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Werewolf in London: Minding the Gap with User-Friendly Energy Optimization Tools Informing Policy Makers through the Energy Transition

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ABSTRACT

Action towards a renewable-centric electricity system needs to occur now; however, energy market incentives are typically aimed at short-term payoffs, leaving questions about optimal ways to achieve United Nations Sustainable Development Goals (SDG) and climate and energy goals established by the European Commission (EC).

Current planning models for this purpose are two-stage models. They typically detail generator, transmission and control/policy system investment on a 30- to 50-year time horizon, coupled to an operational model that shows that the real-time system is resilient to many different scenarios of future demand for electricity. Models of these effects are plentiful in the literature, but often lack a clear user interface to enable policy analysts to direct their application, leading to a gap between data and policy.

Minding this gap, we have developed WEREWOLF (Wisconsin Expansion of Renewable Electricity with Optimization under Long-term Forecasts) as an independent, multi-year planning tool that provides data driven cost and benefit information regarding investments and energy system operations. WEREWOLF engages state of the art computing and data science technology, coupled with strong economic principles of competition and efficiency, to provide cost estimates and scenarios for strategic investments in new energy technologies that will be flexible to the uncertainties of technologies, policies and economics in the rapidly changing energy marketplace. The user-friendly software infrastructure allows policy analysts to directly interface to the model, and in collaboration with the proposer and associates or independently, carry out scenario runs (comparative statics) to explore the design space fully. The open-source WEREWOLF model is available on Github.

This paper will briefly describe the rapidly changing energy landscape in the state of Wisconsin USA, the WEREWOLF model and software infrastructure, and policy scenarios within the state of Wisconsin USA currently explored in the early stages of research. The authors discuss potential advantages of the tool, including its open-source transparency and availability, its user-friendly interface, use of primary data sources, and model outputs in minutes. The authors conclude with addressing current limitations for using such tools to inform policy and planning and possible options to transfer the model to help meet SDG and EC energy and climate goals.

Introduction

The transition to clean and distributed energy resources aligns closely with several United Nations Sustainable Development Goals (SDG), including SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). Decisions taken in this regard will also impact the rate and timing of targets in the 2020, 2030 and 2050 climate and energy goals established by the European Commission. The EC 2030 climate and energy framework calls on meeting greenhouse gas emission cuts of 40 percent from 1990 levels with at least a 32 percent share of renewable energy.

Based on these policy goals and others, it is clear that distributed energy resources (such as solar, wind, storage and others) will form a major part of the portfolio of generation sources of the future, but a renewable-centric electricity system will take some time to design and build. Enabling a renewable-centric electric system requires regulators and system operators to simultaneously consider the short and long-term impact of planning and policy decisions. Planning models that decouple these timescales have the unintended consequence of generating market incentives that are aimed at short-term payoffs rather than enabling an energy system that facilitates stochastic generation. Our software infrastructure, including a time horizon of 30 to 50 years, allows policy analysts to engage the model directly to make more fully informed decisions.

WEREWOLF (Wisconsin Expansion of Renewable Electricity with Optimization under Long-term Forecasts) is a multi-year planning tool that provides data driven cost and benefit information regarding potential investments and operations of the Wisconsin energy system of tomorrow. WEREWOLF engages state of the art computing and data science technology, coupled with strong economic principles of competition and efficiency, to provide cost estimates and scenarios for strategic investments in new energy technologies that will be flexible to the uncertainties of technologies, policies and economics in the rapidly changing energy marketplace. The user-friendly software infrastructure allows policy analysts to directly interface to the model, and in collaboration with the proposer and associates or independently, carry out scenario runs (comparative statics) to explore the design space fully. This tool aims to enable policy makers to make informed decisions, based on access to models and researchers who are experts in the area of energy planning. The tool is intended to guide crucial investments in generation and transmission and help design incentives for investment into green technologies that will work in concert with existing supplies to form the backbone of energy supply, both for industrial and domestic use. The Werewolf model is available on Github.

This paper will briefly describe the rapidly changing energy landscape in the state of Wisconsin USA, the WEREWOLF model and software infrastructure, and policy scenarios within the state of Wisconsin USA currently explored in the early stages of research. The authors discuss potential advantages of the tool, including its open-source transparency and availability, its user-friendly interface, use of primary data sources, and model outputs in minutes. The authors conclude with addressing current limitations for using such tools to inform policy and planning and possible options to transfer the model to help meet SDG and EC energy and climate goals.

