?

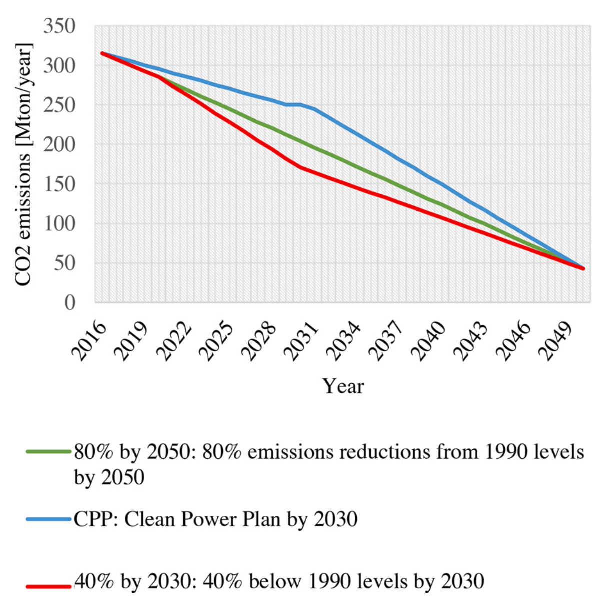


Fig. 1. WECC carbon cap scenarios. In green is the 80 % emissions reductions from 1990 levels by 2050 scenario (labeled as "80 % by 2050"), in blue the Clean Power Plan scenario (labeled as "CPP"), and in red 40 % emissions reductions by 2030 (labeled as "40 % by 2030"). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

5. Results and analysis

5.1. Optimal energy mix for the three scenarios in the long optimization case

To understand the impacts of medium term planning, we must first examine results from the long-run optimizations (Fig. 2). We can observe how in all the scenarios coal power plants are decommissioned progressively over the four periods. Each scenario presents a different transition rate for decommissioning and electricity generation reduction from coal power plants. By period 2030, the scenario that reduces coal power generation the most is "40 % by 2030" with a 1.6 % of participation of coal. The scenario "80 % by 2050" follows it with a 4.0 % and finally the "CPP" scenario with 4.4 % of energy generated by coal.

From the 2020 period to the 2030 period all scenarios present an increase in energy generated by gas power plants. This gas generation increase ranges from 45 % by 2030 ("40 % by 2030") to 48 % ("CPP"). Another trend of interest is the consistent increase in wind and solar power generation from period 2020 until period 2050. Nonetheless, solar and wind generation reach a more significant share only by 2050. By 2050, solar power generates roughly 20 % of the electricity, and wind power around 53 %.

5.2. Comparison of optimal capacity installed in 2030 between the medium and long optimization

Table 1 shows total capacity installed per fuel by 2030 for each of the scenarios under the medium and long optimizations. Fig. 3 aids to identify key differences among the medium and long optimization by showing the difference in installed capacity per fuel in 2030. By 2030, all scenarios in the medium optimization deploy coal, a technology more carbon emissions intensive (i.e. ton CO_2/MWh), at the expense of less deployment of a cleaner one, gas, compared to the long optimization.

In the medium optimization cases, due to their lack of foresight of the stringent carbon cap by 2050, coal power plants are decommissioned at a slower rate than in the long optimization. This results in more installed capacity of coal power plants in the medium optimization—a carbon lock-in. On the other hand, the medium optimization invests less in gas power plants compared to the long optimization. The more carbon intensive mix in 2030 in the medium optimization requires an abrupt technological change (2030–2050, i.e. 20 years instead of 40) to comply with 2050 stringent carbon caps. The scenario that shows the greatest difference in installed coal and gas power plants between the medium and long optimization in 2030 is "CPP". There is an excess of 9.3 GW of coal power plants and a lack of 11 GW of gas.

