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RESEARCH ARTICLE

Assessment of Spatial and Temporal Modeling on Greenhouse Gas Emissions From Electricity Generation

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ABSTRACT This paper highlights the importance of precise assessments of greenhouse gas (GHG) emissions associated with power generation for effective policy making in environmental sustainability. The current assessment approaches based on historical data or estimated generation using energy models may not accurately reflect the reality of future power systems due to the impact of spatial-temporal and techno-economic characteristics of generation mix and load demands. To address this, the paper presents a comprehensive methodology for accurately quantifying the geographical and temporal variations in GHG emissions associated with generating units' operation, startup, and shutdown at an hourly resolution. The methodology is based on a detailed electricity model that considers various sources of generation, techno-economic, and spatial-temporal characteristics of system components. The study demonstrates the effectiveness of the methodology in quantifying GHG emissions in the IEEE RTS-GLMC system, with a focus on CO2, N2O, and CH4. The analysis reveals significant variations in GHG emissions among different generation buses and hours of the year, attributed to the high proportion of renewable energy in the generation mix. The paper emphasizes the inadequacy of examining marginal environmental impacts based on GHG emission intensity alone and suggests a more thorough analysis based on total GHG emissions generation. Finally, the paper emphasizes the crucial role of time-varying and marginal assessment techniques in identifying effective strategies for reducing GHG emissions in the electricity sector, including optimizing the operation and capacity of generation units, energy storage systems, and electric vehicles, including their locations.

INDEX TERMS Energy, GHG emissions, renewable generation, energy storage, electric vehicle.

I. INTRODUCTION

Electricity and heat are considered among the most significant contributors to global CO_2 emissions, with their combined contribution rising from 37.2% in 1990 to 42.8% in 2020 (see Fig. 1) [1]. This is attributed to an increase in the global share of fossil fuels for power production from 7500 TWh in 1990 to 16455 TWh in 2021 [1]. Despite the significant increase in renewable energy penetration since 1990, fossil fuel still dominates global power generation with 65.8% in 2020. Power generation is projected to increase due to the rising demand and electrification of the heat and transport sectors [2].

Such a transition would require electricity generation to be at least competitive from the carbon emission standpoint compared to conventional technologies; therefore, the

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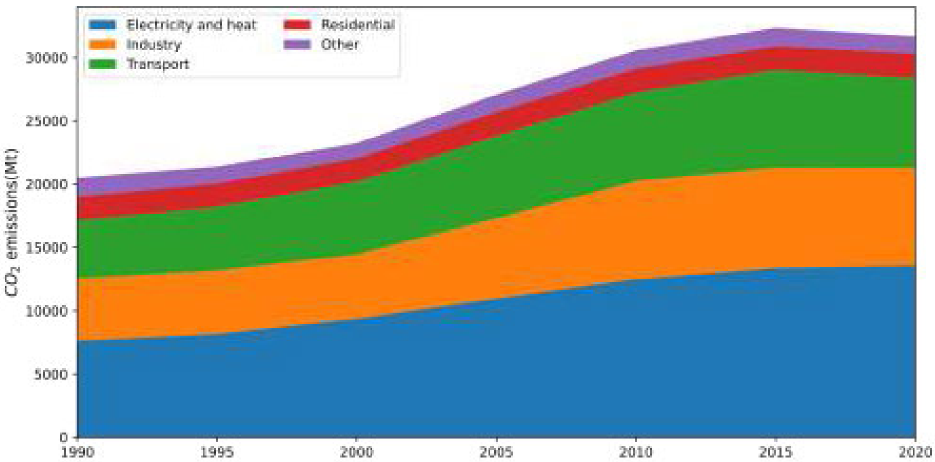

FIGURE 1. Global CO_2 emissions from different sectors in the period 1990-2020 Source: IEA 2022 IEA (2022), Energy Statistics Data Browser, IEA, Paris https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser report.

benefits of electrification can be justified [3]. Hence, the environmental impact of electrification must be evaluated to sustain future regulations and policies without compromising the security of supply. Life cycle assessment (LCA) was introduced to assess the electrical system's environmental impact across all life cycle stages, referred to as CO_2 equivalent (CO_2e). Electricity generation and load demand typically vary depending on the time of day, the season, and the year. Furthermore, the electricity generation mix varies from one moment to the next and can differ in different electrical grids. These specific properties result in evaluating GHG emissions associated with electricity generation as a complex and challenging procedure [4].

The International Organization for Standardization (ISO) (ISO, 20 6a) [5] introduced detailed standards to guide LCA's fundamental framework; however, these standards undetermined the guidelines on how GHG emission of the electrical system can be determined. Typically, (GHG) emissions related to electricity generation can be evaluated using data-based and model-based approaches. The data-based approach involves collecting data on emissions from power plants or other sources and using it to estimate GHG emissions [6], [7], [8], [9]. Since the transparency and credibility of national statistical data on energy and emissions are frequently questioned, the results estimated using statistical data are limited in accuracy and reliability [10]. Moreover, this approach is limited to assessing the previous or current situation and cannot reflect the situation or predict changes in the electrical grid from a future perspective. Some studies use capacity factors, estimated from statistical data, to estimate the actual energy output of a power plant. Subsequently, this information can be combined with emissions factors, which represent the amount of greenhouse gases emitted per unit of electricity generated, to estimate the current or future GHG emissions associated with power generation [11], [12], [13], [14]. The challenge of using capacity factors for greenhouse gas (GHG) emissions estimation is the availability and accuracy of national statistical data. Additionally, using capacity factors can lead to over or underestimation of GHG emissions, as it does not consider the variation of load demand and renewable generation within a particular year. This can result in an incomplete understanding of the system's actual energy output and emissions [15].

Assessment of GHG emissions using simulation models is a practical approach to address previous issues related to data availability and fluctuations of load demand and renewable generation. This approach can predict the future or current generation mix using mathematical models instead of the capacity factor [16]. The accuracy of the results obtained from this method strongly depends on the level of detail considered in the model, including the representation of the power system's physical and operational characteristics and the quality of the input data used in the model [17]. Several studies have used a modelling approach to estimate the GHG emissions for the electricity sector. The existing work ignored the variability of load demand and renewable generations [18], [19], [20], [21]. Although some studies focused on the variations in load demand and renewable generations, variations in marginal emissions cause challenges and could be addressed similarly. In [22], the authors considered the variation of marginal emissions, but they used three snapshots to represent the variability in load demands and renewable generations. Similarly, in [21], the authors considered time-varying and marginal emissions, but they used a few hours per year to evaluate the time-varying and marginal emissions. Using low-resolution data to represent variability in the grid may not provide an accurate picture of the emissions, which can lead to misleading or incorrect conclusions about the environmental impact of the energy system. Although the technical parameters of generation units significantly affect the model accuracy, they were eliminated in most previous studies [17]. In [23], the authors estimated the seasonal and

