Data-Driven Analysis of a NEVI-Compliant EV Charging Station in the Northern Region of the U.S.

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***Abstract*—This study presents a data-driven analysis of a Level-3 EV charging station on a major interstate highway in a northern rural region of the United States, focusing on adherence to the National Electric Vehicle Infrastructure (NEVI) formula program. Utilizing two years of 15-minute smart meter data, this paper presents the power demand dynamics and characteristics of this EV charging station. This study investigates charging trends and behaviors over various time frames, including monthly, seasonal, and weekday periods. The Charging Behavior (CB) index, a novel metric, is developed to quantify and compare charging behavior patterns. Besides, this study investigates the correlation between the power demand of the charging station and the corresponding traffic counts. The result shows that the correlation is particularly relevant in seasonal variations in northern rural areas. The findings from this comprehensive analysis are vital for stakeholders in the power sector, aiding in the strategic planning and optimization of EV charging infrastructure under NEVI compliance, especially in remote regions that have the four-season climate. The study's insights are also crucial for researchers focusing on the sustainable integration of EV infrastructure into existing power grids, addressing both operational planning and demand management.**

***Index Terms*—AMI data, charging behavior, data analysis, EV, EV charging, highway, level-3 charging, NEVI.**

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I. Introduction

DESPITE challenges such as supply chain disruptions, economic uncertainties, and high prices of commodities and energy, electric car sales reached a record high in 2022, surpassing 10 million units, marking a 55% increase compared to the previous year. This growth in electric car sales, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), contributed to a 14% share of electric cars in total car sales, up from 9% in 2021, and brought the total number of electric cars on the global roads to 26 million, with BEVs making up over 70% of this growth [1]. In the second quarter of 2022, the U.S. witnessed a record-breaking 48.4% increase in sales of full battery-electric vehicles (EVs) [2]. In February 2022, the U.S. Departments of Transportation and Energy announced the National Electric Vehicle Infrastructure (NEVI) Formula Program, allocating $5 billion over a five-year period to establish a DC-Fast (Level-3) charging station network along the national interstate highway systems [3], [4], [5].

The NEVI Formula Program aims to mitigate range anxiety for EV owners during long-distance travel, consequently promoting widespread EV adoption across the country. Currently, EV chargers are classified into three levels according to their charging voltages. Level 1 charging utilizes 120V and delivers a 3 to 5 miles range per charging hour. Level 2 charging operates at voltages between 208 V and 240 V, offering a range of 12 to 80 miles per charging hour. Level 3 charging, the fastest method, employs voltages ranging from 400 V to 900 V DC, providing a 100-mile range in just 30 minutes of charging [6]. In contrast to the most common charging stations, such as Level-1 and Level-2, found in urban areas, the charging stations along the highways will be mainly Level-3 charging stations. Since Level 3 charging stations draw considerable energy (kWh) from power grids within a short period, the power demand (kW) will be increased significantly. It will not only necessitate greater electric energy consumption but will also exacerbate the complexity of power system operations and amplify the risks utilities face in the electricity markets.

Rural electric cooperatives have the expansive service territories across the United States and power 56% of the nation's landmass [7], overlapping a significant intersection with the U.S. Interstate Highway System. Therefore, it is essential for electric cooperatives and system operators to have a comprehensive understanding of the demand characteristics associated with

NEVI-compliant EV charging stations located along the U.S. Interstate Highway System, which is crucial for anticipating and mitigating potential complications in grid operation and reliability.

Recent literature in the field of EV charging behavior presents a diverse range of models and algorithms, each contributing to the understanding and optimization of EV charging and its impact on power grid management. The literature presents a range of models and algorithms to optimize EV charging, addressing issues like congestion, grid management, and user satisfaction. Papers [8], [9], [10] explore behavioral influences and game theory models for charging strategies. Papers [11], [12], [13], [14] focus on location placement, load behavior modeling, and charging time forecasts. Real-time tracking and distributed demand response algorithms are discussed in papers [15], [16], with practical insights from field studies in paper [17]. Advanced modeling techniques, such as Stackelberg games and ant colony algorithms, are examined in papers [18], [19], [20] for predicting charging station loads and load forecasting. Papers [21], [22], [23], [24] use survey data and probabilistic methods for optimal charging strategies and station placement. Papers [25], [26] address stochastic nature of EV charging, and papers [27], [28] highlight renewable charging stations and load behavior analysis using smart meter data. The role of AI and machine learning in this domain is underscored in papers [29], [30], [31], [32], [33], where various techniques, including deep reinforcement learning and Long Short-Term Memory Networks, are employed to predict and optimize EV charging behaviors.

Besides, traffic flows and driver behavior have also been incorporated for numerous EV charging load forecasting in recent studies. In paper [34], the authors developed a probabilistic queuing model to transform traffic flow into charging load considering the driver behaviors. Paper [35] presents an EV charging load forecasting technique for households using road network information. Paper [36] introduces a load forecasting method based on a decision-making that considers payment cost, time cost, and route factors. The study [37] investigates the impact of the attitude of EV drivers. An agent-based model is developed to simulate the behavior of EV drivers. The paper [38] proposes a load forecasting method using an affinity propagation clustering algorithm for urban EV charging stations based on residents' travel habits.