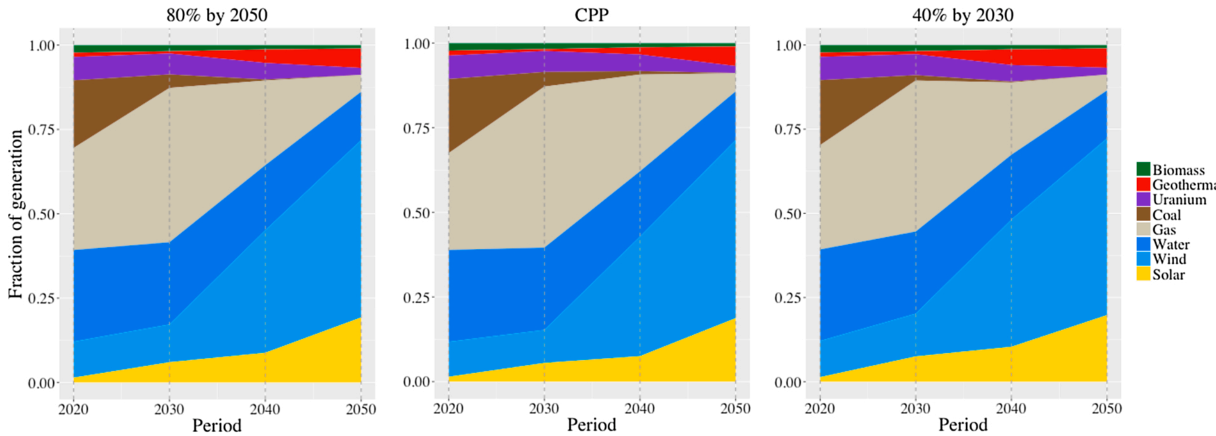


Fig. 2. Energy generation share (as a fraction) per fuel per period for the long optimization for the scenarios studied. On the left side is the "80 % by 2050" scenario, in the middle the "CPP", and on the right side the "40 % by 2030".

Table 1
Capacity installed in gigawatts in the WECC per fuel by 2030 for the scenarios studied. The columns show installed capacity from the medium and long optimization for each scenario in 2030.

	80 % by 2050		CPP		40 % by 2030	
Fuel	Medium	Long	Medium	Long	Medium	Long
Biomass	2.4	2.5	2.4	2.4	2.5	2.5
Coal	5.7	5.5	15.1	5.8	3.8	2.4
Gas	111.9	113.4	104.5	115.0	108.9	111.6
Geothermal	0.5	0.8	0.5	0.6	1.1	1.1
Solar	22.3	21.3	21.3	19.6	27.0	26.2
Storage	0.0	0.0	0.0	0.0	0.0	0.0
Uranium	7.7	7.7	7.7	7.7	7.7	7.7
Water	66.7	66.7	66.7	66.7	66.7	66.7
Wind	39.2	37.6	37.4	33.7	47.4	42.0

5.3. Comparison of optimal energy generation by 2030 between the medium and long optimization

As expected, the difference between the energy generated in the 2030 period in the medium and long optimization follows the same pattern as the capacity installed. Fig. 4 shows the difference in electricity generation by 2030 per fuel between the medium and long optimization.

In all scenarios in the period 2030, the medium optimization generates more electricity from coal plants than in the long optimization. The energy produced by coal plants in the medium optimization exceeds the long optimization from 13 TWh ("80 % by 2050") up to 690 TWh ("CPP"). In general, the excess in generation from coal power plants substitutes generation from gas power plants. "CPP" shows the greatest difference in generation across all scenarios. In the medium optimization, it produces 690 TWh more of energy from coal plants compared to the long optimization. To put this in perspective, 690 TWh is roughly 7.4 % of the total load in the 2030 period. The change in energy for the rest of the scenarios is less than 2 % of the total load by 2030.

This substitution of gas in favor of coal for the "CPP" scenario can be explained by the fact that "CPP" does not have a stringent carbon cap by 2030. Therefore the medium optimization does not transition from more carbon intensive technologies to cleaner ones as early as 2030. However, decisions made for 2030 in the long optimization take into account the stringent carbon cap by 2050. This results in a considerable decommission of coal by 2030 to cost effectively reach the 2050 emissions target.

5.4. Comparison of optimal emissions by 2030 between the medium and long optimization

The explanation behind the carbon lock-in in the medium-term optimizations for "CPP" lies in the optimal CO_2 emissions by 2030. Fig. 5 shows emissions in the year 2030 for all the scenarios for the medium (in yellow) and long (in blue) optimizations. The red dashed lines correspond to the carbon cap for each scenario in 2030. The medium optimization does not have an early foresight of the more stringent carbon

