



A Report On

Quantification and Comparison of Emissions due to Electric Vehicles

A study conducted by Grid Integration Lab, IIT Bombay



Authors

Mr. Angshu Plavan Nath, IIT Bombay

Mr. Akhilesh Panwar, IIT Bombay

Prof. Zakir Rather, IIT Bombay

Reviewers and Contributors

Mr. Rishabh Sethi, Electric Mobility Initiative

Grid Integration Lab, IIT Bombay

Designed by

Angshu Plavan Nath

Disclaimer

While every care has been taken in the collection, analysis, and compilation of the data and information presented in this publication, IIT Bombay and the supporting organisations of this project do not guarantee or warrant the accuracy, reliability, completeness, suitability, or current status of the information contained herein. The information presented in this publication has been prepared based on research and sources considered reliable at the time of publication and is provided without warranty of any kind, express or implied. The views and conclusions presented in this report are solely of the authors, based on extensive research and stakeholder consultations carried out in this study, but not necessarily of the organisation the authors are affiliated to (IIT Bombay). The mention of specific companies, organisations, projects, technologies, products, or services does not imply their endorsement or recommendation by IIT Bombay, supporting organisations, or the authors of this publication. This publication may contain references or links to external websites and third-party sources; the content, accuracy, availability, and continued operation of such external sources remain the sole responsibility of their respective owners or publishers, and IIT Bombay and funding organisations of this study assume no responsibility for such content. IIT Bombay, supporting organisations of this study, and the authors accept no liability whatsoever to any third party for any loss, damage, cost, or expense arising from the interpretation, use of, or reliance upon the information, analyses, conclusions, opinions, or views expressed in this publication.

Acknowledgement

This publication has been prepared by **Grid Integration Lab**, Indian Institute of Technology Bombay (IIT Bombay) under the **Mapping the Impact of EV Charging and Associated Emissions on the Power Grid** project.

We would also like to acknowledge the valuable technical input and guidance provided by Mr. Rishabh Sethi from the Electric Mobility Initiative (EMI) towards the conceptualization and successful undertaking of this study.

We would also like to thank various stakeholders including representatives from CPOs, DISCOMS, EV and Charger OEMs, Think Tanks for their valuable feedback/inputs on the outcome of this study.

We also acknowledge the continued leadership, guidance, and support of Indian Institute of Technology Bombay in executing this project.



भारतीय प्रौद्योगिकी संस्थान मुंबई

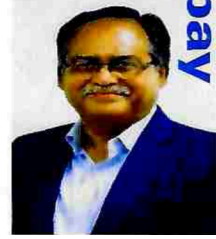
नंदन निलेकनी मुख्य भवन,
पवई, मुंबई-400 076, भारत

Indian Institute of Technology Bombay

Nandan Nilekani Main Building,
Powai, Mumbai-400 076, India

Office : (+91-22) 2572 3488
(+91-22) 2576 7001
Email : director@iitb.ac.in
Website : www.iitb.ac.in

IIT Bombay



शिरीष ब. केदारे, निदेशक

Shireesh B. Kedare, Director

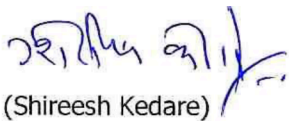
Foreword

India's transition towards electric mobility is an important component of the country's broader efforts to reduce dependence on fossil fuels, improve air quality, and decarbonise the transport sector. However, the environmental benefits of electric vehicles cannot be assessed solely on the basis of the absence of tailpipe emissions. In a power system such as India's, where coal continues to contribute to electricity generation though with falling proportion due to RE integration, it is equally important to quantify the emissions associated with producing the electricity used for charging electric vehicles. The carbon footprint of an electric vehicle is therefore closely linked to the generation mix of power system from which it draws electricity for charging demand. As the number of electric vehicles in India increases substantially over the coming years, understanding this interaction between electric mobility and the electricity sector becomes increasingly important.

This set of two reports on “**Mapping the Impact of EV Charging and Associated Emissions on the Power Grid**” undertaken by **Grid Integration Lab**, Department of Energy Science and Engineering, IIT Bombay, addresses this important question through a detailed assessment of the emissions associated with electric vehicle charging in India. The work evaluates the impact of India's present EV fleet while also examining how electricity demand and associated emissions may evolve as EV adoption increases towards 2030 and beyond. Rather than treating the Indian power system through a single average emission factor, the analysis considers regional differences in generation mix, temporal and seasonal variations in grid emission intensity, differences among vehicle categories, charging behaviour, and the losses associated with delivering electricity to the vehicle.

Importantly, this work goes beyond quantifying the problem. Building upon the assessment of present and future EV-related emissions, the reports identify pathways and recommendations for reducing the carbon footprint of electric vehicle charging. These include better alignment of charging demand with renewable energy availability, smart and coordinated charging, appropriate charging strategies for energy-intensive vehicle fleets, renewable energy integration at charging facilities, improvements in grid infrastructure and flexibility, and continued decarbonisation of electricity supply. The findings therefore underline that electric mobility and power-sector decarbonisation must be viewed as interconnected transitions. Increasing the number of electric vehicles is an important step, but maximising their climate benefit requires parallel attention to how the electricity supplying these vehicles is generated and how charging demand is managed.

I would like to congratulate the **Grid Integration Lab**, authors, researchers, reviewers, participating stakeholders, and supporting organisations whose contributions have made this work possible. I hope that this work will contribute to a more informed discussion on India's electric mobility transition and provide useful insights for policymakers, utilities, industry, researchers, and other stakeholders involved in shaping the future of transportation and the power sector.


(Shireesh Kedare)

CONTENTS

ACKNOWLEDGEMENT	II
CONTENTS.....	IV
LIST OF FIGURES	VI
LIST OF TABLES	IX
EXECUTIVE SUMMARY	1
1 INTRODUCTION.....	5
1.1 OVERVIEW OF THE STUDY	5
1.2 OBJECTIVES OF THE REPORT.....	6
2 STUDY BACKGROUND.....	7
2.1 CONTEXTUAL OVERVIEW	7
2.2 NATIONAL AND REGIONAL ENERGY LANDSCAPE	7
2.3 EVOLUTION OF THE EV ECOSYSTEM.....	9
3 LITERATURE REVIEW	11
3.1 EMISSION ACCOUNTING FRAMEWORKS.....	11
3.2 GLOBAL AND INDIAN STUDIES ON COMPARATIVE ANALYSIS FOR EV AND ICEV EMISSIONS	13
4 INDIAN EV ADOPTION TRAJECTORY AND FLEET CHARACTERISTICS	18
4.1 NATIONAL TRAJECTORY: HOW INDIA'S EV MARKET EVOLVED FROM 2010 TO 2023	18
4.2 EV STOCK BY CATEGORY	20
4.3 REGIONAL SHARE OF NATIONAL EV STOCK BY SEGMENT	20
4.4 IMPACT ON EV CHARGING LOAD	26
5 PROPOSED METHODOLOGY FOR ESTIMATION OF EMISSIONS FROM EVS IN INDIA.....	28
5.1 DETERMINATION OF CHARGING DEMAND FROM EVs	29
5.2 DETERMINATION OF GRID EMISSION FACTOR.....	32
5.3 CALCULATION OF EMISSIONS DUE TO EVs	33
6 ESTIMATION OF GRID EMISSION FACTOR FOR THE INDIAN POWER GRID	35
6.1 GENERATION MIX OF THE INDIAN GRID	35
6.2 GRID EMISSION FACTOR.....	44
7 ESTIMATION OF ENERGY REQUIREMENT BY THE INDIAN EV FLEET	48
7.1 DAILY ENERGY REQUIREMENT	49
7.2 CHARGING LOAD PROFILES.....	51
8 EMISSION ESTIMATION FROM EVS	54
8.1 NATIONAL EV EMISSION ESTIMATION	54
8.2 REGIONAL EV EMISSION ESTIMATES	55

8.3	COMPARISON WITH INTERNAL COMBUSTION ENGINE VEHICLES.....	61
8.4	INTERPRETATION AND IMPLICATIONS.....	68
9	EMISSION ESTIMATION FOR 2030 SCENARIO.....	70
9.1	ESTIMATING EV NUMBERS BY 2030	70
9.2	DEMAND PROFILE FOR 2030	72
9.3	DETERMINATION OF GRID EMISSION FACTOR FOR 2030	74
9.4	EV CHARGING DEMAND LOAD FOR 2030.....	75
9.5	EMISSION ESTIMATION FROM EVs	77
9.6	COMPARISON WITH ICEVs.....	85
10	CONCLUSION	91
	APPENDIX.....	94
	DAILY EMISSIONS - 2023	94
	CATEGORY WISE COMPARISON - 2023	97
	EV CHARGING DEMAND - 2030.....	127

LIST OF FIGURES

FIGURE 1: ALL INDIA INSTALLED CAPACITY (IN GW) AS OF JUNE 2025 (SOURCE: VAHANSEWA).....	8
FIGURE 2: COMPARISON OF WTW AND TTW FOR EV AND ICEV	12
FIGURE 3: COMPARISON OF LIFE-CYCLE GHG EMISSIONS OF EVs AND ICEVs REGISTERED IN EUROPE, THE UNITED STATES, CHINA AND INDIA IN 2021 AND 2030 (PROJECTED)	14
FIGURE 4: ANNUAL REGISTRATION OF EVs IN INDIA AS OF CALENDAR YEAR 2023	19
FIGURE 5: TOTAL STOCK OF EVs IN INDIA AS OF CALENDAR YEAR 2023	19
FIGURE 6: SHARE OF EV STOCK BY CATEGORY AS OF CALENDAR YEAR 2023	20
FIGURE 7: DISTRIBUTION OF 2-WHEELER STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023.....	21
FIGURE 8: DISTRIBUTION OF 3-WHEELER STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023.....	22
FIGURE 9: DISTRIBUTION OF ELECTRIC CAR STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023.....	23
FIGURE 10: DISTRIBUTION OF ELECTRIC VAN STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023	24
FIGURE 11: DISTRIBUTION OF ELECTRIC BUS STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023	25
FIGURE 12: DISTRIBUTION OF ELECTRIC TRUCKS STOCK AMONG THE DIFFERENT STATES OF INDIA AS OF CALENDAR YEAR 2023	26
FIGURE 13: OVERVIEW OF METHODOLOGY USED FOR ESTIMATION OF EMISSIONS.....	28
FIGURE 14: REPRESENTATIVE CHARGING PROBABILITY DISTRIBUTION FOR 4W-PASSENGER VEHICLES	32
FIGURE 15: ALL INDIA WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023	35
FIGURE 16: THE REGIONAL GRIDS OF INDIA.....	37
FIGURE 17: GENERATION MIX OF REGIONAL GRIDS IN INDIA AS OF NOV 2025.....	38
FIGURE 18: WESTERN REGIONAL GRID WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023.....	39
FIGURE 19: NORTHERN REGIONAL GRID WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023.....	40
FIGURE 20: SOUTHERN REGIONAL GRID WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023.....	42
FIGURE 21: EASTERN REGIONAL GRID WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023.....	43
FIGURE 22: NORTHEASTERN REGIONAL GRID WEEKDAY (MONDAY) GENERATION MIX ACROSS FIVE REPRESENTATIVE SEASONS FOR 2023.....	44
FIGURE 23: HEATMAP SHOWING THE AVERAGE DIURNAL AND SEASONAL VARIATION OF GRID EMISSION FACTOR	45
FIGURE 24: TIME VARYING EMISSION FACTORS OF INDIAN REGIONAL GRIDS (WEEKDAY).....	47
FIGURE 25: DAILY ELECTRICITY REQUIREMENT OF THE EV FLEET, DISAGGREGATED BY VEHICLE CATEGORY AND USE TYPE (PRIVATE VS COMMERCIAL) ACROSS INDIA AND INDIVIDUAL REGIONAL GRIDS	50

FIGURE 26: WEEKDAY EV CHARGING LOAD PROFILES FOR INDIA AND REGIONAL GRIDS, SHOWING THE AGGREGATE CHARGING POWER CONTRIBUTION OF DIFFERENT VEHICLE CATEGORIES ACROSS 24 HOURS.	52
FIGURE 27: DIURNAL VARIATION OF NATIONAL EV RELATED CO ₂ EMISSIONS ACROSS FIVE REPRESENTATIVE SEASONS (SUMMER, MONSOON, AUTUMN, WINTER, AND SPRING), SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS.....	54
FIGURE 28: DIURNAL VARIATION OF EV RELATED CO ₂ EMISSIONS IN THE NORTHERN REGIONAL GRID ACROSS FIVE REPRESENTATIVE SEASONS, SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS	56
FIGURE 29: DIURNAL VARIATION OF EV RELATED CO ₂ EMISSIONS IN THE SOUTHERN REGIONAL GRID ACROSS FIVE REPRESENTATIVE SEASONS, SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS	57
FIGURE 30: DIURNAL VARIATION OF EV RELATED CO ₂ EMISSIONS IN THE WESTERN REGIONAL GRID ACROSS FIVE REPRESENTATIVE SEASONS, SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS	58
FIGURE 31: DIURNAL VARIATION OF EV RELATED CO ₂ EMISSIONS IN THE EASTERN REGIONAL GRID ACROSS FIVE REPRESENTATIVE SEASONS, SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS	59
FIGURE 32: DIURNAL VARIATION OF EV RELATED CO ₂ EMISSIONS IN THE NORTH-EASTERN REGIONAL GRID ACROSS FIVE REPRESENTATIVE SEASONS, SHOWING WEEKDAY AND WEEKEND CHARGING PROFILES, ALONG WITH FLEET WISE CONTRIBUTION TO TOTAL ANNUAL EV EMISSIONS	60
FIGURE 33: REGIONAL, SEASONAL, AND FLEET WISE DISTRIBUTION OF DAILY EV RELATED CO ₂ EMISSIONS ACROSS INDIA.	61
FIGURE 34: COMPARISON OF EV EMISSION INTENSITY AGAINST CORRESPONDING ICEV EMISSION INTENSITIES	63
FIGURE 35: NATIONAL AVERAGE EMISSION REDUCTION ACHIEVED BY ELECTRIC VEHICLES RELATIVE TO EQUIVALENT INTERNAL COMBUSTION ENGINE VEHICLES ACROSS VEHICLE CLASSES. VALUES REPRESENT PERCENTAGE CHANGE IN PER KILOMETER CO ₂ EMISSIONS, AGGREGATED ACROSS REGIONS, SEASONS AND DAY TYPES.	64
FIGURE 36: ANNUAL CARBON IMPACT OF THE NATIONAL EV TRANSITION IN INDIA	66
FIGURE 37: REGIONAL AND SEASONAL IMPACT ON EV EMISSION REDUCTION	67
FIGURE 38: FORECASTED EV NUMBERS IN THE BAU SCENARIO	71
FIGURE 39: FORECASTED EV NUMBERS IN SPS	72
FIGURE 40: METHODOLOGY FOR DEMAND PROFILE ESTIMATION FOR 2030	73
FIGURE 41: METHODOLOGY FOR DETERMINATION OF GRID EMISSIONS FACTOR.....	74
FIGURE 42: COMPARISON OF NATIONAL ELECTRIC VEHICLE CHARGING DEMAND PROFILES IN INDIA FOR THE YEAR 2030 UNDER THE BUSINESS-As-USUAL (BAU) AND STATED POLICIES SCENARIO (SPS) CASES.	76
FIGURE 43: REGIONAL, SEASONAL, AND FLEET WISE DISTRIBUTION OF DAILY EV RELATED CO ₂ EMISSIONS ACROSS INDIA IN 2030 BAU SCENARIO.....	78
FIGURE 44: REGIONAL, SEASONAL, AND FLEET WISE DISTRIBUTION OF DAILY EV RELATED CO ₂ EMISSIONS ACROSS INDIA IN 2030 STATED POLICIES SCENARIO.....	79
FIGURE 45: DIURNAL VARIATION OF MARGINAL EMISSION FACTORS (MEF) (IN tCO ₂ /MWh) UNDER THE 2030 BAU SCENARIO ACROSS INDIAN POWER SYSTEM REGIONS (ER: EASTERN REGION, WR: WESTERN	

REGION, NR: NORTHERN REGION, SR: SOUTHERN REGION, NER: NORTHEASTERN REGION, AI: ALL INDIA)	83
FIGURE 46: DIURNAL VARIATION OF MARGINAL EMISSION FACTORS (MEF) (IN tCO_2/MWh) UNDER THE 2030 SPS SCENARIO ACROSS INDIAN POWER SYSTEM REGIONS (ER: EASTERN REGION, WR: WESTERN REGION, NR: NORTHERN REGION, SR: SOUTHERN REGION, NER: NORTHEASTERN REGION, AI: ALL INDIA)	84
FIGURE 47: COMPARISON OF EV EMISSION INTENSITY AGAINST CORRESPONDING ICEV EMISSION INTENSITIES FOR 2030 BAU SCENARIO	85
FIGURE 48: COMPARISON OF EV EMISSION INTENSITY AGAINST CORRESPONDING ICEV EMISSION INTENSITIES FOR 2030 SPS SCENARIO	86
FIGURE 49: COMPARISON OF EMISSION REDUCTION FROM EVs TO ICEVs FOR 2030 BAU SCENARIO	88
FIGURE 50: COMPARISON OF EMISSION REDUCTION FROM EVs TO ICEVs FOR 2030 SPS SCENARIO.....	88
FIGURE 51: REGIONAL AND SEASONAL IMPACT ON EV EMISSION REDUCTION FOR 2030 BAU SCENARIO	90
FIGURE 52: REGIONAL AND SEASONAL IMPACT ON EV EMISSION REDUCTION FOR 2030 SPS SCENARIO.....	90
FIGURE 53: WEEKDAY EV CHARGING LOAD PROFILES FOR INDIA AND REGIONAL GRIDS FOR 2030 BAU SCENARIO, SHOWING THE AGGREGATE CHARGING POWER CONTRIBUTION OF DIFFERENT VEHICLE CATEGORIES ACROSS 24 HOURS.	127
FIGURE 54: WEEKDAY EV CHARGING LOAD PROFILES FOR INDIA AND REGIONAL GRIDS FOR 2030 SPS SCENARIO, SHOWING THE AGGREGATE CHARGING POWER CONTRIBUTION OF DIFFERENT VEHICLE CATEGORIES ACROSS 24 HOURS.	128

LIST OF TABLES

TABLE 1: VEHICLE CATEGORY ASSUMPTIONS USED IN THE ANALYSIS	48
TABLE 2: ICEV EMISSION INTENSITY FACTORS”	62

EXECUTIVE SUMMARY

India's transition to electric mobility is central to decarbonizing the transport sector, improving urban air quality and reducing petroleum dependence. However, electric vehicles (EVs) cannot be treated as uniformly "zero-emission" technologies when their electricity is supplied by a power system that remains substantially dependent on fossil-fuel generation. The emissions associated with EV operation depend not only on vehicle efficiency, but also on where and when charging occurs, the generation mix supplying the grid at that time, transmission and distribution losses, and charging behaviour. These considerations are particularly important in India, where the generation mix varies considerably across regions and seasons and where renewable generation introduces strong time-of-day variations in grid carbon intensity. This report therefore quantifies and compares emissions from EVs and equivalent internal combustion engine vehicles (ICEVs) using a spatially and temporally resolved framework for both present-day conditions and prospective 2030 scenarios.

The analysis shows that India's EV transition is already occurring at significant scale but remains highly concentrated in particular vehicle classes and geographies. By the end of 2023, the registered EV stock had reached approximately 39.7 lakh vehicles, of which two-wheelers accounted for 51.7% and three-wheelers for 43.5%. Together, these two segments represented more than 95% of the registered EV fleet. Passenger cars constituted about 4.4%, while buses, vans and trucks remained relatively small in number. The geographical distribution also differs substantially by segment: two-wheelers are concentrated in western and southern markets, three-wheelers have particularly high penetration in Uttar Pradesh, Bihar, Delhi and Assam, while electric buses are concentrated in a relatively small number of states with active public procurement programmes. Consequently, EV-related electricity demand cannot be inferred from vehicle numbers alone. High-utilisation commercial vehicles and buses can impose disproportionately large energy requirements even when their fleet numbers are small.

To capture these effects, the report develops a bottom-up, spatio-temporal EV emissions modelling framework linking the transport and power sectors. EV electricity demand is estimated separately by vehicle category, ownership/use type and region using registered fleet size, participation factors, daily vehicle-kilometres travelled and vehicle-specific energy consumption. Regional transmission and distribution losses are incorporated to determine the electricity that must actually be generated to supply the charging demand. Daily energy requirements are then converted into time-resolved charging profiles using differentiated charging probability distributions representing private, commercial, home, public and depot-based charging behaviour. These charging profiles are coupled with time-varying regional grid emission factors derived from generation dispatch. The framework covers the five Indian regional grids, Northern, Southern, Western, Eastern and North-Eastern, along with the

national Indian power grid, and incorporates seasonal, weekday/weekend and time-of-day variation. The quantitative comparison primarily addresses operational emissions, rather than a full cradle-to-grave lifecycle assessment.

This high-resolution treatment reveals substantial variation in the carbon intensity of electricity across both geography and time. The Eastern grid remains the most carbon-intensive, with emission factors generally around 0.85–0.95 tCO₂/MWh, reflecting its strong dependence on coal. The North-Eastern grid is at the opposite end of the spectrum, with emission factors typically around 0.18–0.35 tCO₂/MWh because of its greater reliance on hydro and lower coal contribution. The Northern and Southern grids exhibit pronounced intra-day variation as solar and hydro generation influence the generation mix. At the national level, carbon intensity generally reduces during solar-rich daytime hours and rises during the evening, night and early morning as thermal generation assumes a larger share of supply. The implication is important: , and charging schedules can materially affect the carbon benefit achieved by electrification.

For the 2023 EV fleet, the resulting charging-related emissions show corresponding regional, seasonal and temporal variation. National EV-related emissions are highest during periods where relatively high charging demand coincides with higher grid emission intensity. Three wheelers contribute the largest share, at approximately 1.15 million tCO₂ per year, making them the single most important driver of national EV charging emissions. The next largest component is system losses, contributing about 0.4–0.45 million tCO₂ annually. This is a notable result because system losses are often omitted in EV emissions accounting, yet in this case they represent a contribution comparable to major vehicle categories and therefore materially affect national level estimates. Among vehicle categories, two wheelers, heavy passenger vehicles, and light passenger vehicles each contribute on the order of 0.3–0.4 million tCO₂ per year, indicating that emissions are concentrated in high volume and high utilisation categories even when per vehicle energy use is lower than heavy duty categories. In contrast, freight and medium duty categories contribute much less at the national scale: heavy goods vehicles and light goods vehicles remain below roughly 0.1 million tCO₂ annually.

Comparison with equivalent ICEVs shows that electrification already provides a net carbon benefit at the national level, but the size of that benefit varies sharply by vehicle category. Two-wheelers achieve an average emission reduction of approximately 27%, three-wheelers around 13.6%, and light passenger vehicles approximately 23%. Light goods and medium-duty categories provide smaller but generally positive reductions. Heavy-duty electrification is considerably more sensitive to the electricity supply: heavy goods vehicles show only a marginal national average advantage under present conditions, while heavy passenger vehicles are effectively close to parity with their ICE counterparts. For buses in particular, the concentration of depot charging during evening and overnight periods reduces the potential carbon advantage because this demand often coincides with periods of relatively high grid emission intensity.

When aggregated across the existing national EV fleet, the corresponding annual emissions of an equivalent ICEV fleet are estimated at approximately 3.40 MtCO₂, compared with around 2.84 MtCO₂ for the EV fleet. This represents an annual reduction of approximately 0.56 MtCO₂, or 16.5%, under the charging behaviour and grid conditions considered. Most of this reduction is delivered by the large light-duty segments, particularly two- and three-wheelers. The result demonstrates that India's current EV transition is already yielding an overall operational carbon benefit, but also that the benefit is substantially smaller than would be inferred from considering zero tailpipe emissions alone.

Regional results reinforce this conclusion. The North-Eastern region consistently records the largest benefit from electrification, with reductions exceeding 60% and reaching approximately 78% in favourable seasons. The Southern and Northern regions generally provide meaningful reductions, particularly during periods of higher renewable and hydro availability. The Western grid delivers more modest but positive gains. The Eastern region is the most challenging: depending on season and vehicle category, overall benefits can be very small and can become negative for energy-intensive vehicle classes. Thus, the same EV operated with the same energy efficiency can have substantially different climate impacts depending on the grid supplying its electricity.

The report extends this framework to 2030 using two EV-adoption pathways. Under the Business-as-Usual (BAU) scenario, EV stock is projected to exceed 30 million vehicles by 2030, while the Stated Policies Scenario (SPS) produces a much more rapid transition, with EV stock exceeding 80 million vehicles. Two- and three-wheelers continue to dominate both scenarios, although passenger and commercial EV adoption also expands substantially. The increased penetration results in a major increase in electricity demand from transport and makes the interaction between charging and power-system operation increasingly important.

The 2030 analysis indicates a significant improvement in the average emission advantage of EVs relative to present conditions, but also identifies an important system-level constraint. At the national level, seasonal emission reductions relative to ICEVs range from approximately 28–41% under BAU and 28–40% under SPS. Monsoon provides the strongest national benefit, 41.1% under BAU and 40.4% under SPS, while winter produces the smallest reductions. The North-Eastern region remains the strongest performer, achieving approximately 79–91% reductions under BAU and 78–89% under SPS across seasons. The Northern and Southern regions generally achieve reductions of roughly 40–60%, while the Western region remains much more modest at approximately 14–23%. The Eastern region remains the principal challenge, with seasonal reductions ranging from around 12–31% and substantially poorer performance for heavy vehicles. Under the 2030 BAU case, electric heavy goods vehicles in the Eastern region can exhibit approximately 25% higher emissions than their ICE equivalents, demonstrating that electrification of energy-intensive transport is not automatically synonymous with decarbonisation.

Taken together, the results indicate that India should move beyond a policy framework focused only on the number of EVs deployed. The next stage of electric-mobility policy must increasingly address how those vehicles are charged and what generation supplies that charging demand. Electrification of two- and three-wheelers and other light-duty vehicles provides strong near-term emission benefits and remains a high-impact pathway under current grid conditions. For buses, trucks and other energy-intensive fleets, vehicle deployment should increasingly be coupled with renewable-powered depots, daytime or opportunity charging where operationally feasible, energy storage and managed charging. Coal-intensive regions require particularly close coordination between transport electrification and power-sector decarbonisation.

The overarching finding of this report is therefore that EVs provide a clear pathway for reducing transport-sector emissions in India, but the magnitude of the benefit is neither uniform nor automatic. It is governed by the interaction of vehicle efficiency, fleet composition, charging behaviour, network losses, regional generation mix and time-varying grid carbon intensity. The substantial improvement projected towards 2030 confirms the long-term value of electrification, while the regional and temporal differences demonstrate the opportunity to substantially increase its climate effectiveness through cleaner electricity and smarter charging. EV policy and power-sector planning should therefore be treated as an integrated decarbonisation challenge: accelerating electrification must proceed in parallel with grid decarbonisation, renewable-energy expansion and charging strategies that actively align demand with low-emission electricity.

1 INTRODUCTION

The estimation of emissions from EVs is a critical step in evaluating their role in achieving sectoral sustainability goals and decarbonizing the transportation sector. Transportation is one of the largest contributors to global greenhouse gas (GHG) emissions, and electrification presents a promising pathway to mitigate these impacts. However, the true environmental benefit of EVs is not universal; it is strongly influenced by factors such as the regional energy mix, vehicle efficiency, and usage patterns.

India's power sector remains heavily reliant on coal, contributing to high carbon intensity in certain regions. This creates a complex dynamic: while EVs eliminate tailpipe emissions, their upstream emissions from electricity generation can be substantial, particularly where renewable energy penetration is low. This variability underscores the importance of a region-specific approach to emission estimation rather than relying on a single national average. Understanding these variations is essential for policymakers to design targeted strategies that maximize the climate benefits of electrification. This study focuses on estimating emissions arising from the power sector due to EV charging demand, benchmarking them against emissions from internal combustion engine (ICE) vehicles, and identifying the conditions under which EV adoption yields the greatest GHG reductions.

1.1 OVERVIEW OF THE STUDY

The primary objective of this study is to quantify and analyze the GHG emissions associated with EV adoption in India by developing a regionally disaggregated and temporally sensitive emission estimation framework. The aim is to bridge the gap between EV adoption targets and their actual environmental benefits by considering the realities of India's power sector, charging patterns, and vehicle usage profiles.

Specifically, the study seeks to:

1. Assess regional EV adoption patterns across India and map them against state-level generation mixes, renewable energy penetration, and grid carbon intensity.
2. Develop well-to-wheel (WTW) emission estimation methodologies for EVs that integrate electricity generation sources, transmission and distribution (T&D) losses, and charging efficiency, alongside comparable frameworks for internal combustion engine vehicles (ICEVs).
3. Evaluate the influence of charging behavior and infrastructure deployment — including public charging, residential charging, and fleet charging — on state-specific emission outcomes.
4. Compare emissions from EVs and ICEVs under multiple grid and charging scenarios, identifying breakeven conditions for climate benefits.
5. Propose targeted strategies to reduce EV-related GHG emissions, including:
 - a. Increased renewable energy allocation for EV charging, particularly through RE-linked tariffs and dedicated charging infrastructure.

- b. Smart charging approaches that align EV charging demand with periods of high RE availability and low marginal emissions.
6. Formulate evidence-based policy recommendations to maximize the decarbonization potential of EVs through renewable energy–aligned charging strategies, dynamic tariff structures, and V1G/V2G integration.

1.2 OBJECTIVES OF THE REPORT

The primary objective of this report is to quantify and analyze the GHG emissions associated with EV adoption in India by developing a regionally disaggregated and temporally sensitive emission estimation framework. The report aims to bridge the gap between EV adoption targets and their actual environmental benefits by considering the realities of India's power sector, charging patterns, and vehicle usage profiles.

Specifically, the report seeks to:

- Assess regional EV adoption patterns across India and map them against state-level generation mixes, renewable energy penetration, and grid carbon intensity.
- Develop emission estimation methodologies for EVs that integrate electricity generation sources, transmission and distribution (T&D) losses, alongside comparable frameworks for ICEVs.
- Compare emissions from EVs and ICEVs under multiple grid and charging scenarios, identifying breakeven conditions for climate benefits.
- Category and region wise comparison of emissions from EVs and ICEVs.

2 STUDY BACKGROUND

2.1 CONTEXTUAL OVERVIEW

The transportation sector is one of the largest and fastest-growing sources of GHG emissions in India, contributing significantly to urban air pollution and climate change. In 2023, road transport accounted for approximately 12% of India's total CO₂ emissions, with over 90% of these emissions coming from ICEVs powered by petrol and diesel.

The electrification of transport is a cornerstone of India's decarbonization strategy, aligned with national commitments under the Paris Agreement and the country's Net Zero target for 2070. EVs offer the potential for significant reductions in tailpipe emissions and dependence on imported fossil fuels. However, the true environmental benefit of EV adoption depends heavily on the carbon intensity of the electricity used for charging, as well as lifecycle considerations.

Given the country's coal-heavy power sector and regional disparities in generation mix, transmission losses, and renewable energy penetration, there is a pressing need for region-specific emission analysis to guide EV policy, infrastructure deployment, and grid integration planning.

2.2 NATIONAL AND REGIONAL ENERGY LANDSCAPE

India's power sector is in the midst of a significant transition, balancing the twin imperatives of meeting rising electricity demand and decarbonizing the generation mix. As of June 2025, the total installed capacity stood at approximately 484 GW, with thermal power still dominating but renewables showing strong growth as given in Figure 1. The breakdown is:

- Coal and lignite: ~280 GW (~46% of installed capacity) the largest contributor to national electricity, and the primary source of CO₂, SO₂, and NO_x emissions.
- Natural gas: ~20 GW (~6% capacity) – lower CO₂ emissions per unit of energy than coal, but subject to supply variability and price volatility.
- Renewables (solar, wind, biomass, small hydro): ~184 GW (~38% capacity) – solar PV is the fastest-growing segment.
- Large hydro: ~49 GW (~11% capacity) – offers low-carbon electricity and peaking capability, but subject to seasonal variability.
- Nuclear: ~8.7 GW (~2% capacity) – a stable low-carbon base load source, though expansion has been slow.

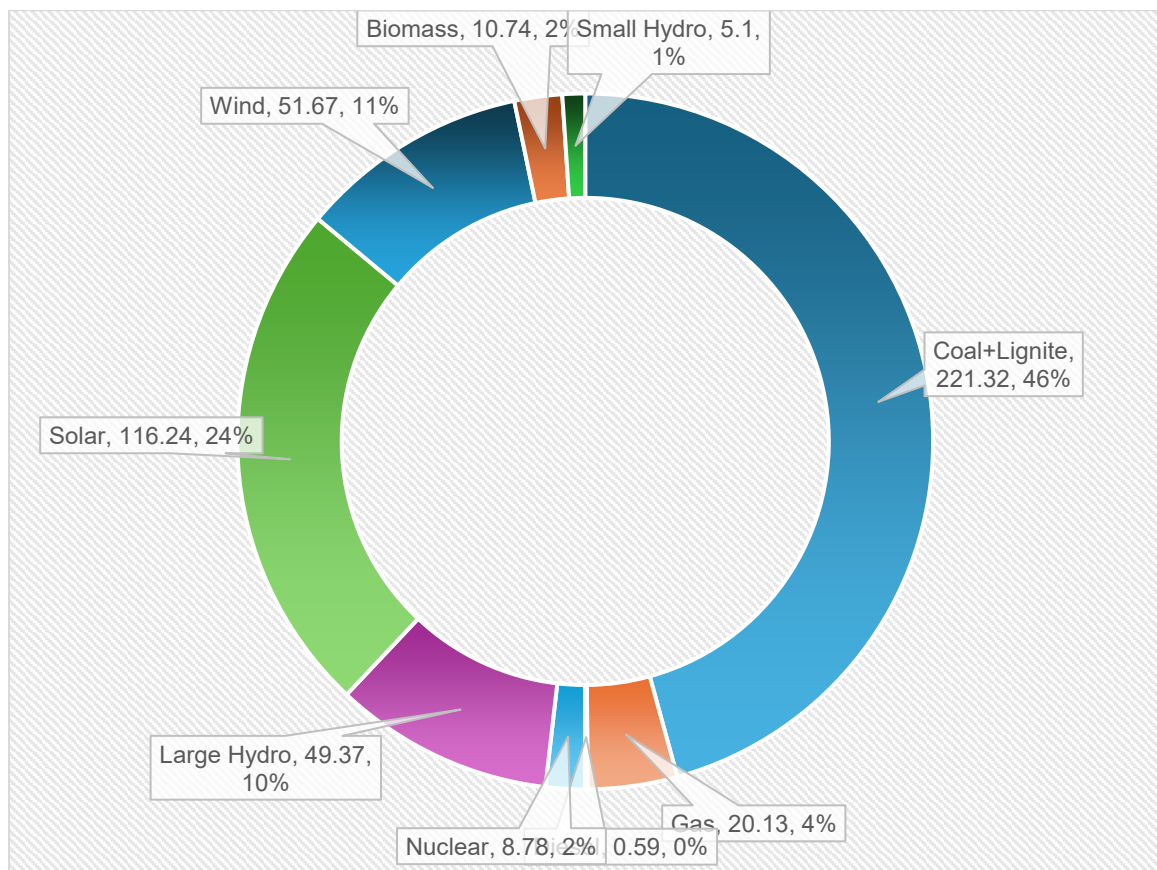


Figure 1: All India installed capacity (in GW) as of June 2025 (Source: VahanSewa)

Despite renewable energy (RE) expansion, the national average grid emission factor remains high at 0.7 kg CO₂/kWh. This is largely because coal-fired generation is often dispatched to meet base and peak loads, especially during periods of low RE output or high demand.

However, India's grid carbon intensity is far from uniform:

- RE-rich states such as Karnataka, Tamil Nadu, Gujarat, Himachal Pradesh, and Rajasthan have lower emission factors due to high shares of wind, solar, and hydro
- Coal-heavy states such as Chhattisgarh, Jharkhand, Odisha, and West Bengal have much higher emission factors. Many of these states are also major electricity exporters to neighbouring regions.

T&D losses further shape the emission profile. T&D losses amplify upstream emissions because more electricity must be generated to deliver the same amount to the end-user. This means that EV charging in states with high T&D losses carries a substantially higher well-to-wheel (WTW) emissions footprint compared to the same vehicle charged in a low-loss, RE-rich state.

In short, the environmental advantage of EVs is highly location-dependent in India, shaped by regional generation mix, marginal generation patterns, and T&D efficiency. This underlines the importance of state-level and time-of-day-specific emission factors for any accurate EV operational emission analysis.

2.3 EVOLUTION OF THE EV ECOSYSTEM

India's electric vehicle ecosystem has evolved from niche experiments to a rapidly scaling market supported by strong policy backing, domestic manufacturing capacity, and growing consumer acceptance.

The first structured policy push came in 2013 with the National Electric Mobility Mission Plan (NEMMP), aimed at reducing fossil fuel dependence, improving energy security, and cutting vehicular emissions. Building on this, the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles in India (FAME-I) scheme was launched in 2015. This provided demand incentives mainly for electric two-wheelers (2Ws) and three-wheelers (3Ws), hybrid passenger cars, and buses. The early years saw low sales volumes, limited model availability, and virtually no public charging network.

The landscape changed in April 2019 with FAME-II, which shifted focus toward high-utilization vehicle categories such as electric buses, 3Ws, and fleet 4Ws, while scaling up support for charging infrastructure. Incentives were larger but tied to technical performance and domestic value addition, encouraging local manufacturing of components and batteries. This was paralleled by state-level EV policies in Delhi, Maharashtra, Tamil Nadu, Karnataka, Kerala, and Gujarat, which introduced subsidies, tax exemptions, and non-fiscal benefits such as free parking and dedicated EV registration plates.

From 2020 onwards, the EV market experienced rapid expansion:

- Established OEMs and startups launched affordable EV models in the 2W and 4W segments.
- Public charging networks expanded, driven by utilities, oil marketing companies, and private charge point operators.
- Battery swapping emerged for commercial fleets, led by players such as Sun Mobility and Battery Smart.
- The Production Linked Incentive (PLI) scheme for Advanced Chemistry Cells (ACC) and the automobile sector attracted large investments in domestic gigafactories.

A significant recent initiative is the PM E-Drive Programme, launched to accelerate the adoption of electric mobility in line with India's climate commitments. PM E-Drive is designed as an umbrella programme that builds on the achievements of FAME while expanding its reach. It targets deeper penetration across all vehicle categories, supports indigenous R&D for EV components, facilitates large-scale deployment of charging infrastructure, and promotes renewable energy integration into EV charging. The programme also emphasizes manufacturing competitiveness through Make in India, ensuring that EV adoption strengthens domestic industry as well as environmental outcomes.

The electric bus segment has also gained traction, with State Transport Undertakings (STUs) in cities such as Delhi, Mumbai, Bengaluru, and Surat integrating e-buses under Gross Cost

Contract (GCC) models. These are supported by FAME-II incentives and concessional financing from agencies like the World Bank and ADB.

Despite strong growth, the market remains skewed toward 2Ws and 3Ws, which account for over 90% of annual EV sales. Four-wheeler private EV adoption, though rising, is still limited by high upfront costs, limited mass-market models, and range anxiety. Adoption is geographically concentrated in a few leading states, with the rest of the country lagging behind due to weaker policy support, lower consumer awareness, and infrastructure gaps.

Looking ahead, the combination of central initiatives such as PM E-Drive, state policies, falling battery costs, and higher renewable penetration in the grid is expected to drive wider adoption across all segments. However, ensuring that this transition maximizes GHG reduction will require smart charging strategies, renewable-linked tariffs, and grid readiness planning, particularly in coal-heavy states where uncoordinated charging could offset environmental gains.

3 LITERATURE REVIEW

The transition to EVs has prompted extensive research on their environmental implications, particularly the emissions associated with their operation and lifecycle. While EVs eliminate direct tailpipe emissions, their true environmental footprint is dependent on the upstream power system that supply electricity for charging. This section critically examines existing literature that has contributed to understanding the emission characteristics of EVs, comparing them to internal combustion engine vehicles (ICEVs), and analyzing the influence of power sector emissions, charging behavior, and regional generation profiles.

3.1 EMISSION ACCOUNTING FRAMEWORKS

3.1.1 Well-to-Wheel (WTW)

The Well-to-Wheel (WTW) emission framework is a widely adopted methodology for quantifying the operational and upstream fuel cycle emissions of vehicles. It plays a critical role in understanding the comparative environmental impact of different vehicle technologies, including internal combustion engine vehicles (ICEVs), battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).

While EVs are widely perceived as "zero-emission vehicles," this label only applies to tailpipe emissions (i.e., direct emissions). The WTW framework ensures a more accurate and system-wide perspective by capturing emissions upstream of the vehicle, particularly those arising from the energy supply chain. This methodology assesses the emissions from the point of fuel extraction to the final use of energy in the vehicle, typically breaking it into two segments:

- **Well-to-Tank (WTT):** This refers to emissions generated during the extraction, processing, conversion, and transportation of the fuel or energy carrier before it reaches the vehicle's energy storage system (i.e., fuel tank or battery).
 - For ICEVs, this includes crude oil extraction, transport, refining into petrol or diesel, and distribution to petrol pumps.
 - For EVs, it includes:
 - Primary energy extraction (coal, natural gas, uranium, solar, wind, etc.)
 - Electricity generation (thermal, hydro, nuclear, or renewable)
 - Transmission and distribution (T&D) losses
 - EV charger efficiency losses

Key emissions sources during WTT include combustion of fossil fuels for generation and process heat, fugitive methane emissions (especially in gas networks), and line losses during electricity transmission.

- **Tank-to-Wheel (TTW):** This includes direct emissions during vehicle operation—from the energy stored in the vehicle being converted to motion.
 - For ICEVs, TTW emissions are primarily CO₂, NO_x, CO, unburned hydrocarbons, and particulate matter (PM) resulting from combustion.
 - For EVs, TTW emissions are zero, since no fuel is burned and no tailpipe exists. However, this does not imply that EVs are emission-free in totality—only in direct use.

In the WTW framework, EVs typically have a TTW of 0 gCO₂/km, but a significant WTT component due to the carbon intensity of the grid.

For ICEVs, WTT includes oil extraction, refining, and transportation of fuels, while TTW includes emissions from combustion. For EVs, WTT includes power plant emissions and T&D losses¹; TTW is zero, as EVs have no tailpipe emissions.

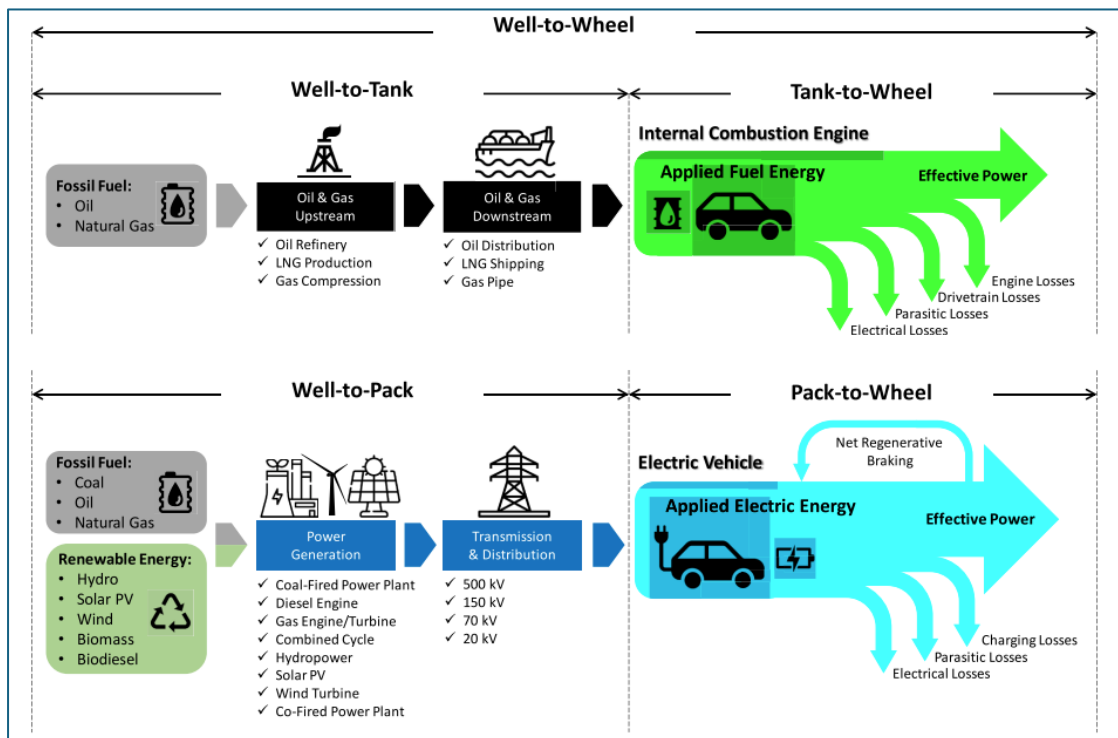


Figure 2: Comparison of WTW and TTW for EV and ICEV ²

3.1.2 Cradle-to-Grave (CTG)

While WTW approaches provide valuable insights into the operational and fuel-related emissions of a vehicle, they do not account for the full life-cycle environmental impacts of vehicle technologies. For a more comprehensive assessment, particularly for policy-making,

¹ A. Al-Buenain, S. Al-Muhannadi, M. Falamarzi, A. A. Kutty, M. Kucukvar, and N. C. Onat, 'The Adoption of Electric Vehicles in Qatar Can Contribute to Net Carbon Emission Reduction but Requires Strong Government Incentives', *Vehicles* 2021, Vol. 3, Pages 618-635, vol. 3, no. 3, pp. 618–635, Sep. 2021, doi: 10.3390/VEHICLES3030037.

² I. Veza, M. Z. Asy'ari, M. Idris, V. Epin, I. M. Rizwanul Fattah, and M. Spraggon, 'Electric vehicle (EV) and driving towards sustainability: Comparison between EV, HEV, PHEV, and ICE vehicles to achieve net zero emissions by 2050 from EV', *Alexandria Engineering Journal*, vol. 82, pp. 459–467, Nov. 2023, doi: 10.1016/J.AEJ.2023.10.020.

sustainability certifications, and corporate carbon accounting, the Cradle-to-Grave (CTG) approach, also known as full Life-Cycle Assessment (LCA) is adopted.

The CTG framework considers emissions and environmental impacts across all life stages of a product or system. For EVs, this includes:

- Raw material extraction and processing (mining of lithium, cobalt, nickel, copper, etc.)
- Battery and vehicle manufacturing
- Transportation of parts and final assembly
- Operational phase (electricity generation, charging losses, maintenance)
- Infrastructure impacts (e.g., EV charging infrastructure, power electronics)
- End-of-life (recycling, disposal, repurposing of batteries)

The CTG framework is typically divided into two sub-phases:

- **Cradle-to-Gate:** Covers all processes from raw material extraction through manufacturing and final product assembly. For EVs, this phase is particularly significant due to the high energy intensity of battery production, which includes:
 - Mining and processing of rare-earth metals (lithium, cobalt, graphite)
 - Electrolyte and cathode material synthesis
 - Battery cell and pack assembly
 - Integration into the vehicle platform
- **Gate-to-Grave:** Includes the operational phase (already captured in WTW), routine maintenance, and end-of-life management. For EVs, the maintenance footprint is typically lower due to fewer moving parts and no engine oil consumption. However, the end-of-life treatment of EV batteries remains a significant environmental and logistical challenge, especially in developing countries with limited recycling infrastructure.

3.2 GLOBAL AND INDIAN STUDIES ON COMPARATIVE ANALYSIS FOR EV AND ICEV EMISSIONS

Multiple recent studies and reports have compared the life-cycle GHG emissions of EVs and conventional ICE vehicles across major automotive markets. A clear consensus has emerged that battery electric vehicles offer significant GHG emissions reductions on a life-cycle basis relative to comparable ICEVs, even when accounting for today's electricity mixes. The magnitude of the benefit, however, depends on regional factors (especially the carbon intensity of electricity generation) and assumptions about vehicle efficiency and lifetime. This section summarizes detailed results from key studies by the ICCT, International Energy Agency (IEA), Argonne National Laboratory, and others, highlighting their LCA scope, assumptions, and quantified outcomes.

ICCT assessed life-cycle GHG emissions of passenger cars (including fuel production, vehicle manufacturing, and disposal) in four regions, Europe, United States, China, and India [4]. It considered average mid-size cars and accounted for real-world fuel/electricity consumption. It found that a medium BEV registered in 2021 produces far lower life-cycle GHG emissions than an equivalent gasoline ICEV in all regions. As illustrated in Figure 1, for cars registered

in 2021 the life-cycle CO₂-equivalent (CO₂e) emissions of a BEV were about 66–69% lower than a gasoline car in Europe, 60–68% lower in the U.S., 37–45% lower in China, and 19–34% lower in India. The smaller percentage in India and China reflects their more coal-intensive electricity grids as of 2021. Importantly, as electric grids get cleaner toward 2030, the gap widens: a BEV projected to be registered in 2030 is estimated to emit 74–77% less than an ICEV in Europe, 62–76% less in the U.S., 48–64% less in China, and 30–56% less in India over its lifetime³.

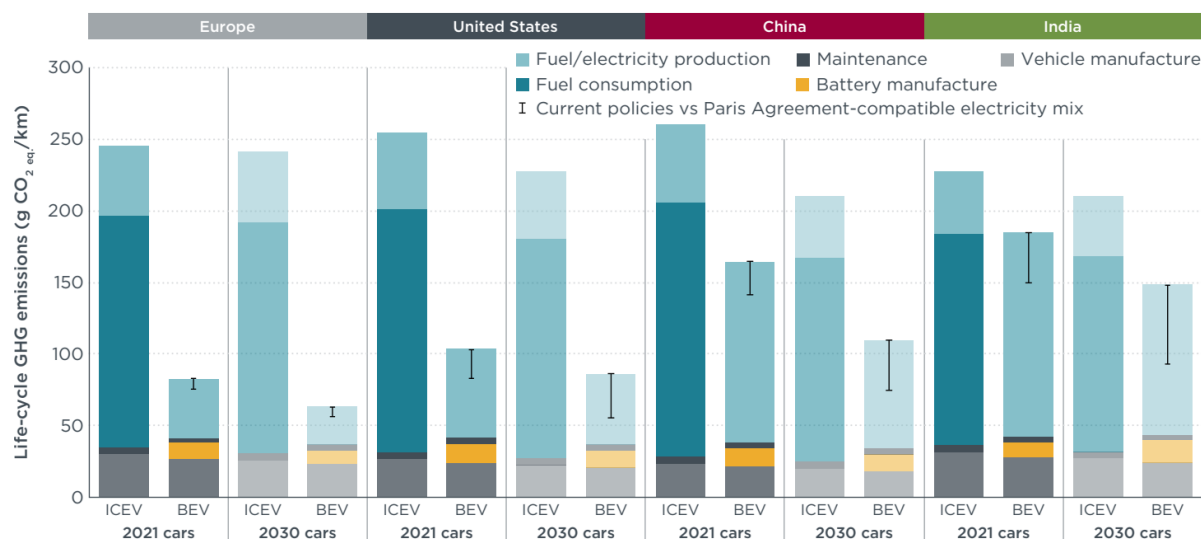


Figure 3: Comparison of life-cycle GHG emissions of EVs and ICEVs registered in Europe, the United States, China and India in 2021 and 2030 (projected)³

IEA has also published global comparative analysis of EV and ICE life-cycle emissions. In the Global EV Outlook 2024, IEA reported that a medium-size BEV sold in 2023 has roughly 50% of the lifecycle emissions of an equivalent gasoline car, on a global average basis [5]. This assumes a 15-year vehicle lifetime (~200,000 km) and includes vehicle production and well-to-wheel emissions. In numeric terms, the IEA estimates about 38 tonnes CO₂(eq) over the lifetime for a conventional medium car vs. ~15 t CO₂(eq) for a medium BEV registered in 2023. The BEV's lifecycle emissions are also about 30% lower than a plug-in hybrid (PHEV) and over 40% lower than a hybrid (HEV) in the 2023 scenario. These benefits grow over time as power sectors decarbonize; by 2035, an average new ICE car is projected to emit 2.5–3 times more CO₂(eq) over its life than a new BEV, depending on policy scenarios⁴.

Multiple peer reviewed articles have also analysed the LCA for EVs and ICEVs. In a separate paper the authors used a hybrid LCA methodology which covers vehicle manufacturing (with detailed treatment of battery production), upstream fuel production (gasoline refining and electricity generation), vehicle operation (tailpipe emissions for ICEVs and PHEVs, power

³ G. Bieker, 'A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars', Jul. 2021. Accessed: Aug. 05, 2025. [Online]. Available: https://theicct.org/sites/default/files/publications/Global-LCA-passenger-cars-jul2021_0.pdf#:~:text=This%20study%20is%20a%20life,the%20most%20relevant%20powertrain%20types%E2%80%9494internal

⁴ IEA, 'Global EV Outlook 2024', 2024. Accessed: Aug. 05, 2025. [Online]. Available: <https://iea.blob.core.windows.net/assets/a9e3544b-0b12-4e15-b407-65f5c8ce1b5f/GlobalEVOutlook2024.pdf>

plant emissions for EVs), maintenance (fluids and tire replacements), construction of charging infrastructure, and end-of-life processing⁵. They even include the emissions from building EV charging stations, although this was found to be <2% of life-cycle CO₂ emissions, while excluding emissions from constructing new gasoline stations (arguing that gasoline infrastructure is already largely in place). They found that on a per-kilometer basis, EVs already have lower life-cycle CO₂ emissions than gasoline ICEVs in China. The average life-cycle CO₂ for a battery EV was 170–186 g/km (170.5 g/km for LFP-battery EVs, 185.9 g/km for NMC-battery EVs), versus 253.1 g/km for a gasoline passenger car (PCV). PHEVs were intermediate at 227.8 g/km on average. In percentage terms, an average BEV in 2018 emitted about 32% less CO₂ per km than an ICEV, and about 18–25% less than a PHEV.

Veza et. al also encompasses both vehicle and fuel life-cycle emissions, but with a focus on operational impacts⁶. Using the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model developed by Argonne Lab, they calculate emissions from vehicle manufacturing (including battery production and the mining of lithium/cobalt) and from fuel production and use⁷. They state that EVs have the lowest emissions of CO₂ (and CO) among the powertrains, achieving about 20%–27% lower CO₂ emissions than gasoline and diesel ICE vehicles⁶. PHEVs also reduce GHG emissions compared to ICE, though only by a small margin: an EV's CO₂ emissions were less than 10% lower than a PHEV's in their analysis. Here the authors analysed the GHG emissions in the Indonesian grid. The authors explicitly note that Indonesia's generation is dominated by coal, natural gas, and oil, making the grid emissions factor quite high. EVs in Indonesia were found to cause much higher power-plant emissions of NO_x, N₂O, SO_x, and PM₁₀ compared to an ICEV. For instance, an EV produced >70% more NO_x and N₂O than an ICE (due to coal combustion in power plants). SO_x and PM₁₀ emissions were 90% and 85% higher for EVs than for ICEVs, respectively. These findings underscore that in a coal-dependent region, EVs can shift emissions from the tailpipe to the power sector, reducing direct CO₂ and CO, but exacerbating grid-related pollutants.

The authors in [2] restrict their boundary to the fuel cycle only, i.e. well-to-wheel emissions. For ICEVs, they include oil extraction, refining, fuel transport, and combustion in the vehicle (tank-to-wheel). For EVs, they include natural gas extraction and processing, pipeline transport, and electricity generation in a power plant. Vehicle manufacturing, maintenance, and disposal are excluded in this study's quantitative analysis. For the compact Nissan Leaf (EV) and a comparable Nissan Versa (ICEV sedan), they found the EV produced ~2,693 g CO₂(eq) per 100 km, whereas the gasoline Versa produced about ~18,700 g per 100 km

⁵ S. Xiong, Y. Wang, B. Bai, and X. Ma, 'A hybrid life cycle assessment of the large-scale application of electric vehicles', *Energy*, vol. 216, p. 119314, Feb. 2021, doi: 10.1016/J.ENERGY.2020.119314.

⁶ I. Veza, M. Z. Asy'ari, M. Idris, V. Epin, I. M. Rizwanul Fattah, and M. Spraggon, 'Electric vehicle (EV) and driving towards sustainability: Comparison between EV, HEV, PHEV, and ICE vehicles to achieve net zero emissions by 2050 from EV', *Alexandria Engineering Journal*, vol. 82, pp. 459–467, Nov. 2023, doi: 10.1016/J.AEJ.2023.10.020.

⁷ 'GREET | Department of Energy'. Accessed: Aug. 05, 2025. [Online]. Available: <https://www.energy.gov/eere/greet>

(calculated from fuel economy and emission factors). Even a larger EV like the Tesla Model X (rated ~6,389 g/100 km) handily outperformed an efficient small ICE car like the Versa.

The importance of charging methods and fleet types is explored by the authors in [8]. This study, focusing on Beijing, China, in 2020, uses an hourly simulation of EV charging behaviour and power system operation to analyze the environmental impacts of different electrification strategies. For private light-duty vehicles (LDVs), the charging mode is a critical determinant of environmental outcomes. Slow-charging private LDVs can lead to an effective reduction in CO₂ emissions, particularly when there is a high penetration of wind power, as it allows charging to occur during off-peak hours and take advantage of otherwise-curtailed wind energy. In stark contrast, fast-charging private LDVs can be counter-productive, as their charging demand often overlaps with the daily peak power demand, necessitating additional coal-fired generation and contributing to higher CO₂ emissions and wind curtailment. The study also reveals a crucial insight regarding air pollution: electrifying public transportation (buses and taxis) is the most effective strategy for reducing emissions of NO_x, a major precursor to air pollution. Despite their smaller fleet size, public buses and taxis are responsible for a disproportionately high share of total NO_x emissions due to their high annual mileage and emission factors. The authors of this paper recommend policies that incentivize off-peak charging and prioritize the electrification of public transport to maximize environmental benefits.

Chen et. al also applies a life cycle GHG analysis to the context of India, a country with ambitious EV targets but a power grid still heavily reliant on coal⁸. The study finds that the GHG mitigation potential of electric 4-wheelers in India today is highly variable and depends on both the geographical region and the time of charging. In the north-eastern states, where the grid is dominated by natural gas and hydroelectricity, a 40% reduction in GHGs is possible, but in the eastern and western regions, which are 89% and 84% coal-powered respectively, electric 4-wheelers can actually lead to an increase of over 15% in GHG emissions. The time of charging is also a significant factor, with overnight charging resulting in higher GHG emissions than daytime charging, and summer charging being more emissions-intensive than winter charging. Given these challenges, the study argues that electric 4-wheelers in India offer only a small GHG reduction potential in the short term, and that a deep, rapid decarbonization of the electricity grid is essential for them to become a viable climate solution. It suggests that a more effective near-term strategy for India is to focus on electrifying its vast fleet of 2-wheelers, which account for over 80% of all vehicles. Electric 2-wheelers can already achieve an average of 20% GHG reduction due to their small battery size and superior energy efficiency, and they do not require the extensive and expensive charging infrastructure needed for 4-wheelers. The paper also highlights the role of advanced hybrid vehicles as an important transitional technology, capable of achieving significant GHG reductions (up to 33% for hybrid

⁸ A. F. N. Abdul-Manan, V. Gordillo Zavaleta, A. K. Agarwal, G. Kalghatgi, and A. A. Amer, 'Electrifying passenger road transport in India requires near-term electricity grid decarbonisation', *Nature Communications* 2022 13:1, vol. 13, no. 1, pp. 1–13, Apr. 2022, doi: 10.1038/s41467-022-29620-x.

gasoline) without requiring any new charging infrastructure. The authors also raise concerns about the demand for batteries, projecting that India's EV ambition would require up to 125 GWh of batteries annually by 2030, putting significant pressure on global supplies of critical minerals and on China's dominant role in the battery supply chain. This necessitates a comprehensive plan for resource efficiency, recycling, and repurposing of battery materials. Finally, the study criticizes current policies, such as India's fuel consumption standards, for miscounting carbon by focusing only on tailpipe emissions and thus creating loopholes that undermine the overall goal of GHG reduction.

4 INDIAN EV ADOPTION TRAJECTORY AND FLEET CHARACTERISTICS

This chapter characterises India's electricity vehicle market using the Government of India VAHAN vehicle registration database accessed through the Parivahan data analytics portal⁹.

4.1 NATIONAL TRAJECTORY: HOW INDIA'S EV MARKET EVOLVED FROM 2010 TO 2023

Figure 4 and Figure 5 together should be read as the market's adoption curve. Three phases are clearly visible. First, 2010 to 2014 is a low volume phase, with annual registrations remaining in the low thousands (for example 4,846 in 2010 and 2,313 in 2014). Second, 2015 to 2019 is an early growth phase where annual volumes rise from 16,046 (2015) to 1,72,850 (2019). This phase coincides with the demand creation period under FAME Phase I, which commenced on 1 April 2015 and was available up to 31 March 2019¹⁰. Third, after the COVID 19 dip in 2020 (141,365), the market enters a rapid scaling phase: annual registrations rise to 4,57,237 in 2021, 11,80,950 in 2022, and 16,81,257 in 2023. The structural break in growth after 2019 is consistent with the start of FAME Phase II (commencing 1 April 2019) and the GST reduction on EVs from 12 percent to 5 percent effective 1 August 2019, both of which strengthened the demand side policy signal for adoption^{11,12}.

⁹ The data for the state of Telangana is not available in the following analysis.

¹⁰ Press Information Bureau, Government of India, "FAME India Scheme," Jul. 9, 2019.

¹¹ Ministry of Heavy Industries, Government of India, "FAME II," accessed Jan. 2026.

¹² Press Information Bureau, Government of India, "GST rate on all electric vehicles reduced from 12 percent to 5 percent ... effective from 1 August 2019," Jul. 27, 2019.

