Impact of EV Charging, Charging Speed, and Strategy on the Distribution Grid: A Case Study

Gerard Albadawi Abiassaf, *Member, IEEE*, and Abd A. Arkadan, *Fellow, IEEE*

***Abstract*—This work presents a methodology to assess the electricity demand due to the electrification of the transportation sector and its impact on the grid in a given geographic area. In addition, it presents the results of a case study within a geographic area up to the year 2050 and investigates ways to mitigate power quality issues due to the integration of light-duty passengers into heavy-duty electrical vehicles (EVs) within the electric grid. This study also investigates the impact of electrical vehicle, charging speed, and preferences on the utility and its distribution network by conducting a sensitivity analysis on the driver's charging preferences at work and at home, and how does it affect the load profile of a distribution grid. The voltage impact on the distribution grid nodes and line capacity limits are evaluated. This work will also investigate ways to mitigate power quality issues using renewable energy and distributed generation resources, while at the same time, finding the optimum EV charging speed and strategy to achieve an overall power system-level optimization of the distribution network.**

***Index Terms*—Electrical vehicles (EVs), EV adoption rates, impact of EV fast charging systems on utility and distribution grids, power flow studies, power mitigation techniques, power quality.**

I. Introduction

ELECTRICAL vehicles (EVs) are considered a feasible alternative to cars with internal combustion engines' (ICEs) to reach zero carbon emissions as required by tougher government environmental policies on carbon emissions [1]. As such, researchers embarked on assessing the electricity demand due to the electrification of the transportation sector and its impact on the grid. Support for EVs integration in the transportation sector is gaining a lot of traction in the public sphere, and car manufacturers' interest in this technology has been growing to keep up with the demand. The governmental push toward this technology as a replacement to carbon-emitting cars requires a huge shift in the industry and it could come with a heavy cost and substantial challenges for utility companies [2]. As such, many utilities are planning to upgrade the grid infrastructure to support EVs integration into the transportation sector.

The continuing increase in EVs will necessitate increased charging infrastructure and much greater electrical grid capacity to catch up with this increased electrical demand. Utilities will have to invest billions of dollars to produce this huge increase in capacity while also considering the challenge of replacing fossil fuels with renewable energy sources. For example, in Austin Texas, during the recent state-wide power outage, due to weather conditions, many EV owners did not have access to operating charging stations and could not drive their cars [3]. This provided a glaring example of how the utility grid will have to support another public sector, which is transportation. Reliability presents an issue for customers who wish to invest in EVs and who will need reassurance that similar outages will not affect their ability to use their vehicles. These are pressing issues going forward. The state of California, for example, plans to get rid of gas-powered cars and trucks by 2035 [4]. This will necessitate a huge increase in electric grid capacity, where there are estimates that, by 2050, the electrification of transportation and other sectors will require double the current U.S. generation capacity [3]. Case studies in this area were conducted to assess the charging demand, which will result from EV charging and what charging infrastructure will need to be in place. For example, the National Renewable Energy Laboratory (NREL) helped the California Energy Commission to figure out the number of EV chargers that will be needed to meet the state's zero-emission vehicle and greenhouse gas reduction goals [5]. In addition, the California Energy Commission conducted an assessment of EV charging infrastructure, analyzing the charging needs to support zero-emission vehicles in 2030 [6]. Also, a study by NREL in Columbus, Ohio, developed a plan for charging EVs in smart cities, in anticipation of the expansion of the region's network of charging stations [7]. Another study was also conducted by NREL to analyze the grid impact of heavy-duty EV charging stations [8]. Moreover, the case study conducted in Shenzhen, China [9], which has the world's largest fleet of electric buses and taxis, estimates the impact of EV charging until 2025. This study is done by forecasting models for projecting future EV ownership as well as probabilistic models for describing EV charging profiles, where the EV fleet is split into four categories: private EV, electric taxi, electric bus, and official EV. In a different study, optimal energy dispatching within the network of smart charging stations for vehicle-to-grid (V2G) operation was developed, and a cyber-physical comodeling method was suggested to assess the impact of EV charging on the distribution grid [10]. Alatise et al. [11] investigated the expansion of EV charging in a 750-acre industrial/commercial site with over 5500 employees and 6000 parking spaces. A load flow analysis was carried out on the 11 kV distribution circuit to examine the

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The authors are with the Department of Electrical Engineering, Colorado School of Mines, Golden, CO 80401-1887 USA. (e-mail: gerardabiassaf1@gmail.com; aaarkadan@mines.edu).