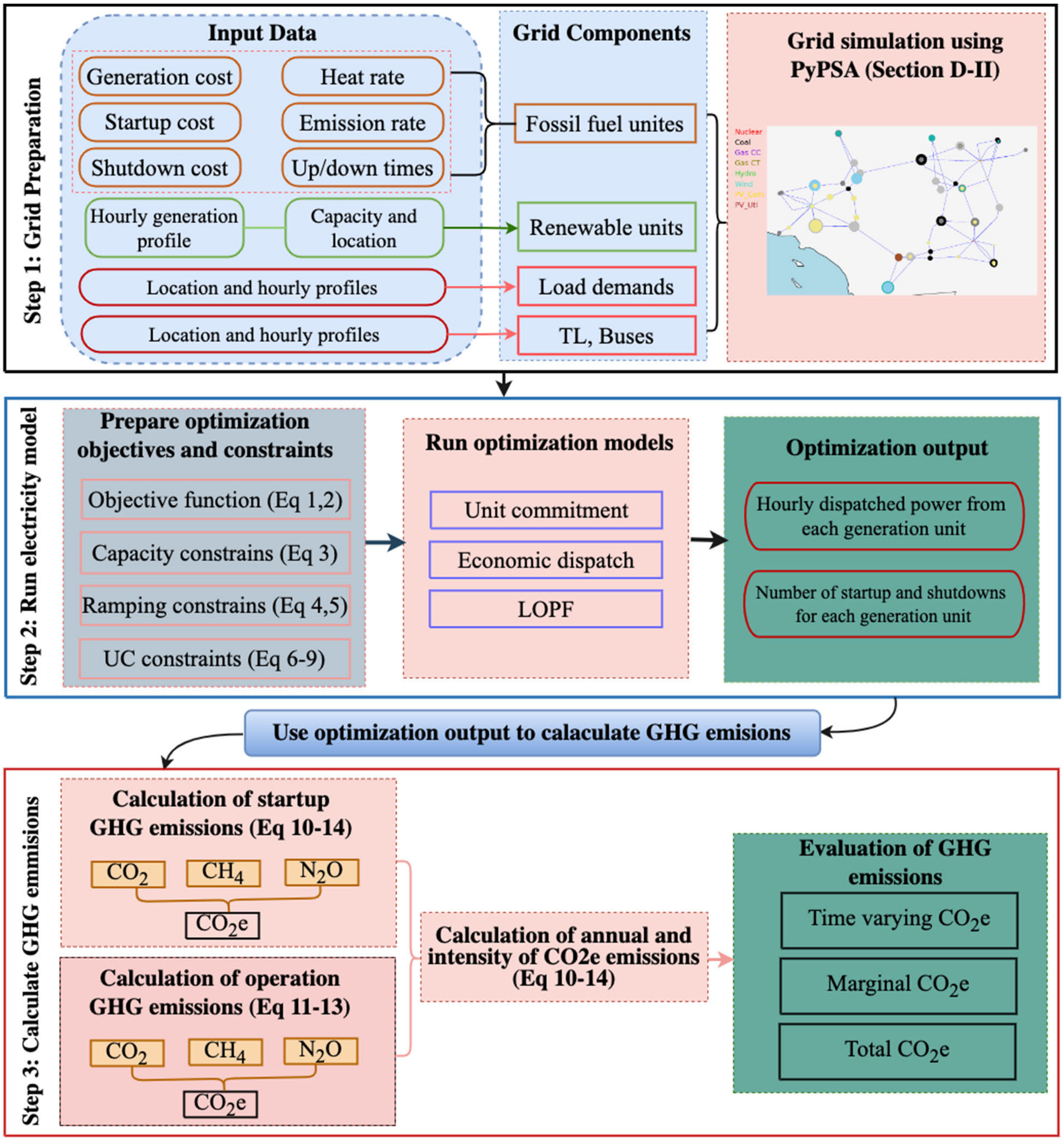

FIGURE 2. Overview of the proposed methods.

zonal marginal CO_2 emissions factors of the Italian electricity system. The authors used ARIMA (AutoRegressive Integrated Moving Average) statistical model to forecast the generation and load demand time series based on historical data. Statistical models can only provide a general idea of future trends based on historical data and patterns. They may not accurately capture the impact of new technologies like renewables, electric vehicles, and energy storage, which can greatly affect future energy generation and demand. Additionally, these models may not account for sudden changes in energy market conditions, policies, and regulations, further affecting their accuracy in predicting future energy scenarios. In [24], the authors employed an electricity system dispatch model to estimate carbon emissions resulting from the integration of new technologies into the electricity grid. However, they ignored the impact of techno-economic parameters and marginal variations of renewable generation and load demands. The issues related to model accuracy have a great influence on the model output, which makes it difficult to conduct an accurate estimation of GHG emissions. So, the detailed information on the electrical grid is highly relevant for any environmental impact assessment [4], [25].

In a system with high penetration of time dependence technologies such as renewable energy, energy storage, and electric vehicle, the number of start-ups and shut-downs of committable generation units can be affected by the other types of generation technology. For example, renewable energy sources like solar and wind power are more variable and intermittent, leading to more frequent start-ups and shut-downs of fossil fuel generation units to maintain system stability [26]. Additionally, certain types of committable generation technologies, such as gas-fired peaker plants, may be more likely to be used for load following and ramping, leading to more frequent start-ups and shut-downs. Hence, the emissions related to start-ups should be considered within the GHG emissions calculations, which have been ignored in previous studies.

This study aims to address a significant gap in the existing literature by providing a comprehensive and accurate method for estimating Greenhouse Gas (GHG) emissions by considering three key factors:

1. A highly detailed power system model is used to estimate dispatched power, which accounts for fluctuations in load demand renewable generation and includes all techno-economic details of all generation units. Additionally, the model accounts for limitations on the capacity of the electrical grid.
2. The study includes emissions from start-ups, which have been overlooked in most previous studies.
3. The ability of this study to estimate the time and marginal variations of GHG emissions is particularly important as it allows to identify the times and regions where emissions are higher and the units that generate higher emissions; this is crucial for taking actions to reduce emissions and meet emissions reduction targets.

Overall, this study significantly contributes to the understanding of GHG emissions in the power generation industry and provides valuable information that can be used to form policy decisions and emissions reduction strategies.

Due to the lack of rigorous scientific knowledge to calculate the shut-down emissions, the work described in this paper does not consider the shut-down emissions, which is one limitation of the study. Also, this approach only considers direct emissions produced by the burning of fossil fuels. Nevertheless, direct emissions from plant operation accounted for most of the life cycle emissions for fossil fuel technologies [27]. It excludes upstream emissions (e.g., coal mining and washing, plant constructions, generation units manufacturing) or end-of-life emissions (i.e., emissions from equipment disposal), which are not negligible but are minor compared to direct emissions.

The rest of the paper is organized as follows. Section II presents the proposed methodology, including the details of the electricity model, the optimization function, the case study, and the adopted technique used to run the optimization models. In Section III, the results of the GHG emissions associated with their geographical location are presented and discussed on an annual and hourly scale. The paper is summarized and concluded in Section IV.

II. METMETHODOLOGY AND CASE STUDY

To assess GHG emission of electricity generation can be summarized in four steps, as illustrated in Fig. 2.

Step 1: Prepare the electrical grid model. The goal of this step is to define the generation capacity, techno-economic and environmental details of each generation unit. Moreover, different hourly profiles of each renewable generation unit and load demand at each bus in the system are estimated in this step, as detailed in Section D-**II**.

Step 2: Run the electricity model. This step is achieved by running of power system simulation model, which simulates a complex power system with different types of energy sources' combinations under other load demands as described in Equations 1-9. The number of start-ups and shut-downs and hourly electricity generation of each generation unit are calculated in this step, as detailed in Section A-**II**.

Step 3: Assessment of greenhouse gas emissions. In this step, the output of power system simulation results from the previous stage is used to calculate the total, time-varying, and marginal GHG emissions and intensity, as detailed in Section C-**II**.

The following sections describe the electricity model and greenhouse gas emissions calculation in more detail.

A. ELECTRICITY MODEL

The optimization model is presented as techno-economic linear functions (Equations 1-2) to minimize the total generation cost. Equations 3-9 illustrate that this optimization model is constrained by physical and technical constraints. A free open-source Python library named Python for Power System Analysis (PyPSA) was employed to simulate the model [28], and the Gurobi optimizer was used to solve the optimization problem as described in Section B-II. The study [17] presents a simulation and validation of the proposed electricity model using PyPSA and Gurobi Optimizer to guarantee the accuracy of assessment results.