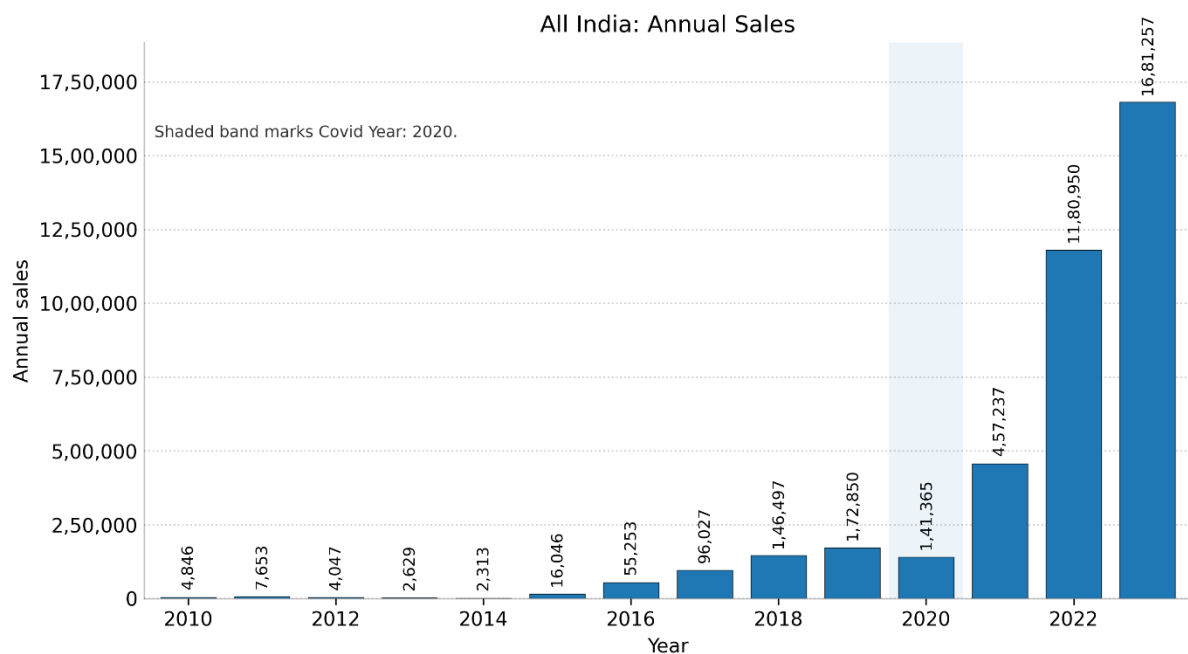


Figure 4: Annual registration of EVs in India as of calendar year 2023¹³

Figure 5 shows the cumulative registered EV stock in India from 2010 to 2023. The registered stock grows slowly up to the mid 2010s, then accelerates sharply after 2016. It increases from 92,787 in 2016 to 3,35,311 in 2018 and 5,08,161 in 2019, followed by continued rise through the COVID 19 year to 6,49,526 in 2020. The most significant expansion occurs after 2020: stock crosses 11,06,763 in 2021, reaches 22,87,713 in 2022, and rises to 39,68,970 in 2023.

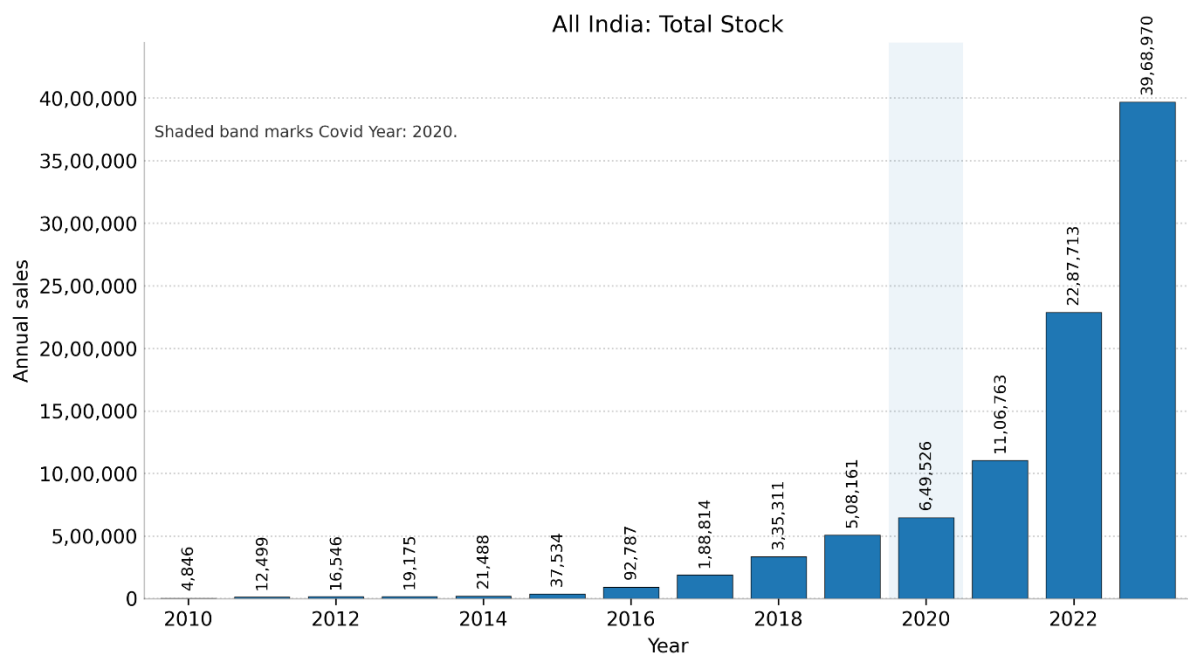


Figure 5: Total stock of EVs in India as of calendar year 2023¹³

¹³ Vahan Dashboard

4.2 EV STOCK BY CATEGORY

Figure 6 summarises the cumulative registered EV stock in India by broad vehicle category. The registered EV fleet is overwhelmingly a **2-wheeler** and **3-wheeler** fleet. Two wheelers account for 20,51,695 (51.7%) and 3 wheelers account for 17,27,462 (43.5%). Together, they constitute about 95.2% of the total registered EV stock. **Cars** form a visible but still small share of the total fleet. The “cars” category totals 1,72,839 (4.4%). From a policy perspective, this indicates that passenger car electrification remains a minority segment in stock terms as of end 2023, even though annual registration momentum can be higher in recent years. Larger and commercial categories remain negligible in stock terms as of end 2023. **Vans** are 9,327 (0.2%), **buses** are 7,130 (0.2%), and **trucks** are 517 (near zero percent). This implies that the current fleet on road is still at an early stage of adoption in heavier duty categories, and that targeted policy design may be required if electrification goals extend strongly into buses and freight.

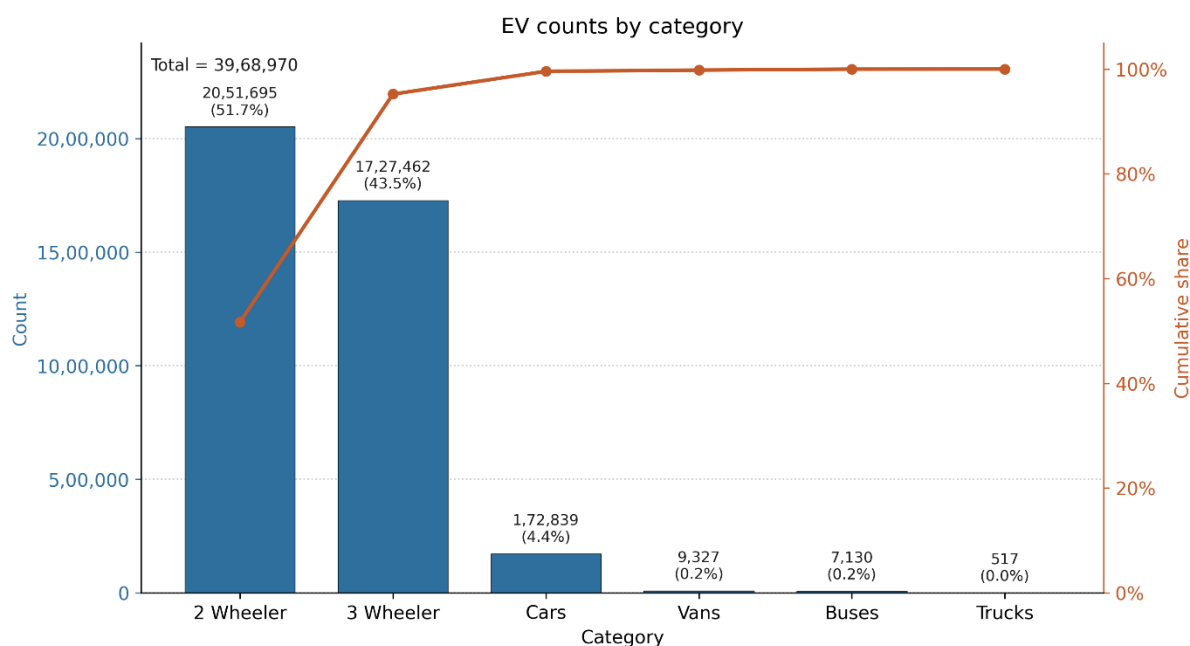


Figure 6: Share of EV stock by category as of calendar year 2023¹³

4.3 REGIONAL SHARE OF NATIONAL EV STOCK BY SEGMENT

Figure 4 and Figure 5 established that India’s EV market moved from a low volume phase (2010 to 2014) into rapid scale up after 2021, while Figure 6 showed that the registered EV stock as of end 2023 is dominated by two wheelers and three wheelers. The next relevant question is therefore geographic: **where is this stock concentrated, and does the geographic pattern differ by vehicle segment**. The following maps show the state level share of the national total within each segment.

4.3.1 2 Wheelers

Two wheelers form the largest EV segment nationally, and the distribution reflects concentration in a few large states with meaningful contributions from several others as shown in Figure 7. Maharashtra accounts for **18.9%**, Karnataka **15.5%**, Tamil Nadu **10.0%**, Gujarat **8.4%**, Rajasthan **7.5%**, and Kerala **6.0%**. Delhi also contributes a visible **4.6%**, and Uttar Pradesh **4.9%**. The policy implication is that even though the 2-wheeler market is widespread, a limited set of states together represent a large portion of the national 2-wheeler stock, so state level actions in these markets can disproportionately influence national outcomes.

Regional share of national total: 2 Wheeler

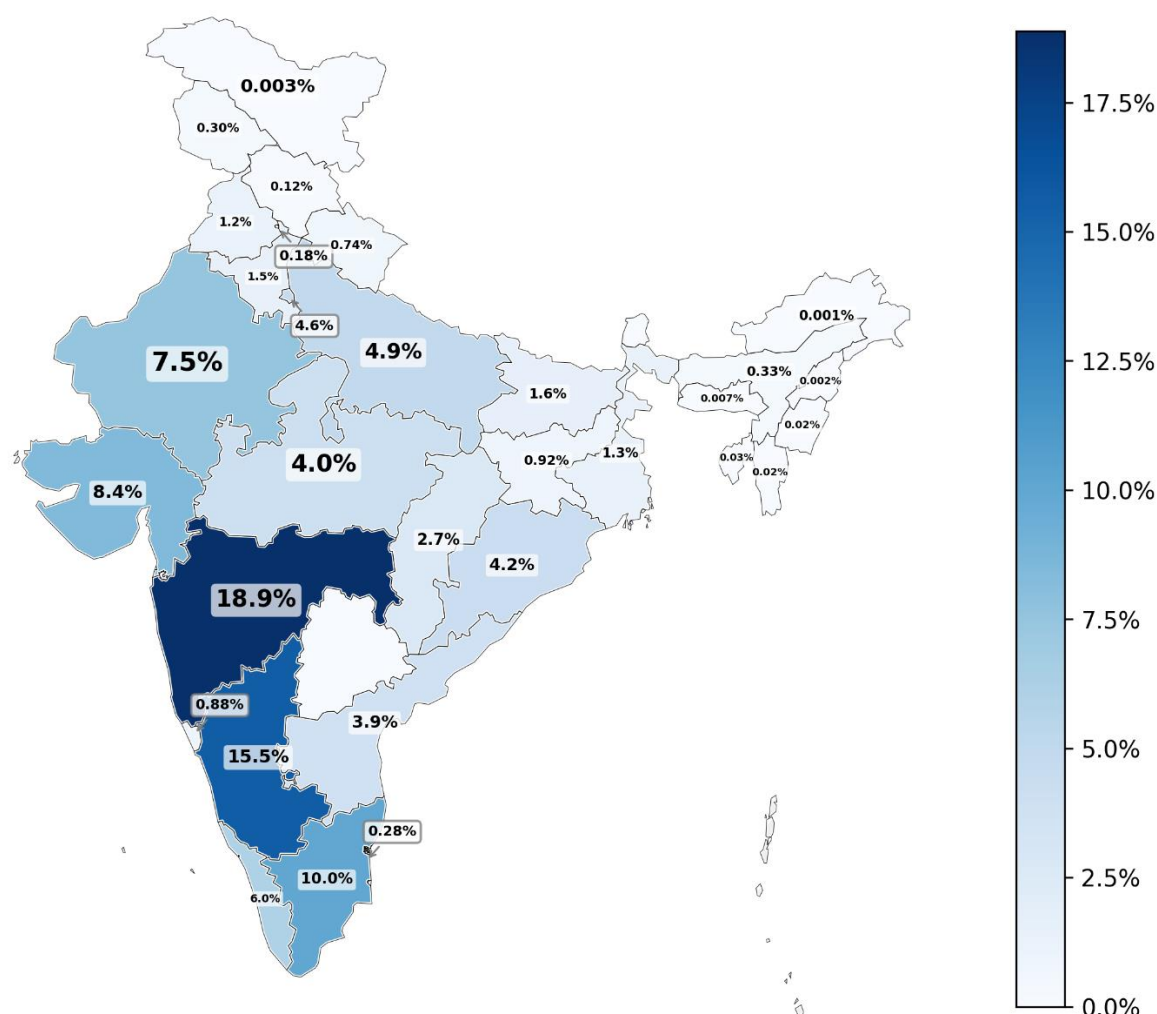


Figure 7: Distribution of 2-wheeler stock among the different states of India as of calendar year 2023

4.3.2 3 Wheelers

Three wheelers show the strongest geographic skew among the high volume segments as shown in Figure 8. Uttar Pradesh alone represents **37.2%** of the national three wheeler EV stock, with Bihar at **11.4%** and Delhi at **9.8%**. Assam contributes **9.0%**, which is notable

because it indicates a concentrated presence in the North East for this segment compared to others. West Bengal contributes **5.3%** and Rajasthan **5.1%**.

Regional share of national total: 3 Wheeler

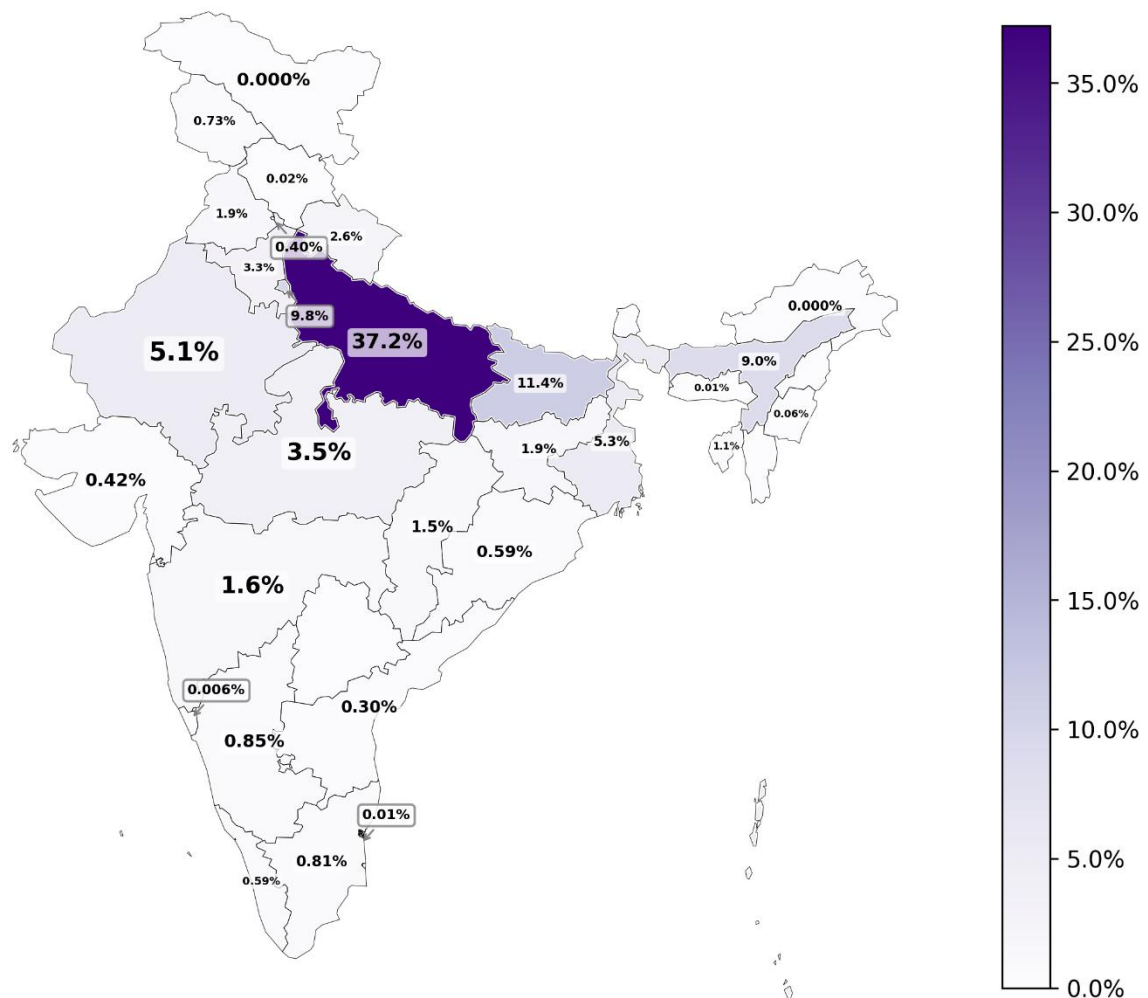


Figure 8: Distribution of 3-wheeler stock among the different states of India as of calendar year 2023

4.3.3 Cars

Electric cars show concentration in major urbanised and higher income markets, but with a broader base than buses as shown in Figure 9. Maharashtra contributes **20.1%**, Karnataka **15.1%**, Delhi **12.2%**, and Kerala **10.9%**. Tamil Nadu and Gujarat each contribute **7.2%**.

Regional share of national total: Cars

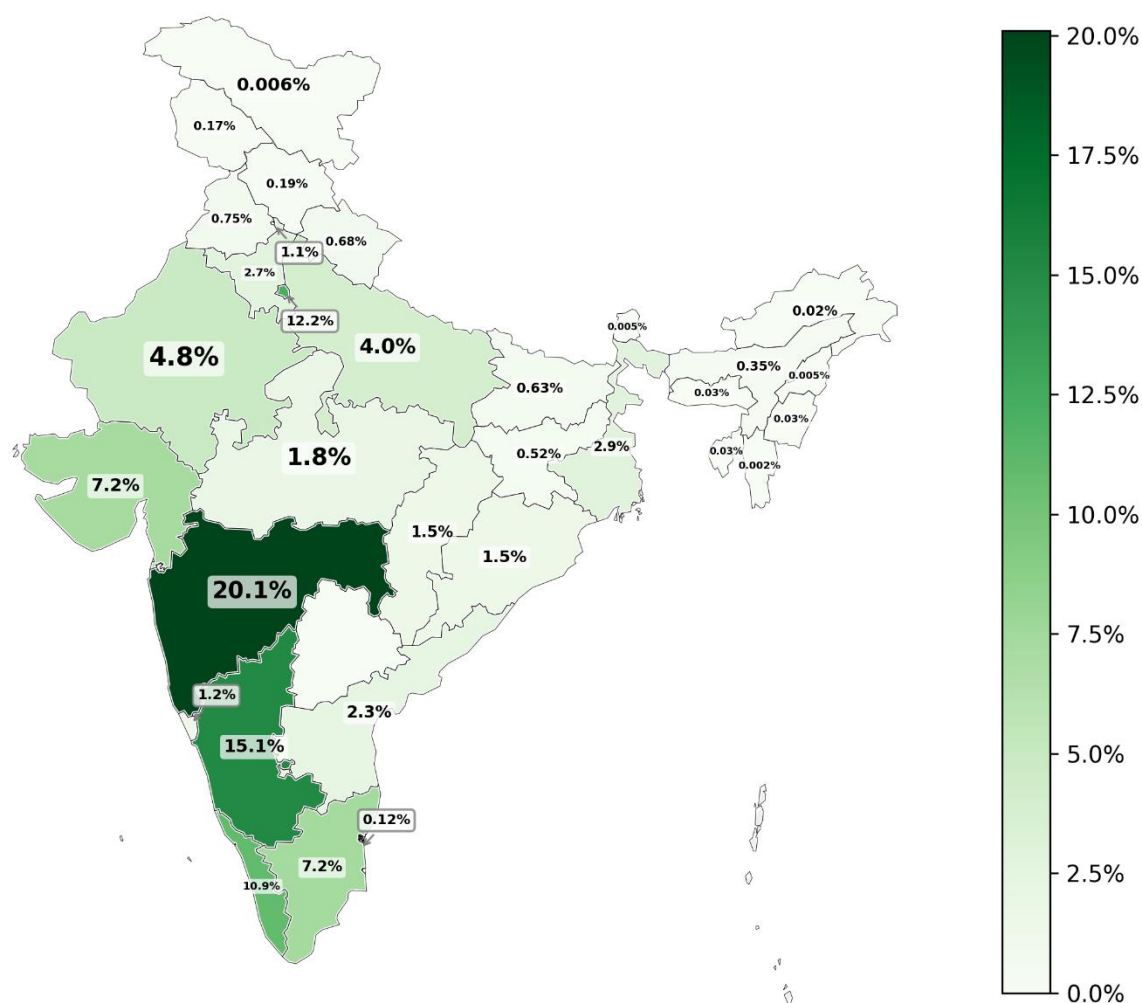


Figure 9: Distribution of electric car stock among the different states of India as of calendar year 2023

4.3.4 Vans

Electric vans show a more distributed pattern as can be seen in Figure 10. Tamil Nadu leads with **21.1%**, followed by Maharashtra at **14.9%**, Chhattisgarh at **11.9%**, and Uttar Pradesh at **8.4%**. Delhi contributes **6.2%** and Assam contributes **5.7%**, indicating that in this segment the distribution extends beyond the largest western and southern markets

Regional share of national total: Vans

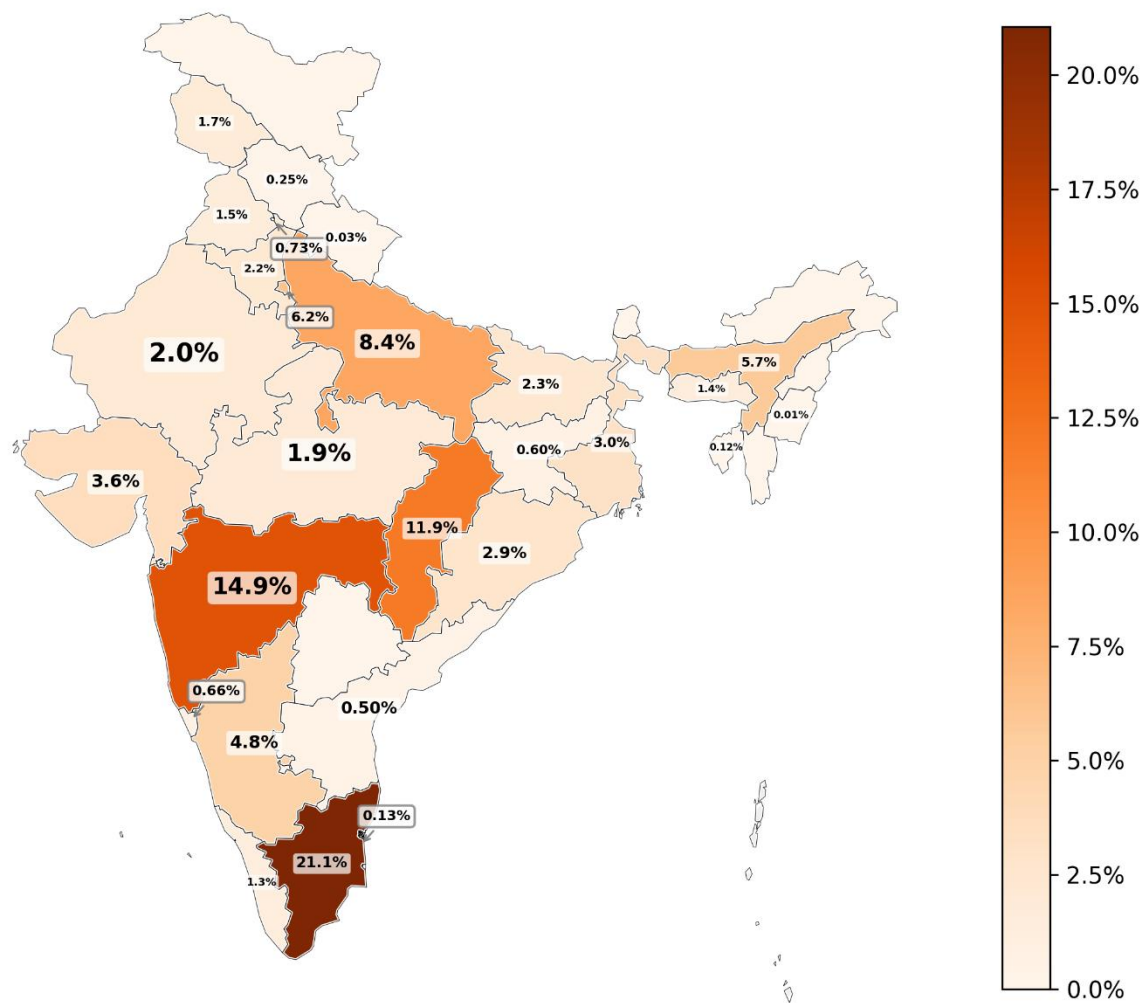


Figure 10: Distribution of electric van stock among the different states of India as of calendar year 2023

4.3.5 Buses

Electric buses are also geographically concentrated, and the pattern differs from two wheelers and three wheelers as shown in Figure 11. Delhi accounts for **24.9%**, Maharashtra **22.1%**, and Karnataka **15.3%**. Uttar Pradesh contributes **10.0%** and Gujarat **9.4%**. Because bus electrification is often driven by public procurement and depot based operations, the concentration aligns with where early procurement and deployment pipelines have been stronger.

Regional share of national total: Buses

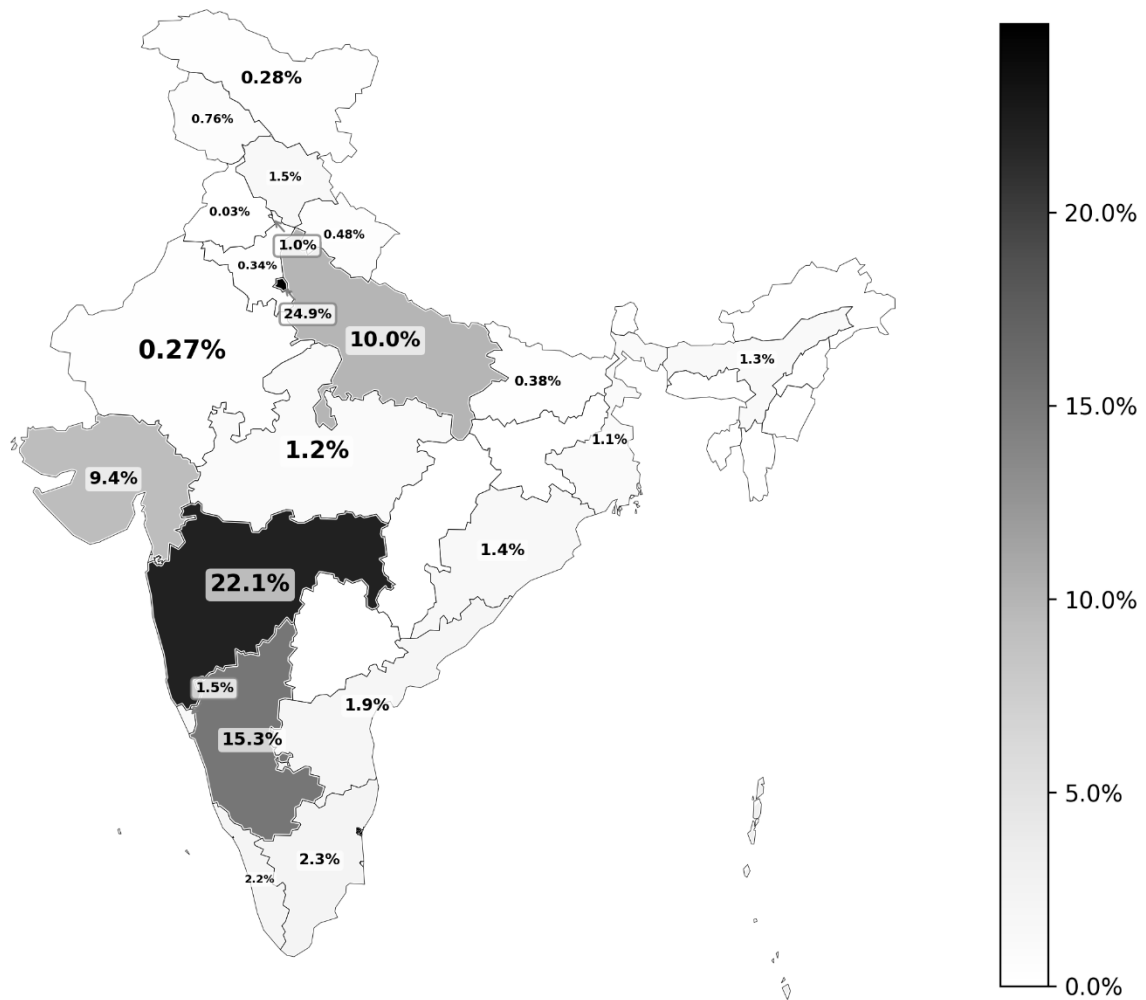


Figure 11: Distribution of electric bus stock among the different states of India as of calendar year 2023

4.3.6 Trucks

The electric truck stock is extremely concentrated as given in Figure 12. Gujarat alone accounts for **51.6%** of the national total, followed by Tamil Nadu at **15.1%** and Rajasthan at **9.9%**. Other states appear at much smaller shares (for example Maharashtra around **4.3%**, Kerala around **3.1%**). This pattern suggests that heavy duty electrification is, as of end 2023, still in an early stage where a small number of states dominate the recorded fleet.

Regional share of national total: Trucks

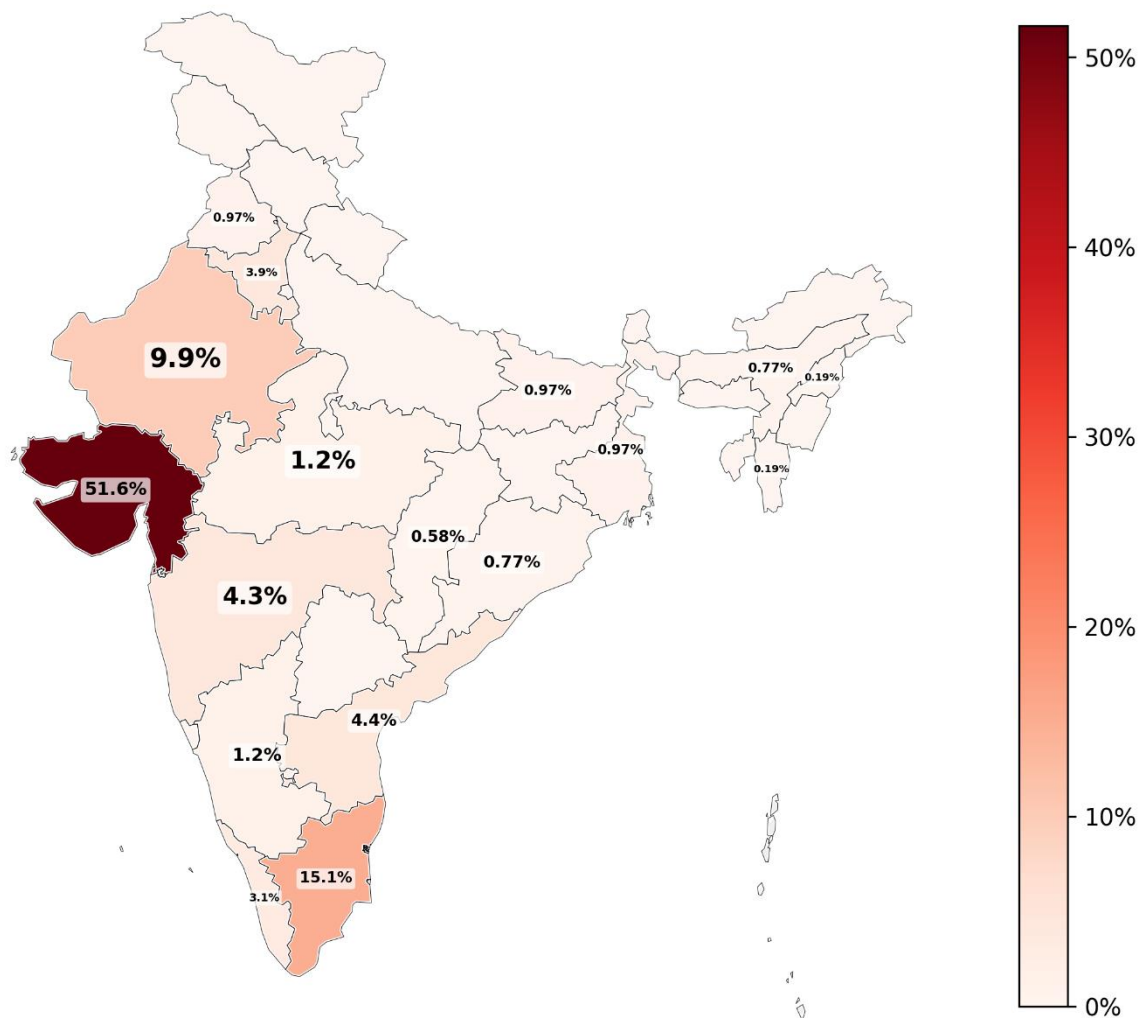


Figure 12: Distribution of electric trucks stock among the different states of India as of calendar year 2023

4.4 IMPACT ON EV CHARGING LOAD

The national EV totals and category mix show that India's registered EV stock is dominated by two wheelers and three wheelers, with cars a smaller share and buses and trucks still small in count. However, the grid and emissions implication is not proportional to vehicle counts, because energy per vehicle and charging power differ sharply by vehicle category. A small number of buses or trucks can create a charging load comparable to thousands of two wheelers. Therefore, the regional distribution maps should be read as a spatial map of future electricity demand growth from EV charging, and as a first indicator of where EV driven emissions will concentrate unless charging is managed.

Two mechanisms connect regional EV stock to emissions.

1. **Where charging happens determines which parts of the grid see new load.** High concentrations in a few states create localised stress on distribution networks and at specific substations, rather than a smooth national average increase.
2. **When charging happens determines the emissions intensity of charging.** The same kWh charged at different times of day can have very different grid emission factors, so regions with concentrated EV charging loads have disproportionate value from managed charging, time of day tariffs, or pairing with renewables.

Even though each 2-wheeler consumes relatively little energy per day, the scale means the cumulative load can become material at the feeder and transformer level in dense urban areas. In states with higher 2-wheeler shares, the charging load is likely to be **distributed and low power**, with a strong home charging component. This profile tends to push charging into the evening and night, which can coincide with higher system demand and potentially higher marginal emissions, depending on the local and regional dispatch.

The **3-wheeler** maps show strong concentration in a few states. This matters because 3-wheelers are typically tied to commercial duty cycles, urban hubs, and intermediate public charging. Their charging demand can be more predictable than private vehicles because it follows daily operating hours and often returns to a base area. In high share states, 3-wheeler electrification can create clusters of charging demand around markets, stands, and fleet operators, which can become local load hotspots even if power levels are modest. From an emissions perspective, 3-wheelers can offer a relatively high leverage opportunity if charging can be shifted toward mid-day or scheduled breaks, since that can align better with solar rich hours in many regions.

Electric cars represent a smaller share of total stock, but they contribute a disproportionate share of charging energy because of higher daily energy needs and larger batteries. Car charging is frequently home based and tends to peak in the evening, increasing the risk of reinforcing system peaks and raising emissions if charging coincides with higher marginal fossil generation. Regions with high car concentration are therefore prime candidates for policies that shape charging time, such as smart charging mandates for new home chargers, incentives for workplace and destination charging, and integration of charging with rooftop solar and storage where feasible. These interventions are especially important in metro dominated markets where local distribution capacity is already constrained.

The **bus** distribution maps therefore function as a direct indicator of where large, lumpy charging loads will appear, typically at depots connected to medium voltage or higher. Emissions impact is particularly sensitive to charging schedules because depot charging can concentrate a large amount of energy into a few hours. If charging is unmanaged, depots may charge immediately after buses return, creating evening peaks and potentially higher emissions.

5 PROPOSED METHODOLOGY FOR ESTIMATION OF EMISSIONS FROM EVS IN INDIA

This section presents the methodological framework used to estimate emissions associated with electric vehicle charging in India at a high temporal and regional resolution. Unlike conventional approaches that rely on static or annual average grid emission factors, the proposed methodology explicitly accounts for time of charging, regional grid characteristics, seasonal variation, and heterogeneous charging behaviour across vehicle fleets.

The core objective of the methodology is to dynamically link EV electricity demand with the time varying carbon intensity of the power grid, thereby enabling a realistic estimation of emissions that reflects actual system operation. The framework integrates inputs from both the transport domain and the power sector domain, ensuring consistency between vehicle usage patterns and grid dispatch conditions.

As illustrated in Figure 13, the methodology follows a sequential process. It begins with the characterization of regional EV fleets and the estimation of their electricity demand based on fleet size, usage intensity, and energy consumption rates. This demand is then distributed temporally using differentiated charging behaviour profiles that capture variations across vehicle categories, ownership types, and day types. In parallel, the power sector module processes actual regional generation dispatch data to derive time resolved grid emission factors, expressed in tCO_2/MWh , for each regional grid.

By combining the temporally resolved charging demand with corresponding grid emission factors, the framework determines the emission profile of EV charging at the regional and national levels. This bottom up, spatio temporal approach enables the assessment of how charging time, location, and fleet composition influence emissions outcomes, and provides a robust basis for evaluating emission reduction potential under current and future grid conditions.

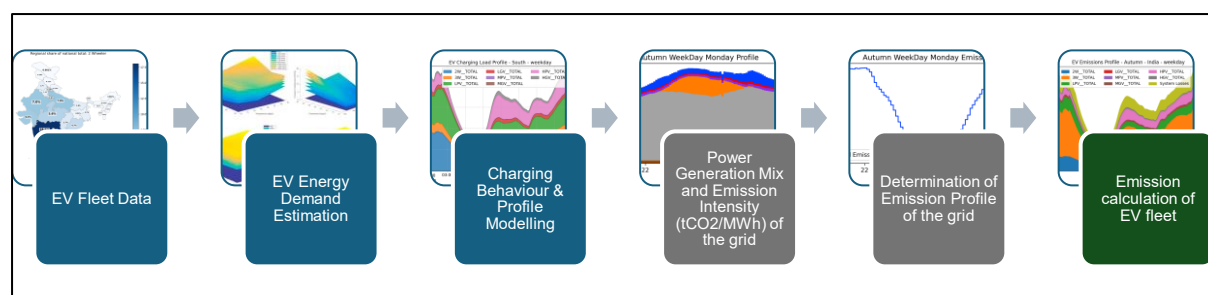


Figure 13: Overview of methodology used for estimation of emissions

5.1 DETERMINATION OF CHARGING DEMAND FROM EVs

The charging curve of EVs in this study represents the distribution of electricity demand arising from EV charging, disaggregated by vehicle category, region, day type, and charging behaviour. Rather than assuming uniform or average charging, the methodology explicitly captures realistic charging patterns driven by vehicle usage, ownership type, access to charging infrastructure, and time-of-day preferences. These charging curves form the critical linkage between the transport energy demand model and the power sector emission intensity model, enabling high-resolution emission estimation.

The charging curve construction proceeds in three sequential steps:

1. **Step 1:** Estimation of daily EV energy demand
2. **Step 2:** Allocation of charging demand across time blocks using probabilistic charging profiles
3. **Step 3:** Adjustment for charging behaviour modifiers such as time-of-day pricing

This approach ensures that charging demand is temporally aligned with grid generation and emission factors, rather than relying on static averages.

5.1.1 Step 1: Estimation of Daily EV Energy Demand

The first step in constructing the EV charging curve is the estimation of the total daily electrical energy demand arising from electric vehicle operation. This step establishes the magnitude of energy that must be supplied through charging, independent of when charging occurs. The estimation is performed separately for each vehicle class and region, allowing the model to capture heterogeneity in fleet composition, vehicle usage patterns, and regional mobility characteristics.

Unlike simplified approaches that assume uniform utilisation of the entire registered EV fleet, the methodology explicitly accounts for daily vehicle activity levels using participation factors. This distinction is critical, as a significant fraction of registered vehicles may remain inactive on any given day due to behavioural, operational, or seasonal factors.

5.1.1.1 Active Vehicle Population

The effective number of vehicles contributing to daily energy demand is calculated as:

$$N_{f,c}^{active}(r, d) = N_f^{stock}(r) \times \theta_{f,c}(d) \times \gamma_{f,c} \quad \text{Eq 1}$$

Where $N_{f,c}^{active}(r, d)$ is the number of active vehicles of category type f , ownership type c in region r and day d , $N_f^{stock}(r)$ is the total registered EV stock of vehicle category f in region r and $\theta_{f,c}(d)$ is the participation factor representing the fraction of vehicles expected to be active on a typical day and $\gamma_{f,c}$ is the ownership share i.e. share of private and commercial vehicles. The participation factor encapsulates real-world usage intensity and varies across vehicle categories and ownership types. For instance, commercial fleets and public transport vehicles

typically exhibit higher participation compared to privately owned vehicles, while weekday and weekend effects can further modulate daily activity levels.

5.1.1.2 Energy Demand

For the active vehicle population, the daily electrical energy requirement at the wheels is computed based on average travel distance and vehicle efficiency:

$$E_{f,c}^{wheels}(r, d) = N_{f,c}^{active}(r, d) \times VKT_{f,c} \times \eta_f \quad Eq\ 2$$

Where $E_{f,c}^{wheels}(r, d)$ is the energy demand, $VKT_{f,c}$ is the average daily vehicle kilometres travelled and e_f is the energy consumption intensity expressed in kWh per kilometre. This formulation links mobility demand directly to energy demand, ensuring that the charging requirement is grounded in actual vehicle usage rather than installed battery capacity or charger ratings. The use of class-specific VKT and consumption values allows the model to differentiate between lightweight vehicles such as two wheelers and energy intensive heavy commercial vehicles, which exhibit significantly different operating characteristics. The resulting $E_{f,r}^{wheels}$ represents the net electrical energy required to propel the vehicle fleet and does not yet account for losses incurred in electricity delivery.

5.1.1.3 Adjustment for System Losses

To translate vehicle-level energy demand into the corresponding electricity demand imposed on the power system, regional transmission and distribution losses are explicitly incorporated:

$$E_{f,c}^{grid}(r, d) = \frac{E_{f,c}^{wheels}(r, d)}{1 - L_r} \quad Eq\ 3$$

Where L_r denotes the aggregate system losses for region r .

Accounting for system losses is essential as generation must supply not only the energy consumed by vehicles but also the losses incurred during delivery. Regional differentiation of loss factors reflects variations in network topology, voltage levels, and operational efficiency across the Indian power system.

The resulting quantity $E_{f,c}^{grid}(r, d)$ represents the total daily electrical energy that must be supplied through EV charging for a given vehicle class and region. This value provides the that is subsequently distributed across time blocks in the charging curve construction.

At the conclusion of this step, the model yields a daily, region- and fleet-specific charging energy requirement. Importantly, this step does not impose any assumptions regarding charging timing or user behaviour. Instead, it establishes a robust energy baseline that is later shaped into time-resolved charging curves through probabilistic charging profiles and time-of-day modifiers.

5.1.2 Step 2: Allocation of charging demand across time blocks using probabilistic charging profiles

While Step 1 determines the total daily electrical energy requirement for each EV fleet and region, the environmental and grid impacts of EV charging are fundamentally time dependent. Electricity emission intensity, generation mix, and system conditions vary significantly across the day and across seasons. Consequently, the same quantity of energy can result in markedly different emissions depending on when it is drawn from the grid. To capture this temporal dependence, the model converts daily charging energy into high-resolution charging curves using a probabilistic time-of-day allocation framework.

5.1.2.1 Behaviour Embedded Charging Profile Modelling

EV charging behaviour is not uniform across the fleet. It is shaped by a combination of vehicle function, ownership structure, access to charging infrastructure, and operational constraints. In this methodology, these behavioural drivers are implicitly embedded within the probability distributions used to allocate charging demand over time.

Charging behaviour is differentiated along three interacting dimensions:

- **Vehicle category** (2W, 3W, 4W-Passenger, 4W-Goods, Vans/Pickup, Trucks, Buses)
- **Ownership and usage type** (private, commercial, public transport)
- **Charging access and charging type** (home charging, depot charging, public charging)

Each combination of these attributes leads to a distinct temporal charging tendency. For example, privately owned light-duty vehicles typically exhibit evening and night-time charging, whereas commercial fleets and public transport vehicles often follow more structured daytime or depot-based charging patterns. These behavioural tendencies are reflected directly in the shape of the charging probability distributions.

For each vehicle category f and category c , a charging probability distribution $\pi_{f,c}(t)$ is defined. The distribution $\pi_{f,c}(t)$ represents the likelihood that charging energy for that fleet is drawn during time block t .

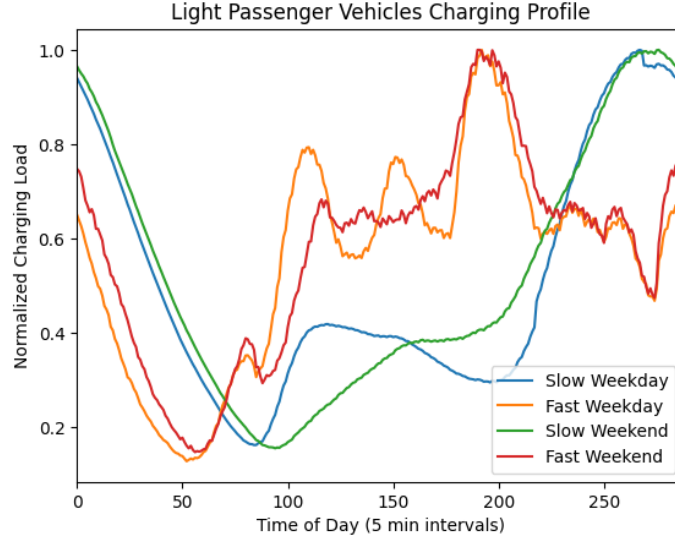


Figure 14: Representative charging probability distribution for 4W-Passenger vehicles

The total daily charging energy at the grid level obtained from Step 1, is allocated across time blocks as follows:

$$P_{f,c,r,d}(t) = E_{f,c}^{grid}(r, d) \times \pi_{f,c}(t) \quad Eq 4$$

Where $P_{f,c,r,d}(t)$ is the charging energy assigned to time block t for vehicle category type f , ownership type c in region r and day d . This formulation ensures strict energy conservation, meaning that the temporal allocation reshapes the demand profile without altering total daily energy consumption.

Aggregating across all vehicle categories yields the regional EV charging load profile:

$$P_{r,d}(t) = \sum_{f,c} P_{(f,c,r,d)}(t) \quad Eq 5$$

The resulting profile represents the composite EV charging curve for a given region, season, and day type.

5.2 DETERMINATION OF GRID EMISSION FACTOR

The emission factor for 2023 is determined directly from the observed generation dispatch data and technology-wise emission intensities. The objective is to compute the actual system-level emission intensity (tCO₂/MWh) based on real operational outcomes at both regional and national levels. Using SCADA-based generation data, the total electricity generated from each technology category, such as coal, gas, hydro, solar, and wind, is aggregated on a time-block basis. For each generation category, the corresponding emission intensity factor (tCO₂/MWh), as specified by the CEA, is applied¹⁴. These emission factors represent the average carbon intensity associated with each technology type. The emissions from each generation category

¹⁴ CEA, "CO₂ Baseline Database for the Indian Power Sector", Central Electricity Authority, Ministry of Power, Govt. of India, Nov 2025. https://cea.nic.in/wp-content/uploads/baseline/2025/12/User_Guide_V_21.0.pdf

are calculated as the product of generation and its emission factor. The total emissions for each time block are obtained by summing across all emitting technologies. The system emission intensity for the time block is then determined by dividing total emissions by total energy served in the block. This procedure is applied separately for each region (NR, WR, SR, ER, NER) and for the national aggregate. The resulting emission intensity represents the weighted average carbon intensity of the actual 2023 generation mix and serves as the baseline for comparison with future projected emission outcomes.

5.3 CALCULATION OF EMISSIONS DUE TO EVs

The emissions associated with EV charging are not intrinsic to the vehicle itself but are a function of the carbon intensity of electricity generation at the time and location of charging. Unlike internal combustion engine vehicles, where emissions are directly proportional to fuel consumption, EV-related emissions are mediated by the power system and therefore vary significantly across regions, seasons, and time of day.

To capture this variability, the methodology adopts a time-resolved, region-specific grid emission factor framework, wherein EV charging demand is dynamically coupled with the corresponding electricity emission intensity. This approach moves beyond conventional well-to-wheel analyses that rely on annual or national average emission factors, which mask critical temporal and spatial heterogeneity in the power system.

Let $EF_r(t)$ denote the grid emission factor of region r expressed in terms of CO₂ per megawatt-hour (tCO₂/MWh). The emission factor represents the average carbon intensity of electricity generation during that time interval and reflects the prevailing generation mix, including contributions from coal, gas, hydro, nuclear, and renewable energy sources.

Emission factors are constructed to match the charging demand profiles, and are differentiated by:

- Regional grid (Northern, Southern, Western, Eastern, North Eastern, and All India)
- Season (five representative seasons)
- Day type (weekday and weekend)

5.3.1 Coupling Charging Demand with Emission Factors

From the charging curve construction, the time-resolved EV charging demand is available as $P_{r,d}(t)$. This is converted to energy demand per time block $E_{r,d}(t)$ expressed in megawatt-hours per time block using the equation below

$$E_{r,d}(t) = P_{r,d}(t) \times \frac{\Delta t \text{ (in mins)}}{60} \quad \text{Eq 6}$$

The emissions attributable to EV charging in a given time block are computed as:

$$GHG_{r,d}^{CO_2}(t) = E_{r,d}(t) \times EF_r(t) \quad Eq\ 7$$

Where $GHG_{r,d}^{CO_2}(t)$ is the CO₂ emissions associated with EV charging during time block t .

5.3.2 Aggregation Across Time and Fleet Categories

The daily emissions for a given vehicle class and region are obtained by summing emissions across all time blocks:

$$GHG_{f,r,d}^{CO_2} = \sum_t E_{f,r,d}(t) \times EF_r(t) \quad Eq\ 8$$

Where $GHG_{f,r,d}^{CO_2}$ is the emissions from vehicle category f , region r and day d and $E_{f,r,d}(t)$ is block-wise energy consumption of fleet type f , region r and day d . Aggregating across all vehicle categories yields the total regional EV charging emissions:

$$GHG_{r,d}^{CO_2} = \sum_f GHG_{f,r,d}^{CO_2} \quad Eq\ 9$$

This structure allows emissions to be analysed at multiple levels of granularity, including:

- Vehicle category
- Fleet ownership type
- Region
- Season
- Time of day

6 ESTIMATION OF GRID EMISSION FACTOR FOR THE INDIAN POWER GRID

6.1 GENERATION MIX OF THE INDIAN GRID

6.1.1 All India Generation Mix

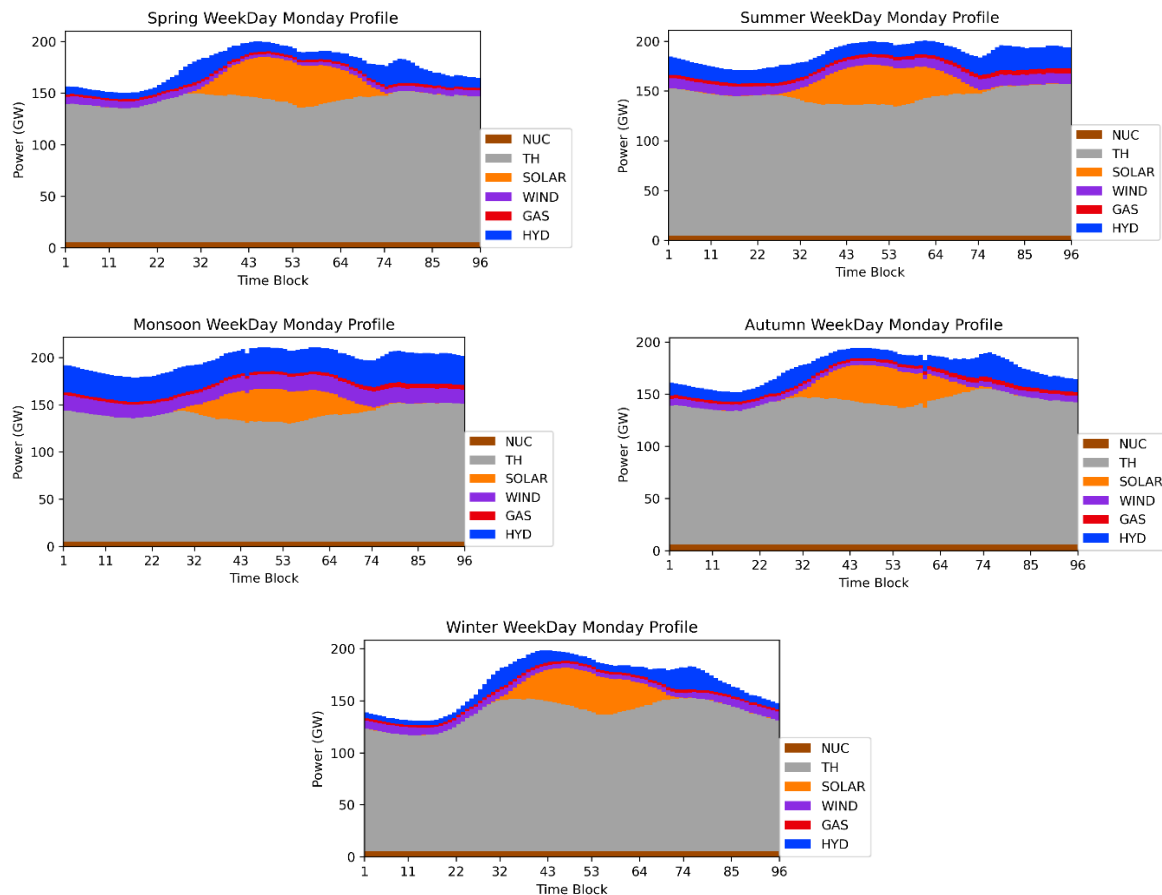


Figure 15: All India weekday (Monday) generation mix across five representative seasons for 2023

The All-India generation mix profiles shown for a representative Monday across seasons in Figure 23 reveal a power system that is dominated by thermal generation, with renewables shaping the intraday dynamics. Across all five seasons, thermal power forms the continuous base of the stack, remaining broadly stable through the day and accounting for the largest share of generation at every time block. This reflects the role of coal-based plants as the primary balancing and baseload resource in the national grid, with only limited diurnal flexibility. Nuclear generation appears as a small but constant contribution, flat across all time blocks and seasons, indicating its operation as an inflexible baseload source with negligible response to short term demand or renewable variability.

In all seasons, *solar output* ramps up sharply from the morning hours, peaks between late morning and early afternoon, and declines rapidly after sunset. The magnitude and shape of this solar peak vary seasonally. Summer and spring exhibit the highest and broadest solar contribution, driven by longer daylight hours and higher irradiance, while winter shows a narrower and lower peak due to shorter days and lower sun angles. Monsoon solar output is visibly suppressed and flatter compared to summer and spring, reflecting cloud cover and rainfall, even though the timing of the peak remains similar. This solar driven midday dip in thermal generation is clearly visible in all seasons, demonstrating partial displacement of coal during daylight hours rather than a reduction in total demand.

Wind generation contributes a modest but seasonally differentiated layer to the mix. During the monsoon season, wind output is significantly higher and more sustained across the day, reflecting strong and persistent wind regimes over large parts of the country. In contrast, wind contributions during winter, spring, and autumn are lower and more variable, while summer shows moderate wind output with some diurnal structure. Although wind does not dominate the stack at any point, its seasonal strength during monsoon materially reduces the reliance on thermal generation during both day and night.

Hydropower plays a critical balancing role and exhibits both seasonal and diurnal variability. Monsoon months show the highest hydro contribution, consistent with reservoir inflows and run of river availability, and hydro output remains elevated across most time blocks. In other seasons, hydro generation is lower on average but ***shows targeted increases during peak demand periods, particularly in the evening hours, indicating its use as a flexible resource to meet ramps after solar decline.*** The evening rise in hydro generation is visible across all seasons, coinciding with the sharp fall in solar output and the onset of residential demand peaks.

Gas based generation appears as a relatively small but responsive component of the mix. Its contribution increases slightly during evening and early night hours across seasons, suggesting limited use for peaking or grid support rather than continuous operation. However, the overall share of gas remains marginal compared to thermal coal, underscoring its constrained role in the current Indian generation portfolio.

6.1.2 Differences among the regional grids

India's regional grids exhibit pronounced differences in generation mix and operational behaviour due to variations in resource endowment, historical capacity addition, demand composition, and grid interconnections. While the national grid aggregates these effects into a smoother average profile, the underlying regional patterns remain highly heterogeneous and are central to understanding spatial differences in emission intensity and the environmental performance of electricity consumption.

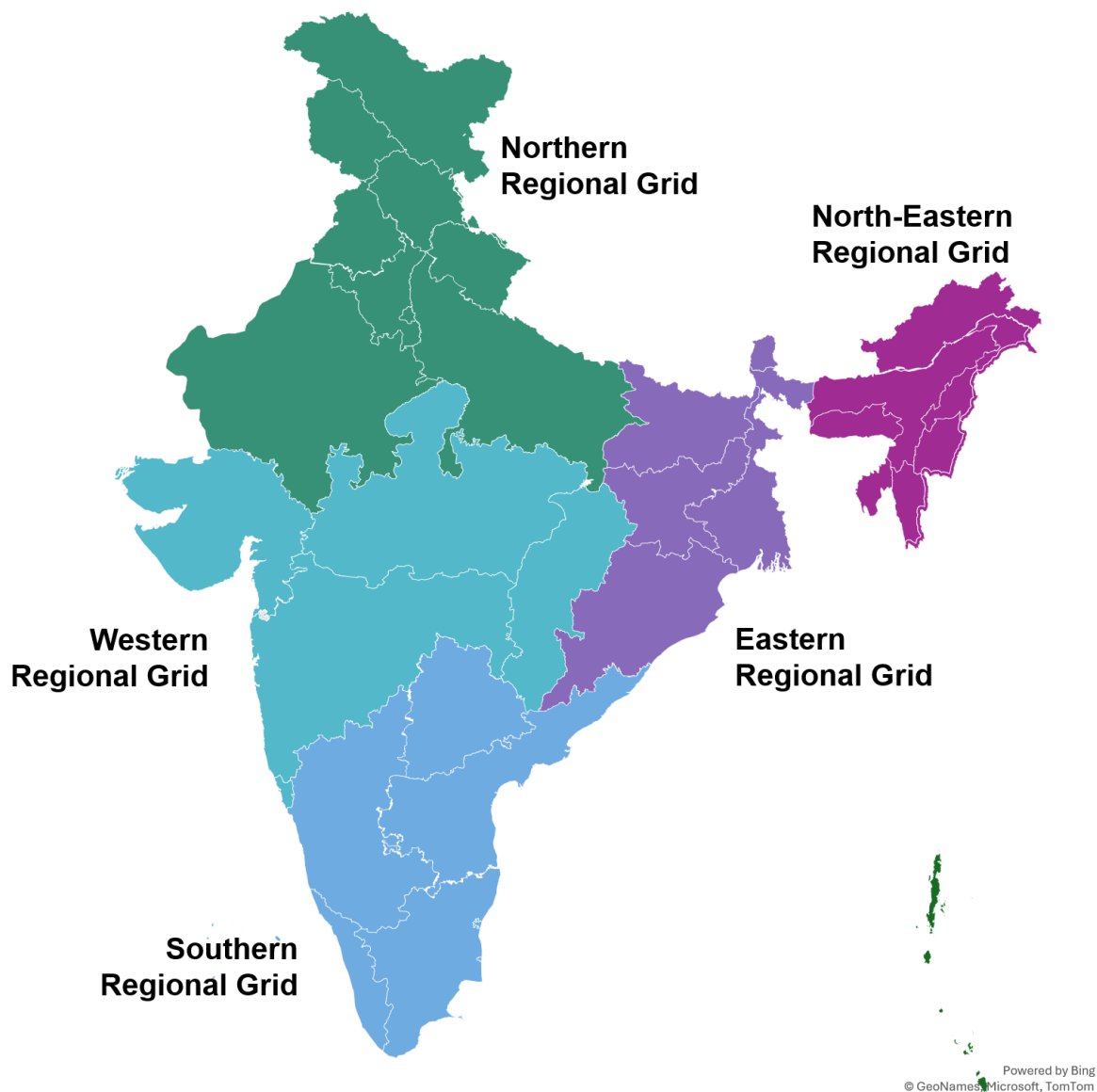


Figure 16: The Regional Grids of India

The installed generation capacity mix as of Nov 2025 shown in Figure 17 across India's regional grids shows clear contrasts in reliance on thermal power versus renewables. The Western Grid is the most coal heavy, with 84.671 GW of coal capacity, alongside the largest solar fleet at 49.633 GW and a substantial wind base of 23.857 GW, plus 9.399 GW of oil gas and 3.24 GW of nuclear, indicating a system where high renewable penetration sits on top of a very large thermal backbone. The Northern Grid has 51.849 GW of coal, but it is also strongly supported by hydro at 21.416 GW and solar at 45.479 GW, with smaller contributions from wind at 5.209 GW, nuclear at 2.22 GW, and oil gas at 5.712 GW, implying significant daytime decarbonisation potential driven by solar but continued evening dependence on coal and gas. The Southern Grid is more diversified, combining 48.575 GW of coal with 35.416 GW solar and 24.916 GW wind, supported by 13.596 GW hydro, 3.32 GW nuclear, and 3.807 GW oil gas, making it one of the most balanced portfolios across firm and variable resources. The Eastern Grid remains predominantly coal centric with 40.385 GW coal, while hydro stands at

5.988 GW and variable renewables are comparatively limited, at 1.761 GW wind and only 0.369 GW solar, consistent with higher average carbon intensity. The North Eastern Grid is distinct in scale and composition, with minimal coal at 0.75 GW, a larger hydro presence at 2.023 GW, and modest oil gas at 1.701 GW, alongside small hydro 0.329 GW and solar 0.483 GW, reflecting a hydro led system with limited thermal dependence.