However, there are three major research gaps in existing literature, including:

- Insufficient Insight into NEVI-Compliant Level-3 EV Charging Station: Existing research primarily focuses on level-1 and level-2 charging stations, resulting in a gap in understanding the load characteristics specific to NEVI-compliant Level-3 EV charging facilities.
- Inadequate Research on Seasonal Variations Affecting EV Owner Travel Habits: Current studies incorporating traffic or travel data in analyzing EV charging loads tend to neglect the influence of seasonal changes on the highway travel patterns of EV owners.
- Overgeneralization from Traffic Data: Research utilizing traffic data often assumes that the number of EVs on the road is proportionate to the overall traffic volume, potentially oversimplifying the relationship.

Moreover, due to commercial constraints and the relatively scarce presence of NEVI-compliant Level-3 charging stations in the U.S., existing research does not incorporate actual data from these types of stations. This paper aims to bridge these research gaps and facilitate the NEVI formula program's development by examining a NEVI-compliant Level-3 DC-fast charging station located on a major interstate in the Northern High Plains of the US. Leveraging two years of actual smart meter data, the study aims to reveal distinct charging patterns and behaviors specific to NEVI-compliant Level-3 charging stations in rural areas, thereby offering vital insights into a comparatively unexplored facet of EV infrastructure.

The key contributions of this paper are as follows:

- Providing a detailed analysis of the charging demand patterns for a NEVI-compliant Level-3 EV charging station using two years of real-world 15-minute resolution smart meter data.
- Evaluating the daily, monthly, and seasonal load factors over a two-year period to assess the efficiency and cost-effectiveness of a NEVI-compliant Level-3 EV charging station in the Northern United States.
- Investigating the relationship between hourly traffic patterns and load demand, specifically to demonstrate the correlation between traffic volume and Level-3 EV charging demand in the rural regions of the Northern United States.

The rest of the paper is structured as follows. Section II introduces this NEVI-compliant EV charging station and the data used in this study. The charging pattern analysis is presented in Section III. Section IV analyzes the charging behavior and load factors. Section V shows the regression analysis between traffic volume and charging behavior. The conclusion is provided in Section VI.

II. Introduction of the Charging Station and Data

As of now, only 509 EV charging stations in the U.S. meet the criteria set by the NEVI formula program [39]. The corridors form an extensive network that facilitates EV transportation across the nation. Charging stations are widely distributed with a pronounced presence along these corridors. This widespread distribution extends beyond urban localities, ensuring that rural areas are also served, which is crucial for the adoption and convenience of EV usage in less populated regions. However, the central parts of the country especially the Northern Great Plains exhibit a sparser distribution of charging stations. This study focuses on a NEVI-compliant Level-3 charging station installed in the Northern High Plains of the U.S., located on a frequently utilized major interstate, particularly popular with tourists during the summer. The vicinity is known for various notable landmarks and attractions that draw visitors in the summer. The station is in a small rural town with approximately 900 residents, having a minimal direct influence on the charging demand. Consequently, it is reasonable to infer that most of the charging station's usage originates from interstate travelers. The region experiences four distinct seasons, each with its own

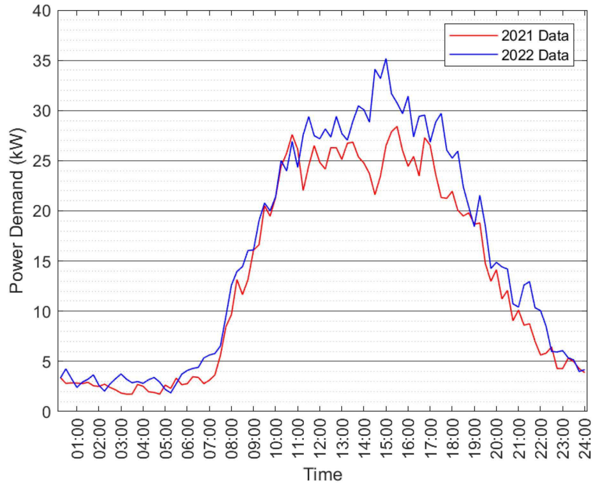

Fig. 1. Average daily power demand.

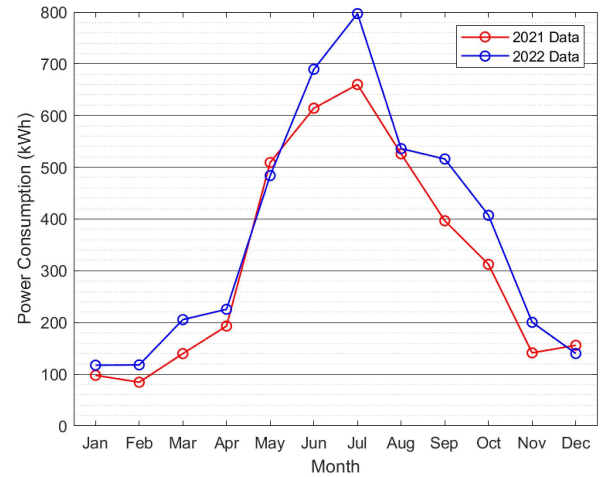

Fig. 2. Average daily power consumption per month.

weather and temperature patterns, influencing charging behavior. Equipped with eight charging ports capable of up to 150 kW at any time, this station is a fitting example of rural charging stations along major interstates in the Midwest region of the U.S., providing valuable insights for this specific context. The local utility provided the smart meter charging data of 2021 and 2022. The regional Department of Transportation supplied 2022 hourly traffic data of the interstate highway. A traffic monitoring device is installed near this charging station, ensuring that the data accurately reflects the vehicular volume passing by this charging facility.

