scientific reports

OPEN

Observing the impact of renewable electricity on the emission factors of electric vehicles using electricity generation data

Xingrui Zhang✉, Juhao Su & Yiming Zhou

By analyzing the electricity generation data of Texas from 2007 to 2024, this study computes the average emission factors (AEF) of electric vehicles and observes how the AEF evolved with changes in grid mixes. The paper observes both temporal and the long-term trends within Texas AEF, and it was observed that the primary source of variation within the AEF comes from the time-varying supply of renewable energy. In addition to developing a tool to forecast the AEF, this study found that adopting solar and wind power generation simultaneously allowed the two energy sources to compensate for each other's diurnal and seasonal patterns, making EV charging sustainable across all times. A 3-D framework for peak identification of AEF considering both diurnal and seasonal variation was proposed, and it was observed that the peaks in AEF had shifted over the years and that the current governmental recommendation to charge during the evenings could potentially be modified to encourage charging across all times of the day save for very specific time intervals.

Keywords Electric vehicles, Carbon emissions, Emissions factor, Charging

The electrification of the transportation system is one of the key pathways by which carbon emissions of the transportation sector can be reduced. The electric vehicle's powertrain entails no tailpipe emissions and boasts significantly higher energy efficiency compared to internal combustion engines. However, electric vehicles (EVs) are not without their environmental consequences, as the electricity that powers them tends to result in carbon emissions during the generation process. As such, the emissions factor of an electric vehicle is equivalent to that of the electricity said vehicle drew power from.

Many studies have been published regarding the quantification and the reduction of electric vehicle charging carbon emissions. In most of the studies, electric vehicles were treated as marginal loads to the grid and the focus was typically on "when to charge a vehicle", or in other words, charging strategies. Tu et al. examined the context of Toronto and Hamilton area and concluded that a scenario where charging is only allowed after 3 am would result in the lowest emissions compared to other simulated scenarios[1]. Powell et al. conducted a simulation on the data of Western United States up to 2037, observed short to medium run marginal emissions factors, and concluded that demand response would be more effective in carbon reduction when combined with a carbon pricing scheme[2]. Arvesen et al. simulated the power system of Europe up to year 2050 and concluded that EVs would be more sustainable when charging occurs during daytime due to the abundance of solar power[3]. Li et al. took the context of Tianjin, China, and combined local time-of-use strategy with marginal emissions factors and derived smart charging strategies[4]. Xu et al. examined the impact of different charging strategies on the carbon emissions of Europe in 2050, taking into consideration the effect of battery degradation[5]. Gai et al. estimated GHG emissions for 5 different charging strategies in Ontario[6]. Mills and MacGill proposed a framework of assessment that considers the GHG emissions of EVs as a function of when and where EVs are charged[7].

EV charging is directly connected to the grid, as such, to study EV charging is essentially to study the grid, or to a broader context, the energy system. Many studies have drawn correlation between economic growth and carbon emissions of energy, including and especially renewable energy. Atems and Hotaling found that energy generation, be it renewable or non-renewable, had a positive impact on economic growth[8]. The EKC hypothesis dictates time-varying correlation between renewable consumption and economic growth. Rahman et al. drew positive correlation between renewable energy and employment levels in India[9]. Salahuddin et al. advocated that Kuwait capitalize on her vast solar and wind resources[10]. Dong et al. proved the EKC valid at the global panel,

Department of Civil Engineering, The University of Hong Kong, Pokfulam, Hong Kong, China. ✉email: xzhang-147@connect.hku.hk

but found that the mitigation effect of renewable energy could be offset by the increase in energy consumption resulting from economic growth[11].

Gaps in knowledge can be identified. For one, since the economy is correlated with energy generation, and that EVs draw energy from the grid, economic development should have an indirect impact on the carbon emissions of electric vehicles. From a policy making standpoint, shocks in EV emissions should be derivable using fluctuation in economic conditions, with the impact pathway being the effect of economic growth on the composition of grid mixes. Such has seldomly been discussed. For another, as the penetration of EVs deepens over the years, the charging of EVs has grown in scale and now deserves to be considered as a part of regular average loads. While most early EV emission studies focused solely on marginal loads and emissions factors, average emission factors have received considerably less attention in the literature, apart from Zhang et al.'s work in California[12]. As the penetration of EVs deepens, it has become considerably more important to consider the electricity load of EV as a part of the regular load, which emphasizes the importance of incorporating average emissions factors into discussion. Lastly, studies on EV charging optimization rely on charging strategies that stipulate charging only at certain time periods. Such may lack practicality as it may be unrealistic to impose mandates on charging behavior. An alternative pathway towards EV carbon reduction may be to balance the renewable output of the grid and to compensate for the lack of certain renewable sources during certain times using alternative renewable sources, thereby making electricity (and thereby EV charging) less carbon intensive across all time periods.

In the Texas-specific context, the current effort to deepen EV penetration have been exerted exclusively to satisfy the demands of EV owners. Specifically, the scoring plans within the Texas Electric Vehicle Infrastructure Plan of 2024 stipulated the requirement for staffing and training, financial feasibility, commercial benefits, construction compliance and cost, and cyber security[13]. All of which were designed with the EV owner's convenience in mind. However, the effort to study and improve the carbon reduction potential of the EVs in Texas had been considerably less. With the only notable contribution being the current advisory by the TXDOT to charge between 10 pm to 6 am when wind energy is abundant[14].

The pathway to addressing the aforementioned issues, and to explore the possibility of EV emissions reduction across all time periods requires a comprehensive observation on the average emissions factors, typically derived using the grid mixes of fine granularity. This study, in the context of Texas, derives the average emissions factors of EV charging using electricity generation data, and observes for (1) the evolution of emissions factors with changes in grid mixes over time, and (2) the reaction of emissions factors towards shocks in economic growth.

Methodology

Research data

This research paper seeks to explore the time-dependent variation in EV charging carbon intensity by observing the dynamics of the electricity grid. The primary source of data pertains to the electricity generation mix of the power grid of a region, in this case the State of Texas. The source data that serves as the basis of the study is the publicized electricity generation data (fuel mix reports) by the Energy Reliability Council of Texas (ERCOT), which contains electricity generation output of all generation sources every 15 min (hereby referred to as "settlement period") in the period between the start of 2007 all the way to present[15].

The raw data was then pre-processed. To describe the means by which data is treated, several concepts need to be introduced:

1. Total Energy Output: The total energy generated by all generation sources at a time, calculated as the sum of all outputs during each settlement period.
2. Grid Mix: The percentage share of the output of a particular generation source in relation to the total generation. For each settlement period, it is calculated as $\frac{Energy\ Produced\ by\ Source}{Total\ Energy\ Output} * 100\%$.
3. Emissions Factor: The amount of carbon emitted per each unit of energy generated, with the unit gCO2eq/kWh. It is calculated as the sum of all products between source-specific grid mix percentage and their corresponding emissions factor, or $\sum Grid\ mix * Emissions\ Factor$.

For each of the settlement periods, the grid mix percentages were calculated for each of the generation source so that the emissions factor of electricity can be calculated for each of the settlement periods. The emissions factor for each of the generation sources is extracted from Horvath and Stokes and Kadiyala et al. as: 1059 gCO2eq/kWh for Coal fire, 696 gCO2eq/kWh for natural gas, 17 gCO2eq/kWh for nuclear power, 56 gCO2eq/kWh for biomass, 31 gCO2eq/kWh for wind, 64 gCO2eq/kWh for solar, 28 gCO2eq/kWh for geothermal, and 21gCO2eq/kWh for hydroelectric[16,17]. Even in cases when no fuel is combusted, such as in the case of wind and solar, emissions may also result, since the factors consider all lifecycle aspects in addition to fuel combustion. The factor for hydroelectric power was extracted from a different reference other than Horvath and Stokes[17], and may have slightly different system boundaries. The effect was considered trivial given the low grid mix percentage of hydro in the Texas grid.

Natural gas generation, starting 2008, had been detailed into the generation "Gas" and "Gas-CC", both refers to generation of electric energy via natural gas, and their proportions had not evolved significantly over the course of the study period. The two sources are hereby considered to be both within the "Natural Gas" category.