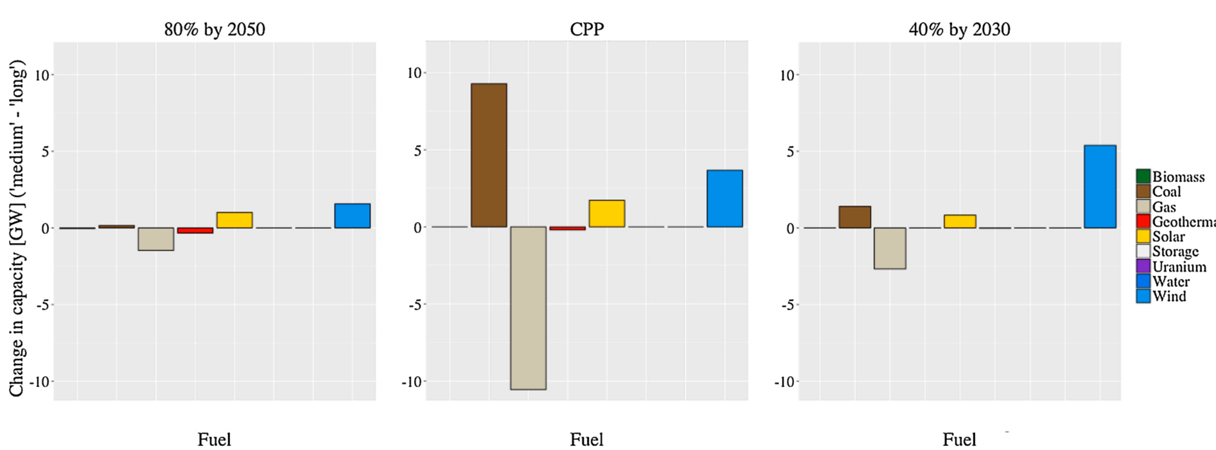


Fig. 3. Change in capacity installed in gigawatts per fuel by 2030 for the scenarios studied. The difference corresponds to capacity per fuel installed by 2030 in the medium optimization minus the capacity installed in 2030 in the long optimization. On the left is the "80 % by 2050" scenario, in the middle the "CPP" scenario (where more coal and less gas are installed in the medium optimization), and on the right side the "40 % by 2030" scenario.

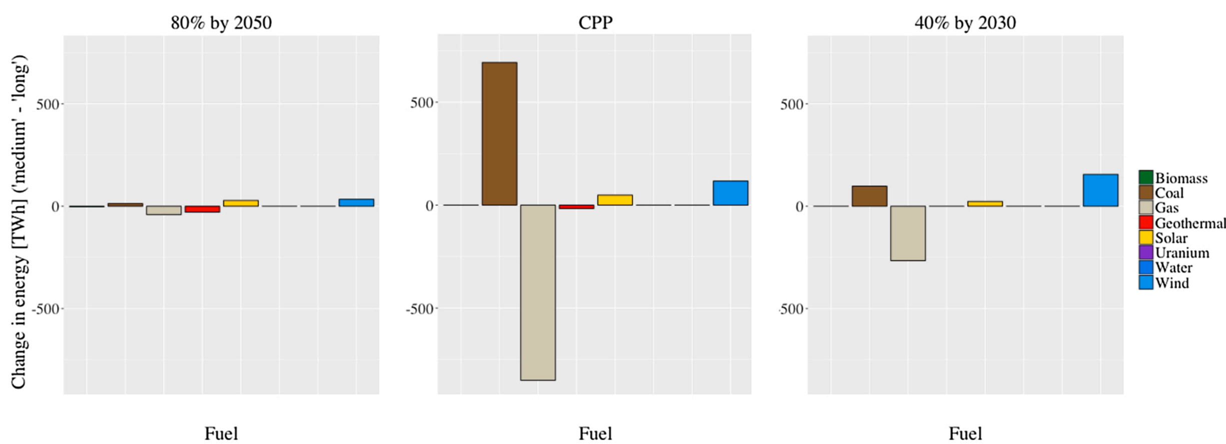


Fig. 4. Change in energy generated in terawatt hour per fuel during the period 2030 for the scenarios studied. The difference corresponds to the generation per fuel by 2030 in the medium optimization minus the generation in 2030 in the long optimization. On the left is the "80 % by 2050" scenario, in the middle the "CPP" scenario (where more coal and less gas are deployed in the medium optimization), and on the right side the "40 % by 2030" scenario.

