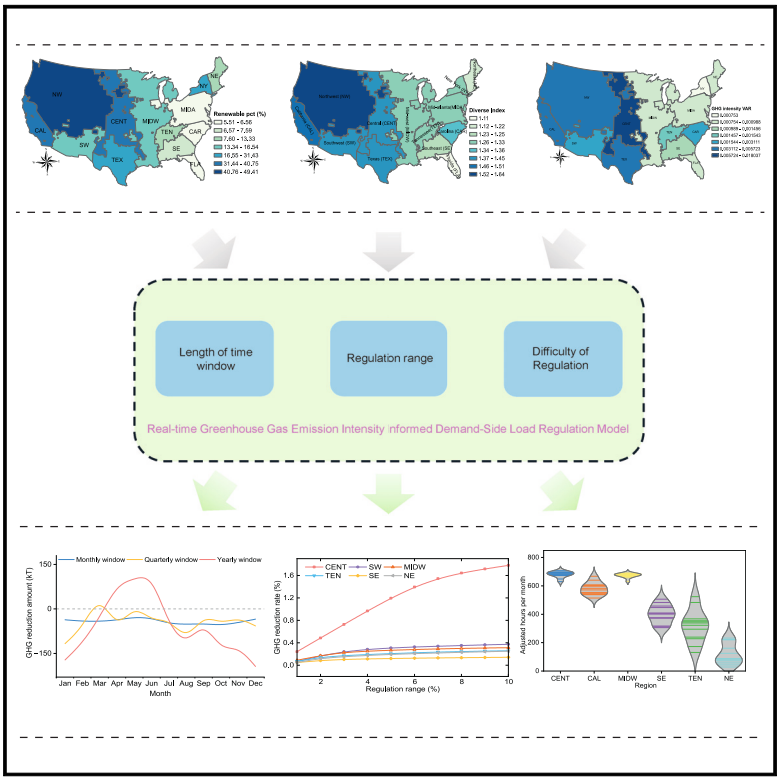
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Real-time greenhouse gas emission intensity informed demand-side load regulation for power grid decarbonization

Graphical abstract



Highlights

- A demand-side load regulation model using real-time greenhouse gas intensity is proposed
- Three different dimensions of demand-side regulation strategies are proposed
- Demand-side regulation strategies for different energy system types are analyzed

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In brief

Li et al. present a novel approach to decarbonizing electricity consumption by using real-time greenhouse gas emissions data. By aligning energy use with periods of lower greenhouse gas intensity, their strategy effectively reduces emissions without compromising energy consumption needs. This method is particularly effective in regions rich in renewable energy, demonstrating annual emission reductions of over 30%. Their findings underscore the potential for scalable, tailored strategies across diverse power grids, offering actionable solutions to support US goals for achieving net-zero-carbon electricity by 2035.

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Real-time greenhouse gas emission intensity informed demand-side load regulation for power grid decarbonization

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SCIENCE FOR SOCIETY The United States (US) aims to achieve net-zero-carbon electricity by 2035, necessitating innovative approaches to both energy consumption and generation. Our research examines the use of real-time greenhouse gas (GHG) emissions data to adjust electricity usage, thereby reducing the carbon footprint without decreasing overall energy consumption. This strategy proves to be particularly effective in regions rich in renewable energy, where annual optimization could lead to emission reductions of over 30%. Scaling this strategy presents both opportunities and challenges. Specifically, different power grids will require tailored approaches; for example, grids with a mix of energy sources could widen consumption adjustment ranges to enhance carbon reduction. Conversely, areas with varying GHG intensity fluctuations may respond differently to the costs of load regulation, necessitating customized policies. This approach provides a scalable and actionable solution for US decarbonization efforts, leveraging real-time data to achieve significant environmental impact.

SUMMARY

The US targets net-zero-carbon electricity by 2035, emphasizing the need for both supply- and demand-side strategies in the power sector. Our study focuses on demand-side carbon reduction via load regulation, using real-time greenhouse gas emission data to optimize electricity use without reducing overall consumption. Our multi-scenario analysis indicates significant potential for carbon footprint reduction by adapting strategies to specific grid characteristics. For example, California could have 32.58% more emission reduction with annual instead of quarterly optimization. In grids with diverse generation resources, expanding adjustment ranges from ±5% to ±8% can boost carbon reductions from 1.19% to 1.64%. Our results also reveal low greenhouse gas intensity fluctuation areas as more cost sensitive in electricity consumption than high greenhouse gas intensity fluctuation areas, providing essential insights for policymakers.

INTRODUCTION

In addressing climate change, carbon reduction strategies are imperative across various sectors, each presenting distinct challenges and pathways for mitigation. From industrial innovation and transportation electrification to sustainable agricultural practices and efficient waste management, the approaches to decarbonization are manifold.[1–4] However, the electricity sector represents a critical pivot in this endeavor, where the integration of renewable energy and the enhancement of energy efficiency emerge as key mechanisms. This study narrows its focus to the power system, highlighting its essential role in the United States (US) carbon reduction efforts and setting the stage for an in-depth examination of leveraging real-time greenhouse gas (GHG) emission intensity to optimize electricity consumption for enhanced emission mitigation.

The US stands as one of the world's leading contributors to GHG emissions, with carbon dioxide (CO_2) emissions from fossil fuel combustion reaching approximately 4.9 billion metric tons in 2022.[5] This accounts for about 97% of its total annual emissions, underscoring the country's reliance on fossil fuels. Despite making up only 4.18% of the global population,[6] the US is responsible for around 13.6% of worldwide CO_2 emissions, making the US the second-largest contributor after China (30.7%) in

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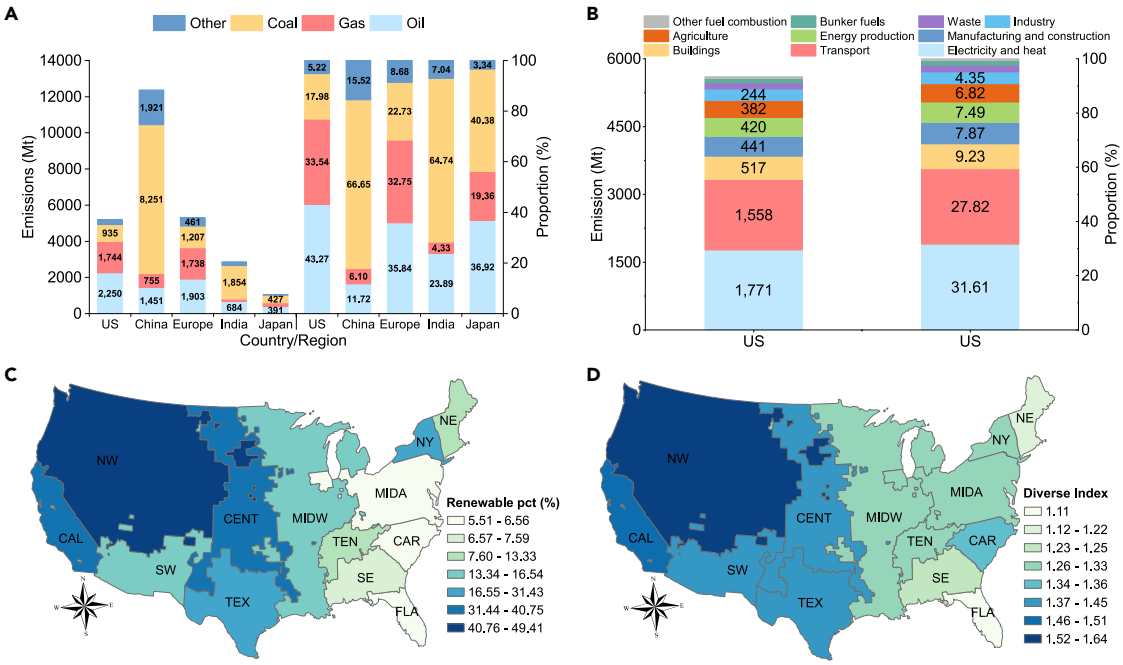


Figure 1. Analysis of the current status of carbon emissions and energy mix in the US

(A) The US has the second-largest carbon emissions in the world, totaling 4.9 billion metric tons in 2022, with oil contributing the most.