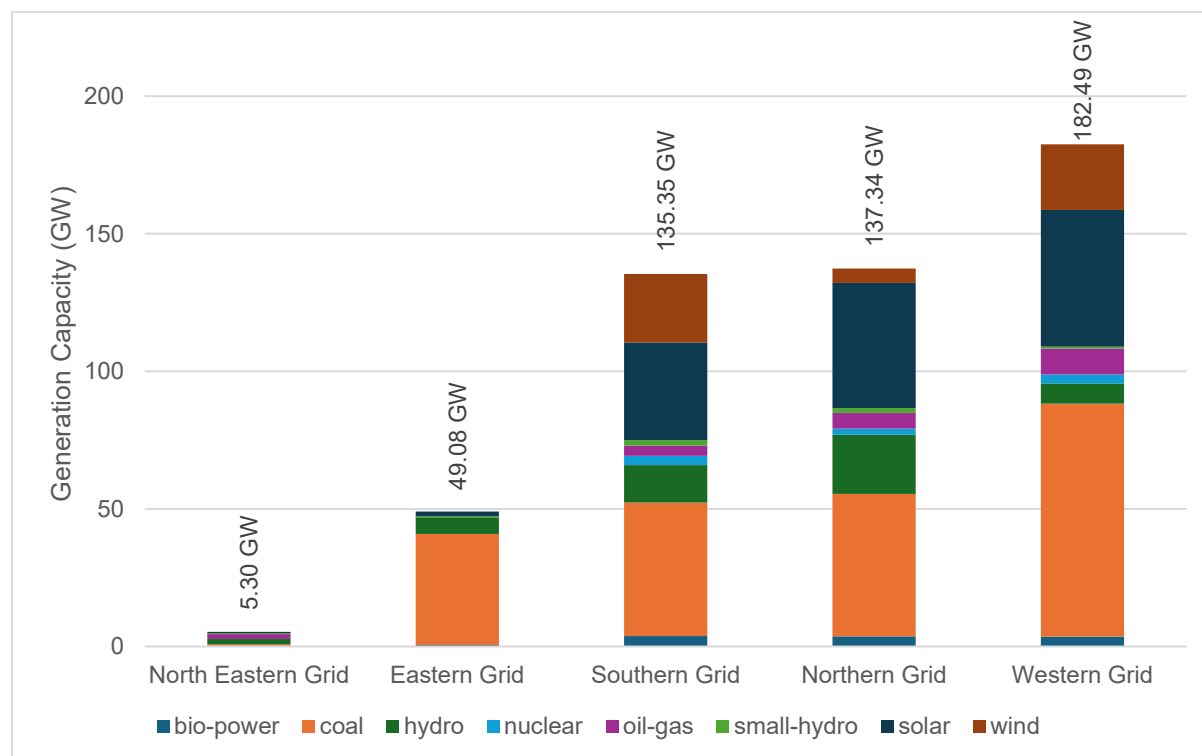


Figure 17: Generation mix of regional grids in India as of Nov 2025¹⁵

6.1.2.1 Western Regional Grid

The Western regional grid has the largest thermal backbone among the five regions, with 84.671 GW of coal capacity and 9.399 GW of oil and gas, and this dominance is clearly visible in every seasonal profile where thermal generation forms the thick base layer through all 96 time blocks as shown in Figure 18. On this base, the region's very large renewable fleet, especially 49.633 GW of solar and 23.857 GW of wind, drives the main intraday reshaping of the stack. In spring and autumn, total generation typically sits around the high 50s to mid 60s GW, and a clear solar wedge appears from late morning to afternoon, peaking around mid day and reducing the thermal share during those hours. Summer shows a flatter day shape with total generation mostly in the high 70s to low 80s GW and a moderate solar contribution through mid day, while the late evening and night blocks show a slightly thicker gas layer, indicating additional flexible support during higher demand hours. Monsoon is distinctive because wind becomes materially stronger and more sustained across the day, with the wind band staying visibly thicker than in other seasons, while solar remains present but muted, consistent with seasonal weather effects. Winter shows the strongest demand driven ramp,

¹⁵ NITI Aayog, "India Climate & Energy Dashboard", Accessed on Dec 2025. <https://iced.niti.gov.in/energy/electricity/generation/capacity>

with the stack rising sharply from roughly 50 GW in the early blocks to close to 70 GW around the daytime peak, and solar again providing the largest daytime relief to thermal generation before the system returns to thermal dominance toward evening. Across all seasons, hydro in the Western grid remains a relatively small balancing layer in these profiles despite 7.392 GW of hydro capacity, while nuclear stays nearly flat and small in magnitude. An additional feature in the Western grid profiles is the evening ramping of hydro generation, visible as a thickening of the hydro band after solar starts declining in the late afternoon and into the evening blocks. This pattern indicates that hydro is being dispatched strategically to manage the net load ramp created by the simultaneous rise in demand and fall in solar output, thereby reducing the need for an equally sharp ramp from coal and gas units.

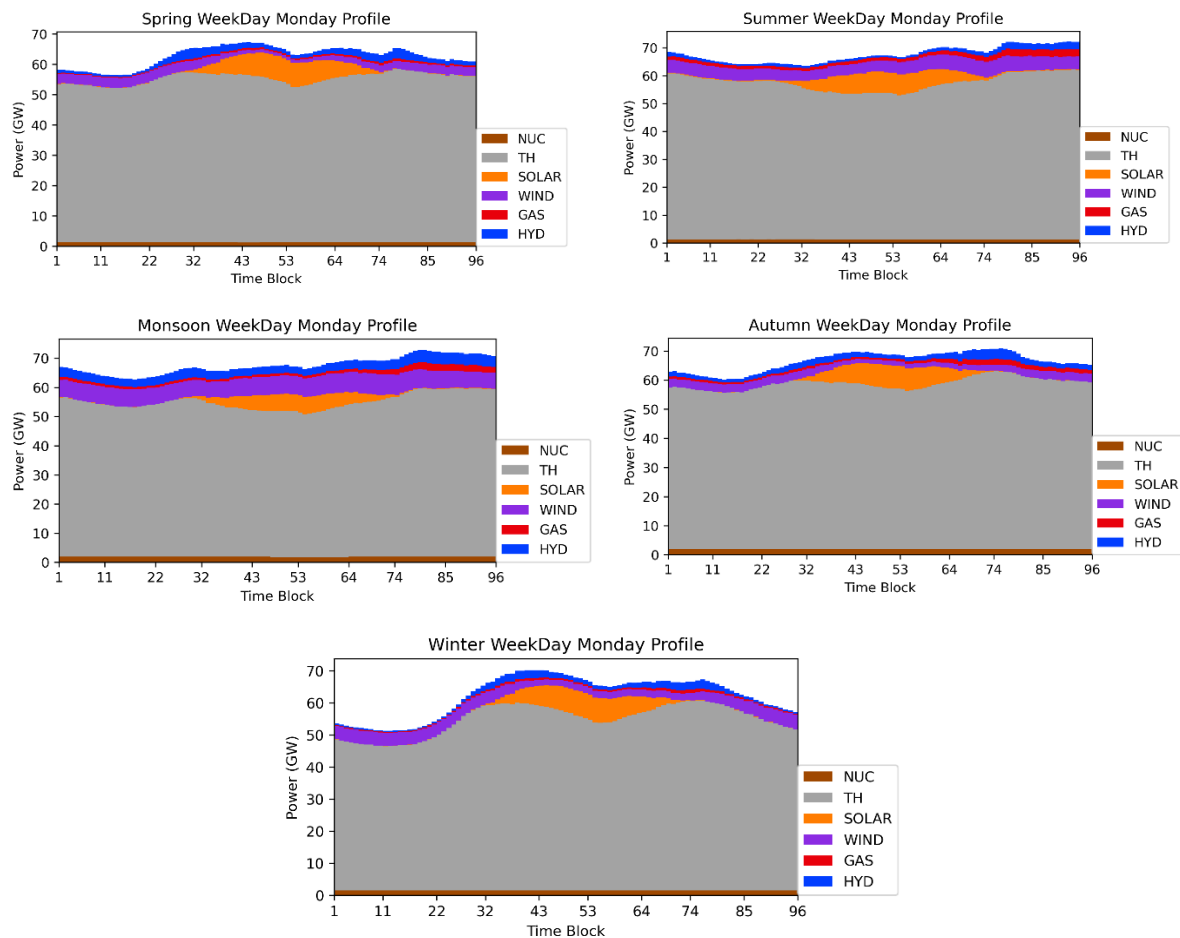


Figure 18: Western Regional Grid weekday (Monday) generation mix across five representative seasons for 2023

6.1.2.2 Northern Regional Grid

The Northern regional grid profiles show a generation mix where thermal generation remains the structural base, but hydro and solar together create some of the strongest within day shaping seen across India. Across all seasons, the thermal block sits as a relatively stable foundation through the 96 time blocks, typically around the high 20s to low 30s GW in these weekday Monday profiles, indicating that coal units carry much of the continuous load. Over this base, solar contributes to a significant demand in spring, summer, autumn, and winter,

rising sharply from late morning, peaking around the middle of the day as a broad orange wedge, and then falling rapidly toward evening, which visibly reduces the thermal share during daylight hours. Hydro plays an equally important but different role: it is consistently present through the day and then ramps up strongly in the evening after solar declines, filling the net load ramp and supporting the evening peak. This evening hydro response is visible in every season, but monsoon is particularly distinctive because hydro remains very high and sustained even outside peak hours, forming a thick blue band for most of the day, reflecting high water availability and increased dispatch flexibility. Wind remains comparatively minor in the Northern grid profiles, appearing as a thin and fairly steady layer, and gas contributes as a small balancing component that becomes more noticeable during the evening and later hours when the system needs additional flexibility. Nuclear is nearly flat and small throughout, consistent with its limited capacity in the region. Overall, the Northern grid exhibits a clear daytime relief from solar and a pronounced evening support from hydro, making its emission intensity highly sensitive to when demand occurs, especially around the post sunset ramp.

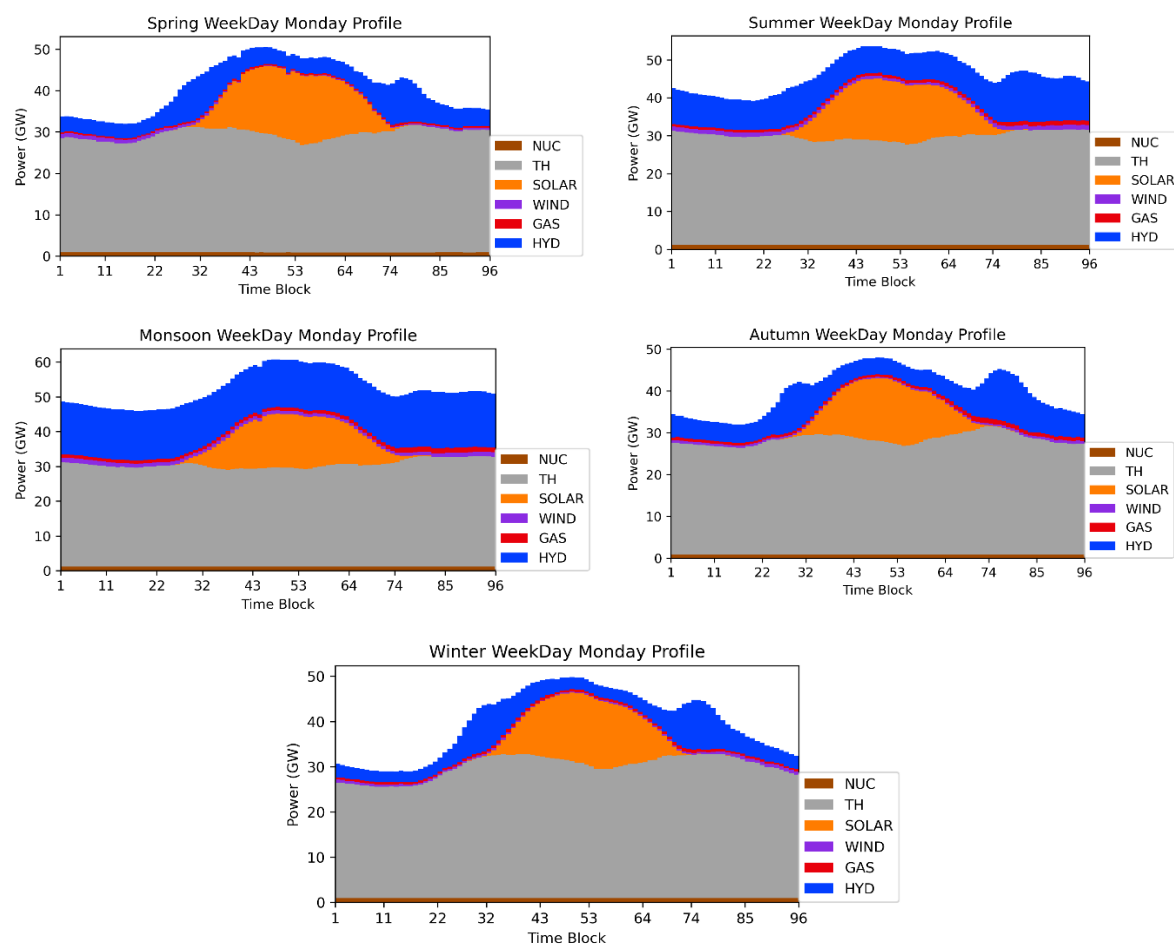
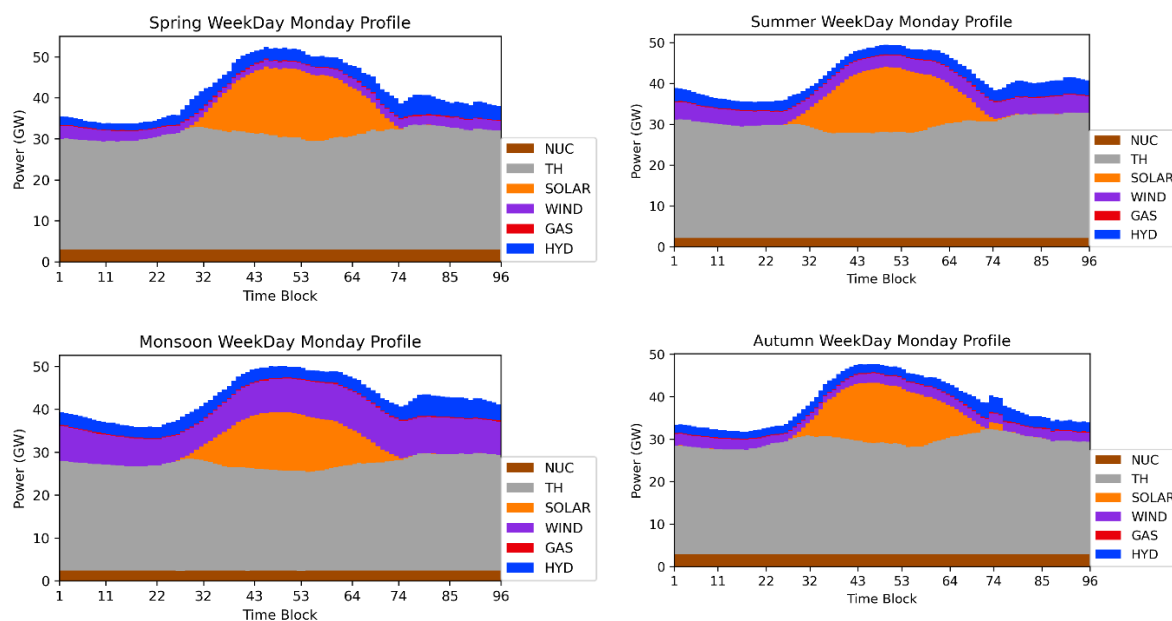


Figure 19: Northern Regional Grid Weekday (Monday) generation mix across five representative seasons for 2023

6.1.2.3 Southern Regional Grid

the Southern grid's diurnal profiles are a direct reflection of a highly diversified portfolio in which variable renewables are large enough to reshape dispatch rather than merely add a marginal layer. With 48.575 GW of coal providing the firm backbone, the grid simultaneously carries 35.416 GW of solar and 24.916 GW of wind, which explains why the solar wedge becomes prominent in spring, summer, autumn, and winter and why the wind band remains consistently visible across most time blocks, especially in monsoon when wind strengthens. The presence of 13.596 GW of hydro and 1.938 GW of small hydro provides additional flexibility for ramping support, which aligns with the observable evening hydro thickening after solar declines. Nuclear capacity of 3.32 GW appears as a flat, steady contribution across the day, consistent with baseload operation, while 3.807 GW of oil gas capacity explains the thin but responsive gas layer that becomes more noticeable during evening and late hours when the system requires fast balancing. In contrast to the Northern grid, where solar capacity is even higher at 45.479 GW but wind is much lower at 5.209 GW, the Southern grid's dual high solar and high wind capacities reduce the extent to which the post sunset ramp must be covered by thermal alone, producing a smoother transition into the evening.



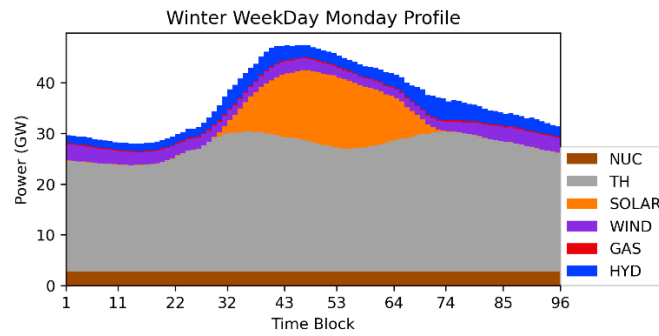
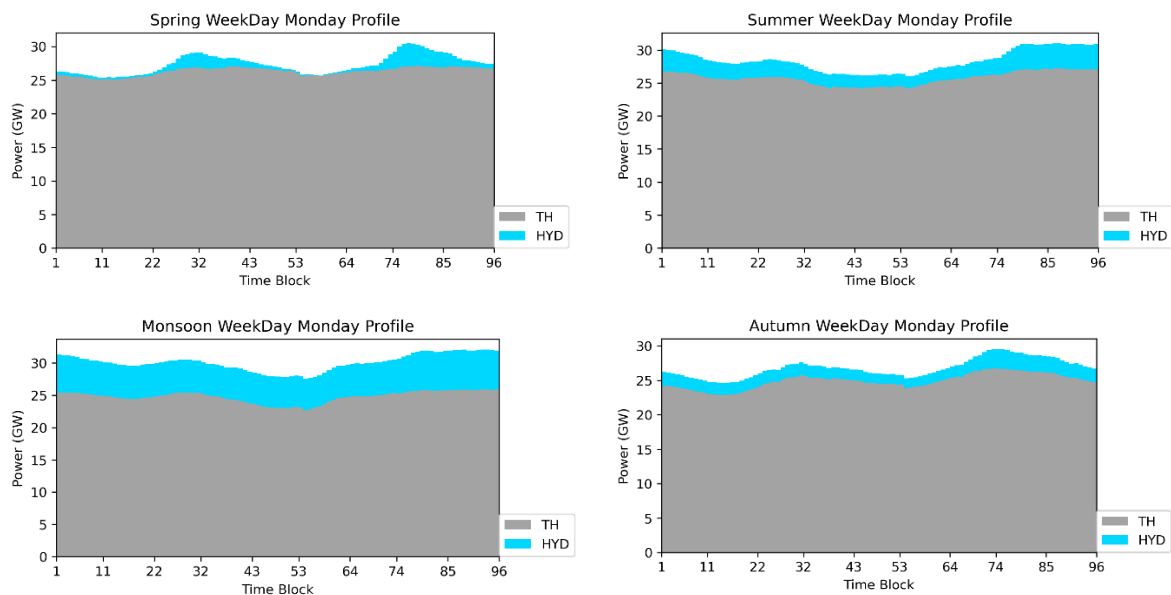


Figure 20: Southern Regional Grid Weekday (Monday) generation mix across five representative seasons for 2023

6.1.2.4 Eastern Regional Grid

the Eastern regional grid profiles are consistent with a system that is overwhelmingly coal dominated and only weakly shaped by variable renewables. The capacity table shows 40.385 GW of coal in the Eastern grid, while hydro stands at 5.988 GW and variable renewables are comparatively quite small. This composition explains why the generation stack appears largely as a thick, steady thermal block across all 96-time blocks and across seasons, with little visible midday solar wedge and only a thin wind contribution. Hydro appears as a secondary layer that can increase modestly during certain hours, particularly around the evening peak, but its magnitude remains limited relative to the coal base, so it cannot substantially reshape the net load the way it does in hydro rich regions. The result is a relatively flat dispatch structure with limited diurnal relief from renewables, implying that the grid's emission intensity remains persistently high across most hours and shows weaker daytime improvements compared to the Western, Northern, or Southern grids.



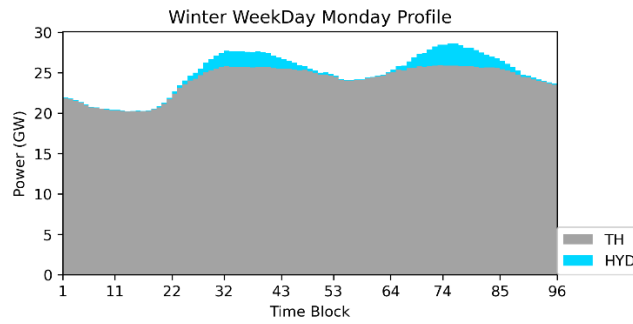
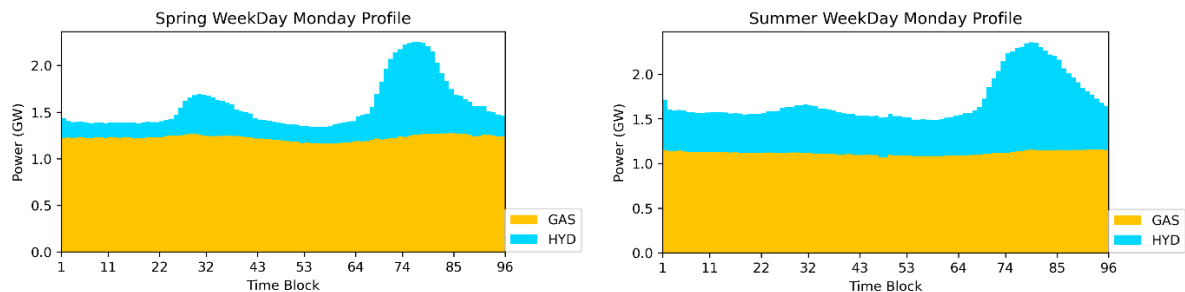


Figure 21: Eastern Regional Grid Weekday (Monday) generation mix across five representative seasons for 2023

6.1.2.5 Northeastern Regional Grid

The North Eastern grid profiles, shown here as the combined output of gas and hydro, align closely with the region's installed capacity mix, where firm generation is dominated by oil and gas capacity of 1.70096 GW and hydro resources of 2.023 GW plus 0.32935 GW of small hydro, while coal capacity is very small at 0.75 GW and solar at 0.48303 GW with negligible wind. This is why the stack is essentially split between a relatively flat gas block and a visibly flexible hydro layer that provides most of the intra day variation. Across all seasons, gas output remains close to a steady base around roughly 1.1 to 1.2 GW, indicating that gas plants are being run in a quasi baseload manner to provide continuous supply and system inertia support in a smaller grid. Hydro output, in contrast, is clearly dispatched to follow net load, with modest daytime changes and a pronounced ramp in the evening hours, peaking around the late evening blocks in spring, summer, autumn, and winter, where hydro rises sharply above its daytime level. Monsoon stands out because the hydro contribution is higher and more sustained across the entire day, consistent with increased water availability and reduced dispatch constraints, which also leads to the highest total generation among the seasons in this set of plots. The overall implication is that, unlike coal heavy regions where thermal dominates both energy and ramping, the North Eastern grid's operational flexibility and seasonal variability are primarily hydro driven, with gas providing the stable foundation and hydro absorbing the evening peak and ramping requirement.



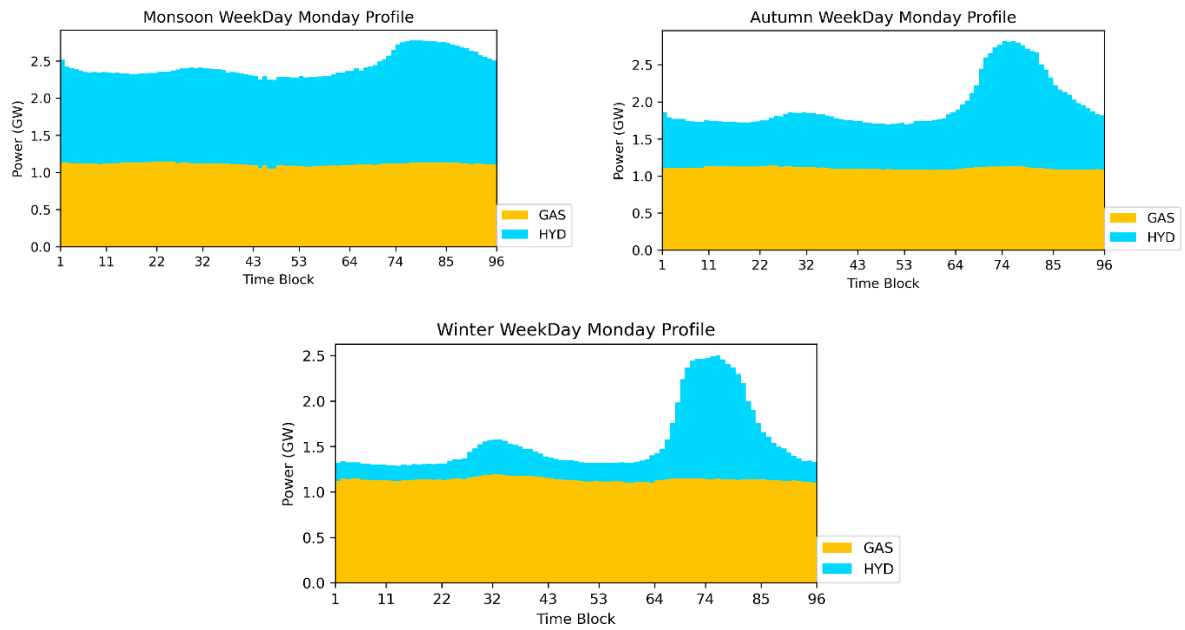


Figure 22: Northeastern Regional Grid Weekday (Monday) generation mix across five representative seasons for 2023

6.2 GRID EMISSION FACTOR

6.2.1 Average Diurnal Emission Factor of the Indian Grid

At the national level, the Indian power system is often characterised using a single average grid emission factor, typically expressed in tCO_2 per MWh. This average value provides a convenient benchmark for high level comparisons between electric vehicles and internal combustion engine vehicles. However, the results from the present analysis clearly demonstrate that such an approach masks substantial temporal and spatial variability inherent in the Indian grid.

A strong and persistent diurnal pattern is evident across all seasons and days of the week in the All India heatmap shown in Figure 23. Emission intensity is consistently lowest during the mid day window, roughly between time blocks 32 to 64, corresponding approximately to 10:00 to 16:00 hours. This period is marked by yellow to green shades, indicating reduced carbon intensity. The underlying driver of this pattern is the high contribution of solar generation during daylight hours, which displaces coal based generation at the margin across multiple regions simultaneously.

In contrast, emission intensity rises sharply during the evening, late night, and early morning hours, spanning time blocks 65 to 96 and 1 to 31. These periods are dominated by orange to red shades across nearly all seasons and days, reflecting the increased reliance on coal fired power plants in the absence of solar generation. This diurnal contrast persists regardless of whether the day is a weekday or a weekend, indicating that generation mix effects dominate over modest demand variations.

The All India heatmap shows that the difference between the cleanest and most carbon intensive hours can be substantial, approaching nearly a twofold variation within the same day. This has direct implications for EV emission accounting, as charging during night time off peak hours may be associated with significantly higher emissions than charging during mid day solar rich periods.

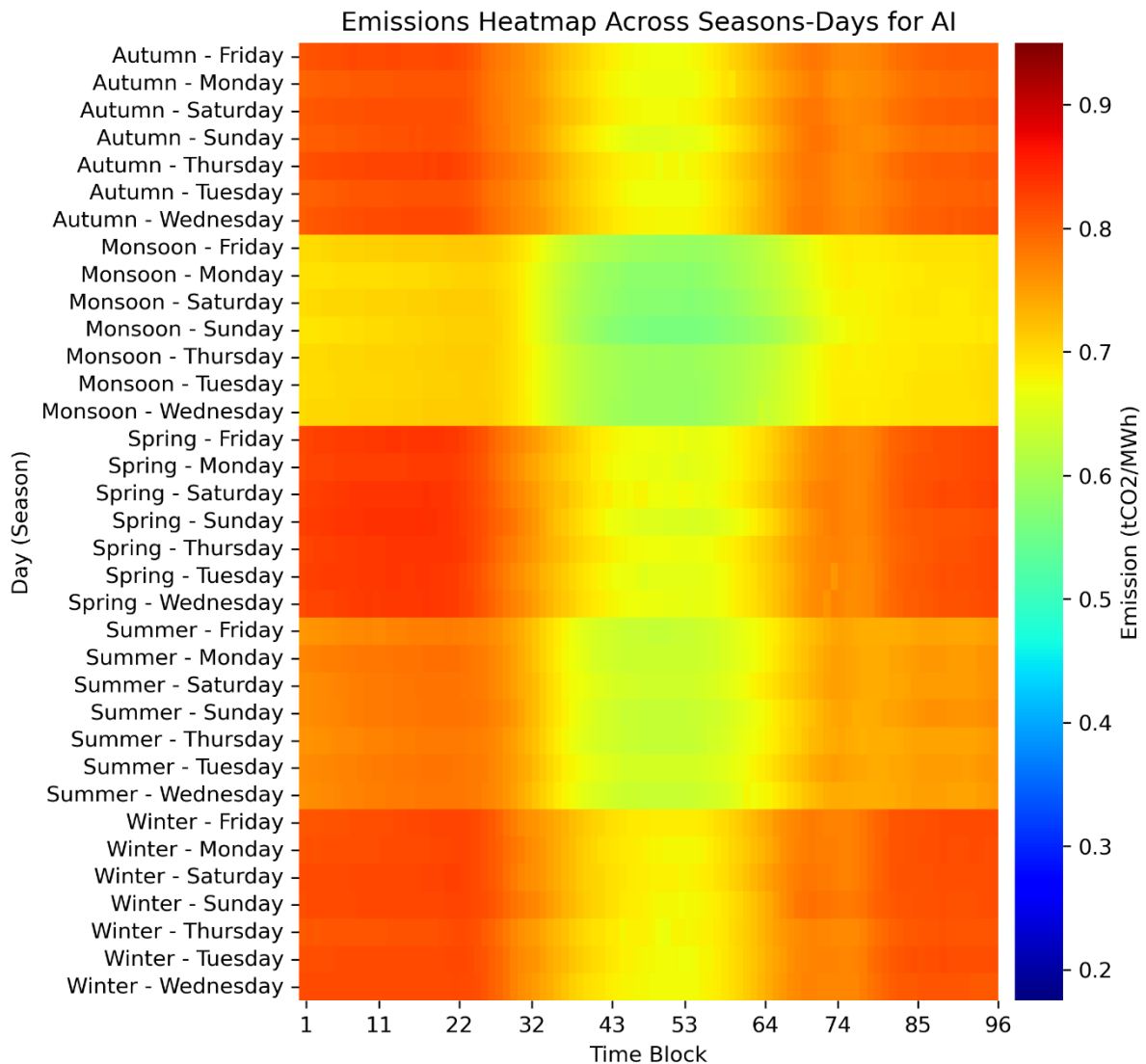


Figure 23: Heatmap showing the average diurnal and seasonal variation of grid emission factor

6.2.2 Regional Emission Factors

Figure 24 illustrates the weekday diurnal emission factor profiles of India's regional grids based on actual 2023 dispatch data from GRID-INDIA. Clear regional contrasts are observed in both absolute emission levels and intra day variability, reflecting differences in generation mix and renewable penetration.

6.2.2.1 Northern Region (NR)

The Northern grid displays one of the higher diurnal variability among all regions. Emission factors decline sharply from morning levels of around 0.75–0.80 tCO₂/MWh to mid day minima

of 0.50–0.55 tCO₂/MWh, driven by substantial solar generation. However, this benefit is reversed rapidly during evening and night hours, where emission factors rise back to 0.75–0.80 tCO₂/MWh, indicating strong coal ramp up. This pronounced swing makes charging time particularly critical in the Northern region.

6.2.2.2 Eastern Region (ER)

The Eastern grid exhibits the highest emission factors among all regions, with values remaining consistently high throughout the day. Emission factors range approximately from 0.85 to 0.95 tCO₂/MWh, indicating a strong dependence on coal based generation.

6.2.2.3 Western Region (WR)

The Western grid shows moderate emission intensity with limited diurnal spread, ranging from about 0.72 to 0.85 tCO₂/MWh. A visible mid day reduction is observed around noon, though the absolute reduction remains modest compared to the Southern grid. The relatively flat profile suggests a diversified mix with coal remaining marginal during most hours, despite growing solar capacity.

6.2.2.4 Southern Region (SR)

The Southern grid consistently records low to moderate emission factors, with values typically ranging between 0.45 and 0.75 tCO₂/MWh. A deep and sustained mid day trough is observed, reaching close to 0.45 tCO₂/MWh, reflecting high solar and hydro contribution. Even during evening peaks, emission factors remain lower than coal dominant regions, underscoring the comparatively cleaner generation mix of the Southern grid.

6.2.2.5 North Eastern Region (NER)

The North Eastern grid exhibits the lowest emission factors nationally, with values mostly confined between 0.18 and 0.35 tCO₂/MWh. Emission intensity remains low throughout the day due to the dominance of hydroelectric generation. While a slight evening increase is visible, the overall profile remains substantially cleaner than other regions, making the North East the most favourable region for EV charging from an emissions perspective under current grid conditions.

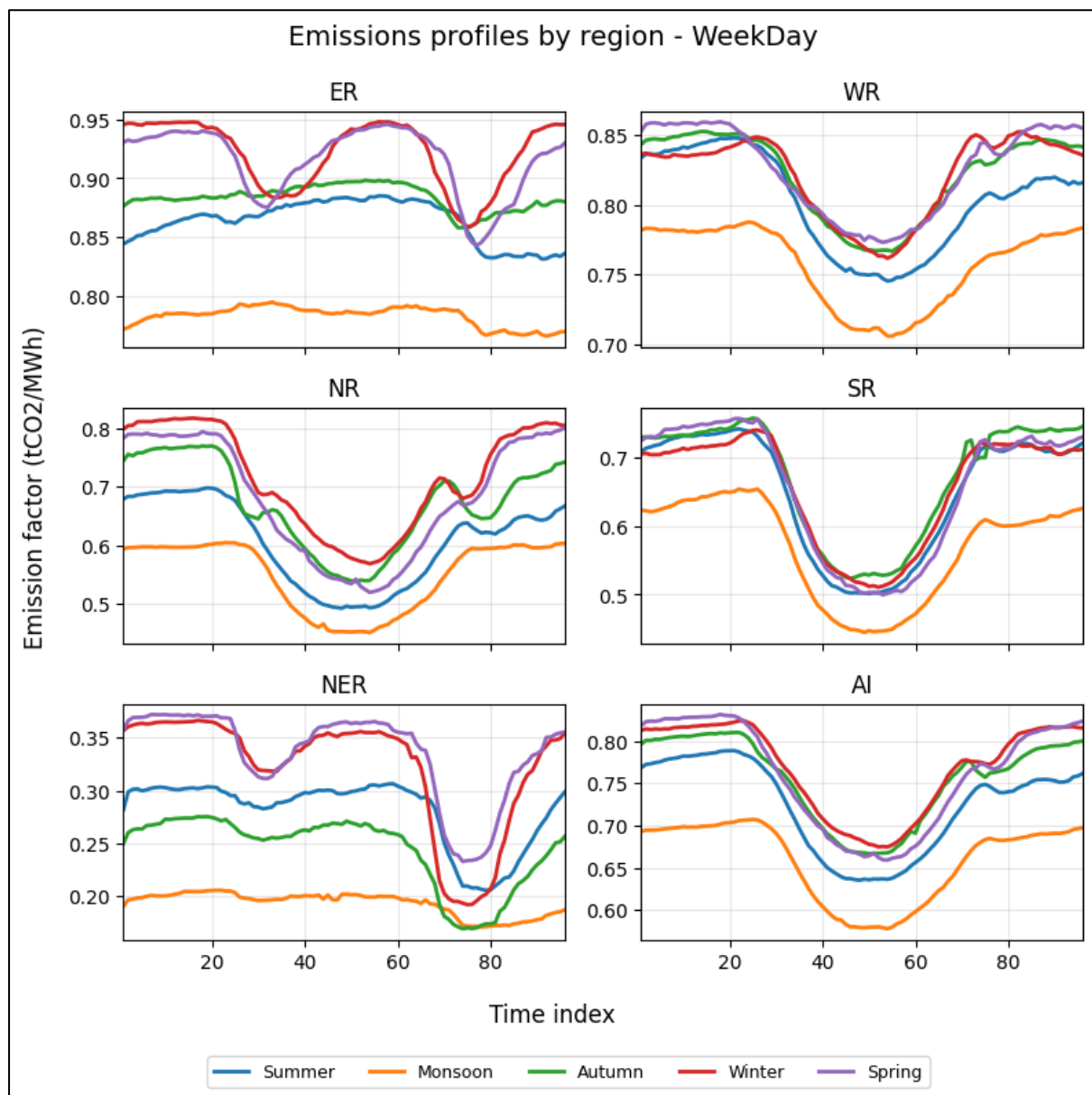


Figure 24: Time varying emission factors of Indian regional grids (Weekday)

7 ESTIMATION OF ENERGY REQUIREMENT BY THE INDIAN EV FLEET

To estimate electricity demand from different electric vehicle categories, each vehicle class is parameterised using representative activity, efficiency, battery, and charging characteristics. These parameters are used consistently across the regional demand analysis and subsequent charging and grid impact studies.

Daily electricity consumption is derived from the product of average daily distance travelled and vehicle class specific energy intensity as mentioned in Section 5.1.1.

Table 1: Vehicle category assumptions used in the analysis

Vehicle category	Use type	Daily distance (km per day)	Energy intensity (kWh per km)	Battery capacity (kWh)
2W	Private	28 ¹⁶	0.035 ¹⁷	3
2W	Commercial	50 ¹⁶	0.035 ¹⁷	3
3W	Commercial	60 ¹⁸	0.065 ¹⁹	8
LPV	Private	35 ¹⁸	0.175 ¹⁷	45
LPV	Commercial	140 ¹⁸	0.175 ¹⁷	45
LGV	Commercial	80 ¹⁸	0.250 ²⁰	45
MPV	Commercial	130 ¹⁸	0.600 ²²	90
MGV	Commercial	130 ¹⁸	0.650 ²²	120
HPV	Commercial	200 ²¹	1.000 ²²	300
HGV	Commercial	300 ²¹	1.300 ²³	350

Notes on assumptions

- Private usage is assumed only for two-wheelers, three-wheelers, and light passenger vehicles. Commercial usage dominates for freight vehicles, buses, and medium and heavy goods vehicles.
- Energy intensity values are based on published literature, fleet reports, and manufacturer disclosures, as cited in the corresponding references.

¹⁶ Akhilesh Sati, Lydia Powell, Vinod Kumar Tomar, "Road emission control: Electrifying personal mobility in India". Observer Research Foundation. 2021

¹⁷ S. A. Mandavgane and A. B. Mandavgane, "Vehicle energy consumption and emission modeling of electric two-wheelers in Indian cities," Applied Energy, vol. 124, pp. 95–103, 2014

¹⁸ International Council on Clean Transportation (ICCT). "A case study of Pimpri-Chinchwad, India" 2024

¹⁹ EV Reporter, "Top electric 3W cargo vehicles (L5)". Retrieved February 2, 2026, from <https://evreporter.com/top-electric-3w-cargo-vehicles-l5>

²⁰ FEST Auto, "Driving green: Understanding energy consumption of electric vans" 2023. Retrieved February 2, 2026, from <https://www.linkedin.com/pulse/driving-green-understanding-energy-consumption-electric-vans/>

²¹ International Transport Forum, "A pathway to zero-emissions trucking in India", International Transport Forum Policy Papers, OECD Publishing, Paris. 2024

²² IITB Analysis

²³ Christian Mascarenhas, "From real operation: consumption values of electric trucks in special applications" Designwerk AG, 2025. Retrieved February 2, 2026, from <https://www.designwerk.com/en/post/e-truck/from-real-operation-consumption-values-of-electric-trucks-in-special-applications/>

7.1 DAILY ENERGY REQUIREMENT

This section quantifies the electricity demand imposed on the power system by different electric vehicle fleets across India. It estimates the energy requirement by disaggregating the national EV stock into vehicle categories and regions, and linking fleet size, daily vehicle kilometres travelled, and technology specific energy consumption rates. By explicitly accounting for ownership patterns, participation factors, and regional system losses, the analysis derives realistic estimates of daily and aggregate electricity demand attributable to EV adoption. This fleet level energy requirement forms a critical input to the subsequent charging load modelling and emission assessment, as it establishes the magnitude and spatial distribution of EV induced electricity demand that interacts with the underlying generation mix and time varying grid conditions.

Figure 25 presents the estimated daily electricity requirement of the EV fleet, disaggregated by vehicle category and use type (private and commercial) and day type (weekday and weekend) across India and the five regional grids. The values shown represent aggregate daily energy demand in kWh and capture the combined effects of fleet size, utilisation intensity, and vehicle specific energy consumption.



Figure 25: Daily electricity requirement of the EV fleet, disaggregated by vehicle category and use type (private vs commercial) across India and individual regional grids

At the national level, commercial fleets dominate EV electricity demand across all major vehicle categories and on both weekdays and weekends. Commercial three wheelers account for the largest share, with a weekday demand of approximately 4.94 GWh and a weekend demand of 3.09 GWh, reflecting reduced activity during weekends but continued high utilisation. Light passenger vehicles also contribute substantially, with weekday demand of 0.77 GWh for commercial use and 0.69 GWh for private use, declining to 0.53 GWh and 0.49 GWh, respectively, on weekends. Private two wheelers contribute 1.28 GWh on weekdays and 0.91 GWh on weekends, while commercial two wheelers account for 0.25 GWh and 0.18 GWh, indicating a clear weekday peak driven by commuting and commercial activity.

Heavy vehicle categories, although smaller in fleet size, impose significant electricity demand due to their high energy intensity. Commercial heavy passenger vehicles require approximately 1.36 GWh per day, with similar values observed on weekdays and weekends, reflecting relatively inelastic public transport demand. Heavy goods vehicles contribute around 0.21 GWh per day, while medium passenger and goods vehicle categories remain below 0.01 GWh, even on weekdays.

Strong regional heterogeneity is evident. The Northern grid exhibits the highest EV electricity demand among regions, driven largely by commercial activity. Commercial three wheelers consume approximately 2.74 GWh on weekdays and 1.72 GWh on weekends, while commercial heavy passenger vehicles require 0.52 GWh on both day types. Light passenger vehicles show balanced contributions from private and commercial fleets, with weekday demand of 0.15–0.16 GWh, declining moderately on weekends.

The Western grid also shows substantial demand across multiple categories. Commercial three wheelers consume 0.60 GWh on weekdays and 0.38 GWh on weekends, while private two wheelers account for 0.54 GWh on weekdays and 0.39 GWh on weekends. Commercial heavy passenger vehicles in the West contribute approximately 0.47 GWh per day, highlighting the importance of electric buses and shared mobility services in the region.

In the Southern grid, EV energy demand is more evenly distributed across vehicle categories. Commercial LPVs consume 0.27 GWh on weekdays and 0.19 GWh on weekends, closely matched by private LPVs at 0.25 GWh and 0.18 GWh, respectively. Private two wheelers contribute 0.46 GWh on weekdays and 0.33 GWh on weekends, indicating widespread electrification across personal mobility categories. Heavy passenger vehicles add approximately 0.31 GWh per day, with limited weekday weekend variation.

The Eastern grid is dominated by commercial three wheelers, which require 0.96 GWh on weekdays and 0.60 GWh on weekends. Private vehicle demand across most categories remains relatively small, with private two wheelers consuming 0.10 GWh on weekdays and 0.07 GWh on weekends, reflecting lower private EV penetration.

The North Eastern region exhibits the lowest EV electricity demand across all vehicle categories. Commercial three wheelers contribute 0.51 GWh on weekdays and 0.32 GWh on weekends, while most other categories remain below 0.02 GWh, consistent with lower adoption levels and shorter daily travel distances.

7.2 CHARGING LOAD PROFILES

The EV charging load profiles exhibit pronounced temporal and regional variations, driven by differences in fleet composition, usage patterns, and dominant vehicle categories as shown in Figure 26.



Figure 26: Weekday EV charging load profiles for India and regional grids, showing the aggregate charging power contribution of different vehicle categories across 24 hours.

At the national level, EV charging demand shows a clear bimodal structure. At the national level, aggregate EV charging demand reaches a night-time peak exceeding 500 MW during the early morning hours (00:00–02:00), primarily driven by commercial three wheelers (3W), private 2 wheeler and 4 wheeler and heavy passenger vehicles (HPV) charging after daily operations. A second, broader peak appears around midday (11:00–14:00), reflecting

opportunity charging and depot based charging for commercial fleets. An evening rise is observed post 18:00, coinciding with return of private vehicles. Across all hours, 3W charging dominates total load, followed by LPVs and HPVs, while goods vehicles contribute marginally.

In the Northern region, peak EV charging load around 221 MW, with a dominant midday peak driven almost entirely by commercial three wheelers and buses. This aligns with the region's high daily energy requirement for commercial fleets, where 3W and HPV categories account for a substantial share of total demand. The Western region exhibits peak loads of approximately 143 MW, occurring during both late-night hours. Unlike the North, the West shows a more distributed charging profile, with significant contributions from private 2W and LPVs in addition to commercial fleets. This reflects the region's diversified energy demand, where private vehicle usage contributes meaningfully to the total daily energy requirement alongside commercial operations.

In the Southern region, peak charging loads remain lower, around 90–100 MW, with a pronounced night-time peak and a moderate midday rise. This pattern mirrors the region's daily energy requirement, which is spread more evenly across private and commercial vehicle categories. The dominance of private 2W and LPV charging suggests home-based overnight charging as a key driver of peak demand. The Eastern region shows the lowest absolute peak, approximately 70–75 MW. Charging peaks are closely aligned with commercial three wheeler operations, consistent with the region's daily energy requirement being overwhelmingly dominated by 3W fleets. Limited private vehicle penetration results in lower night-time charging and more pronounced activity-linked peaks.

Overall, the observed peak charging loads are a direct manifestation of daily energy requirements shaped by vehicle usage intensity rather than fleet size alone. Commercial fleets with high daily mileage and energy demand not only dominate total electricity consumption but also drive sharp daytime and midday peaks, while private fleets contribute to smoother night-time and evening loads. These findings underline the importance of aligning charging strategies with vehicle usage characteristics to manage peak demand, integrate renewable generation, and minimise grid stress.

8 EMISSION ESTIMATION FROM EVs

This section presents the results of the high resolution emissions assessment for electric vehicle charging, derived by coupling EV electricity demand with time varying grid carbon intensity. The results are reported across India and its five regional grids, considering multiple vehicle categories, ownership patterns, and charging behaviours²⁴. Emissions are evaluated at fine temporal resolution, allowing the impact of time of charging, seasonal renewable availability, and regional generation mix to be systematically examined. This approach enables a direct comparison of emission outcomes across regions and fleet types, and facilitates an assessment of the conditions under which EV adoption delivers net emission reductions relative to internal combustion engine vehicles.

8.1 NATIONAL EV EMISSION ESTIMATION

Figure 27 presents the diurnal profile of daily EV related CO₂ emissions for India across five representative seasons, distinguishing between weekday and weekend charging, along with the contribution of different vehicle fleets to total annual emissions.

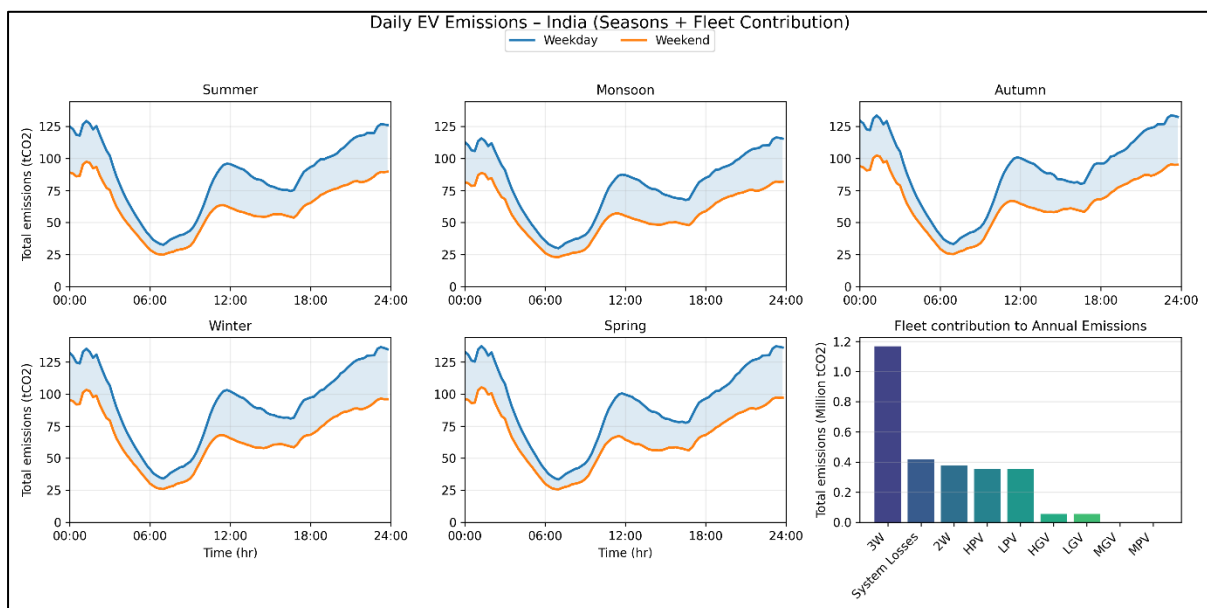


Figure 27: Diurnal variation of national EV related CO₂ emissions across five representative seasons (summer, monsoon, autumn, winter, and spring), showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions.

Across all seasons, daily EV emissions show a strong and consistent diurnal pattern. On weekdays, emissions peak during late night and early morning hours, reaching approximately 120–135 tCO₂ between 20:00 and 03:00, depending on the season. In contrast, the lowest

²⁴ It is assumed that, within a given region, the shape of the EV charging profile remains unchanged across seasons and varies only by type of day (weekday or weekend). Seasonal variation in emissions therefore arises exclusively from changes in grid generation mix and carbon intensity, rather than from seasonal shifts in charging behaviour. This assumption allows a clear isolation of power sector effects on EV emissions while retaining behavioural differentiation between weekday and weekend charging patterns.

emissions occur during early morning to mid day hours. Across seasons, the minimum weekday emissions fall to about 30–40 tCO₂ around 06:00–08:00, representing a reduction of nearly 70–75% relative to night time peaks. Weekend emission profiles follow the same temporal shape but at a consistently lower magnitude. Peak weekend emissions remain below 95–100 tCO₂ during night hours and fall to approximately 25–30 tCO₂ during the mid day minimum.

Seasonal variation in emission magnitude is clearly observable. Winter and autumn exhibit the highest emissions, with weekday night time peaks approaching 125–130 tCO₂, while monsoon and spring show comparatively lower peaks, limited to around 110–120 tCO₂. Early morning emissions during the monsoon are consistently the lowest across the year, dropping close to 30 tCO₂, whereas winter mid day emissions remain slightly higher at around 35–40 tCO₂. These differences directly reflect seasonal changes in grid carbon intensity rather than changes in charging behaviour, as the charging profile shape is held constant across seasons.

The fleet wise contribution to annual EV emissions shows a highly skewed distribution dominated by a few categories. Three wheelers (3W) contribute the largest share, at approximately 1.15 million tCO₂ per year, making them the single most important driver of national EV charging emissions. The next largest component is system losses, contributing about 0.4–0.45 million tCO₂ annually. This is a notable result because system losses are often omitted in EV emissions accounting, yet in this case they represent a contribution comparable to major vehicle categories and therefore materially affect national level estimates. Among vehicle categories, two wheelers (2W), heavy passenger vehicles (HPV), and light passenger vehicles (LPV) each contribute on the order of 0.3–0.4 million tCO₂ per year, indicating that emissions are concentrated in high volume and high utilisation categories even when per vehicle energy use is lower than heavy duty categories. In contrast, freight and medium duty categories contribute much less at the national scale: heavy goods vehicles (HGV) and light goods vehicles (LGV) remain below roughly 0.1 million tCO₂ annually.

8.2 REGIONAL EV EMISSION ESTIMATES

This subsection presents region wise estimates of EV related CO₂ emissions across India's five regional grids, explicitly accounting for differences in grid generation mix, carbon intensity, and EV penetration.

8.2.1 Northern Regional Grid

Across all seasons, the Northern regional grid exhibits a pronounced diurnal pattern in EV related emissions, with weekday peaks reaching around 45–52 tCO₂ during night and late evening hours (00:00–03:00 and 20:00–24:00) as shown in Figure 28. Emissions consistently drop to their minimum during early morning hours, reaching about 8–12 tCO₂ around 06:00–08:00, indicating a reduction of nearly 75–80% relative to peak values. Weekend emissions follow the same temporal shape but remain lower by approximately 8–12 tCO₂ across most

hours, reflecting reduced charging demand rather than a shift in charging timing. Seasonal differences are evident, with winter and autumn showing the highest emission levels, while monsoon exhibits the lowest emissions throughout the day, consistent with lower grid emission intensity during that season.

The fleet wise contribution highlights that three wheelers (3W) dominate EV emissions in the Northern region, contributing approximately 0.55–0.6 million tCO₂ annually. System losses form the second largest component, at around 0.15–0.18 million tCO₂, underscoring their significance in regional emission accounting. Light passenger vehicles (LPV) and heavy passenger vehicles (HPV) contribute moderately, each below 0.15 million tCO₂, while two wheelers (2W) and goods vehicles (LGV, HGV, MGV) contribute marginally. Overall, the results indicate that high grid carbon intensity combined with large active fleets makes the Northern region one of the highest contributors to national EV emissions.

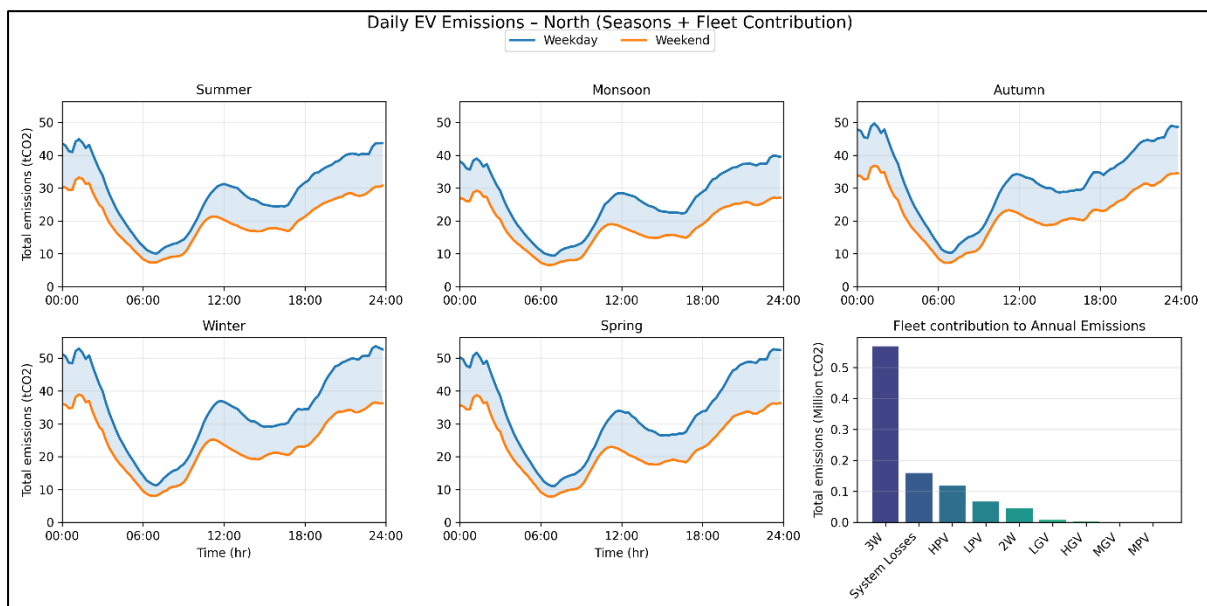


Figure 28: Diurnal variation of EV related CO₂ emissions in the Northern regional grid across five representative seasons, showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions

8.2.2 Southern Regional Grid

In the Southern grid, the diurnal emissions pattern in Figure 29 is best interpreted in the context of the underlying charging requirement, which is dominated by private vehicle energy demand, particularly 2W and LPV. This dominance is reflected in the fleet contribution bar chart shown in Figure 29, where 2W (≈ 0.12 million tCO₂) and LPV (≈ 0.11 million tCO₂) together account for the majority of annual EV emissions, followed by commercial HPV (≈ 0.07 million tCO₂) and system losses (≈ 0.05 million tCO₂). Because most charging energy comes from these private categories, the temporal shape of emissions is largely governed by when home based charging occurs and how that charging aligns with the Southern grid's relatively cleaner generation mix.

Consistent with this charging driven demand profile, emissions rise during periods of higher aggregate charging and higher marginal grid intensity, and fall during lower demand periods. On weekdays, total EV emissions peak at roughly 18–21 tCO₂ during late night and end of day hours (00:00–03:00 and 20:00–24:00), and drop to about 4–6 tCO₂ around 06:00–08:00. Weekend emissions follow the same pattern but remain lower by about 3–5 tCO₂ across most hours, consistent with reduced total charging energy requirement on weekends rather than a shift in charging timing. Seasonal differences are comparatively modest, with monsoon and spring showing the lowest emissions and winter and autumn slightly higher peaks.

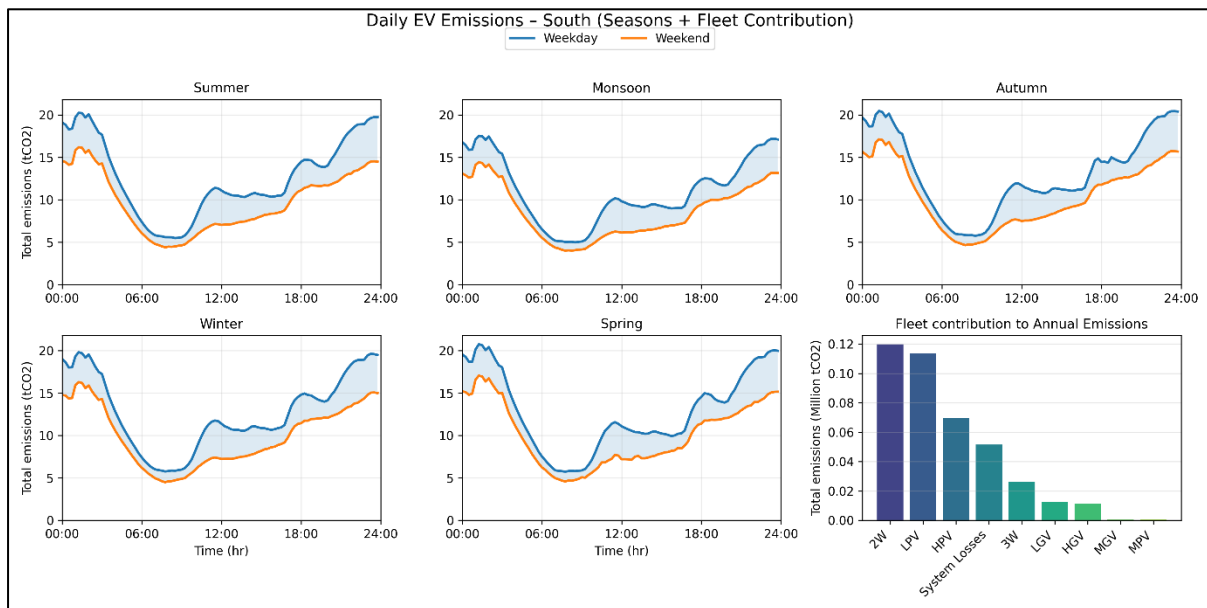


Figure 29: Diurnal variation of EV related CO₂ emissions in the Southern regional grid across five representative seasons, showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions

8.2.3 Western Regional Grid

For the Western regional grid, the EV emission profiles closely follow the structure of the underlying charging load and the distribution of energy demand across vehicle categories shown in Figure 26. As seen in the weekday charging profile, private vehicle categories dominate total charging power, with 2W, 3W, and LPV together forming the bulk of the aggregate load throughout the day, while HPV contributes a pronounced mid day and afternoon peak. This charging structure is consistent with the energy requirement heatmap shown in Figure 25, where the Western region shows high daily energy demand from 3W (≈ 0.60 GWh weekday commercial) and 2W (≈ 0.54 GWh weekday private), followed by LPV (≈ 0.25 – 0.27 GWh) and HPV (≈ 0.47 GWh).

