A Novel Air Quality Metric for Evaluating Production Cost Model Dispatch Decisions

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***Abstract*—Production Cost Model (PCM) studies evaluate power system performance over numerous metrics. This paper demonstrates a novel workflow that bridges PCM with air quality metrics to improve understanding of how generator dispatch decisions in PCM simulations can impact pollutant emission calculations and air quality metrics. Using this workflow, we integrate meteorological data and Gaussian dispersion models to evaluate the impact of local generator emissions on air quality. We demonstrate a PCM study that quantifies the effect on air quality across communities by connecting different types of power generation.**

***Index Terms*—Production Cost Model, Air quality, Generation mix, MTDC**

I. Introduction

Production Cost Model (PCM) studies help inform system-level decision-making with cost-benefit analysis, enable cross-domain studies, and quantify system response and impact metrics. Historically, PCMs have served as powerful tools for simulating short-term power system operations, focusing on minimizing costs while ensuring system reliability.

A. Background

Beyond technical feasibility, PCM applications have been expanded to include strategic bidding behavior and risk in competitive electricity markets [1]. Incorporating emission constraints into economic dispatch, as demonstrated by Ramanathan [2], marks a new innovation in the extension of PCM beyond traditional cost minimization objectives. Recent research has further integrated environmental metrics into PCM studies, e.g., examining tradeoffs between cost optimization and emission reductions [3]. Similarly, Diakov et al. [4] bridged capacity expansion models and PCM tools to align long-term generation planning with short-term operational requirements. These studies underscore the versatility of PCM as it evolves to address multiple objectives.

Air quality is intrinsically tied to energy systems, especially the emissions from electricity generation [5]. Select census districts can often face detrimental air quality caused by pollutants such as particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), sulfur oxides (SO_x), and ozone precursors [6].

B. Contribution

This paper presents a novel metric to measure effects of generation dispatch on local air quality. This metric has minimal computational overhead and can be readily generated by typical PCM outputs. While traditional approaches to modeling air quality have focused narrowly on atmospheric conditions and pollutant transport, they often overlook the dynamic ways in which changes in energy system operations, such as generation dispatch decisions, impact local air quality. This siloed approach limits our ability to ask meaningful questions about how energy system transitions, such as the integration of different generation sources, influence air quality across communities.

In this study, we demonstrate a novel workflow that bridges power system simulations with air quality metrics to enable a more dynamic understanding of energy systems' impacts. Specifically, we connect generator dispatch data produced in power systems simulation experiments to air quality equity metrics like the Air Quality Index (AQI). Using this workflow, we integrate meteorological data and Gaussian dispersion models to evaluate the impact of emissions on communities. To support transparency and reproducibility, the modeling workflow presented in this paper is implemented using open-source software and is publicly available [7]. This linkage allows us to answer questions that were previously beyond reach: *How will altering the composition of energy generation impact air quality in different communities over time?*

Such questions, while central to energy planning and policy, remain difficult to address without an integrated framework combining electricity system simulations and air quality modeling. On one hand, power systems researchers can simulate the impacts of different system configurations on generator dispatch, but these simulations rarely consider how emissions affect air quality of specific local communities. On the other hand, air quality researchers model pollutant dispersion and AQI, but often isolate these calculations from the operational dynamics of the energy system. By integrating PCM and pollution dispersion modeling, we show how energy system decisions directly inform air quality metrics, a critical step toward assessing future energy transitions. Our approach is particularly relevant for investigating different system configurations. For example, investments in multi-terminal di-

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rect current (MTDC) and radial system configurations have the potential to reshape generator dispatch patterns, reduce emissions, and ultimately improve local air quality. However, quantifying these benefits requires coupling energy system simulations with detailed air quality assessments, which this workflow addresses.

To illustrate practical applications, we focus on WECC, a region with diverse energy sources and significant environmental disparities, and compare the impact of three different generation integration scenarios on AQI. By answering new questions about air quality variation across communities, this workflow lays the foundation for more holistic energy system planning.

The rest of the paper is organized as follows, Section II describes the new air quality metric, Section III describes the methods and assumptions to compute CO_2 emissions, Section IV covers the data, methods, and tools used in the PCM study and the scenarios looked at in this paper, Section V displays the results from the PCM study scenarios, and Section VI concludes the paper.

II. Air Quality Metric

We measure air quality equity by examining the air quality index (AQI) at the community level. To do this, we evaluate the contributions of emissions from electricity generators within a 100-mile radius of each community. The generator dispatch data in megawatt hours (MWh) is converted to emission rates of CO, NO_2, SO_2, $PM_{2.5}$ and PM_{10} in grams per second, based on the fuel type. Emission rates and meteorological data (e.g., wind speed, temperature) are used to estimate the daily pollutant concentrations in each community via a Gaussian dispersion model, while accounting for background levels from preexisting data. Using these concentrations, we calculate the daily AQI of each community over the course of a year to assess the impact of three different integration scenarios on air quality.