Disruptive Challenges in the Electricity Sector

In the State of Wisconsin, USA (part of the Mid-Continent ISO or MISO), disruptive market actions are taking place in real time. A review of the MISO interconnection cue in February 2021 indicated there was 6766 MW of solar (47 projects), 1093 MW of wind (7 projects), and 295 MW of battery storage (8 projects) (MISO, 2021). Were all projects in the MISO interconnection cue ultimately delivered, Wisconsin's electricity grid would have a percentage of renewable generation on par with the target renewable generation share of the European Commission's 2030 energy and climate goals. The transformation of Wisconsin's electricity grid therefore provides a reasonable example to share with an audience focused on evaluation of energy planning in England or Europe.

Driven by new market economics and consumer demand, policy makers at all levels of government have announced ambitious climate goals. Wisconsin Governor Tony Evers issued an executive order with a goal of 100 percent carbon-free electricity within the state of Wisconsin by 2050. The state's two largest cities, Madison and Milwaukee, and the largest county, Dane County, have issued similar goals. Many of Wisconsin's investor-owned, municipal, and cooperative utilities have announced goals of transitioning to carbon-free electricity by 2050. Investor-owned utility Alliant Energy recently announced plans for 1 GW of solar in Wisconsin by 2023. Other utilities, such as Xcel Energy, have established community-based solar and wind projects enabling customers to opt-in for clean energy. Examples of investor-owned utilities working with local governments to increase renewable generation have proliferated, such as the City of Madison and Dane County working with Madison Gas & Electric for several large solar arrays to supply renewable energy to power city and county operations. To contribute toward its 100% renewable energy goals, the City of Madison invested in a public-private partnership to develop solar photovoltaic arrays in rural Wisconsin communities at the site of the corporate headquarters of Organic Valley, the largest cooperative of organic dairy farmers in the United States. Major private sector companies in the State of Wisconsin have made similar commitments to decarbonize the electric grid or make investments in renewable energy (100% Renewable Madison, 2018).

Decarbonizing Wisconsin's grid provides additional benefits to the state's economy, people, and natural resources. A recent study estimated that shifting to domestic production of electricity through renewable energy generation would increase state gross domestic product (GDP) by (USD) $14 billion and create 162,000 net jobs while increasing tax revenue by (USD) $600 million. Associated social and environmental health benefits from reduced carbon dioxide (CO2) emissions are valued at (USD) $4.6 billion and avoided human health damages at (USD) $21.1 billion (Abel, Spear 2019).

While the authors applaud these actions to increase opportunities to supply clean energy to the state of Wisconsin USA, the fact remains that there are many paths to meet the goals we have recently discussed within the state of Wisconsin USA, just as the UN SDG goals or the EC energy and climate goals. Optimization is about trade-offs. As the pace of change quickens, policy makers require user-friendly tools that enable them to forecast impacts of their decisions more quickly and to take into account stakeholders who have not previously been at the table and technologies that may not have been deployed at a large scale or at all. While the optimal mix of resources will be unique to each jurisdiction based on its mix of natural resources, existing infrastructure and stakeholders, tools such as WEREWOLF can be applied to any jurisdiction to help inform decision making and enable policy makers to choose the balance that best meets the interests of their constituents.

Using Data Driven Policy Decisions to Achieve Optimal Outcomes

Governments make policy decisions that have long-term consequences, often driven by political, social, and economic concerns that change more rapidly. Policies should be informed by evidence, and must both exploit the options that emerge, and be robust to variations in future circumstances. Wind and PV generation sources operate cleanly, but present operational characteristics that are radically different from traditional fossil-fuel and nuclear sources. Such sources' power outputs are inherently stochastic, with near zero variable cost of production, and hence require fundamental planning changes from a number of naturally risk-averse companies. Uncertainty is pervasive over multiple time scales, from the very fast scale of electrical switching operations, out to the twenty- or thirty-year horizon of capacity procurement. Risk-averse investors seek positive risk-adjusted returns that will be absent in competitive markets that price only energy supplied. A new approach is required, and that approach must link policy, investment, and operational decisions in a structured way, robust to stochastic events at multiple time scales.

WEREWOLF Model Structure

Not surprisingly, models for studying the decarbonization of energy systems are receiving considerable attention in the literature. Many of these models, for example (Graf and Marcantonini 2017), focus on the intermittency of renewables and the effect of this on backup thermal generation and/or storage. The investment paths of these models are either prescribed in advance or simulated by estimating net present values of candidate investments at each stage and then incrementing the model by one-time step with selected investments in place.