(B) The US carbon emissions in 2020. This shows absolute emissions and their percentages, highlighting significant emissions from electricity and heat: 1,771 Mt (31.61%).

(C) The share of renewable energy in the energy mix in 2023 for 13 North American Electric Reliability Corporation (NERC) regions across the US. The Central and Western (49.41% in Northwest [NW], 40.75% in CAL, and 40.05% in CENT) have significantly higher shares than the Eastern (5.51% in FLA, 6.14% in CAL, and 6.56% in Mid-Atlantic [MIDA]).

(D) Shannon-Wiener diversity index for 13 NERC regions of the US. The top three regions include NW, CENT, and Mid-West (MIDW). The bottom three regions are Tennessee (TEN), Southeast, and Northeast.

global rankings (Figure 1A). Within the US, the electric power sector is a major emissions source, responsible for about 31.61% of total GHG emissions, followed closely by the transportation sector at 27.82% (Figure 1B).[7] These figures reveal the extensive impact of the US power system on national emissions and underscore the urgent need for reform within this sector to meet the country's climate goals and commitments.

As indicated by Energy Information Administration (EIA) data, the combined share of renewable energy sources in US electricity generation has grown from approximately 13% in 2014 to about 21% in 2023,[8] significantly moving toward sustainability, as evidenced by decreasing GHG emission intensity. However, this transition has not been uniform across regions, largely due to varying natural resources, policy frameworks, and infrastructure capacities (Figure 1C). For example, the Central (CENT) region and Texas (TEX) have capitalized on consistent wind patterns and open spaces to lead in wind energy adoption (35.68% in CENT and 24.22% in TEX). The Northwest (NW), benefiting from abundant water resources and suitable topography, relies heavily on hydropower (30.76%), while California's (CAL) sunny climate and supportive policies position it as a solar leader (18.72%). Another important indicator with significant geographical differences is energy diversity, which refers to the abundance and balance of energy resources in a region's energy structure. In this paper, energy diversity is calculated using the Shannon-Wiener diversity index, which takes into account not only the quantity of different energy resources but also the contribution of each resource to the overall energy mix. For a detailed breakdown of the calculation methodology, please consult Equation 8. A region with a high energy diversity index benefits from a more balanced energy structure, which enhances the stability and flexibility of its energy supply. According to our analysis, the NW, CAL, and Southwest (SW) showcase balanced energy mixes that strengthen grid resilience, while regions s Florida (FLA), the Northeast (NE), and the Southeast (SE) rely on more limited portfolios, potentially reducing their adaptability to future changes (Figure 1D).[9] These regional disparities in energy mix and infrastructure highlight substantial obstacles to uniformly reducing GHG emissions across the US electric power system, as each region faces distinct limitations and dependencies that complicate a cohesive national strategy.

In response to these challenges, the US has set ambitious targets to decarbonize its electric power system, with a goal of achieving net-zero emissions in the electricity sector by 2035.[10] This vision is supported by a broad set of initiatives designed to transform the energy landscape. Key strategies include accelerating the deployment of renewable energy sources, such as wind and solar, enhancing energy efficiency across buildings and industries, and increasing electric vehicle adoption to reduce emissions from transportation, and implementing

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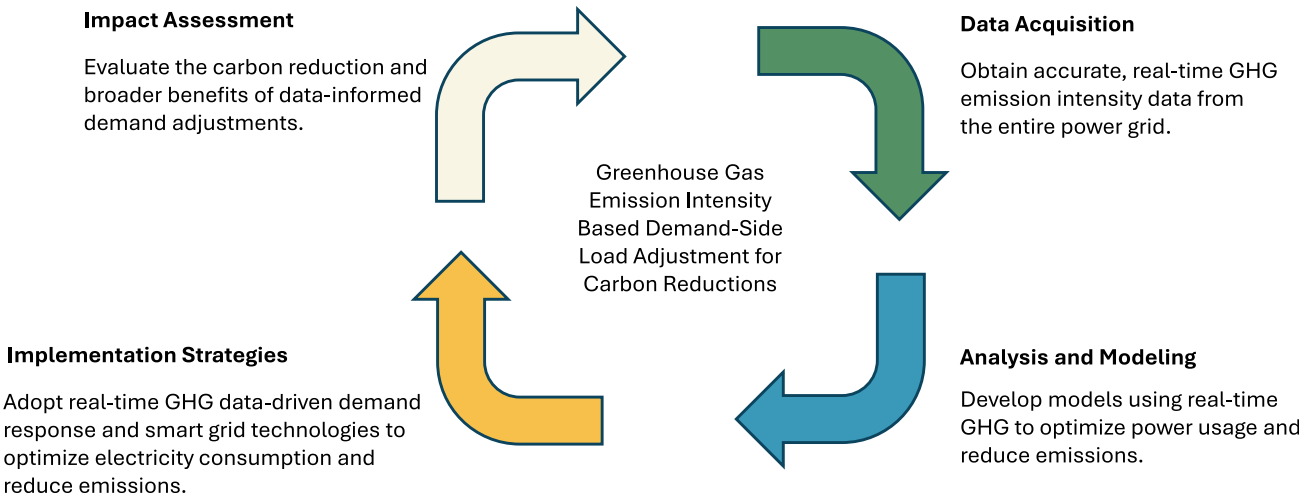


Figure 2. Technical pathway with GHG emission intensity-based demand-side load regulation for carbon reductions in the US power system

complementary policies that support sustainable agricultural practices and forest management. Additionally, carbon capture and storage technologies are being developed for application in sectors where emissions are difficult to eliminate, while green hydrogen production is promoted as a promising solution for decarbonizing heavy industry.[11–15] Collectively, these strategies outline a comprehensive decarbonization roadmap aimed at reducing emissions, transforming the power sector, and positioning the US as a leader in global sustainability efforts.