Upon completion of preliminary calculations, the data was then to be processed into time series form. In the case of this study, parameters of interest, for one, is the monthly grid mix percentage for each of the generation source, calculated by dividing the energy generated by said source in a month by the total energy generation for each of the generation source. The monthly grid mix percentage will then be combined with the aforementioned emissions factor to calculate the monthly emissions factor. Secondly, this study is also interested in data series specific to different times of the day. In this regard, 24 time series for the monthly emissions factor of each of the 24 h of the day were created. Each monthly data point on the time series for each hour of the day was calculated by averaging the emissions factor of all settlement periods at that hour within said month. To put state a sample calculation, the datapoint for the emissions factor of hour 12:00 of the day in month Jan 2023 was calculated by averaging the emissions factors of all settlement periods between 11:45 – 12:15 of everyday within the first month of 2023.

Certain parameters will serve as features to aid the forecast of emission factors at various times of the day. These parameters also provide models with interpretability, which facilitates the derivation of policy implications. Traditionally, the features that are most often used to interact with total energy consumption and total carbon emissions are the unemployment rate and the Gross Domestic Products. However, in the case of this paper the two aforementioned parameters suffer from a variety of challenges. For one, the COVID-19 pandemic had induced a surge in unemployment rate during the period between 2020 and 2022 which according to Bhat et al.[18] and Zhang and Yang[19] constituted a disruption by OLS standards and led to the unraveling of established relationship between unemployment rate and other parameters. For another, the GDP figures in a state are published at quarterly frequency while all other data used are in monthly frequency. Therefore, the property value index published by Freddie Mac was used as a reflection of economic growth and the hotness of the property market/desirability of living in TX, as housing value was generally stable during COVID despite the moderate growth[19]. Another useful parameter that reflects economic growth is the number of issued permit (TXBPPRIV), which reflects economic growth and investment levels by simulating the level of economic activities within the State of Texas.

Time series models

The study utilizes time series analysis to generate results. Specifically, there will be two scenarios in which time series models are to be used. The first one being cases in which explainability of the model is as relevant as forecast accuracy. In this case results generated via model interpretation is just as important as forecasting accuracy. As such, interpretable time series models that are widely used in econometrics were used.

The representative models chosen are the Vector Autoregression Model and the Vector Error Correction Model, which construes the current value of the target variable as a combination of the past values and regression features (indicators) and the target variable itself. The mathematical representations of the VAR model and the VECM model are presented in Eqs. (1) and (2).

$$\text{Target Variable}_{t} = \alpha_{0} + \alpha_{1}\text{Target Variable}_{t-1} + \ldots + \alpha_{p}\text{Target Variable}_{t-p} + \beta_{1}\text{Indicator (I)}_{t-1} + \ldots + \beta_{p}\text{I}_{t-p} + u_{t} \quad (1)$$

$$\Delta \begin{bmatrix} \text{Target Variable}_{t} \\ \text{Indicator}_{t} \end{bmatrix} = \sum\nolimits_{i=1}^{p-1} \Phi_{i} \Delta \left[\begin{matrix} \text{Target Variable}_{t-i} \\ \text{Indicator}_{t-i} \end{matrix} \right] + \Pi \begin{bmatrix} \text{Target Variable}_{t-1} \\ \text{Indicator}_{t-1} \end{bmatrix} + Cd_{t} + u_{t} \quad (2)$$

Results

Overview of the Texas electricity grid

One should be aware that commercial EVs did not see large scale implementation until 2017/2018, and the emissions factors calculated for pre-2017 do not qualify as "EV charging emissions factor" since widespread EV adoption had yet to occur. With that being said, data before 2017 nevertheless serve as valuable training data to better simulate the period from 2017 afterwards when EV came into existence, and should be considered. This subsection provides an overview of the evolution of the composition of the electricity grid of Texas. The monthly grid mix percentage of major generation sources and the resulting emissions factor is presented in Fig. 1. Since the beginning of 2007, significant shifts have occurred within the Texas grid mix, resulting in decreasing carbon intensity of electricity over time. The primary driver of change was the emergence of wind power, which evolved from taking up less than 10% of the grid in 2007 to taking up around 20% of the grid in 2024; the rise of solar power, which saw significant increase starting 2018 and had reached an average grid mix of 10% in 2024; and the abolishment of coal, which saw its share decreasing from 35% in 2007 to less than 20% in 2024. The share of nuclear power remained steady across the study period, and the primary source of fossil fuel energy had steadily been natural gas.

The shift in monthly aggregate grid mix also has an impact on the diurnal patterns of the grid mix, and this section takes the evolution of the grid on June 1 st across various years as an example. The diurnal grid mix patterns in June 1 st in the year 2012, 2018, 2021, and 2024 were presented in Fig. 2. Over the years, the percentage of wind power in the total energy output had been increasing, however, the availability of wind power varies across different times of the day and is more abundant from 17:00 pm to 7:00 am. As the total capacity of wind power increases, so does the magnitude of the diurnal variation. Another energy source may be required to compensate for the unstable pattern of wind availability throughout the day, and in the year 2024 said source appeared to be solar power, as solar power is capable of superseding wind power during 7:00–17:00 of the day and supply up to 20% of the grid.

In addition, the availability of wind may also variate spontaneously across different days, as a particular day may have a random chance of having a relative abundance of wind (June 1 st 2024) or a paucity of it (June 1 st 2021). The variation, unfortunately, appears to have been compensated by natural gas and more importantly, coal fire, as despite the steady decrease of overall share of coal, June 1 st 2021 saw a share of coal-fire power of 20%, which was near identical to the share of coal in June 1 st 2018 with relatively abundant wind power but when the overall share of coal fire was considerably higher. The share of natural gas and nuclear power remained steady.

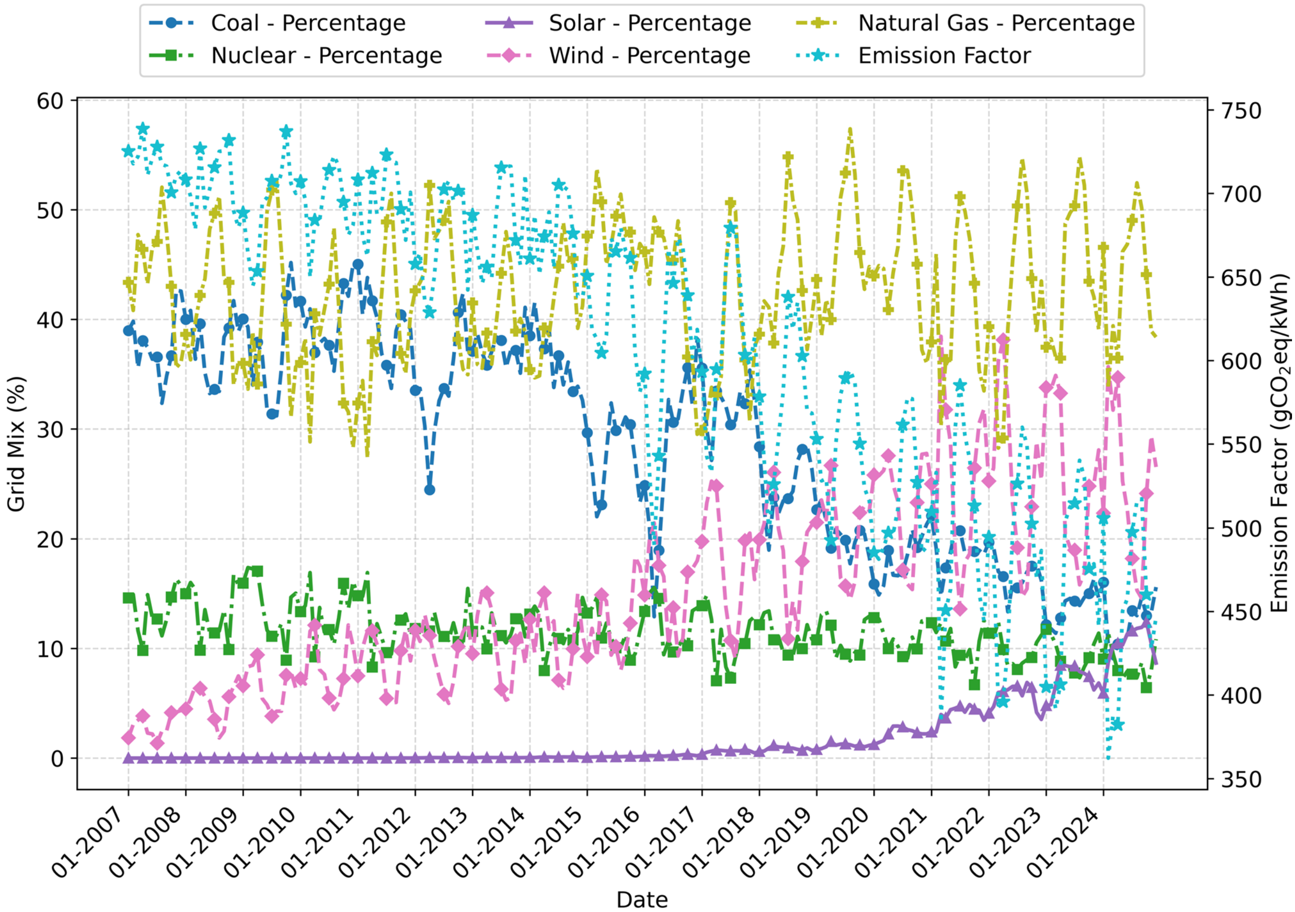

Fig. 1. Texas electricity emissions factor and grid mix % of major generation sources.