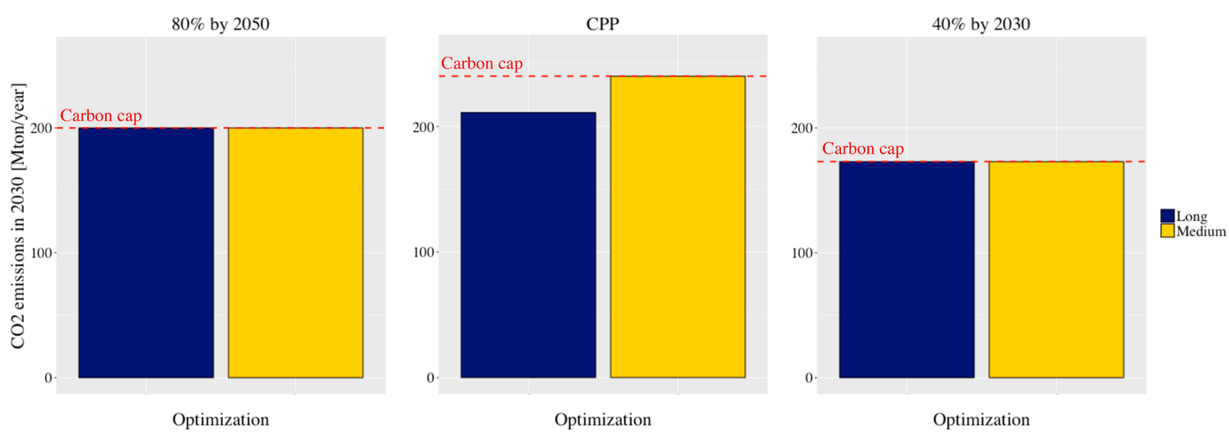


Fig. 5. CO_2 emissions in the year 2030 for the medium (yellow) and long optimization (blue). The red dashed line represents the carbon cap for the year 2030 for each scenario. On the left side is the "80 % by 2050" scenario, in the middle the "CPP" scenario, and on the right side the "40 % by 2030" scenario. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

caps it will have to face after 2030 during its second optimization stage. Therefore, it is optimal to emit as much carbon as its 2030 cap allows. This can be observed where yellow bars are at the same height as the carbon cap.

For the "CPP" case, the long optimization emits less carbon (blue bar) in 2030 than the carbon cap. This occurs because the long optimization has perfect foresight in 2030 of the more stringent carbon cap target in 2050. Therefore, the long optimization realizes that it is cost effective to start deploying cleaner energy as early as 2030 in order to optimally reach the stricter emissions goal of 2050. This shows the importance of optimizing the power system in the long-term when medium term policies are weak.

In the case of the medium optimization for "CPP", due to its lack of foresight, it emits CO_2 at the maximum allowed in 2030. Therefore, the second step of the medium optimization has to transition more abruptly to cleaner technologies to achieve the 2050 target. This capacity expansion is suboptimal (Refer to Cost analysis section).

On the other hand, for the scenarios "80 % by 2050" and "40 % by 2030" optimal carbon emissions in the year 2030 in the case of the long-term optimizations are equal to their respective carbon caps. This suggests that the carbon caps in 2030 for "80 % by 2050" and "40 % by 2030" are well aligned with the carbon cap in 2050. Therefore, through these two scenarios we show that stronger medium-term policies yield to an expansion of the power grid closer to the optimal expansion resulting from optimizing in the long-term.