In addition to the broad policy and financial support driving decarbonization, a substantial body of academic research explores diverse aspects of emission reduction across the energy sector.[16–19] However, much of the existing research emphasizes renewable integration and efficiency improvements in supply systems, often limiting the application of real-time GHG emission intensity data to supply-side strategies only and overlooking its potential in demand-side practices. In contrast, the demand side is the most significant factor shaping the decarbonization roadmap.[20] This restriction hinders the development of more integrated and effective decarbonization strategies.[21–25] Addressing this gap requires a shift from isolated supply-side measures to an integrated approach that applies real-time GHG emission data to both supply- and demand-side management. This unified application represents a promising and underexplored pathway for enhancing carbon reduction in the power sector. By aligning electricity consumption with periods of lower GHG intensity, this approach optimizes renewable energy utilization and allows for more precise emission control, demonstrating the potential for demand-side measures to significantly complement traditional, supply-focused solutions. This combined strategy directly addresses a critical research gap by expanding decarbonization efforts to incorporate responsive, data-driven demand-side interventions, thereby advancing system-wide carbon reduction and creating a broader environmental impact.[26,27]

Building on the current state of research, this study introduces an optimization model that integrates real-time GHG emission intensity data with mechanisms for dynamically adjusting electricity demand, aiming to minimize carbon emissions through optimal consumption patterns. For an in-depth explanation of the load regulation optimization model, refer to the first section of the method chapter (load regulation optimization model). Using historical emission intensity data, this study tests the feasibility of aligning electricity consumption with periods of lower GHG intensity (Figure 2), pioneering the use of real-time emission data in demand-side energy management. The study addresses three main innovations: first, it examines how real-time GHG data can optimize electricity demand by aligning consumption with low-intensity periods. Second, it explores the scenarios in which the model's three regulatory dimensions—extent of adjustment (vertical range), time window of adjustment (horizontal range), and sensitivity of regulation across power systems. Finally, it tests the applicability and effectiveness of this demand-side regulation model across regions with diverse energy mixes, including variations in renewable penetration, diversity of energy sources, and emission intensity fluctuations. Notably, emissions reductions achieved via demand-side adjustments are attributed to the overall power sector, aligning with generation-side GHG metrics. Although these adjustments occur on the consumption side, they contribute directly to reducing emissions across the power system. This approach aligns with using generation-side GHG intensity as the standard metric, treating emissions reductions as a cumulative outcome of both supply and demand actions rather than as isolated contributions. These findings contribute targeted insights for demand-side management in decarbonization, offering practical guidance for energy stakeholders and policymakers aiming to reduce sectoral emissions.

The remainder of this paper is structured as follows: the results section begins with an analysis of temporal dynamics and regional variations in renewable energy integration across the US power system. It then examines demand-side load regulation's impact on carbon reduction across regions with varying renewable energy penetration rates and energy outcome diversity. We assess how emission intensity fluctuations influence carbon reduction through demand-side regulation. The

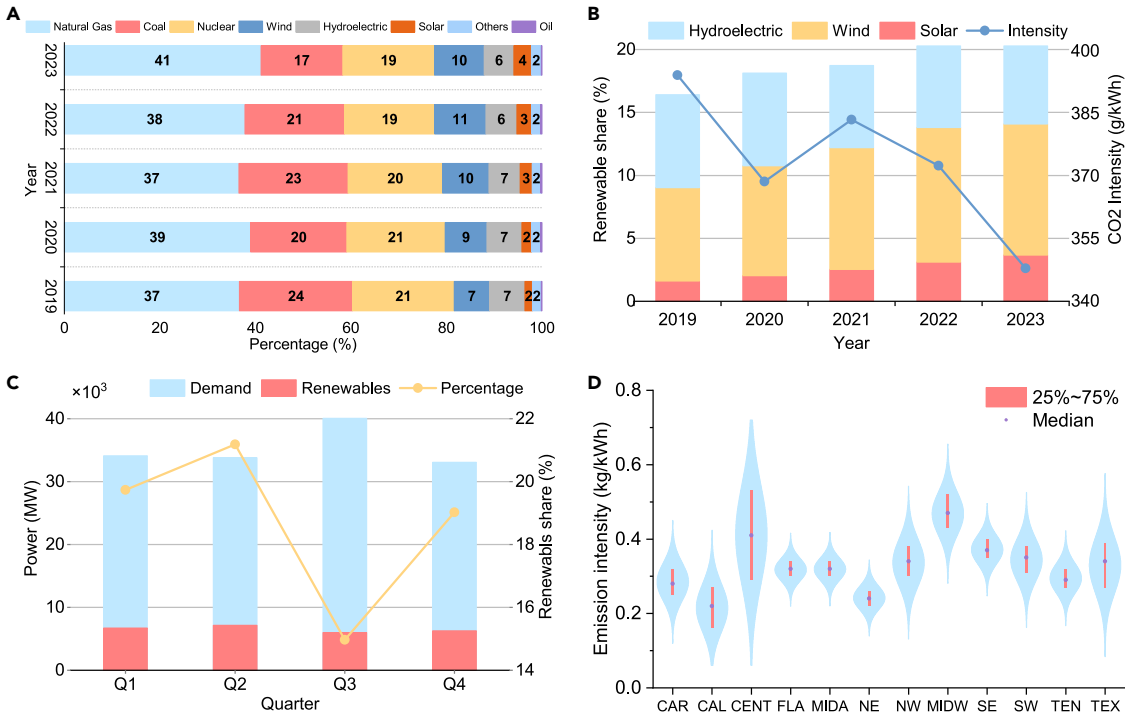


Figure 3. Analysis of the current state of the US power system

(A) Share of all forms of electricity generation in the US energy mix over the years 2019–2023. The share of wind and solar energy in the energy mix has been gradually increasing over the past 5 years, while the share of coal, hydro, and nuclear energy has been gradually decreasing, and the share of natural gas in the energy mix has been increasing as a result of the increase in total electricity consumption. The share of other forms of energy and oil generation in the overall energy mix has not changed much.

(B) Changes in the share of renewable energy in the energy mix and carbon emission intensity over the years 2019–2023. The overall share of renewable energy has been gradually increasing and, as a result, there has been an overall trend toward lower CO_2 emission intensity.

(C) Average generation capacity of renewable energy sources and average electricity demand and the share of renewable energy sources in energy demand for each quarter of the 5-year period for the US. It has the highest demand for electricity in the third quarter, while in this quarter, renewable energy generation is the lowest of the four quarters, while in the second quarter renewable energy generation is the highest, but the demand for electricity is the lowest of the whole year, from which we can also see that there is a big inconsistency between the current renewable in the generation of energy pattern and the overall pattern of electricity consumption.

(D) Emission intensity distributions across US power regions. This violin plot shows the emission intensity distributions (kg CO_2 kWh^{-1}) across twelve US power regions. Each region's distribution is represented by a light blue shape, with the red bar indicating the interquartile range (25th to 75th percentile) and the purple dot marking the median. The regions vary in emission intensity spread, with CENT showing the widest range, while FLA and NE have more consistent, narrow distributions.

sensitivity analysis section explores how the magnitude, time horizon, and flexibility index of load regulation affect carbon reduction outcomes. In the discussion section, we address the study's limitations, key conclusions, and potential directions for future research. Finally, a detailed account of the proposed approach is presented in the methods section, enabling reproducibility and future adaptation.

RESULTS

Temporal dynamics and regional variations in renewable energy integration in the US power system

The results section begins by analyzing the 2023 US power system across three critical aspects, each directly linked to a dimension of demand-side load regulation. First, we examine regional renewable energy penetration, which determines the feasible time window for demand-side load regulation—the length of time over which renewable energy can be effectively leveraged. Second, we analyze the diversity of energy sources in each region's mix, which influences system stability and thereby defines the vertical scope of regulation—the range of demand-side adjustments possible within each region. Lastly, we assess the range of fluctuations in GHG emission intensity, which establishes the level of regulatory sensitivity. Regions with minimal fluctuations have limited room for demand-side adjustments, while those with broader emission intensity variations present more opportunities for effective regulation. These analyses not only provide a detailed snapshot of the current US electricity system but also form the basis for selecting regions to test the demand-side regulatory model, aligning regulatory strategies with regional energy characteristics for optimized emission reductions.