In line with this charging driven demand, daily EV emissions in the Western grid peak at approximately 32–36 tCO₂ during late night and evening hours on weekdays, and fall to around 8–10 tCO₂ during early morning hours (06:00–08:00) as shown in Figure 30. Weekend emissions remain consistently lower by about 6–8 tCO₂, reflecting reduced total energy demand rather than a shift in charging timing. Seasonal variation is moderate, with winter and

autumn exhibiting the highest emission peaks, while monsoon shows slightly lower emissions, despite similar charging profiles, due to a cleaner generation mix. The fleet contribution plot further confirms that 2W and 3W are the largest contributors to annual EV emissions in the Western region, followed by LPV, HPV, and system losses, whereas LGV, HGV, MGW, and MPV contribute marginally, despite their higher per vehicle energy intensity. Overall, the Western region illustrates how emissions are governed by the interaction of high private and para transit energy demand with time varying grid carbon intensity, rather than by heavy duty vehicle

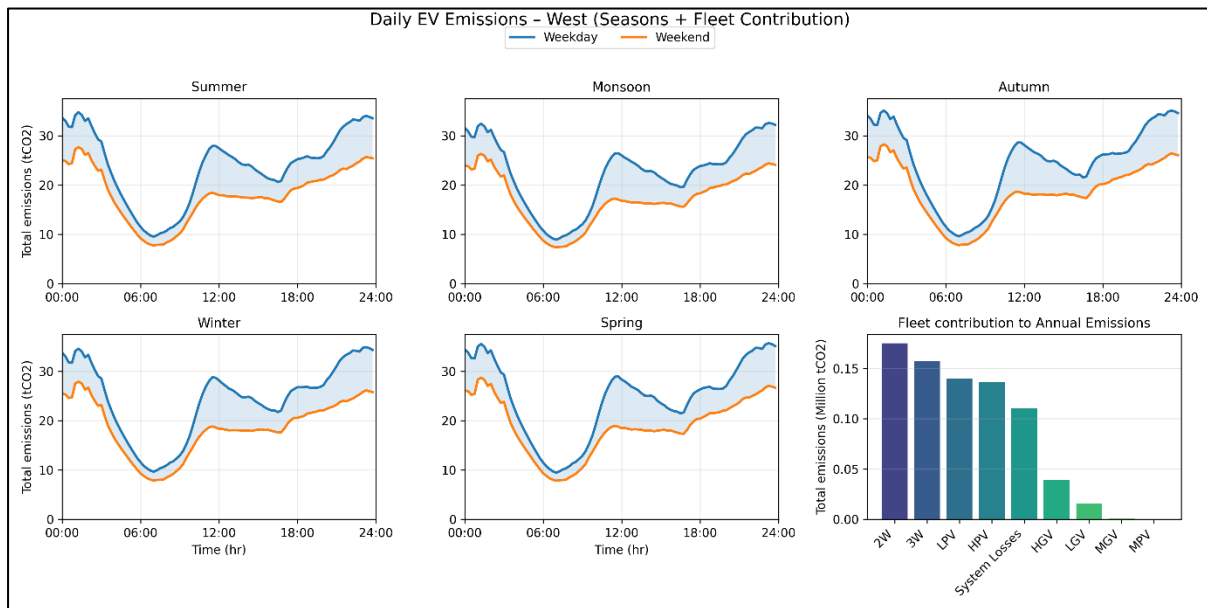


Figure 30: Diurnal variation of EV related CO₂ emissions in the Western regional grid across five representative seasons, showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions

8.2.4 Eastern Regional Grid

For the Eastern regional grid, EV emission patterns are strongly shaped by the dominance of three wheelers in both charging load and total energy requirement, coupled with the most coal intensive generation mix among India's regional grids and relatively high system losses. Reflecting this charging driven demand, daily EV emissions in the Eastern region peak at approximately 18–21 tCO₂ during late night and evening hours on weekdays and fall to around 4–6 tCO₂ during early morning hours (06:00–08:00). Weekend emissions follow the same diurnal pattern but remain lower by roughly 4–6 tCO₂, consistent with reduced commercial activity. Seasonal variation is visible but modest compared to regional differences, with winter and autumn exhibiting slightly higher emissions than monsoon and spring. The fleet contribution plot further highlights that 3W dominates annual EV emissions (≈0.27 million tCO₂), followed by system losses (≈0.08 million tCO₂) and LPV, while goods vehicles and heavy passenger vehicles contribute marginally. This highlights that, in addition to a coal heavy generation mix, high transmission and distribution losses further amplify EV related emissions in the Eastern grid.

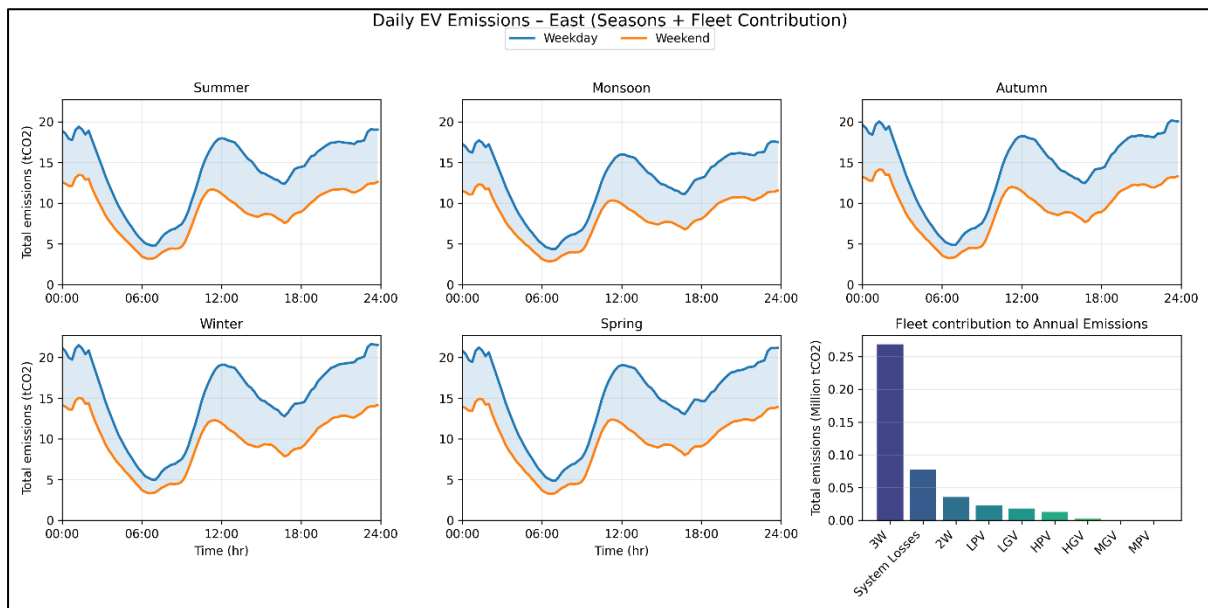


Figure 31: Diurnal variation of EV related CO₂ emissions in the Eastern regional grid across five representative seasons, showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions

8.2.5 North-Eastern Regional Grid

For the North Eastern regional grid, EV emissions remain an order of magnitude lower than other regions, reflecting both low absolute EV energy demand and a relatively clean generation mix dominated by hydro resources. The daily emission profiles show modest weekday peaks of only 2.5–3.2 tCO₂ during late night and evening hours, with minima dropping to around 0.4–0.6 tCO₂ during early morning hours (06:00–08:00). Weekend emissions follow the same diurnal shape but are lower by roughly 0.5–0.8 tCO₂, consistent with reduced vehicle activity. Seasonal variation is visible but limited in magnitude, with winter and spring showing slightly higher mid day peaks, indicating that even with similar charging patterns, emissions remain low due to the underlying grid characteristics.

The low emission levels are directly explained by the regional charging requirement and fleet composition. The fleet contribution analysis shows that 3W accounts for the largest share of annual EV emissions (≈0.045 million tCO₂), followed by system losses (≈0.01 million tCO₂) and HPV, with all other vehicle categories contributing negligibly.

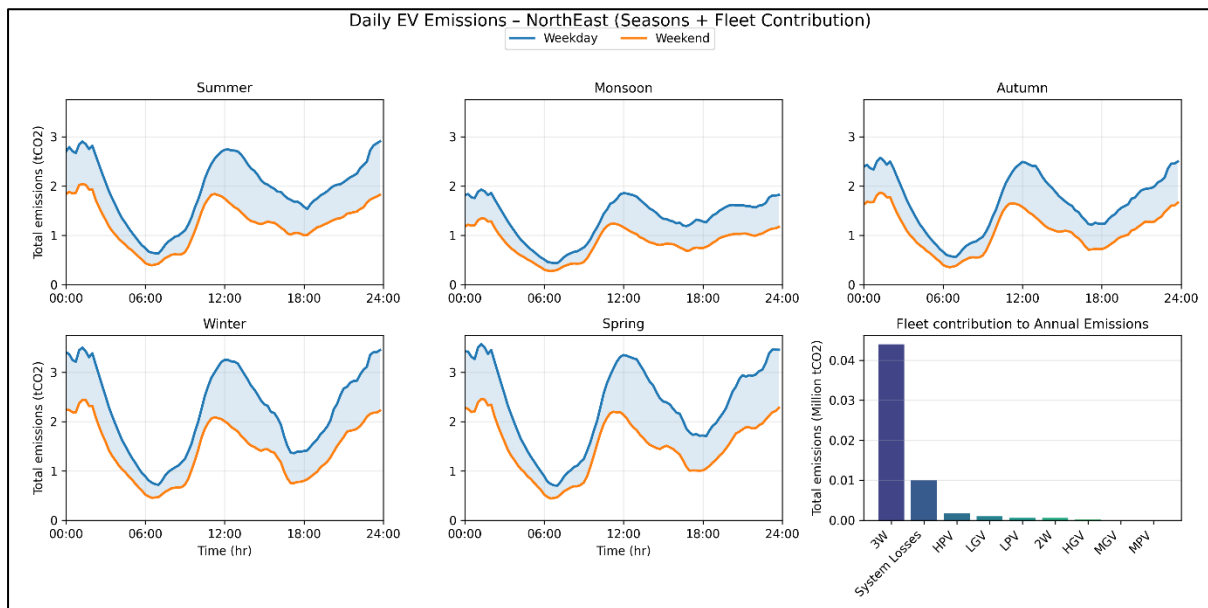


Figure 32: Diurnal variation of EV related CO₂ emissions in the North-Eastern regional grid across five representative seasons, showing weekday and weekend charging profiles, along with fleet wise contribution to total annual EV emissions

8.2.6 Summary

Figure 33 provides a consolidated summary of EV related CO₂ emissions across regions, seasons, day types, and vehicle fleets, and effectively captures the key findings of this chapter. A clear regional hierarchy emerges. The Northern grid consistently records the highest EV emissions across all seasons and day types, driven by a combination of high EV activity and a coal dominated generation mix. The Western grid follows, with moderately high emissions reflecting substantial charging demand from private and para transit fleets. The Southern and North Eastern grids exhibit significantly lower emissions, highlighting the strong mitigating role of cleaner generation mixes dominated by hydro and renewables.

Across all regions, weekday emissions are systematically higher than weekend emissions, reflecting higher aggregate charging energy rather than changes in charging timing. Seasonal variation is evident but secondary to regional effects: monsoon and spring generally show lower emissions, while winter and autumn exhibit higher totals, particularly in coal intensive regions. From a fleet perspective, three wheelers and light passenger vehicles dominate emissions in most regions, underscoring the importance of high utilisation fleets, while heavy vehicle categories contribute comparatively less at the aggregate level despite higher per vehicle energy intensity. Importantly, system losses form a visible and non negligible component of total emissions across all regions, reinforcing that neglecting network losses can lead to systematic underestimation of EV related emissions. Overall, the figure succinctly demonstrates that EV emission outcomes in India are governed more by regional grid characteristics and fleet composition than by season alone, validating the need for spatially and temporally resolved emission assessment frameworks.

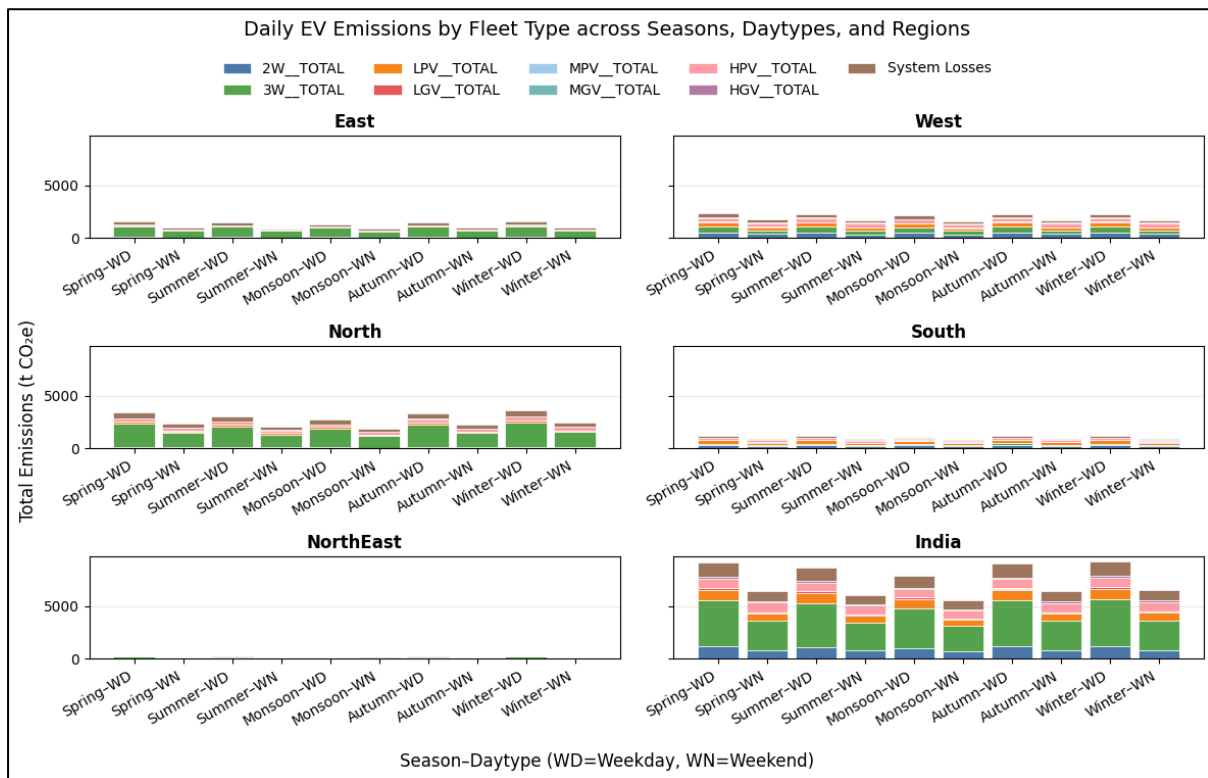


Figure 33: Regional, seasonal, and fleet wise distribution of daily EV related CO₂ emissions across India.

8.3 COMPARISON WITH INTERNAL COMBUSTION ENGINE VEHICLES

This section compares the emission intensity of electric vehicles with that of equivalent internal combustion engine vehicles across vehicle categories, regions, and seasons. By evaluating emissions on a per kilometer basis, the analysis highlights how the environmental benefits of electrification vary with grid carbon intensity, vehicle energy demand, and charging conditions, and identifies categories and regions where EVs deliver robust emission reductions as well as cases where benefits are marginal or negative under current grid conditions.

8.3.1 Comparison basis and metrics

The comparison between electric vehicles and internal combustion engine vehicles is carried out using average emission intensity expressed in gCO₂ per km, enabling a consistent, normalized assessment across vehicle categories and regions. EV emission intensities are derived from the time resolved coupling of vehicle electricity demand with regional grid carbon intensity, including transmission and distribution losses, and are averaged across seasons and day types.

ICEV emission intensities are adopted as fixed class specific factors, representative of real world Indian driving conditions. The ICEV emission factors used in this analysis are given in Table 2, sourced from national and peer reviewed studies on Indian road transport emissions. Emission reduction from electrification is quantified as the relative difference between ICEV

and EV emission intensities for each vehicle class, region, and season, allowing identification of segments where EV adoption delivers robust, marginal, or negative emission benefits under current grid conditions.

Table 2: ICEV emission intensity factors^{25,26,27,28}

Vehicle category	2W	3W	LPV	LGV	MPV	MGV	HPV	HGV
Emission Factor (eq. CO₂/km)	0.042	0.065	0.20	0.25	0.59	0.65	0.85	1.12

8.3.2 Vehicle category level comparison across regions and seasons

Figure 34 presents a detailed comparison of average EV emission intensity (gCO₂ per km) against corresponding ICEV emission intensities across vehicle categories, seasons, and regional grids, providing a clear synthesis of where EVs deliver robust emission benefits and where these benefits become marginal or negative.

For light duty vehicle categories (2W, 3W, LPV), EVs consistently outperform ICEVs across all regions and seasons. Nationally, EV emission intensities for 2W range from 0.027–0.032 gCO₂/km, compared to an ICEV benchmark of 0.042 gCO₂/km, yielding emission reductions of approximately 20–35%. Similarly, 3W EV emission intensities (0.046–0.054 gCO₂/km nationally) remain below the ICEV factor of 0.065 gCO₂/km but with reduced margins. The benefit remains robust in the South and North East, while in the East and North, winter and autumn values approach the ICEV benchmark, indicating sensitivity to grid carbon intensity.

For LPVs, EV intensities at the national level lie between 0.157–0.184 gCO₂/km, consistently lower than the ICEV value of 0.20 gCO₂/km, with the largest benefits observed during the monsoon season. These trends are particularly strong in the Southern and North Eastern regions, where EV intensities are lowest due to cleaner generation mixes.

For light goods vehicles (LGV), EVs continue to show emission advantages in most regions, though the margin narrows. National EV emission intensities for LGVs lie between 0.193–0.226 gCO₂/km, compared to an ICEV factor of 0.25 gCO₂/km. In the South and West, EV LGV intensities remain clearly below ICEV levels across all seasons, whereas in the East and

²⁵ World Resources Institute (WRI). 2015. India-Specific Road Transport Emission Factors. New Delhi: World Resources Institute. <https://shaktifoundation.in/wp-content/uploads/2017/06/WRI-2015-India-Specific-Road-Transport-Emission-Factors.pdf>

²⁶ Government of India. n.d. Vehicle-wise Emission Factors (PM, NO_x, HC, CO, and CO₂) for Vehicles Running on Petrol, Diesel, and CNG. Open Government Data Platform India.

<https://www.data.gov.in/resource/vehicle-wise-emission-factors-pm-nox-hc-co-and-co2-vehicles-running-petrol-diesel-and-cng>

²⁷ Iyer, N. V. 2012. A Technical Assessment of Emissions and Fuel Consumption Reduction Potential from Two and Three Wheelers in India. Washington, DC: International Council on Clean Transportation.

²⁸ TERI (The Energy and Resources Institute). 2022. Freight GHG Calculator: Methodology Report. New Delhi: The Energy and Resources Institute. https://www.teriin.org/sites/default/files/2022-10/Freight_GHG_Calculator_Methodology_Report.pdf

North, winter and autumn values approach the ICEV benchmark, indicating diminishing benefits under coal intensive conditions.

For medium and heavy vehicle categories (MPV, MG, HPV, HGV), the emission comparison becomes strongly region dependent. At the national level, MPV EV emission intensities (0.47–0.55 gCO₂/km) are comparable to but generally lower than the ICEV factor of 0.59 gCO₂/km, suggesting modest average benefits. However, for MG and HPV, national EV emission intensities (MG: 0.62–0.72 gCO₂/km; HPV: 0.76–0.89 gCO₂/km) approach or marginally exceed ICEV benchmarks (0.65 and 0.85 gCO₂/km, respectively) in coal heavy seasons.

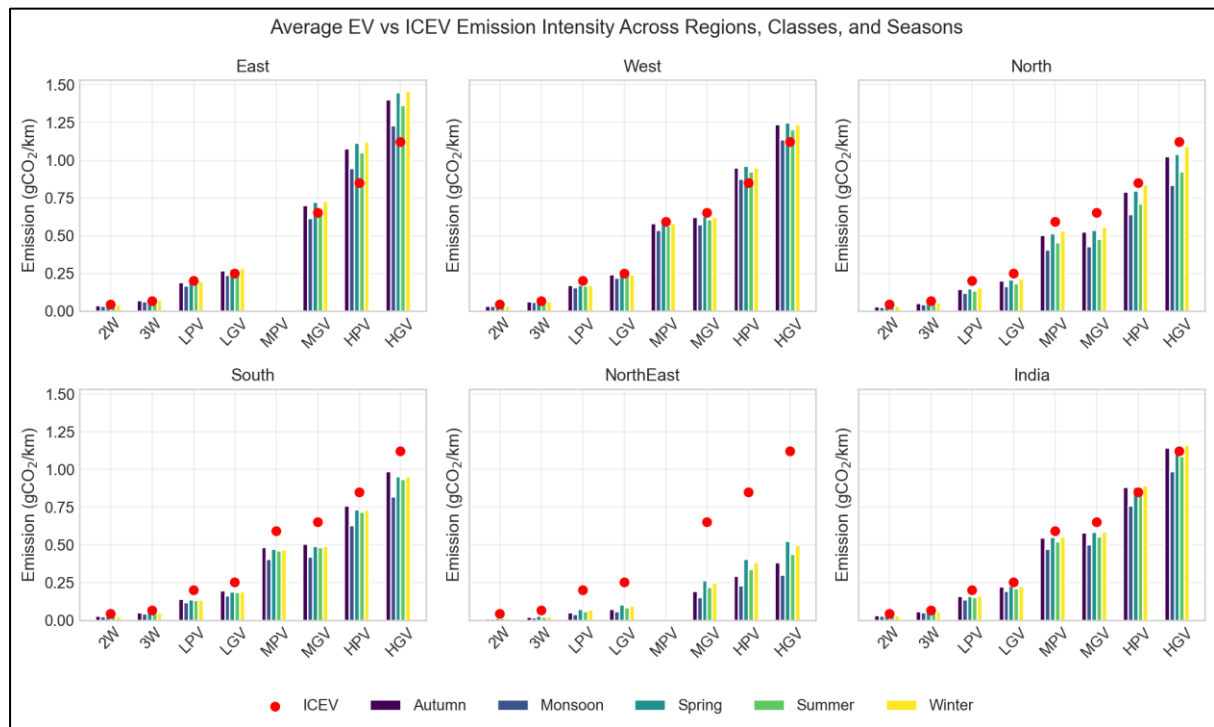


Figure 34: Comparison of EV emission intensity against corresponding ICEV emission intensities

In coal dominated regions, particularly the Eastern grid, EV emission intensities for HPV and HGV clearly exceed ICEV levels in several seasons. For instance, HGV EV emission intensities in the East reach 1.36–1.46 gCO₂/km, well above the ICEV benchmark of 1.12 gCO₂/km, while HPV values exceed 1.1 gCO₂/km. In contrast, in the Southern and North Eastern regions, EV emission intensities for all vehicle categories remain comfortably below ICEV levels, even for heavy duty vehicles, due to the cleaner generation mix.

8.3.3 National level vehicle category performance

Figure 35 summarises the national average emission reduction achieved by EVs relative to ICEVs, aggregated across regions, seasons, and day types, and clearly highlights the strong heterogeneity in performance across vehicle classes.

Light duty vehicle segments deliver the strongest and most reliable emission benefits. Two wheelers achieve the highest national average reduction of approximately 27%, followed by three wheelers at about 20%. These benefits are driven by a combination of low per kilometer energy consumption and high utilisation, which allows EVs in these segments to outperform ICEVs even under relatively carbon intensive grid conditions. Light passenger vehicles (LPV) and light goods vehicles (LGV) also show consistent positive outcomes, with average emission reductions of 23% and 13.6%, respectively. These results indicate that electrification of light duty and urban mobility segments already delivers meaningful emission savings at the national scale.

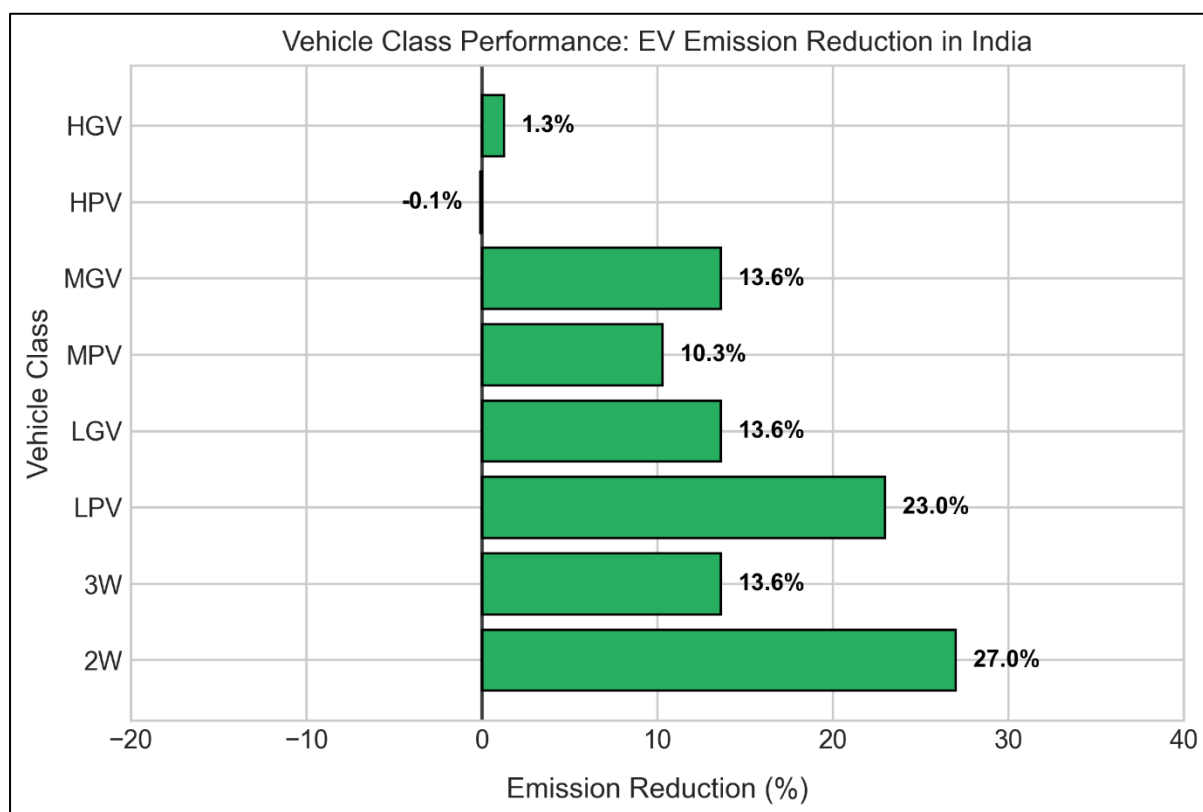


Figure 35: National average emission reduction achieved by electric vehicles relative to equivalent internal combustion engine vehicles across vehicle classes. Values represent percentage change in per kilometer CO₂ emissions, aggregated across regions, seasons and day types.

For medium passenger vehicles (MPV), the national average reduction is more modest at around 10.3%, reflecting greater sensitivity to grid emission intensity and charging conditions. While EVs in this segment generally outperform ICEVs, the margin of benefit is smaller and varies substantially across regions and seasons, indicating that further grid decarbonization would significantly enhance emission gains.

In contrast, medium and heavy duty vehicle segments exhibit more limited gains. Medium goods vehicles achieve a moderate national average reduction of approximately 13.6%, indicating that electrification can deliver net benefits at scale, albeit significantly smaller than those observed in light duty segments. Heavy goods vehicles show only a marginal average

reduction of about 1.3%, while heavy passenger vehicles remain close to parity with an average reduction of –0.1%, suggesting negligible net benefit at the national level.

The observed emission outcomes for heavy passenger vehicles, particularly buses, are closely linked to their distinct charging patterns, which differ markedly from light duty segments. As illustrated by the national weekday charging profile in Figure 26, bus charging demand is strongly concentrated during late evening and night time hours, driven by depot based overnight charging following daily operations. This charging window largely coincides with periods of limited or zero solar generation and a coal dominated marginal generation mix, as reflected in the seasonal and day wise emission intensity heatmap. Across all seasons, grid emission factors remain elevated from the evening peak through early morning hours, with the lowest carbon intensity consistently occurring during mid day when solar generation is highest.

As a result, a significant share of electricity consumed by electric buses is drawn during high emission intensity periods, which substantially erodes the potential climate benefit of electrification despite the high energy efficiency of electric drivetrains. This temporal misalignment between bus charging demand and low carbon generation availability explains why heavy passenger vehicles exhibit negligible or marginal national average emission reductions, even when electrification is scaled. These results underscore that, for bus fleets, the timing of charging is as critical as the volume of energy consumed, and that unmanaged overnight depot charging under current grid conditions limits achievable emission benefits.

Overall, the national level comparison demonstrates that electrification benefits are strongly segment dependent. Light duty vehicles emerge as clear priority segments for near term emission reduction, while heavy duty electrification requires complementary measures, such as renewable based depot charging, managed charging aligned with low carbon periods, and accelerated grid decarbonization, to deliver consistent and meaningful emission benefits at scale.

8.3.4 Net national impact of EV transition

Figure 36 presents the net annual carbon impact of transitioning from ICEVs to EVs at the national level, using a waterfall representation to show how different vehicle classes contribute to the overall change in emissions. Starting from a baseline of approximately 3.40 million tonnes CO₂ per year for the equivalent ICEV fleet, the transition to EVs results in a net reduction to about 2.84 million tonnes CO₂, corresponding to an aggregate saving of roughly 0.56 million tonnes CO₂ annually under current grid conditions, equivalent to about **16.5%** relative to the ICEV baseline.

The largest emission reductions are driven by high volume light duty segments, particularly three wheelers (≈ 0.26 MtCO₂ reduction) and two wheelers (≈ 0.17 MtCO₂ reduction), reflecting both their large fleet size and consistent per kilometer emission advantages. Light passenger vehicles (LPV) and light goods vehicles (LGV) provide additional, though smaller, reductions

of around 0.11 MtCO₂ and 0.01 MtCO₂, respectively. In contrast, the contribution from heavier segments is comparatively small. Light goods vehicles (LGV) provide only a marginal reduction (about 11.0 kT CO₂), while medium passenger vehicles (MPV), medium goods vehicles (MGV), heavy passenger vehicles (HPV), and heavy goods vehicles (HGV) contribute reductions that are close to zero at the national level (each on the order of a few kT CO₂).

Figure 36 results indicate that national emission reductions from EV adoption are strongly driven by light duty electrification, especially 2W, 3W, and LPV segments. Heavy duty and bus electrification can still contribute, but achieving meaningful reductions at scale will require complementary measures such as renewable aligned charging strategies, opportunity or flash charging where feasible, and continued grid decarbonization.

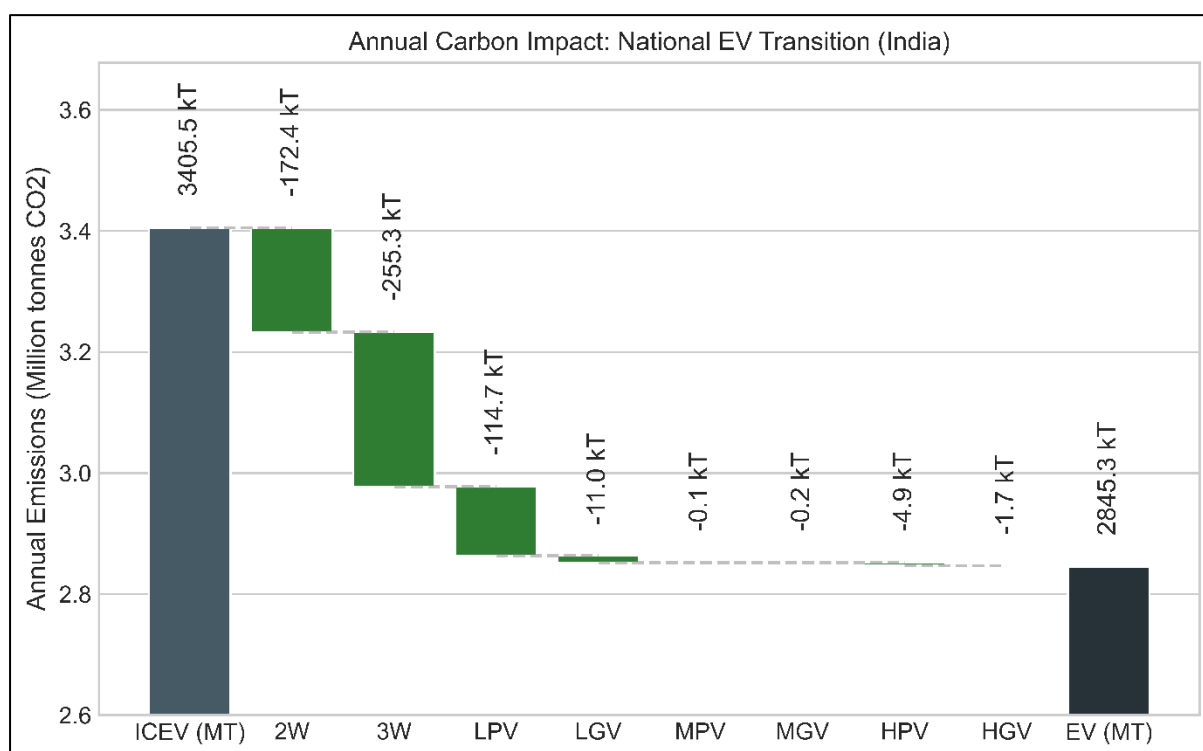


Figure 36: Annual carbon impact of the national EV transition in India

8.3.5 Regional and seasonal variability in emission benefits

The emission reduction benefits of electric vehicle adoption exhibit pronounced regional and seasonal variability, driven primarily by differences in grid generation mix, renewable energy availability, and temporal charging patterns. Figure 37 summarizes the relative emission reductions achieved across India's regional grids for representative seasons, benchmarked against equivalent ICEV fleet emissions.

The North Eastern region consistently delivers the highest emission reductions, exceeding 60% in all seasons and reaching up to 78% during the monsoon. This strong performance reflects the region's high share of hydroelectric generation and low reliance on coal based power, resulting in low marginal emission factors throughout the day. Seasonal variations are

comparatively muted in this region, indicating that EV emission benefits remain robust even under changing demand and generation conditions.

The Southern and Northern regions show moderate to strong emission reductions, typically in the range of 20–37%, with the highest benefits observed during the monsoon and summer seasons. These periods coincide with increased availability of renewable generation, particularly solar and hydro, which lowers grid emission intensity during key charging hours. In contrast, reductions are smaller during winter and spring, when coal based generation plays a larger role in meeting demand.

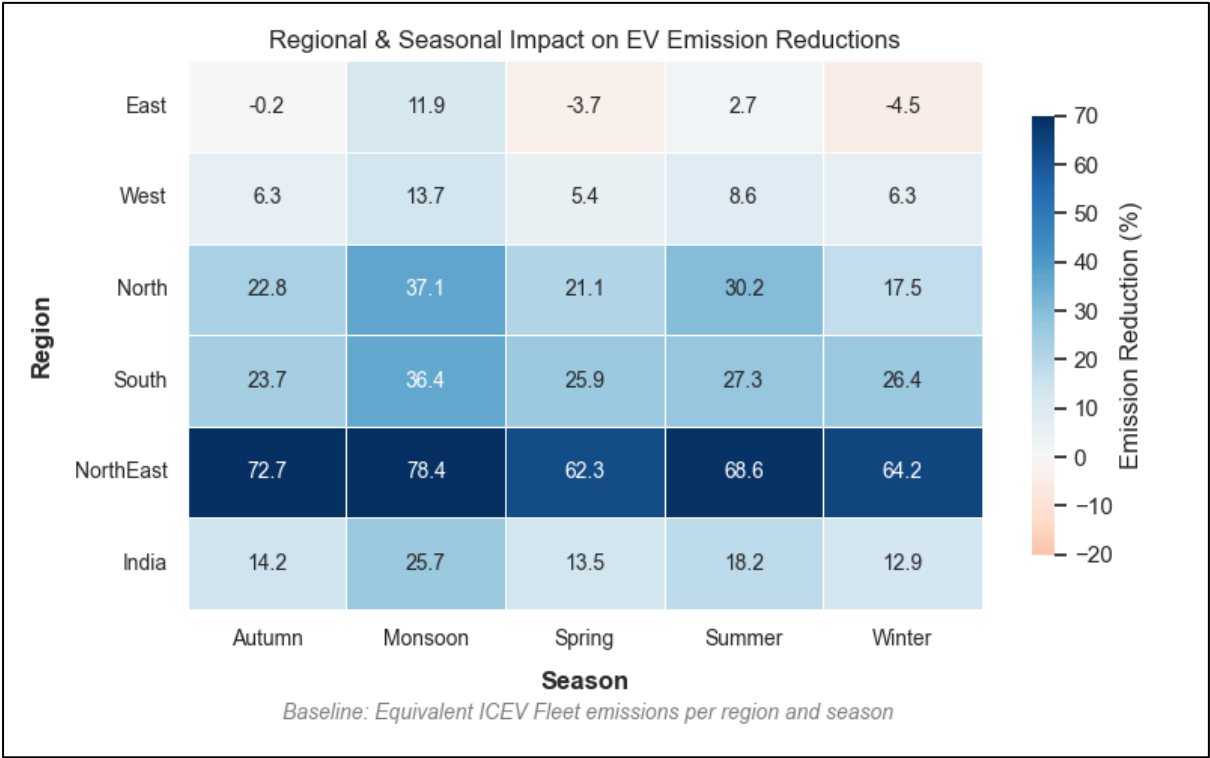


Figure 37: Regional and Seasonal impact on EV Emission Reduction

The Western region exhibits modest but consistently positive emission reductions, generally between 5–14% across seasons. While renewable penetration is significant, the continued presence of fossil generation limits the magnitude of achievable benefits. Seasonal variability in the West is less pronounced compared to the North and South, reflecting a more balanced but carbon intensive generation mix.

In contrast, the Eastern region shows highly variable and in some seasons negative emission outcomes, with reductions ranging from –4.5% to +11.9%. During spring and winter, electrification can lead to marginal emission increases, driven by a heavy reliance on coal dominated generation and limited renewable availability during typical charging periods. These results underscore that EV adoption in coal intensive regions does not automatically translate into emission benefits without complementary measures.

At the national level, average emission reductions range from approximately 13% to 26%, with the highest benefits observed during the monsoon season and the lowest during winter and spring. This seasonal pattern reflects the aggregate influence of renewable generation availability across regions, particularly the role of solar and hydro resources.

8.4 INTERPRETATION AND IMPLICATIONS

Taken together, the results provide a comprehensive, system level understanding of how electric vehicle adoption translates into emission outcomes in the Indian context. Across vehicle classes, regions, and seasons, the analysis demonstrates that EV emission benefits are neither uniform nor automatic, but emerge from the interaction between vehicle energy intensity, charging behaviour, and the spatio temporal carbon intensity of the power grid.

At the vehicle class level, electrification delivers the strongest and most consistent benefits in light duty segments, particularly two wheelers, three wheelers, and light passenger vehicles. These segments combine relatively low energy consumption per kilometer with charging patterns that partially overlap with lower emission periods, resulting in national average emission reductions of roughly 13–27%. Medium goods and medium passenger vehicles achieve moderate reductions, while heavy passenger and heavy goods vehicles remain close to parity under current conditions. This highlights that drivetrain efficiency alone is insufficient to guarantee emission reductions in energy intensive segments.

From an aggregate national perspective, the cumulative carbon impact is dominated by light duty electrification. Despite their lower per vehicle emissions, two and three wheelers and light passenger vehicles contribute the bulk of the ~560 kT CO₂ annual reduction due to their large fleet sizes and high daily activity. In contrast, heavy vehicle segments contribute only marginally to national reductions, reinforcing that fleet composition matters as much as per vehicle performance when assessing system wide impacts.

The regional and seasonal analysis further reveals strong spatial heterogeneity in outcomes. Regions with high shares of hydro and renewable generation, particularly the North East and Southern grids, consistently deliver lar

ge emission reductions across all seasons. Coal dominated regions, especially the Eastern grid, exhibit highly variable and in some seasons negative outcomes, indicating that EV adoption in such regions can fail to deliver climate benefits without parallel grid decarbonization. Seasonally, emission reductions are highest during the monsoon and summer months, reflecting increased renewable availability, and lowest during winter and spring when fossil generation dominates the margin.

Crucially, the temporal alignment between charging demand and grid emission intensity emerges as a central determinant of outcomes. This is particularly evident for electric buses and heavy vehicles, whose reliance on overnight depot charging concentrates electricity

consumption in emission intensive night time periods with limited solar availability. As a result, their national average emission benefits remain muted despite large energy displacement from liquid fuels.

These findings carry several important implications for policy and infrastructure planning. First, prioritizing light duty electrification delivers the highest near term emission returns under existing grid conditions. Second, regional differentiation is essential: uniform national assumptions mask substantial variation in real world outcomes. Third, for heavy duty and public transport electrification, charging strategy design is as critical as vehicle deployment. Measures such as opportunity and flash charging, renewable based depot charging, managed charging aligned with low carbon periods, and continued grid decarbonization are necessary to unlock meaningful emission reductions at scale.

8.4.1.1 Key Implications

- **Grid Decarbonization is Mandatory:** The data proves that an EV is only as clean as the plug it connects to. For regions like the East, promoting EV adoption without first cleaning the power grid is counterproductive for the climate. Policy should prioritize grid-greening in coal-heavy belts to avoid "exporting" tailpipe emissions to power plant chimneys.
- **Prioritize Urban Micro-Mobility:** Since 2W and 3W classes provide the most significant absolute carbon savings, subsidies and infrastructure (like battery swapping) should remain focused here. These classes provide the "biggest bang for the buck" in India's current energy landscape.
- **Strategic Charging Windows:** The seasonal data suggests that "Smart Charging" could be a major tool. If users are encouraged to charge more during high-renewable periods (like the Monsoon or during peak solar hours in Spring), the national average reduction of 14.2% – 25.7% could be pushed significantly higher.

9 EMISSION ESTIMATION FOR 2030 SCENARIO

While the preceding sections assessed emission outcomes under current grid conditions and present day charging behaviour, long term climate benefits of vehicle electrification depend critically on how both the transport and power sectors evolve over time. Looking ahead to 2030, India is expected to witness substantial growth in EV adoption across all vehicle segments, alongside significant changes in generation mix driven by renewable energy expansion, storage deployment, and policy led decarbonization targets.

This section extends the developed modelling framework to a forward looking 2030 scenario, integrating projected EV fleet penetration, evolving charging demand, and anticipated changes in regional and temporal grid emission intensity. The objective is to quantify how emission outcomes may shift under plausible future conditions, and to assess whether segments and regions that currently exhibit limited or marginal benefits can deliver meaningful emission reductions as the grid becomes cleaner.

9.1 ESTIMATING EV NUMBERS BY 2030

To estimate electric vehicle penetration by 2030, a bottom up forecasting approach was adopted to capture heterogeneity across vehicle categories and geographies. Rather than relying on aggregate national projections, EV adoption was projected separately for each vehicle category at the state level, and subsequently aggregated to regional and national totals. This approach ensures consistency with observed adoption patterns, policy implementation differences, and regional market maturity.

The forecasting process begins with state wise and category wise historical time series data on vehicle registrations, which serve as the primary input. These time series were extended to 2030 under two policy consistent scenarios.

- The Business As Usual (BAU) scenario reflects a continuation of current adoption trends and policy momentum,
- The Stated Policies Scenario (SPS) incorporates announced targets, incentive schemes, and regulatory commitments at the central and state levels.

9.1.1 BAU Scenario

The BAU scenario reflects a continuation of current adoption trends and policy momentum, without assuming additional acceleration from new or enhanced policy interventions beyond those already in effect. Under this trajectory, total EV stock grows steadily over the decade, reaching just over 30 million vehicles by 2030 as shown in Figure 38. The expansion is overwhelmingly driven by two wheelers and three wheelers, which together account for the majority of the projected fleet throughout the forecast horizon.

Light passenger vehicles also show a gradual but sustained increase in stock, contributing a smaller yet non negligible share of the total fleet by 2030. In contrast, freight and heavy duty segments including light goods vehicles, medium goods vehicles, heavy passenger vehicles, and heavy goods vehicles remain limited in absolute numbers under the BAU pathway.

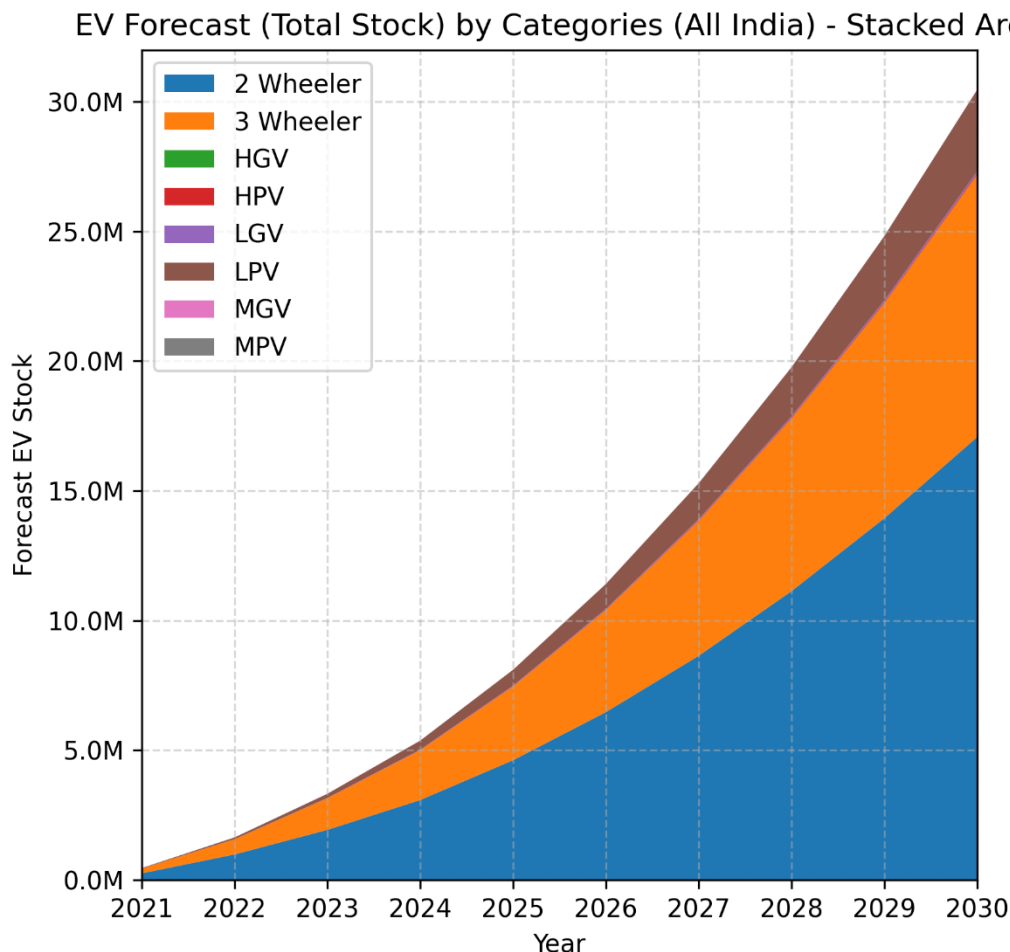


Figure 38: Forecasted EV numbers in the BAU Scenario

9.1.2 Stated Policies Scenario

Figure 39 illustrates the projected evolution of India's EV stock under the Stated Policies scenario, which incorporates announced national and state level targets, incentive schemes, and policy commitments expected to influence adoption through 2030. Compared to the BAU pathway, this scenario reflects a significantly accelerated transition across all vehicle categories.

Under the Stated Policies trajectory, total EV stock expands rapidly, reaching over 80 million vehicles by 2030, nearly three times the BAU projection. As in the BAU case, two wheelers and three wheelers dominate the fleet, together accounting for the majority of total EV stock throughout the forecast horizon. However, the absolute scale of adoption is substantially higher, with two wheelers alone exceeding 45 million vehicles by 2030 and three wheelers approaching 25 million.

Light passenger vehicles experience stronger growth under this scenario, reflecting improved cost parity, expanding charging infrastructure, and policy support for private EV adoption. Freight and heavy duty segments also show visible acceleration relative to BAU, particularly light goods vehicles and medium duty categories, although they continue to represent a smaller share of the total fleet in absolute terms.

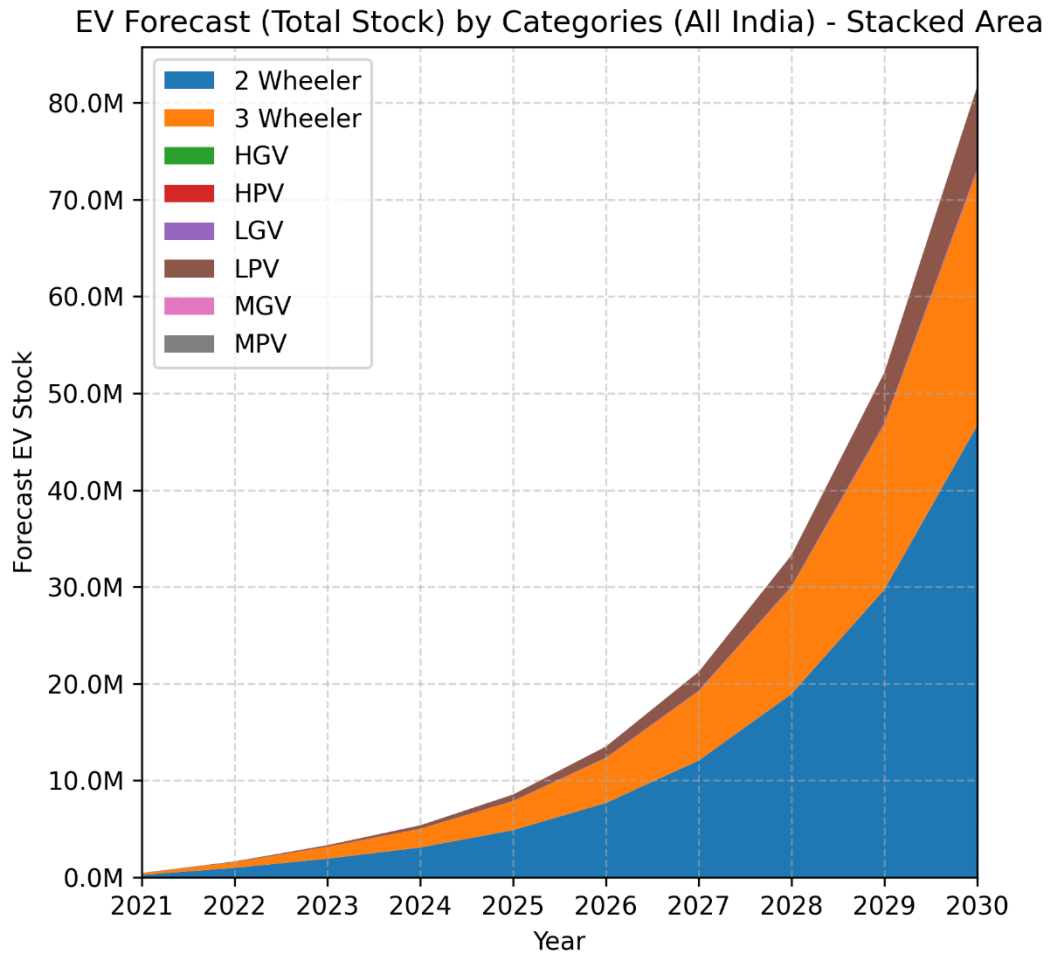


Figure 39: Forecasted EV numbers in SPS

9.2 DEMAND PROFILE FOR 2030

The estimation of demand growth and EV growth for the year 2030 is carried out through a structured three-step methodology, as shown in Figure 40, to clearly isolate the contribution of electric vehicles from the underlying system demand. Initially, a clean historical baseline for 2023 is constructed using SCADA data at both regional and national levels, which provides the actual demand and generator dispatch profiles. Since the recorded 2023 demand already includes EV consumption, the EV demand for 2023 is independently estimated and subtracted from the actual SCADA demand. This step is essential to obtain a non-EV base demand profile. The resulting profile represents the true underlying system demand without the

influence of EV charging load. This corrected base profile is then normalized to obtain a per-unit (PU) demand curve that captures the intrinsic shape characteristics of the system load.

In the second step, the normalized 2023 non-EV demand profile is scaled to 2030 using the Central Electricity Authority (CEA) projected peak demand targets for 2030 [ref]. The PU profile derived from 2023 is multiplied by the projected 2030 peak demand to generate the 2030 base demand profile without EV load. This scaling approach assumes that while the magnitude of demand increases over time, the fundamental temporal shape of the non-EV load profile remains similar to the historical year after appropriate normalization.

Finally, the EV demand for 2030 is estimated separately based on projected EV growth trajectories, charging patterns, and energy consumption assumptions. This projected EV load is then added to the scaled 2030 non-EV base profile. The final aggregation yields the total projected demand for 2030, explicitly capturing the incremental impact of EV adoption. By separating EV demand estimation from base demand growth, the methodology ensures transparency in quantifying EV-driven load growth and avoids double counting. This framework allows clear identification of how much of the future demand increase is attributable to general economic growth and how much is specifically due to EV penetration.

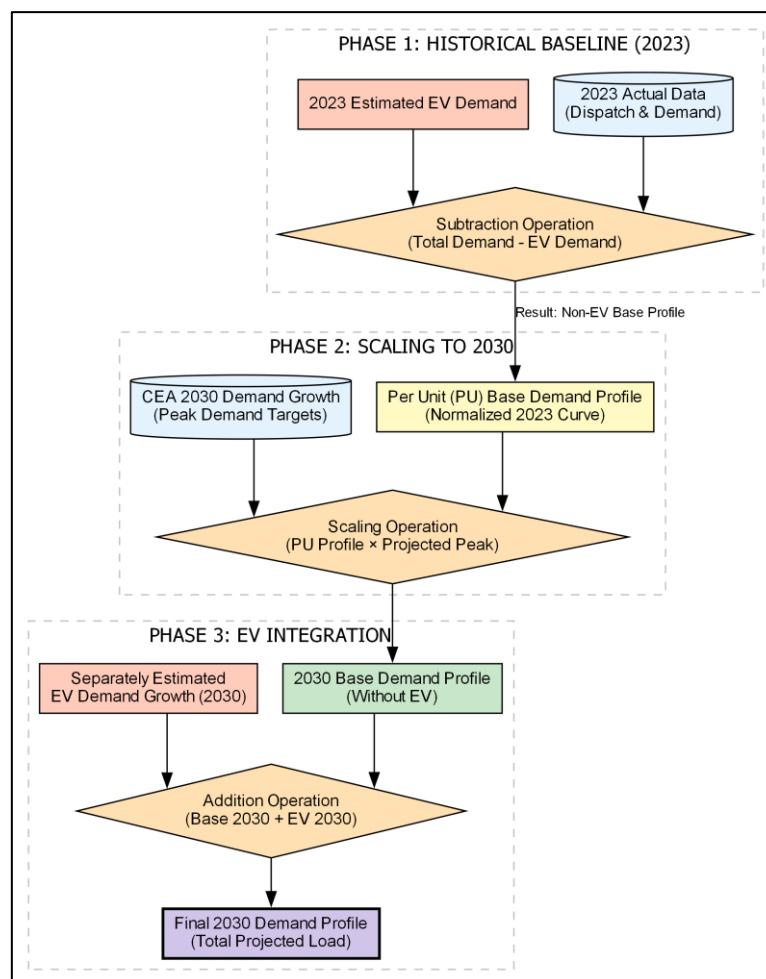


Figure 40: Methodology for demand profile estimation for 2030

9.3 DETERMINATION OF GRID EMISSION FACTOR FOR 2030

The estimation of emission intensity for 2030 follows a structured framework, as shown in Figure 41, that combines projected generation mix, availability scaling, optimal dispatch simulation, and a marginal (causal) emission assessment approach.

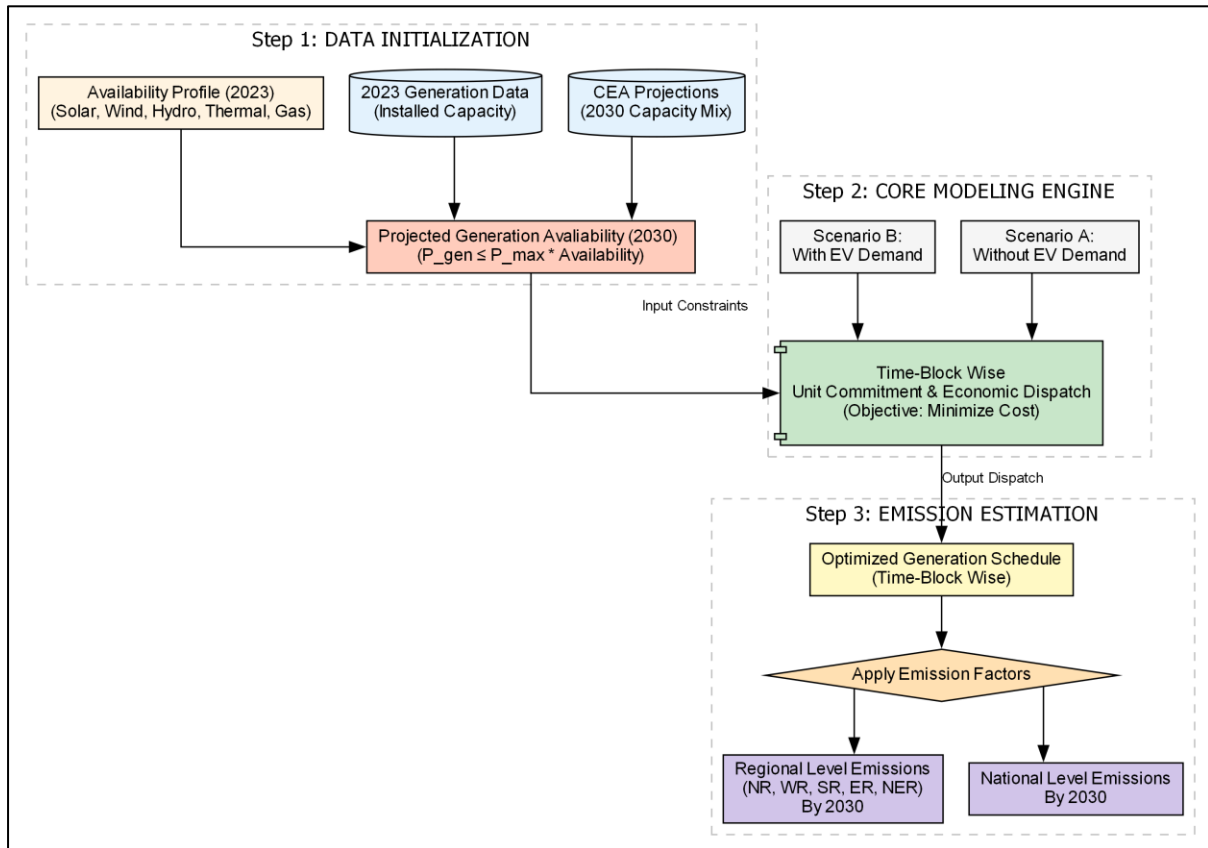


Figure 41: Methodology for determination of grid emissions factor

First, similar to the normalization approach adopted for demand projection, the 2023 generation dispatch data is used to construct per-unit (PU) availability profiles for each generation category (solar, wind, hydro, thermal, gas, etc.). These PU availability profiles capture the temporal behavior of different technologies. The profiles are then scaled according to the CEA projections of the 2030 installed capacity mix²⁹. This scaling ensures that while the magnitude of capacity changes to reflect 2030 projections, the intra-day availability characteristics remain consistent with observed operational patterns. The regional capacity mix for 2030 is determined by proportionally distributing projected capacities based on the existing regional composition and projected expansion plans.

Using the projected 2030 generation capacities and corresponding availability profiles, a time-block-wise optimization model (Unit Commitment and Economic Dispatch) is developed. The

²⁹ CEA, "CO2 Baseline Database for the Indian Power Sector", Central Electricity Authority, Ministry of Power, Govt. of India, Nov 2025. https://cea.nic.in/wp-content/uploads/baseline/2025/12/User_Guide_V_21.0.pdf

objective of the model is cost minimization subject to operational constraints, including generation limits, availability constraints, and demand balance. Two scenarios are simulated: (i) Scenario A – without EV demand, and (ii) Scenario B – with EV demand added to the projected 2030 base load profile. The output of this model provides the optimized generation schedule across all time blocks for both scenarios. Emission estimation is then performed by applying technology-specific emission factors to the optimized dispatch schedule. This yields total emissions (tCO₂/day) and emission intensity (tCO₂/MWh) at both regional and national levels for 2030.