Our model is closer in spirit to the classical system planning models such as MARKAL (Fishbone and Abilock 1981) and its modern implementation in the TIMES system (Loulou and Labriet 2008; Loulou 2008). Other similar planning models are ReEDS (Cohen et al. 2019) and GEM (Bishop and Bull 2008). Our model extends these to include uncertainty in operations. In its simplest form, this gives a two-stage model in which stage one invests in capacity and stage two operates this in different states of the world. A multistage version would invest in capacity over several stages, and in each stage operate the system subject to the realized uncertainty in operating conditions.

A number of authors have developed models similar to ours. In the United States (Boffino et al. 2019) study the effect of emissions reduction in ERCOT, the Texas electricity market. The Texas electricity market is unique in that it is almost completely independent of neighboring electric grids; this eliminates the need to consider electricity imports/exports that might occur in the region and tragically, recent extreme weather events in Texas have brought to public awareness the severe limitations of such a policy choice. Similar models to that in Boffino et al. have emerged for Europe, for example the EMPIRE model for capacity expansion developed by (Skar 2016). Similar to our model, EMPIRE restricts capacities of generators using a stochastic availability factor (e.g., wind and run-of-river hydroelectric plant). The EMPIRE model does consider imports/exports between countries in a simplified sense that there is only one electrical node per country.

In the following subsections we describe our model as it is applied to the electricity system within the state of Wisconsin, which is part of MISO. The structure of the WEREWOLF model is closely related to a two-stage stochastic optimization model of Kok et al. although the descriptive equations for electricity flow are simplified (Kok, Philpott, and Zakeri 2018). The WEREWOLF model is also different from the Kok et. al. model in that there are no large hydroelectric power plants in Wisconsin. There are hydropower opportunities in Manitoba, Canada, but transnational boundary flows were not considered as part of this work.

In the WEREWOLF model we seek to understand the spatial distribution of renewable energy investments within Wisconsin's electrical grid under policy scenarios that require high penetration rates of renewable technologies. Since our model is only focused on the portion of the electrical grid within Wisconsin's political borders, we included model parameters that restrict investments in renewable technologies to be confined to Wisconsin state boundaries. WEREWOLF's input data structures allow models to be built down to the county level for the entire United States and the user can aggregate an arbitrary number of adjacent counties together into customized regions. The simulated transmission network is then recreated by a modified Delaunay triangulation method that is fully automated. This allows a user to test the impact that the model's structure has on the sensitivity of the solution. To our knowledge there are no stochastic optimization models that focus on state level renewable energy investments that allow for easy structural transformations. This aggregation can be seen in Figure 1.

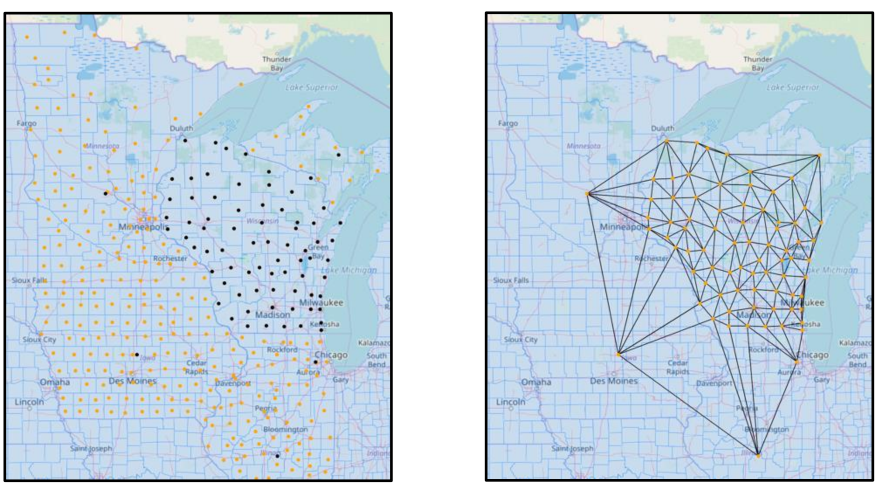

Figure 1: (LEFT) A map of the disaggregated node system in the model (orange markers) alongside the aggregated boundary node system (black markers). (RIGHT) A map of the synthetic transmission network that was created from the automated triangulation methods.