III. Charging Pattern Analysis

A. Average Daily Charging Demand

This section presents a comparative analysis of the average daily power demand at the Level-3 EV charging station along an interstate over two years, 2021 and 2022, as illustrated in Fig. 1. The comparison shows consistent average power demand patterns for both years. Notably, post-11 AM until 7 PM, the demand trajectories diverge, with 2022 experiencing higher demand levels than 2021. Specifically, the peak demand in 2022 occurs at 35 kW around 3:30 PM, whereas in 2021, it peaks slightly later at 4 PM, reaching 29 kW. Despite the similarity in timing of peak demand, the year 2022 shows an upward trend in power usage at this EV charging station compared to the previous year.

An abnormal pattern observed in Fig. 1 is the inverse demand trend between 13:00 and 15:00, where the charging demand in 2021 was significantly lower than in 2022. This variation is primarily attributed to the impact of the pandemic. Given the charging station's proximity to a gas station and rest area, the Covid-19 pandemic resulted in a decreased number of people stopping at this rest area for lunch or coffee breaks during their road trips in 2021.

B. Daily Charging Consumption of Each Month

The study analyzes and presents the average daily power consumption per month at an interstate EV charging station for the years 2021 and 2022, with findings depicted in Fig. 2. The data reveal that, with the exceptions of May and December, each month in 2022 had a higher average daily power consumption than in 2021. The yearly consumption pattern forms a bell curve, peaking in the summer months, a trend that remained consistent across both years. However, the months recording the lowest average daily consumption differed yearly, with February marking the lowest in 2021 at 84.61 kWh, and January being the lowest in 2022 at 117.58 kWh. The peak consumption was observed in July, with 660 kWh in 2021 and an increase of 797.03 kWh in 2022, representing the most substantial absolute growth in average daily consumption of 137.03 kWh year-over-year. March experienced the highest percentage growth, with a 46.96% increase in average daily power consumption from 2021 to 2022. Fig. 2 clearly indicates that the charging consumption during the summer months of 2021 was significantly lower than in 2022, a trend that is consistent with the observations made in Fig. 1. The Covid-19 pandemic played a major role in this discrepancy, as many travelers opted not to stop at this location for lunch or a coffee break. Consequently, the summer charging consumption in 2021 was markedly less than in 2022.

C. The Lowest Charging Consumption Month

The study sets out to discern the shifts in power demand at an EV charging station over two years, focusing on the months with the lowest and highest consumption. Fig. 3 illustrates the average daily power demand for February 2021 and 2022. The comparison reveals no distinct pattern in demand between the two years. Each year exhibits significant spikes in demand around 9 AM to 10 AM and again at 6:20 PM, accompanied by smaller, more frequent spikes roughly every hour. Beyond these coinciding peaks, there is a notable variability in the demand patterns between the two years. For instance, a peak in demand at approximately 9:30 AM in 2021 registers at 13 kW, whereas in 2022, the demand at the same time is significantly lower at just 2.5 kW. Additionally, the demand spikes in 2022 are generally more significant, in the range of 10–14 kW, contributing to a

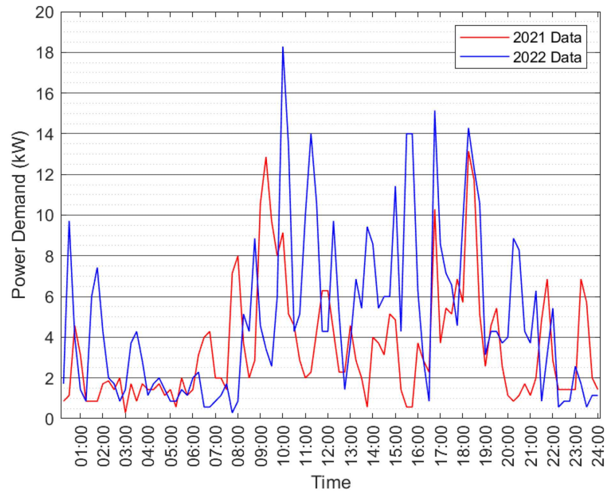

Fig. 3. Average daily power demand for February.

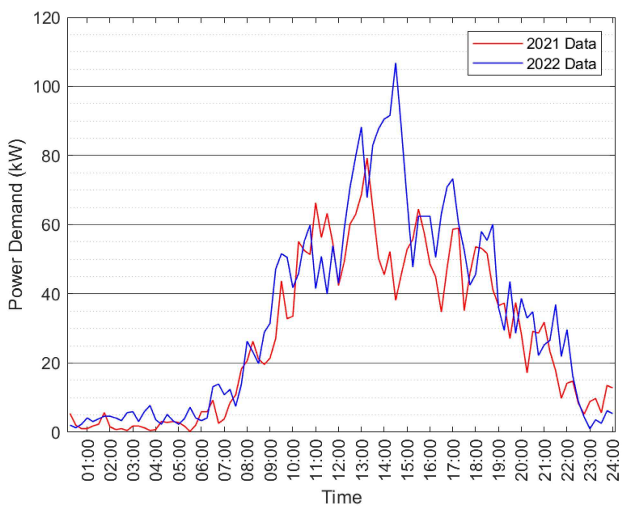

Fig. 4. Average daily power demand for July.