However, since the 2030 generation mix includes storage technologies such as batteries, the determination of EV-attributable emissions is not straightforward. Battery charging and discharging behaviour may shift generation across time blocks. Charging during the day may be supplied partly by renewable energy but can also require emission-intensive thermal generators to operate. Similarly, nighttime discharge may offset thermal generation. Therefore, the gross emission intensity cannot directly reveal the incremental impact of EV demand. To address this complexity, a causal (marginal) emission approach is adopted, given in equation (number). The marginal emission factor (MEF) represents the incremental emissions caused by an incremental change in demand. In this framework, total daily emissions are computed for both scenarios (with and without EV demand). The difference between the two total emissions is attributed primarily to the additional EV load. This incremental emission is then normalized by the total EV energy consumption for the day, yielding a marginal emission factor expressed in tCO₂/MWh. This marginal factor captures the true system-wide impact of EV demand, including indirect effects arising from storage operation and dispatch shifts.

Finally, this marginal emission factor is used to adjust the base (non-EV) emission intensity profile. The EV contribution is incorporated proportionally into each time block by scaling based on EV energy consumption and normalizing with respect to total block energy. This provides an adjusted emission intensity (tCO₂/MWh) and total emissions (tCO₂/day) that explicitly reflect the incremental impact of EV penetration in 2030.

9.4 EV CHARGING DEMAND LOAD FOR 2030

Figure 42 presents the projected national EV charging demand profiles for 2030 under the Business As Usual (BAU) and Stated Policies Scenario (SPS), distinguishing between weekday and weekend charging behaviour. The profiles reflect the combined impact of projected EV stock, fleet composition, usage intensity, and charging behaviour, aggregated across all vehicle categories.

Under the BAU scenario, EV adoption follows a continuation of current trends and policy momentum, without assuming additional acceleration from new or enhanced interventions. Total EV stock increases steadily over the decade, reaching just over 30 million vehicles by

2030. As a result, aggregate charging demand remains moderate in scale, with weekday peak loads in the range of 4–5 GW and weekend peaks around 3–3.5 GW. The diurnal profile exhibits a clear night time and early morning peak, driven primarily by residential charging of private two wheelers and passenger vehicles, followed by a secondary mid day rise associated with commercial fleet activity.

In contrast, the Stated Policies Scenario reflects announced national and state level targets, incentive programmes, and enabling policy measures that significantly accelerate EV adoption across all segments. Under this trajectory, total EV stock expands rapidly to over 80 million vehicles by 2030, nearly three times the BAU projection. This rapid scale up translates directly into a substantial increase in electricity demand from EV charging. Weekday peak loads rise sharply to approximately 11–12 GW, while weekend peaks approach 8–9 GW, indicating a step change in both energy and capacity requirements imposed on the power system.

Despite the large difference in absolute magnitude, the shape of the charging profile remains broadly consistent across scenarios, suggesting that charging behaviour assumptions are similar and that the increase in demand is primarily driven by fleet growth rather than structural shifts in charging timing. Both scenarios show pronounced early morning peaks, a mid day shoulder linked to commercial and opportunity charging, and a renewed rise during evening hours as private vehicles return and begin charging. Weekday demand consistently exceeds weekend demand across all hours, reflecting higher vehicle utilisation and commercial activity.

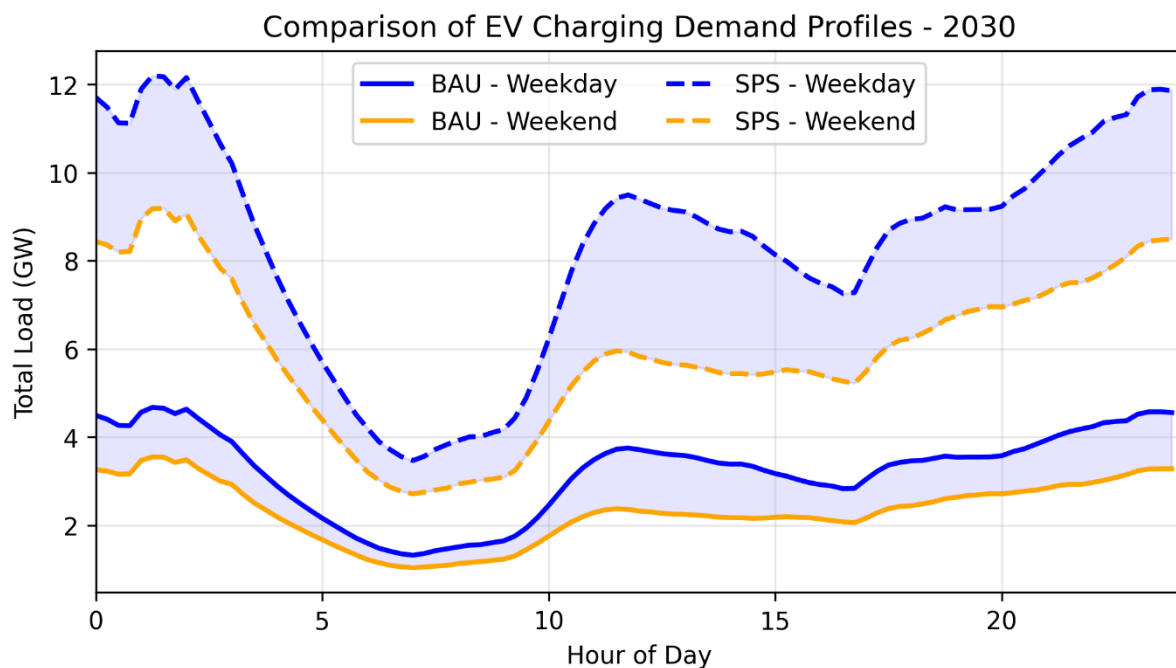


Figure 42: Comparison of national electric vehicle charging demand profiles in India for the year 2030 under the Business-As-Usual (BAU) and Stated Policies Scenario (SPS) cases.

9.5 EMISSION ESTIMATION FROM EVs

Figure 43 and Figure 44 compare the total daily EV related CO₂ emissions in 2030 across regions, seasons, and day types under the Business As Usual (BAU) and Stated Policies (SPS) scenarios, respectively. In both figures, emissions are aggregated across vehicle categories and include the contribution from system losses.

9.5.1 Overall national comparison

At the national level, daily EV emissions increase substantially when moving from the BAU to the Stated Policies scenario. Under BAU, total daily emissions typically lie in the range of 40–60 thousand tCO₂ per day, depending on season and day type. In contrast in the stated policies scenario, on weekdays, total daily EV emissions range from approximately 132 thousand to 159 thousand tCO₂ per day. The lowest weekday emissions occur during the monsoon season (≈ 132.5 ktCO₂/day), reflecting lower grid emission intensity due to higher availability of hydro and wind generation. In contrast, winter and autumn exhibit the highest weekday emissions, at ≈ 158.7 ktCO₂/day and ≈ 158.5 ktCO₂/day, respectively. Spring and summer lie slightly lower but remain elevated, with weekday emissions of ≈ 156.2 ktCO₂/day and ≈ 145.2 ktCO₂/day.

This increase is primarily driven by the scale effect of accelerated EV adoption. While per-vehicle emission intensity is expected to improve by 2030 due to grid decarbonization, the rapid expansion of EV stock under the SPS scenario leads to higher absolute emissions from EV charging at the system level.

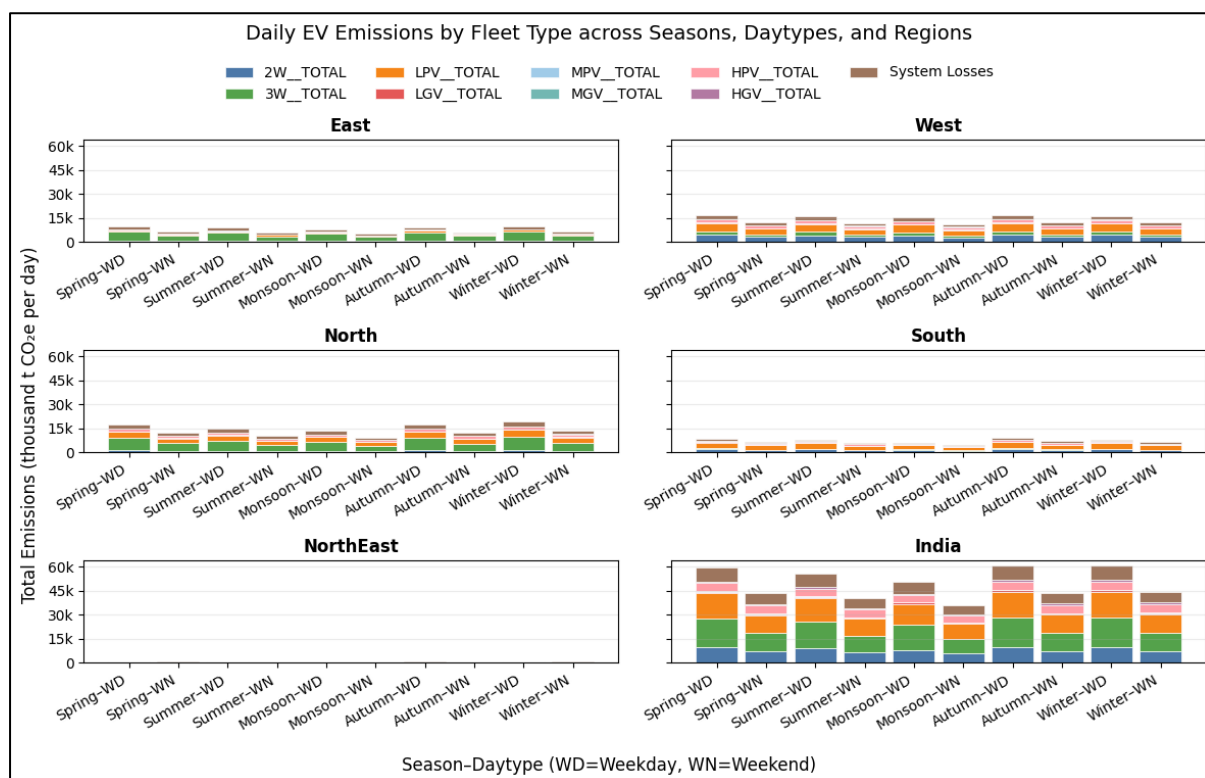


Figure 43: Regional, seasonal, and fleet wise distribution of daily EV related CO₂ emissions across India in 2030 BAU scenario

9.5.2 Regional Comparison

Across regions, the relative ranking of emission magnitude remains broadly unchanged between BAU and SPS, but the absolute scale of emissions increases significantly in all regional grids under the policy driven pathway.

The Northern and Western regions continue to dominate daily EV emissions in both scenarios. Under BAU, their daily emissions typically fall in the range of 12–18 thousand tCO₂ per day. Under the SPS scenario, these values rise sharply, with weekday emissions frequently reaching 25–40 thousand tCO₂ per day, particularly during winter and autumn. The prominence of these regions reflects the combination of high EV adoption levels and relatively more carbon intensive generation mixes.

The Southern region consistently exhibits lower daily emissions compared to the North and West in both scenarios, owing to its cleaner electricity mix. Nevertheless, the impact of scale is still evident. Under BAU, daily emissions are typically around 4–7 thousand tCO₂ per day, while under SPS they increase to approximately 10–15 thousand tCO₂ per day, indicating a near doubling despite lower grid emission intensity.

The Eastern region also shows a pronounced upward shift in daily emissions under the SPS scenario. Although overall EV penetration remains lower than in the North and West, the coal dominated generation mix leads to relatively high emissions per unit of charging. As a result,

daily emissions increase from roughly 5–9 thousand tCO₂ per day under BAU to 12–20 thousand tCO₂ per day under SPS, depending on season and day type.

The North Eastern region remains the lowest emitting region in both scenarios. Even under the Stated Policies pathway, daily emissions remain below 5 thousand tCO₂ per day, reflecting both lower EV penetration and a hydro dominated generation mix. However, the relative increase from BAU to SPS is still evident, underscoring that scale effects persist even in cleaner grids.

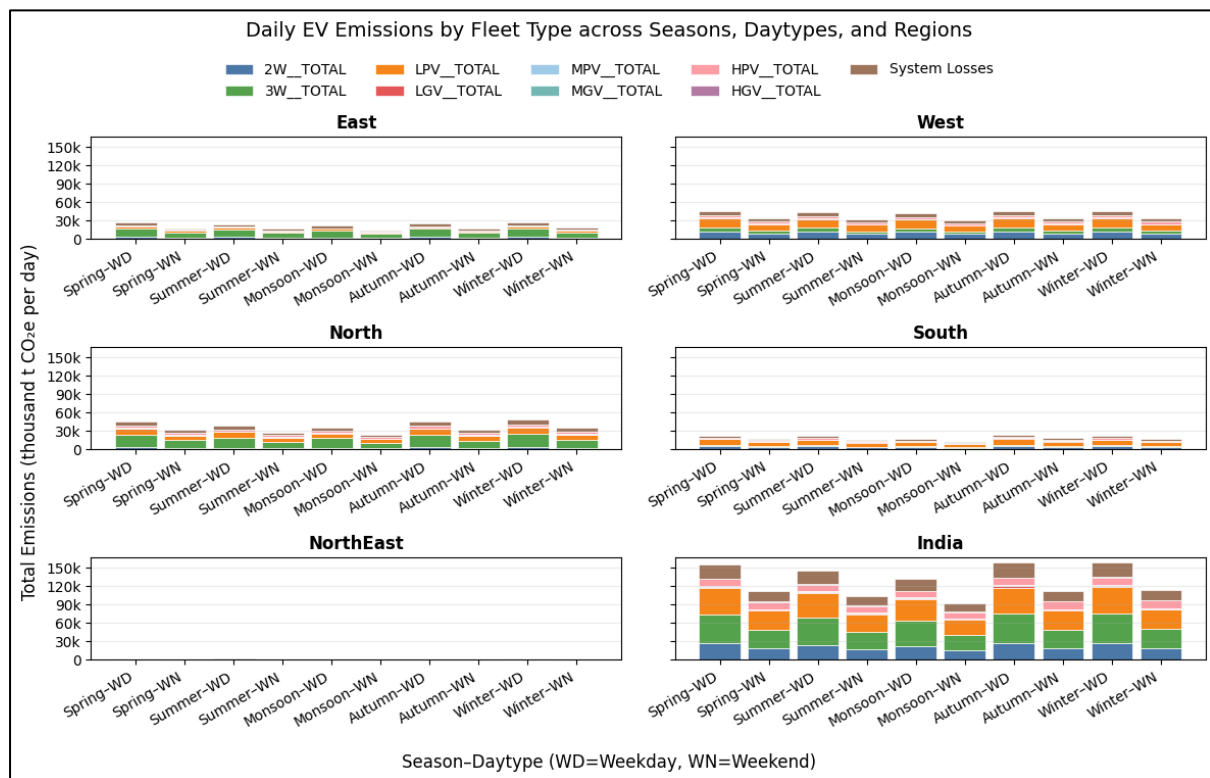


Figure 44: Regional, seasonal, and fleet wise distribution of daily EV related CO₂ emissions across India in 2030 stated policies scenario

9.5.3 Impact on Emissions from the Power Sector: Marginal Emission Factors: BAU vs SPS Comparison

The large scale integration of electric vehicle charging demand by 2030 is expected to interact strongly with power system generation, storage, and dispatch patterns, thereby influencing emissions from the electricity sector. Unlike conventional loads, EV charging introduces additional demand that is temporally flexible and regionally heterogeneous, with charging behaviour varying across regions, seasons, and time of day. Consequently, the emissions impact of EV integration cannot be accurately assessed using average grid emission factors alone, as such metrics do not capture the incremental system response to EV demand.

This section assesses the impact of EV charging integration on power sector emissions using a marginal emission based framework that explicitly accounts for the causal generation and storage response to EV charging demand. In the 2030 scenarios considered, battery energy

storage systems are actively dispatched as part of system operations, and the emissions associated with battery charging are therefore included in the marginal emission factor estimation. By capturing the combined effects of thermal generation, renewable availability, and storage dispatch, this approach enables a robust quantification of the incremental emissions attributable to EV charging across regions and diurnal periods.

The marginal emission factor (MEF) shown in Figure 45 and Figure 46 is expressed in units of tCO_2/MWh and represents the incremental emissions associated with each additional megawatt hour of EV charging demand in a given 15 minute time block. In other words, the MEF quantifies how much additional CO_2 is emitted by the power system when EV charging demand increases marginally at that specific time, accounting for the actual generation and storage resources that respond to the incremental load. This interpretation is critical, as it directly links the timing of EV charging to its emissions impact on the power sector.

9.5.3.1 General Diurnal Patterns

Across all regions and both scenarios, MEF exhibits a consistent diurnal pattern characterized by lower values during midday hours (approximately 10:00-16:00) and higher values during evening and early morning hours (18:00-06:00). This pattern reflects the influence of solar generation, which displaces higher-emission thermal generation during peak sunlight hours, thereby reducing the marginal emissions associated with incremental demand. Conversely, during evening hours when solar generation ceases and demand peaks, the power system must dispatch more carbon-intensive marginal generators, elevating the MEF.

The nighttime hours (22:00-06:00) generally show elevated but relatively stable MEF values, as baseload coal and gas generation dominate during these periods. The sharpest increases in MEF typically occur during the evening ramp period (17:00-20:00), when solar generation rapidly declines while demand remains high or continues to increase.

9.5.3.2 Regional Comparisons

- **Eastern Region:** The Eastern region shows the lowest absolute MEF values among all regions under the BAU scenario, with daytime minimums around $0.004 \text{ tCO}_2/\text{MWh}$ and nighttime peaks reaching approximately $0.015 \text{ tCO}_2/\text{MWh}$. The SPS scenario shows substantially higher MEF values, with nighttime peaks reaching approximately $0.041 \text{ tCO}_2/\text{MWh}$, nearly a $3\times$ increase over BAU.
- **Western Region:** The Western region exhibits low-to-moderate MEF values with minimal seasonal variation. Under BAU, daytime values reach approximately $0.003\text{-}0.006 \text{ tCO}_2/\text{MWh}$, while nighttime peaks approach $0.012 \text{ tCO}_2/\text{MWh}$. The SPS scenario shows elevated nighttime values reaching approximately $0.018\text{-}0.035 \text{ tCO}_2/\text{MWh}$, representing a $1.5\text{-}3\times$ increase.
- **Northern Region:** The Northern region displays the most dramatic increase in MEF values between scenarios. In BAU, the region shows moderate values with daytime minimums around $0.005\text{-}0.009 \text{ tCO}_2/\text{MWh}$ and nighttime peaks of approximately

0.020-0.027 tCO₂/MWh. Under SPS, winter nighttime MEF reaches approximately 0.067 tCO₂/MWh, representing roughly a 2.5-3× increase over BAU.

- **Southern Region:** The Southern region exhibits relatively high MEF values with moderate seasonal variation. Under BAU, daytime values range from 0.005-0.010 tCO₂/MWh, while nighttime peaks reach approximately 0.015-0.020 tCO₂/MWh. The SPS scenario shows elevated values, with nighttime peaks reaching 0.038-0.050 tCO₂/MWh, representing approximately a 2-2.5× increase over BAU.
- **North Eastern Region:** The NorthEast region shows high absolute MEF values under both scenarios, despite having the cleanest average grid emissions. Under BAU, the region exhibits daytime minimums around 0.010-0.020 tCO₂/MWh and nighttime peaks reaching approximately 0.030-0.040 tCO₂/MWh across seasons. The SPS scenario shows substantial increases, with nighttime peaks reaching approximately 0.060-0.080 tCO₂/MWh, representing a 2× increase.

9.5.3.3 Seasonal Variations

Seasonal variation in MEF is most pronounced in regions with significant hydroelectric capacity. The NorthEast, North, and South regions all show distinct seasonal patterns:

- **Monsoon season** (green lines) generally exhibits the lowest MEF values within each region, particularly during midday hours, reflecting abundant hydroelectric generation that reduces reliance on thermal marginal generators.
- **Winter season** (purple lines) consistently shows the highest MEF values across most regions and time periods, as reduced hydroelectric output forces greater dependence on coal and gas at the margin.
- **Spring, Summer, and Autumn** show intermediate values, with summer benefiting from solar generation during midday hours but experiencing higher MEF during evening hours.

In the Eastern and Western regions, seasonal variation is minimal, suggesting that the marginal generation mix in these coal-dominated grids remains relatively constant throughout the year.

9.5.3.4 BAU vs SPS Scenario Comparison

A critical finding is that the SPS scenario exhibits substantially higher MEF values than the BAU scenario across nearly all regions, time periods, and seasons, typically 2-3 times higher. This increase reflects the combined effect of two interrelated factors:

1. **Higher Absolute EV Demand:** The SPS scenario assumes nearly three-fold higher EV penetration compared to BAU, resulting in substantially greater total EV charging load that must be met by the power system. This higher demand pushes the system further up the generation merit order curve.

2. **Higher Relative EV Demand (EV Share of Total Load):** Importantly, the MEF increase also reflects that EV demand represents a larger proportion of total electricity demand in the SPS scenario. In BAU, with lower EV penetration, EV charging constitutes a relatively small fraction of total system load, meaning that incremental EV demand can often be absorbed by mid-merit generators without significantly altering the overall dispatch. In contrast, under SPS, EV charging becomes a substantial component of total demand, particularly during certain hours. This means that new generators may turn online to serve the EV load in SPS scenario, thus increasing the emission in the block.

Finally, the magnitude of the MEF is also influenced by the relative contribution of EV charging demand to the total regional electricity demand. In periods when overall system load is high, such as during summer months in the Northern Region, the incremental impact of EV charging on emissions is comparatively smaller. During these periods, total demand is dominated by non EV loads, and the marginal generation response to additional EV demand is diluted within the broader system dispatch. Conversely, during lower load periods or in regions with smaller total demand, EV charging can represent a larger fraction of marginal demand, resulting in a more pronounced emissions impact per unit of EV energy consumed.

9.5.3.5 Implications for EV Charging Strategy

The diurnal patterns and scenario comparisons provide clear guidance for optimal EV charging timing from an emissions perspective

1. **Optimal Charging Window:** Across all regions and scenarios, the period from approximately 11:00-15:00 represents the lowest-MEF charging window, coinciding with peak solar generation. In the SPS scenario, the importance of this window is magnified—charging during midday can reduce marginal emissions by 60-85% compared to evening charging, versus 50-70% in BAU.
2. **Evening Peak Avoidance Critical Under High EV Penetration:** The period from 18:00-21:00 represents the worst time for EV charging. This suggests that unmanaged charging concentrated during evening hours could result in substantially higher total emissions under aggressive EV deployment scenarios.
3. **Diminishing Returns Without Grid Transformation:** The fact that MEF escalates significantly as EV demand increases (while the generation mix remains similar) demonstrates diminishing marginal climate benefits from EV deployment without concurrent grid decarbonization. Each additional EV in the SPS scenario contributes more marginal emissions per kWh charged than in the BAU scenario.

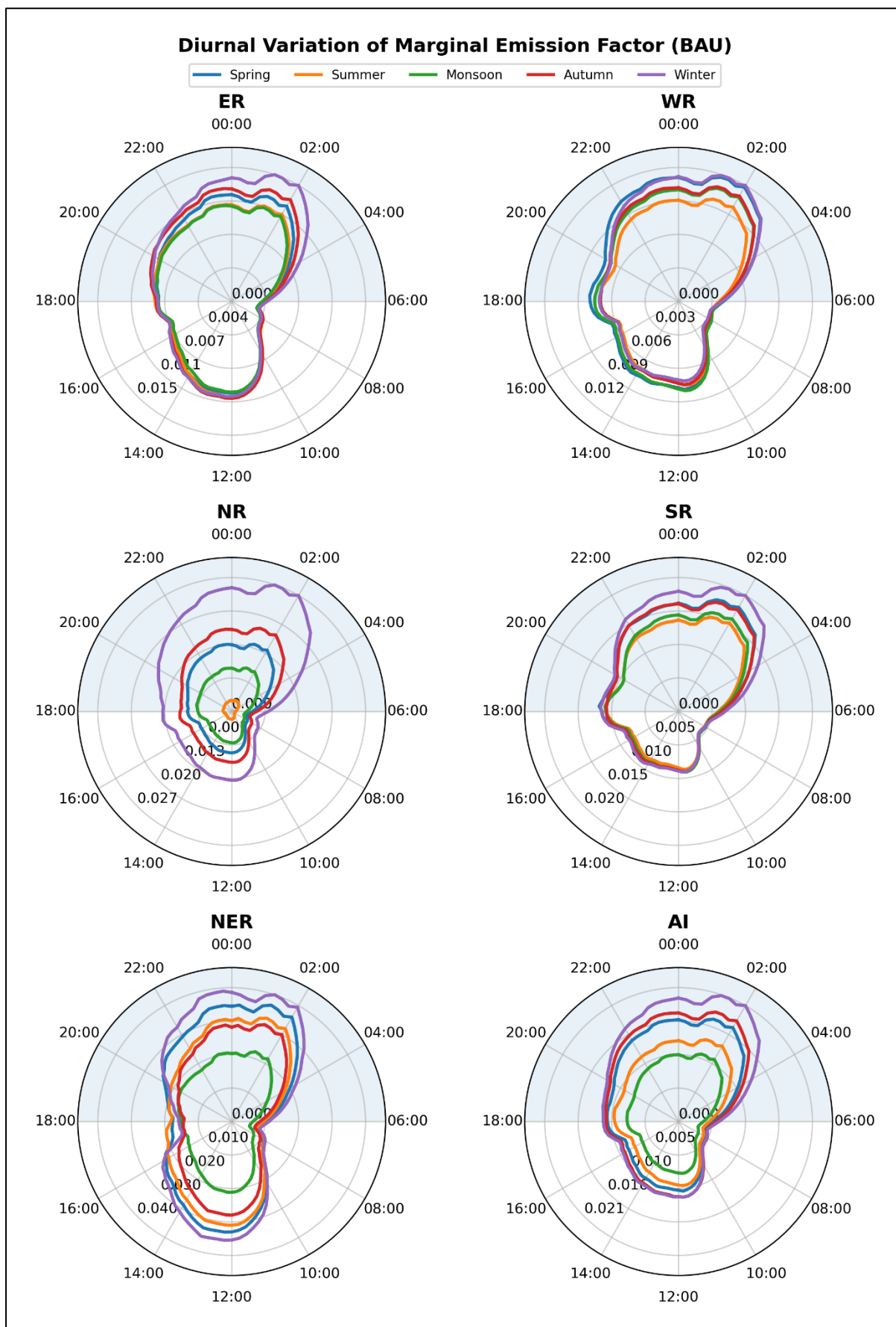


Figure 45: Diurnal variation of marginal emission factors (MEF) (in tCO_2/MWh) under the 2030 BAU scenario across Indian power system regions (ER: Eastern Region, WR: Western Region, NR: Northern Region, SR: Southern Region, NER: Northeastern Region, AI: All India)

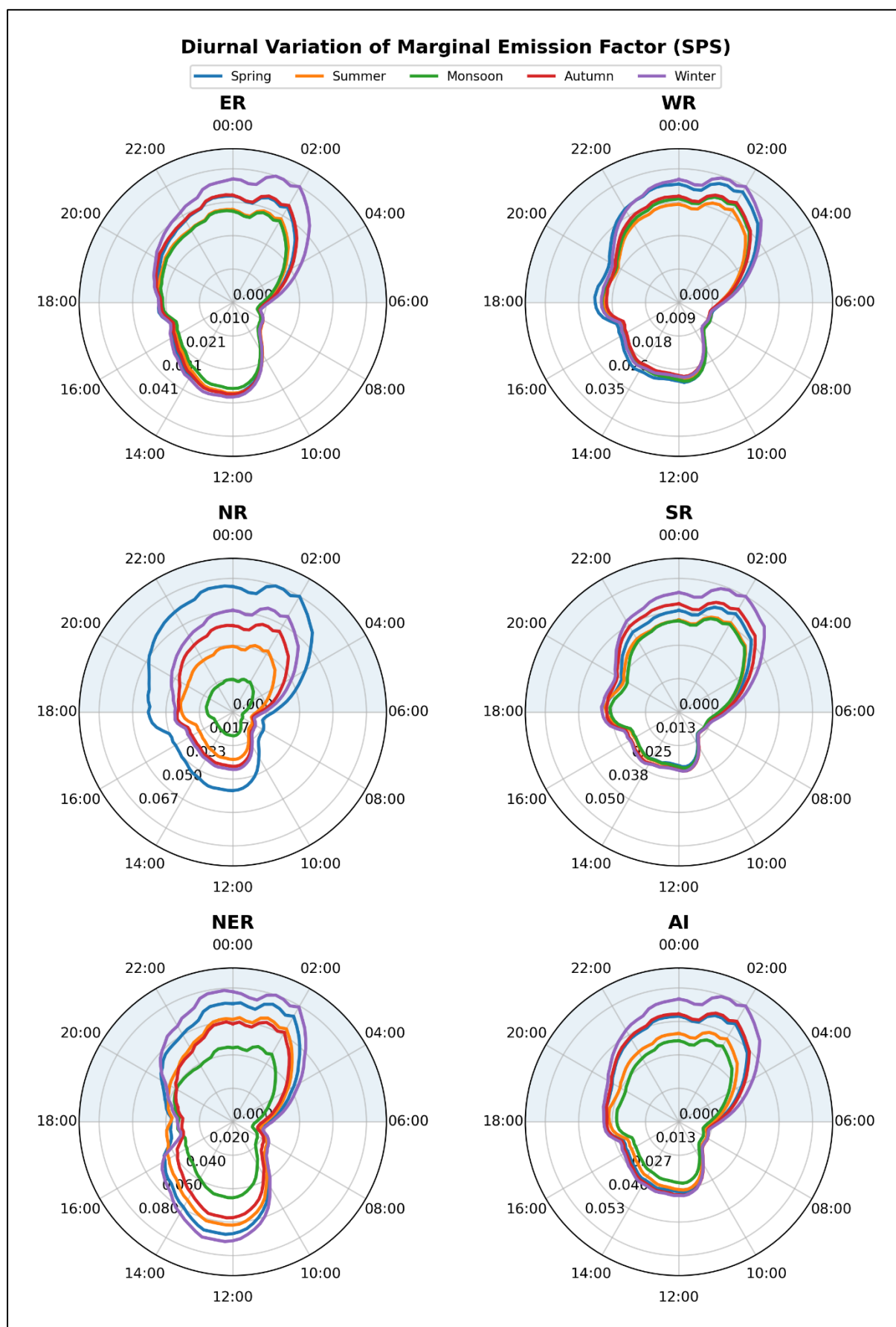


Figure 46: Diurnal variation of marginal emission factors (MEF) (in tCO_2/MWh) under the 2030 SPS scenario across Indian power system regions (ER: Eastern Region, WR: Western Region, NR: Northern Region, SR: Southern Region, NER: Northeastern Region, AI: All India)

9.6 COMPARISON WITH ICEVs

9.6.1 Vehicle category level comparison across regions and seasons

Figure 47 and Figure 48 compares the average emission intensity (gCO₂/km) of EVs and ICEVs across vehicle classes, regions, and seasons for the 2030 BAU scenario and 2030 SPS scenario. EV emission intensities are shown for five representative seasons, while ICEV emission intensity is shown as a reference benchmark for each vehicle class.

9.6.1.1 Overall comparison

Across light duty vehicle segments, including two wheelers (2W), three wheelers (3W), and light passenger vehicles (LPV), EVs consistently exhibit lower emission intensity than ICEVs in all regions and across all seasons. Even in regions with relatively higher grid carbon intensity, the EV emission bars remain well below the corresponding ICEV reference points, indicating a clear per kilometre emission advantage for electrification in these segments under BAU conditions in 2030.

For medium and heavy vehicle categories, including medium passenger vehicles (MPV), heavy passenger vehicles (HPV), and heavy goods vehicles (HGV), the comparison becomes more region dependent. While EVs generally retain a lower emission intensity than ICEVs, the margin of benefit narrows substantially in coal dominated regions and during high emission seasons such as winter and autumn.

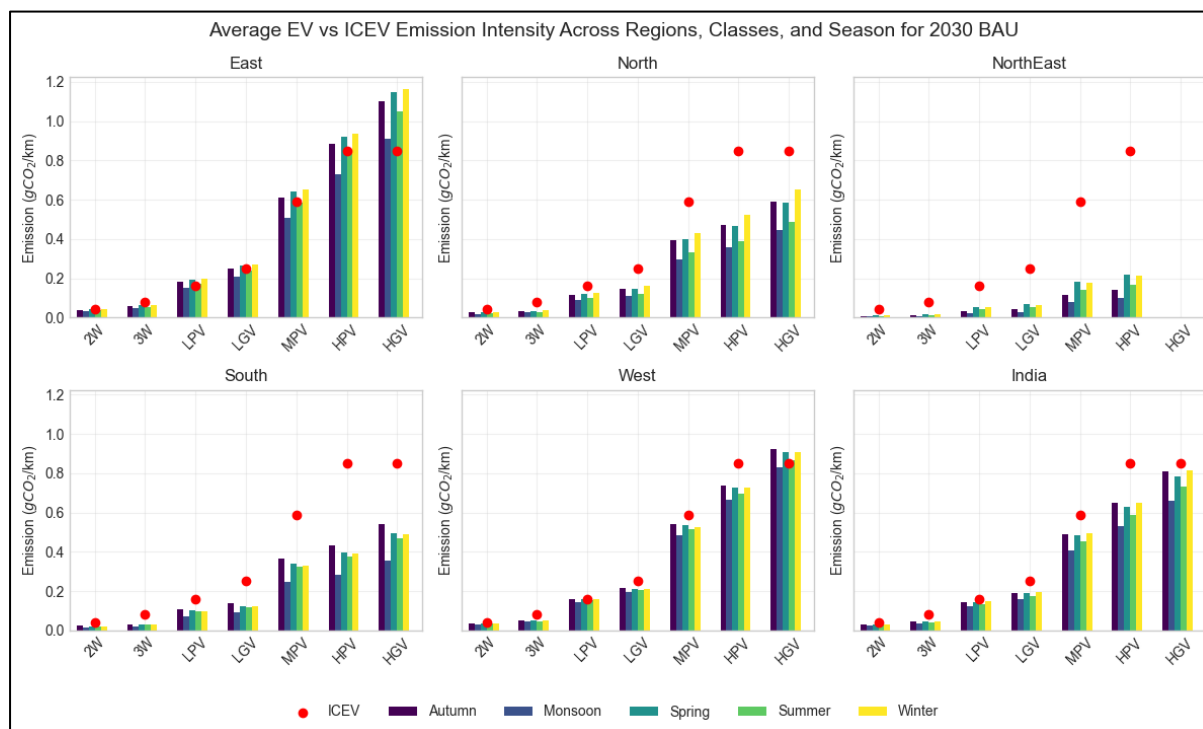


Figure 47: Comparison of EV emission intensity against corresponding ICEV emission intensities for 2030 BAU scenario

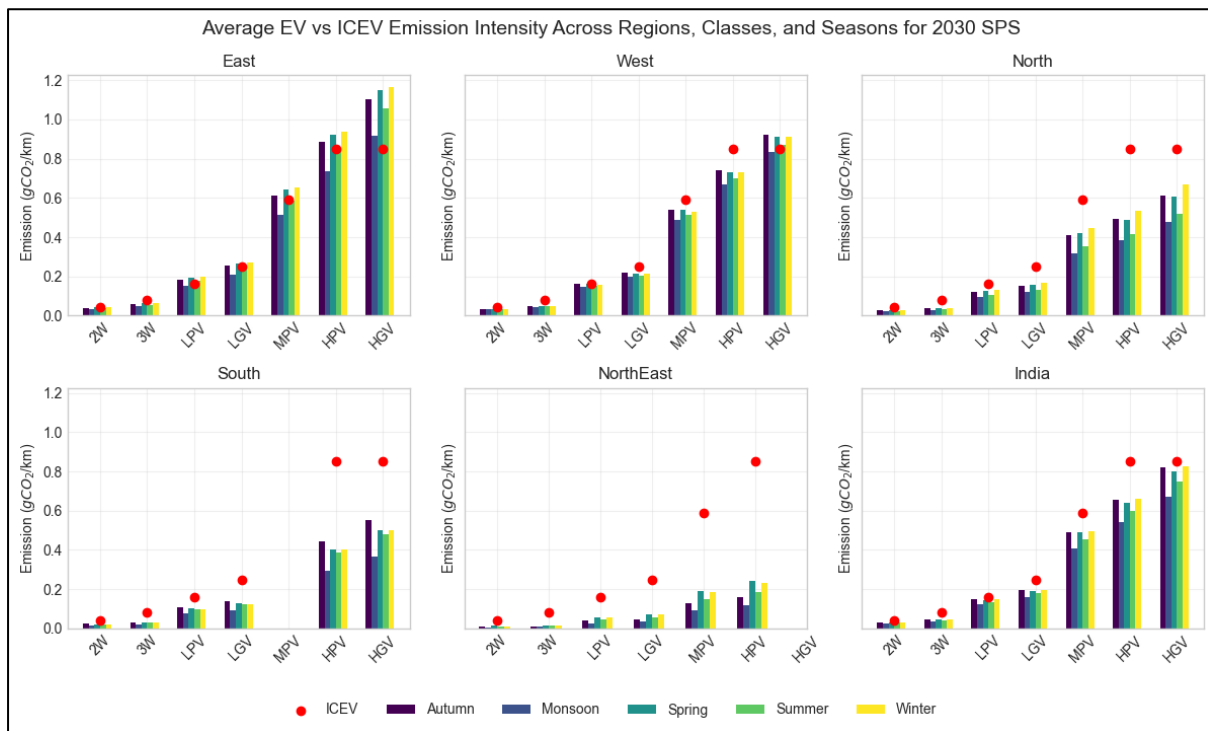


Figure 48: Comparison of EV emission intensity against corresponding ICEV emission intensities for 2030 SPS scenario

9.6.1.2 Regional Insights

The Northern, Southern and North Eastern regions show the largest EV advantage over ICEVs across all vehicle classes. In these regions, EV emission intensities remain low even for heavier vehicle classes, reflecting the strong influence of hydro and renewable generation in the electricity mix. As a result, EVs outperform ICEVs decisively across all seasons.

In the Western region, EVs continue to show lower emission intensity than ICEVs across all vehicle classes, but the gap reduces for MPV, HPV, and HGV segments, particularly during winter and autumn. This indicates sensitivity to seasonal variation in grid carbon intensity.

The Eastern region presents the most constrained case for EV emission benefits. For heavier vehicle classes, particularly HPV and HGV, EV emission intensity during high emission seasons becomes comparable to or, in some cases, higher than ICEVs. This underscores the limited climate benefit of electrifying heavy vehicles without parallel grid decarbonization or clean depot charging in coal dominated regions.

9.6.2 Category Wise Emission Reduction

Figure 49 and Figure 50 show the percentage emission reduction of EVs relative to ICE vehicles for each vehicle class across regional grids in 2030, under the BAU and SPS scenarios, respectively. Positive values indicate emission reductions from electrification, while negative values indicate cases where EV emissions exceed those of ICE vehicles.

Across both scenarios, 2W and 3W consistently achieve substantial emission reductions across all regions. Reductions typically fall in the range of 5–80%, with the highest benefits

observed in regions with cleaner electricity mixes. The Eastern region shows the lowest reductions for these vehicle classes at approximately 5–10%, while the NorthEast region achieves the highest reductions at around 80%.

In contrast, medium and heavy vehicle categories—including LPV, LGV, MPV, HPV, and HGV—exhibit a much wider spread in outcomes, with emission reductions strongly dependent on regional grid carbon intensity. In coal-dominated regions, particularly the Eastern region, heavy-vehicle categories show marginal or even negative emission reductions, with HGV experiencing approximately -25% (indicating 25% higher emissions than ICE equivalents) under the BAU scenario.

The NorthEastern region delivers the strongest emission reductions across all vehicle classes, reflecting its high share of hydro and renewable generation. In this region, all vehicle classes achieve reductions exceeding 70–80%. The Southern region also performs well, with reductions ranging from approximately 45–70% across vehicle classes, with lighter vehicles achieving the higher end of this range.

India as a whole shows moderate reductions across most vehicle classes, typically in the 15–50% range, with lighter vehicles performing better than heavier ones. The Western region demonstrates similar patterns to the national average, with reductions of approximately 10–55% depending on vehicle class.

The Northern region shows intermediate outcomes. Light-duty vehicles (2W, 3W, LPV) maintain reductions in the 30–60% range, but heavier vehicle classes (HPV, HGV) experience significantly reduced benefits, typically in the 35–45% range.

The Eastern region presents the most constrained case. While 2W vehicles still achieve approximately 5–10% reductions, the benefits decline sharply with vehicle weight. HGV exhibits negative emission reductions of around -25% under BAU, indicating that heavy EV operation on a coal-intensive grid actually increases emissions compared to conventional vehicles. HPV shows near-zero reductions, and other heavy vehicle categories achieve only marginal benefits of 0–5%.

.

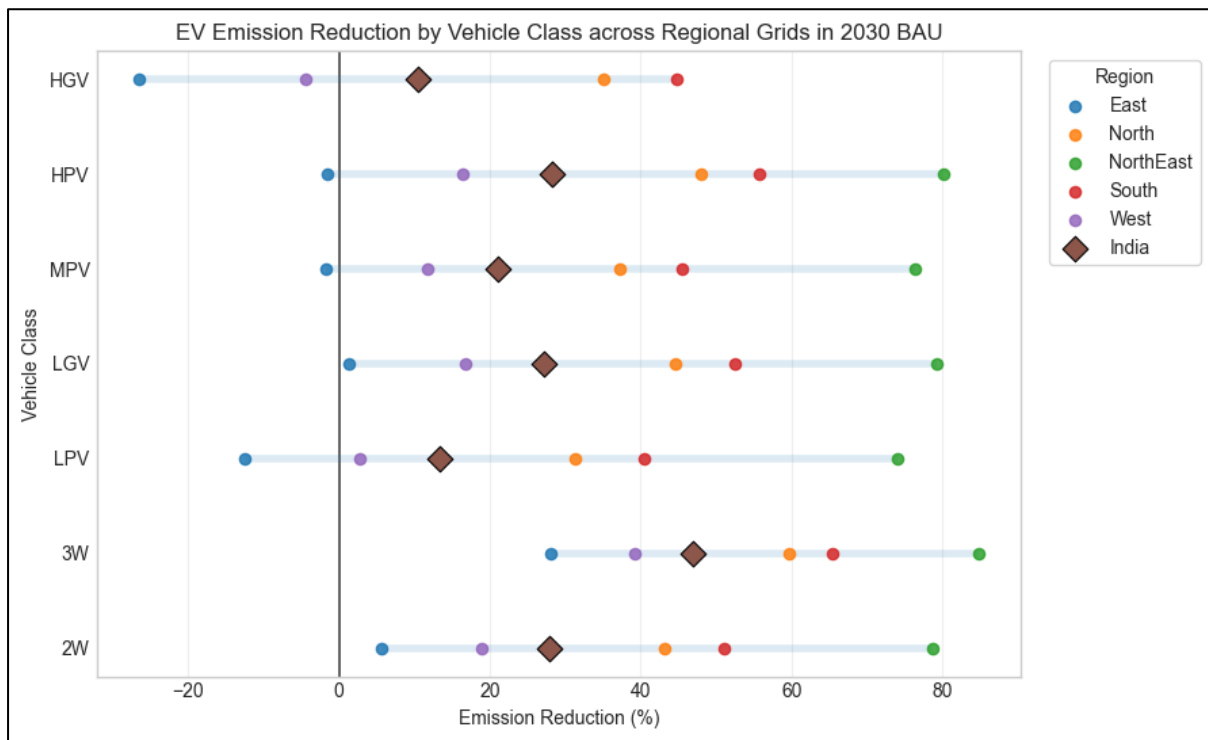


Figure 49: Comparison of emission reduction from EVs to ICEVs for 2030 BAU scenario

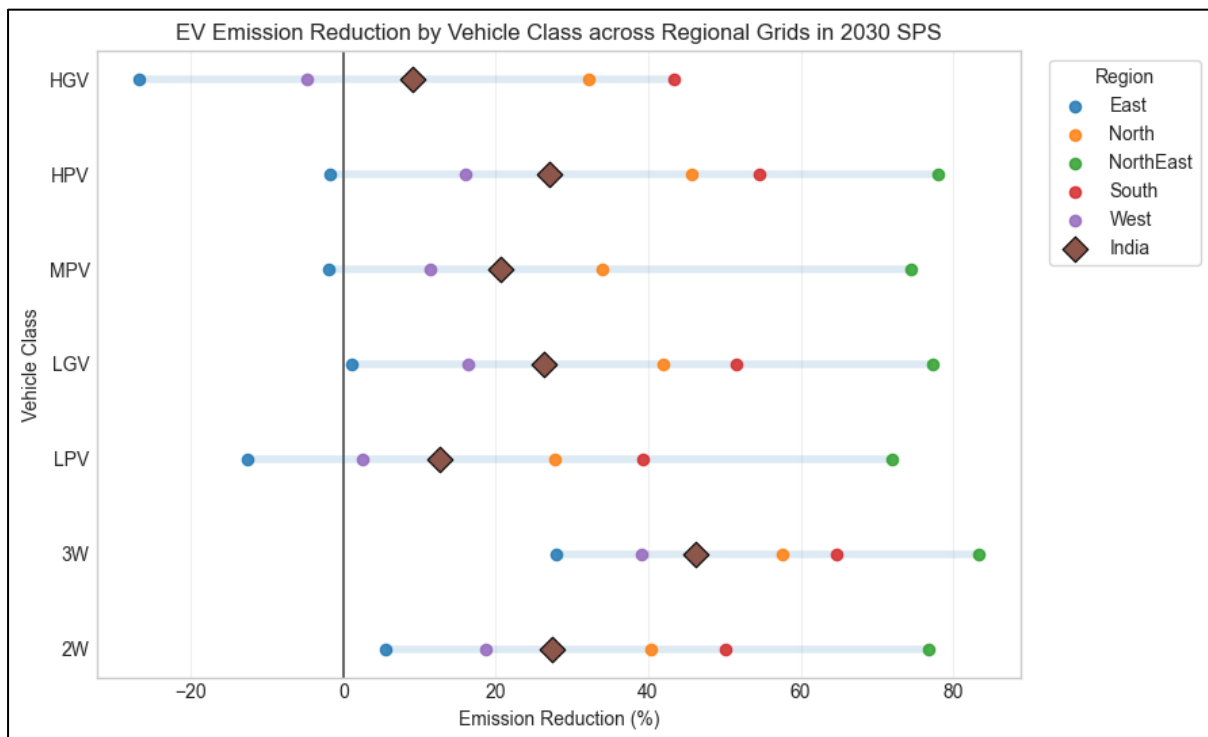


Figure 50: Comparison of emission reduction from EVs to ICEVs for 2030 SPS scenario

9.6.3 Regional and seasonal variability in emission benefits

The monsoon season consistently delivers the highest emission reductions across most regions in both scenarios. At the national level, monsoon achieves 41.1% emission reduction under BAU and 40.4% under SPS, the strongest performance of any season as shown in Figure 51 and Figure 52. This advantage stems from increased hydroelectric generation

during the monsoon months, which temporarily reduces grid carbon intensity. Summer follows as the second-best performing season nationally, with reductions of 34.6% (BAU) and 33.9% (SPS), likely benefiting from higher solar generation and improved hydroelectric reservoir levels.

In contrast, winter, autumn, and spring show notably lower emission reductions. Winter achieves only 28.2% (BAU) and 27.6% (SPS) at the national level, while autumn performs similarly at 28.7% (BAU) and 28.1% (SPS). Spring shows 29.6% (BAU) and 28.9% (SPS). These seasons experience reduced hydroelectric output and increased reliance on thermal generation for heating and other seasonal demands, elevating grid carbon intensity.

The NorthEast region demonstrates exceptional and consistent performance across all seasons, with emission reductions ranging from 78.8% to 90.6% under BAU, and 77.8% to 89.3% under SPS. Even in the worst-performing season (spring), the NorthEast achieves nearly 79% emission reduction, exceeding the best performance of most other regions. This reflects the region's predominantly hydroelectric power supply, which maintains low carbon intensity year-round.

The North and South regions show strong but more variable performance. The North ranges from 42.8% to 60.5% under BAU (41.2% to 57.8% under SPS), while the South spans 41.2% to 60.7% under BAU (40.5% to 59.6% under SPS). Both regions benefit significantly during monsoon season, achieving approximately 60% emission reductions, but experience notable deterioration during winter and autumn when reductions drop to the low-to-mid 40% range.

The West and East regions present the weakest cases for EV deployment. The Western region shows modest reductions ranging from 14.4% to 22.8% under BAU (14.6% to 22.7% under SPS), with minimal seasonal variation. The Eastern region performs worst overall, with reductions spanning only 11.8% to 31.1% under BAU (11.3% to 30.4% under SPS). During winter, the Eastern region achieves merely 11.8% emission reduction under BAU, indicating that EVs offer minimal climate benefit in this coal-dominated grid during low-renewable-generation periods.

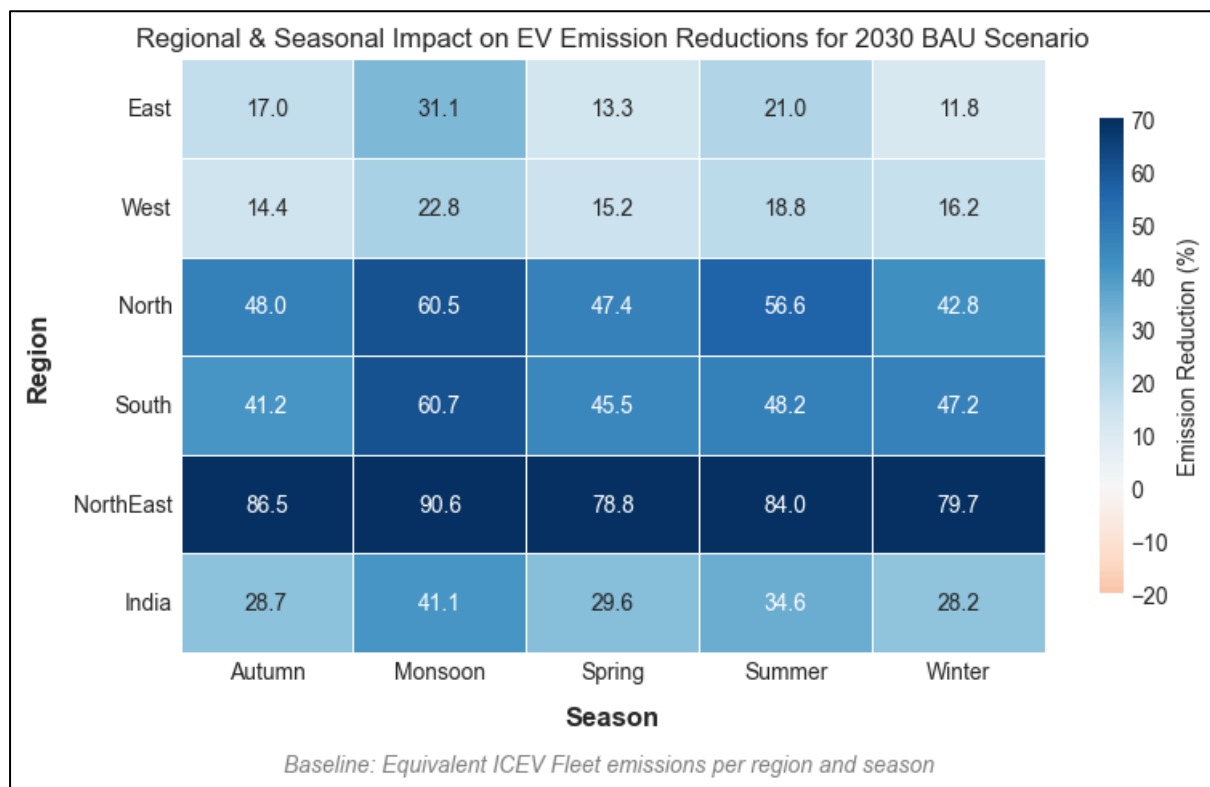


Figure 51: Regional and Seasonal impact on EV Emission Reduction for 2030 BAU scenario

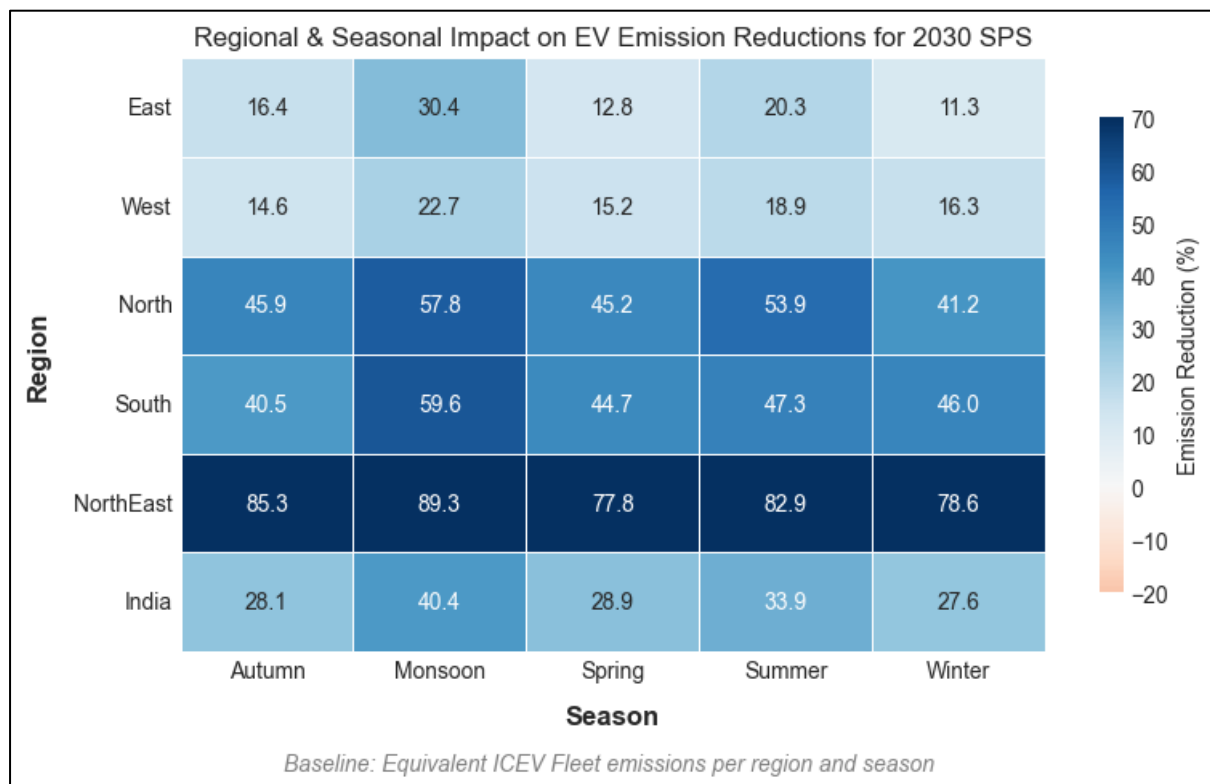


Figure 52: Regional and Seasonal impact on EV Emission Reduction for 2030 SPS scenario

10 CONCLUSION

This study provides a comprehensive, system-level assessment of the emissions implications of EV adoption in India, spanning present-day (2023) conditions and forward-looking 2030 scenarios under both Business As Usual (BAU) and Stated Policies Scenario (SPS) trajectories. By combining vehicle-level energy use modelling with regionally resolved power system emissions analysis, the report demonstrates that EV-related emission outcomes are neither uniform nor automatic, but emerge from complex interactions between vehicle characteristics, charging behaviour, grid composition, and system operations.

The 2023 analysis establishes that electrification delivers clear and robust emission benefits in light-duty vehicle segments, particularly two-wheelers, three-wheelers, and light passenger vehicles. These segments combine low energy consumption per kilometre with charging patterns that partially overlap with lower-emission periods, resulting in consistent national-average emission reductions. In contrast, medium and heavy-duty vehicle segments exhibit significantly weaker benefits, and in some coal-dominated regions approach parity or even underperform internal combustion engine vehicles. This highlights that drivetrain electrification alone is insufficient to guarantee emission reductions, especially for energy-intensive vehicle classes operating on carbon-intensive grids.

At the national scale, the cumulative emissions impact is dominated by light-duty electrification. Despite relatively modest per-vehicle savings, two- and three-wheelers and light passenger vehicles account for the majority of total emission reductions due to their large fleet sizes and high utilisation. Heavy-duty vehicles contribute only marginally to national emission reductions under current conditions, underscoring the importance of fleet composition and activity patterns when evaluating system-wide climate impacts.

The 2030 analysis extends this understanding by explicitly accounting for the causal response of the power system to EV charging demand using a marginal emissions framework. By estimating marginal emission factors (MEFs) in units of tCO_2/MWh , the analysis captures the incremental emissions associated with each additional unit of EV charging demand, including the effects of thermal generation dispatch, renewable availability, and battery energy storage operations. This approach provides a more accurate and policy-relevant assessment than average grid emission factors, particularly under high EV penetration scenarios.

Across both BAU and SPS scenarios, strong diurnal patterns in MEFs are observed. EV charging during mid-day hours consistently results in substantially lower marginal emissions than charging during evening and night-time periods. In most regions, daytime charging leads to 40–60% lower emissions per MWh than night-time charging, with even larger differentials under the SPS scenario. This reflects the dominant role of solar generation and favourable marginal dispatch conditions during daylight hours. The North-Eastern region emerges as a

notable exception, where limited variable renewable penetration and a generation mix dominated by gas and hydro lead to relatively similar MEFs across day and night.

Regional and seasonal heterogeneity remains a defining feature of emissions outcomes. Regions with high shares of hydro and renewable generation, particularly the North-Eastern and Southern grids, consistently deliver strong emission reductions across seasons and scenarios. In contrast, coal-dominated regions, especially the Eastern grid, show limited and highly variable benefits, with EV electrification offering minimal climate advantage during high-emission seasons. Seasonal effects are most pronounced in hydro-rich regions, with monsoon periods delivering the strongest emission reductions and winter months exhibiting the weakest performance.

A critical insight from the 2030 analysis is that higher EV penetration under the SPS scenario does not automatically translate into proportionally lower emissions. While overall grid decarbonisation reduces average emission intensity, marginal emission factors increase substantially, often by a factor of two to three, relative to BAU. This increase reflects both the higher absolute EV charging demand and the growing share of EV demand in total system load, which pushes the power system further up the generation merit order and activates more emission-intensive marginal resources. As a result, each additional unit of EV charging demand in the SPS scenario can have a higher marginal emissions impact than in BAU, unless accompanied by changes in charging behaviour and system flexibility.

Despite the increase in marginal emission factors under higher EV penetration scenarios, the analysis shows that total emissions from electric vehicles in 2030 are lower than those from corresponding ICE vehicles across most vehicle categories and regions. Figure 49 and Figure 50 compare the percentage emission reduction of EVs relative to ICE vehicles under the 2030 BAU and SPS scenarios, respectively, highlighting that electrification continues to deliver net emission benefits at the vehicle level, even under more emission-intensive marginal conditions.

Across both scenarios, light-duty vehicle segments, particularly two-wheelers (2W) and three-wheelers (3W), consistently achieve substantial emission reductions across all regions. Reductions typically range from 5% to 80%, with the highest benefits observed in regions with cleaner electricity mixes. The Eastern region exhibits the lowest reductions for these vehicle classes, at approximately 5–10%, reflecting its coal-dominated generation mix, while the North-Eastern region achieves the highest reductions, approaching 80%, due to its strong reliance on hydro and renewable generation.

Medium and heavy vehicle categories, including light and medium passenger vehicles (LPV, MPV), light and heavy goods vehicles (LGV, HGV), and heavy passenger vehicles (HPV), exhibit a much wider spread in outcomes. In these segments, emission reductions are highly sensitive to regional grid carbon intensity. In coal-dominated regions, most notably the Eastern region, heavy vehicle electrification delivers marginal or even negative emission reductions.