Raw Data Sources

Models such as WEREWOLF require large, detailed datasets in order to instantiate the model. These data form the building blocks of the model that will ultimately be solved. The optimization model is, to a large extent, a generalized tool that can represent any geographic region as long as the underlying data structures are complete. These data typically come from distributed sources and must be harmonized together under one data convention (i.e., labeling schemes, units, etc.). In order to enable flexibility in the model formulation the data framework must also include all the necessary mapping relationships that would enable aggregation/disaggregation of raw data to fit a customized scheme. Once all of these details have been captured, it would be possible to apply the WEREWOLF framework to other regions, EU member states, etc.

In the specific instance of the WEREWOLF model, the geographic mapping scheme allows disaggregation of generator and load data down to the county (FIPS) level, where it can then be aggregated back into user-specified regions. Generator data was collected from the Environmental Protection Agency's (EPA) National Electric Energy Data System (NEEDS) v6 database. The NEEDS database contains generation unit records used to construct the model plants that represent existing and planned/committed units within EPA's larger modeling applications. The NEEDS data includes plant type (21 different classes), geographic, operating, air emissions, and other data on these generating units. The NEEDS database is used as an input dataset into EPA's Power Sector Modeling Platform (referred to as IPM). Demand data for IPM modelled regions is also made publicly available in the form of a load duration curve for all 8760 hours in a year. The IPM modelled regions are provided in a county-level aggregation form; the load duration curves must then be disaggregated to county-level by proportioning out the load by a population weighting factor. The disaggregation scheme could impact some areas that are low population density but have significant industrial loads, but public data to describe these loads with greater fidelity could not be located.

In addition to the EPA datasets, we utilize data collected by the National Renewable Energy Laboratory (NREL) for use in the ReEDS model (Cohen et al. 2019). We use the NREL ReEDS data to describe solar and wind renewable technologies throughout the United States. Data for solar and wind resources represent the richest data in the WEREWOLF model. Solar data is available for seven different classes of installation; each installation type is differentiated by the solar resource (irradiance in kWh/m^2/day) that is available at a particular location. NREL also documents the ultimate solar potential (MW) that is available (constrained by land availability) for every region. Solar capacity factors are documented by technology type, regions, and all 8760 hours in a year. Solar cost curves (approximated as piecewise constant functions) are also supplied by technology type, region, and cost bin. We do not utilize concentrating solar technology data for the WEREWOLF model, but NREL does support this technology type as well. NREL wind data follows the same structure for capacity, capacity factor and cost. Wind resources in the ReEDS model specify 15 different classes of offshore wind resources and 10 different onshore wind resources. Data on capital costs, operating costs, emissions factors, transmission line capacities, and other technology specific parameters (charge rates for batteries, efficiencies, etc.) are mostly populated from sources compiled by the US Energy Information Administration (EIA).

Transforming Data

Time Domain Aggregation – Once the raw data is compiled, harmonized, and formatted, there are a few necessary data transformation steps that must be performed in order to reduce model complexity. While model complexity can be controlled through various geographical aggregation schemes, it is also important to aggregate the time domain from hours into a *loadbloack*. A loadblock is a collection of hours that have similar valued loads. We create loadblocks by sorting all 8760 hours of load data into a strictly convex function and then approximating this curve with a piecewise constant function. An example of this discretization is shown in Figure 2. Care must be taken in order to keep track of which hours get sorted into which loadblock because the model will need to reference this data when specifying the stochastic scenarios for renewable technologies.

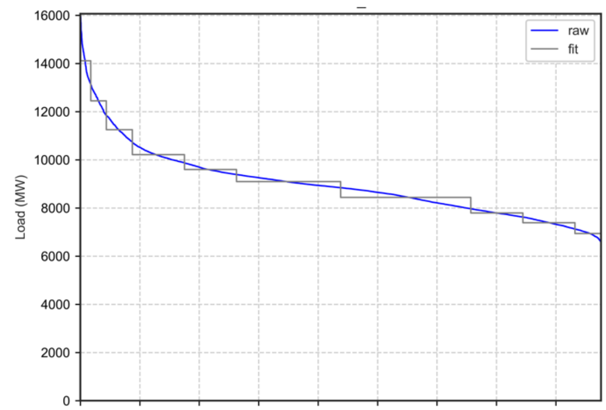

Figure 2: Load duration curve and the associated loadblock functional approximation.

Stochastic Scenarios – The WEREWOLF model only considers wind and run-of-the-river hydropower plants as stochastic resources. Solar is not considered to be stochastic as it is highly correlated with the hour of the day (i.e., even if it is cloudy, there will still be some electricity generated). Wind and run-of-the-river hydropower are more stochastic as they depend directly on current weather conditions and can vary from 0 MW output to their maximum MW output over a short period of time. It is therefore necessary to create a number of scenarios that represent a number of possible futures (windy, not-windy, rainy or dry) – we do this by randomly perturbing the capacity factor data from NREL for both wind and hydro resources and storing these alternative futures as a new dataset. The stochastic part of the objective function will then average across all of these scenarios such that the expected costs are minimized (rather than simply using deterministic cost).