In the comprehensive analysis of the US energy mix over the past 5 years (2019–2023), a discernible shift toward renewable

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Table 1. Case design

Cases	Scenarios	Brief summary	Regions	Strategies
Penetration	high	regions with high renewable energy penetration	CAL, TEX, NY	time window size
	low	regions with low renewable energy penetration	CAR, MIDA, FLA	
Diversity	high	regions with diverse energy types	NW, CENT, MIDW	adjustment limits
	low	regions lacking diversity in their energy types	TEN, SE, NE	
GHG intensity	high	high GHG intensity range	CENT, TEX, NW, MIDW, CAL, SW	adjustment sensitivity
	low	low GHG intensity range	FLA, MIDA, NE, SE, TEN, CAR	

energy sources is evident, marking a pivotal transition in the nation's energy landscape (Figure 3A). The data illustrate a consistent increase in the share of wind (from 7% to 10%) and solar energy (from 2% to 4%), reflecting broader efforts to embrace cleaner, more sustainable energy sources. Conversely, traditional energy sources such as coal (from 24% to 17%), hydro (from 7% to 6%), and nuclear (from 21% to 19%) have witnessed a gradual decline in their share of the energy mix, a trend paralleled by an uptick (from 37% to 41%) in natural gas usage—attributable to its relatively clean and flexible nature in meeting the rising electricity demand and eliminating the impact of renewable energy integration on the grid. This dynamic underscores a complex interplay between advancing renewable energy integration and the phased reduction of reliance on fossil fuels and other conventional energy forms, signaling a critical reorientation of the US energy strategy toward sustainability.

Further analysis reveals that the growing penetration of renewable energy into the energy mix has catalyzed a notable decrease in GHG emission intensity (from 394 to 348g kWh^{-1}) over the same period (Figure 3B). This trend not only exemplifies the environmental benefits of shifting toward renewables but also highlights the effectiveness of policies and technologies aimed at reducing carbon emissions. However, the journey toward a fully renewable-powered grid is met with challenges, notably the temporal and seasonal mismatches between renewable energy generation and electricity demand (Figure 3C). The highest demand for electricity is recorded in the third quarter, a time when renewable generation is at its lowest, particularly underscoring the inefficiencies in matching supply with demand. Conversely, the second quarter sees the peak in renewable generation against the backdrop of the year's lowest demand, spotlighting the critical need for strategies to bridge these discrepancies.

Analyzing the range of fluctuations in GHG emission intensity across US regions reveals distinct patterns that reflect underlying regional differences in energy resource use and infrastructure (Figure 3D). Regions such as CENT, TEX, and NW exhibit substantial variability in GHG intensity, with broad interquartile ranges indicating frequent fluctuations in emissions. This variability reflects these regions' reliance on a mix of fossil fuels and intermittent renewable resources such as wind, creating both challenges and opportunities for demand-side regulation. The high fluctuation range suggests a greater potential for implementing flexible regulatory adjustments that can align consumption with periods of lower emission intensity, thereby optimizing carbon reduction. In contrast, regions such as NE, Mid-Atlantic (MIDA), and FLA show relatively narrow ranges in emission intensity, reflecting a more stable energy mix with lower reliance on renewables. This stability implies limited flexibility for demand-side load regulatory interventions, as the scope for emission-based adjustments is more constrained.

Case study 1: Decarbonizing power systems in regions with high renewable energy penetration

Based on the previous in-depth study of the US power system, we select and divide 12 US North American Electric Reliability Corporation (NERC) power system regions into three types for six scenarios, which are detailed in Table 1. These three types of regions will be applied to each of the three case studies that follow in order to test the feasibility of the demand-side load regulation model in different power system scenarios, and also these three types of power systems correspond to the testing of the demand-side load regulation model's three adjustable dimensions, which we call the three types of optimization strategies, namely the magnitude of load regulation, the size of the time window for load regulation, and the sensitivity of load regulation.

Drawing upon the thorough examination of the US power system delineated in the preceding section, we have built a framework comprising three distinct cases, which collectively encompass six scenarios as detailed in Table 1. This framework is designed to investigate the implications of demand-side load regulation, guided by real-time GHG emission intensity metrics, on the mitigation of carbon emissions within the power system across a diverse array of scenarios. Through this exploration, we aim to unravel the nuanced effects and potential benefits of implementing demand-responsive strategies, specifically tailored to the dynamic nature of GHG emission intensity, thereby contributing to a more sustainable and carbon-efficient power infrastructure.

In analyzing regions with high renewable energy penetration, the NW, CAL, and TEX stand out with renewable shares of 49.27%, 39.96%, and 32.47%, respectively, in 2023, led by hydro, solar, and wind.[9] To manage the variability of wind and solar, CAL and TEX have significantly invested in grid batteries, with CAL reaching 6.6 GW of capacity in 2023 and planning an increase to 8.5 GW by 2024,[28] while TEX is set to expand from its current 5.6 to 6.2 GW by 2024.[29] Unlike these two, the NW, relying on stable hydropower, requires fewer grid batteries. Despite the differences in their renewable sources, all three regions experience volatility in GHG emission intensity, with CAL and TEX facing fluctuations due to solar and wind patterns, and the NW achieving a more balanced clean energy share.