Compilation and forecasting of average electric vehicle emissions factor

Electric Vehicles (EV) draws energy from the electricity grid as they charge, as such, the carbon intensiveness of electric vehicles varies according to grid dynamics. Given the seasonal and diurnal variation of the electricity grid mix, charging electric vehicles at different times of the day in different months will bring about different levels of environmental impact. Such is the reason why as stated in the methodology section monthly time series data was compiled for emissions factor of every hour of the 24 h of the day. For ease of presentation, data of only hours of multiples of 3 were presented. They are visualized in Fig. 3.

As the capacity of wind and solar power increased, three changes were brought upon the carbon intensity of various times of the day. The first is the decrease of carbon intensity across all times of the day, meaning that the effect of renewable energy is significant across the entirety of every day within a year. Second, since renewable energy sources (such as wind and solar), displays different level of availability across the day and at different times of the year, an increase in their capacity also increases the variation of EV charging carbon emissions across different times of the day and different months of the year. The lifecycle carbon emissions of EV charging at year 2007 lay approximately at 730 gCO2eq/kWh regardless of times of the day nor months of the year. Come 2024, however, the annual variation in emissions factor displayed amplified seasonality patterns and displayed values ranging from as low as less than 300 gCO2eq/kWh to more than 600gCO2eq/kWh.

Last but not least, although the implementation of renewables decreases EV charging carbon intensity across all time of the day, an increase in capacity impacts different times of the day differently. Therefore, the third change brought upon by the increase in renewable capacity is the shift in EV charging carbon intensity of a certain time of the day in relation to other times of the day. During the time before 2017, the predominant source of variation within the grid was the time-varying wind power, as a result, nighttime electricity, especially that at 3 am when wind power was the most abundant, had much lower carbon intensity compared to electricity during daytime. After 2020, however, the emergence of solar power made the carbon intensity of EV charging lower during daytime, and consequently daytime electricity such as that at 12:00 of the day became the cleanest.

The time series of models were used in an attempt to forecast the emissions factors. In that regard, two trials were used to ensure robustness before and after COVID-19. The first trial used all data before 2017 as the training data in order to forecast the emissions factor of 2017 (as the year 2017 was around the time when the commercial EV concept was first introduced in many areas), and the second trial used all data before 2024 as the training data in order to forecast the emissions factor of 2024. If the forecasting proves decently accurate, then by utility standards the methodology of this paper can be used as a tool to forecast EV charging carbon intensities at

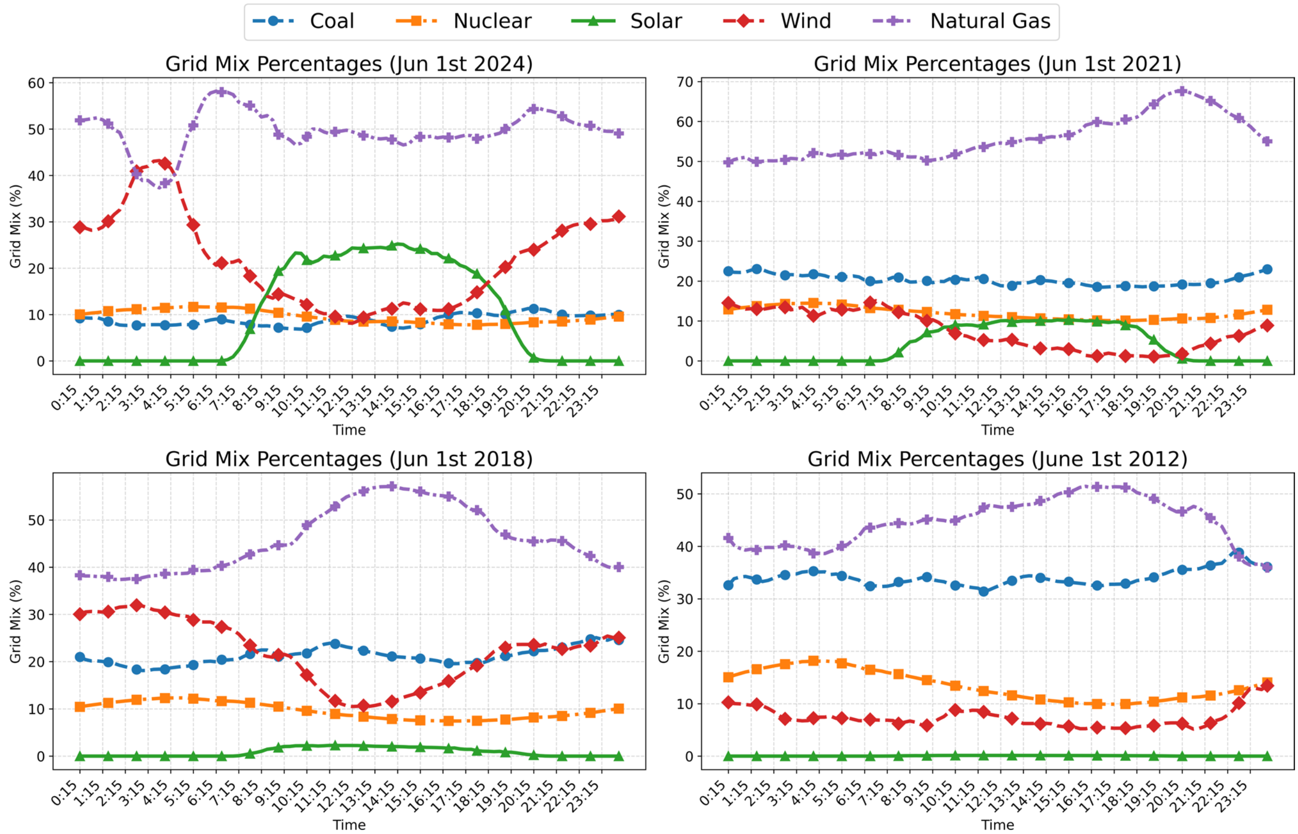

Fig. 2. Sample diurnal grid dynamics.

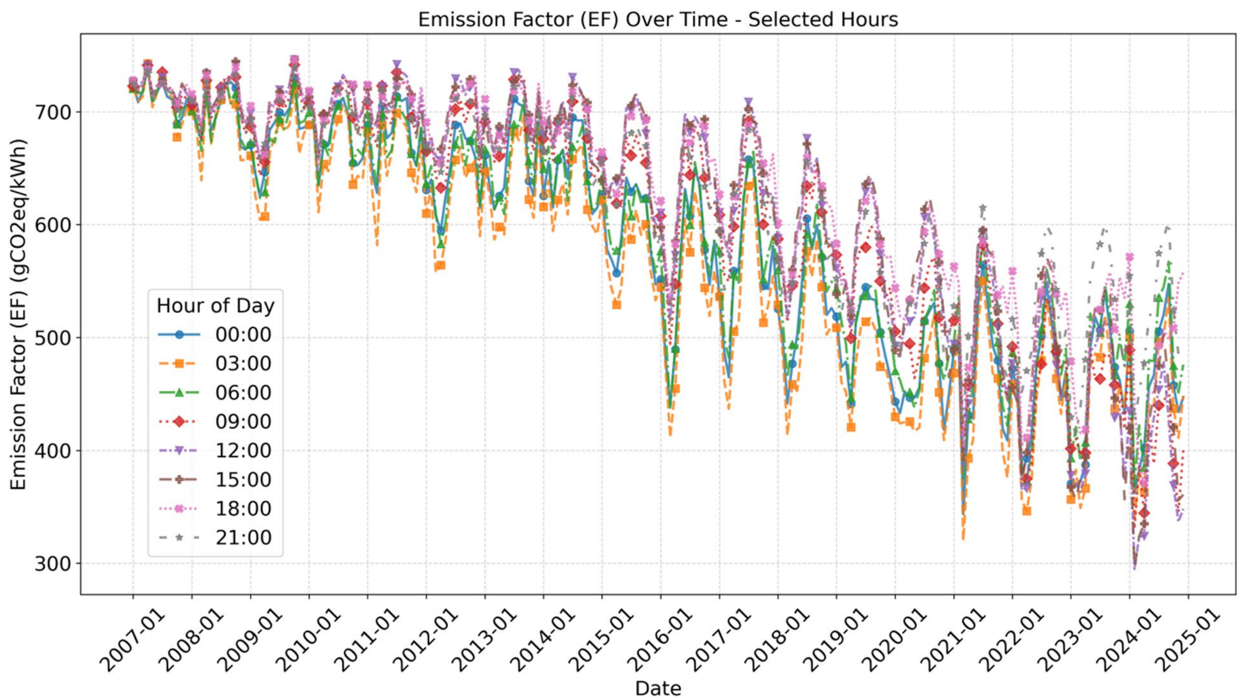

Fig. 3. Monthly emissions factor of different times of the day.

various times of the day over every month of the year. The results in table format can be used for policy making purposes and advising users of EV on what the best practices are.