1) OBJECTIVE FUNCTION

As stated in Equations 1 and 2, the main goal of the objective function is to meet the load demands at the lowest possible generation cost. The generation cost comprises three parts—marginal, start-up, and close-down costs. The marginal cost of all generators includes operating and maintenance costs, which vary depending on the type and location of the generation unit. The overall annual generation cost is defined in Equation 1 as the sum of the annual costs of dispatched power from each generator at each bus in the system.

$$\begin{aligned}\mathrm{Min}\sum_{t=1}^{T=8760}\Big[\sum_{b=1}^{B}\Big(\sum_{g=1}^{G}\mathrm{C}_{g,b}.\mathrm{P}_{g,b}(t)\Big)\,\Delta t \\ +\sum_{b=1}^{B}\sum_{g=1}^{G}\Big(\mathrm{C}_{g,b}^{+}+\mathrm{C}_{g,b}^{-}\Big)\Big] \qquad (1)\end{aligned}$$

where $C_{g,b}$ is the dispatch cost associated with 1MWh by a generation unit g on bus b. $P_{g,b}(t)$ describes the hourly power dispatched by generation unit g on bus b. Assuming unit commitment initiates at t, the startup and shutdown costs for a given generation unit g are represented by $C^+_{g,b}$ and, $C^-_{g,b}$ respectively. G, B, and T represent the total number of generators, buses, and simulation hours. The optimization model is performed over several periods t with various generation and demand conditions to determine the optimal generation mix. The study period can have a different temporal resolution (Δt), which was one hour for this analysis.

At any given bus, the hourly demand $P_{g,b}(t)$ must be met by either local generation or by transmission L's power flow $P_{l,b}(t)$.

$$\sum\nolimits_{b=1}^{B}\sum\nolimits_{g=1}^{G}\mathrm{P_{g,b}(t)}\pm\sum\nolimits_{l}\mathrm{P_{l,b}(t)}=\sum\nolimits_{b=1}^{B}\mathrm{P_b(t)} \quad (2)$$

2) CAPACITY CONSTRAINTS

For each generation technology category, the decision variables focused on how much capacity could be deployed during a specified time period on a specific bus. The hourly output power of each generator was constrained by the entire capacity of each generation technology. The dispatch powers $P_{g,b}(t)$ are a part of each dispatchable generator in a single bus across the electrical grid (where g is a specific generator at bus b and time t), and they are constrained as follows:

$$\mathcal{U}_{g,b}(t)*\widetilde{\mathcal{P}}_{g,b}(t)*\overline{\mathcal{P}}_{g,b}\leq\mathcal{P}_{g,b}(t)\leq\mathcal{U}_{g,b}(t)*\ddot{\mathcal{P}}_{g,b}(t)*\overline{\mathcal{P}}_{g,b} \quad \forall\, g,b,t \quad (3)$$

where $U_{g,b}(t)$ describes the operational status of a generator g at the bus b in binary form $\mathrm{U_{g,b}(t)}\in\{0,1\}$, to show if the generator g is running (1) or not (0) at a specific period of time t. $\tilde{P}_{g,b}(t)$ is the per-unit power available from both renewable and thermal unit g on bus b at any given time t, while $\ddot{\mathrm{P}}_{g,b}(t)$ indicates the per-unit power from the plant's de-rating. $P_{g,b}(t)$ is the rating capacity of generator g on bus b. For a semi-flexible thermal generation unit, $\widetilde{\mathrm{P}}_{g,b}(t)=0$ and $\mathrm{P_{g,b}(t)}$=1, however in the case of a fluctuating renewable generation unit, $\tilde{P}_{g,b}(t)$ and $P_{g,b}(t)$ represent the weather-dependent generated power.

3) RAMPING CONSTRAINTS

Ramping constraints refer to the limits on the rate at which a power generation unit can increase or decrease its output power. These limits are typically imposed for technical and operational reasons, such as to protect the power system's integrity and the generation unit's equipment [28]. The ramp rate can be defined as the maximum rate of increase (R^+) or decrese (R^-) in change of power output over a given period of time, usually measured in MW/min or MW/h as described in this study. It depends on the type of generator, technology, and capacity.

Throughout the optimization process, the following constraints are imposed on the outputs of the generators to ensure the optimal functioning of the system.:

$$-\mathcal{R}^-*\overline{\mathcal{P}}_{g,b}\leq(\mathcal{P}_{g,b}(t)-\mathcal{P}_{g,b}(t-1))\leq\mathcal{R}^+*\overline{\mathcal{P}}_{g,b} \quad \forall\, t\in\{1,\ldots\mathcal{T}\} \quad (4)$$

During the start-up and shutdown processes, the ramping values may differ from those of normal operating conditions. Therefore, specific constraints are imposed to maintain optimal operating conditions as follows:

$$\begin{aligned}&\left[-\mathcal{R}_0^+*\mathcal{U}_{g,b}(t)-\mathcal{R}_1^+(\mathcal{U}_{g,b}(t-1)-\mathcal{U}_{g,b}(t))\right]\overline{\mathcal{P}}_{g,b}\\&\leq(\mathcal{P}_{g,b}(t)-\mathcal{P}_{g,b}(t-1))\\&\leq\left[\mathcal{R}^+*\mathcal{U}_{g,b}(t-1)+\mathcal{R}_0^+(\mathcal{U}_{g,b}(t)-\mathcal{U}_{g,b}(t-1))\right]\overline{\mathcal{P}}_{g,b}\end{aligned} \quad (5)$$

wherein, (R_0^+) and (R_1^-) denote the ramping up and down values specifically for during the start-up and shutdown conditions. This study assumes that the ramping limits for renewable generation units are equal to their nominal power output. However, for conventional generation units, the limits can vary based on the type and size of the unit. The assumption made is that the ramping limits during startup and shutdowns are the same as during normal operation. Section V of the Data Availability Statement provides specific ramping limits for each generation unit.

4) UNIT COMMITMENT CONSTRAINTS

The generation units are regularly started and stopped to fulfil the load requirements, including online and offline reserve generation units. The online generation unit must operate for the least uptime (T^+_{min}); similarly, the offline generation unit must be shut down for the least downtime (T^-_{min}), as described by Equations 6 and 7:

$$\sum\nolimits_{t'=t}^{t+T_{min}^+}\mathrm{U_{g,b}(t')}\geq\mathrm{T_{min}^+(U_{g,b}(t)-U_{g,b}(t-1))} \quad \forall\, t\in\{1,\ldots|T|-1\} \quad (6)$$

$$\sum\nolimits_{t'=t}^{t+T_{min}^-}(1-\mathrm{U_{g,b}(t')})\geq\mathrm{T_{min}^-(U_{g,b}(t-1)-U_{g,b}(t))}\ \forall b,g,t \quad (7)$$

In case the generator has recently been started on at the time t then $\mathrm{U_{g,b}(t-1)}=0$, $\mathrm{U_{g,b}(t)}=1$, and $\mathrm{U_{g,b}(t-1)-U_{g,b}(t)}=1$, and thus, it must be kept running for at least T^-_{min} Periods.

With regard to non-zero start-up cost $C^+_{g,b}$, for every time associated with each time t, the objective function must be modified by the inclusion of inequality $\mathrm{C^+_{g,b}(t)}\geq 0$, as illustrated below:

$$\mathrm{C^+_{g,b}(t)}\geq\mathrm{C^+_{g,b}(U_{g,b}(t)-U_{g,b}(t-1))} \quad \forall\, b,g,t \quad (8)$$

The inequality is only non-zero at the startup point, hence $U_{g,b}(t)-U_{g,b}(t-1)=1$ when $C^+_{g,b}(t)=C^+_{g,b}$.

Consequently, Equation 9 describes the shutdown costs when $C^-_{g,b}(t)\geq 0$:

$$\mathrm{C^-_{g,b}(t)}\geq\mathrm{C^-_{g,b}(U_{g,b}(t-1)-U_{g,b}(t))} \quad \forall\, b,g,t \quad (9)$$

B. OPTIMIZATION SOLVER

The electricity model that is formed in Section II-A with objective functions with constraints Eqs. [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13] is a mixed-integer linear programming (MILP) problem. A MILP problem can be solved using an open-source or commercial optimization solver such as a GUROBI mathematical programming solver. Gurobi is a state-of-the-art optimization software package that can be used to solve a wide range of optimization problems, including (MILP) problems. A free Gurobi academic license was implemented by the Pyomo Python library to solve the optimization problem in this study [29], [30]. Gurobi uses a number of different techniques to solve MILP problems, and it can automatically select the most appropriate method based on the specific characteristics of the problem. In this study, the technique used by Gurobi to solve the optimization problem is the branch and bound. Branch and bound is a general optimization algorithm that involves dividing the feasible region of the problem into smaller subproblems and solving each of these subproblems optimally. The implementation of the electricity model and optimization problem using PyPSA and Gurobi optimizer is detailed in the study [28].