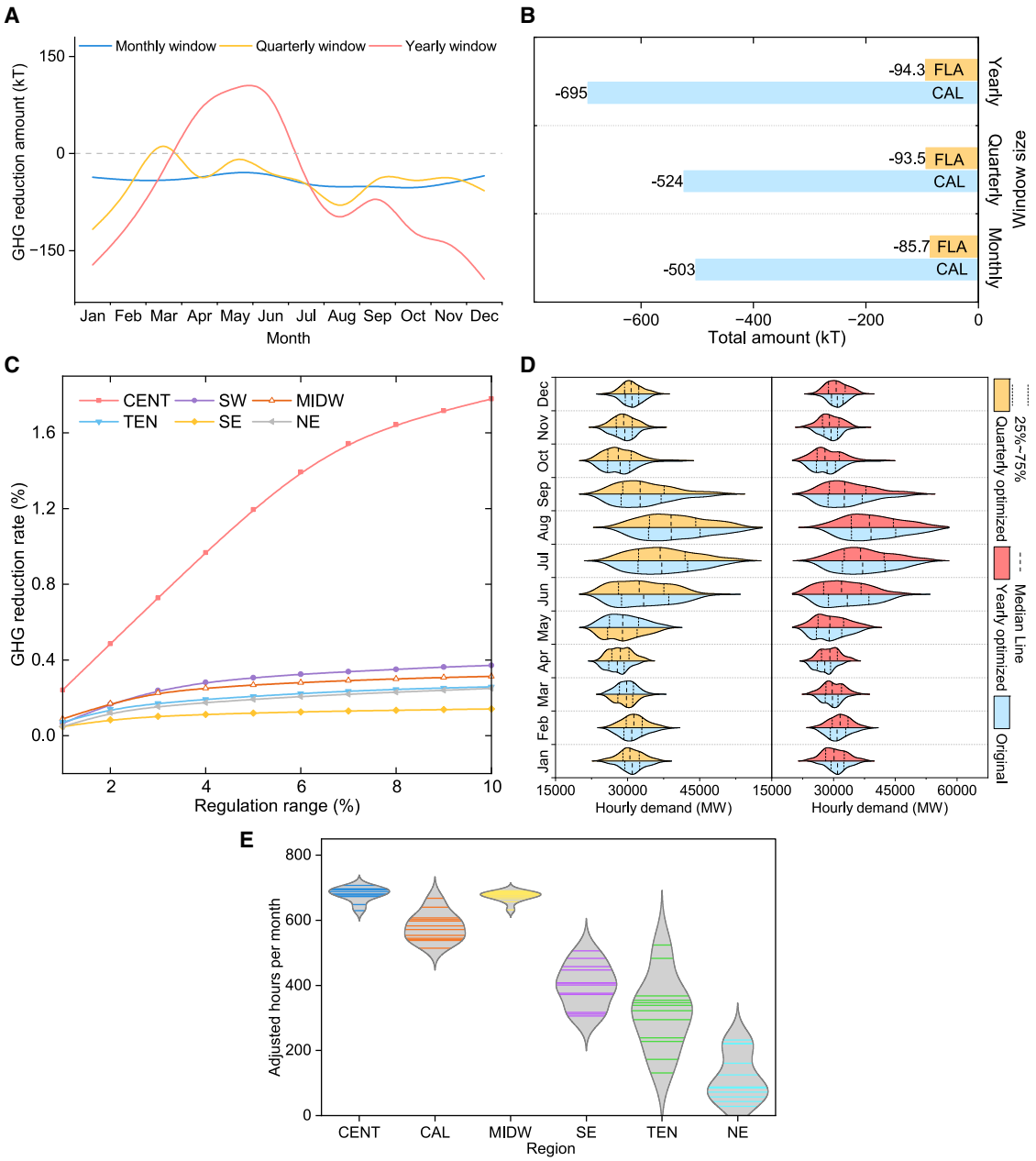


Figure 4. Results of three strategies applied to different power systems

(A) In the CAL region, different window sizes led to distinct abatement patterns, with the yearly window increasing emissions in second quarter, corresponding to the period of lowest GHG intensity.

(B) The CAL region, with high renewable penetration, has greater carbon reduction capacity than the FLA region with low renewable penetration.

(C) Regions with diverse generation resources achieve greater carbon reductions at higher regulation ranges than those with homogeneous resources.

(D) Demand-side regulation significantly reshapes electricity demand distribution, with regulatory ranges strongly impacting outcomes.

(E) With the same weighting factor λ, areas with low GHG intensity fluctuations require fewer adjustment hours per month, while those with high fluctuations experience more evenly distributed adjustments.

Future expansions are ambitious, with TEX aiming to add 36 GW of solar facilities over 5 years and CAL targeting zero-carbon electricity by 2045.[30] These plans underscore the regions' commitment to enhancing renewable integration, emphasizing the critical role of tailored grid management and storage solutions in achieving sustainable and reliable power systems amidst varying renewable landscapes.

Compared with other regions with robust renewable energy integration, FLA, Carolina (CAR), and MIDA emerge as the three US regions with the lowest renewable penetration rates in 2023,

recording renewable energy contributions of merely 4.94%, 5.44%, and 6.56%, respectively.[9] Predominantly powered by natural gas, FLA and MIDA generate 65.2% and 43.8% of their total energy from this source, while CAR distinguishes itself with a substantial 45.2% reliance on nuclear energy.[31,32] In response to the pressing need for a sustainable energy transition, these regions are embarking on ambitious renewable energy projects. FLA has set a visionary goal to deploy 30 million solar panels by 2030, aiming for a zero-carbon electricity grid by 2035.[33] MIDA, leveraging its strategic coastal location, is poised to expand its renewable portfolio through significant investments in offshore wind power, aiming to enrich its energy mix with cleaner, wind-generated electricity.[34] Meanwhile, in the CAR region, Duke Energy, a leading utility in this area, is charting a green future with plans to add over 4,000 MW of renewable capacity, signaling a transformative shift toward embracing renewable energy sources to meet their future energy needs and sustainability goals.[35]

In regions with substantial renewable energy penetration, the predictability of GHG emission intensity becomes notably challenging, primarily due to the significant seasonal variability inherent in renewable energy generation. This variability underscores the critical importance of selecting an appropriate time window for optimization strategies aimed at reducing GHG emissions. A narrower time window enhances the precision of GHG emission intensity forecasts, whereas a broader window facilitates a more holistic integration of annual energy patterns. For instance, an analysis of CAL's power system reveals that when optimization strategies are applied on a monthly or quarterly basis, the overall annual fluctuation in carbon reduction remains relatively modest. However, an annual optimization approach indicates an anomalous increase in carbon emissions during the second quarter—coinciding with the period of lowest GHG emission intensity and significant reductions in the subsequent quarters (Figure 4A). This suggests that annual optimization strategies shift loads to the second quarter to exploit lower GHG emission intensity levels, thus highlighting the necessity for regions to augment their energy storage capacities for extended durations. Despite a significant increase in emissions in the second quarter, emissions for the year are reduced by 695 kT (Figure 4B). The difference arises because the annual optimization window allows for broader coordination by considering GHG emission intensity over the entire year, enabling greater emission reductions, whereas the monthly window is constrained by a shorter time horizon, limiting its effectiveness. Furthermore, the relationship between the time window of optimization strategies and total carbon reduction is substantiated by data, which also demonstrates this phenomenon in regions with lower clean energy penetration, such as FLA (Figure 4B). A comparative analysis between CAL and FLA, despite similar levels of annual electricity consumption (263.9 TWh for CAL and 262.2 TWh for FLA in 2023[9]), exhibits a pronounced disparity in their carbon reduction capabilities, attributed to the variance in clean energy penetration rates.

Case study 2: Decarbonizing power systems in regions with diverse energy sources

Leveraging the Shannon-Wiener diversity index, our analysis outlines three distinct regions that exhibit a pronounced diversity in the types of power resources. These regions, specifically CENT, SW, and Midwest (MIDW), stand out for their varied energy portfolios. These selected regions demonstrate a commendable balance in their energy portfolios, with renewable energy shares amounting to 41.18%, 16.91%, and 16.98%, respectively.[9] The broad spectrum of generation types not only augments the stability and reliability of the power system but also equips it to adeptly manage load fluctuations. This diversified energy approach, characterized by a relatively even distribution across various generation resources, enables the power system to maintain operational efficiency and resilience against systemic demands.

In contrast, regions such as TEN, SE, and NE exhibit a more homogeneous mix of generation resources, paired with a markedly lower prevalence of clean energy, contributing shares of just 9.96%, 7.25%, and 13.56%, respectively. TEN's energy matrix is predominantly fueled by nuclear power, comprising 44.25% of its total generation, whereas SE and NE rely heavily on natural gas, which constitutes 53.75% and 57.26% of their respective total generation outputs.[9] The limited diversity within their generation resources inherently diminishes the stability and reliability of their grids compared with those with a more varied energy mix. In order to delve deeper into the impact of these differences, our analysis adjusts the range of load regulation with the aim of identifying their impact on the overall results.