The trial forecast of year 2017 using all data up to said year is summarized in Table 1. Year 2017 was a year in which the variability of the grid comes primarily from the varying availability of wind. As a result, vertically (that is, across different hours of the day), the carbon intensity of EV charging across all of the months was comparably higher during 9:00–18:00 compared to evenings. Horizontally (that is, across different months of the year), since wind power in Texas appeared more abundant from Oct to Mar the following year, the carbon intensity of EV charging was generally lower during winter and spring (Oct to March) as compared to summer and early fall (Apr to Sept).

The forecast is highly accurate, with only small deviation from the ground truth. The vast majority of the data point summarized in Table 1 achieved an error of less than 5%, and none of the data points had an error above 15%.

The forecasting results for 2024 can be compared with that in 2017 in order to make in-depth observation to how the carbon intensity of electricity, and therefore EV charging, has evolved as a result of evolution in grid mixes. The results are shown in Table 2. The carbon intensity of EV charging in 2024 is lower overall compared to 2017. Additionally, since solar power had been introduced to the grid, the "peaks" of carbon intensity described in Table 2 had been cut, as the carbon intensity at noon, now empowered by solar, becomes cleaner than electricity in the evening. This does not mean that the variation no longer exists, however, and the relative carbon intensity between different times simply shifted in pattern. There are certain times of the day, when the supply of solar power and wind power are simultaneously abundant, such as 9 am of the day, when the carbon intensity of EV charging hits the lowest point. The combo effect manifests horizontally as well, as the month of April and November that experience simultaneous abundance of wind and solar have the lowest overall carbon intensity of the entire year. Also, in the year 2017 months with more wind resources (and thus a higher share of wind power within the grid) were less carbon intensive months with less wind. In 2024 such is still true for night times without a supply of solar. However, for times of the day when sunlight is abundant, specifically 9:00 to 19:00, the carbon intensity of EV charging between Apr and Oct is nearly as carbon intensive as that of the other, more wind-abundant months, if not less carbon intensive.

The capacity of wind within a month depends on the climate conditions, which brings about spontaneous fluctuations that cannot be captured by econometric models. As such, there are cases in which wind power is less abundant than usual, resulting in lower output and higher carbon intensity, as in the case of January 2024; and cases in which wind power is more abundant than expected, resulting in lower carbon intensity than

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg/Std
00:00	537/537	487/498	465/528	559/581	560/621	622/647	658/687	652/673	604/638	546/613	543/608	581/587	568/57
01:00	538/514	469/468	449/494	528/554	542/599	611/620	644/667	647/653	586/608	532/578	531/575	567/551	554/59
02:00	538/514	460/458	439/488	511/551	522/582	602/602	636/657	640/642	572/591	519/566	528/575	557/551	544/60
03:00	536/521	461/458	437/478	505/543	513/564	596/589	634/643	641/633	568/585	513/557	528/567	554/549	541/60
04:00	539/531	464/466	442/496	512/559	511/580	599/595	636/656	644/641	572/586	514/562	536/583	560/571	544/60
05:00	554/550	475/483	455/517	531/577	522/596	609/609	641/666	653/654	580/605	526/583	554/607	573/599	556/57
06:00	576/569	498/508	482/539	556/592	547/621	624/636	654/680	664/669	601/629	552/607	574/623	589/616	577/53
07:00	600/593	527/540	517/560	578/608	567/638	634/652	662/686	676/679	621/656	578/634	597/638	606/631	597/46
08:00	604/588	535/543	528/567	581/613	586/653	652/674	680/703	682/685	625/656	582/636	605/640	609/625	606/47
09:00	609/599	556/553	549/568	598/610	607/653	658/681	691/712	692/697	649/679	600/663	622/651	619/626	621/44
10:00	621/600	577/554	553/563	597/601	607/647	666/681	693/704	692/698	653/695	620/678	628/664	633/628	628/41
11:00	618/587	584/541	558/552	604/590	615/648	681/686	702/707	696/701	661/701	621/686	626/668	633/620	633/42
12:00	611/580	589/541	571/560	612/593	626/654	693/693	708/715	698/718	676/722	628/704	628/677	626/625	639/43
13:00	605/586	589/558	580/583	624/610	633/665	698/704	710/728	696/735	686/739	637/716	629/684	620/639	642/43
14:00	599/595	584/576	586/604	631/629	635/676	699/716	707/739	694/745	688/748	643/722	628/694	617/655	643/42
15:00	594/604	579/584	586/611	635/636	635/679	696/718	702/741	692/745	688/747	645/721	625/698	618/663	641/42
16:00	594/609	574/588	580/613	635/639	637/680	692/717	697/738	688/742	686/744	647/719	626/699	622/669	640/42
17:00	603/609	576/586	577/609	631/636	637/678	686/712	692/732	683/737	683/741	648/720	633/701	644/669	641/39
18:00	627/608	585/577	577/592	625/617	632/661	681/694	688/714	681/719	679/729	654/717	639/697	662/661	644/36
19:00	623/614	586/587	579/591	623/609	629/652	674/688	684/708	680/714	680/719	665/705	622/685	648/656	641/35
20:00	607/602	565/583	571/592	633/610	632/656	669/690	683/712	685/713	679/710	646/690	602/666	636/644	634/40
21:00	595/585	542/566	548/583	627/611	632/659	664/692	684/716	686/708	662/694	619/672	591/648	628/628	623/46
22:00	577/569	524/544	518/570	605/608	612/651	651/684	673/713	676/700	641/676	594/652	575/635	613/614	605/49
23:00	555/555	505/522	489/556	584/600	588/643	636/672	666/705	664/688	624/659	569/636	560/627	598/605	587/54
MAPE	2.15%	2.50%	6.80%	3.55%	8.16%	2.41%	3.70%	3.09%	5.72%	10.05%	9.03%	2.49%	-
MAE	12.66	13.87	33.79	19.83	47.08	15.86	25.02	21.13	37.25	59.92	53.44	15.12	-

Table 1. VAR EV charging carbon intensity forecasting results for year 2017 (unit: gCO2eq/kWh, format: "Ground Truth/Forecasted Value").