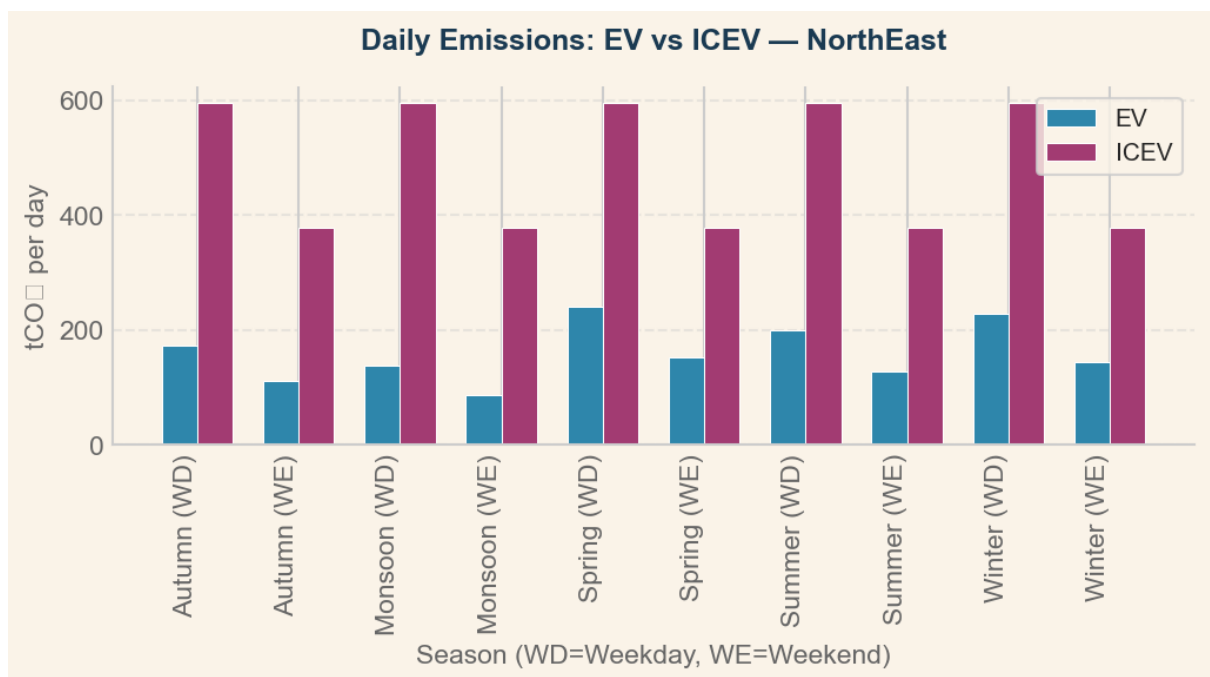
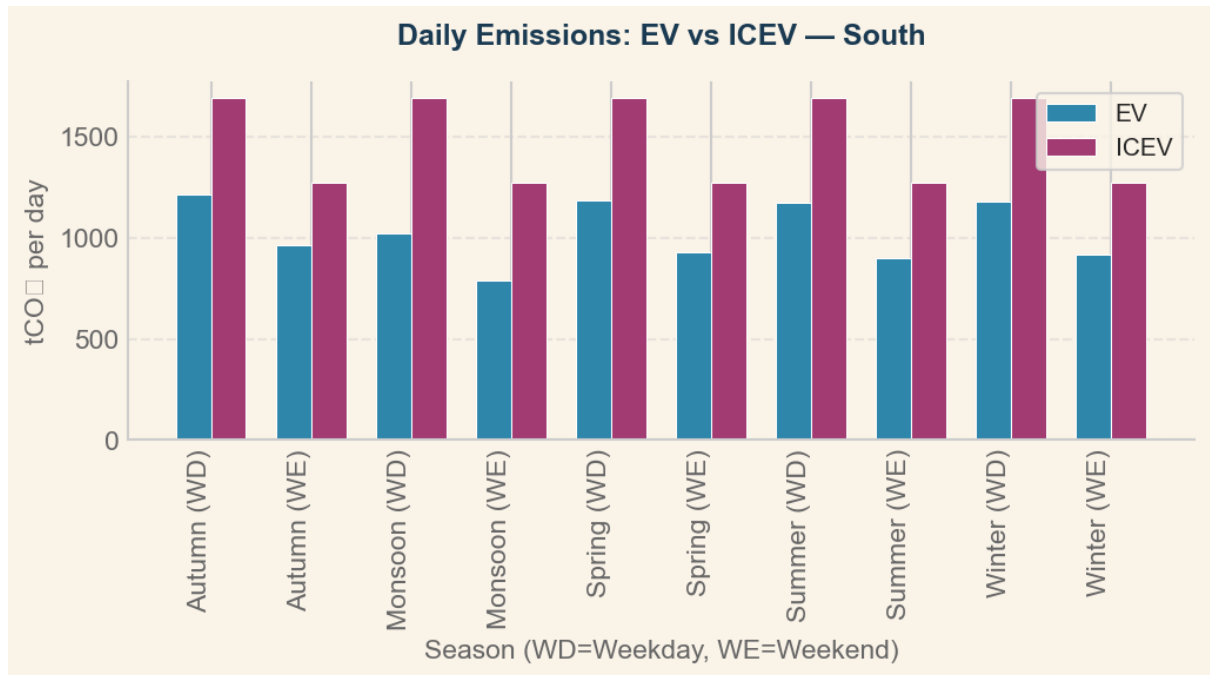
Under the BAU scenario, heavy goods vehicles (HGVs) in the Eastern region exhibit approximately –25% emission reduction, indicating higher emissions than their ICE counterparts. HPV and other heavy categories in this region show near-zero or very limited benefits.

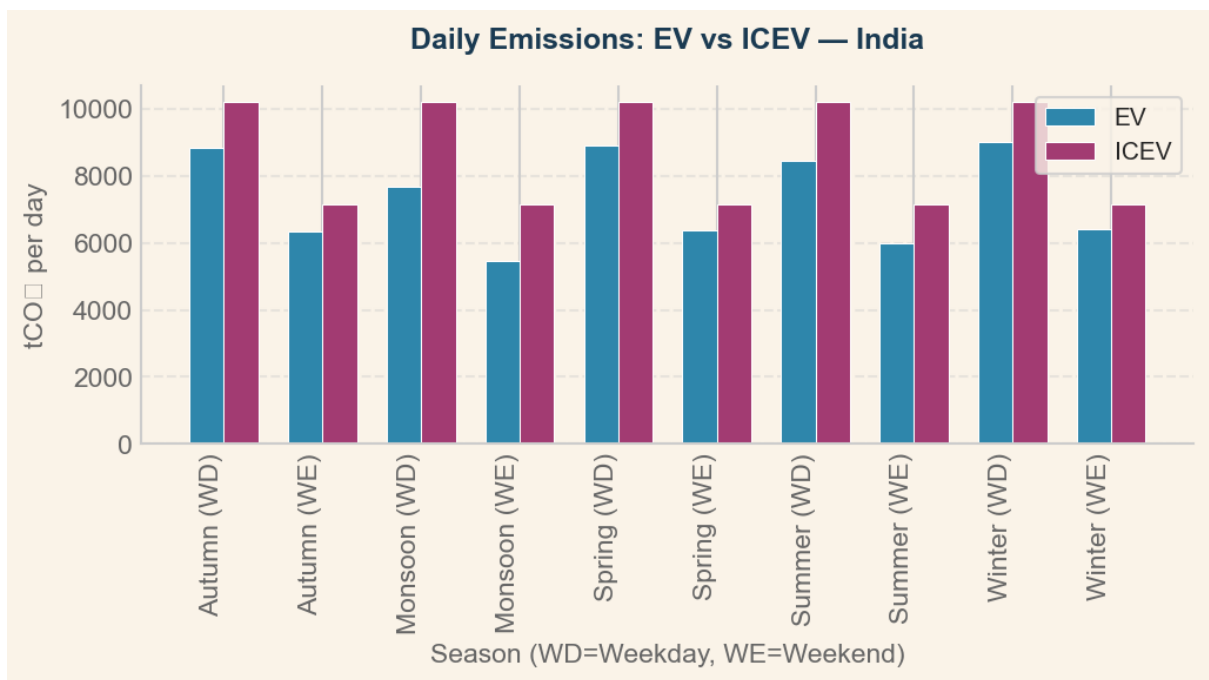
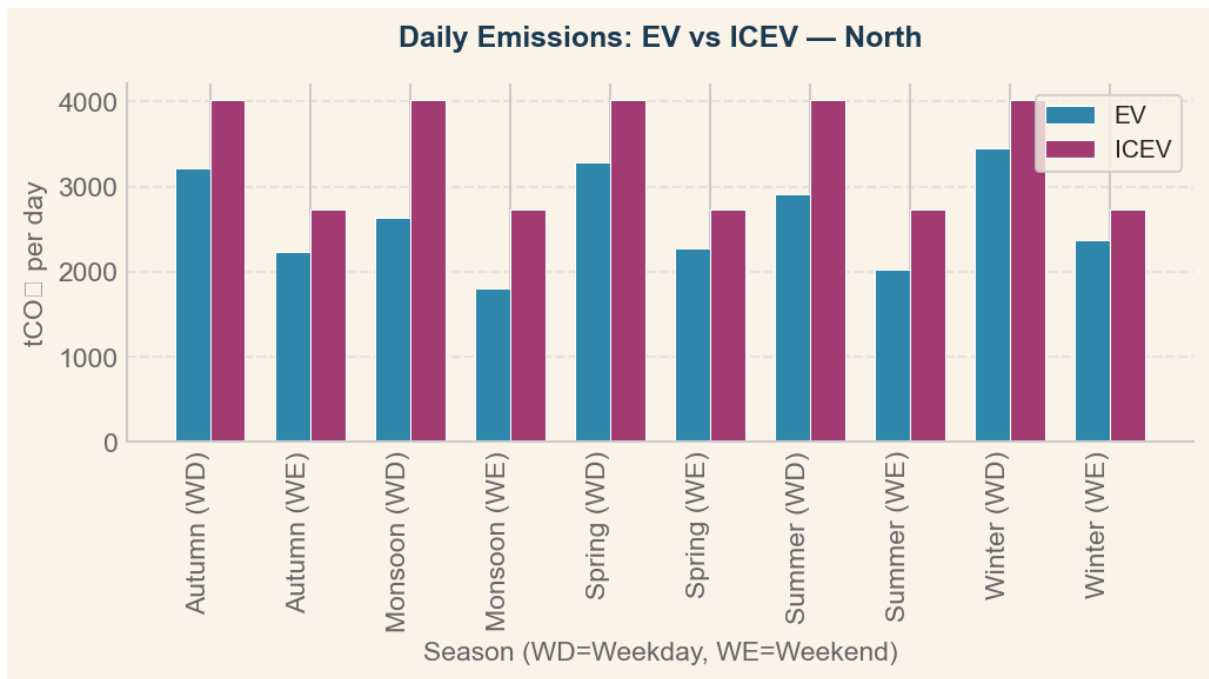
Regional contrasts remain pronounced. The North-Eastern region delivers the strongest and most consistent emission reductions across all vehicle classes, with reductions exceeding 70–80% under both BAU and SPS scenarios. The Southern region also performs strongly, achieving reductions of approximately 45–70%, with lighter vehicles at the upper end of this range. At the national level, India shows moderate but positive reductions across most vehicle classes, typically in the 15–50% range, again with stronger performance in lighter vehicle segments. The Western region broadly mirrors national trends, while the Northern region exhibits intermediate outcomes, with light-duty vehicles maintaining reductions of 30–60% but heavier vehicle categories seeing more constrained benefits in the 35–45% range.

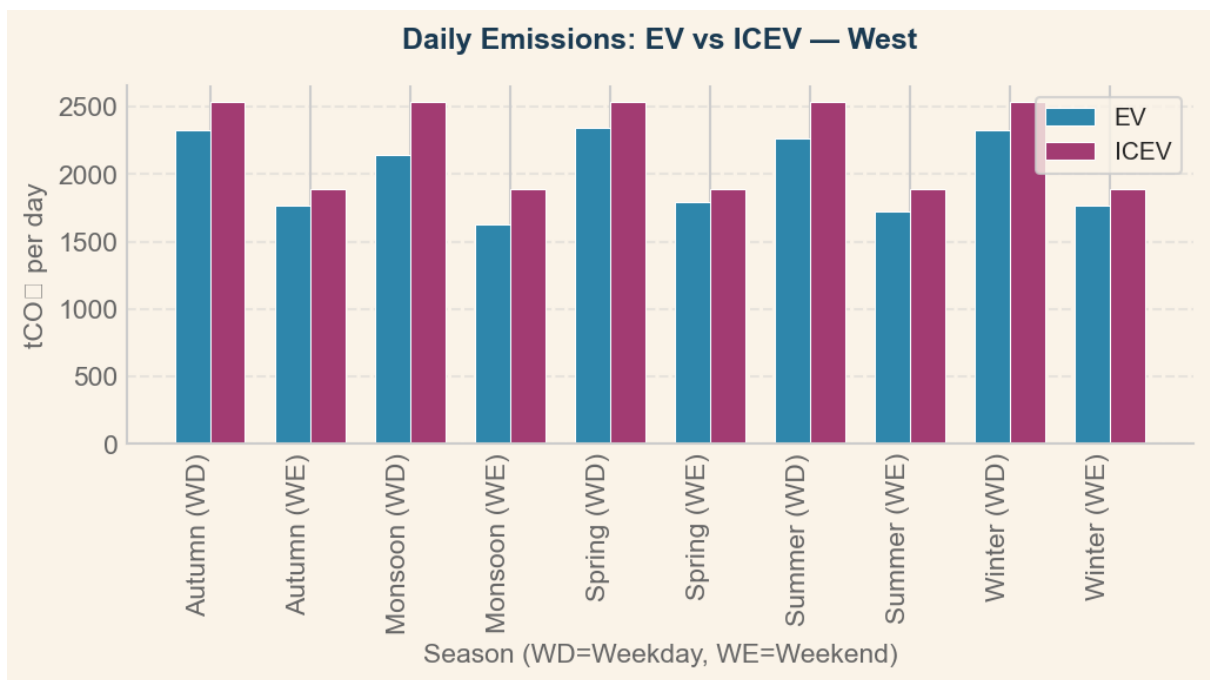
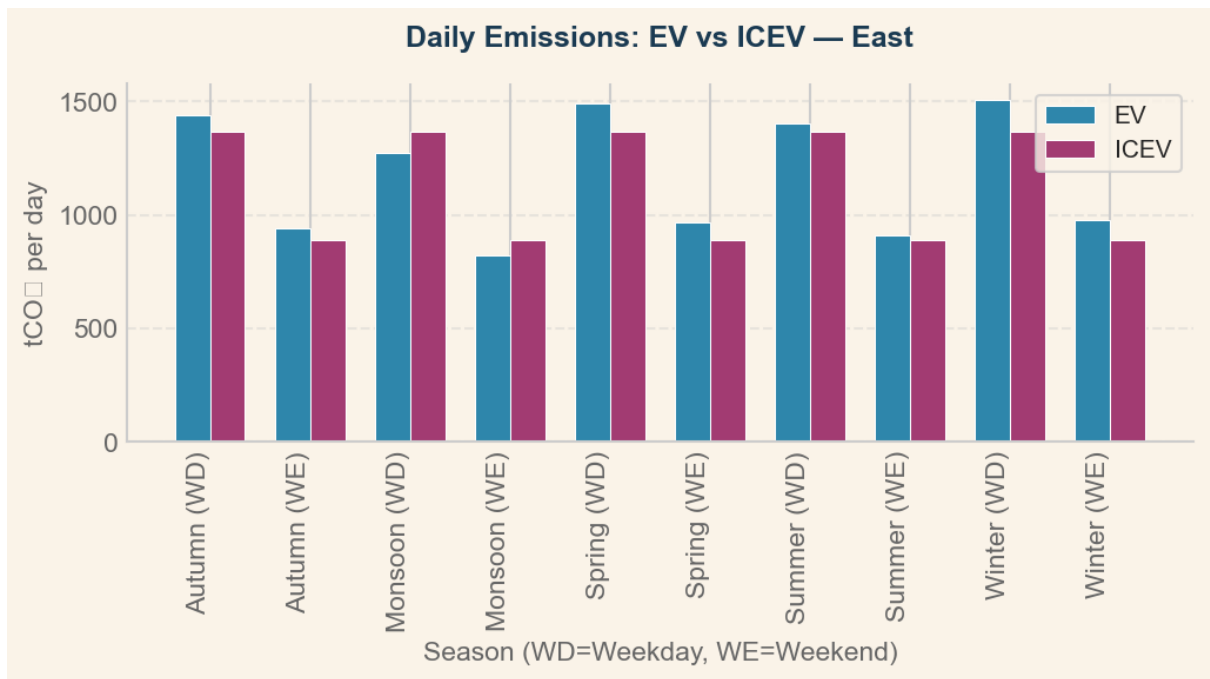
Taken together, these results indicate that electrification remains a net-positive decarbonisation pathway for road transport in 2030, but that the magnitude and robustness of emission reductions vary sharply by vehicle class, region, and grid conditions. While light-duty electrification delivers reliable benefits across scenarios, the climate effectiveness of medium- and heavy-duty electrification depends critically on parallel progress in grid decarbonisation and charging strategy design.

APPENDIX

DAILY EMISSIONS - 2023

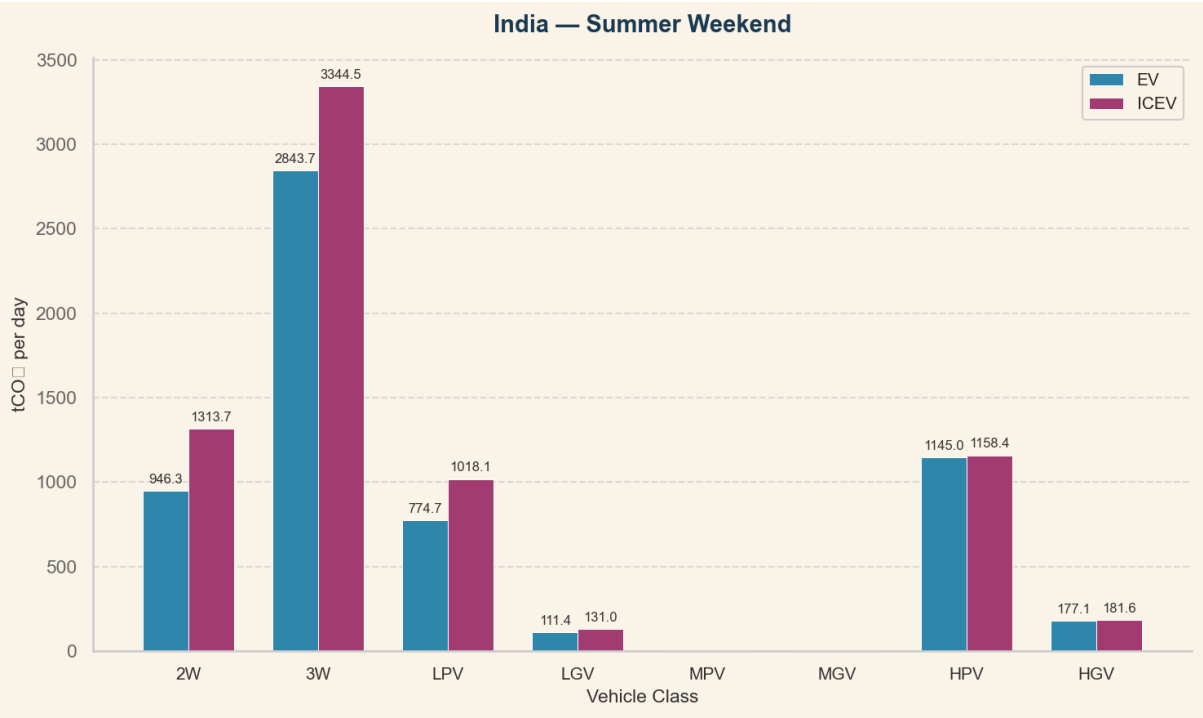
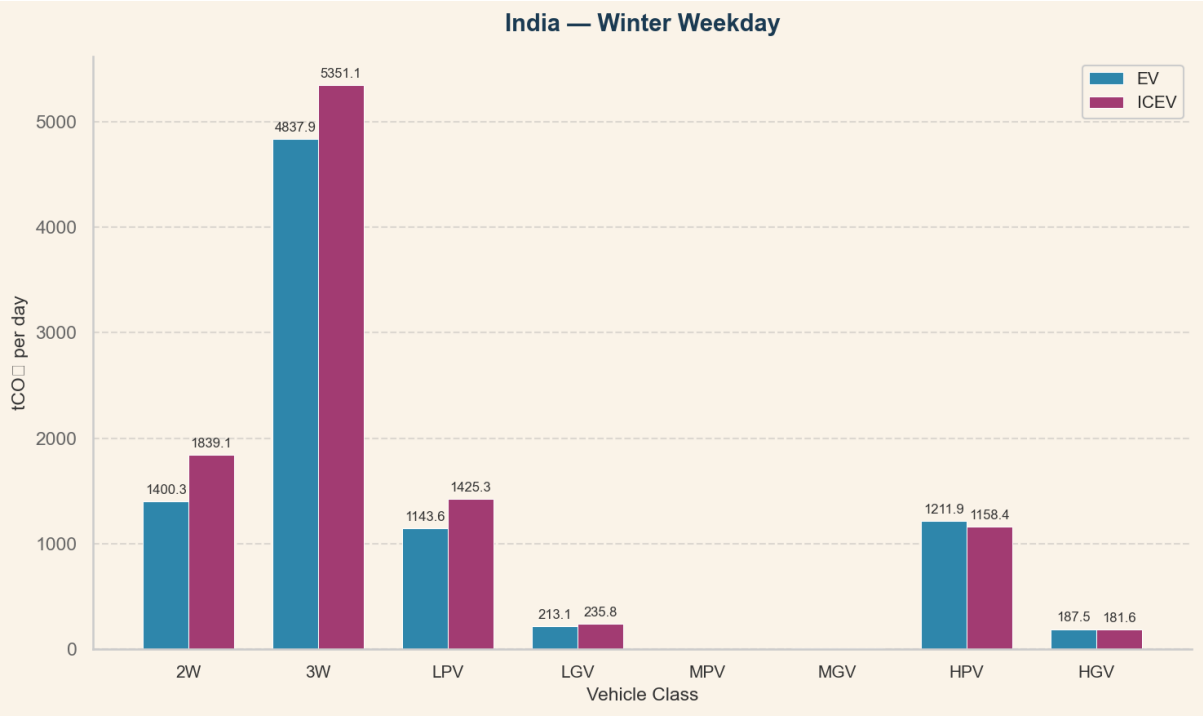


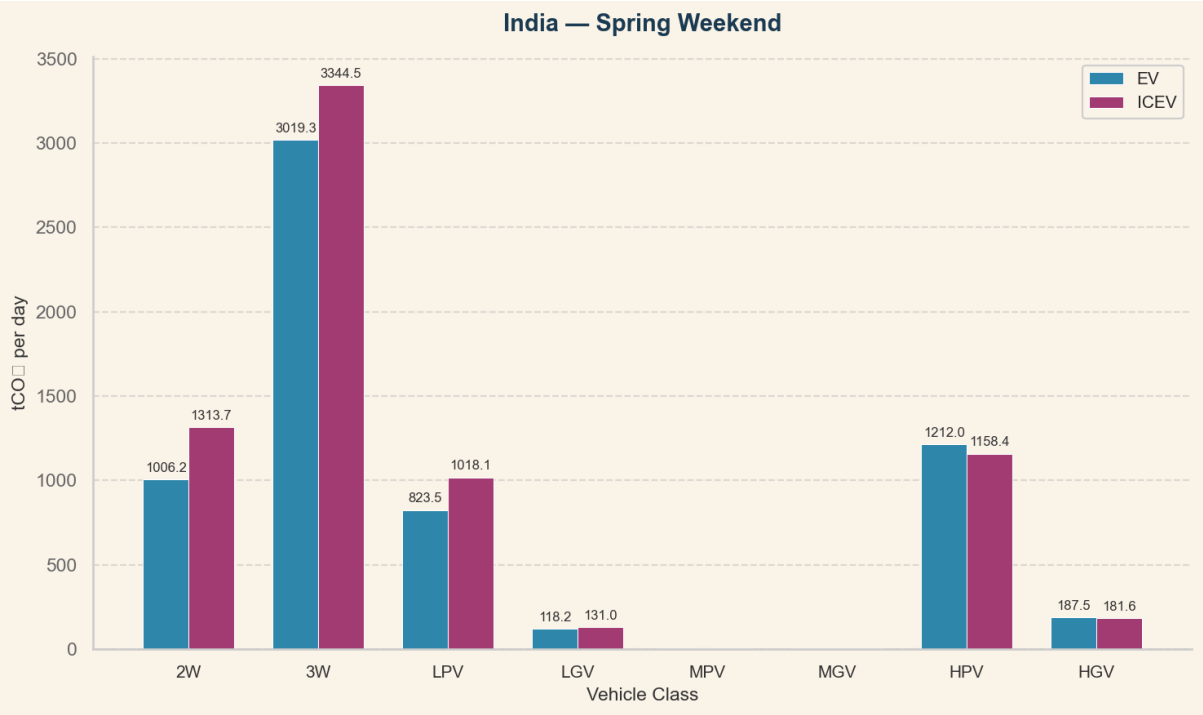
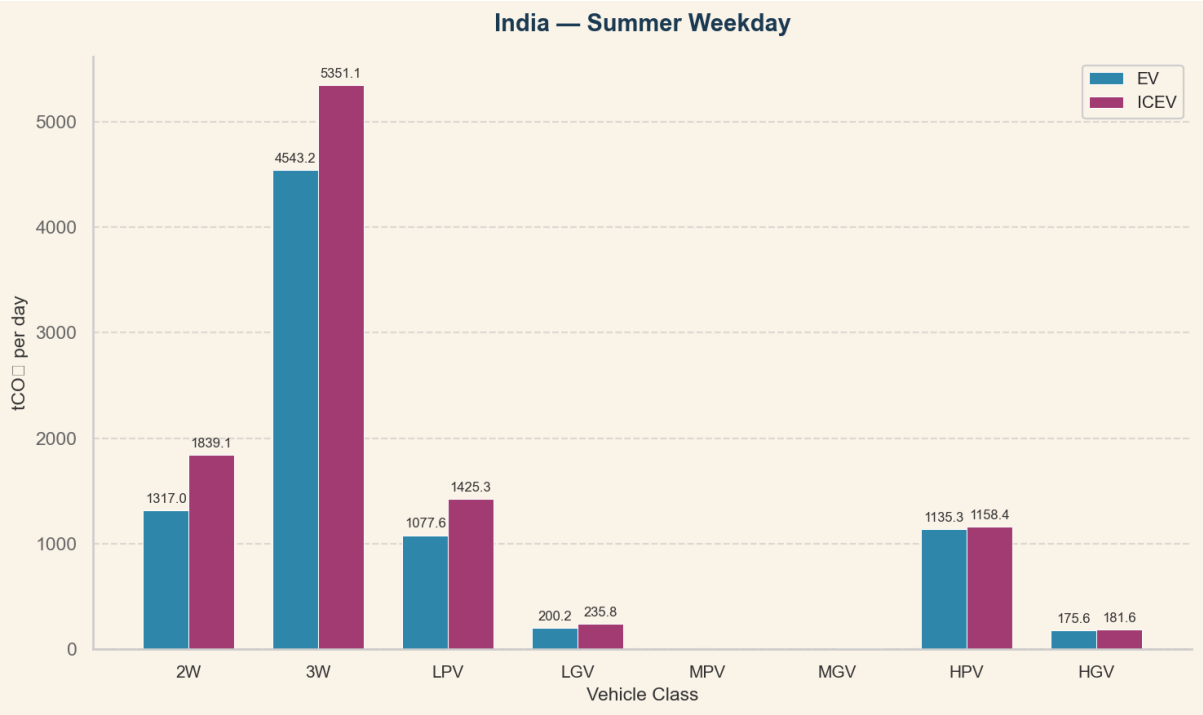


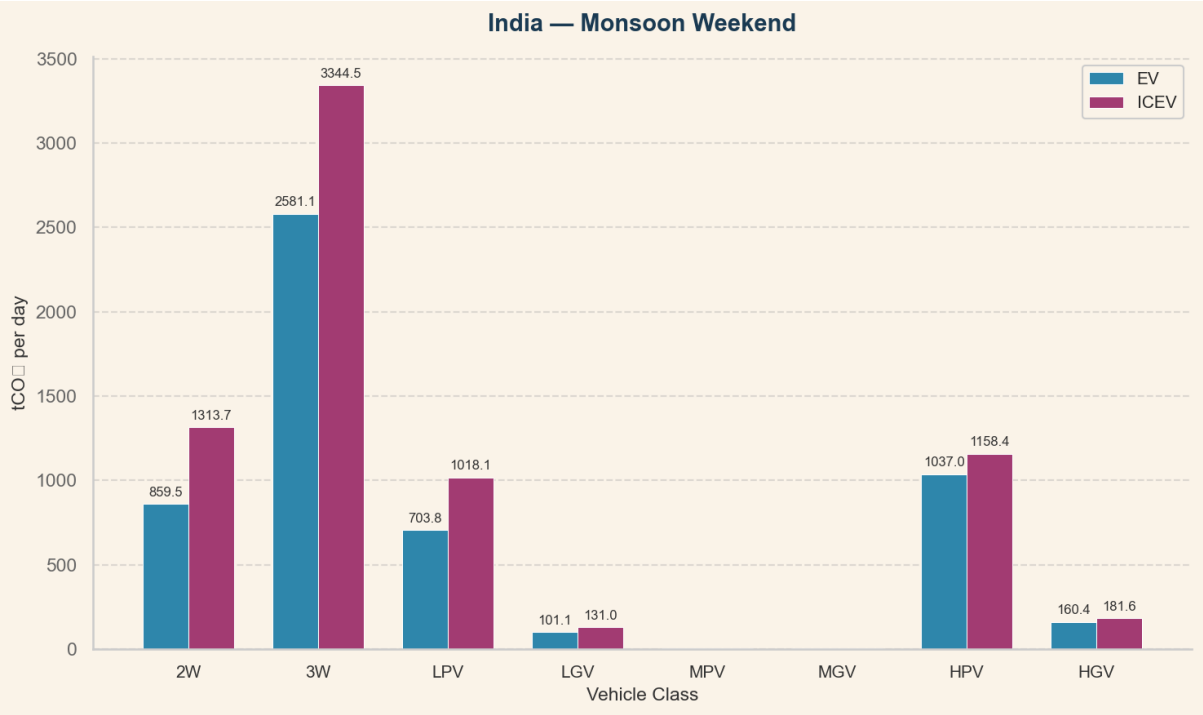
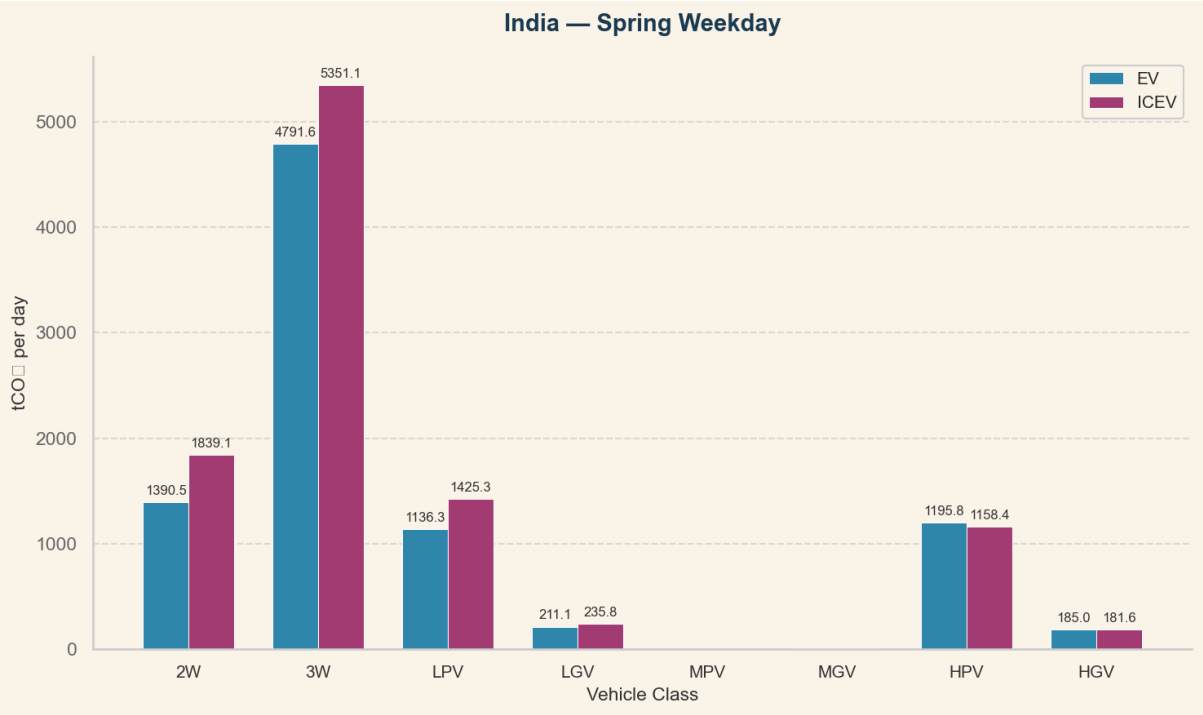


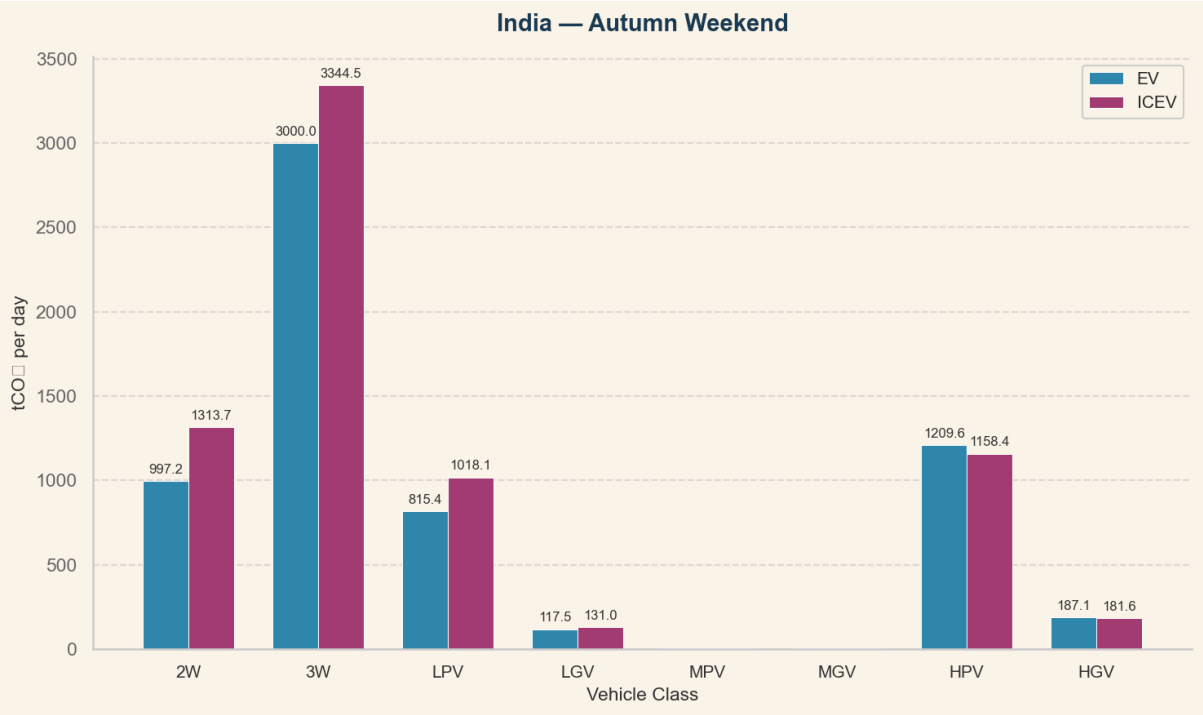
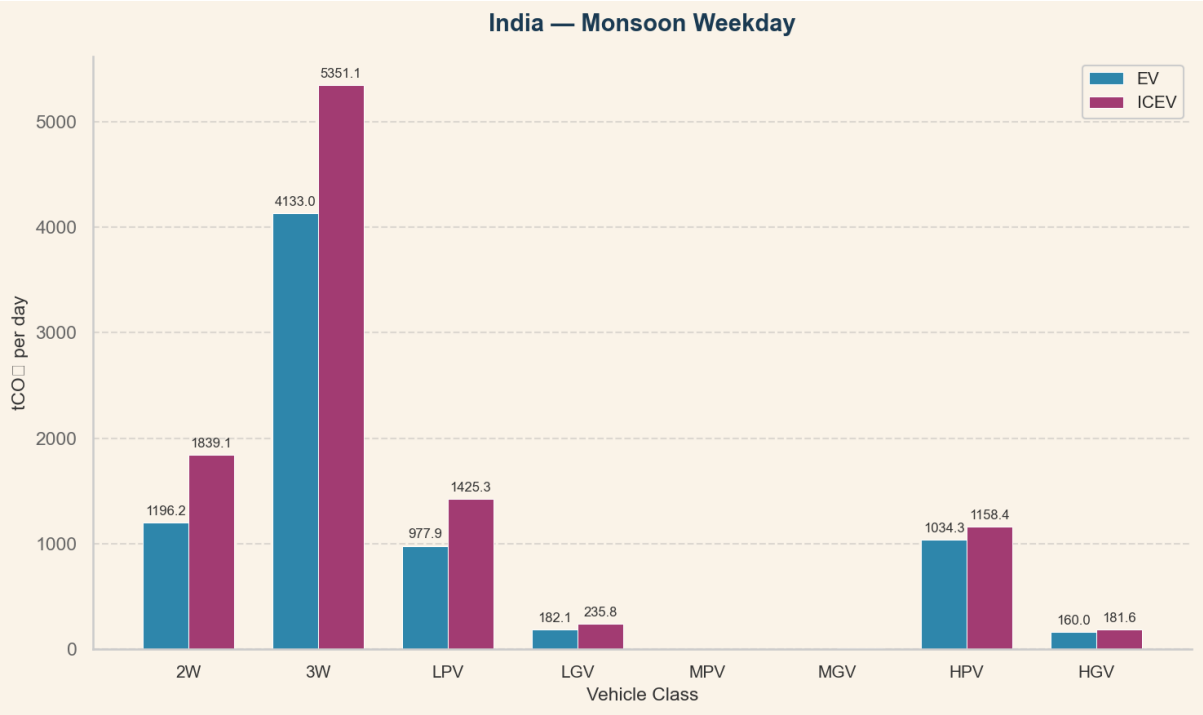
CATEGORY WISE COMPARISON - 2023

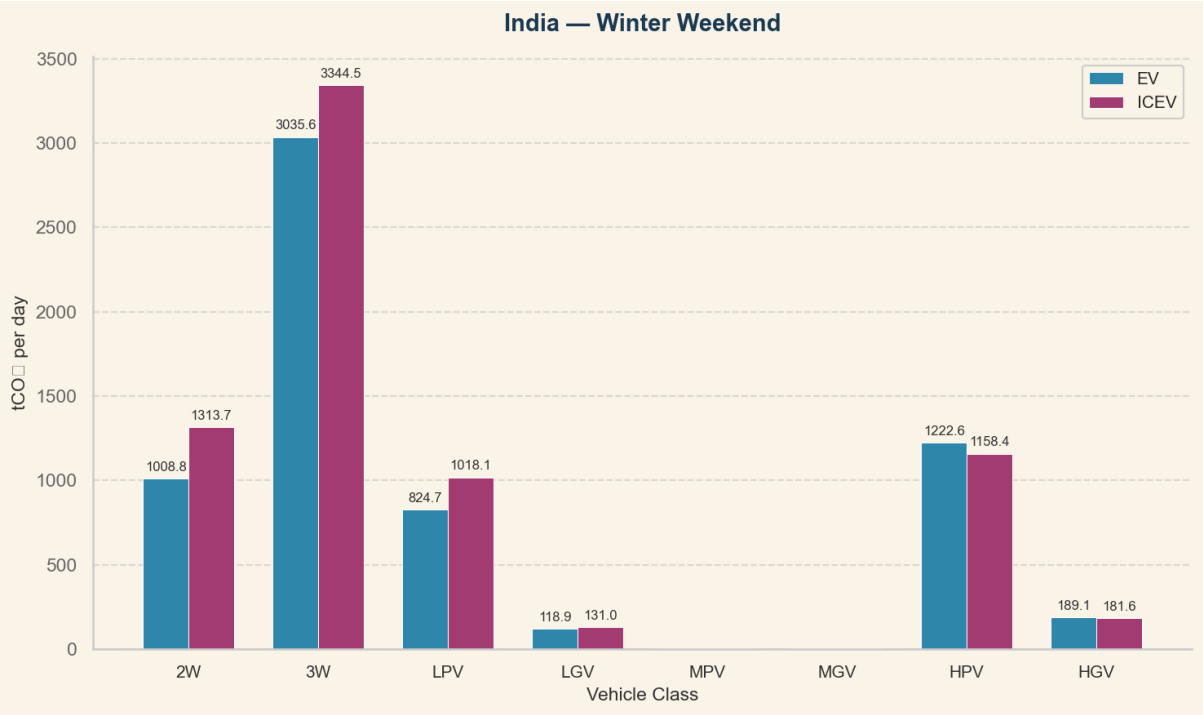
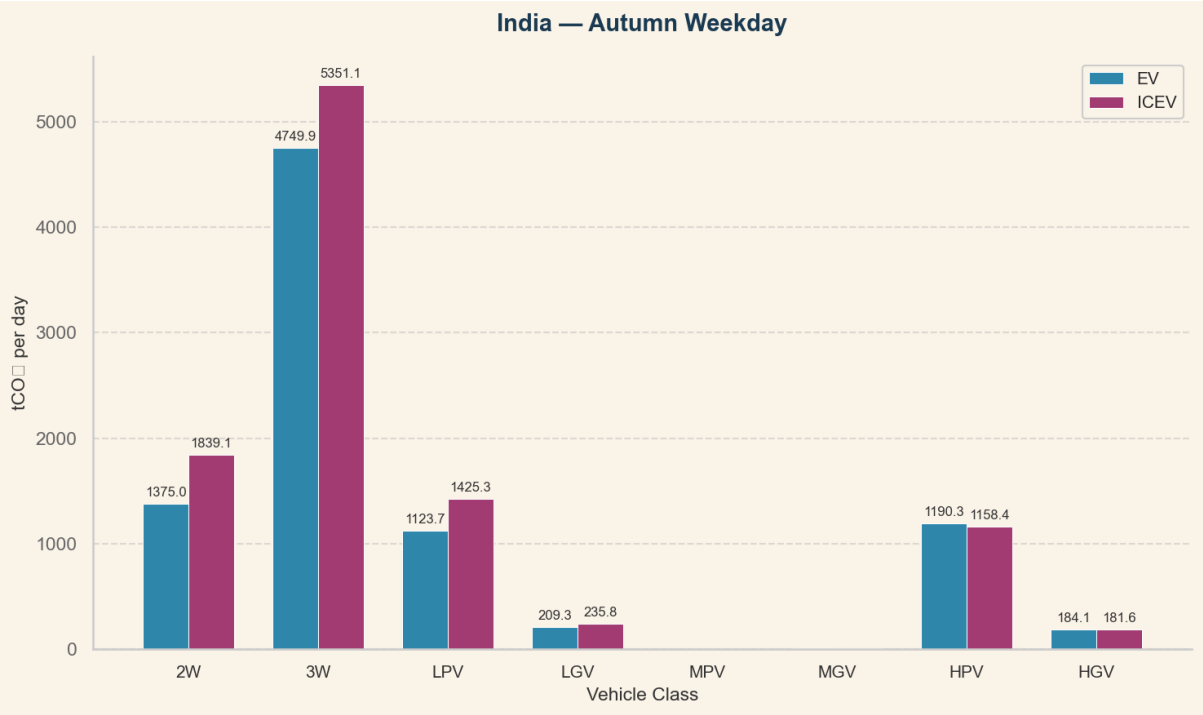
India



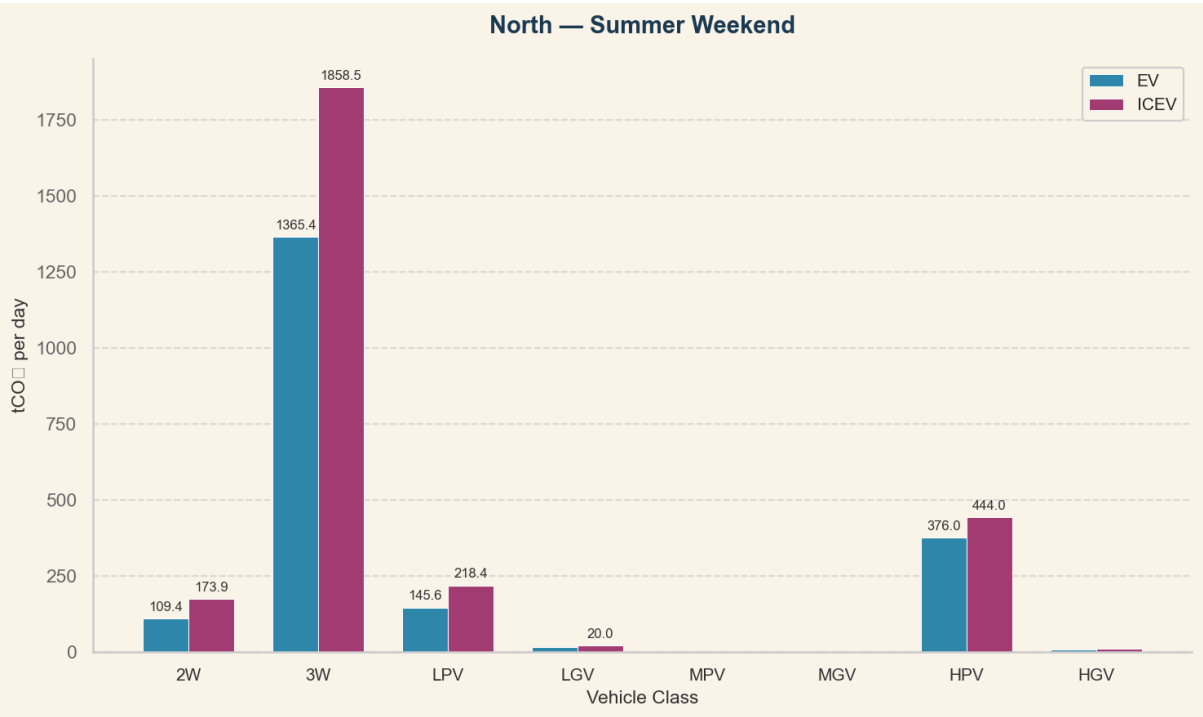
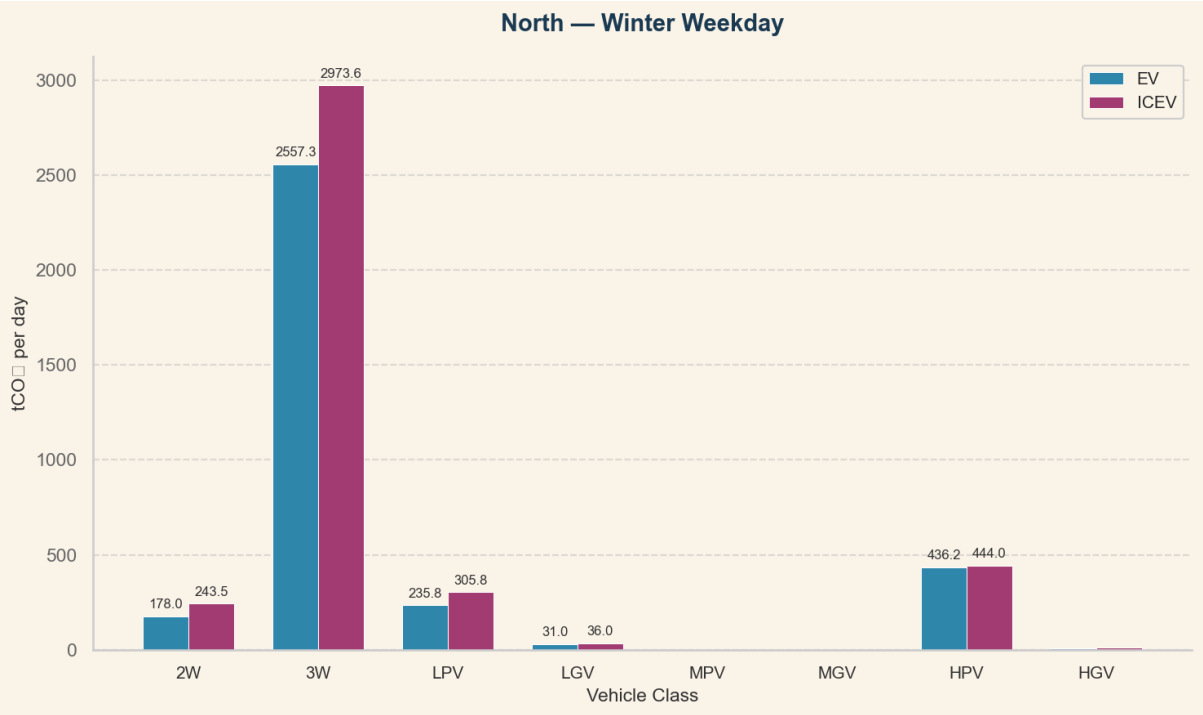


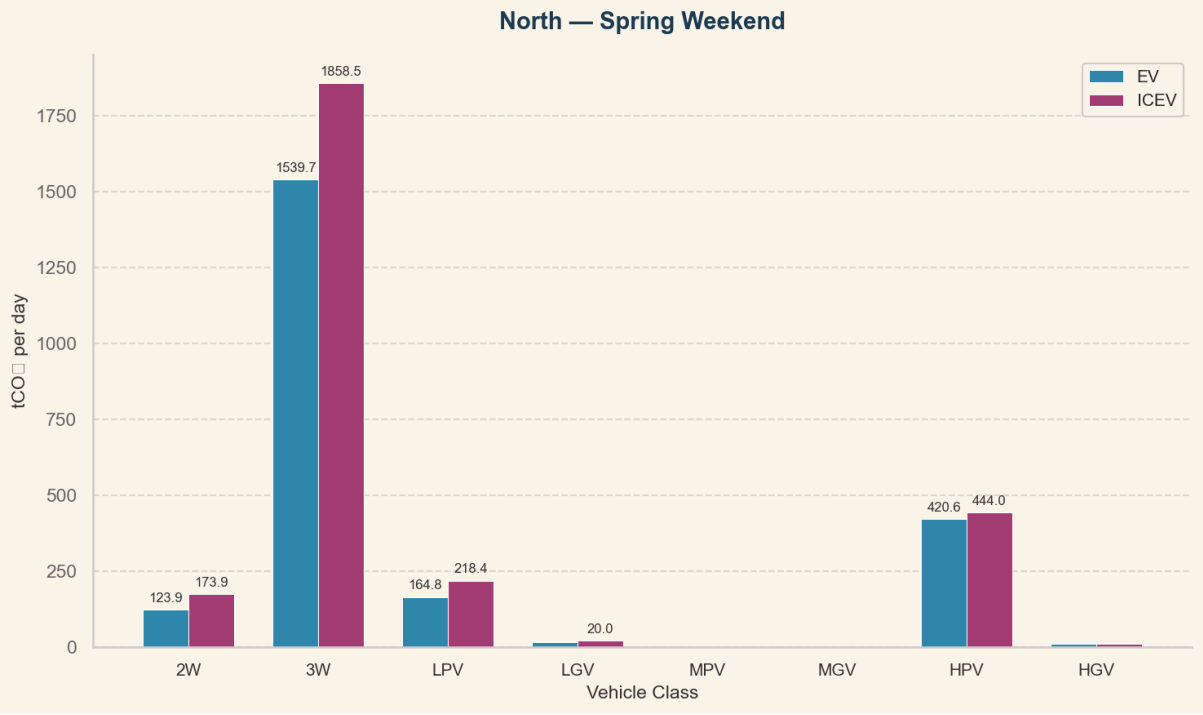
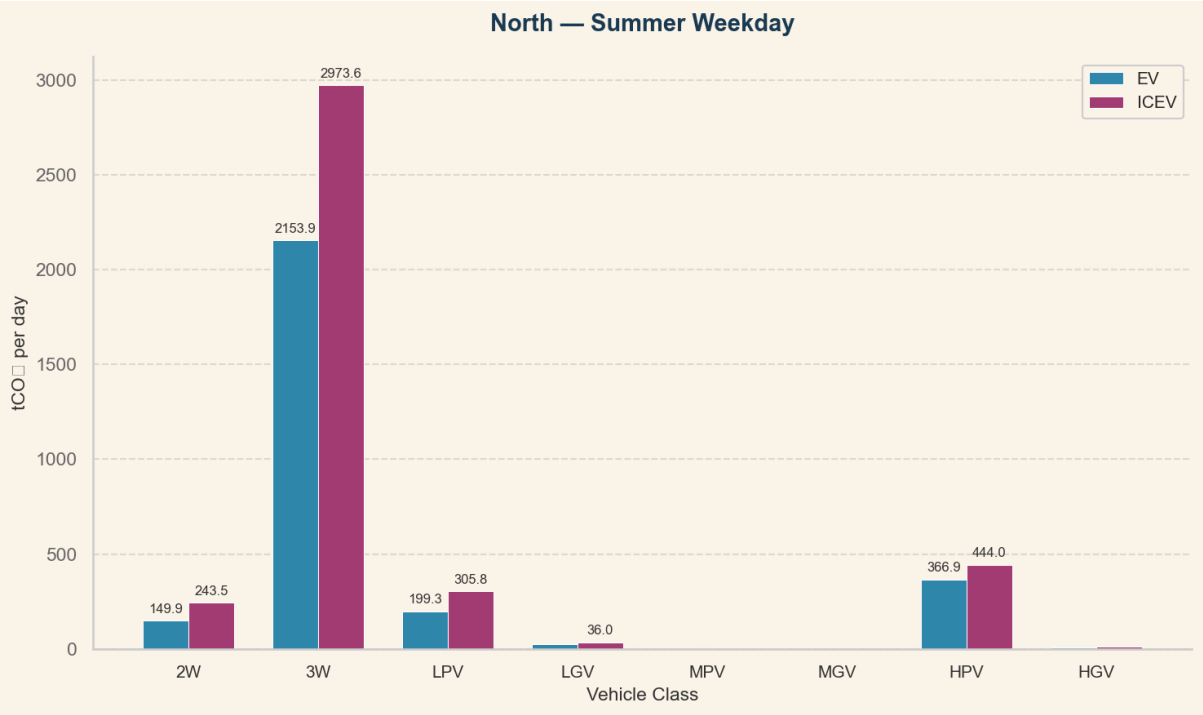


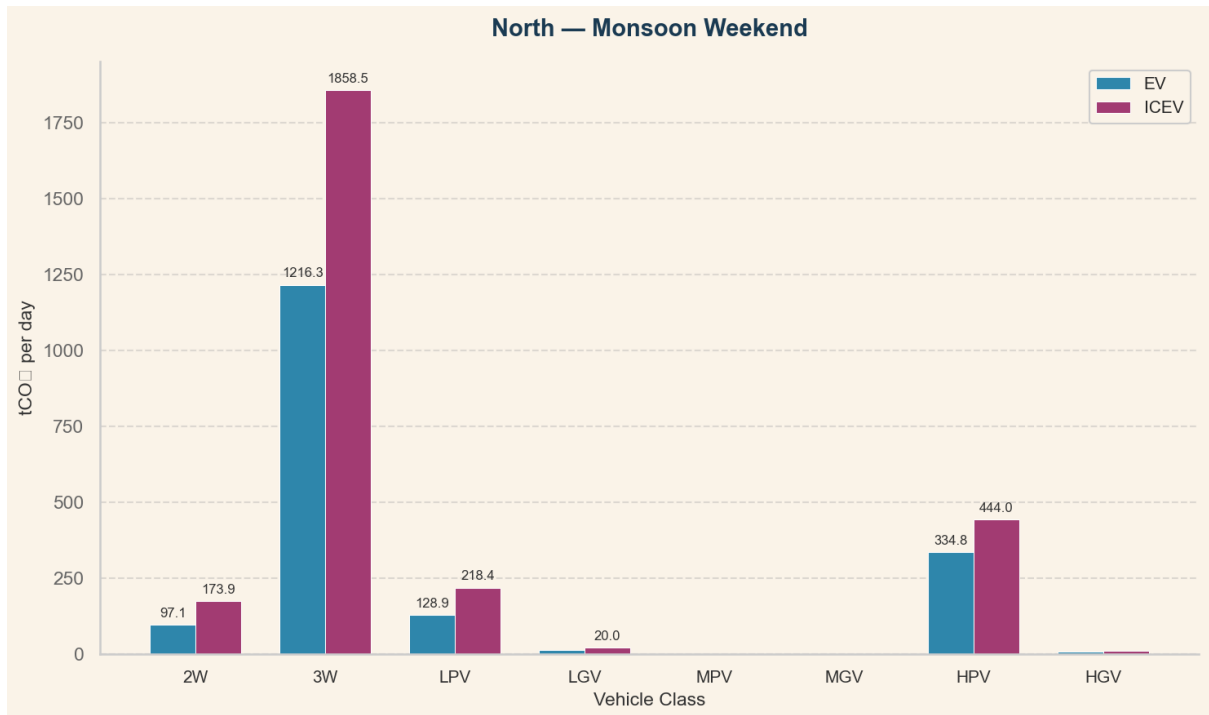
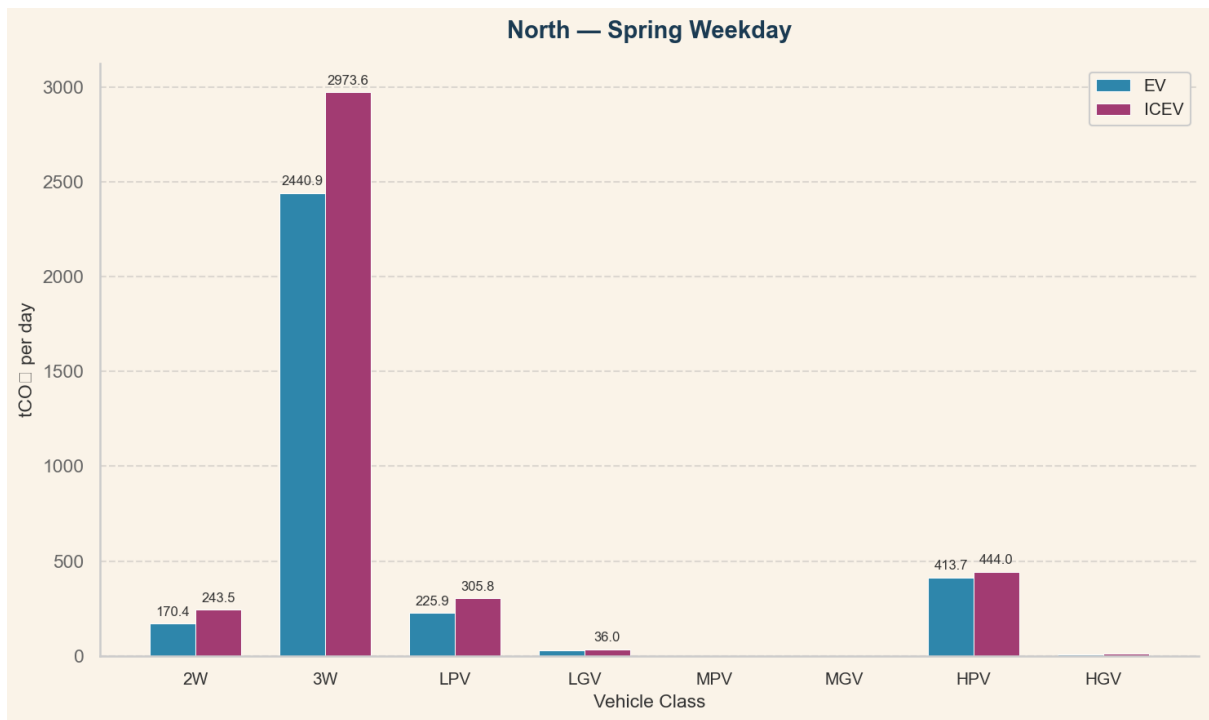


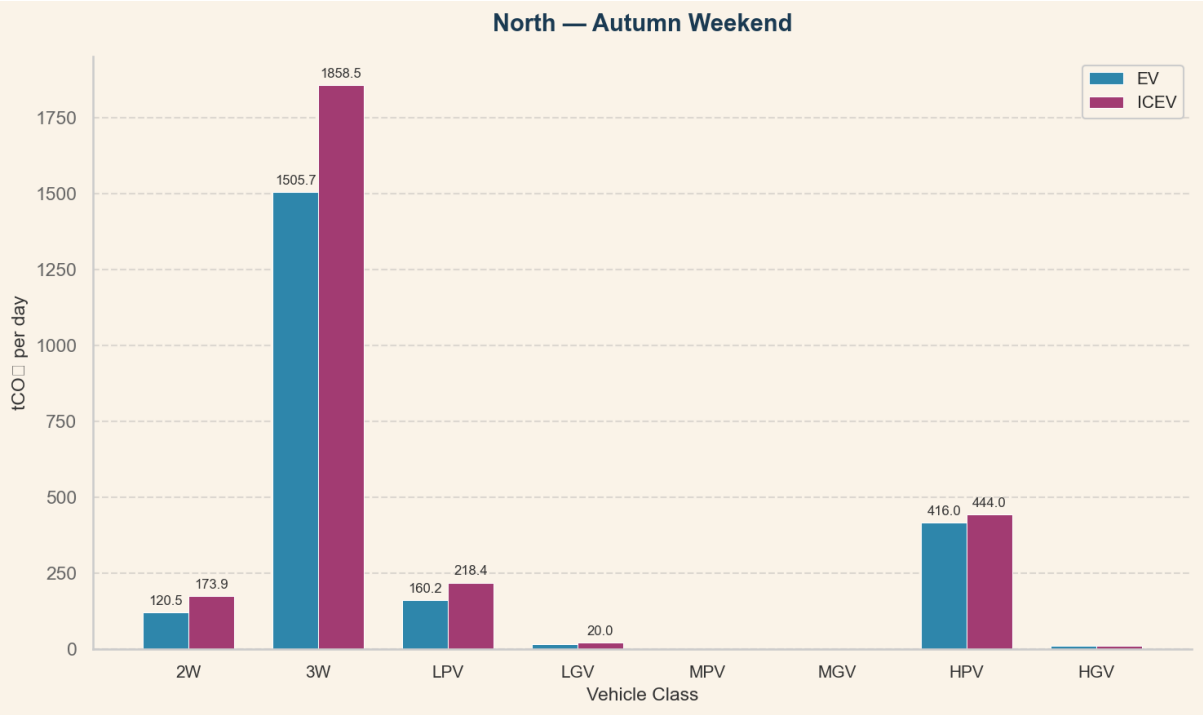
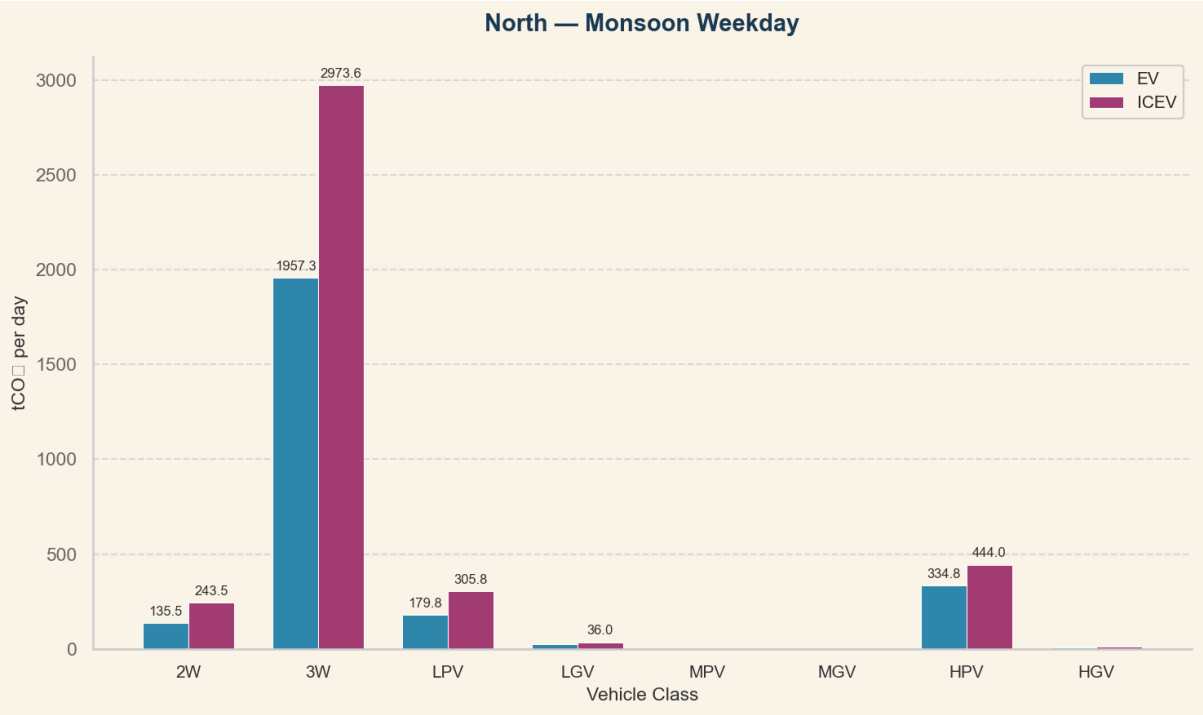