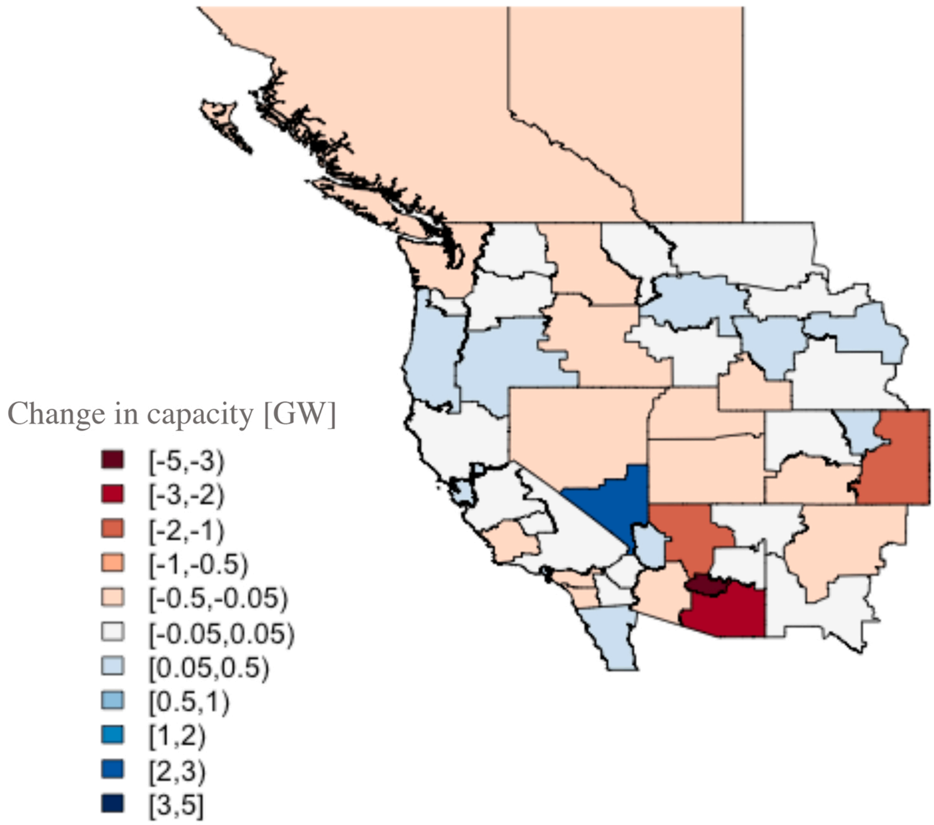
In practice, one way to cope with the lack of foresight of optimizing in the medium term would be to enforce more stringent policies for 2030. These policies would be designed to mimic the optimal results of the long optimization. For example, for the "CPP" scenario, we would need to force a 26 % carbon emissions reductions from 1990 levels by 2030 (which corresponds to the optimal reductions achieved in the long optimization by 2030).

5.5. *Clean Power Plan carbon lock-in maps in 2030*

Fig. 6 shows the difference in installed capacity by 2030 between the medium and long optimization for coal (bottom) and gas (top) for the "CPP" scenario for each zone. Darker blue represents more installed capacity in the medium optimization, while darker red means less. In general, there is a substitution between installed coal and (lack of installed) gas power plants in the medium optimization among the geographical zones.

5.6. *Cost analysis*

Fig. 7 shows the increase in cost per period from using the medium optimization instead of the long optimization. There are minor to no savings in 2020 and 2030 from using the medium optimization. Thus, there is no economic benefit of having weaker policies by 2030. However, the expansion and operation of the power system from the medium



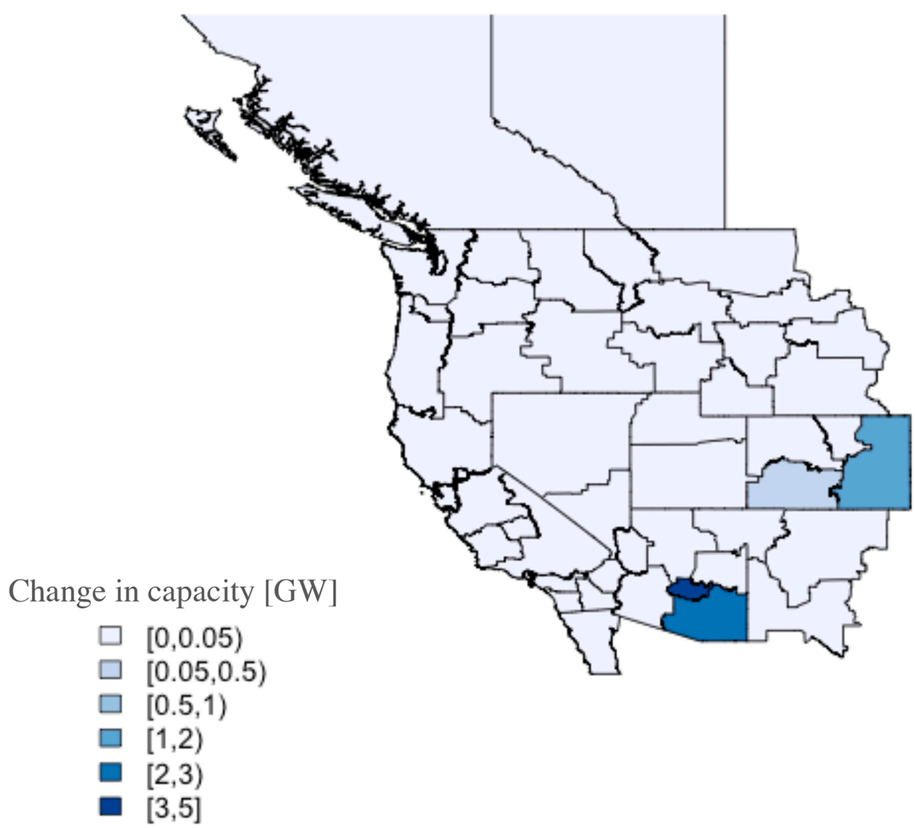


Fig. 6. Change in gas (top) and coal (bottom) power plants' capacity in gigawatts by 2030 for the "CPP" scenario. The difference corresponds to capacity installed by 2030 in the medium optimization minus the capacity installed by 2030 in the long optimization.