40% rise in power consumption for February 2022 compared to February 2021. These observations highlight the unpredictable nature of power demand at the charging station during the colder months, which are traditionally associated with lower consumption despite an overall increased demand.

D. The Highest Charging Consumption Month

Fig. 4 presents the average daily power demand for July in 2021 and 2022 at the EV charging station, highlighting a more consistent and coherent pattern of charging demand for both years. The power demand for both years typically rises at 8 AM and tapers off around 8 PM, forming a bell curve. The early morning and late evening demands are similar for both years. However, the afternoon and early evening hours of 2022 show notably higher demand, with more pronounced hourly spikes, echoing the pattern observed in February. The peak average power demand during a 15-minute interval in 2022 reached 107.5 kW around 3 PM, in stark contrast to the corresponding period in 2021, which saw a demand just shy of 40 kW. These significant demand peaks are observed throughout the day, including 1:30 PM, 3 PM, 5:30 PM, and 7 PM.

Similar to the trends observed in Figs. 1 and 2, the Covid-19 pandemic in 2021 significantly influenced EV travel behaviors. Many travelers chose not to stop at the rest area for lunch or a coffee break, leading to a substantial decrease in charging demand between 13:00 and 15:00 in 2021 compared to 2022.

The fluctuations in tourist activity around multiple attractions, including National Parks and Historical Sites, significantly influence the analysis for February and July. The selection of these months for detailed examination intends to highlight the variations in charging demand that mirror the annual peaks and troughs in visitor numbers. Figs. 3 and 4 collectively demonstrate an increase in average power demand at the Level-3 EV charging station along an interstate between 2021 and 2022. In months with traditionally lower consumption, such as February, there is an overall increase in demand, though the daily demand patterns remain quite erratic for both years. Conversely, in higher consumption months like July, there is a noticeable consistency in demand patterns, with notable increases in average demand during the afternoon and early evening hours between the two years. These observations suggest that power companies and EV charging station operators should carefully consider these fluctuating demand patterns based on the time of year. Such insights are crucial for accurately assessing the load and impact of EV charging stations on interstate systems, aiding in better resource allocation and infrastructure planning to accommodate varying demand levels throughout the year.

E. Seasonal Charging Patterns

In this study, a detailed monthly analysis of power consumption and demand at an interstate EV charging station revealed a distinct correlation with seasonal temperature variations. To understand the impact of seasonal changes on power consumption and demand, the data was categorized into four distinct seasons based on the local climate characteristics, which are Winter (December-February), Spring (March-May), Summer (June-August), and Fall (September-November). The findings, detailed in Fig. 5, provide a comparative analysis of the average daily power consumption for each season at the charging station across the years 2021 and 2022.

The analysis in Fig. 5 highlights that Summer months exhibit significantly higher power consumption levels compared to other seasons. The consumption levels in Spring and Fall are moderately consistent, averaging between 300–400 kWh. Notably, Fall showed the most pronounced increase in average daily consumption year-over-year, with a 32% surge, equating to an additional 91.14 kWh. Similarly, Spring, Summer, and Winter also experienced increases, albeit with different magnitudes, ranging from 9-12% and equating to increases of 24.17 kWh, 74.17 kWh, and 11.69 kWh, respectively. To provide a comprehensive understanding of these seasonal shifts, the paper will further analyze the average daily power demand during the Winter and Summer seasons for both 2021 and 2022.

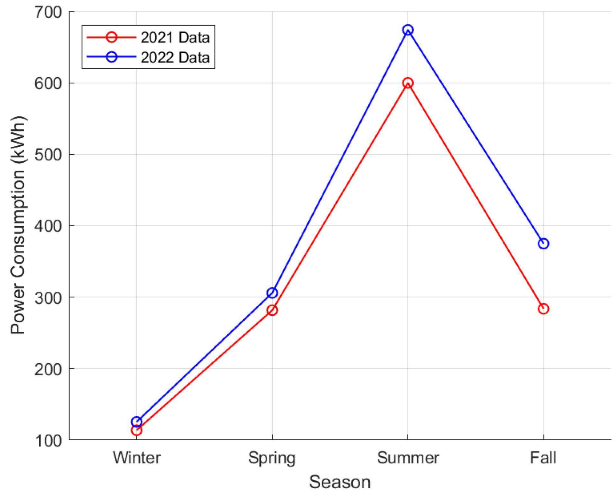

Fig. 5. Average daily charging consumption each season.

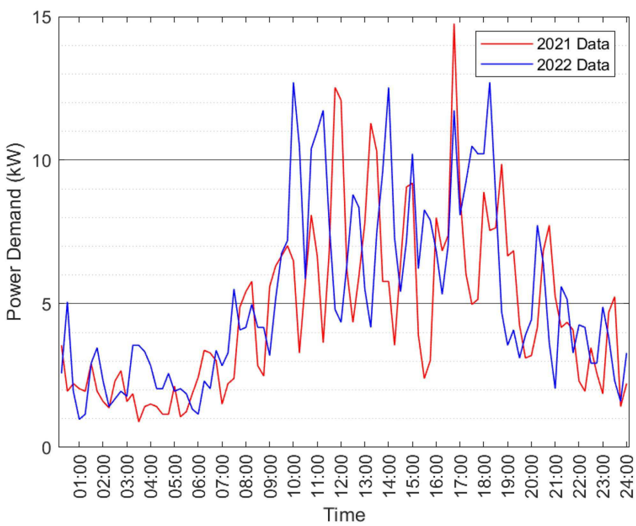

Fig. 6. Average daily power demand for Winter.