C. GHG EMISSIONS CALCULATION

The GHG emissions resulting from the combustion of fossil fuels that produce CO_2, CH_4, and N_2O and GHGs (CO_2, CH_4, and N_2O) are typically presented in CO_2 equivalent or "CO_2e".

The total life cycle GHG emissions from all generation units in the system (*GHG*) can be calculated as a total annual CO_2e emission divided by the annual generation of the system as:

$$\mathrm{GHG\ (kg/kWh)} = \frac{\mathrm{Total\ CO_2e\ emissions\ (tone/year)}}{\mathrm{Total\ system\ generations\ (MWh/year)}} \tag{10}$$

The CO_{2e} emissions for each generation units were calculated with the following formulas:

$$\begin{aligned}&\mathrm{Total\ CO_2e\ emission\ (tonne/year)}\\ &\quad = \mathrm{Total\ normal\ operation\ CO_2e\ emissions}\\ &\qquad + .\mathrm{start_{up}\ CO_2e\ emissions}\end{aligned} \tag{11}$$

$$\begin{aligned}&\mathrm{Total\ normal\ operation\ CO_2e\ emission}\\ &\quad = \sum\nolimits_{b,g=1}^{B,G}\left[\sum\nolimits_{t=1}^{T=8760}\left(P_{g,b}(t) * HR_{g,b} * ER_{g,b}\right)\right]\\ &\qquad * 10^3 * 453.6\end{aligned} \tag{12}$$

where:

$P_{g,b}(t)$ is the hourly generated power by generation unit g located at bus b, predicted as described in Equations 1-5.

$HR_{g,b}$ is heat rate (BTU/kWh) of generator g at bus b, and $ER_{g,b}$ is CO_2e emission rate (Lbs./MMBTU) of generator g at bus b.

The factors 10^3 and 453.6 are used to convert the units of heat and emission rates to MMBTU/MWh and tonne/MMBTU respectively.

The CO_2e is typically based on CO_2, CH_4, and N_2O specific Global Warming Potentials (GWP). Each GHG constituent has a different heat-trapping capability; the corresponding GWP has been calculated to reflect how long the gas remains in the atmosphere, on average, and how strongly it absorbs energy relative to CO_2. Gases with a higher GWP absorb more energy per pound than gases with a lower GWP. Factors used to calculate CO_2e (GWP) equal 1 for CO_2, 25 for CH_4 and 298 for N_2O based on IPCC's fourth assessment report (AR4). Therefore, the equation to calculate the emission rate of CO_2e based on each of the sources is [31]:

$$\begin{aligned}&ER_{g,b}\\ &\quad = \left[ER_{CO_2} * GWP_{CO_2}\right] + \left[ER_{CH_4} * GWP_{CH_4}\right]\\ &\qquad + \left[ER_{N_2O} * GWP_{N_2O}\right]\end{aligned} \tag{13}$$

$$\begin{aligned}&\mathrm{Start\ up\ (CO_2e)\ emission}\\ &\quad = \sum\nolimits_{b,g=1}^{B,G}\left[\sum\nolimits_{n=1}^{N_c}\left(SHC_{g,b,n} * ER_{g,b}\right)\right.\\ &\qquad \left. + \sum\nolimits_{n=1}^{N_h}\left(SHH_{g,b,n} * ER_{g,b}\right)\right]\end{aligned} \tag{14}$$

where:

N_c and N_h are the total number of start-ups of generator g at bus b at cold and hot conditions, and they are estimated by the model described in Section A-**II**.

SHC (Start Heat Cold): the required heat to start up from the cold condition in a Metric Million British Thermal Unit (MMBTU) per start-up.

SHH (Start Heat Hot): the heat necessary to start-up from hot conditions of the generator in MMBTU per start-up.

Equations 11 and 13 are used to evaluate hourly and marginal GHG emissions by calculating the total emissions either at each hour or at each bus in the system.

D. CASE STUDY

The National Renewable Energy Laboratory's (NREL) 2019 dataset (labelled IEEE RTS-GMLC) is utilised for the case study presented herein. This model is an abstracted power model whose load patterns, transmission network, and generators are all firmly defined [33]. This case study contains 106 high voltage transmission lines rated within 138 and 500kV, 73 buses, 58 one-year hourly load profiles, and 155 generation units. The generation capacity was modified to contain 54 conventional and 80 renewable generators. Among the conventional generation units are a 400 MW nuclear power plant, 16 coal-fired units rating between 76 and 350 MW and 37 natural gas-fired units rating between 55 and 355 MW.

The renewable capacity involved 20 hydroelectric generation units, each with a capacity of 50 MW, 56 PV generation units rated between 9.1 and 125.1 MW, and 4 wind generation units with capacities ranging from 148 to 847 MW. The emission rates, heat rate, and fuel price of each generator are also detailed in IEEE RTS-GLMC. Fig. 3(a) shows the geographic variations of the cumulative capacity of each generation technology in RTS-GLMC.

The electrical grid data includes the transmission capacity, length and impedance of each transmission line. The load profiles are arranged in hourly intervals across a one-year period, allowing consideration of different time steps,

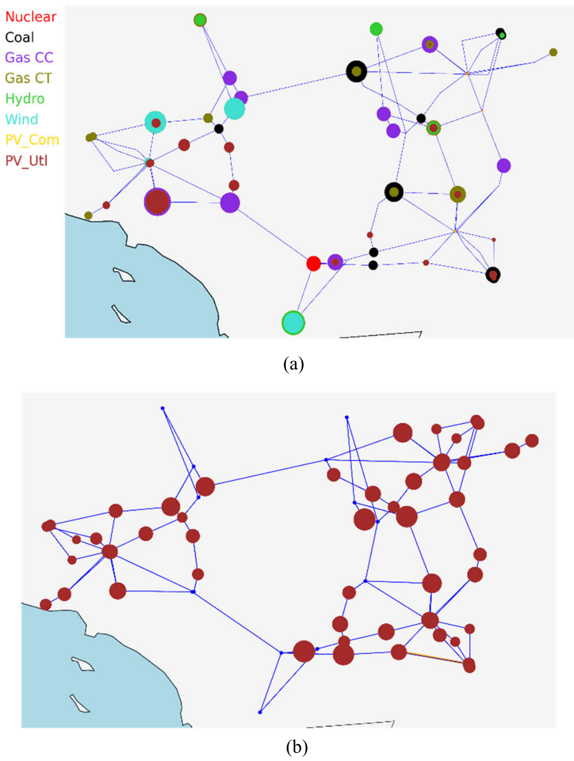

FIGURE 3. **(A). The layout of RTS-GMLC, annotated with relative size and location of generation capacity [17]. (B). The Peak Load Distribution of RTS-GMLC, annotated using the bus's location [17].**

including seasonal, weekly, and daily changes. The maximum geographical load distribution is shown in Fig. 3(b). The model has been tested and validated with the full non-linear power flow [32] and production cost models [17], available in the open-source system known as PyPSA [28].

III. RESULTS AND DISCUSSION

Based on the output of the electricity model described in Section **A-II**, the Equations described in Section B-II are used to calculate the GHG emissions at start-up and normal operating conditions. Results and discussion are divided into three subsections. Subsection **D-III** discusses the system the variation of system emission over time. Subsection E-III3.2 details the marginal GHG emission at each bus over the system. The detailed results for different generation technologies and GHG contributors at start-ups and regular operations are presented in subsection F-III.