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effects of the increased load from EV charging on the main transformer's thermal limits. Recommendations were then made on how best to equip future distribution systems for increased EV charging. Moreover, Paudyal et al. [12] describe the development and results of an EV hosting capacity tool used to quantify the effects of injecting large numbers of EV charging loads and to determine the available capacity of the existing distribution feeders in order to maintain reliable and affordable grid operations. This type of tool could assist utilities in better preparing for grid operations in the near future, as well as investigating the impact and effectiveness of load management strategies, such as peak pricing and smart charging. Also, more studies in this field, such as [13], examined the public distribution network in terms of the percentage increase in harmonic distortion caused by EV charging station penetration. The voltage profile was studied as the EV load increased to determine bus capacity at certain total harmonic distortion levels. Also, Chawrasia et al. [14] illustrated the modeling of an EV load and its impact on the distribution system in order to determine the best location for charging stations. This concept was realized on the IEEE 33-bus distribution system, and it was demonstrated that it can have a significant impact on power grid stability and the best location for installing charging stations. Also, Zhu et al. [8] present a grid impact analysis of heavy-duty EV charging stations. This was important to consider because heavy-duty EVs will require extremely fast charging rates in order to reduce charging time and will generate extremely high charging loads, especially when multiple vehicles charge at the same time. The analysis was performed on both the IEEE 34-bus system and a realistic feeder from California using a systematic procedure developed to analyze the potential impact of charging station placement on the grid.

Because EV charging will directly impact distribution networks, researchers would need to study and model distribution systems that will provide substantial help for the industrial sector, especially utility companies, in addressing this new challenge. As such, the work in this article would be valuable in complementing the existing studies on the impact of EV charging since it specifically models the anticipated EV growth, and how it would impact a distribution network's power quality until 2050, which is different than the other existing research. A new research algorithm, transportation energy and mobility pathway options (TEMPO) model [15], is also utilized to model EV adoption rates by class, battery size, and technology. This study also provides utilities with a technical and practical understanding of what to expect in the next 30 years from EV charging. This work presents a methodology to assess the electricity demand due to the electrification of the transportation sector. The main contributions of this work are the development of a methodology that utilizes readily available tools and conducting a case study to evaluate the impact of EV charging on a small utility servicing a specific geographic area up to the year 2050. As such, the study outcomes are as follows: This will be accomplished by estimating how many EVs will be on the road in the next 20–30 years, from light-duty to heavy-duty EV fleets; how the EV charging profiles would look like; and how will this impact the grid's distribution network. Output data from NRELs TEMPO [15] will be used to estimate EV adoption rate profiles, which will in return be used as an input to the EV infrastructure projection (EVI-Pro) tool, EVI-Pro Lite [16], to project the electrical load demand for a city/urban area and to evaluate the impact of EV fast charging systems on the distribution network through a sensitivity analysis of the driver's charging preferences. In addition, this work will study the impact on the grid's distribution nodes. It will be done by building the power system distribution network based on IEEE 33-bus distribution test system [17], using real-time data from a residential feeder in an upper-middle-class region with a higher propensity of EV adoption. The EV loads are added to the feeder to study its impact on the grid nodes. This work will also investigate ways to mitigate power quality issues using renewable energy and distributed generation (DG) resources, while at the same time, finding the optimum EV charging level and strategy to achieve an overall power system-level optimization of the distribution network.