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg/Std
00:00	506/421	362/356	382/382	402/415	456/436	467/490	505/492	520/492	547/508	457/463	434/450	447/429	457/54
01:00	503/430	348/355	376/378	376/408	440/418	454/475	497/482	503/483	539/505	446/454	421/450	450/439	446/56
02:00	501/433	342/357	377/377	365/404	437/406	446/467	495/473	500/475	534/495	438/446	416/447	448/439	442/57
03:00	500/434	337/365	380/378	363/404	442/405	440/464	496/464	502/468	535/487	437/440	411/447	448/441	441/58
04:00	508/445	338/377	390/385	364/416	446/415	443/471	503/470	510/472	540/491	441/448	418/456	454/452	446/60
05:00	515/457	346/390	404/399	373/435	458/428	459/481	515/480	525/482	553/502	453/460	430/472	462/469	458/60
06:00	530/473	368/414	422/424	385/458	480/453	479/502	535/499	545/502	567/520	475/482	451/496	476/490	476/60
07:00	550/487	401/444	444/456	405/484	492/477	484/517	547/513	563/520	582/537	499/504	472/518	490/507	494/57
08:00	550/474	386/432	440/449	387/466	462/463	437/498	504/495	527/511	563/528	503/503	424/511	480/492	472/57
09:00	489/405	331/362	387/381	344/399	424/397	388/433	440/420	441/425	458/446	388/418	345/419	400/390	403/47
10:00	458/383	315/337	353/356	327/370	401/381	390/422	428/411	425/403	417/420	339/393	332/391	365/364	379/45
11:00	445/370	304/327	333/342	325/365	394/390	410/442	440/436	449/429	417/437	347/401	331/387	351/355	379/50
12:00	435/358	295/319	324/332	324/363	401/397	429/463	454/461	478/458	427/458	369/414	337/385	348/347	385/57
13:00	425/354	288/315	321/330	329/367	410/404	440/477	466/477	493/476	440/476	393/425	345/382	349/341	392/62
14:00	420/351	288/314	319/328	337/372	418/409	445/484	470/486	502/484	450/488	410/433	348/379	353/337	397/64
15:00	420/353	296/315	324/330	335/379	426/414	449/485	475/490	503/488	457/494	420/438	356/379	361/338	402/63
16:00	434/368	312/331	336/345	345/394	436/428	451/492	482/497	505/497	462/507	429/456	385/400	389/362	414/58
17:00	490/442	351/396	353/388	358/437	442/473	451/532	488/531	503/535	473/543	443/515	499/498	505/477	446/57
18:00	572/515	442/459	388/433	371/463	451/488	451/553	493/549	507/555	498/568	508/553	548/564	557/558	482/61
19:00	578/499	472/461	445/464	422/479	471/500	467/540	511/546	539/562	582/596	583/577	525/554	533/528	511/53
20:00	567/478	446/445	477/472	481/512	512/532	515/559	557/565	591/581	621/602	561/565	505/525	508/498	529/49
21:00	555/462	424/418	451/450	477/496	517/524	527/563	574/570	588/576	603/579	524/535	485/502	488/473	518/53
22:00	537/444	401/394	424/422	453/464	497/489	505/533	546/543	561/544	584/550	498/504	464/480	469/454	495/53
23:00	518/432	380/373	398/402	428/441	479/461	486/510	521/519	537/518	565/529	478/482	448/465	458/443	475/53
MAPE	14.55%	6.82%	2.30%	12.60%	4.18%	8.67%	4.07%	4.78%	7.10%	4.89%	8.73%	2.66%	-
MAE	72.22	23.42	8.65	46.43	18.79	39.14	20.23	24.44	36.45	19.95	34.52	11.58	-

Table 2. VAR EV charging carbon intensity forecasting results for year 2024 (unit: gCO2eq/kWh, format: "Ground Truth/Forecasted Value").

forecasted, as in the case of April. The fluctuation, in turn, results in deviation of the forecast from ground truth. To compensate for that, it is suggested that a parameter representing climate conditions be introduced as an exogenous variable to be modeled. In the absence of such data, however, the forecast generated through pure econometric means should still be considered viable, given the low mean absolute percent error.

EV charging emissions factor at different times of the day React differently to economic conditions

It was validated in Saboori et al. and Zhang et al. that the correlation between renewable energy consumption and economic growth in Texas appeared to be a positive one[20,21]. Therefore, economic growth in the state of Texas will co-move with the capacity of Texas's renewable energies, potentially inducing shifts in electricity carbon intensities, and in turn EV emissions factors. This subsection explores relevant effects. The relationships were observed using impulse-response of VECM models. Said method has the advantage in interpretability, since the curves tends to be smoother and easy to interpret.

Two other studies had observed the energy use in Texas in detail, with both drawing positive correlation between economic conditions and carbon reduction efforts[20,21]. Their findings were confirmed by the VECM models as well. As shown in Fig. 4, past shocks in building permit figure (and thus the level of economic activity) and in housing value induce positive reaction in emissions factor in the short term but ultimately have a negative impact on the present EV charging emissions factor at 12:00 of the day. A reasonable interpretation of such interaction, as proposed in Zhang et al.[21], is that the grid needed to compensate for the additional demand caused by growth using non-renewable sources at first, but the use of renewable sources eventually supersedes.

The magnitudes of the shocks are in number of standard deviations above and below the mean, the periods are measured in months. Analysis was also done using the emissions factors at all other times of the day as the response variable, and the trials returned curves of similar shapes but different magnitudes. Meaning that the impact of economic growth on the EV charging emissions factor across different times of the day is consistent in terms of mechanism but different in terms of magnitudes and significance.

The negative responses of emissions factors at different times of the day towards shocks in economic growth is summarized in Table 3. All of the responses are negative, meaning that economic growth promotes sustainable development in Texas and leads to lower carbon intensity of EV charging across all time periods. However, the magnitudes of shocks are higher for certain hours of the day and lower for others. Specifically, according to Table 3 the peak in response induced by shocks in building permit figures occurred during evening hours, during which as previously discussed was the times of the day when wind capacity was abundant. The response

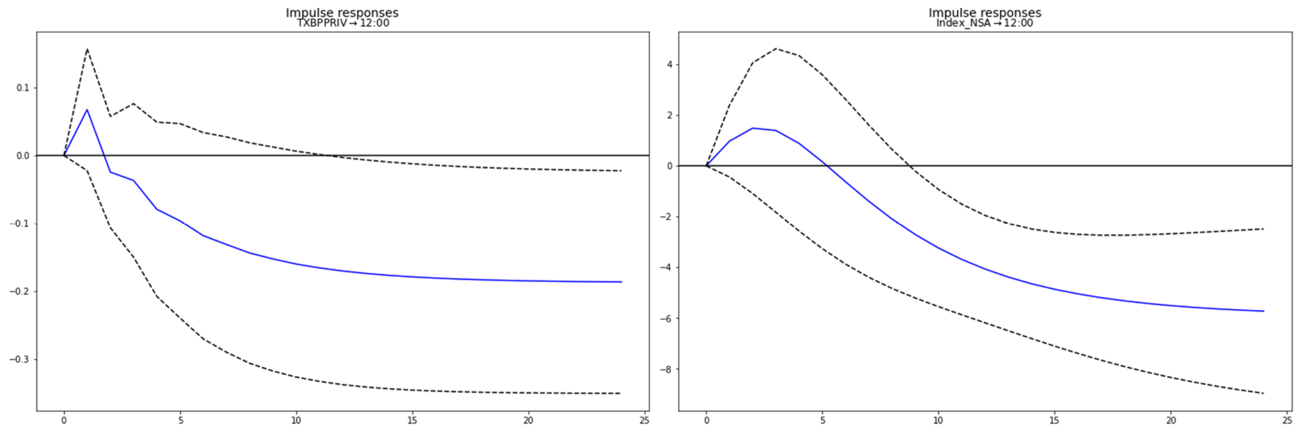

Fig. 4. Impulse (Left: Building Permit, right: Housing Value) -Response (Emissions Factor: 12:00) Curves.

Impulse variables/ Time of the Day	Texas issued building permit	Texas housing value
0:00	−0.23 (−0.1, −0.36)	−4.2 (−2, −6.4)
1:00	−0.23 (−0.1, −0.36)	−5 (−2, −8)
2:00	−0.23 (−0.1, −0.36)	−5 (−2, −8)
3:00	−0.23 (−0.1, −0.36)	−5 (−2, −8)
4:00	−0.24 (−0.1, −0.38)	−5.5 (−2, −9)
5:00	−0.24 (−0.11, −0.37)	−6 (−2, −10)
6:00	−0.25 (−0.11, −0.39)	−6 (−2, −10)
7:00	−0.25 (−0.11, −0.39)	−6 (−2, −10)
8:00	−0.24 (−0.1, −0.38)	−7 (−2, −12)
9:00	**−0.1***	**−8 (−4, −12)**
10:00	**−0.1***	**−8 (−4, −12)**
11:00	**−0.12***	**−6 (−2, −10)**
12:00	**−0.17 (−0.02, −0.32)**	**−5 (−2, −8)**
13:00	**−0.19 (−0.04, −0.34)**	**−5 (−2, −8)**
14:00	**−0.19 (−0.04, −0.34)**	**−5 (−2, −8)**
15:00	−0.19 (−0.04, −0.34)	−4.5 (−2, −6)
16:00	−0.19 (−0.04, −0.34)	−4 (−1, −7)
17:00	−0.2 (−0.05, −0.35)	−6 (−3, −9)
18:00	−0.27 (−0.11, −0.43)	−8.5 (−3, −14)
19:00	−0.25 (−0.11, −0.39)	−7 (−2, −12)
20:00	−0.25 (−0.15, −0.35)	−4.5 (−2, −7)
21:00	−0.25 (−0.16, −0.34)	−4 (−2, −6)
22:00	−0.24 (−0.13, −0.35)	−4 (−2, −6)
23:00	−0.22 (−0.1, −0.34)	−4 (−2, −6)

Table 3. Response of EV emissions factors towards past shocks in Building permit and housing value (Unit: number of standard deviations, *: insignificant at 95% CI, convention: mean response magnitude (95% confidence interval)).

to shocks in building permit figures is the weakest during daytime hours, including and especially the time between 9:00 to 12:00. On the other hand, the period between 9:00 to 14:00 of the day had been the diurnal peak of the emissions factor's response towards shocks in property value.