A. TIME-VARYING EMISSIONS

Fig. 4 shows monthly generation mix and CO_2e emissions for different generation technologies. Significant distinctions in terms of CO_2e emissions are observed between months and generation technologies. The GHG emissions are higher in the summer (i.e., 1 June -31 August) and lower in the winter (i.e., 1 Dec -29 Feb), with some exceptions, for example, November. The difference in the GHG emission is mainly explained by the higher share of renewables and lower load in the low-emission months (e.g., more wind production in the winter months compared to summer). However, the peak in emissions is caused indirectly by increasing the need for gas power in the summer months. Solar and hydro generations have a higher potential during the peak load periods of the year, so the capacity share of solar and hydro generation could be increased to reduce the impact of fossil emissions in the summer months for this electricity model.

In Fig.5, the hourly GHG emissions present the distribution of daily fluctuation in the GHG emissions in a day. It indicates how much the hourly generation mix influences the emissions over a day. A significant difference can be observed between day and night hours. Although the peak load hours are between 14:00 to 18:00, the peak in emissions occurred at 17:00 and 20:00. This difference between peak load and peak GHG emissions is primarily due to the high availability of renewable generation, especially solar PV, within the peak load hours.

Here, three scenarios can be established to reduce GHG emissions. First, due to the high wind generation availability during peak emissions hours, increasing the share of wind capacity can reduce the dependence on fossil fuel generation (gas CC), which leads to a significant reduction in GHG emissions. The second scenario is introducing energy storage to shift the timing of generation. The third scenario can be established by using off-peak electricity with special tariffs, which encourages load flexibility in the consumer to reduce peak load in the network and decrease the intra-day variation. However, the second and third scenarios can only change the time variation of the GHG emissions associated with the shifted load or stored energy. While the aggregated amount of daily GHG emission can stay constant if there are no changes in renewable generation curtailment.

In Fig. 6, the hourly GHG emissions are plotted on a heatmap to provide a clear overview of the pattern of daily fluctuation in GHG emissions over the entire year. Each column in the heatmap corresponds to a single day of the year, while each row corresponds to a single hour of the day annotated with color and text indicating the amount of GHG emissions. There is a significant variation between different times of the day. This difference is more significant during the summer when the emission peak is observed between 2:00 pm and 11:00 pm. In contrast, a less emission-intensive emission peak is observed between 2:00 pm and 11:00 pm during the winter season. This is mostly due to the varying availability of photovoltaic (PV) generation during the day and night hours, as well as the seasonal variation in load.

To estimate the GHG emissions of the electricity system with a high share of intermittent renewable resources and energy storage, it is recommended to use hourly environmental data instead of average annual data. Compared to yearly average data, hourly data may provide more accurate results; however, it may increase the complexity of the assessment process.

B. MARGINAL EMISSIONS

Beyond estimation of the marginal environmental impacts are economic concerns about the cost and emissions of the

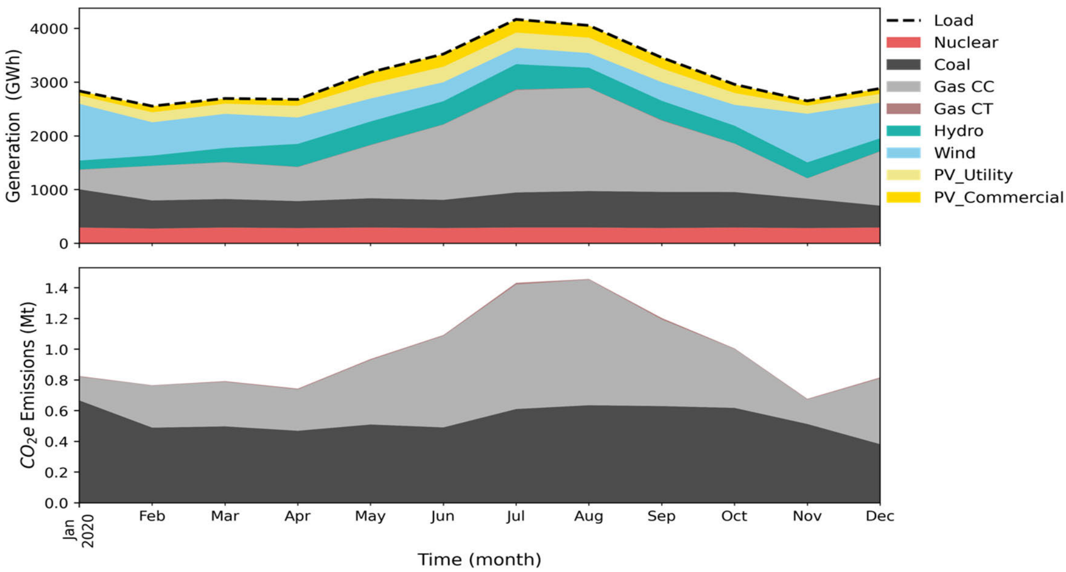

FIGURE 4. Total generation mix and CO_2e emissions of the generation mix each month for the year categorized by generation technologies.

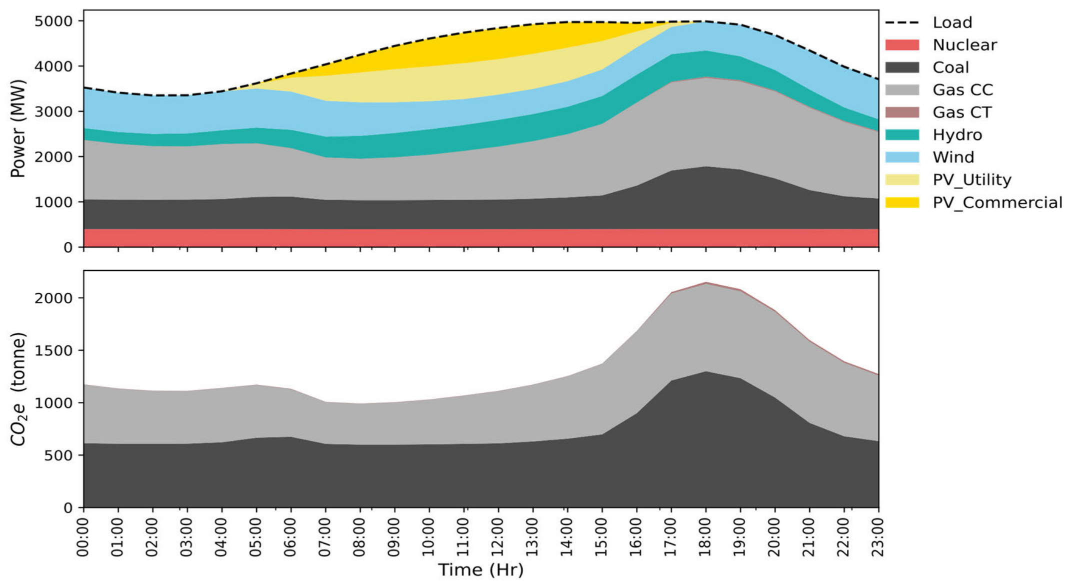

FIGURE 5. Hourly average time-varying GHG emissions (bottom) and generation (top) labeled with their generation unit contributors.

electricity system in both the operational and planning stage. Accurately estimating these emissions is essential for setting optimal policies about changing the generation mix and capacity. Moreover, it is necessary for comprehensive analyses of where to deploy new technologies such as energy storage and electric vehicle.

Fig. 7 and Fig. 8 show the variation of total annual CO_2e emission and generation mix over the system labeled with generation unit contributors. Fig. 7 shows region 2 (buses between 201 and 223) has the highest total amount of CO_2e emissions, and the highest individual bus emissions with annual CO_2e emission equal to 1.752 Mt/year at bus 223. These significantly high emissions are a result of coal and Gas CC generation units with high emission rates at these buses as illustrated in Fig. 8. Although buses 215 and 222 have a higher generation share than some buses in the system, the total annual emissions at these buses equal 0. This is because all generation share of these buses come from renewable sources such as hydro and solar, or nuclear. On the other hand, at bus 207, the total annual emissions are equal to zero as the primary source of generation is Gas CT where the cost of electricity generation is high hence it is not dispatched in the model (see Fig. 8).