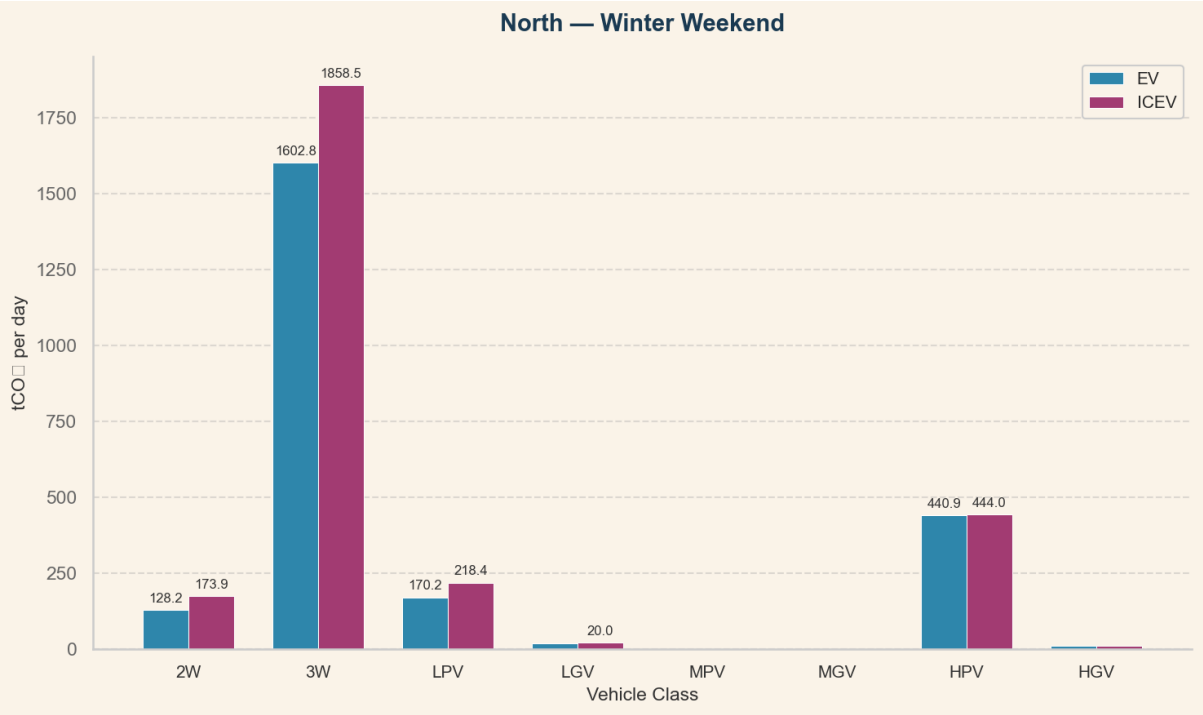
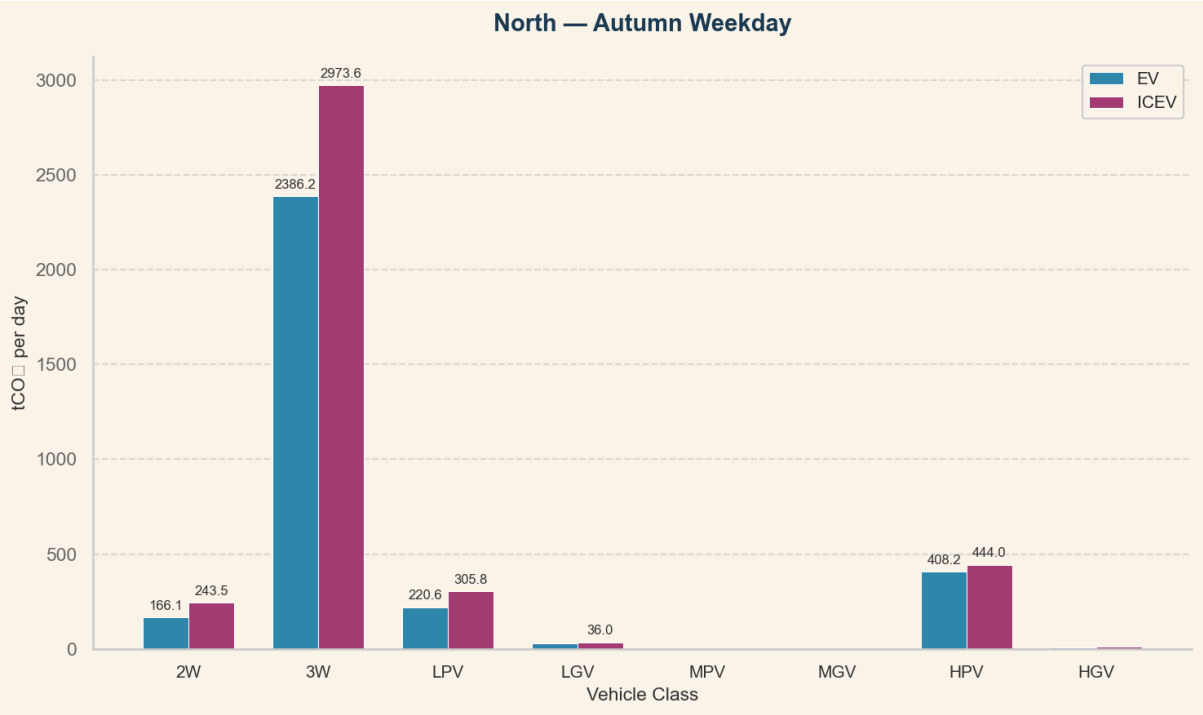
Northern Regional Grid



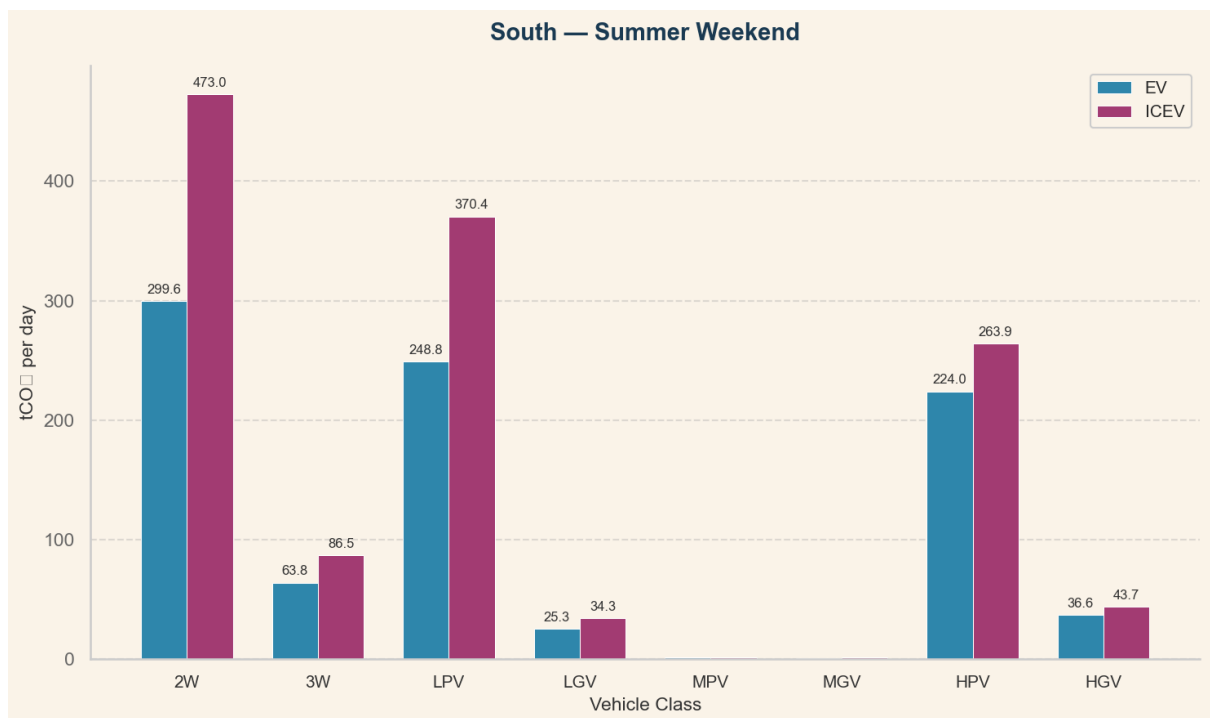
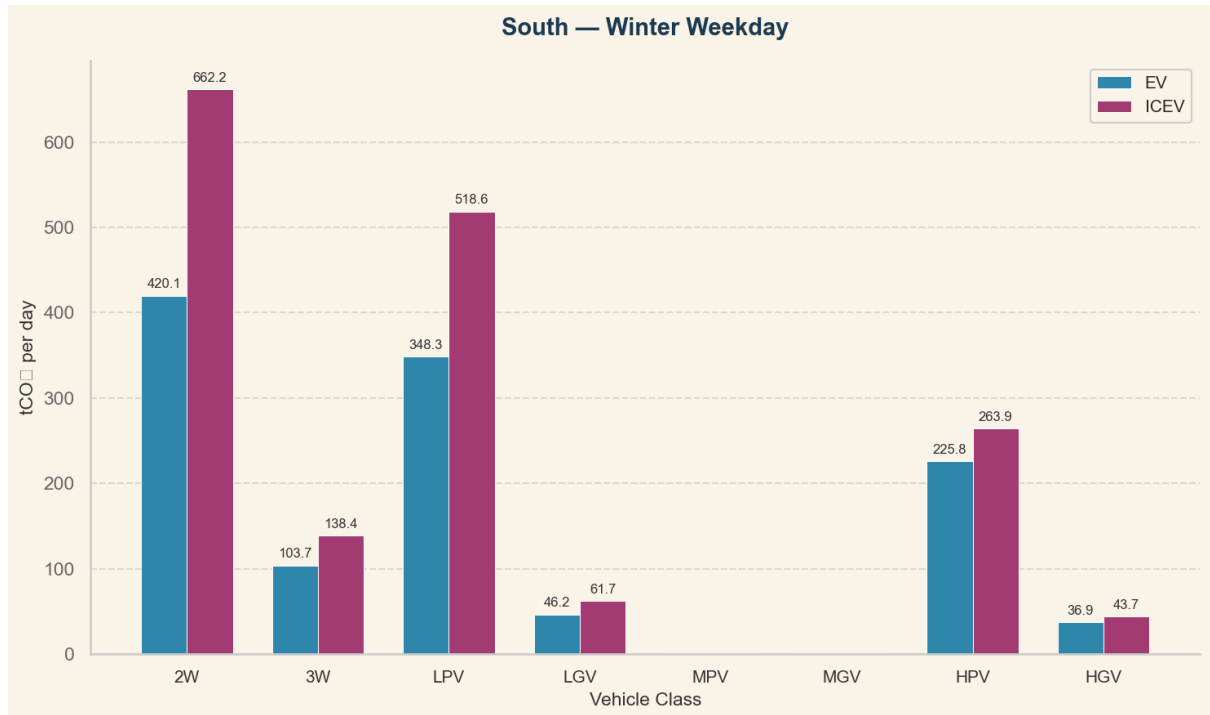


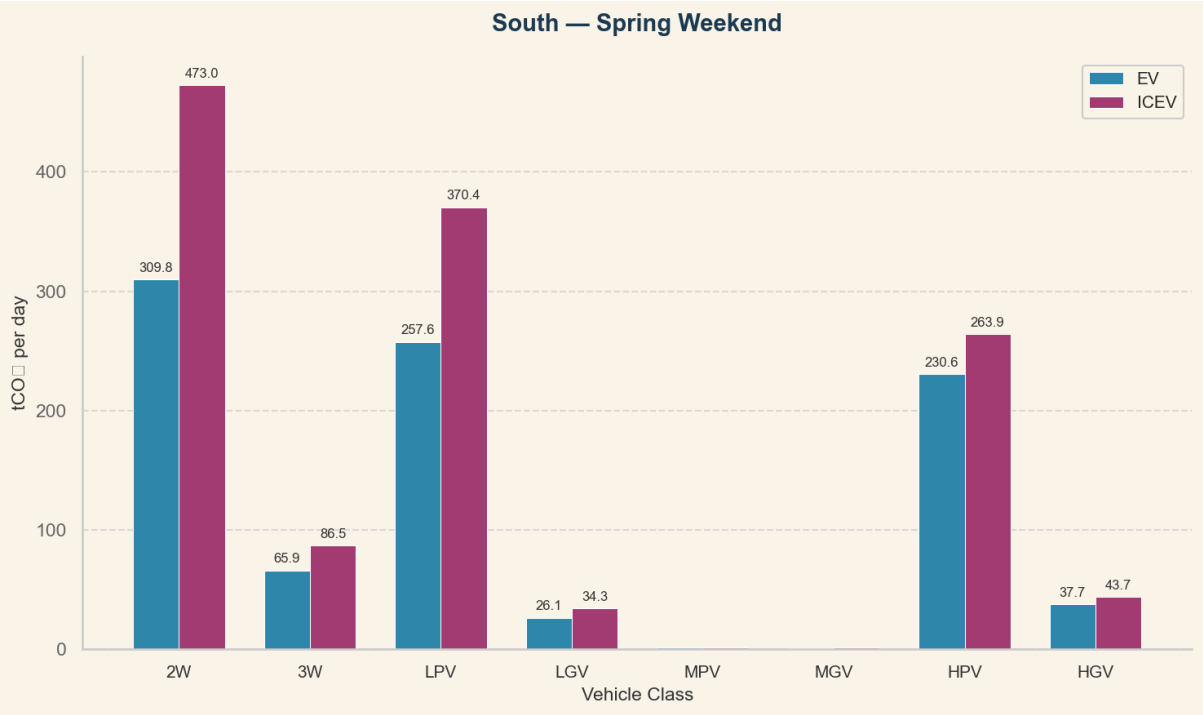
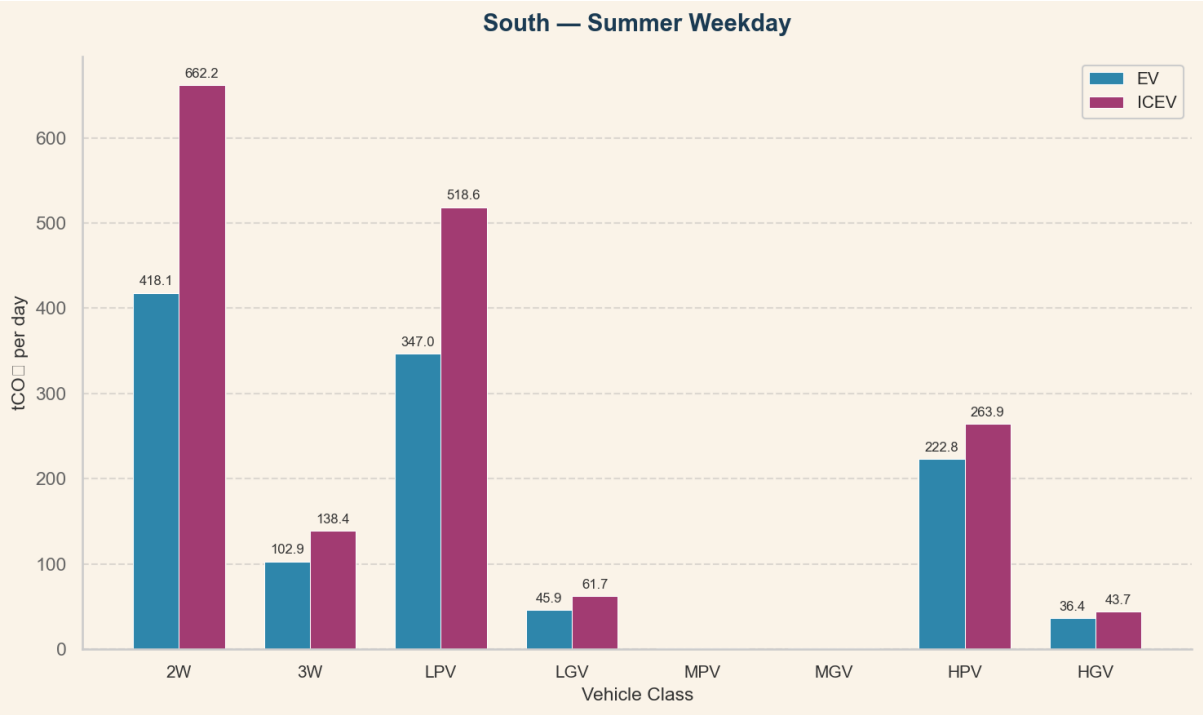


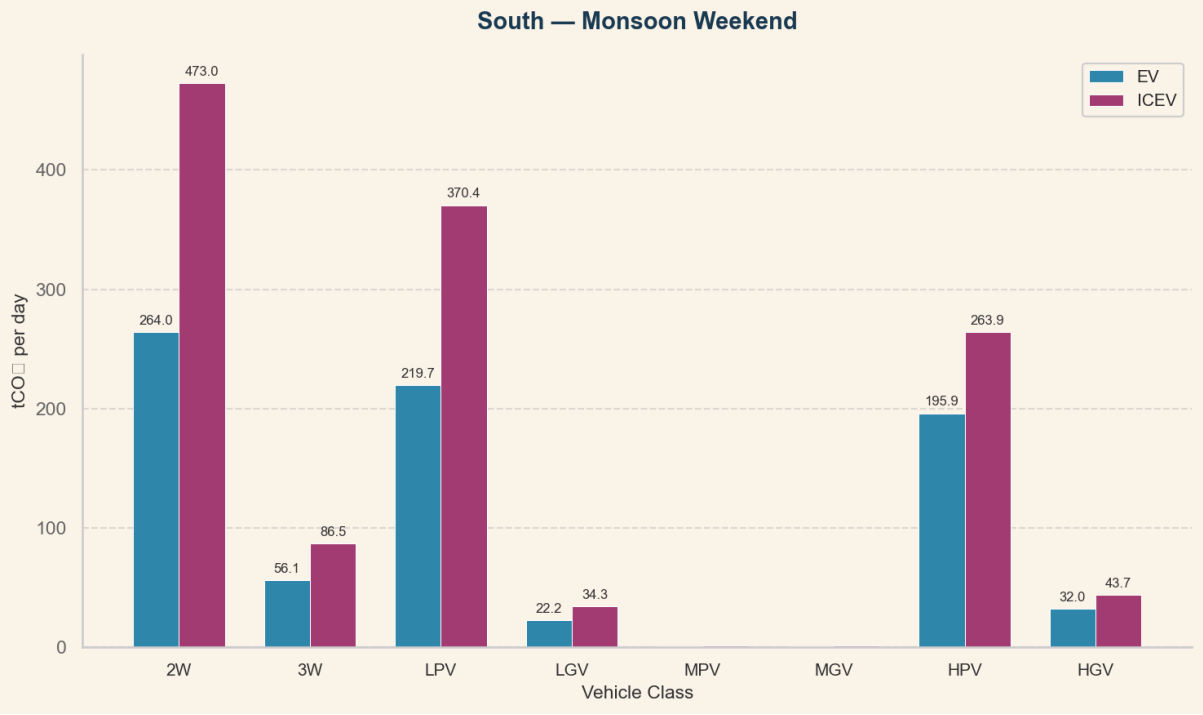
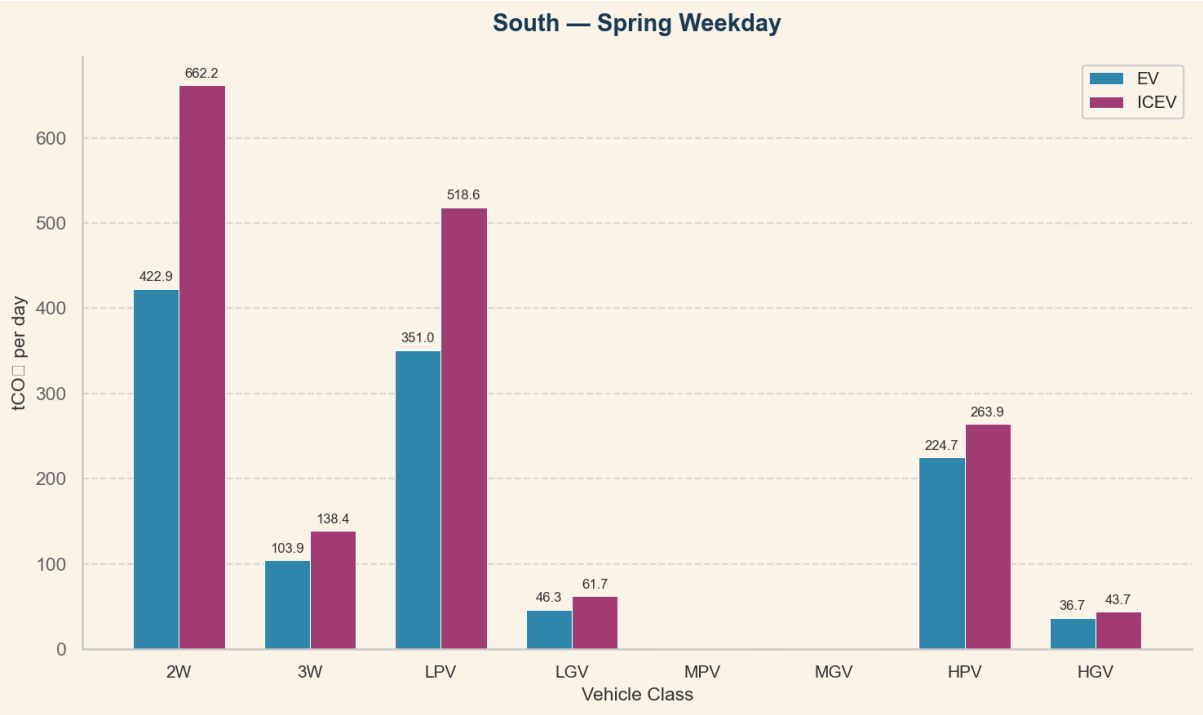


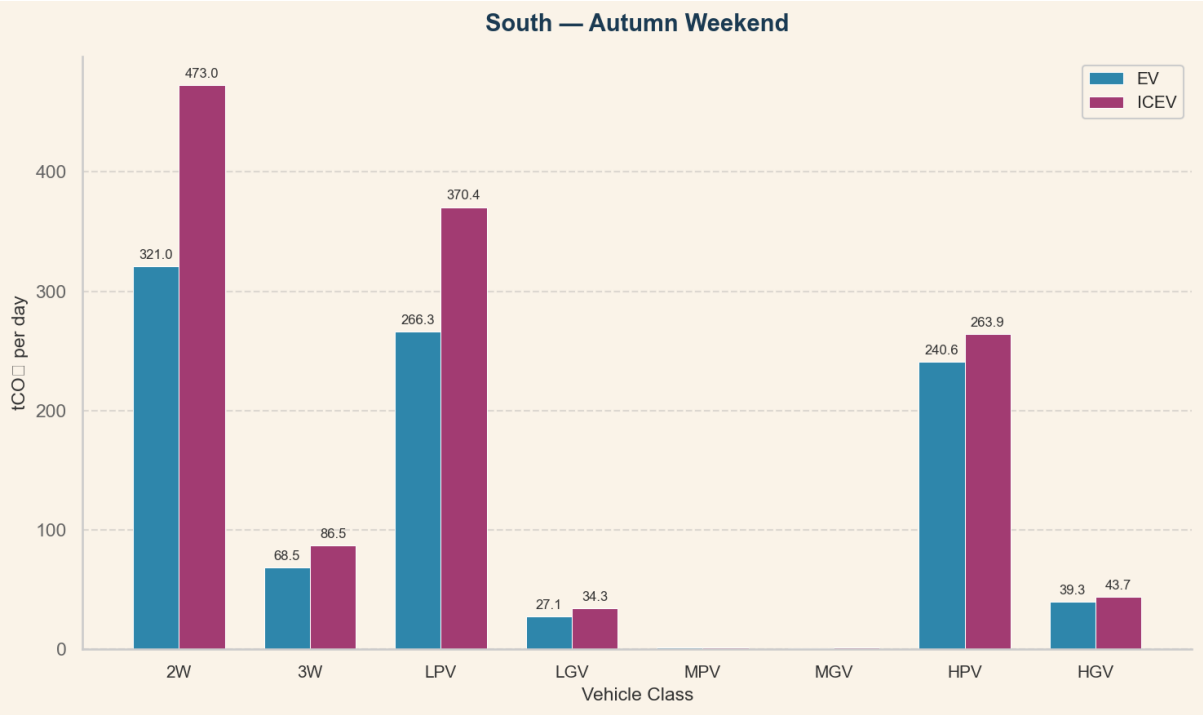
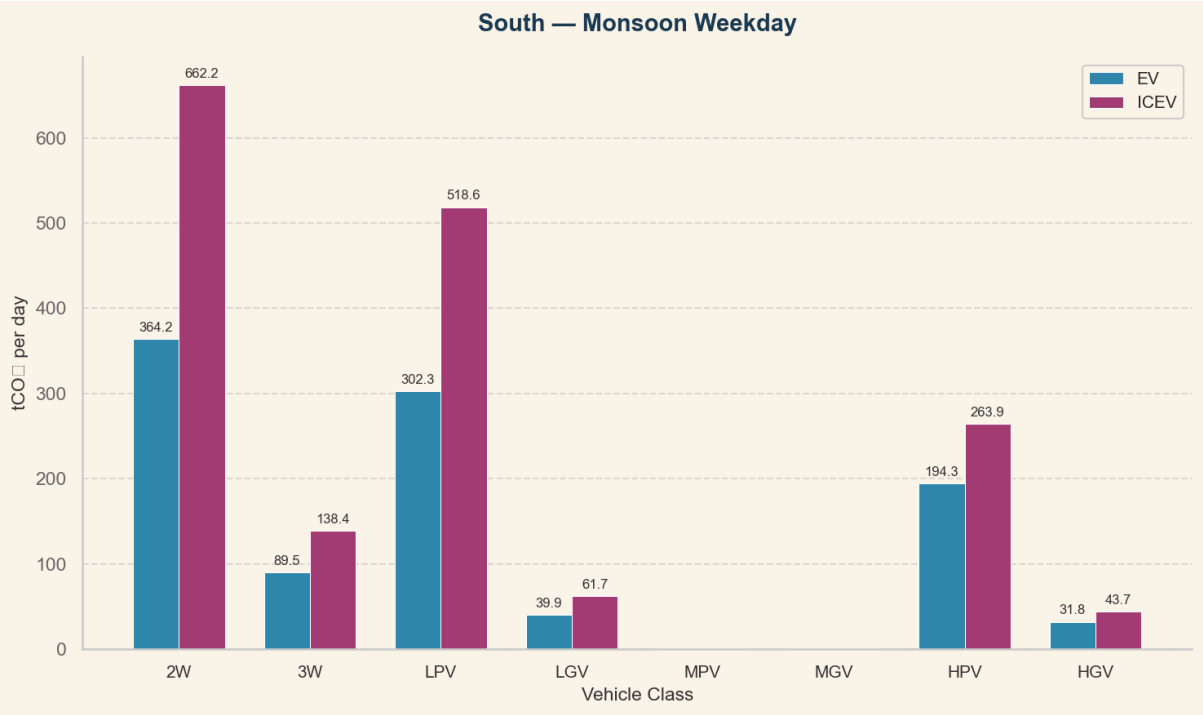


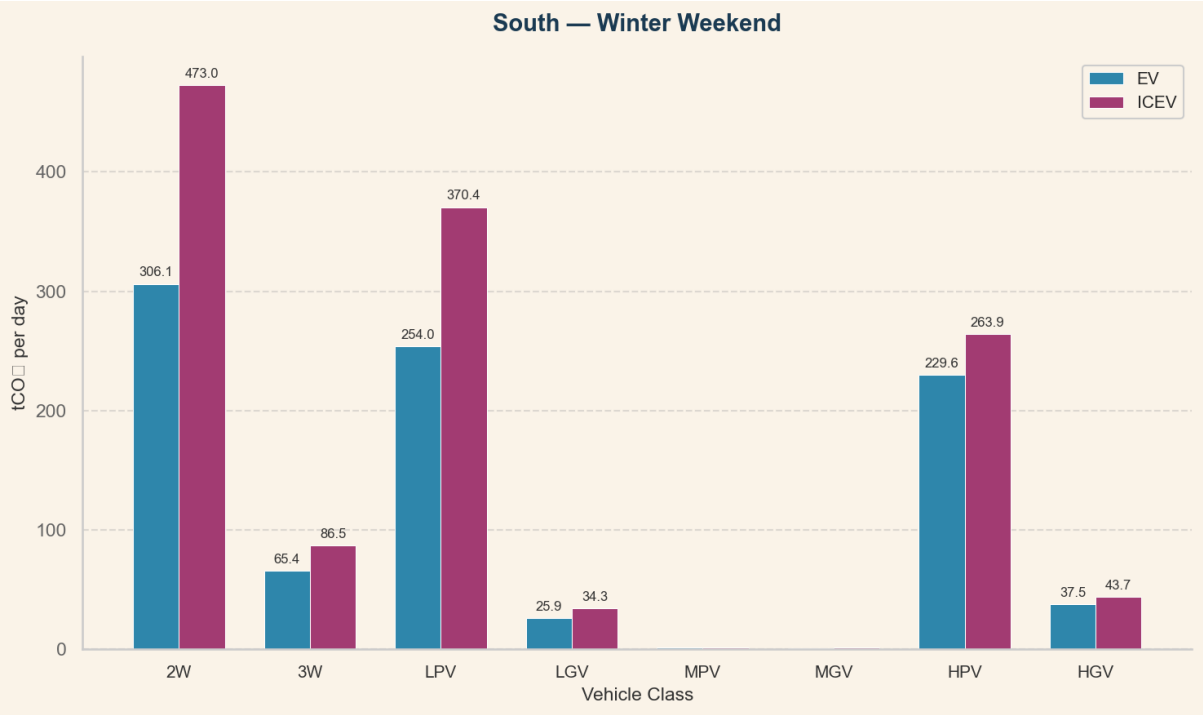
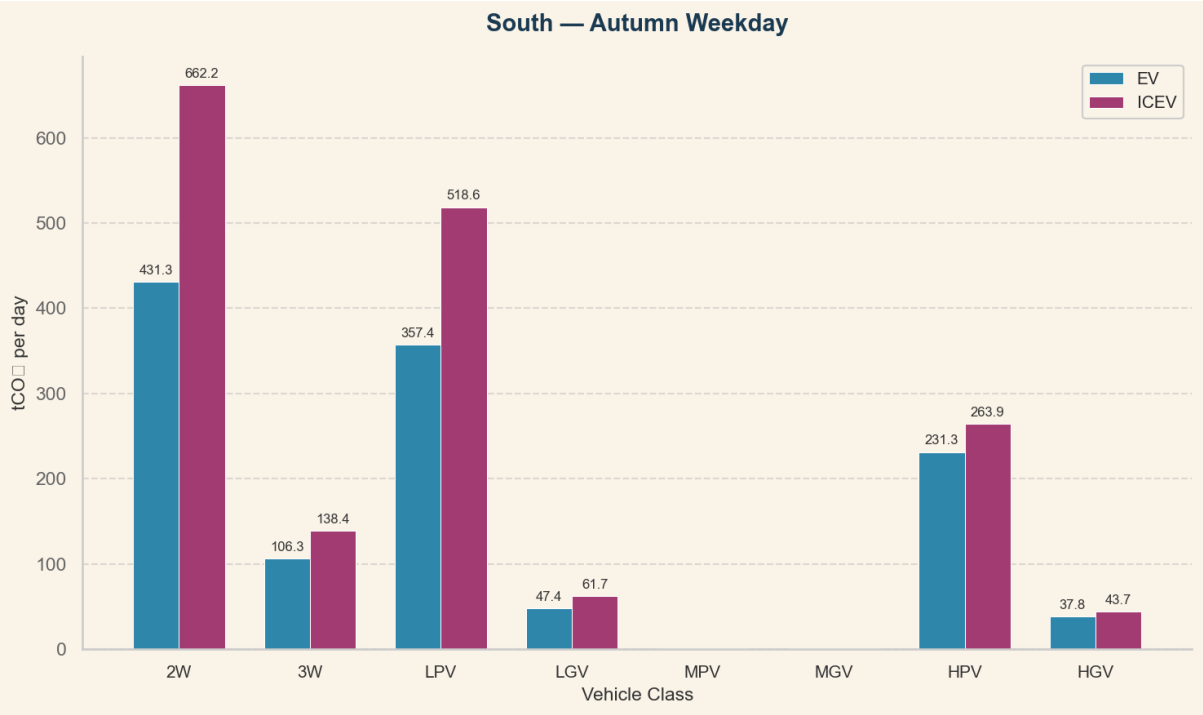
Southern Regional Grid



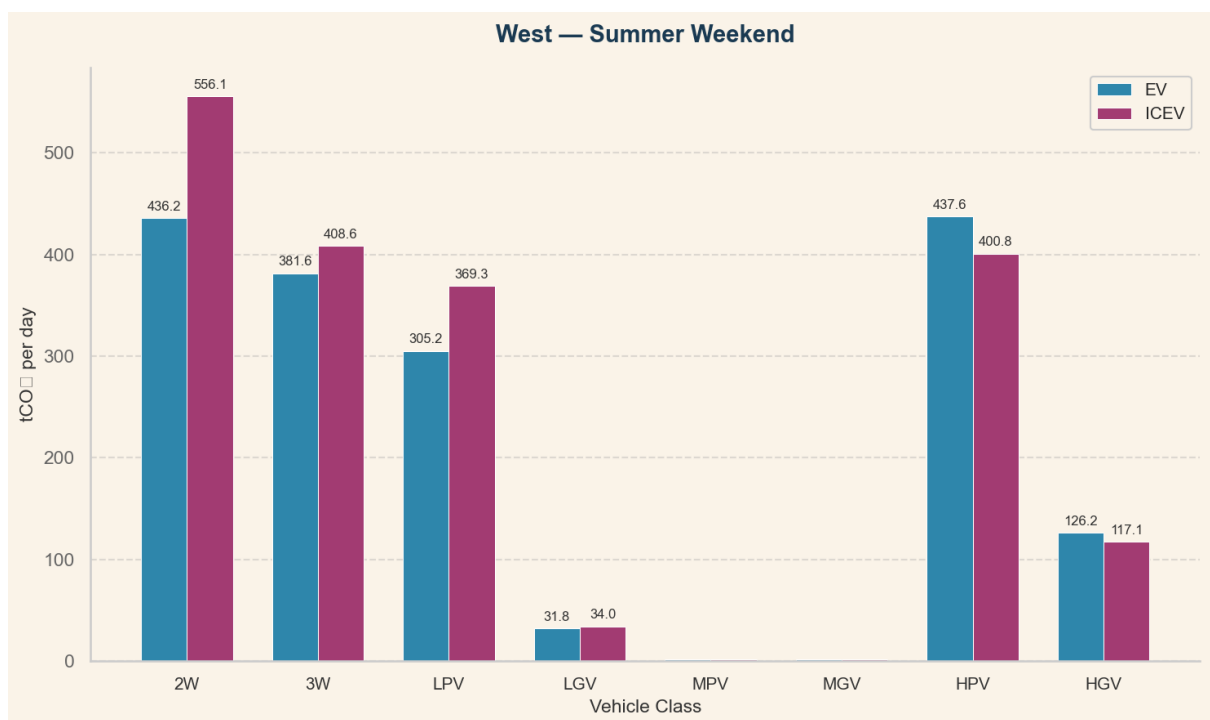
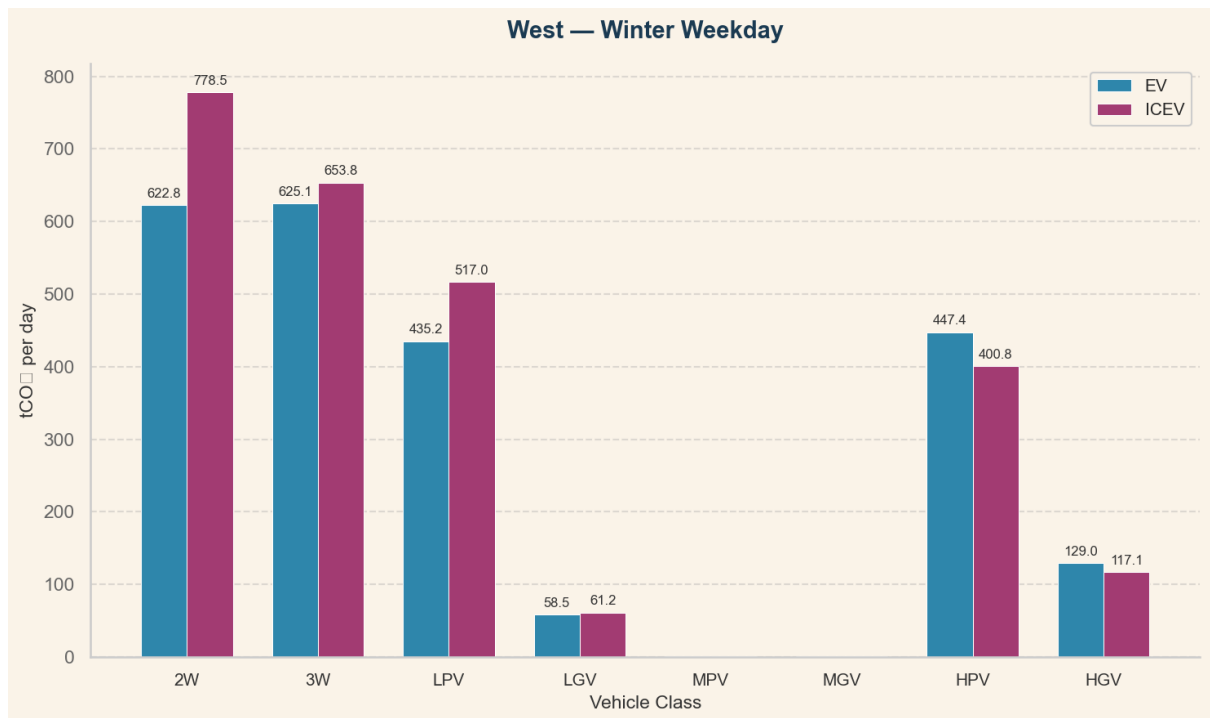


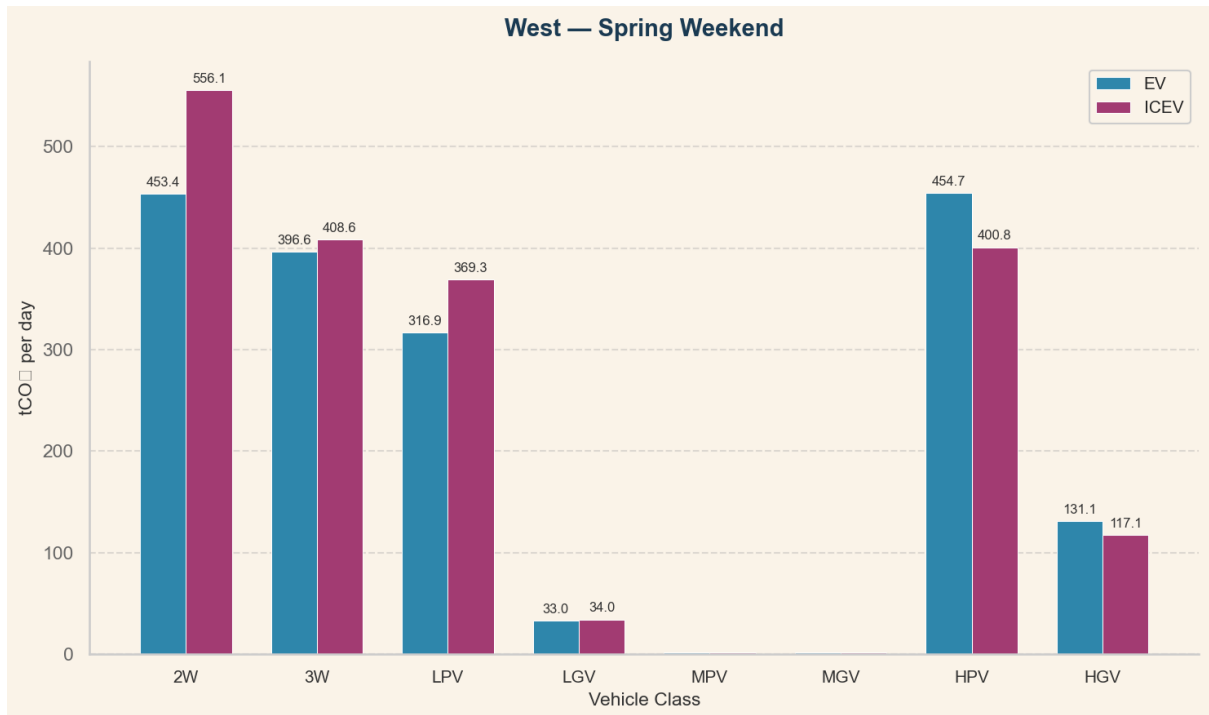
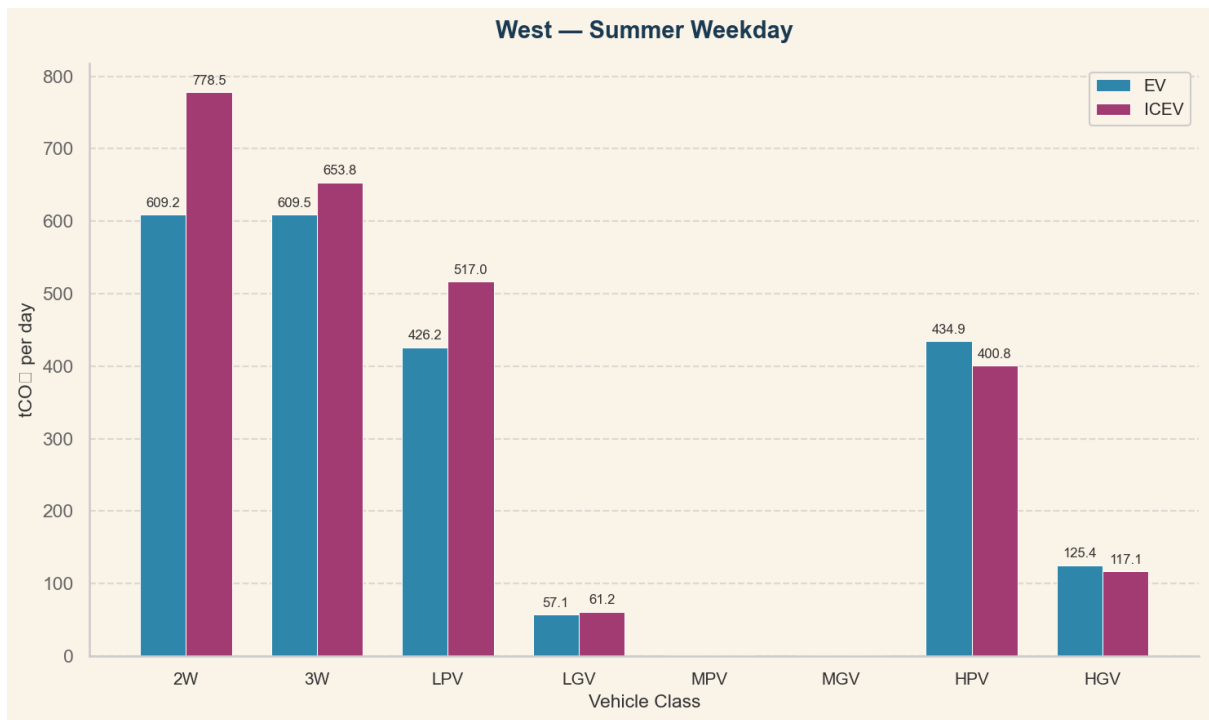


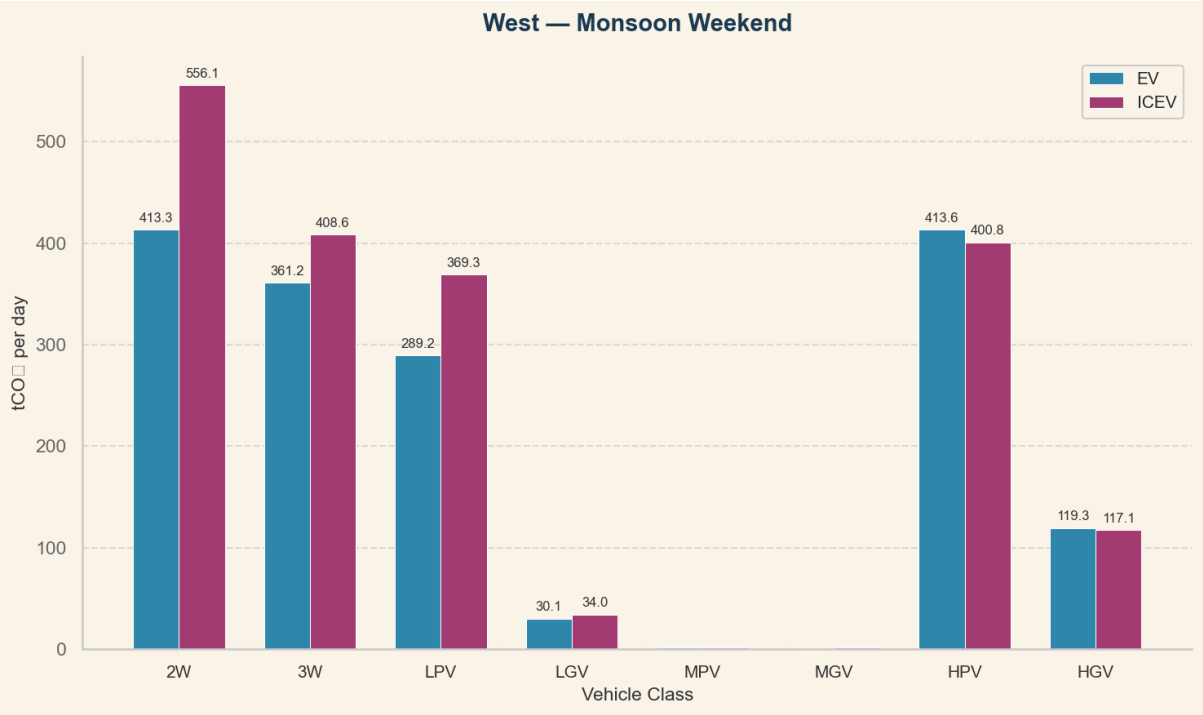
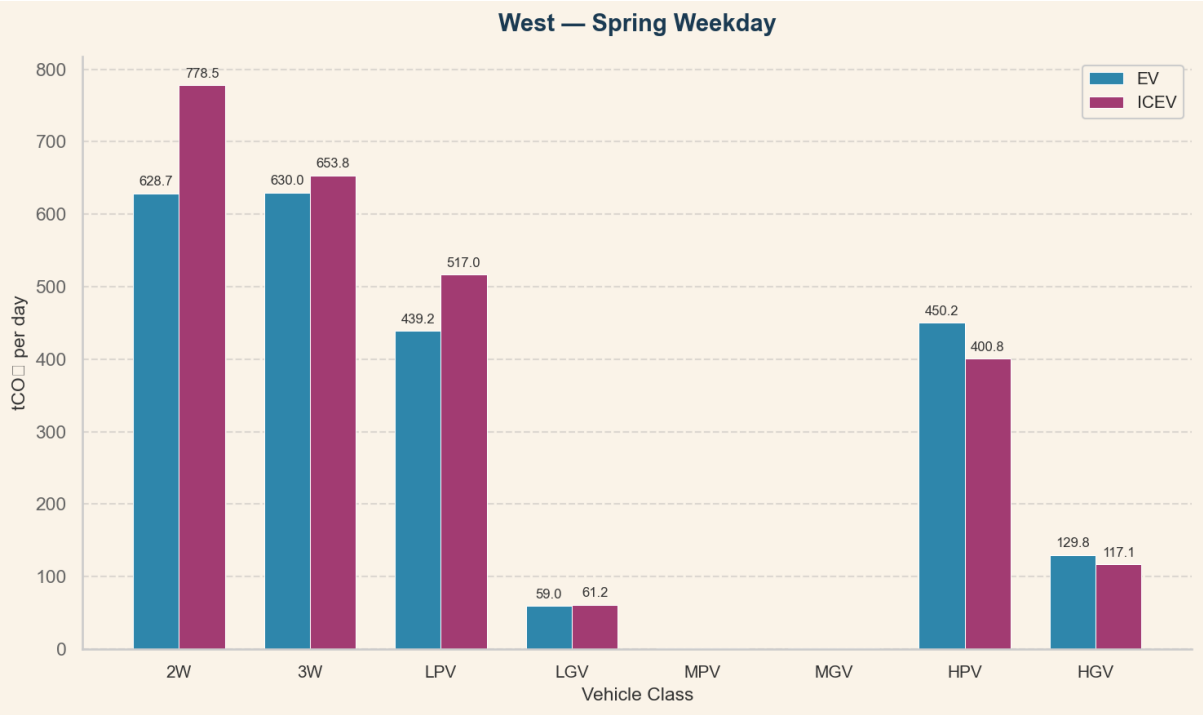


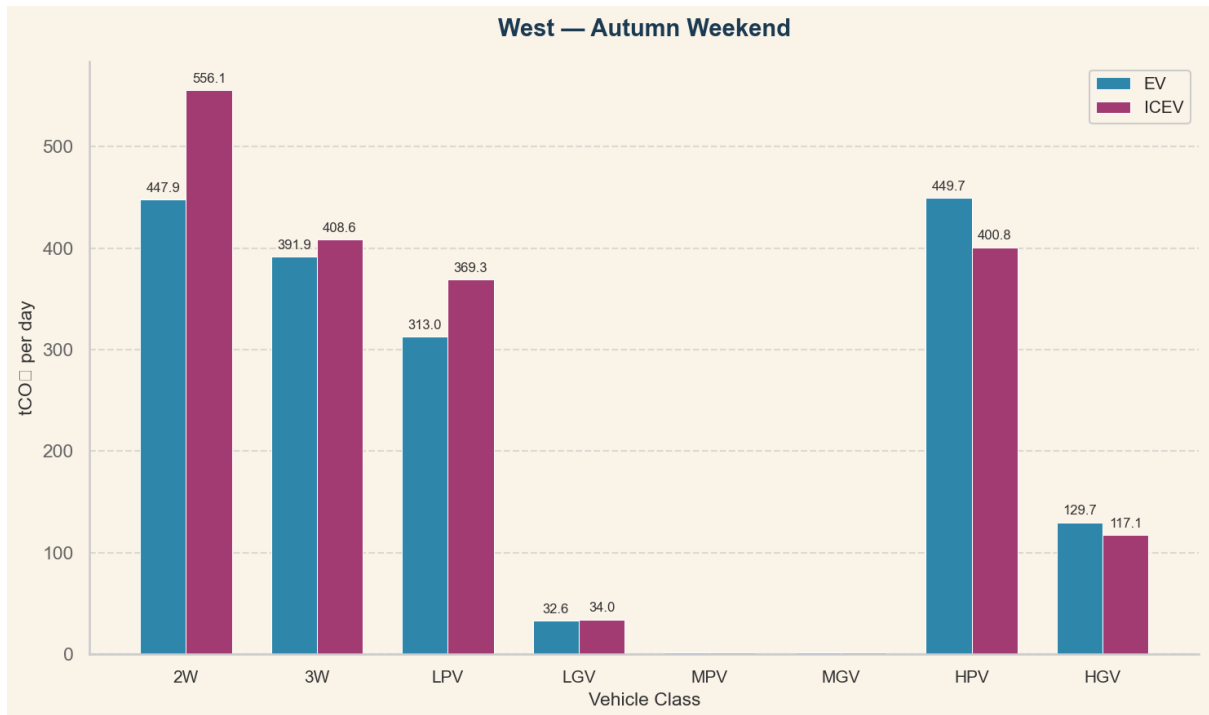
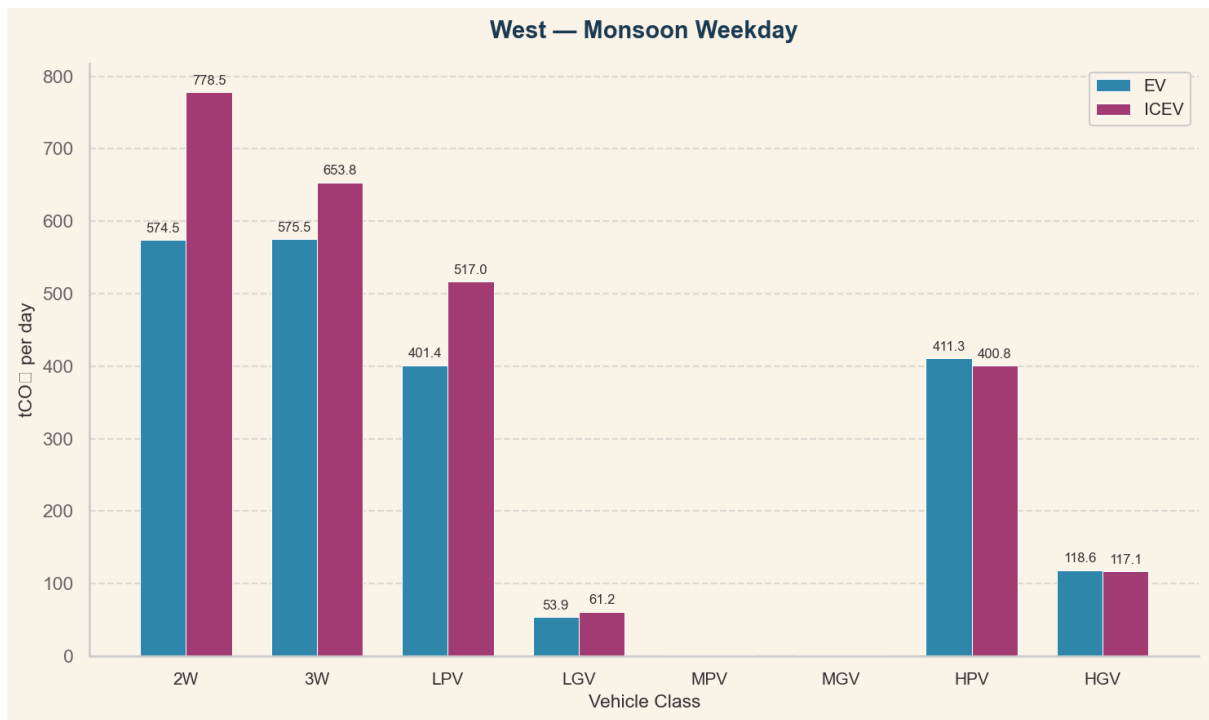


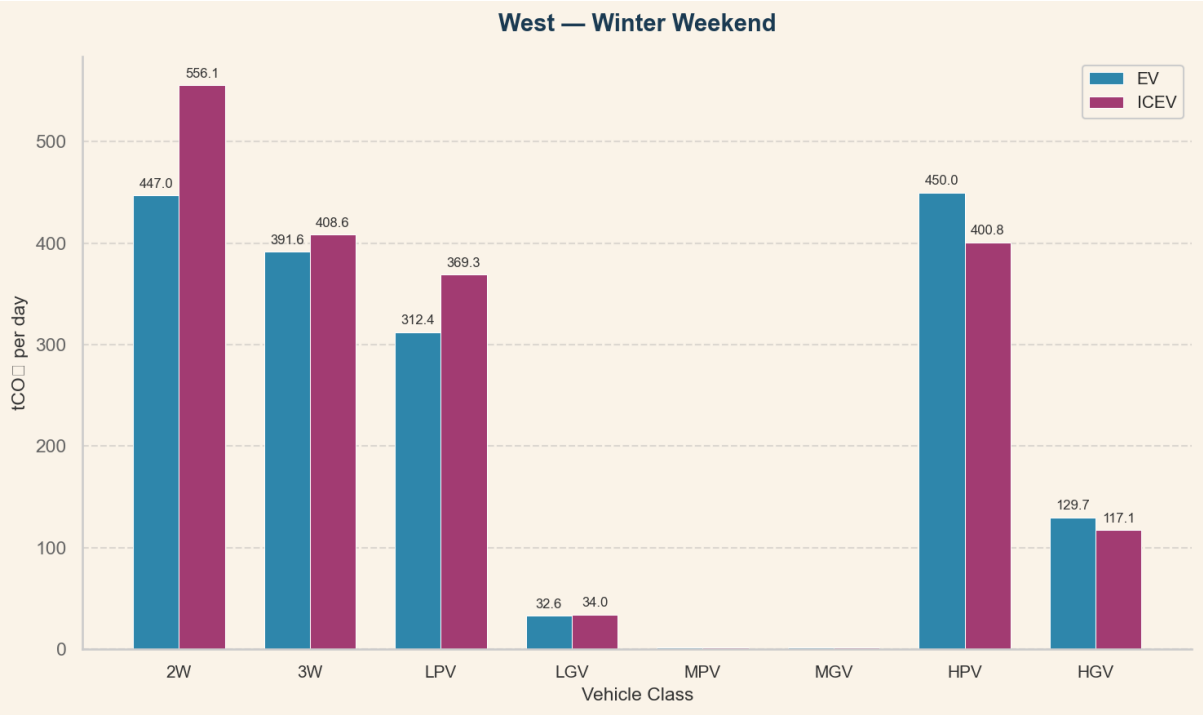
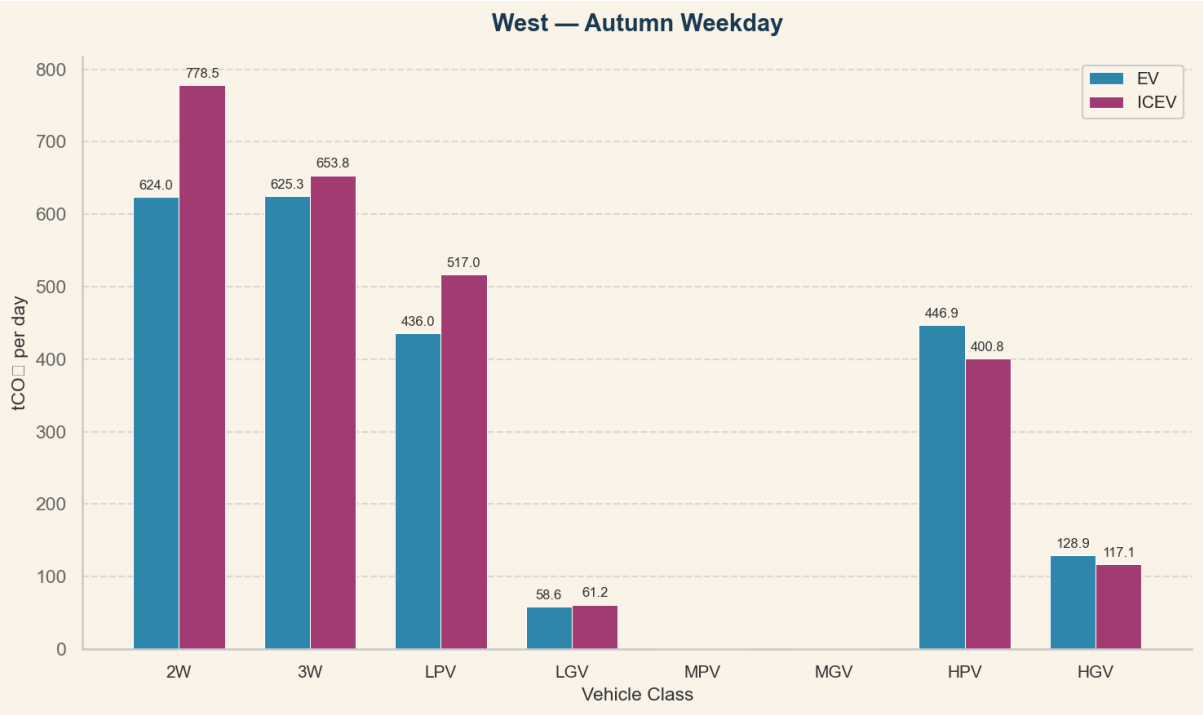
Western Regional Grid