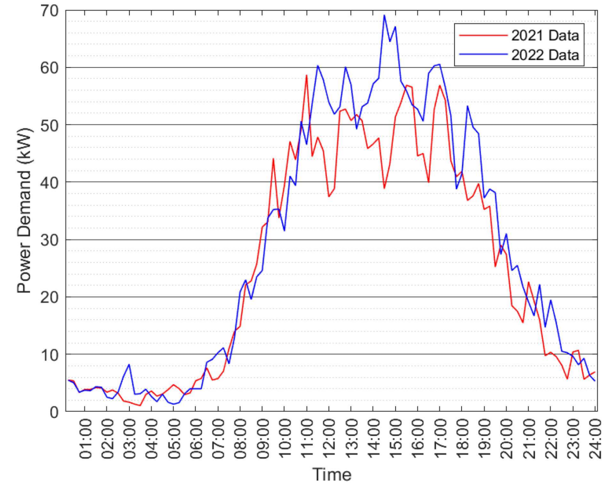

Fig. 7. Average daily power demand for Summer.

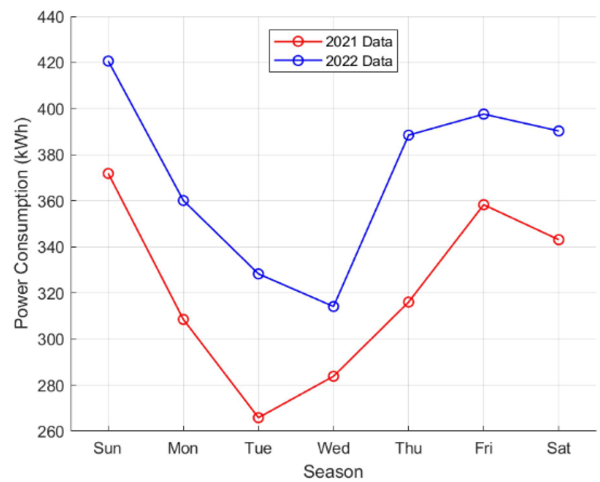

Fig. 8. Average daily power consumption per week.

Fig. 6 illustrates the average 15-minute interval power demand during the Winter season for the years 2021 and 2022 at the EV charging station. The data initially appears quite erratic throughout the day. However, a closer examination reveals similar patterns in early morning and late evening demand across both years. There are noticeable hourly demand spikes during the daytime, though their intensity varies by year. In 2021, the most significant spikes occurred at approximately 5 PM (nearly 15 kW) and 12 PM (12.5 kW), with other relatively minor spikes. In contrast, 2022 doesn't exhibit spikes as high as 15 kW but shows several substantial spikes around 10 AM, 11 AM, 2 PM, 5 PM, and 6:30 PM, each close to 12 kW. This pattern of increased demand spikes contributes to the overall higher consumption observed in Winter 2022 compared to 2021.

Fig. 7 presents a totally different scenario for the Summer season's average daily power demand in 2021 and 2022. The data reveals a much higher overall demand with more consistent and less variable patterns compared to Winter. Both years display a more pronounced bell curve, with similar early morning and late evening demands. The demand in both years starts to increase around 8 AM and begins to decrease after 6:30 PM, lasting until around midnight. The peak demand period, from 11 AM to 6:30 PM, shows significantly higher demand in 2022 compared to 2021. The highest demand shifts from 58 kW at 11 AM in 2021 to 69 kW at 2:30 PM in 2022, with 2022 consistently maintaining higher demand levels throughout this period, except for a few brief intervals where 2021 surpasses.

F. Weekly Charging Patterns

This section of this study examines the influence of the day of the week on charging consumption at the charging station over two years. Fig. 8 presents the average daily power consumption for each weekday at the charging station for 2021 and 2022. The data indicates that the weekends, encompassing Friday through Sunday, experience higher average consumption compared to the weekdays.

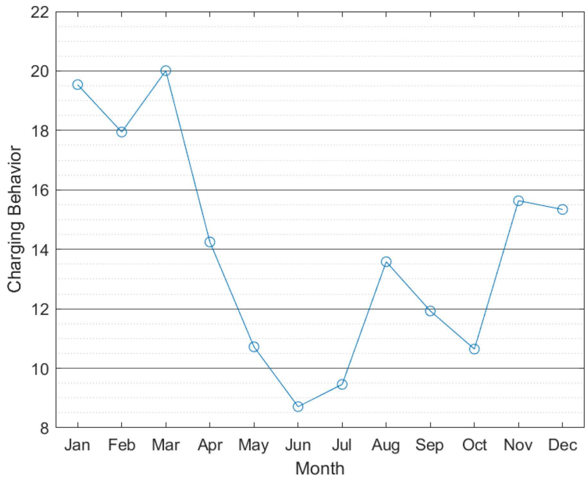

Fig. 9. Charging behavior index for each month.