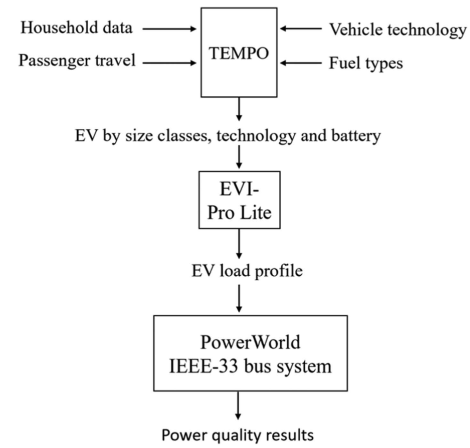

Fig. 1. Case study methodology.

The rest of this article is organized as follows. In Section II, we present the details of the methodology used. The case study results and mitigation techniques are considered in Section III. Section IV presents the sensitivity analysis scenarios with respect to EV charging speed and strategy. Section V describes the limitations, future work, and contribution to the field. Finally, Section VI concludes this article.

II. Proposed Methodology

The methodology developed for this work involves the use of the TEMPO model [15], the EVI-Pro tool [16], and building a scaled distribution network for the geographic zone of interest based on the IEEE 33-bus system [17]. An overview is given in Fig. 1 .

A. TEMPO Model

The first step in the proposed methodology is to assess the increased electrical demand over the next 30 years in a geographic zone by finding the expected EV adoption rate in that zone. For this purpose, the TEMPO model, which was developed by NREL, is used [15]. TEMPO can perform cross-sectoral

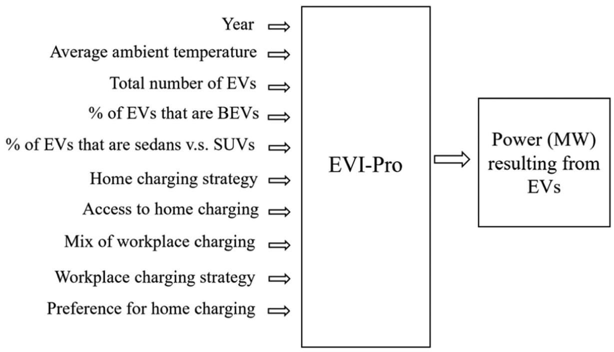

Fig. 2. Travel modes, technologies, and fuels considered in TEMPO.

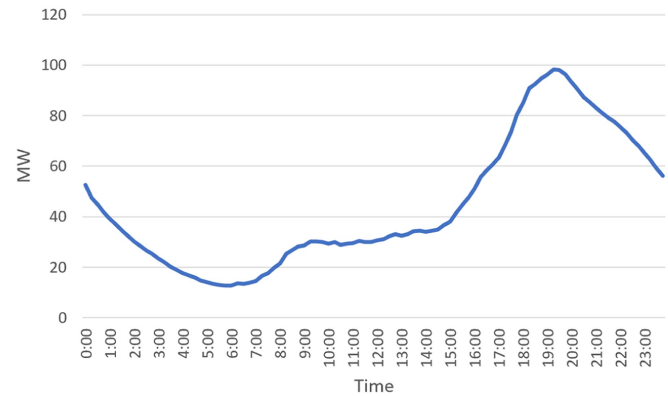

Fig. 3. EVI-PRO Lite 2030 EV load profile computed in 15-min intervals over a period of 24 h during a weekday.

analysis, including the better assessment of electricity loads, demand response potential, and EV charging. TEMPO can model passenger and freight demand at the national level and for household demand as well while focusing on five different geographic classifications: urban, suburban, second city, small town, and rural. Also, TEMPO can also be configured to represent specific regions, such as states or counties, by mapping the proportion of different household types in the areas of interest. It can generate among other things EV adoption rates by technology, battery size, and vehicle size classes in a given year. TEMPO requires the following data sources to model energy consumption and emissions within the transportation sector: household data, passenger travel, freight travel, vehicle technologies, and fuels. The algorithm also considers the following in its modeling structure: passenger transportation energy use, household-level travel demand, household travel options, household travel choice, household stock module, household technology attributes, freight transportation energy use, freight demand, freight mode of choice, freight technology of choice, freight technology attributes, and commercial vehicle stock modules. The algorithm also considers the main attributes for both passenger and freight energy models' analysis, such as travel modes, that are split into size classes (passenger and freight), technologies (ICEs, hybrid EVs, fuel cell EV, and plug-in electric vehicle (PEV) both plug-in hybrid and battery EVs with multiple ranges), and fuel types (petroleum fuels, natural gas, biofuels, electricity, and hydrogen), as shown in Fig. 2.