Fig. 7 shows that region 1 (buses from 101 to 123) has the second-largest annual CO_2e emissions. Over this region, bus 123 has the highest amount of GHG emissions equal to 0.938 Mt/year. The annual GHG contribution at buses 102, 115, and 116 are relatively high for region 1, varying

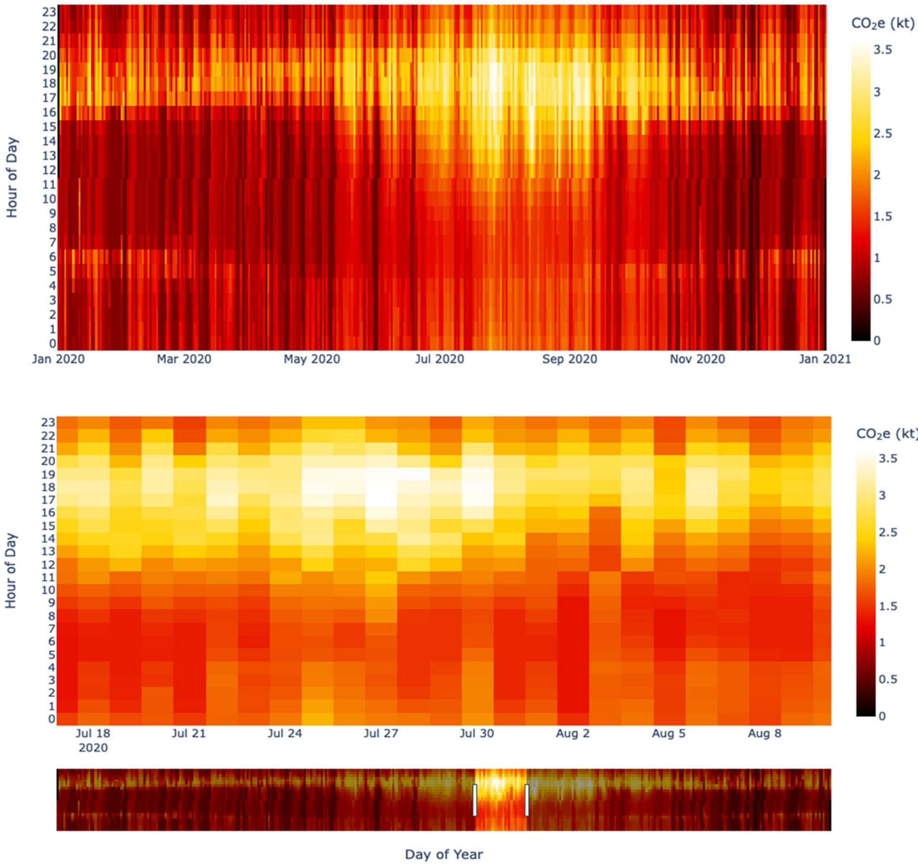

FIGURE 6. Heatmap of GHG emissions for each hour interval for one full year and the zoomed-in 21 days peak interval (see Appendix H-VI of the interactive map).

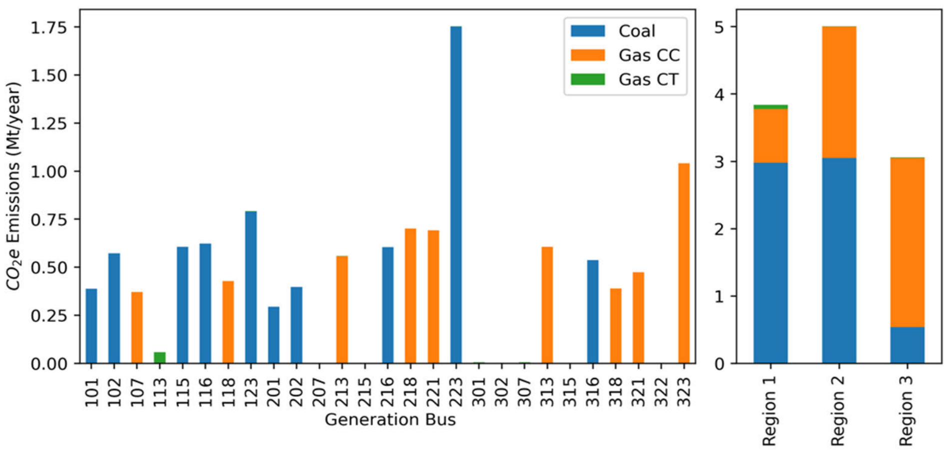

FIGURE 7. Marginal CO2e emissions and classified by their contributors.

between 0.855 and 0.938 Mt/year. Although these buses have lower generation shares, the higher shares of GHG emissions are because of the dispatch of coal power plants which are installed at these buses, with only a small contribution from a PV power plant at bus 102. At buses 103, 104, 113, 119, the GHG emissions are almost 0 because the generation at these locations is by PV (except for a small amount of GHG emissions due to the share of Gas CC at bus 113). Buses 121 and 122 have the largest share of the generation mix with zero emissions as the energy sources are totally renewable (wind, hydro) and nuclear.

Region 3 has the lowest GHG emissions contribution over the system, and the significant amount of GHG emissions comes from Gas CC generation units. The highest level of emission occurs at bus 323, equal to 1.042 Mt/year. The GHG emissions at buses 313, 316, and 321 vary between

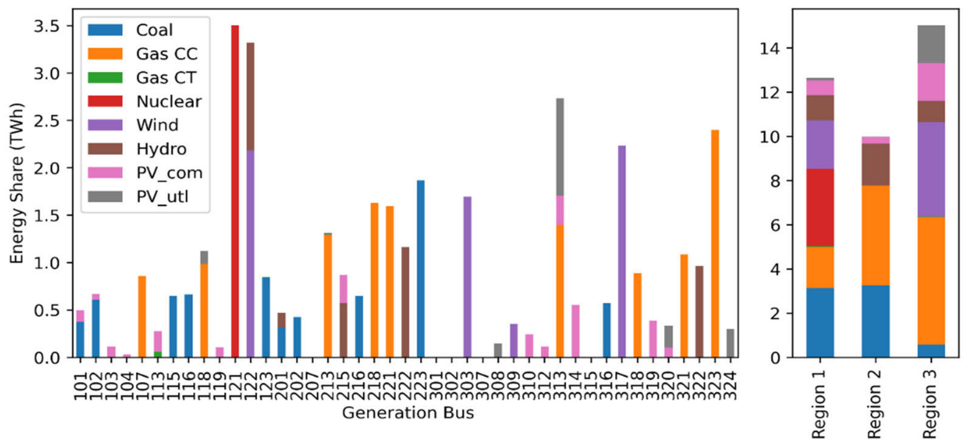

FIGURE 8. Marginal generation mix classified by their contributors.

0.306 and 0.607 Mt/year, and the main contributor is also Gas CC generation units. GHG emissions at the remaining buses in region 3 equal 0. Although region 3 has the most prominent energy share, it has the lowest GHG emissions over the system (see Fig. 7 and Fig. 8). This is due to the high share of renewable generation units such as PV, wind, and hydro, almost equal to half of the generation mix at region 3 and the lowest percentage contribution of coal generation units.

In Fig. 9, the total annual and intensity of CO_2e emissions at each bus are annotated with geographical locations to show marginal variations in the environmental impact over the entire system. As shown in Fig. 9, there are two significant contrasts between the geographical variations of total and intensity values of GHG emissions. First, CO_2e intensity at buses 207, 301, 302, and 307 have large values ranging between 761 kg/MWh and 976 kg/MWh. In contrast, the total annual CO_2e emissions are small (12.5E-5 and 5.55E-3 Mt/year), and the primary source of generation is Gas CC which has an emission intensity equal to 761 kg.