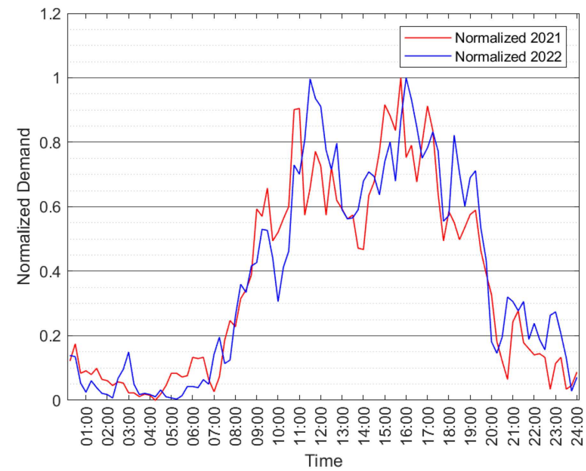

Fig. 10. Normalized average daily power demand for June.

IV. Charging Behavior and Load Factors

A. Behavior Difference Index Term

To distinguish the chaotic charging behaviors across 2021 and 2022, the demand data for each month is normalized in this study. This normalization enables a clearer explanation of the parallels or discrepancies in charging behaviors across the two years.

To quantitatively assess the variations in charging behaviors between the two years, this paper introduces a novel metric termed the Charging Behavior (*CB*) Index. The *CB* Index is proposed to quantify the degree of similarity or disparity between two datasets, with a value of 0 indicating identical behavior and values approaching infinity signifying complete divergence. This index provides a standardized way to evaluate and compare charging patterns over different time periods. *CB* is defined in (1) as

$$CB = \sum_{n=1}^{n} |2021Data_n - 2022Data_n| \tag{1}$$

where n is the number of data points and *2021Data* and *2022Data* are normalized data sets for identical time periods, such as months, seasons, days, etc. If *CB* is zero, that means the demands for both years are identical leading to the same behavior. The larger the *CB* is, the more the behaviors deviate from each other. In Fig. 9, the charging behavior of each month in 2021 and 2022 are plotted.

The analysis reveals distinct seasonal trends in charging behavior at the EV charging station when comparing data from 2021 and 2022. During the colder months, specifically January, February, and March, the charging behavior exhibits considerable inconsistency, as reflected by higher Charging Behavior (CB) index values. Conversely, the charging patterns tend to be more aligned in the warmer months of May, June, and July, indicated by lower CB values. March recorded the highest CB value at 20.01, signifying a significant disparity in charging behavior between the two years, while June presented the lowest CB value at 8.71, indicating greater similarity. To enhance the understanding of these variations in charging demand, the study includes a graphical representation of the normalized average daily power demand for months exhibiting high, low, and transitional *CB* values. This graphical analysis provides a more detailed perspective on the similarities and differences in charging patterns at the station between 2021 and 2022 across different times of the year.

B. Daily Demand of Charging Behaviors Comparison

As shown in Fig. 9, June has the lowest Charging Behavior (CB) index of 8.71 and exhibits the most significant similarity in charging patterns between 2021 and 2022, as indicated by the data. Fig. 10 displays the normalized average power demand for June in both years, showing high consistency with only a few notable variances. Key deviations are observed at 10 AM, 11:30 AM, and 6:30 PM. Specifically, at 10 AM, the 15-minute demand in 2021 surpasses that of 2022, whereas the 11:30 AM and 6:30 PM intervals show higher demand in 2022 compared to 2021.

Distinguishing from the low CB value of June and March, with a high CB of 20.01, exhibits notably less similarity in charging behaviors between 2021 and 2022, as depicted in Fig. 11. The demand patterns for this month are characterized by frequent spikes and rapid decreases, occurring at varying times and intensities across the two years. During the early hours from 12 AM to 10 AM, the 2022 data reveals four pronounced spikes in demand at 1:30 AM, 4:30 AM, 6 AM, and 9 AM, which are not mirrored in the 2021 demand profile. In the daylight hours, both years demonstrate erratic and inconsistent demand patterns. A particularly stark instance is observed in 2022, where the demand sharply transitions from the peak 15-minute interval to nearly zero between 6 PM and 7 PM.

The reduced consistency and lower base demand during the winter months, attributed to fewer travelers on the interstates in the region, contribute to this variability. Such seasonal fluctuations in travel patterns lead to a more unpredictable and less comparable charging behavior, particularly in months like March.

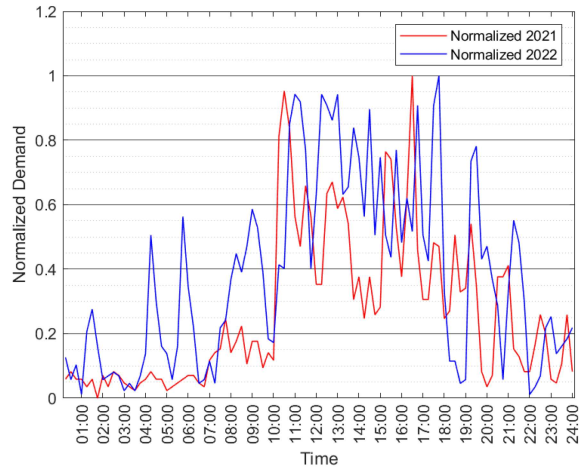

Fig. 11. Normalized average daily power demand for March.