This discrepancy indicates that although both building permit figures and housing values reflect economic growth, they influence renewable implementation differently. The property value affects emissions factor during daytime, when solar power is abundant, the most, meaning that the property value is more strongly associated with the capacity of solar power. Such can be reasonably explained by the fact that hotter property market means the production of new single-family units, and thus additional solar distributed generation capacity in the form of rooftop solar panels.

On the other hand, building permit figures, which represent the level of economic activities and in turn the level of investment, had been more strongly correlated with the capacity of wind power. Such is due to the fact

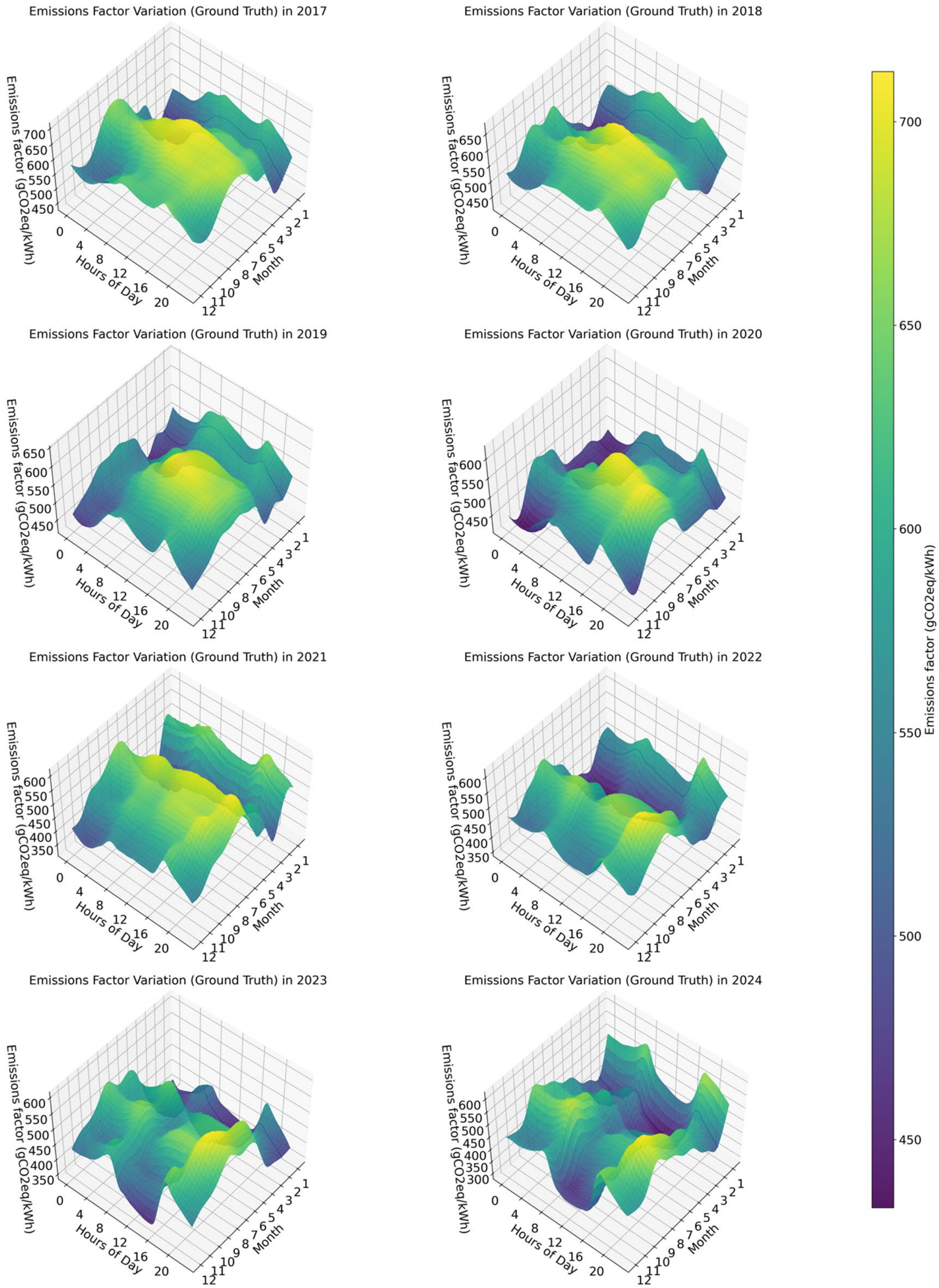

Fig. 5. Texas EV emissions factors 2017–2024.

that wind power generation places comparably low reliance on distributed generation and is primarily driven by infrastructure investments.

The evolution of Texas EV charging emissions factors

Figure 5 summarized the TX EV charging emissions factors from 2017 to 2024. This section discusses the evolution of the EV charging emissions factors over the years as a result of renewable energy penetration within the electricity grid. In the year 2017, the primary source of renewable energy came from wind power generation, which as previously discussed is relatively abundant during evening hours and during the period outside of Apr to Oct of the year. The variation induced by wind power manifested in 2017, as the peak of emissions factors within said year lay at the daytime during the months between Apr and Oct while the valley of factors occurred around Feb, during evening hours, when wind power was the most abundant.

Since 2017, two changes had occurred regarding the renewable landscape of the TX emissions factors. First, the capacity of wind power generation continued to increase, improving overall renewable penetration and lowering the overall magnitude of emissions factors. Second, the introduction of solar power had begun to fill the gap of wind power, as solar power has high availability during daytime and in summer months. The supplement of solar power towards wind power had a leveling effect on the emissions factors all across the board, meaning that the emissions factors during former peaks in carbon intensities began to fall, and that the peaks in emissions factors had begun to shift from where it was in 2017.

Solar power penetration increased incrementally from 2017 to 2024, but a significant shift in emission factor peaks did not occur until 2021. Up until 2020, the peaks in annual emissions factor had been at the noon hours from Apr to Oct, however, as the penetration of solar power deepened, the diurnal emissions factor during said months began to even. For the year 2021 and 2022, the emissions factor landscape evolved. The peaks in average emissions factors shifted from a pinnacle at noon hours during April to October to being a row of peaks going all across the day at an overall lower magnitude. To interpret, this means that the implementation of solar power had begun to even the diurnal emissions factors during days within summer months, and that charging at any time of the day during summer results in equal global warming potential during summer 2021–2022.

The penetration of solar power within the grid also had an impact on the location of bottom points of emissions factors. Up until 2020, the lowest point in average emissions factors had been at the evening hours of Feb to April, when wind power was the most abundant. Starting 2021, however, the implementation of solar power within the State of Texas had also caused the emissions factors midday during months around February to decrease and fall to the same level as the emissions factor at nighttime during said months, where the annual bottom point of carbon intensity once had been. As a result, what appeared to be “basins” for emissions factors magnitude have grown to form a valley of low points across all times of the day, and charging at any time during months around Feb in the year 2021 and 2022 would result in similar carbon intensity.

As renewable penetration deepened, with the rate of solar power outpacing that of wind power, the landscape of average emissions factors within a year has shifted completely in the year 2023 and 2024 and compared to 2017–2020. For one, the peaks in emissions factors have shifted from midday during summer months to the evening hours of summer months, when neither wind nor solar power had strong output. On the other hand, the lowest point in the map for carbon intensities had shifted from the evening hours during months around Feb to the daytime during said months. With the increased output of solar power, the lowest point in diurnal emissions factor across any months in 2023 and 2024 has been during daytime when solar output is strong instead of during nighttime with stronger wind power. As such, the current recommendation by TXDOT to charge between 10 pm to 6 am deserves to be re-evaluated.