B. EVI-Pro Tool

As can be appreciated from Fig. 1, the methodology utilizes the EVI-Pro tool, which was developed by NREL to estimate EV charging infrastructure needed in a specific region, in addition to the load (MW) resulting from an estimated number of EVs to meet a given demand [16]. It considers multiple factors, such as data about personal vehicle travel patterns, EV classes' sizes, technology vehicle battery size, average ambient temperature in the area, percentage of plug-in vehicles that are all-electric, percentage of plug-in vehicles that are sedans, mix of workplace charging levels, access to home charging, and preference for home charging versus workplace charging. It is used by researchers to analyze the typical daily travel patterns of vehicles and estimate related charging demand.

The web-based version of EVI-Pro Lite was used in this case study to generate the load profiles (MW) over a weekday in 15-min data intervals, and for a specific region, to find the associated power demands on the grid. In addition, this tool will be utilized to change the charging levels and preferences for both home charging and work charging to assess the impact of fast versus slow charging on the load profile and, consequently, on the grid nodes. The inputs/outputs and data flow in EVI-Pro Lite are shown in Fig. 3.

C. Scaled Distribution Network Using IEEE 33-Bus System

The IEEE has provided various test systems to support research in power systems. This system was developed in 1989 by Baran Wuto [17]. The IEEE 33-bus distribution test system has gained popularity and has been widely used to study different problems in traditional distribution systems. The original version of the IEEE 33-bus distribution system consists of 33 buses, 32 of which are fixed and a slack bus at 1.0 p.u. and no reactive power compensation units. The grid is supplied by a feeder connected to the first bus (slack bus), and no other power generation units exist in the grid [17]. The IEEE 33-bus system was originally built with a certain percentage of the total load placement at each grid node to simulate the behavior of a general distribution network being fed from a main feeder. In this case study, the main feeder for the 33-bus distribution network corresponds to a real feeder, and the system was designed similarly to the original 33-bus system with the total load corresponding to the utility existing load level plus additional EV charging loads. This total load was spread across the 33-bus distribution system nodes according to the same percentage of load placement of the original 33-bus system. Therefore, it is used in building the distribution system in the PowerWorld tool using real-time data from a residential feeder.

III. Case Study Application and Results

In this work, a case study was conducted within the El Paso County in Colorado Springs, CO geographic area. The Colorado Springs Electric Utilities Company was chosen for this case study since it primarily supplies electricity to the city of Colorado Springs, where the bulk of El Paso County residents

TABLE I
2030 EV Adoption Rates by Vehicle Size Classes

	Light and midsize	SUV and pickup	Electric buses	Total EVs
	31 176	40 952	221	72 349
% of Total EVs	43.1%	56.6%	0.3%	

TABLE II
2030 EV Adoption Rates by Technology and Battery Size

	PHEV-25	PHEV-50	BEV-100	BEV-300
% of Total EVs	0.872%	21.2%	1.588%	76.33%

TABLE III
2050 EV Adoption Rates by Vehicle Size Classes

	Light and midsize	SUV and pickup	Electric buses	Total EVs
Projected Numbers	224 538	287 899	5 771	518 208
% Of Total EVs	43.33%	55.55%	1.11%	