Formulation Details

The first model we consider is a stochastic version of an LP for the Wisconsin wholesale electricity market. This model there is no storage available (i.e. no stored hydro or batteries). We solve:

$$
\begin{array}{llcll}
\text{P: min} & \psi & = & \sum_{k\in\mathcal{K}} \left(K_k(x_k) + L_k(z_k)\right) + Z & \\
\text{s.t.} & Z & = & \sum_{b\in\mathcal{B}} H_b \left(\sum_{k\in\mathcal{K}} C_k y_{k,b} - V(d_b - r_b)\right), & \\
& 0 \le x_k & \le & u_k, & k \in \mathcal{K}, \\
& 0 \le z_k & \le & x_k + U_k, & k \in \mathcal{K}, \\
& 0 \le y_{k,b} & \le & z_k, & k \in \mathcal{K}, b \in \mathcal{B}, \\
& 0 \le r_b & \le & d_b, & b \in \mathcal{B}, \\
& d_b & \le & \sum_{k\in\mathcal{K}} y_{k,b} + r_b, & b \in \mathcal{B}.
\end{array}
$$

where

- $k \in K$ denotes different generating technologies;
- $b \in B$ indexes load blocks where H_b denotes the number of hours in block b, and $\sum_{b\in B} H_b$ gives the number of hours in a year;
- the variable z_k is the capacity invested in technology k;
- variable cost for technology k is defined as C_k respectively;
- annual fixed cost for technology k is defined as M_k;
- the load in load block b is d_b, and value of lost load is V;
- $y_{k,b}$ denotes the production (MW) of technology k in each hour in load block b;
- r_b denotes the load shed (MW) in each hour in load block b.

We account for existing capacity using the parameter U_k , and we split the annual fixed cost M_k into a capital investment cost K_k and an annual maintenance cost $L_k(z_k)$ on existing and new capital. Note that we could also adjust the cost data C_k to account for a constraint on renewables, perhaps using a carbon tax, but we will defer that discussion for future work. We extend the above analysis to account for uncertainty. The uncertainty will manifest itself in various ways that we will endeavor to model in a two-stage stochastic modeling framework. Our approach to modeling uncertainty closely follows that of (Kok, Philpott, and Zakeri 2018). The types of uncertainty we consider will account for short-term uncertainty in wind and run-of-river generation. As stated above, for purposes of this model, we do not treat solar power (utility scale or distributed solar PV) as stochastic in nature; this assumption may be relaxed in future modeling efforts.

Stochastic Power Generation

We extend the model described in P to include specific technologies that are subject to uncertainty by introducing a new scenario indexing variable (ω) that represents a random future state of the world. The ω index is a tuple that describes all the stochastic futures that were created by data transformations. The parameter $\mu_{k,i,b}(\omega)$ for technology k in region i denotes a proportional reduction in its capacity in load block b and random event ω. Here μ is used in constraints on the generation (recourse variables) $y_{k,i,b}(\omega)$ that hold in each of the scenarios ω: $y_{k,i,b}(\omega) \leq \mu_{k,i,b}(\omega) z_{k,i}$. Note that $z_{k,i}$ is now indexed by both region i and technology k. The stochastic social planning model is as follows. We seek a solution that minimizes a risk-adjusted capital and operating costs. Within this framework we can start to envision various types of policy constraints on non-renewable generation.

Model Constraints and Extensions

Standard constraint formulations are possible that would test different policy scenarios -- limits on total CO_2 emissions, capacity limits on non-renewable generation, etc. The stochastic formulation allows for other interesting emissions constraint formulations that might more accurately reflect policy realities. For example, the WEREWOLF model allows the user to build in *chance constraints* that allow the user to choose to limit the average total emissions, total emissions in every stochastic scenario, or restrict annual emissions to zero (if modeling deep decarbonization targets) for a user-controlled fraction of the scenarios. These three formulations represent different mathematical descriptions of a single policy to “reduce emissions by *X*%”. We previously discussed that the model was formulated with a flexible structure in terms of the description of the transmission system, but with a few programmatic options the user can also explore which type of emissions constraints they wish to impose. Being able to move between modelling regimes allows the analyst and the policy makers to understand the solution space more broadly than if a deterministic model were simply run over and over again for different sets of data inputs.