As the penetration of solar power becomes even deeper with additional investment in infrastructure and improved incentives for local distributed generation, it can be reasonably speculated that the lowest points of emissions factor will form a consistent valley during daytime across any months of the year. Wind power would follow up and supplement solar power during downtime, and the charging of EVs will become sustainable at any time without the need of a deliberate charging strategy.

Discussion

Summary of results

Overall, through the implementation of wind power and later solar power, the carbon intensity of electricity (and thereby emissions factors of EVs) had been steadily decreasing over the years, meaning that the electric option had become increasingly more sustainable. A closer look at the diurnal patterns of the grid yields three important facts, (1) the long-standing source of renewables in Texas is wind power, which is more abundant at night, (2) the newly emerging solar power capacity is helpful in cutting the carbon intensity peaks at noon caused by wind power shortages, making electricity less carbon intensive throughout the entire day, (3) when supply of renewable dwindles as a result of spontaneous climate effects, other renewable energy alongside coal fire and natural gas generation would compensate.

Monthly emissions factors at different times of the day were compared between 2024 and 2017, and it was discovered that in the year 2017 electricity was less carbon intensive at night than during the day. However, in 2024, through the implementation of solar power, the diurnal fluctuation in emissions factors had weakened, and charging throughout the day may be equally sustainable, if not more so at noon. This also means that the current recommendation by the Texas Department of Transportation to charge electric vehicles from 10 pm to 6 am when wind capacity is abundant may be challenged, as solar power has substituted wind power as the renewable source EV can draw from in the day, EV charging has become less carbon intensive throughout the entire day. The results of the study have shown that, the daily peak in emissions factors has shifted to the time period of 6:00–7:00 and 20:00–22:00, when wind power waned but solar power had yet to catch up. To put this in numbers, in the year 2017 charging during the evening results in 15% less carbon emissions compared to doing so during the day, as the emissions factors during evenings averaged at around 550 gCO2eq/kWh while that at noon neared 650 gCO2eq/kWh. In 2024, however, the emissions factors were calculated to be averaged at around 400 gCO2eq/kWh all across the day. In fact, with deeper solar power penetration the average emissions factor at noon in 2024 was at around 380 gCO2eq/kWh while that during evenings was at around 420 gCO2eq/kWh. This means that charging during the day in 2024 was in fact ~ 10% less carbon intensive than doing so during evenings. As such, a more effective charging strategy is to encourage charging across all times of the day save for the time between 6:00–7:00 and 20:00–22:00.

The compensating effect between solar and wind manifests when comparing emissions factors between different months as well. As the calculated emissions factors of the year 2017 (the time around which commercial EVs are introduced) and 2024 were calculated and compared, it was discovered that in the year 2017, EV charging was less carbon intensive during months when wind capacity was high (Oct to Apr) while carbon intensity outside said timeframe was comparably high. In the year 2024, however, the months between Apr and Oct of the same year had similar emissions factor as all other months, if not lower, such is primarily due to the summer months having a higher supply of sunlight, compensating for its lack of wind power compared to other months. This also means that an alternative to developing charging strategies in order to reducing carbon emissions is to modify the grid and integrate multiple types of renewable energy sources to ensure coverage at any time.

Multi-variate time series models were used in an attempt to forecast emissions factors and grid mix percentages of renewable sources. Forecasting of emissions factors proved viable using Vector Autoregression Models, as the forecasted values for both 2017 and 2024 are close to the ground truth and carry utility value. Climate factors may affect capacity of renewable energy, causing its output to be higher or lower than expected. Such effect is completely spontaneous by pure econometric standards, and to compensate for that the impact of climate needs to be modeled using an exogenous variable. With that being said, the overall accuracy of the forecasts tends to remain consistently high despite the occasional impact of weather.

Confirming with findings of Zhang et al. and Saboori et al., past shocks in economic conditions in Texas promotes renewable penetration and decreases energy carbon intensities[20,21], meaning that economic growth in Texas promotes the use of sustainable energy and leads to lower carbon intensity of electric vehicle charging. Since economic growth promotes sustainable energy consumption, and sustainable energy has a different level of availability throughout the day, the impact of economic growth on EV emissions factors varies throughout the day. The difference is primarily in the form of magnitudes. The shocks in the number of building permit had an impact that was the most significant during nighttime, meaning that the level of economic activities is more associated with the traditional Texas renewable that is wind. On the other hand, shocks in property value had strong effect across all time periods, but was the strongest during daytime. Evidence justifying such variation is that part of the solar power in the State of Texas relies on local distributed generation, including and especially roof-top panels. As such, the higher the property price, the more desirable Texas homes are to the market, and the more solar panels installed and thus the higher capacity.

An additional factor to be considered is the possibility of evolution in emissions factors. Over the course of the study period, there has not been evidence that energy production technologies had significantly evolved: the emissions factor of fossil fuel generation comes primarily from the combustion of fuel, the impact of which is primarily determined by the chemical composition of coal and natural gas. While the impact of renewables can be considered to be next to none in comparison to that of fossil fuel generation regardless of systems boundaries. As such, the study assumes static emissions factors across the study period.

There are, however, possibilities that fossil fuel generation will have decreased emissions factors in the future. The likely cause of such would be energy efficiency improvements, including and especially full adoption of a combined cycle generation for natural gas, which has yet to occur but is certainly possible in the future. Future studies are advised to consider changes in emissions factor, should the need arise.

Peak cuts in carbon intensity: the two dimensions of grid dynamics

Methodology-wise, this paper reflects one of the first attempts to analyze EV charging emissions using grid dynamics data of high granularity (in 15 min intervals). The only comparable study is Zhang et al., which conducted an EV emissions study using California generation data in settlement periods of 5 min provided by California Independent System Operator (CAISO)[12]. Similar to that of Texas, the grid mix and emissions factors of California also exhibits diurnal patterns, as given the high capacity of solar power in California electricity is considerably cleaner at noon. The difference, however, lies in that Zhang et al. in the context of California had a study period of only 5 years, during which the capacity of various sources did not vary significantly[12]. As such, comparison from year to year (similar to how this paper compares 2017 to 2024) cannot be made and the emissions factors of the entirety of the 5-year period are summarized in one sum average in a single table. This study however, with its considerably longer study period, is able to observe how capacity change of various renewable sources affects the relative magnitude of emissions factor between different month of the year. As mentioned earlier, the emergence of solar power compensated the paucity of wind between Apr to Oct of the year, making the carbon intensity of EV charging generally even among months in 2024. Such was not the case in 2017, as the relative paucity of wind made electricity more carbon intensive during summer than in other months.

Comparing this paper with Zhang et al., it can be stated that policy studies on the grid should consider two dimensions: the *vertical variation* and the *horizontal variation*[12]. Vertical variation, as observed in the columns of Tables 1 and 2, refers to how the integration of various sources affect the grid mix and emissions factors within each day. The vertical variation observed in this paper is the abundance of wind making electricity cleaner during nighttime while solar power lowered EV emissions factor during daytime. The current recommendation of TXDOT to charge between 10 pm and 6 am also falls within that category. Addressing vertical variation is to study diurnal patterns, thereby advising the population on the best course of action to take in a particular day. Horizontal variation, on the other hand, has to do with how a particular month within a year compares with other months in said year. The results that fall within the horizontal variation category is how the relative scarcity of wind power made EV charging more carbon intensive from Apr to Oct in year 2017, and that the peak in emissions factors during summer months was partially cut in 2024 with the increase in solar capacity. The increased solar capacity in the State of Texas had been beneficial in "peak cutting" the emissions factor in the horizontal direction. Addressing horizontal variation is to optimize fuel mixes so that demands can be met sustainably all across the year, rather than having considerably higher capacity in certain months and being insufficient in other months.

The vertical and horizontal variation have simultaneous effect and effective identification of peaks within the emissions factor of the grid demands concurrent consideration of both dimensions. Therefore, the idea of "peak cutting", which traditionally had to do with total loads and power demand and presented in 2-D form, should be considered as a three-dimensional gradient in the case of emissions factors if the peak is to be correctly identified. A sample demonstration of the method is presented in Fig. 5, for the year 2017 and 2024 in the State of Texas. From Fig. 5, it can be observed that the row of peaks in 2017 at around 12:00 have become a valley in 2024, and that the global peak in the emissions factor within a year has shifted from mid-day in months from May to July in 2017 to the early morning and late night of August/September in 2024. Both of these observations conform with the findings of the paper.