commute to work, and where almost 66% live [18]. The shift to renewable energy resources has been growing substantially at the Colorado Springs Utilities and EV adoption rates are increasing quickly, which will require the utility to rapidly prepare the electric grid to accommodate this shift. In 2020, the city of Colorado Springs had 2308 EVs on its roads [19]; however, currently, there are approximately 5241 EVs on the road, a more than 227% increase [18]. In the remainder of this section, we discuss the implementation of the case study on Colorado Springs utility's network, using the methodology of Fig. 1, that involves the development of related TEMPO input data. The output data obtained from TEMPO are fed to EVI-Pro Lite tool, which projects the electrical load demand in El Paso County. Next, the impact of the EV load demand within Colorado Springs utility's network is studied. It is done by building the power system representing colorado springs utilities (CSUs) electric grid distribution network based on the IEEE 33-bus distribution test system with scaled loads corresponding to CO Springs total load demand.

A. Application and Results of TEMPO

As can be appreciated from Fig. 1, the input data specific to El Paso County were prepared and were used to generate output data from TEMPO. The output data from TEMPO for the year 2030 are shown in Tables I and II. Moreover, the output data from TEMPO for the year 2050 are shown in Tables III and IV. Tables I and III highlight the total EV adoption rates for 2030 and 2050, respectively, by vehicle class and size. As can be appreciated from Tables I and III, the forecasted total EV adoption rate was increased in El Paso County during the period 2030–2050, from 72 349 to 518 208 EVs, which represents an increase of 616%. Also, Table III presents the dominance of light and midsize EVs as well as electric SUVs and pickup trucks. In addition, Tables II and IV present the total EV adoption rate by battery size, classified into four categories:

1) battery EVs with a 300-mile range on a single charge (BEV-300);
2) battery EVs with a 100-mile range on a single charge (BEV-100);
3) plug-in hybrid EVs with a 25-mile range on a single charge (PHEV-25);
4) plug-in hybrid EVs with a 50-mile range on a single charge (PHEV-50).

Also, as can be appreciated from Tables II and IV, the numbers of BEV-300 and PHEV-50 are expected to occupy most of the market share. This could overload the distribution network, especially during peak load hours, since higher battery capacities require more charging power.

TABLE IV
2050 EV Adoption Rates by Technology and Battery Size

	PHEV-25	PHEV-50	BEV-100	BEV-300
% of Total EVs	0.22%	5.03%	3.5%	91.24%

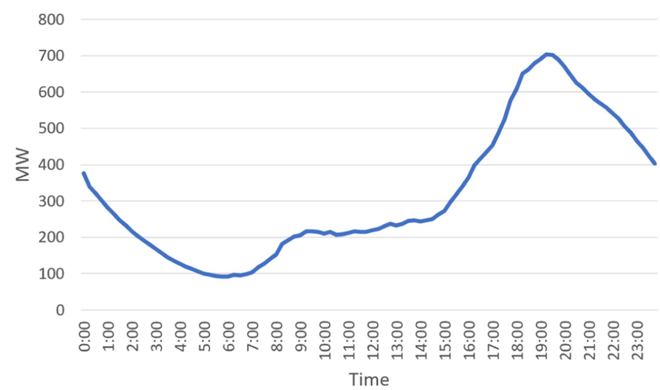

Fig. 4. EVI-PRO Lite 2050 EV load profile computed in 15-min intervals over a period of 24 h during a weekday.

B. Application and Results of EVI-Pro Lite

As was noted earlier, the EVI-Pro Lite algorithm takes as input the output data of TEMPO, as shown in Tables I through IV. In addition, it assumes scenarios that are based on the location of choice, in this case, the city of Colorado Springs (CO). Inputs and assumptions for the EVI-Pro Lite tool for 2030 and 2050 are shown in Table V. Table V represents a summary of the inputs that were considered for this case study in the EVI-Pro Lite tool simulation software [16], as well as input values from Tables I through IV. Table VI presents the predicted demand peak load in 2030 and 2050 that was generated through EVI-Pro Lite. The EVI-Pro Lite tool generates the total load profile (MW) in Colorado Springs resulting from EV demand for both 2030 and 2050, as shown in Figs. 3 and 4 and summarized in Table VI, which presents the peak load demand from EV loads for both 2030 and 2050 with corresponding peak times. As can be appreciated from Table VI, there is approximately a 617%