It is often discussed in policy circles that an incentive system could be put in place that would encourage emissions reductions rather than require them by law. This formulation is also available as part of the flexible WEREWOLF design (and is an extension of the model described in *P).* This reformulated model is able to probe the level of exogenously determined payment (the incentive) that must be made to the electrical generator in order to reduce emissions from their generator fleet.

WEREWOLF Model Policy Scenarios

The authors gathered recommendations from the Wisconsin Governor’s Task Force on Climate Change (WTFCC, 2020) to generate our sample policy scenarios. Specifically, we look to inform the following recommendations from the Task Force Report:

1. Develop electricity storage for critical infrastructure
2. Support hybrid-electric vehicles, electric vehicles, and infrastructure
3. Set utility carbon-reduction goals

For purposes of this report, we look at Recommendations #1 and #2 (above) within the context of having an active utility carbon-reduction goal or not. The two policy experiments (referenced as A & B below) are designed to investigate the impact on…

A. … generator investments (with and without carbon reduction goals); and,
B. … generator investments from electric demand shocks that result from increased adoption of electric vehicles (with and without carbon reduction goals)

The carbon reduction goals for both policy experiments follow the WTFCC report baseline methodology that by 2030 net carbon emissions from the power sector should be at least 60% below 2005 levels and that by 2050 the power sector net carbon emissions should be 100% below 2005 levels. These decarbonization goals are consistent with EU climate and energy goals and the Paris Agreement. For purposes of operating the WEREWOLF model, we interpret "power sector net carbon emissions" simply as "power sector total carbon emissions" that occur within the state of Wisconsin (in units of metric tons of CO_2). The WEREWOLF model boundary includes many detailed aspects of the electric grid operation but does not include other relevant systems that could be used to offset emissions from the electric power sector (forestry, agriculture, transportation, etc.). For our purposes of our policy scenarios and discussion, we used a policy baseline value of 49.2 million metric tons of CO_2 in 2005 (Public Service Commission of Wisconsin, Wisconsin Energy Statistics, 2020).

Policy Scenario A – Impact of Carbon Goals on Generator Investments

We generate two model instances in order to investigate the impact of a 60% reduction on the state of Wisconsin's in-state carbon emissions by 2030. The first instance simply runs the model, where overall system costs are minimized, without a carbon constraint ("No Carbon Goals"). The second model instance also minimizes the overall system costs, but the carbon constraint is now active ("Carbon Goals"). The 2030 generator mix for both scenarios are shown against the 2020 baseline in Figure 1.

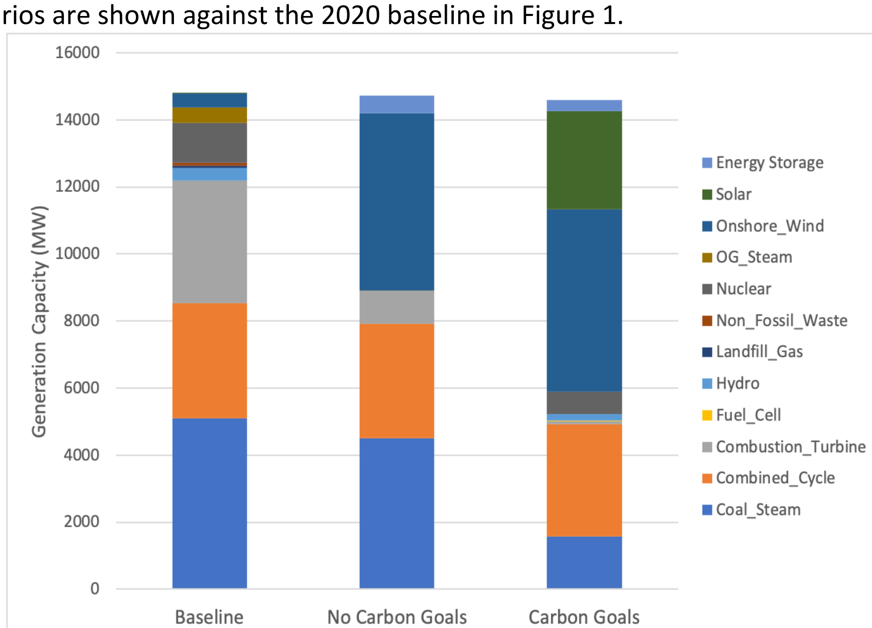

Figure 1: Generation capacity mix in 2030 for different policy scenarios.