In contrast, the total CO_2e emissions at buses 313 and 323 are significant (0.607 Mt/year and 1.042 Mt/year), while the CO_2e intensities are relatively small (222 kg/MWh and 433.7 kg/MWh). The main reasons for the first state are: the energy sources at these buses are from fossil fuel, and installed capacity is minimal. This means dividing small values of total emissions by relatively smaller values of generation mix leads to relatively high emissions intensity. Another reason is the start-up emissions contributions at buses 207, 301, and 307 are equal to 215 kg/MWh, 77.6 kg/MWh, and 202.6 kg/MWh, respectively. These large amounts of start emissions lead to a considerable rise in emissions intensity. Two reasons for decreasing the emissions intensity at buses 313 and 323, although they have a considerable number of emissions. First, at bus 323, Gas CC's primary energy source has lower emission intensity equal to 426.2 kg/MWh, and the share of start-up emission is meagre. Second, the generation share at bus 313 is a mix of fossil fuel with low emission intensity (Gas CC) and PV generation with zero emissions. So, for accurate marginal environmental impact assessment, it is not enough to assess only emission or emission intensity, and it is recommended to evaluate both.

C. TOTAL EMISSIONS

This section presents the different sources of GHG emissions and how the amount of GHG emissions is affected by considering start-up emissions of generation units. Since different generation technologies have other efficiencies, the generated electricity from 1 MMBtu of the primary energy source differs for each generation technology. Fig. 10 shows the total annual CO_2e emission and generation share from each generation technology. The emissions for each generation unit include emissions due to fuel combustion at start-up and normal operating conditions. As shown in Fig. 10 although the generation share of coal power plants is smaller than the share of other fossil fuel power plants, coal power plants have the highest amount of GHG emissions. Electricity share by coal power plants presents 18.5% of the total generation mix, while Gas CC power plants have the highest generation share, equivalent to 32.3%. As a result, the coal power plant emissions represent more than 55% of total emissions while Gas CC's share equals 44%.

GHG emission is a combination of three pollutants, CO_2, CH_4, and N_2O, generated with different percentages depending on the type of primary energy source. Table 1 and Fig. 11 compare CO_2, CH_4, and N_2O from other generation technology at start-up and normal operating conditions. In typical operation conditions, coal generation units have significantly larger CO_2 and N_2O emissions than gas generation units, CT or CC. At the same time, Gas CT generation units produce a more significant amount of CH_4 than coal and Gas CC generation units. This is expected since coal's carbon and nitrogen contents are much higher than those of other fuels. Gas CC generation units have a considerable amount of CO_2 and N_2O emissions compared to coal and Gas CT generation units with start conditions. Gas CC generation

TABLE 1. Summary of annual start-up, operational, and total CO2E emissions categorized by gas contributor and operating power plants (million tonnes).

Type	Operation (Mt)				Startup (Mt)				Total (Mt)
	Coal	Gas CC	Gas CT	Total	Coal	Gas CC	Gas CT	Total	
CO_2	5.712	4.127	0.035	9.875	34.48E-3	72.75E-3	11.52E-3	120E-3	9.994
N_2O (CO_2e)	678E-6	0.000	0.00	1.878	4.88E-3	18.53E-3	5.87E-3	29.3E-3	1.907
CH_4 (CO_2e)	80.82E-2	1.051	1.88E-2	6.78E-4	4.1E-6	0.00	0.00	4.1E-6	6.82E-4
Total CO_2e	6.521	5.176	0.056	11.754	39.36E-3	91.28E-3	17.39E-3	148E-3	11.902

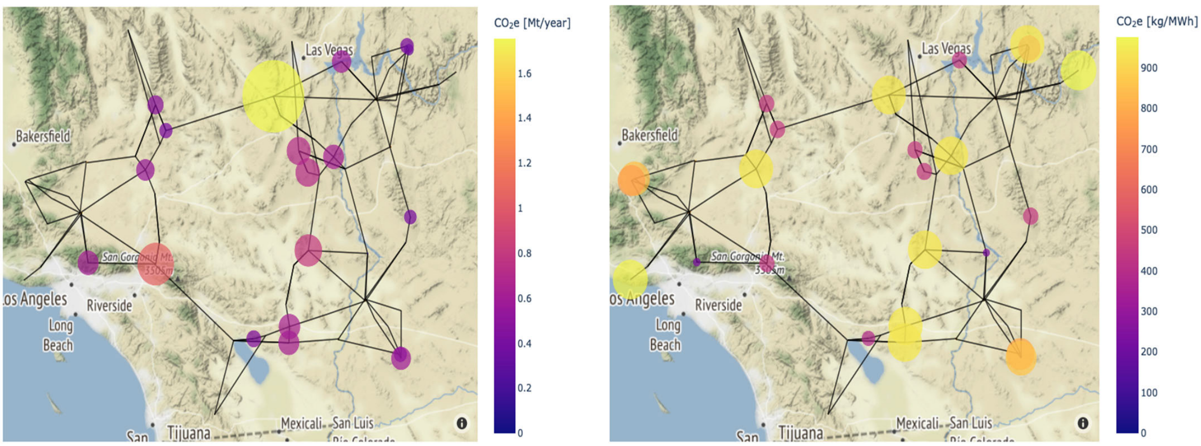

FIGURE 9. Distribution of total (Left) and intensity (Right) of GHG emissions at each bus in the system (see Appendix of the interactive map).

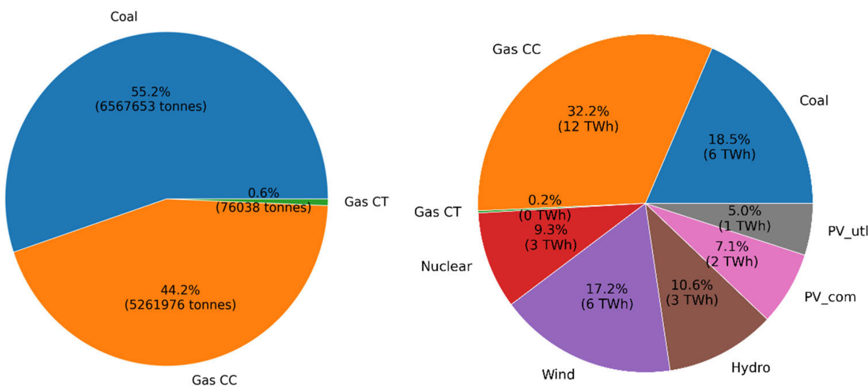

FIGURE 10. Total annual GHG emissions (left) and generation mix (right) categorized by generation technology.

units are more flexible and can be started on and off more easily compared to coal generation units or more cheaply compared to gas CC generation units. Different pollutants have a significant contribution during start-up conditions, so, for a more accurate environmental assessment, this source of emissions should not be ignored. Fig. 11 represents the total annual emissions for electricity generated at start-up and normal operating conditions. The start-up GHG emissions represent 1.2% of total emissions, and this could be higher if more intermittent sources of renewable generation units are installed. The whole life cycle GHG emissions from all generation units in the system are calculated as described in Section B-II. As described by Equations 10-14, the annual generated energy by all types of generation units is 37.65 TWh and each generated MWh produces 316.17 kg of CO_2e emissions: 4 kg at start-up conditions and 312.17 kg during normal operating conditions.