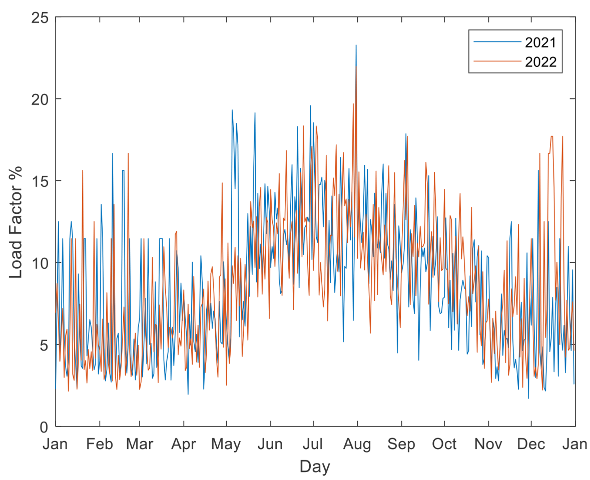

Fig. 12. Monthly load factor of 2021 and 2022.

C. Load Factors

To understand the charging load characteristics, the daily load factor of this charging station is also analyzed and plotted for 2021 and 2022. In power systems, the daily load factor is defined as follows:

$$\mathit{Daily\ Load\ Factor} = \frac{\mathit{Daily\ Average\ Load}}{\mathit{Daily\ Peak\ Load}} \times 100\%$$

Based on the results in Fig. 12, warm months have relatively larger load factors than cold months. It means that the charging station is used more consistently during warmer months. This is mainly due to increased travel and outdoor activities in warmer weather in the Northern US, leading to a steadier use of EV charging services.

V. Traffic Counts and Charging Behavior Regression Analysis

The Introduction of this paper highlighted the utilization of traffic counts for forecasting EV charging load in recent publications, which assume that EV charging demand is proportional to traffic flows. This concept posits that increased road traffic correlates with more electric vehicles. To examine the validity of this assumption, the study received hourly traffic data from the regional Department of Transportation. An analysis was then conducted to explore the correlation between traffic counts and EV charging demand, aiming to either substantiate or question this widely held belief and to enhance the understanding of the interplay between road traffic patterns and EV charging activities. In this section, the average daily traffic pattern of each month in 2022 is plotted in Fig. 13, which shows that August has the most traffic counts passing through the charging station, and December 2022 has the least traffic counts. The traffic flow patterns closely follow the daylight time.

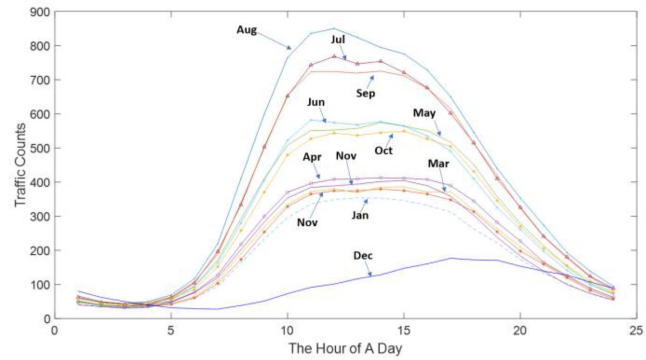

Fig. 13. Average daily traffic number of each month in 2022.

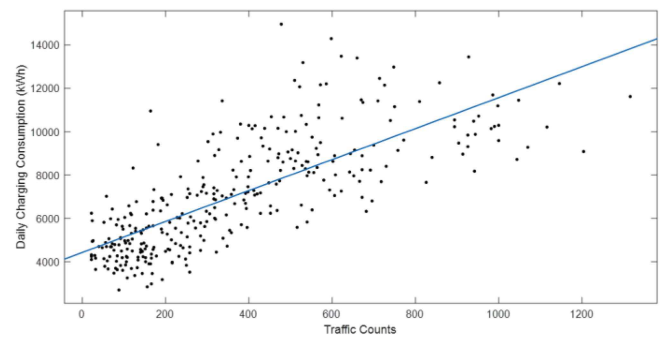

Fig. 14. Daily charging consumption and daily traffic volume of 2022.

A. Charging Load Consumption and Traffic Counts

Fig. 14 presents a plot of the daily charging power consumption and corresponding traffic volumes for 2022. It shows a relatively linear regression between daily charging power consumption and daily total traffic volume. To further investigate the correlation between daily charging power consumption and daily traffic volumes, the degree of linearity in these relationships is quantitatively assessed by the coefficient of determination, also known as R^2. These R^2 values are comprehensively detailed in Table I, offering insights into the strength and consistency of the relationship between traffic volumes and charging power consumption across different time periods. The coefficient of determination, denoted as R^2, is a pivotal statistical

TABLE I
R^2 FOR EACH MONTH OF 2022

Time	R^2 Values
January	0.0617
February	0.1575
March	0.2021
April	0.2108
May	0.2524
June	0.3249
July	0.0943
August	0.0113
September	0.1077
October	0.2822
November	0.0276
December	0.0036
Annual	0.5744

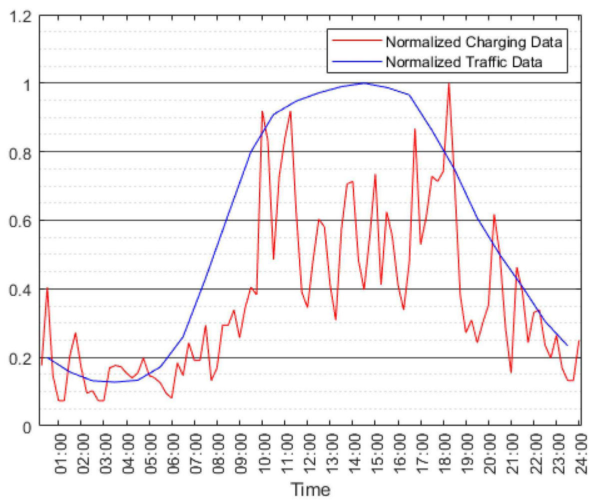

Fig. 15. Winter daily charging behavior and traffic volumes.

metric in regression analysis. It evaluates the model's goodness of fit, offering a quantifiable measure of the extent to which the variance in the dependent variable can be predicted from the independent variable. This coefficient, expressed as a value ranging between 0 and 1, essentially captures the proportion of the total variation in the dependent variable attributable to the variability in the independent variable, thereby providing crucial insight into the predictive strength and relevance of the regression model.