It is not surprising that as carbon reductions are enacted, the need for clean energy sources increases. The results of WEREWOLF suggest that much of the coal steam generators are shut down by 2030 if a 60% carbon reduction policy is enacted. The results also suggest that a large portion of the current combustion turbine generation capacity should also be shut down. The total generation capacity from these shutdowns is largely supplanted with an additional 5 GW of wind and onshore wind power and 2.9 GW of solar photovoltaic systems (both distributed and utility scale solar) in the "Carbon Goals" scenario. Investment in intermittent generators is a prominent feature in both the "No Carbon Goals" and "Carbon Goals" scenarios, which highlights the fact that these sources are currently economical when compared against other generator technologies. The generation from these intermittent sources incentivizes investment in energy storage technologies (+521 MW for "No Carbon Goals" and +345 MW for the "Carbon Goals" scenario). WEREWOLF's decision to build storage is based on being able to arbitrage across time slices; storage systems enable electricity that was generated at a lower price to be stored and sold during peak demand (and price) time periods. Electricity storage systems also play an important role in frequency regulation during actual grid operation, but these ancillary services are not considered part of the value proposition within the context of WEREWOLF. Another interesting feature of these results is that nuclear, a low-carbon (but not necessarily low-waste) technology, would still play a role where deep carbon reductions are necessary. If carbon policies are not enacted, nuclear is expensive enough to maintain that it would be better to shut down the plant and build other intermittent resources. Costs for long-term storage of spent nuclear fuels and other nuclear fuel life cycle costs are not currently included in the model.

It should be discussed that the additional 5 GW of onshore wind highlights a modeling constraint on additional generation capacity. If left unconstrained, the WEREWOLF model would choose to build up to 20 GW of onshore wind in Wisconsin, and zero additional solar PV. Modeling parameters such as these are often necessary to include to avoid unrealistic corner solutions (these parameters can capture much of the market effects that are impossible to model -- land-use permitting, political influence, etc.). However, these tunable parameters are often difficult to understand without broader input from experts from various backgrounds. It is the overall goal of the WEREWOLF project to engage in these transparent discussions and use the Werewolf framework to fairly evaluate all proposals and data inputs. Future iterations of WEREWOLF could begin to account for these tunable parameters.

Scenario B – Impact of EV Deployment on Generator Investments

In this policy scenario we model widespread adoption of light duty electric vehicles (EVs) in the state of Wisconsin and the additional load's impact on generator investment decisions. Specifically, we estimate what might happen if 10% of all current gasoline vehicles are taken off the road and replaced with EVs by 2030. It is possible to estimate the average power (and therefore energy over the entire year) needed to move all these vehicles if some modeling assumptions are made about the average gasoline vehicle efficiency (24.9 miles per gallon), annual vehicle miles traveled (12,000 miles), and the number of light duty vehicles (LDV) in the U.S. (approximately 193 million vehicles). This data is national in scope, so we downscale it by a population weight (by FIPS code) and apply the additional MWh load to the electric grid in a region-specific way. We also make assumptions about the aggregate charging profile of all EV users in order to add a time-specific dimension to this national data. We assume that the aggregate charging profile might be sinusoidal in nature with a peak charging rate occurring in the after work/early evening hours (only one peak period per day). This pattern was designed to mirror other daily home energy demand trends (i.e., hot water usage, HVAC energy consumption, etc.). Ultimately, these estimations result in an additional 180,000 MWh (after adjusting for EV drive-train efficiency gains) that must be supplied in Wisconsin each year for every 1% of light duty vehicles that are converted to EVs. Wisconsin currently generates almost 60 million MWh of electric energy, so each additional 1% of light-duty vehicles added to the grid requires additional electric energy equivalent of 0.3% (0.003).

While the adoption of EVs in Wisconsin is quickly gaining momentum (from 2017-2018 the EV market grew 24% from the previous year), it was still less than 1% of total vehicles. Due to the small current market of