Conclusion and policy implications

The State of Texas should continue its renewable energy policies and divert its GDP growth into infrastructure development that further enhances renewable capacity. In addition, it was observed that the capacity of renewable energy can vary depending on its availability. The variability patterns can be both diurnal or across different times of the month. When the capacity of renewables subsides during certain times, non-renewable sources typically take its place in the grid. However, in the State of Texas an alternative was presented, and the varying capacity of wind power was decoupled by the varying capacity of solar power, which happens to be in abundant supply when wind isn't. The two sources compensate each other, making EV charging less carbon intensive all year around and regardless of the times of the day. This means that the current policy recommendation to charge EVs 10:00 pm to 6:00 am made by the Texas Department of Transportation may deserve re-evaluation, as wind power is no longer the only factor that deserves consideration.

Since the average emissions factor of the State of Texas had started to become uniform across the day, a policy alternative may be to encourage charging at alternative time periods and to discourage charging at other time periods. The results of the study have shown that, the daily peak in emissions factors has shifted to the time period of 6:00–7:00 and 20:00–22:00, when wind power waned but solar power had yet to catch up. A more effective policy recommendation may be to avoid charging at those hours of the day instead.

Energy dynamics are closely linked to economic conditions. As economic conditions impact the grid, they, consequently, affect EV charging carbon emissions. However, what deserves consideration is that the effect of economic growth on emissions factor at different times of the day is different. In the case of this paper, the corresponding policy recommendation is that while increase in both the level of economic activities and property price lead to increased renewable consumption, the level of general economic activities is more closely associated with wind power capacity while the property price is strongly correlated with solar power capacity.

The study supplements the discussion on EV charging by extensively discussing average emissions factors in addition to marginal ones. The average emissions factors represent the carbon intensity that is the most likely to be achieved if charging is done at a certain time and serves as a useful indicator when formulating high-level charging strategies that may overlook nuanced relationships. There are, however, constraints that may be specific to certain days or certain areas, such as peak demand management, grid stability, and infrastructure constraints, meaning that considerations of both marginal and average emissions factors are equally important.

Data availability

All code and data used to generate the results are included as supplementary files, Specifically "PaperData V2.zip".

Received: 17 June 2025; Accepted: 29 October 2025
Published online: 27 November 2025

References

1. Tu, R., (Jessie) Gai, Y., Farooq, B., Posen, D. & Hatzopoulou, M. Electric vehicle charging optimization to minimize marginal greenhouse gas emissions from power generation. *Appl. Energy*. **277**, 115517. https://doi.org/10.1016/j.apenergy.2020.115517 (2020).
2. Powell, S., Martin, S., Rajagopal, R., Azevedo, I. M. L. & de Chalendar, J. Future-proof rates for controlled electric vehicle charging: comparing multi-year impacts of different emission factor signals. *Energy Policy*. **190**, 114131. https://doi.org/10.1016/j.enpol.2024.114131 (2024).
3. Arvesen, A. et al. Emissions of electric vehicle charging in future scenarios: the effects of time of charging. *J. Ind. Ecol.* **25**, 1250–1263. https://doi.org/10.1111/jiec.13144 (2021).
4. Li, J., Wang, G., Wang, X. & Du, Y. Smart charging strategy for electric vehicles based on marginal carbon emission factors and time-of-use price. *Sustainable Cities Soc.* **96**, 104708. https://doi.org/10.1016/j.scs.2023.104708 (2023).
5. Xu, L., Yilmaz, H. Ü., Wang, Z., Poganietz, W. R. & Jochem, P. Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. *Transp. Res. Part. D: Transp. Environ.* **87**, 102534. https://doi.org/10.1016/j.trd.2020.102534 (2020).
6. Gai, Y., Wang, A., Pereira, L., Hatzopoulou, M. & Posen, I. D. Marginal greenhouse gas emissions of ontario's electricity system and the implications of electric vehicle charging. *Environ. Sci. Technol.* **53**, 7903–7912. https://doi.org/10.1021/acs.est.9b01519 (2019).
7. Mills, G. & MacGill, I. Assessing greenhouse gas emissions from electric vehicle operation in Australia using Temporal vehicle charging and electricity emission characteristics. *Int. J. Sustainable Transp.* **11**, 20–30. https://doi.org/10.1080/15568318.2015.1106243 (2017).
8. Atems, B. & Hotaling, C. The effect of renewable and nonrenewable electricity generation on economic growth. *Energy Policy*. **112**, 111–118. https://doi.org/10.1016/j.enpol.2017.10.015 (2018).
9. Rahman, M. R., Rahman, M. M. & Akter, R. Renewable energy development, unemployment and GDP growth: South Asian evidence. *Arab. Gulf J. Sci. Res.* **42**, 1044–1059. https://doi.org/10.1108/AGJSR-04-2023-0152 (2023).
10. Salahuddin, M., Alam, K., Ozturk, I. & Sohag, K. The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions in Kuwait. *Renew. Sustain. Energy Rev.* **81**, 2002–2010. https://doi.org/10.1016/j.rser.2017.06.009 (2018).

11. Dong, K., Dong, X. & Jiang, Q. How renewable energy consumption lower global CO2 emissions? Evidence from countries with different income levels. *World Econ.* **43**, 1665–1698. https://doi.org/10.1111/twec.12898 (2020).
12. Zhang, X., Martin, E. & Shaheen, S. The dynamics of the California electric grid mix and electric vehicle emission factors. *Energies* **18**, 895. https://doi.org/10.3390/en18040895 (2025).
13. TXDOT. *Texas Electric Vehicle Infrastructure Plan* (Charging Plan/Texas Electric Vehicle Charging Plan.pdf, 2024). https://ftp.txdot.gov/pub/txdot/get-involved/statewide/EV
14. TXDOT. EV charging stations. https://www.txdot.gov/discover/ev-charging-stations.html (2025).
15. ERCOT & Generation https://www.ercot.com/gridinfo/generation (2025).
16. Kadiyala, A., Kommalapati, R. & Huque, Z. Evaluation of the life cycle greenhouse gas emissions from hydroelectricity generation systems. *Sustainability* **8**, 539. https://doi.org/10.3390/su8060539 (2016).
17. Stokes, J. & Horvath, A. Life cycle energy assessment of alternative water supply systems (9 pp). *Int. J. Life Cycle Assess.* **11**, 335–343. https://doi.org/10.1065/lca2005.06.214 (2006).
18. Bhat, M. R., Jiao, J. & Azimian, A. The impact of COVID-19 on home value in major Texas cities. *IJHMA* **16**, 616–627. https://doi.org/10.1108/IJHMA-05-2021-0058 (2023).
19. Zhang, X. & Yang, E. Have housing value indicators changed during COVID? Housing value prediction based on unemployment, construction spending, and housing consumer price index. *Int. J. Hous. Markets Anal.* **17**, 242–260. https://doi.org/10.1108/IJHMA-01-2023-0015 (2023).
20. Saboori, B., Gholipour, H. F., Rasoulinezhad, E. & Ranjbar, O. Renewable energy sources and unemployment rate: evidence from the US States. *Energy Policy*. **168**, 113155. https://doi.org/10.1016/j.enpol.2022.113155 (2022).
21. Zhang, X., Xu, S. & Wang, Y. Observing the interaction between energy generation carbon emissions and economic conditions could consider generation, intensity, and times of the day. *Environ. Sci. Pollut Res.* **31**, 63635–63651. https://doi.org/10.1007/s11356-024-35422-z (2024).

Acknowledgements

AcknowledgementThis paper re-uses the data generated from the following paperZhang, X., Xu, S. & Wang, Y. Observing the interaction between energy generation carbon emissions and economic conditions could consider generation, intensity, and times of the day. Environ Sci Pollut Res (2024). https://doi.org/10.1007/s11356-024-35422-zThe authors would like to thank Mr. Shuai Xu, of Univ of Southern California, for his generous support during data pre-processing.The authors would also like to thank Prof Jintao Ke, of Univ of Hong Kong, for his class of CIVL 7018 that provided the background knowledge to our project.

Author contributions

Credit StatementConceptualization-X.Z.; Data Curation-X.Z, J.S, Y.Z; Formal Analysis-X.Z, J.S, Y.Z; Methodology-X.Z; Project Administration-X.Z; Software-J.S; Supervision-X.Z; Validation-J.S; Visualization-J.S, Y.Z; Writing-Original Draft-X.Z; Writing- review & editing-J.S., Y.Z.

Funding

This paper received no external funding.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-26528-6.

Correspondence and requests for materials should be addressed to X.Z.