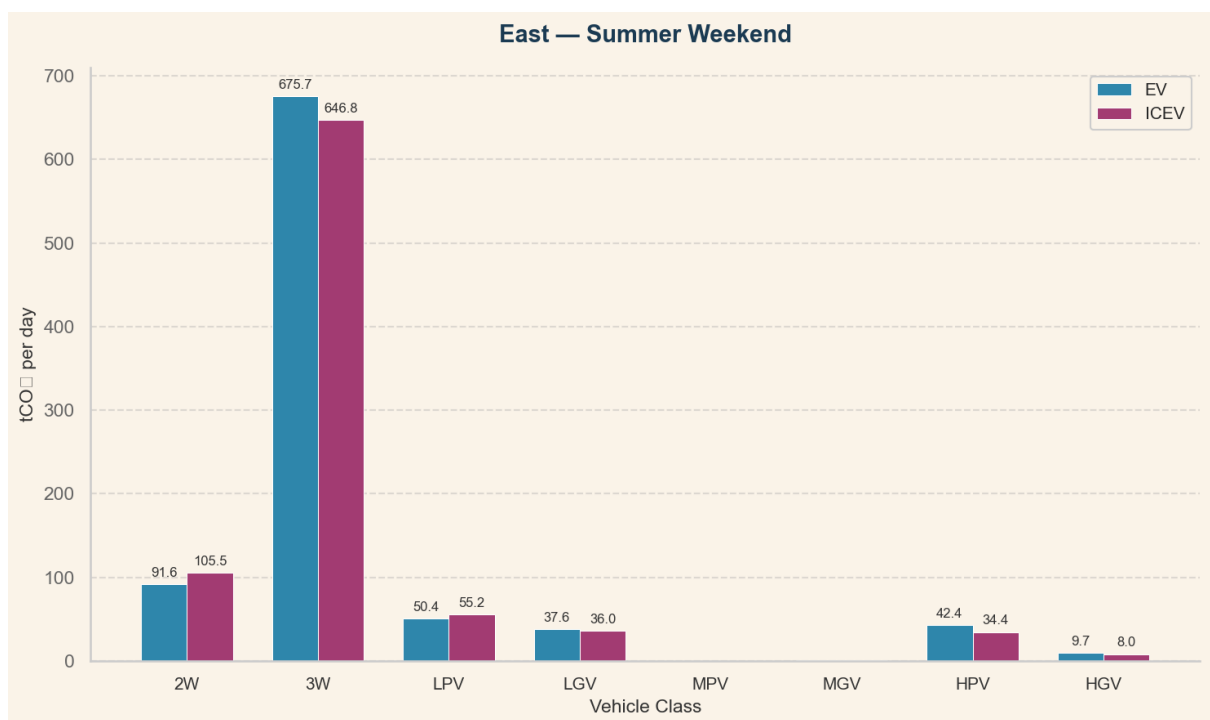
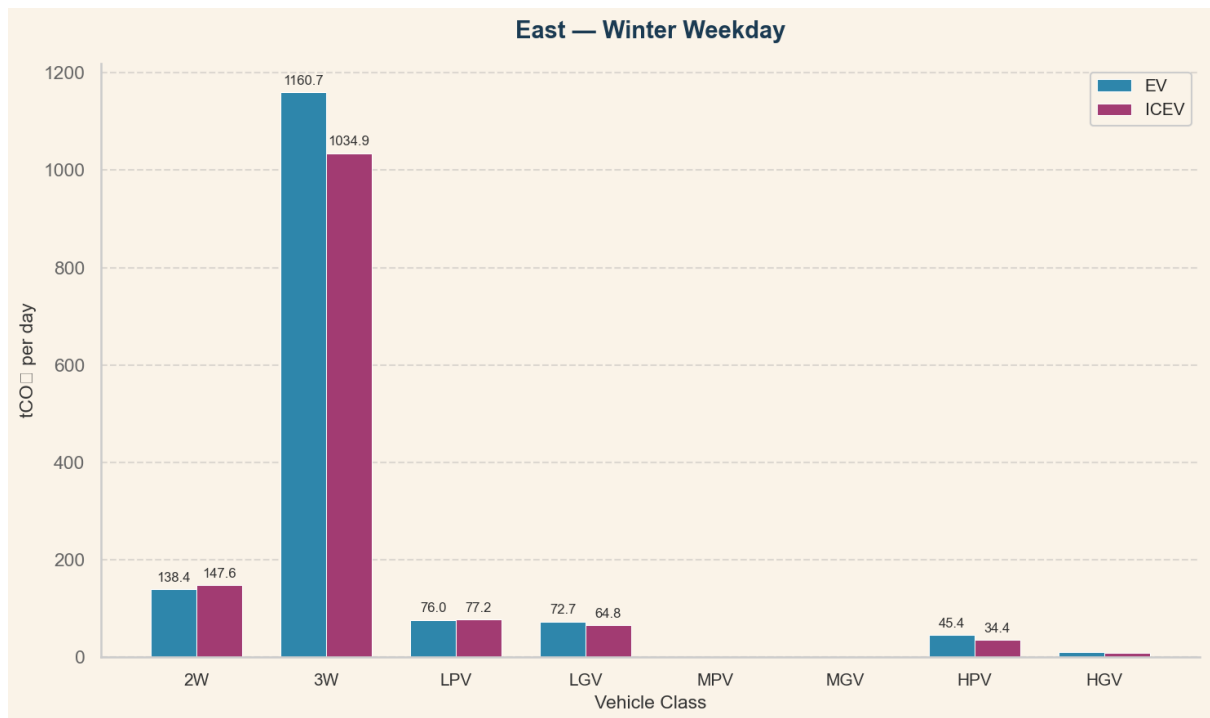


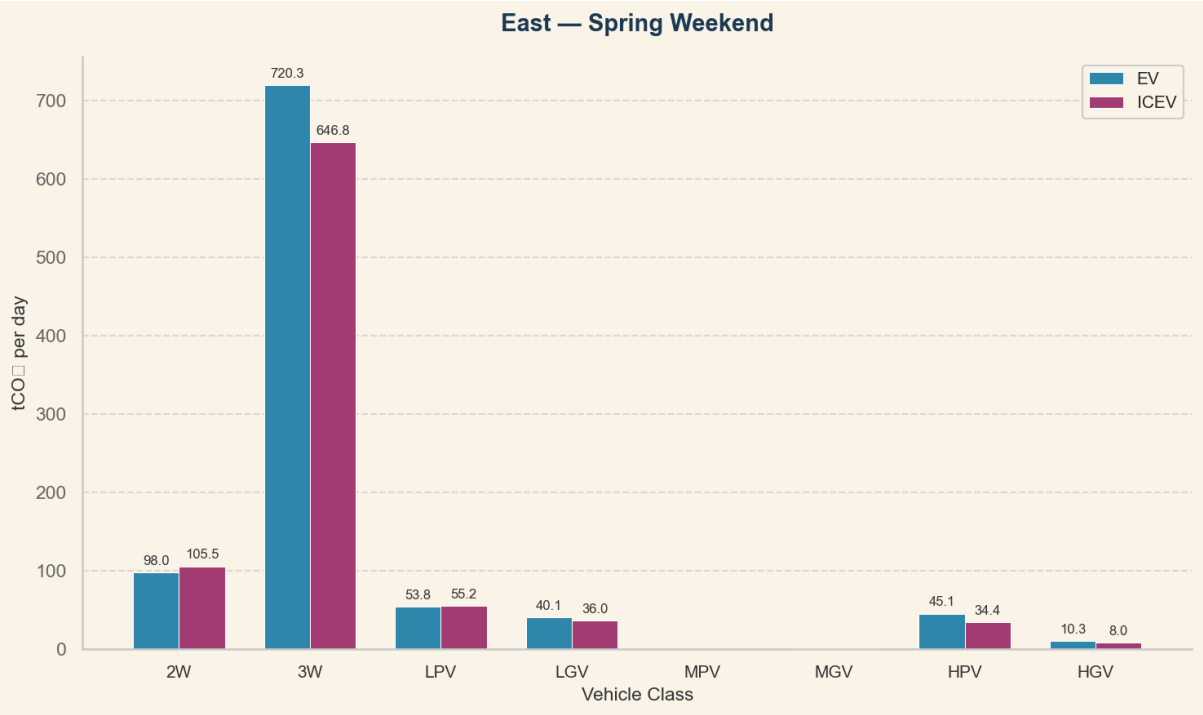
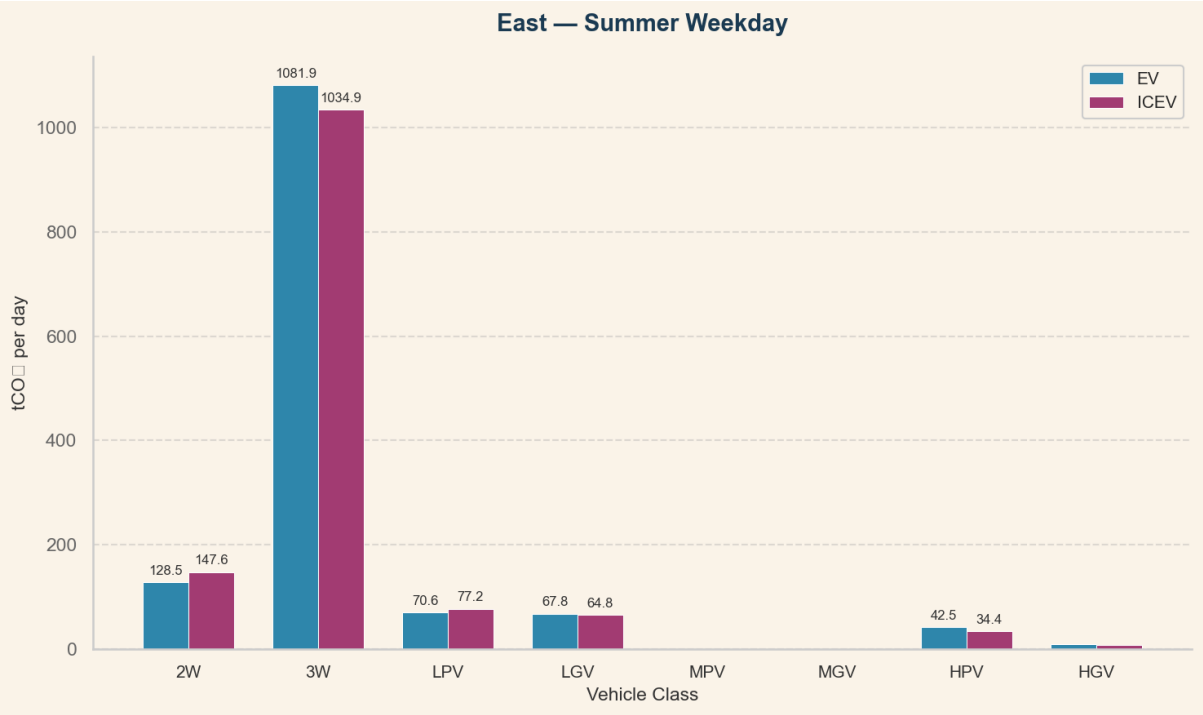


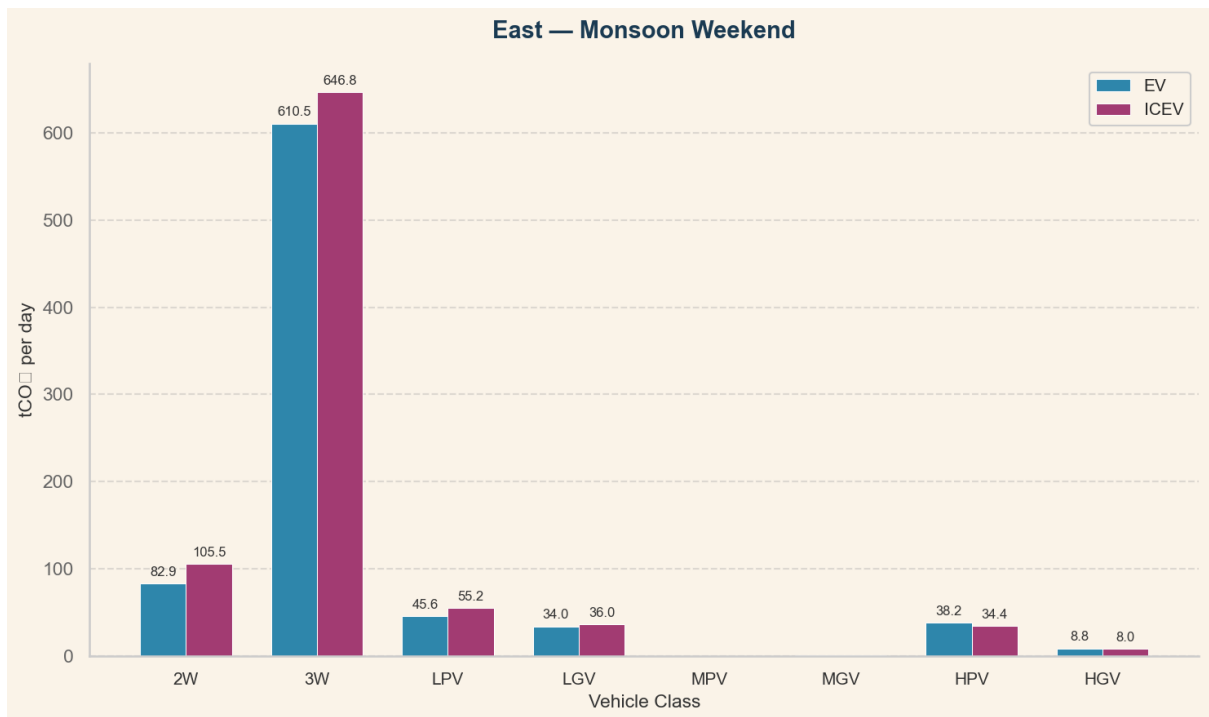
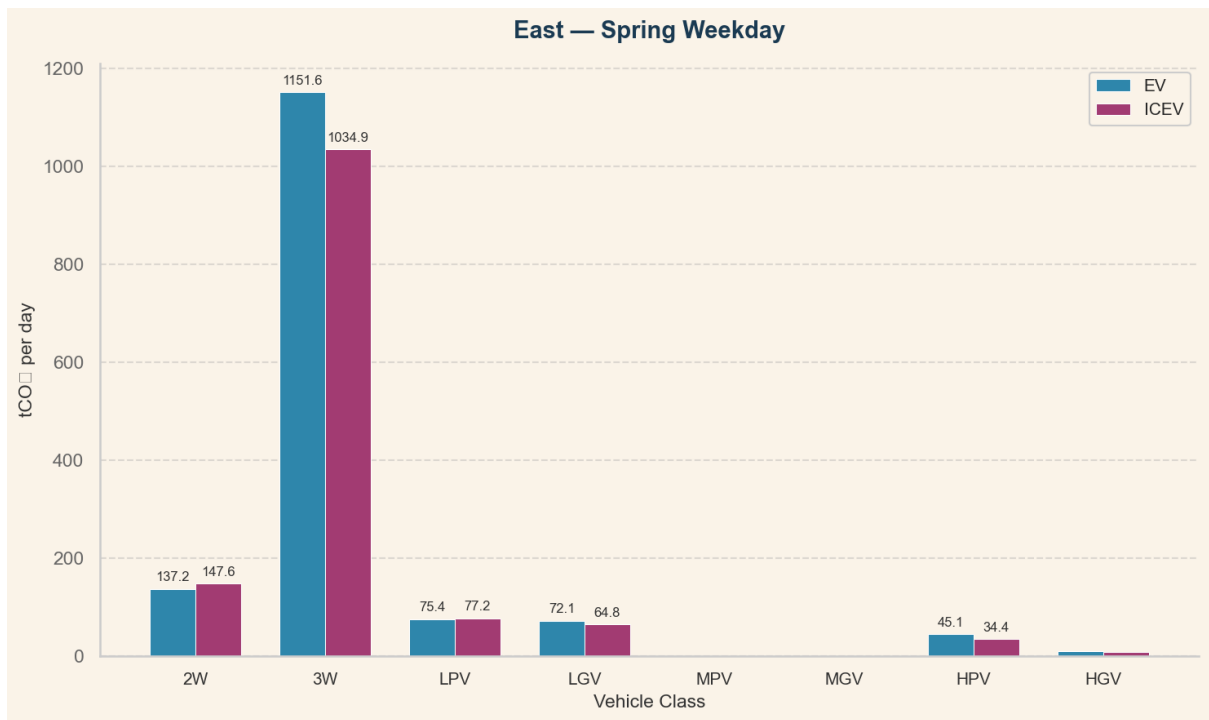


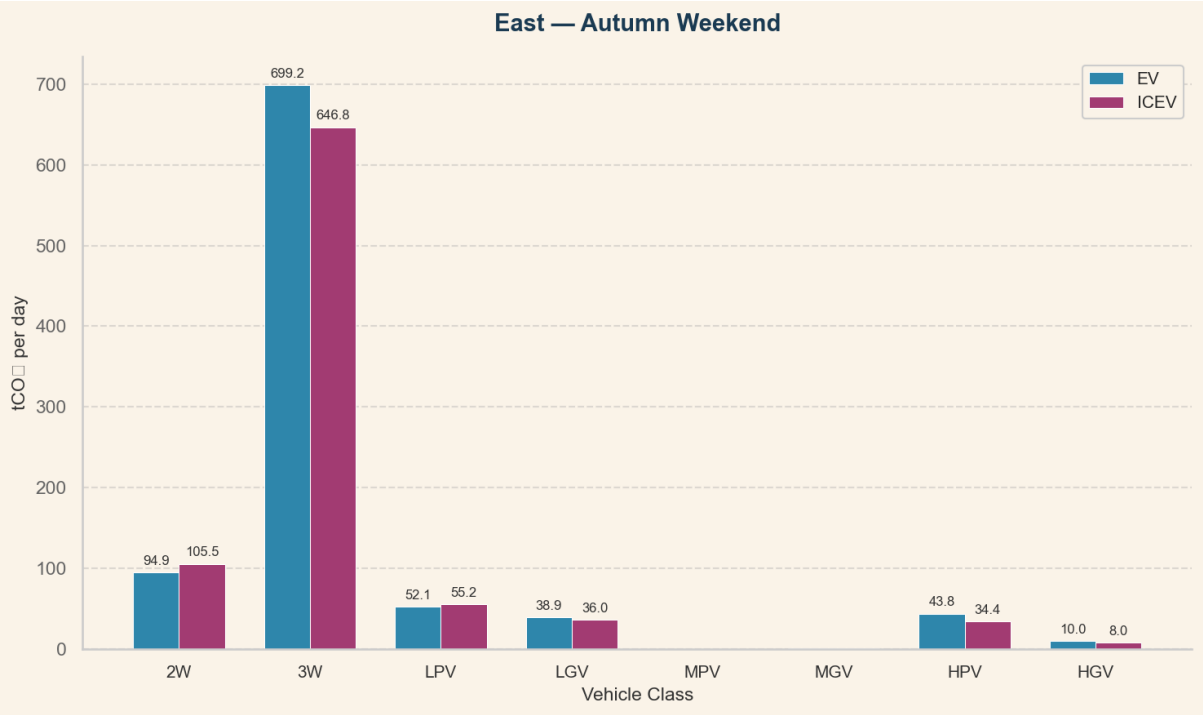
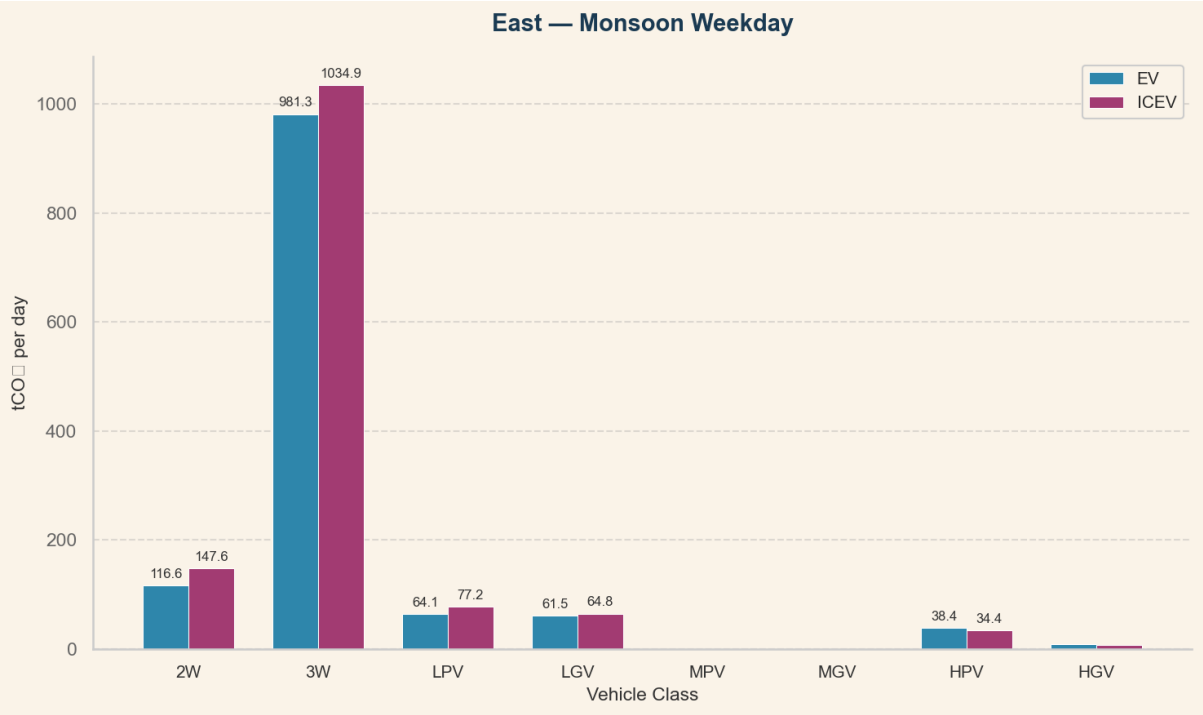


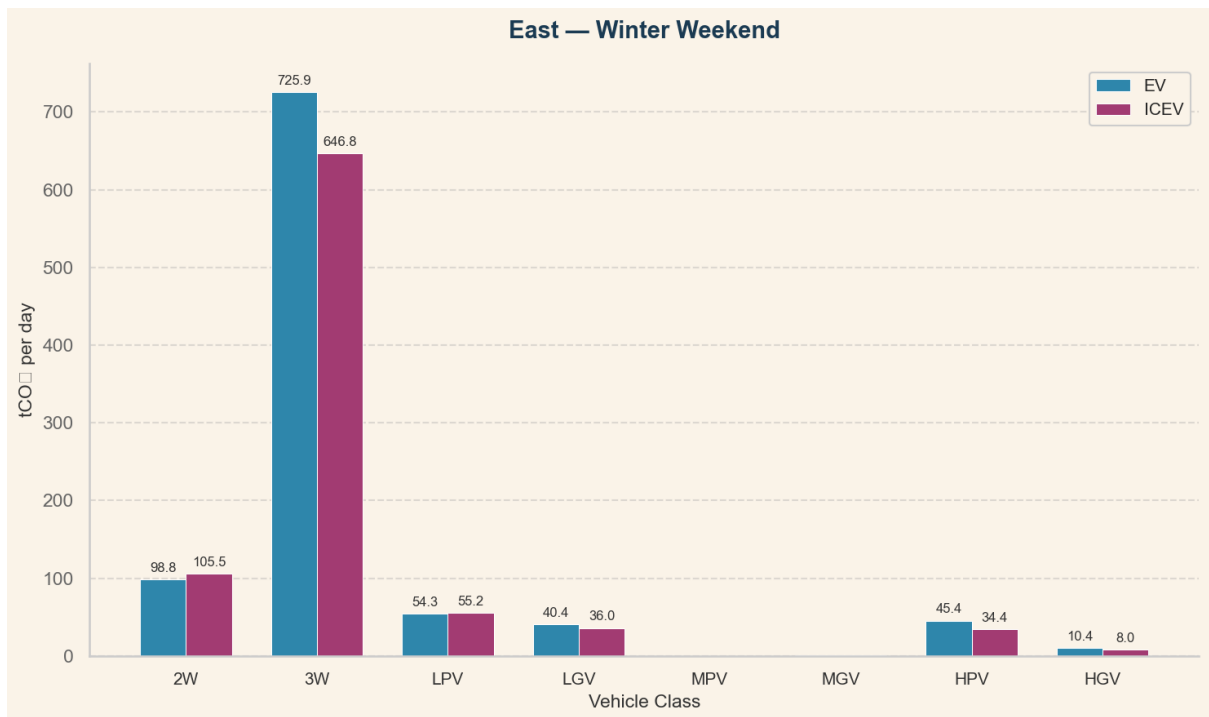
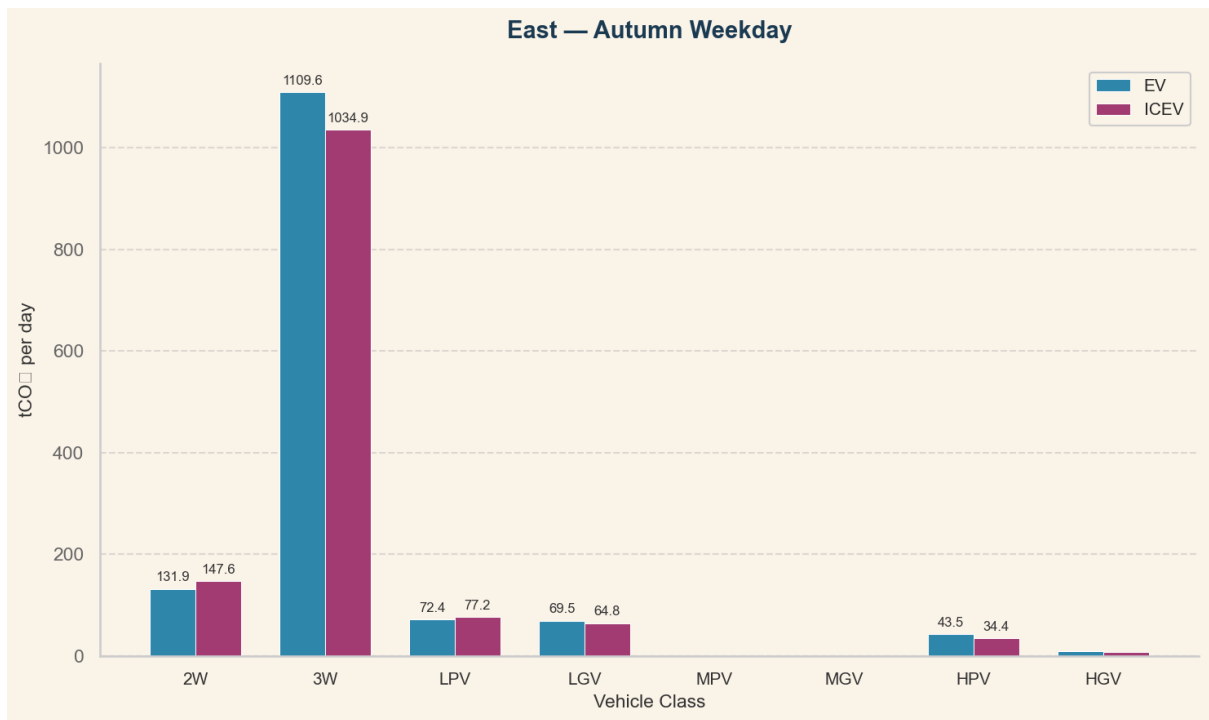
Eastern Regional Grid



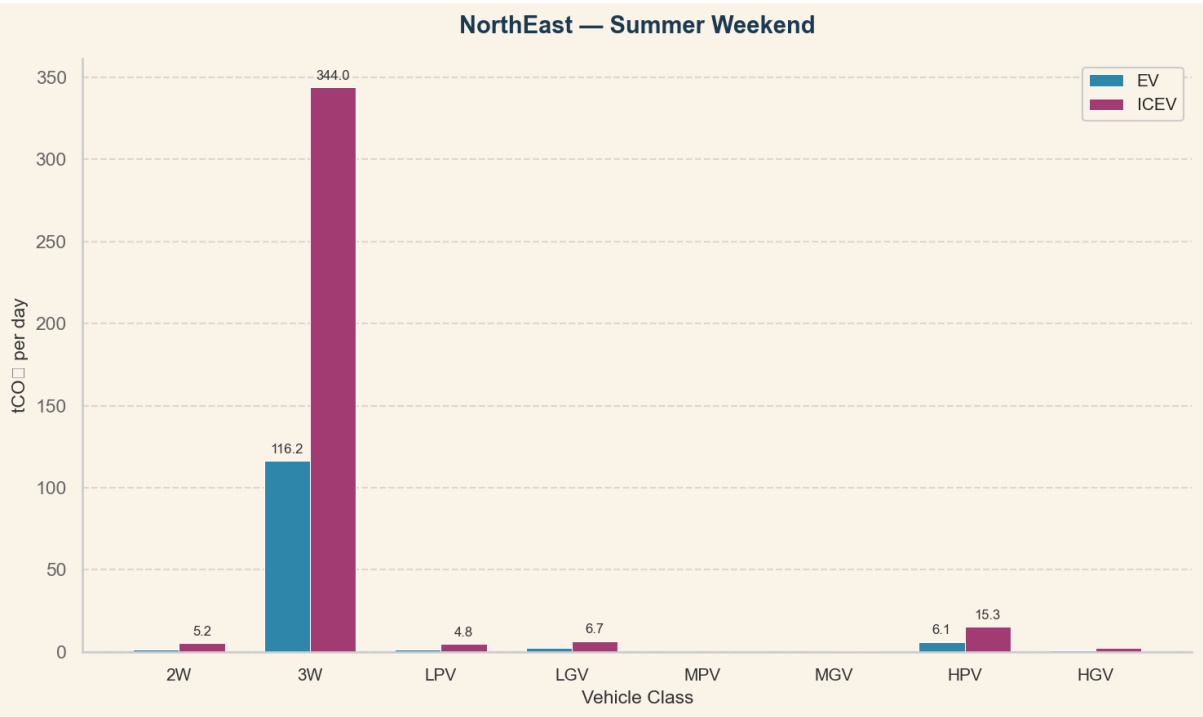
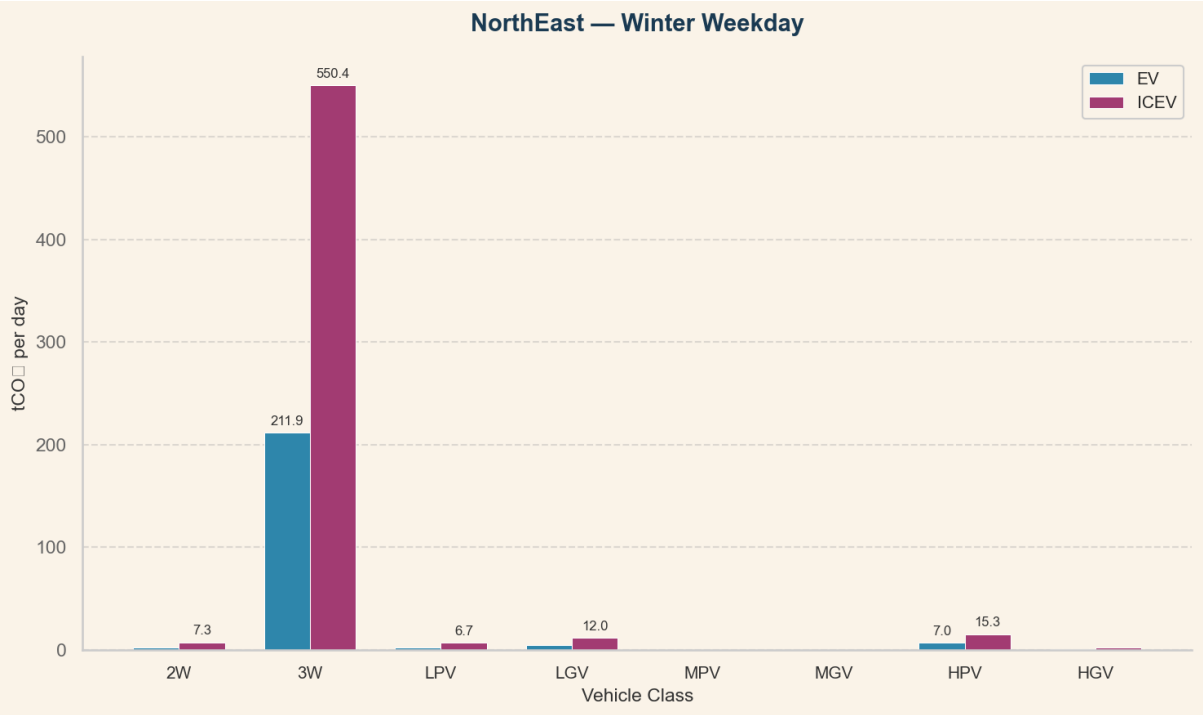


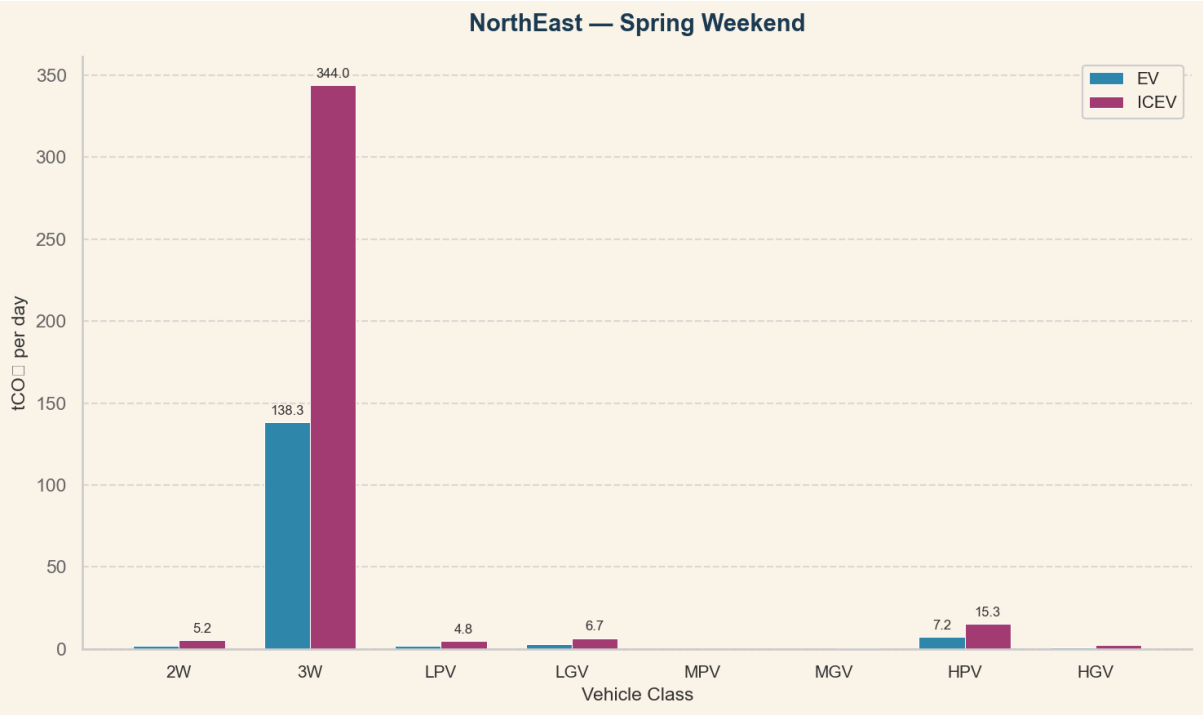
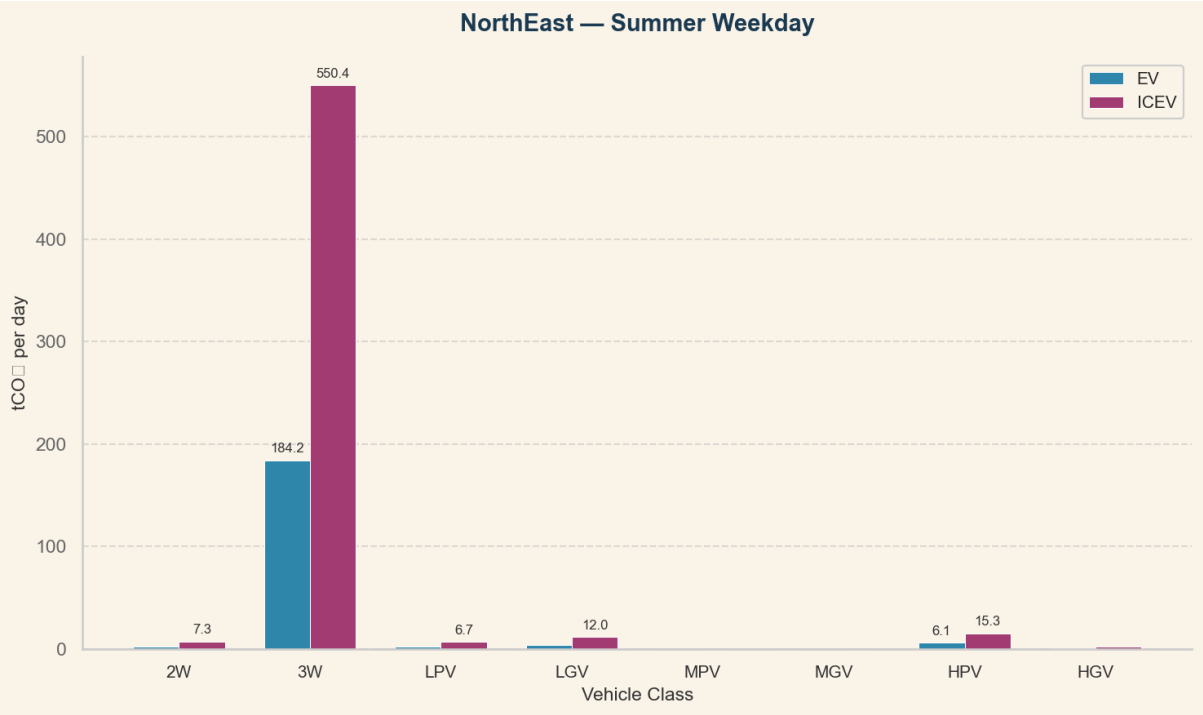


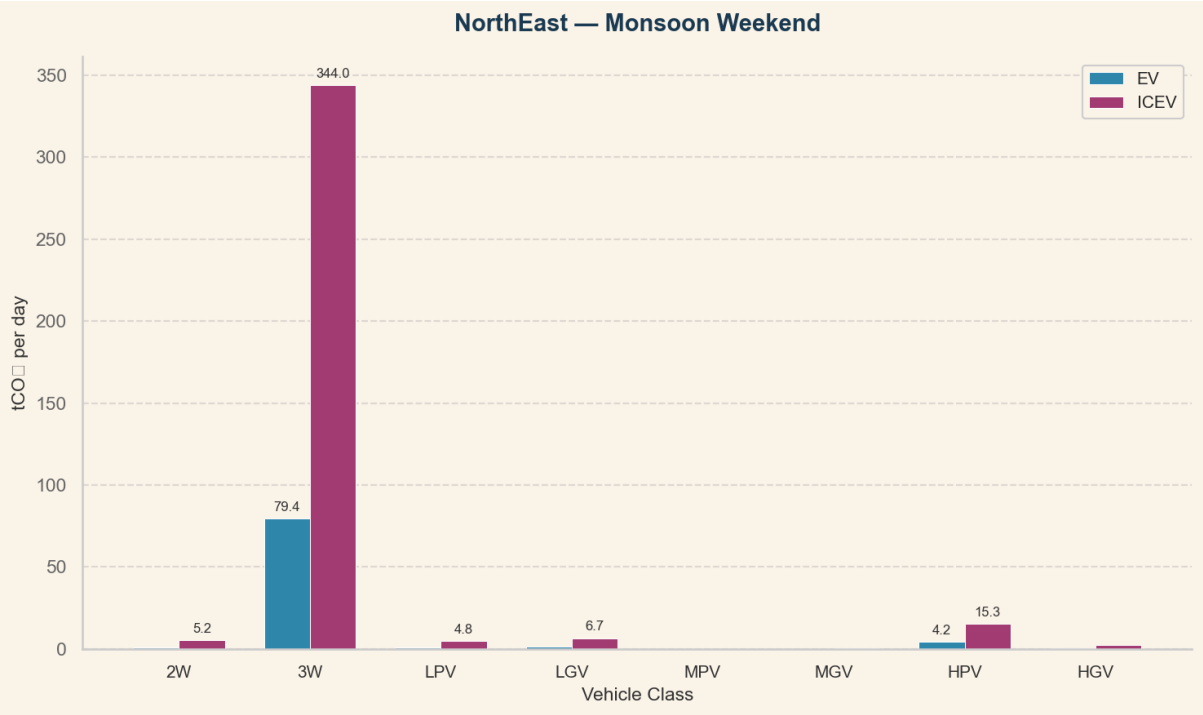
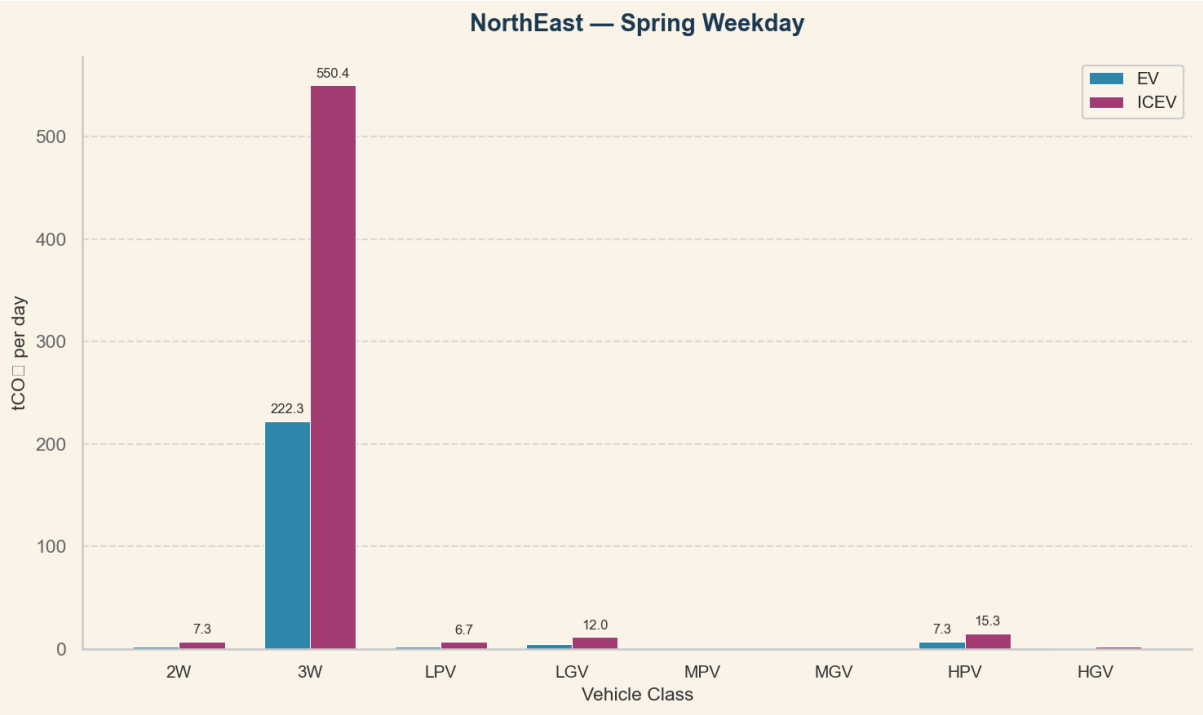


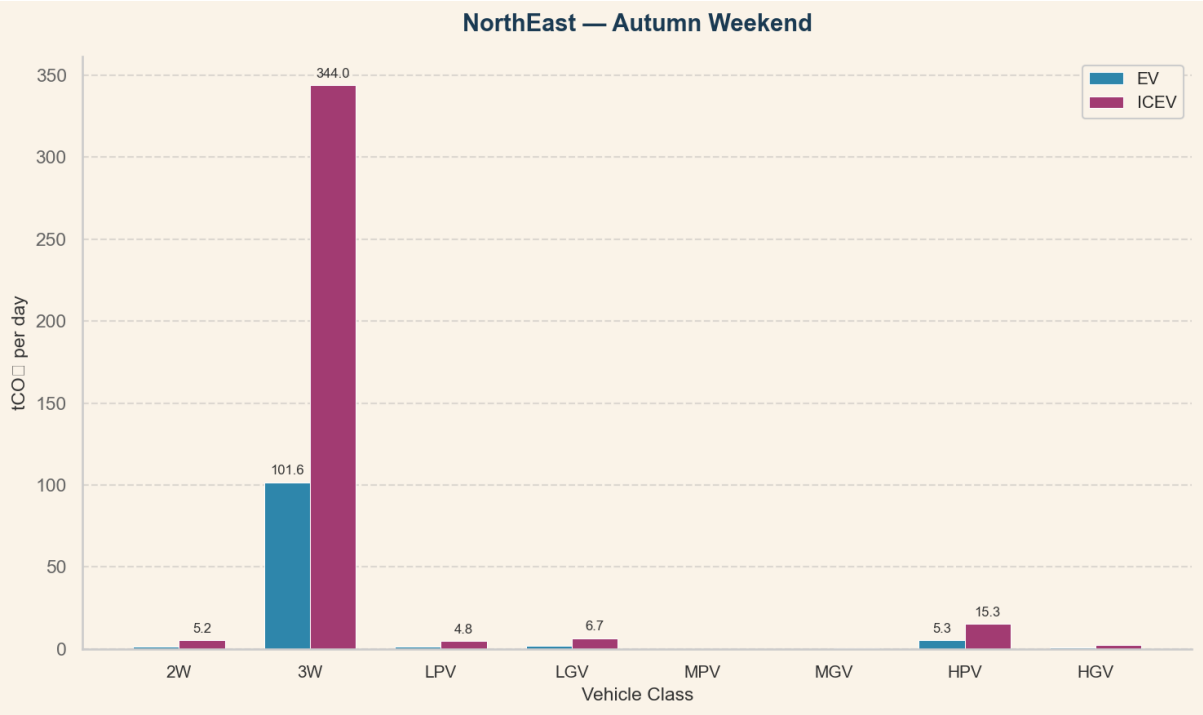
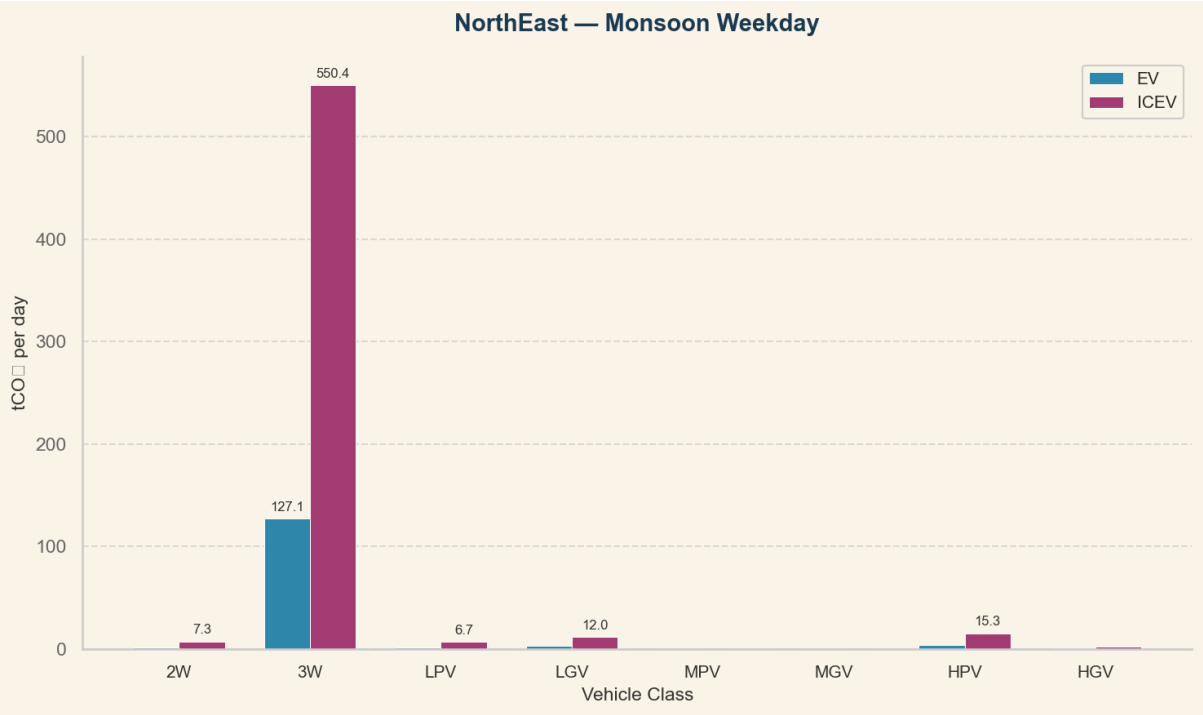


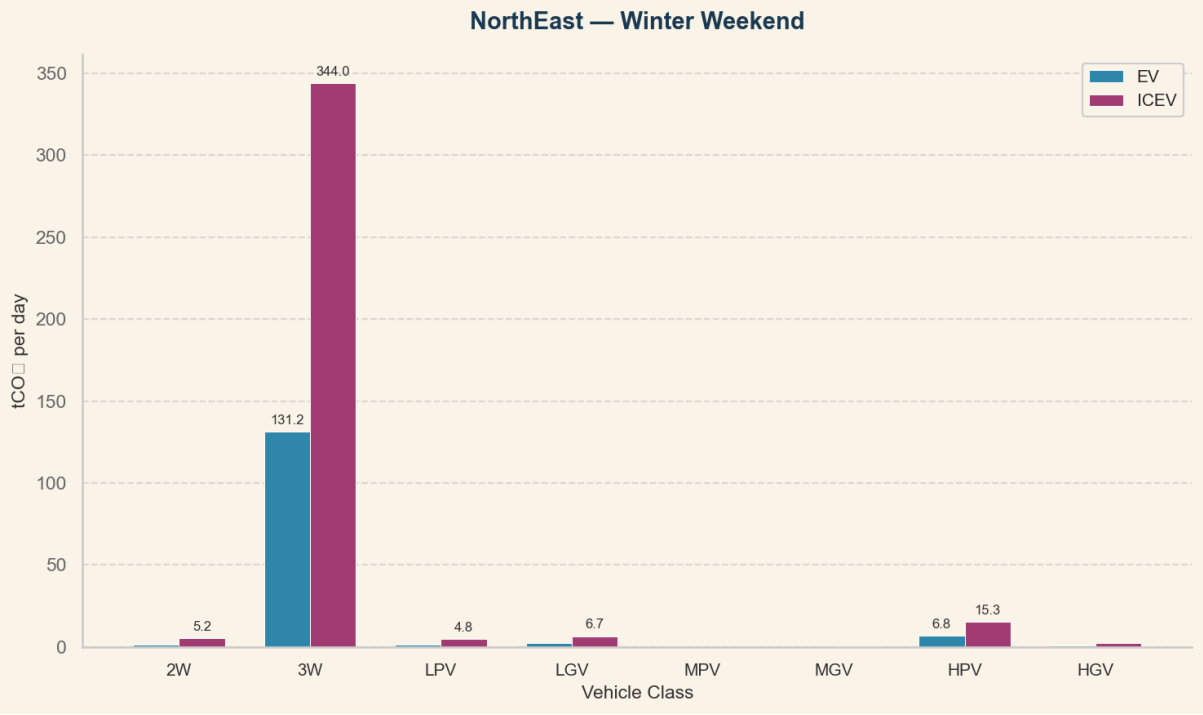
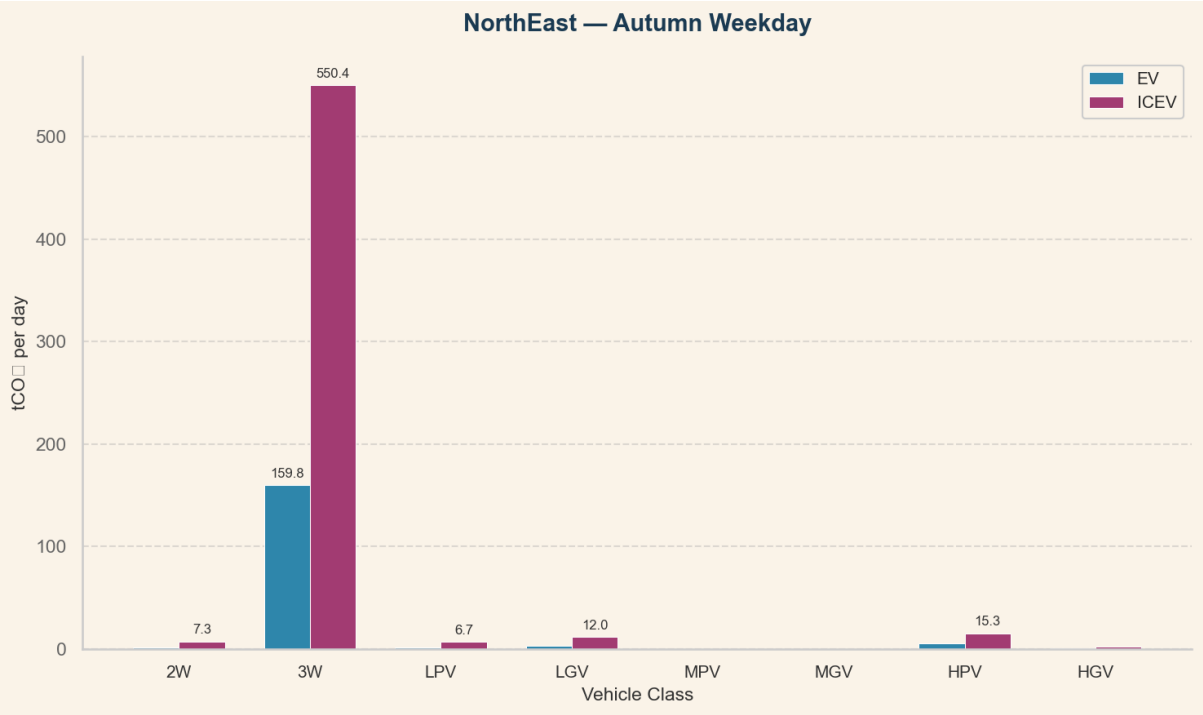
North-Eastern Regional Grid











EV CHARGING DEMAND - 2030

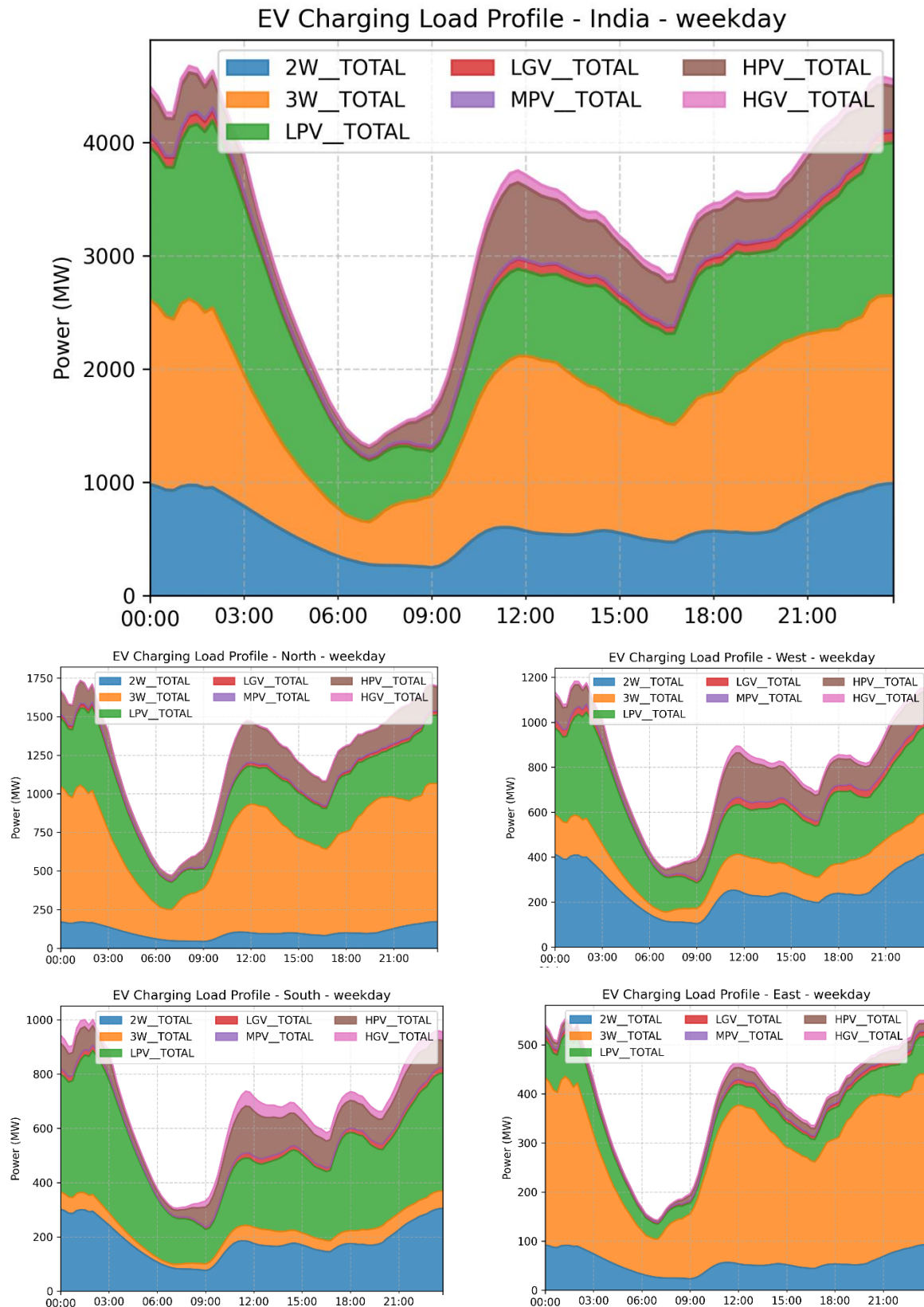


Figure 53: Weekday EV charging load profiles for India and regional grids for 2030 BAU scenario, showing the aggregate charging power contribution of different vehicle categories across 24 hours.

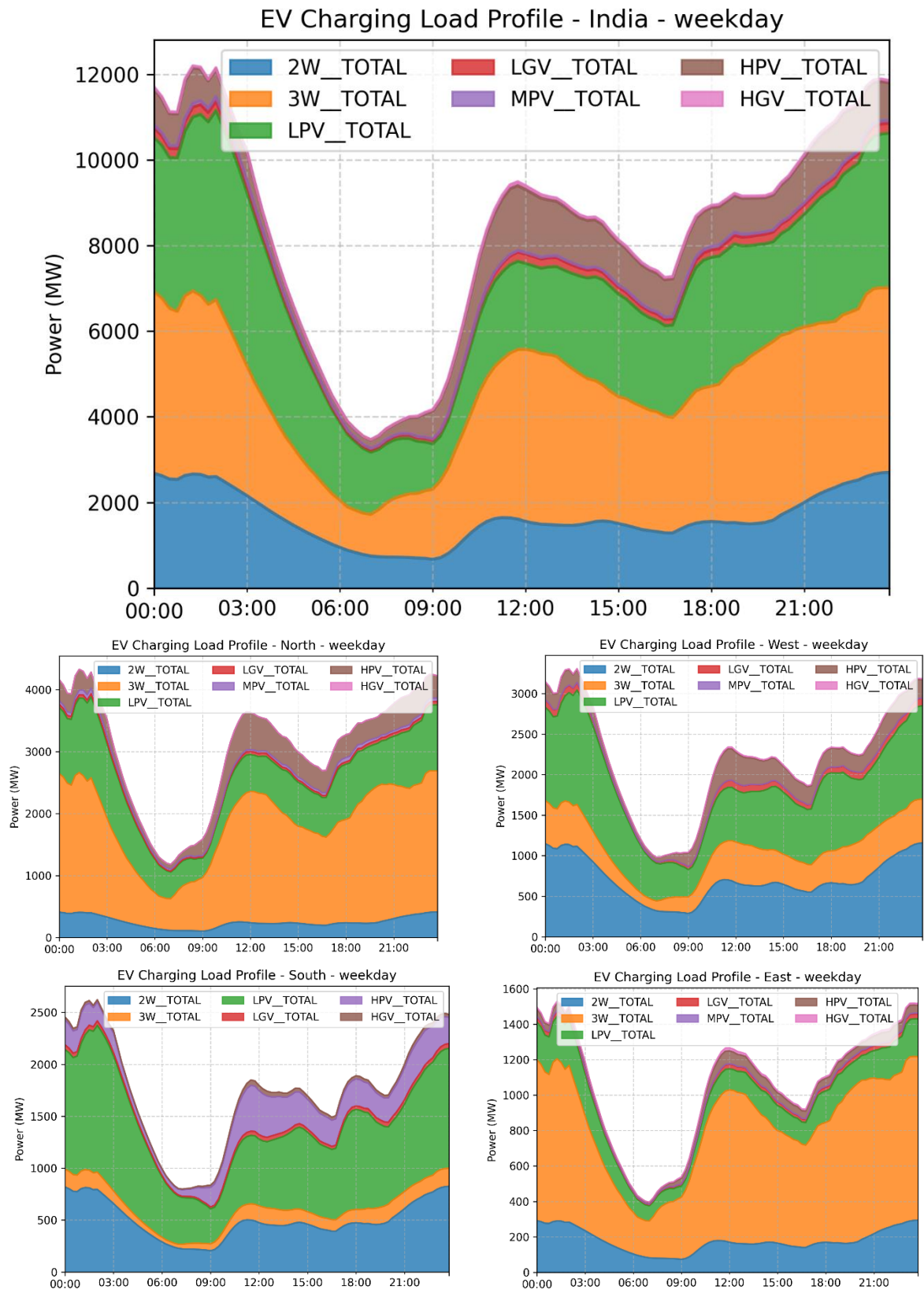


Figure 54: Weekday EV charging load profiles for India and regional grids for 2030 SPS scenario, showing the aggregate charging power contribution of different vehicle categories across 24 hours.



Published by:
Grid Integration Lab (GIL), IIT Bombay

Address:
Grid Integration Lab,
Department of Energy Science and Engineering,
Indian Institute of Technology Bombay,
Powai, Mumbai,
Maharashtra 400076

September 2026

Reach us at:



GIL



GIL