TABLE V
2030 AND 2050 EVI_PRO LITE TOOL INPUTS

Year	2030	2050
Plug-in EVs in the fleet	72 349	518 208
Average ambient temperature	50 °F	50 °F
Plug-in vehicles that are all-electric (This filter provides threshold levels)	75% (This means there are more than 75% of vehicles that are all-electric)	75% (This means there are more than 75% of vehicles that are all-electric)
Plug-in vehicles that are sedans (Body types are broken up into two categories: sedans and SUVs)	50% (This means there is almost an equal distribution among body types)	50% (This means there is almost an equal distribution among body types)
Mix of workplace charging	50% Level 1 and 50% Level 2 Immediate	50% Level 1 and 50% Level 2
Access to home charging	100% with 50% Level 1 and 50% Level 2	100% with 50% Level 1 and 50% Level 2
Preference for home charging	100%	100%
Home charging strategy	Immediate—as fast as possible	Immediate—as fast as possible
Workplace charging strategy	Immediate–as fast as possible	–as fast as possible

TABLE VI
2030 AND 2050 EV LOAD DEMAND AND PEAK TIMES

Year	2030	2050	% Change
Total EV peak load (MW)	98.26	703.78	617%
Peak Time	19:15	19:15	

increase in EV load from 2030 to 2050. In addition, it shows the same peak load time of 7:15 P.M. in 2030 as well as in 2050.

C. Building the Distribution Network Based on the IEEE 33-Bus System

The Colorado Springs Utility network distribution system was modeled according to the IEEE 33-bus distribution system. Actual feeder data (MW and MVAR) were used, and they are shown in Fig. 5. This feeder circuit is within the Colorado Springs' Utilities distribution network, in a residential area that is considered upper middle class, and with a higher propensity of EV adoption. Colorado Springs Utilities have a total of 180

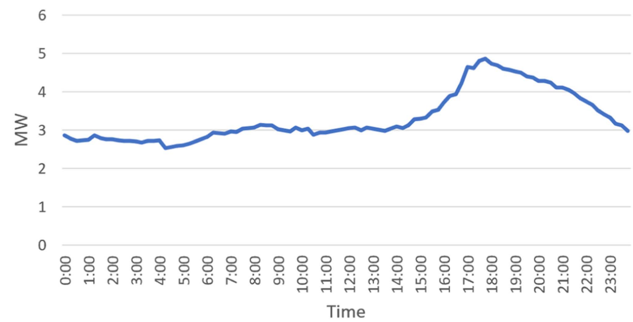

Fig. 5. CSUs feeder load computed in 15-min intervals over a 24 h period without EV load.

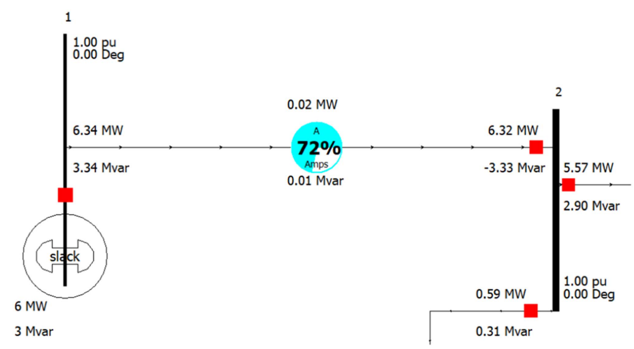

Fig. 6. Screenshot of the feeder level in PowerWorld as a part of the complete IEEE 33-bus distribution system used in this study.