A. Community Selection

To identify communities at particular risk of poor air quality, we utilize a screening tool [8]. The screened data is filtered to only U.S. states within the WECC region, and then by burden factors directly related to energy or associated health impacts of energy production:

- Energy cost $\geq 90^{\text{th}}$ percentile
- $PM_{2.5}$ in the air $\geq 90^{\text{th}}$ percentile
- Asthma $\geq 90^{\text{th}}$ percentile
- Percentage of people in households whose income is less than or equal to twice the federal poverty level $\geq 65^{\text{th}}$ percentile.

We identify 19 communities within the WECC states that meet *all four* criteria listed. These communities are shown in Table I.

Note that when there are several communities within the same county, we choose one central location between all of the selected census districts to perform our calculations.

TABLE I
WECC Disadvantaged Community Classification

2010 Census tract ID	County	State/Territory
6007003001	Butte	California
6019000700	Fresno	California
6019000902	Fresno	California
6019001000	Fresno	California
6019002000	Fresno	California
6019005403	Fresno	California
6019007802	Fresno	California
6029000400	Kern	California
6029001202	Kern	California
6029001300	Kern	California
6029001500	Kern	California
6029002200	Kern	California
6037242100	Los Angeles	California
6037242600	Los Angeles	California
6077002201	San Joaquin	California
6077002503	San Joaquin	California
6107004200	Tulare	California
41029000100	Jackson	Oregon
41035971200	Klamath	Oregon

TABLE II
Average Fuel per MWh of Electricity Production, 2022

Fuel Type	Fuel per MWh
Coal	0.57 ton/MWh
Natural Gas	7420 scf/MWh

B. Computation

We break down the process of calculating the AQI into four steps.

Step 1: We use latitude and longitude coordinates for each of our generators as well as each community of interest to calculate the geodesic distance between every generator and the community and use this distance to isolate generators by type within 100 miles.

Step 2: The rate of each emission type stemming from each generation source in g/s are calculated using fuel mass conversion data [9], shown in Table II, and emission factors [10], [11], shown in Table III. For coal, an overfeed stoker firing configuration is assumed. We assumed 1% weight sulfur content of coal as fired to determine the emission factor for SO_x. To get the emission factor for $PM_{2.5}$ we summed the contributions from both filterable PM and total condensable PM.

These data can be applied to the day ahead market generator dispatch data from our simulations to calculate the emission rate of each pollutant.

Step 3: A Gaussian plume dispersion model is used to determine the concentration of pollutants at each community, given its distance from the emission source. A Gaussian dispersion model uses a normal distribution to predict how a plume of air pollution spreads through the atmosphere, assuming pollution concentrations are highest at the plume center, which drifts from the source assuming steady-state wind conditions. Key inputs include emission rate and wind speed. A detailed analysis of the Gaussian plume model is

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TABLE III
COAL AND NATURAL GAS EMISSION FACTORS.

Pollutant	Coal Emission Factor (lb/ton)	Natural Gas Emission Factor (lb/10^6 scf)
SO_x	38	0.6
NO_x	7.5	190
CO	6	84
$PM_{2.5}$	16.04	7.6
PM_{10}	6	7.6

provided in [12]. Wind speed data is obtained from the ERA5-Land hourly data from 1950 to present data set [13].

Gaussian plume models assume steady-state, constant conditions, and do not vary with time. As a result, we do not account for changes in wind direction and instead assume the worst-case scenario that the wind is blowing in the direction of the community from the generator. Future work could incorporate dynamic wind fields by using a more advanced dispersion model such as a Gaussian puff model [14], which allows for temporal resolution. We initialize a separate instance of the dispersion model for each hour and for each community using wind speed and temperature data from the appropriate location and time to determine pollutant concentration contributed from power plant emissions.

Power plant emissions are not the only contribution to poor air quality. Background concentration of pollutants for each community of interest are gathered from the EPA AirData Air Quality Monitors [15], which includes information from several locations throughout the WECC region. To determine background levels, we look for the closest monitors to our community of interest and pull values from the most current year with available data. For each pollutant, we take the arithmetic mean of the concentration for the selected year. Since the background concentration also includes contributions from power plant emissions, we subtract the mean concentration of pollutants attributed to power plant emissions and then add back the simulated emissions from PCM.

Step 4: AQI is determined based upon the concentration of the following pollutants: CO, NO_x, SO_x, $PM_{2.5}$, PM_{10}, and O_3. Power plants contribute to ozone formation but do not directly emit ozone. As such, we do not have enough data to accurately predict ozone emission and omit ozone contributions from our AQI calculations. We compute the AQI using the EPA daily air quality reporting standards [16] and report the maximum hourly AQI calculated for each day.