EV adoption in Wisconsin, it is not certain that even at the rapidly increasing pace now underway, EVs market penetration would reach levels where the additional load would impact generator investment decisions. This result is supported from the output of the Werewolf model. The system optimal economic solution (i.e., a solution that one would achieve if there was only one decision maker without policy intervention) would suggest that by 2030 the generator mix in Wisconsin would be primarily made up of combustion turbine, combined cycle, coal steam, and onshore wind power plants (see "2030 Baseline" in Figure 2). Total carbon emissions from the 2030 Baseline case are calculated to be 41.28 MMTonnesCO2 (0.54 MTonnesCo2/MWh), which is very similar to current day emissions (39.26 MMTonnesCO2 and 0.66 MTonnesCO2/MWh). If 10% of the LDV fleet were converted to EV, the generation mix would not vary dramatically, except that energy storage technologies would be economical in order to arbitrage time periods due to the intermittent nature of vehicle charging. Total carbon emissions for this scenario increase to 42.4 MMTonnesCO2 (0.55 MTonnes/MWh). Post hoc analyses suggest that the 10% adoption rate would remove approximately 1.06 MMTonnesCO2 from annual transportation sector emissions – net emissions for the power sector would then be 42.4 – 1.06 MMTonnesCO2 or about 41.34 MMTonnesCO2 per year. This result suggests that a "rising tide raises all ships" approach to carbon policy would be necessary to be effective; one cannot simply rely on individual technologies (i.e., EVs) to reduce carbon emissions that occur throughout the economy. In order to reduce the carbon intensity of the electric grid, which is used to charge EVs, carbon policies should be applied directly to the operation of the power sector.

We are now interested in two additional scenarios where we constraint power sector emissions to be 60% lower than the baseline and assume a 10% and a 50% penetration of EVs into the LDV market by 2030. In both cases, it is economical for nuclear power to be part of the overall generation mix; wind and solar PV work to push coal power plants down from 5 GW to 2 GW of capacity. The WEREWOLF output also shows that combustion turbine generators are shed from the generation mix as EV deployment reaches 10% (with carbon goals). As EV deployment increases, the need for combustion turbine generators returns. As with Scenario A the WEREWOLF results show that the additional intermittent resources incentivize energy storage technologies in Figure 2 below.

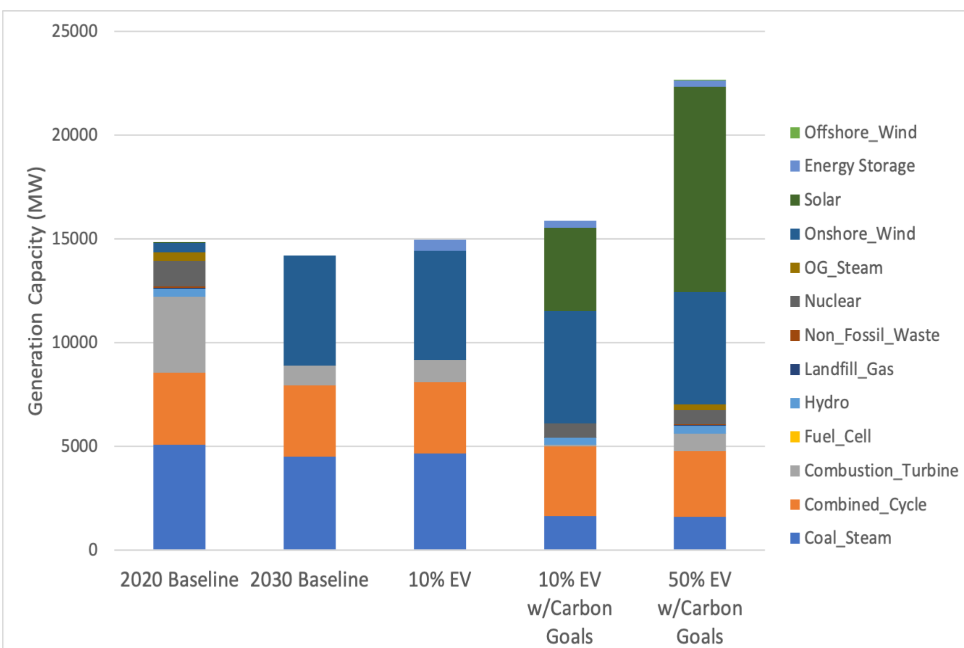

Figure 2: Impact of EV deployment on generator investment decisions in 2030 with and without carbon reduction policy.

Conclusion

While there is no silver bullet to enable an energy transition free of difficult choices and trade-offs, WEREWOLF's user-friendly interface enables policy analysts to quickly assess opportunities. It's open source and transparent data driven scenario analysis can enable stakeholders to fully understand inputs and outputs to help enable policy makers in determining optimal paths to achieving goals such as Wisconsin's 100% carbon-free electricity, the European Union 2030 Climate & Energy Policy Framework and the United Nations Sustainable Development Goals. Availability of data could be a barrier to performing this type of analysis in England or in Europe. However, if the availability of data is not a barrier, a tool like WEREWOLF can enable stakeholders to mind the gap between data and policy while planning energy systems of the future.

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