In our case study, we analyzed the variations in GHG reduction rates across six regions by incrementally adjusting the load regulation range, starting from ±2% and progressing up to ±10%. As illustrated in Figure 4C, a clear disparity emerges: regions with lower renewable energy abundance consistently exhibited significantly lower GHG reduction rates across all load adjustment ranges when compared with regions with higher renewable energy abundance. This difference in GHG reduction efficiency underscores the key role that a diversified energy mix plays in enhancing the power system's ability to navigate and adapt to load fluctuations. Another particularly notable finding is the significantly higher GHG abatement rate in the CENT region compared with other regions. This outcome is primarily driven by CENT's extensive penetration of renewable energy sources and its highly diversified energy mix, which together enable more effective demand-side load adjustments and optimize shifts to periods of lower GHG intensity. This analysis underscores the critical advantage of regions with abundant and diverse renewable energy resources, as their enhanced adaptability and resilience allow for significantly higher GHG reduction rates, particularly through effective demand-side load management strategies.

The violin plots on the hourly power demand distribution of CENT across various months reveals the impact of demand-side load regulation at ±4% and ±8% (Figure 4D). These plots provide insights into the data's spread and density, highlighting shifts in median and percentile positions. Demand-side load regulation noticeably alters power demand distribution, with the ±8% scenario showing a greater spread in extreme values, indicating increased variability, especially during high-demand seasons like winter and summer. Interestingly, July and August exhibit a reduced demand spread under the ±8% scenario, suggesting effective regulation strategies that compress demand variability. The shifting median lines across different scenarios

underscore the influence of load regulation on the central tendency of demand. This underscores the significant, yet complex, impact of demand-side load regulation on power demand distribution, emphasizing the importance of seasonally tailored management strategies to either curb or amplify demand variability based on the desired outcomes.

Case study 3: Decarbonizing power systems in high and low GHG intensity fluctuation areas

In case study 3, we shift our focus from the subjects of our previous two studies—the impact of clean energy integration and the diversity of energy sources on GHG emission intensity—to explore how GHG emission intensity fluctuations influence carbon reduction efforts. This case study contrasts six high GHG intensity fluctuation areas—CENT, TEX, NW, MIDW, CAL, and SW with six low GHG intensity fluctuation areas—FLA, MIDA, NE, SE, TEN, and CAR. In the preceding case studies, these regions were classified based on their varying levels of renewable energy penetration and energy abundance. However, in this case study, we have reclassified the regions according to the extent of fluctuation in their GHG intensity (Figure 3D). This regrouping allows us to analyze the performance of the third regulatory dimension proposed in this study—the ease of adjustment—within diverse energy systems. Furthermore, this approach facilitates a comprehensive horizontal comparison of the emission reduction outcomes for each region, applying the same emission reduction model. By doing so, we aim to gain deeper insights into the adaptability and effectiveness of the model across different energy landscapes.

To mitigate the impact of load adjustments on both the daily lives of residents and the routine operations of businesses, the design of our objective function incorporates a penalty term related to the duration of load adjustments. This inclusion not only facilitates a substantial reduction in carbon emissions but also minimizes the adjustment period, thereby alleviating potential inconveniences. The weighting factor for this penalty term, denoted as λ, symbolizes the economic cost associated with load adjustments on the consumer side.

The comparative analysis of adjusted hours across high and low GHG intensity fluctuation area indicates that high GHG intensity fluctuation areas more amenable to adjustment, leading to a higher annual total of adjusted hours—an average of 581 h for high GHG intensity fluctuation areas as opposed to 391 h for low GHG intensity fluctuation areas (Figure 4E). Moreover, regions characterized by a high range of GHG intensity fluctuation benefit from having not only a greater number of adjustable hours each month but also a relatively consistent number of adjustable hours across months. This stability enhances operational convenience and predictability in implementing load regulation strategies. Conversely, in regions with low GHG intensity fluctuation areas, the average number of adjustable hours per month is not only significantly lower but also varies substantially from month to month. This irregularity inadvertently increases the complexity and potential costs associated with load regulation, posing challenges to achieving efficient and cost-effective adjustments.

Sensitivity analysis

Due to the future development of energy technologies, infrastructure development, and continued US investment in the energy sector, we have conducted a sensitivity analysis. In the experimental results of case 2, we have analyzed the impact of the range of load adjustment on the results. For the sensitivity analysis we focused on the following three aspects: (1) the impact on the carbon reduction effect by changing the share of renewable energy in the future energy mix, in this study, we hypothesize a continual rise in renewable energy's share of the future energy mix, and accordingly adjust the current hourly generation capacities by various percentages, (2) the amount of energy redundancy in the system that can be used for load regulation, and (3) the degree of difficulty of regulation, i.e., the value of the weighting factor λ, on the basis of the benchmark (the allowable adjustment range is $\pm 5\%$, with a quarterly time window for optimization and an adjustment penalty of 0).

The carbon reduction effect of the proportion of renewable energy growth in the future power system varies from region to region, taking as an example the effect of the combination of the proportion of solar and wind growth in the future development of the energy system in the CAL and TEX regions. As shown in Figure 5A, on the basis of the existing energy mix, the effect of increasing solar in CAL is much higher than that of increasing wind by the same proportion, which produces a larger amount of carbon reduction. The opposite is true for the TEX region, which is rich in wind resources and has a high installed wind capacity.

The benchmark scenario in our case study assumes that the increased load for load regulation is supplied by surplus clean energy that would otherwise be curtailed, and we assume the national average curtailment rate for renewables is 10% as an upper bound. This reflects the constraint that sufficient curtailed energy must be available to enable load adjustments (e.g., a 5% load increase requires at least 5% surplus energy). In the sensitivity analysis, we explore future scenarios where curtailment rates could vary between 2% and 18% due to factors like increased transmission capacity, energy storage, and renewable energy deployment. As shown in Figure 5B, reductions in the curtailment rate have a more pronounced effect on the results than increases in available capacity, particularly in regions with high renewable energy penetration. This is because lower curtailment rates limit the availability of surplus clean energy for load regulation, reducing the system's adjustment potential. In contrast, increased available energy has a smaller impact since the regulation cap does not fully utilize the additional resources in regions already abundant in renewable energy.

We tested the effect of the value of λ on the number of regulated hours in both high and low GHG intensity fluctuation typical areas. As the value of λ increases, the number of regulated hours decreases in both areas, but the low GHG intensity fluctuation area is more sensitive, a result that also matches the previous test results (Figure 5C).

DISCUSSION

Based on comprehensive modeling and analysis, this study demonstrates the differences in the choice of real-time GHG emission intensity-based demand-side load regulation strategies for different power systems to help minimize power system carbon emissions in the contiguous US. We also consider the impact of future increases in the share of clean energy on the