III. METHODS AND ASSUMPTIONS TO CALCULATE EMISSIONS

Carbon emissions are estimated using generation fuel type and dispatch decisions. We are only considering carbon dioxide (CO_2) emissions. There are two other major emission sources: methane (CH_4) and nitrous oxide (N_2O). Methane and nitrous oxide emissions from electricity generators are fairly insignificant, as more than 98.5% of emissions contributed from generators are carbon dioxide [17].

Consuming different fuels will produce varying rates of emissions. We find that our emission rates are 0.336 and 0.181 metric tons CO_2/MWh for coal and natural gas, respectively [18]. Finally, we multiply by the generator dispatch data to get metric tons CO_2 emitted from each generator and sum this up over the entire year for each of our integration scenarios.

IV. METHODS AND DATA

A. Scenarios

The PCM studies used in this paper were carried out using a 240 bus representation of the western interconnection grid in the United States (MiniWECC model), the network for this model was last updated by CAISO [19]. The model was updated by aggregating the WECC Anchor Data Set from 2032, with some additional renewable energy data, as described in [20].

Radial and meshed topology integration scenarios are evaluated for interconnecting five new low/no-emission generators. These five generators are interconnected to existing buses either radially or through a multi-terminal direct current (MTDC) network that also connects the five generators together. This study closely follows the design considerations for both topologies as discussed in [21], [22]. These connected generators were allowed to update their bids for each day-ahead market that is simulated in these studies. For both of these scenarios LMP data from the base case for the points of interconnection of the generators (which remained the same for both scenarios).

Because proprietary PCM software, such as GridView, generally does not allow bid cost updates during simulation, we used the open source EGRET [23] unit commitment engine and built a wrapper to move through time and update the data based on the original input data from the GridView PCM. Generators were added in EGRET at each point of interconnect and modeled as a thermal generator to allow updates to bid costs and generator maximum limits for each hour of the day ahead market.

B. Generator Variability

Resource availability forecasts were created following the algorithm in [24]. This approach reproduces the statistical characteristics of forecasts published by system operators. For this analysis, the standard deviation and autocorrelation (lag of one) of mainland wind plants in CAISO were used to produce fictitious forecasts. Samples from a distribution with this standard deviation are autocorrelated, scaled to the capacity of the plant, and added to the power production series at each time point. For each plant, 30 forecasts were created.

For each day, a 30x24 array of 30 forecast scenarios is produced for each of the 24 hours in the day corresponding to each bus. For each bus, those forecasts are used to generate a DA bid that is communicated to the EGRET model for participation in the DA market.

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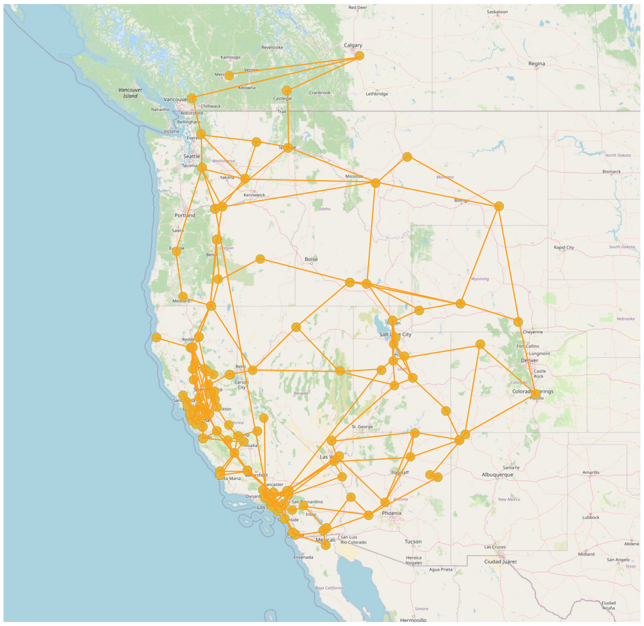

Fig. 1. The MiniWECC power system model transmission lines and buses in the MiniWECC model are plotted here using the GPS coordinates for each of the buses.