B. Charging Behavior and Hourly Traffic Volume

Table I reveals notable variations in the linear regression coefficients across different months, indicating a diverse range of relationships between charging behavior and traffic data. This section explores the daily correlation between charging patterns and traffic flow, utilizing hourly data to capture the dynamic interplay between these variables across different seasons. To quantitatively assess the disparity between the dynamics of charging behavior and traffic volumes throughout the day, a comparative analysis of normalized data points is conducted for each season. Figs. 15, 16, and 17 present a detailed illustration of this relationship, showcasing the charging behavior and traffic volume patterns specifically in winter, summer, and

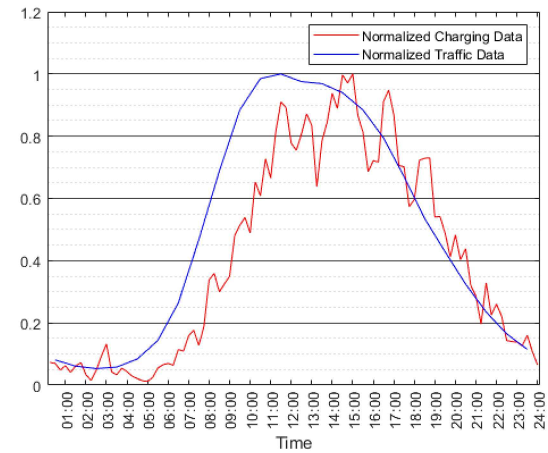

Fig. 16. Summer daily charging behavior and traffic volumes.

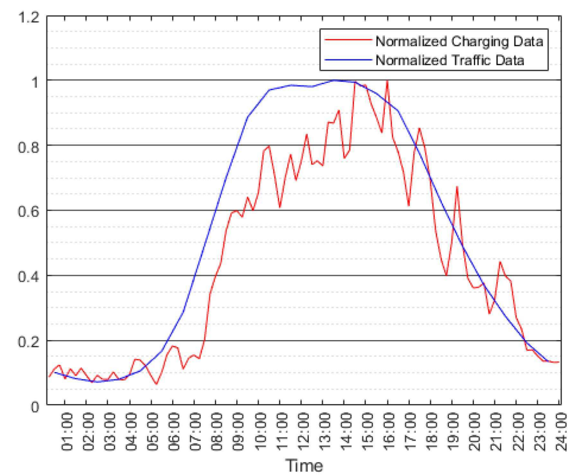

Fig. 17. Shoulder daily charging behavior and traffic volumes.

TABLE II
SEASONAL ABSOLUTE DIFFERENCE

Season	*AD*
Winter	4.7922
Summer	2.6449
Shoulder	2.3346

the shoulder seasons, respectively. These visual representations provide a deeper understanding of the temporal fluctuations in EV charging demand relative to traffic trends under varying seasonal conditions. To quantify the difference between charging behavior and traffic volumes, the absolute difference (*AD*) is defined as follows:

$$AD = \sum_{t=1}^{24} |Normalized\ Charging\ Data\ (t) \\ -Normalized\ Traffic\ Data\ (t)|$$

Table II reveals that the *AD* exhibits a strong seasonal dependency. In the winter season, particularly in the Northern region of the US, the *AD* is notably higher than during the summer and shoulder seasons. This trend is primarily attributed to the reduced proportion of EVs among all traffic during the colder months compared to warmer seasons. Consequently, this finding underscores the limitation of relying solely on traffic counts or data for NEVI-compliant EV charging load forecasting in Northern regions. It suggests that any charging forecasting model based on traffic data should be tailored to account for the seasonal variations in EV percentages.

V. Conclusion and Future Work

This study provides an analysis of load dynamics at a NEVI-compliant EV charging station in the Northern High Plains of the U.S., utilizing two years of actual smart meter data. This study demonstrates marked seasonal fluctuations in charging demand, peaking in the warmer months, and identifies a distinct seasonal relationship between EV charging demand and traffic volume. Specifically, in the winter, especially in the Northern US, the *AD* is significantly greater than in summer and shoulder seasons. This phenomenon is mainly due to the lower percentage of EVs used for long-distance travel in the colder months compared to the warmer seasons. This relationship diverges from the commonly assumed linear regression in previous studies, suggesting a more complex interplay between these variables across different seasons. These findings are particularly pertinent for the power sector, underscoring the importance of flexible management strategies for EV charging infrastructure in rural and seasonally varied regions. The insights gained can inform resource distribution, policy development, and strategic planning for upcoming EV charging stations in line with the NEVI formula program and changing consumer needs. In future work, as more NEVI-compliant stations are deployed, there is a need for advanced load forecasting models that incorporate geographic and traffic data, as well as seasonal influences, to improve the precision of load predictions for NEVI-compliant EV charging infrastructure.

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