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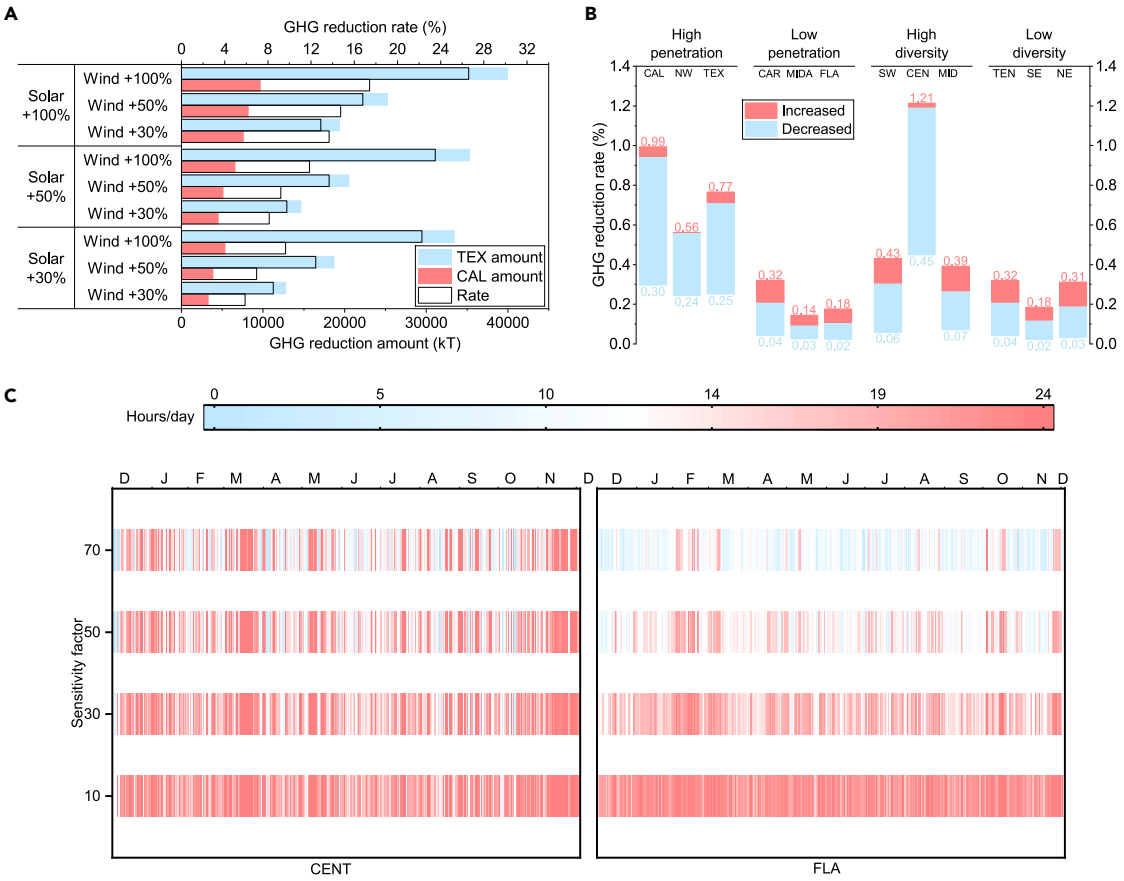


Figure 5. Sensitivity analysis of key results

(A) The carbon reduction effect of the proportion of renewable energy growth in the future electricity system varies from region to region. An increase in the share of solar energy in the CAL region will result in greater carbon reduction. The growth of wind energy will have a greater impact on the carbon reduction capacity of TEX.

(B) Reductions in the availability of clean energy have a greater impact on the carbon-reducing capacity of regions than increases in the availability of clean energy, and such results are more pronounced in regions with high renewable energy penetration.

(C) The time to be adjusted decreases for increasing values of λ in both high and low GHG intensity fluctuation areas, but it decreases faster in low GHG intensity fluctuation areas.

carbon reduction capacity of each region. Choosing the right optimization strategy and renewable energy focus for different regions can reduce the carbon emissions of the power system to a greater extent. There are a number of caveats to this analysis that should be cautioned against, the first of which is that while we explored the results of various strategies for different power system types, we did not discuss the costs associated with these strategies, such as the increased cost and technical difficulty of long-term energy storage associated with increased optimization cycles. Second, for this study, although we carefully evaluated the power system structure and electricity consumption patterns within the region and focused on the carbon reduction effects of load regulation within the region, we did not further discuss the impact of inter-regional power transmission on real-time GHG emission intensity and the carbon reduction effects. Third, we did not consider the short-term dynamic complexity of GHG emission intensity brought about by load regulation, such as the potential mismatch between changes in load and actual changes in generation due to factors like grid curtailment and operational constraints. Fourth, the overall impacts of demand-side load regulation on society's productive life, including public acceptance, may be extensive and significant, but beyond the scope of this study. The results of this analysis show that demand-side load regulation can achieve a very significant reduction in carbon emissions. However, for such large-scale load adjustments to be practically implemented, they must be supported by effective policies at the national and sectoral levels. Admittedly, our analysis does not quantify the impact of policy support, but it is evident that demand-side load regulation cannot be realized solely through individual or market-driven efforts. These policies should include not only demand-side measures, such as upgrading grid infrastructure to integrate real-time GHG emission intensity data, implementing dynamic time-of-use pricing models to incentivize load shifts, and deploying energy-efficient appliances and smart meters at scale, but also power generation-side measures, such as establishing

clean energy standards that mandate a minimum percentage of renewable energy in the grid mix and providing tax credits or grants for investments in wind, solar, and energy storage technologies. At the same time, it is also important to set medium and long-term planning targets in conjunction with the comprehensive goal of achieving net-zero-carbon electricity by 2035. This study provides a systematic and objective assessment of the carbon reduction capacity of both the generation side and the demand side, including the capacity to be deployed, which is consistent with the above objectives. In the long run, the speed and cost of reducing carbon emissions from the power system through demand-side regulation may be affected by new technological innovations that are currently at an early stage and completely unforeseen. Therefore, proactive and timely adjustment of policy deployment to the current state of technological development will maximize the potential of new technologies. In actual grid operations, renewable energy sources, especially solar and wind, are subject to large curtailment due to power balancing, transmission and other constraints, especially in regions with high renewable energy penetration. Utilizing these zero-carbon energy sources will not only increase the return on investment in power generation but also maximize the carbon reduction capacity of the power system. This study focuses on the impact of demand-side regulation strategies on the carbon reduction capacity of different types of power systems in the US. It contributes to the growing body of research on decarbonizing power systems by demonstrating that demand-side load regulation can effectively reduce GHG emissions. While achieving net-zero-carbon electricity in the US by 2035 requires a comprehensive and multifaceted approach, this method provides a practical and actionable strategy to support broader decarbonization goals. In a net-zero-carbon electricity future, the electric power system will provide an opportunity for renewable energy to indirectly increase the efficiency of renewable energy and accelerate its share of the energy mix. The US has an abundance of renewable resources sufficient to provide the clean energy needed for its zero-carbon power goal, and the addition of demand-side adjustments will further accelerate this process and minimize the cost of this goal. Countries should also adopt strategies based on the characteristics of their respective power systems to meet the opportunities and challenges of energy efficiency and emissions reduction and ultimately work together to achieve the long-term goal of a net-zero-carbon world.

METHODS

In this study, we investigate the efficacy of various demand-side load adjustment strategies tailored to real-time GHG emissions intensity for power grids characterized by diverse energy mixes and demand patterns. Our objective is to formulate optimized control strategies specific to the unique characteristics of different power systems, ultimately minimizing their carbon footprint. Leveraging data from the US EIA, we categorize the 13 NERC regions into six representative scenarios across three distinct classes. These classifications are based on key factors influencing emissions: clean energy penetration, fuel source diversity, and electricity consumption patterns. We propose targeted optimization strategies for each grid category. For instance, in regions with varying clean energy penetration levels, we assess the impact of adjusting the optimization window size on emissions reduction. For grids boasting a more diverse mix of energy sources, we explore how modifying the load adjustment range influences the results. Finally, in areas with distinct electricity consumption patterns, we primarily focus on how the difficulty of regulating demand affects the overall effectiveness of the strategies.