D. COMPARATIVE STUDY

This section presents a comparison between the proposed methodology and the state-of-the-art comparative study to highlight the significance and precision of the proposed

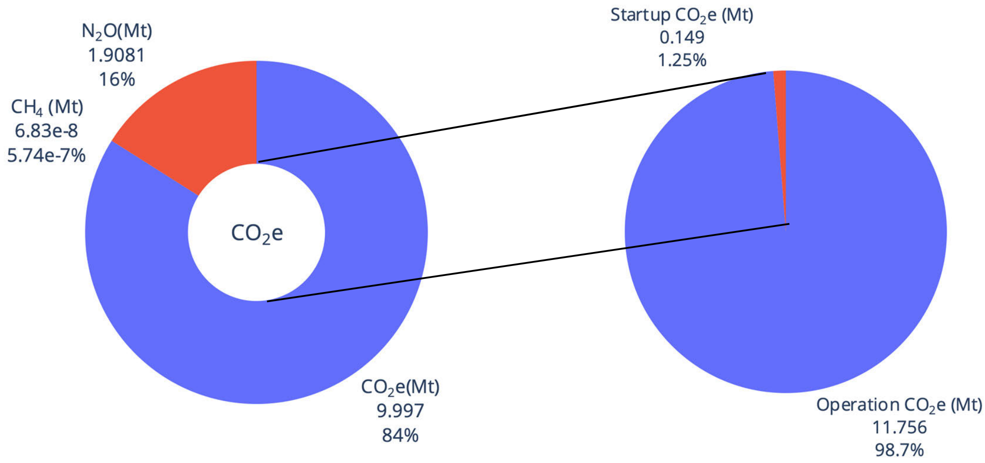

FIGURE 11. Total CO_2e emissions during start-up and normal operating conditions from different contributors.

TABLE 2. Comparison of the proposed methodology with previously published methods.

Comparison factor	Proposed Methodology	Comparative study Ref [24]
Model accuracy		
Included techno-economic parameters	1. ramping limits. 2. min up and down time. 3. min output power. 4. operation & maintenance cost. 5. startup and shutdown costs. 6. grid capacity constrain.	1. ramping limits. 2. operation & maintenance cost.
Temporal variations of renewables and load demands	• Included	• included
Geographical variations of renewables and load demands	• 50 load profiles • Detailed profile for each renewable unit.	• Single load profile. • Wind and solar generations represented by single profile for each.
Start-up and shutdown emissions	• Included	• Ignored
Results and discussions		
Marginal intensity (Mt/year at each bus)	• Presented	• Unpresented
Marginal intensity (Mt/year at each bus)	• Presented	• Unpresented
Total intensity (kg/MWh)	265.487 kg/MWh	77 kg/MWh
Annual emissions	9.997 (Mt)	2.9 (Mt)

approach. As shown in TABLE 2, the proposed methodology and the comparative study have differences in their approach and results. The proposed methodology includes more techno-economic parameters such as ramping limits, minimum up and down time, minimum output power, operation and maintenance cost, startup and shutdown costs, and grid capacity constraints. The comparative study only considers ramping limits and operation and maintenance costs for model accuracy.

In terms of considering variations in renewables and load demands, the proposed methodology takes a more detailed approach with 50 load profiles and a detailed profile for each renewable unit. The comparative study uses a single load profile and represents wind and solar generation with a single profile. The proposed methodology also includes start-up and shutdown emissions, while the comparative study ignores these emissions.

The proposed methodology presents the marginal intensity of emissions at each bus, while the comparative study does not. The total intensity of emissions in the proposed methodology is 262.3-265.487 kg/MWh with startup and shutdown emissions considered, while the comparative study has a total intensity of 77 kg/MWh. The proposed methodology results in a higher annual emission of 9.997 Mt, compared to the comparative study's annual emission of 2.9 Mt. In conclusion, model parameters play a significant role in determining the accuracy of the results obtained from a simulation model. It is essential to carefully consider and set the model parameters to ensure that the results are accurate and reflect the real-world behavior of the system.

IV. CONCLUSION AND RECOMMENDATIONS

Estimates of GHG emissions for current and future electricity network scenarios are lacking temporal and spatial resolution. In this study, the accuracy of GHG emissions estimation was improved by using a precise electricity model with high spatial-temporal and techno-economic details. Moreover, the GHG emissions during the start-up of generation units were included for a more accurate assessment. The analysis shows that the GHG emissions of generation can fluctuate over short (daily) and medium (monthly) timeframes depending on the type of generation mix. The results show that solar generation leads to daily and seasonal variations in GHG emissions. Other renewable generation such as wind and hydro, cause seasonal variations in GHG emissions. The highest emission peak was observed during the summer months between 2:00 pm and 11:00 pm. It is recommended that a time-varying GHG emissions assessment rather than an annual average should be employed for both real-time load demand management systems for carbon emissions and also for long-term decision-making about the future generation mix. Similarly, GHG emissions vary geographically, over the system's buses, due to the location of different fossil fuel generation units and the availability of renewable generation. Region 2 had the highest annual CO_2e emissions at 1.752 Mt/year at bus 223, primarily from coal and gas CC generation units. The lowest emission is 1.042 Mt/year, located at bus 323 in region 3, primarily from gas CC generation units. On the other, the study found that the highest emission intensities were observed at buses 207, 301, 302, and 307, with values ranging between 761 kg/MWh and 976 kg/MWh. The comparison between the total GHG emissions and GHG emissions intensity over the buses in the system shows that the two factors can have different distributions geographically. Therefore, both should be considered for assessing GHG emissions. Furthermore, GHG emissions assessment can be used to find the optimal location for electrical vehicle integration and for new capacity of renewable generation and energy storage.

V. DATA AVAILABILITY STATEMENT

The data supporting the study's outcomes are publicly accessible on Github and PyPSA.

APPENDIX A ALIST OF SYMBOLS AND ABBREVIATIONS

A. SETS

- b Bus number, $b \in \{1, \ldots |\mathcal{B}|\}$, where $\mathcal{B}$ is the number of buses in the grid.
- g Generator number, $g \in \{1, \ldots |\mathcal{G}|\}$, where $\mathcal{G}$ is the number of generation unit.
- T Simulation period, $t \in \{1, \ldots, \mathcal{T}\}$.

B. PARAMETERS

- $\mathcal{C}_{\mathrm{g,b}}$ Cost of generation one MWh by a generation unit g on bus b.
- $\mathcal{ER}_{gb}$ Emission rate (Lbs./MMBTU) of generation unit g on bus b.
- $\mathcal{HR}_{\mathrm{g,b}}$ Heat rate (BTU/kWh) of generation unit g on bus b.
- $\overline{\mathcal{P}}_{\mathrm{g,b}}$ Rating power of generation unit g on bus b.
- $\mathcal{R}^{+}, \mathcal{R}^{-}$ Generation unit ramping up and down rates.
- $\mathcal{R}_0^{+}, \mathcal{R}_1^{+}$ Generation unit ramping up and down rates at startup and shutdown.
- $\mathcal{C}^{+}_{\mathrm{g,b}}(\mathrm{t})$, Generator g_{th} start-up and shut down costs on bus.
- $\mathcal{C}^{-}_{\mathrm{g,b}}(\mathrm{t})$ B when the generator starts or shuts with unit commitment at time t.
- $\mathcal{T}^{+}_{\mathrm{min}}$ Minimum up-time of generation unit g.
- $\mathcal{T}^{+}_{\mathrm{min}}$ Minimum down-time of generation unit g.
- $\Delta\mathrm{t}$ Time resolution (one hour).

C. VARIABLES

- $\mathcal{P}_{\mathrm{g,b}}(\mathrm{t})$ Generated power by generation unit g on bus b and time t.
- $\widetilde{\mathcal{P}}_{\mathrm{g,b}}(\mathrm{t})$ Power availability of generation unit g on bus b and time t *as a* per unit .
- $\overline{\mathcal{P}}_{\mathrm{g,b}}(\mathrm{t})$ Power availability of generation unit g on bus b due to generation unit de-rating as a per unit.
- $\mathcal{U}_{\mathrm{g,b}}(\mathrm{t})$ Binary status of generation unit g on bus b and time t.

D. ACRONYMS

- Gas CC Combined-Cycle gas power plant (CC)
- Gas CT Combined-Turbine gas power plant (CT)
- GWP Global Warming Potentials
- PV Photovoltaics

APPENDIX B
APPENDIX BINTERACTIVE FIGURES

The html file contains the interactive plotting for Fig. 6 and Fig. 9.

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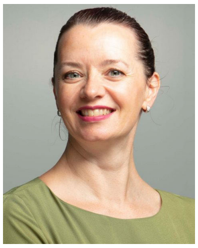

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