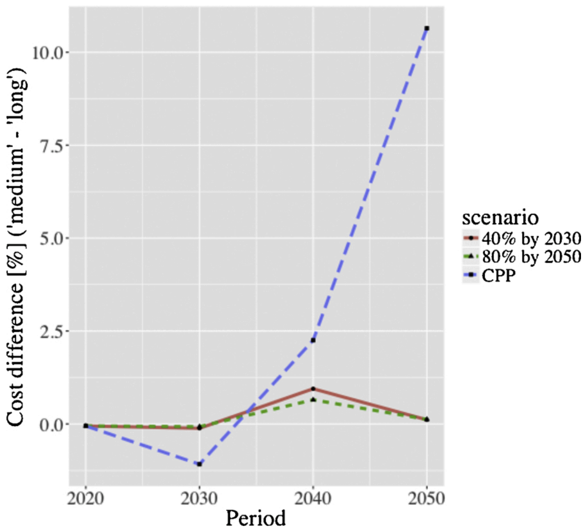


Fig. 7. Increase in cost per period from using the medium optimization instead of the long optimization. The red solid line represents cost increases from "40 % by 2030" scenario, the short dashed green line corresponds to "80 % by 2050," and the long dashed blue line represents "CPP" scenario.

optimization in 2040 and 2050 is more expensive than the cost incurred by the long optimization in those periods. The most extreme case is for the "CPP" scenario, where the total cost of expanding and operating the grid in 2050 is 11 % more expensive than for the long optimization. In other words, the cost of electricity in 2050 obtained from using the medium optimization is of \$179.70/MWh, instead of \$162.41/MWh achieved by the long optimization. Thus, we have shown the sub optimality of the solution provided by the medium optimization. This is due to the more abrupt transition to clean energy that has to take place in the last two decades. This contrasts the expansion and operation of the long optimization for "CPP" because it transitions progressively over the decades to meet its 2050 carbon cap cost effectively. In the other two scenarios, the increase in cost is small. Nonetheless, this minor increase in cost in 2040 and 2050 reflects the fact that more coal is deployed in 2030 instead of gas compared to the long optimization. Therefore, these two scenarios also have to adjust their grid in the last two decades, but to a lesser extent compared to "CPP". Thus, their medium-term carbon policies are strong enough to allow a closer-to-optimal transition to meet the strongest carbon cap policy by 2050.

6. Conclusions and policy implications

Throughout this work we study the question of planning the power system in the medium (2030) or long-term (2050). Results are conclusive by depicting a higher deployment of coal power instead of gas by 2030 in the medium-term optimizations compared to results from the long-term optimizations for the same year. Conversely, the long-term optimizations show a progressive transition towards a cleaner electric grid from early stages (2030).

The medium-term optimizations do not foresee the more stringent carbon cap by 2050. Thus, they have to transition quicker to a cleaner grid in the last two decades (second step of the optimization) instead of progressively transitioning during the four periods. This is clearly observed in the "CPP" case, where its carbon cap by 2030 is inactive in the long optimization. This means that it is optimal to emit less CO_2 than it is required in 2030 to achieve the 2050 goals cost effectively.

To address the impact of medium term planning, we recommend to either place more stringent targets in the medium term (2030) or plan until 2050 with its more restrictive carbon cap by the end of the simulation. Given that it is impractical to suggest regulators to optimize the grid until 2050, we recommend to design stronger near-term policies (e.g. 2030) that would result in mimicking decisions made by optimizing in the long term. For the "CPP" scenario, instead of enforcing a reduction on emissions to 11 % below 1990 levels by 2030, a reduction in emissions by 26 % in 2030 in the WECC would mimic the optimal and cost-effective energy transition of planning in the long-term.

Author contributions

P. H.G. designed the study, research questions and wrote the main manuscript text. P.H.G. and J.J. developed the new code required for the novel medium optimization problem. All authors discussed the analysis and edited the manuscript.

Declaration of Competing Interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.tej.2021.106925.

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