Load regulation optimization model

To achieve a balance between minimizing carbon emissions and minimizing disruption to production and daily life, we employ a multi-objective optimization as described in Equation 1.

$$\min \quad \sum_{t=1}^{T} E_t + \lambda \sum_{t=1}^{T} z_t \qquad \text{(Equation 1)}$$

The first term prioritizes the reduction of total carbon emissions across the power grid for each hour within the optimization cycle (T). The second term serves as a penalty term, discouraging excessive and frequent load adjustments. This penalty is directly proportional to the total number of adjusted hours (represented by the summation of the binary variable z_t), where z_t equals 1 when a non-zero load adjustment occurs at a specific time t and 0 otherwise. The weighting factor, λ (with $\lambda > 0$), controls the relative importance of minimizing emissions versus minimizing disruptions caused by load adjustments. This approach ensures that optimized strategies not only prioritize carbon reduction but also consider the impact on daily operations and grid stability. Building upon the optimized load adjustment strategy, Equation 2 details the calculation of carbon emissions.

$$E_t = (1 + x_t) \times d_t \times e_t \qquad \text{(Equation 2)}$$

This equation incorporates several key variables. The first, x_t, represents the load adjustment percentage for a specific hour t. This percentage can range from a negative value (indicating a reduction in demand) to a positive value (indicating an increase in demand), with its range constrained by predefined limits that define the extent of adjustment. The second variable, d_t, captures the baseline electricity demand at that same hour t. Finally, e_t reflects the crucial factor of real-time GHG emission intensity at the time point t. By multiplying these elements, Equation 2 calculates the optimized carbon emissions for each hour within the defined cycle.

$$\sum_{t=1}^{T} (1 + x_t) \times d_t \geq D_t \qquad \text{(Equation 3)}$$

The total demand satisfaction constraint in Equation 3 enforces a critical constraint within the optimization framework. It ensures that the total electrical energy demand after implementing the optimized load adjustments must be greater than or equal to the total demand before adjustments D_t.

$$x_t \times d_t \leq c_t^{\max} \qquad \text{(Equation 4)}$$

$$(1 + x_t) \times d_t \geq c_t^{\min} \qquad \text{(Equation 5)}$$

In the generation capacity constraints of Equations 4 and 5, we set the adjustable range for each hourly regulation, where c_t^{max} and c_t^{min} are the maximum and minimum regulation capacity, respectively. Essentially, Equations 4 and 5 define the operational limits of the power grid, ensuring that the optimized load adjustments remain within the feasible range for power generation at each specific time point.

$$z_t \geq \frac{x_t}{M} \quad \text{(Equation 6)}$$

$$z_t \geq -\frac{x_t}{M} \quad \text{(Equation 7)}$$

The binary variable activation constraints in Equations 6 and 7 utilize the Big M method to establish a crucial link between the binary variable z_t and the load adjustment factor x_t. If a non-zero load adjustment occurs at a specific hour t, indicated by x_t taking a value other than zero, then the binary variable z_t must be equal to 1. Conversely, if there is no adjustment (x_t equals zero), since minimizing the objective function, z_t must be 0. Here, M is an arbitrarily large number. The model relies on several key parameters. The maximum available regulation capacity c_t^{max} reflects the limit for re-integrating curtailed renewable generation (capped at 10% of total generation[36,37]) within an optimization cycle. The minimum capacity c_t^{min} ensures demand never falls below the grid's baseline, defined by the combined capacity of unregulatable sources such as coal and nuclear at each hour. In the first two case studies, the penalty term coefficient is deliberately set to zero, as the primary objective is to investigate the influence of grid renewable energy penetration and the diversity of energy resources on carbon emission reductions achieved through various optimization strategies. This approach allows for an unimpeded evaluation of these factors without the added complexity of penalizing deviations. In contrast, the subsequent case studies shift the focus toward assessing the impact of fluctuations in GHG intensity on the ease of system adjustment. This involves a detailed analysis of variations in adjustable time horizons, which directly influence the system's adaptability to changes in emission intensity. For the benchmark scenario, the value of the weighting factor, λ, is set at 50, chosen arbitrarily to establish a point of reference for comparison across different cases.

Classification and selection of grid types

To encompass the diverse characteristics of the US power grid, we establish six representative scenarios categorized across three key dimensions. The first considers clean energy penetration, with high and low scenarios reflecting the prevalence of renewable sources. The second dimension focuses on generation resource richness, categorized as high and low based on the diversity of fuel sources within the grid. Each of these scenarios includes three sub-regions, capturing the range of characteristics within each scenario. Finally, the 12 regions analyzed in the earlier case studies were categorized into two groups based on the range of their GHG intensity fluctuations. This classification served two purposes: first, to rigorously test the model's third adjustment dimension, which accounts for adaptability to varying levels of fluctuation; and second, to create a comparative framework that facilitates a horizontally evaluation of the regions. By contrasting these groups, the study provides valuable insights into how different fluctuation characteristics influence the performance and feasibility of optimization strategies, enriching the overall analysis. Leveraging data for the year 2023, we established a robust categorization framework for the 13 NERC regions. This framework comprises six distinct scenarios classified across three key dimensions. The first dimension, i.e., clean energy penetration, differentiates regions based on the relative contribution of solar, wind, and hydroelectric generation to their total annual output. High and low penetration scenarios were established using this metric.

$$H = -\sum_{r}^{R}(P_r \ln P_r) \quad \text{(Equation 8)}$$

The second dimension focuses on generation resource richness, which reflects the diversity of fuel sources within each grid. The Shannon-Wiener diversity index (Equation 8) was employed to quantify this richness, with higher index values indicating a more diverse mix of generation resources. In Equation 8, R represents the type of all generation resources in the grid and P_r is the percentage of total generation from the r^{th} generation resource. We acknowledge a potential overlap between penetration and richness; however, strategic adjustments were made to avoid redundancy. For example, the CENT exhibited a higher abundance ranking despite its second-highest penetration ranking. To capture this nuance, it was categorized as high abundance. Conversely, the TEX ranked higher in penetration than abundance, and thus, it was classified as high penetration. This approach ensures each scenario effectively represents the unique characteristics of the respective region. Finally, We conducted a comprehensive analysis of the hourly GHG emissions intensity for power generation across 12 regions analyzed in the previous case studies in 2023. Based on the magnitude of their GHG intensity fluctuations, these regions were systematically categorized into two distinct groups: high fluctuation and low fluctuation. This classification enabled a deeper exploration of the variability in emissions intensity, providing a foundation for assessing the implications of these fluctuations on regional energy dynamics and the effectiveness of different adjustment strategies.

RESOURCE AVAILABILITY

Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Jie Zhang (jiezhang@utdallas.edu).

Materials availability

This study did not generate new materials.

Data and code availability

- Raw input data have been deposited at Mendeley data under the https://doi.org/10.17632/jfcc62strg.1, and raw results have been deposited at Zenodo under the https://doi.org/10.5281/zenodo.14658398 and are publicly available as of the date of publication. All other data reported in this paper will be shared by the lead contact upon request.

- All original code has been deposited at Zenodo under the https://doi.org/10.5281/zenodo.14658398 and is publicly available as of the date of publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

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AUTHOR CONTRIBUTIONS

Conceptualization, H.L., G.S., A.M., and J.Z.; methodology, H.L., G.S., and S.S.; investigation, H.L., G.S., and S.S.; writing – original draft, H.L. and G.S.; writing – review & editing, H.L., G.S., A.M., and J.Z.; funding acquisition, A.M. and J.Z.; resources, H.L. and G.S.; supervision, A.M. and J.Z.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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