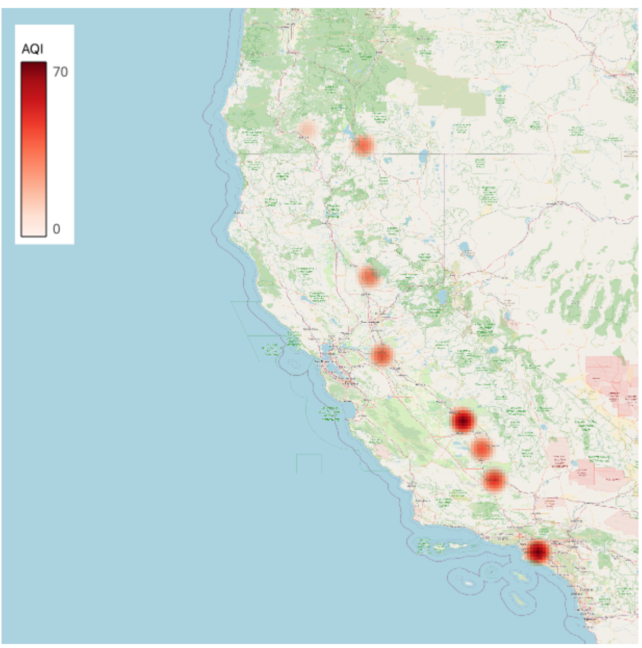

Fig. 2. Average AQI across the simulated year for the base case.

C. Co-Simulation Toolbox

CoSim Toolbox (CST) [25] is a suite of tools that supports HELICS-based co-simulations by providing a Python class for HELICS API calls, data collection between federates, and metadata management. In this application, CST was used to coordinate information sharing between the MTDC simulation, the market simulation, and historical data inputs for the simulations.

TABLE IV
SIMULATED ANNUAL AVERAGE AQI FOR EACH SCENARIO

Location	Base AQI	Radial AQI	MTDC AQI
Butte Co, CA	34.66	34.57	34.39
Fresno Co, CA	70.19	68.79	65.50
Kern Co, CA	48.26	48.55	48.62
Los Angeles Co, CA	70.20	70.18	68.81
San Joaquin Co, CA	40.57	33.05	26.16
Tulare Co, CA	41.08	41.24	41.13
Jackson Co, OR	16.07	16.11	16.05
Klamath Co, OR	34.91	34.94	34.76
Average	44.49	43.43	41.93

TABLE V
SIMULATED TOTAL EMISSIONS, 2032

Scenario	**CO_2 Emissions (metric tons)**
Control	110796490
MTDC	73735812
Radial	77748230

D. Results

The average AQI results across one simulated year for each community are shown in Table IV and Figure 3. We can see that on average, the MTDC and radial scenarios improve air quality in communities. The most significant reduction in AQI occurs in San Joaquin County, which reduces AQI by 18.5% in the radial integration scenario, and by 35.5% in the MTDC case, nearly doubling the improvement in air quality. The remaining locations are not changed by significant margins.

The 2032 simulated CO_2 emissions for each scenario are shown in Table V and Figure 3. We can see that both interconnection scenarios significantly reduce CO_2 emissions over the course of one year. The radial and MTDC integration scenarios reduce emissions by 33048260 (28.8%) and 37060678 (33.4%) metric tons CO_2, respectively.

The code associated with this workflow is publicly available through the `pyso` repository maintained by Pacific Northwest National Laboratory [7]. This repository includes tools for processing PCM dispatch outputs, calculating emissions, and evaluating air quality metrics for community-level analysis.

V. CONCLUSION AND APPLICATION

We have presented a new workflow to understand the effects of the topology of the power grid and the incorporation of low/no-emission plants on the air quality index in selected communities throughout the WECC region. This workflow couples energy system simulations with detailed air quality assessments that can inform policy decisions.

To incorporate the proposed metric, system operators could add constraints to the day-ahead market that adjust generator dispatch based on AQI or other emission thresholds, prioritizing reductions in emissions near targeted areas. For long-term planning, the metric could be used to simulate different integration scenarios to evaluate the impact on AQI in selected communities.

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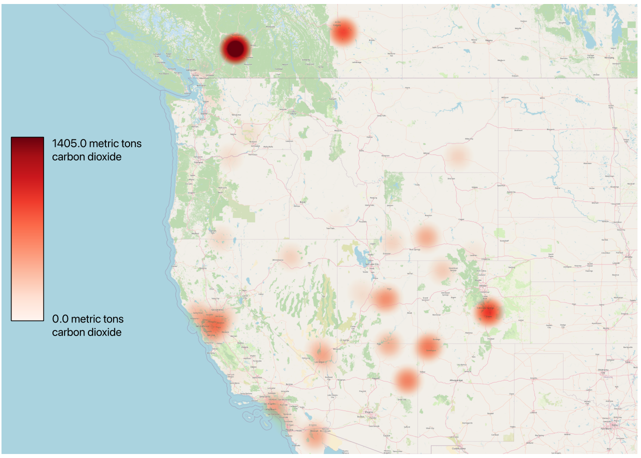

Fig. 3. Average CO_2 emission in the year 2032 in the control case.

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