feeders across their grid area and currently have a total demand of approximately 5000 GWh with EVs constituting a significantly small percentage of approximately 0.09% of the city's total annual energy demand. The total electrical energy demand in 2030 and 2050 without EVs is expected to remain almost the same at the current level of 4 932 000 000 kWh [19]. The IEEE 33-bus distribution network was built in PowerWorld and is shown in Fig. 6. An *S*(base) of 100 MVA and *V*(base) of 15 kV were assumed since it is common for current line capacities for distribution systems to be within the range of 300–400 A, and distribution line load can be as high as 1200 A [20]. A line capacity limit of 5 MVA is assumed on all the system's branches (15 kV $\times$ 333.33 A $=$ 5 MVA), except for few lines, where a 10 MVA capacity limit was assigned, since those lines are closest to the feeder and will carry more power. Line capacity limits of 10 MVA were assumed for the following branches: from buses 1 to 2, 2 to 3, 3 to 4, 4 to 5, and 5 to 6. The power factor of the feeder circuit is approximately 0.98 leading. This is based on multiple samples of reactive versus active power data obtained for the Colorado Springs' Utilities. The leading power factor is due to the circuit being entirely underground, and the cable having a capacitance that creates negative reactive power. In the remainder of this section, the results of the case study scenarios, as shown in Table VII, are presented.

D. Case Study Scenarios

The scaled IEEE 33-bus model was used to run a power flow analysis in the PowerWorld simulator using the Newton Raphson technique. In this case study, four scenarios were considered, as

TABLE VII
CASE STUDY SCENARIOS

Case Scenario	Description
#1	2030 with uniform EV load distribution
#2	2050 with uniform EV load distribution
#3	2050 with 50% additional EV load distribution
#4	2050 with 100% additional EV load distribution

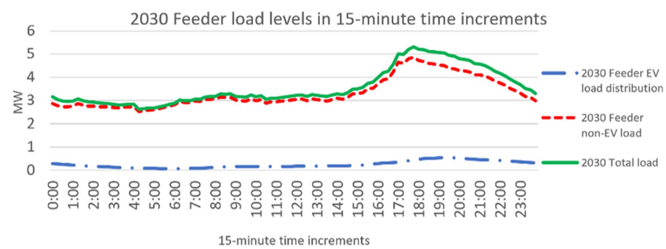

Fig. 7. Case 1 2030 feeder load levels computed in 15-min time increments.

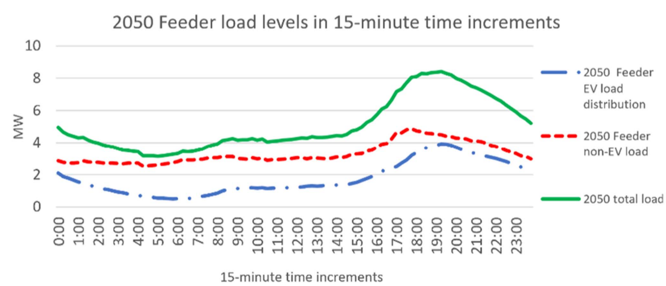

Fig. 8. Case 2 2050 feeder load levels in 15-min time increments.

shown in Table VII. Case scenario-1 of 2030 was chosen because most states in the U.S. are trying to meet carbon emission goals closest to zero by 2030 [5]. Case scenario-2 for the year 2050 was chosen because it is estimated that, by 2050, the electrification of the transportation sector will require almost double the current U.S. generation capacity [3]. In addition, case scenarios-3 and 4 were considered because the feeder circuit under study within the Colorado Springs' Utilities distribution network is in a residential area that is considered upper middle class, and with a higher propensity of EV adoption. Therefore, it is expected that this feeder will have a higher EV load due to the potential of a higher EV adoption rate, which would impact the power distribution system.

The power flow simulation for case scenarios 1, 2, 3, and 4 was performed using the load profile levels, as shown, respectively, in Fig. 7, Fig. 8, Fig. 9, and Fig. 10. The load profiles are shown over a 24-h period in 15-min time increments. The 2030 curves in Fig. 7 represent three load profiles:

1) utility non-EV load;
2) EV load;
3) total load.

For cases 1 and 2, the 2030 and 2050 feeder EV load distributions were obtained from the EVI-Pro Lite results, as shown in Fig. 3 and Fig. 4, respectively. This was done by dividing the total amount of the EV load over the 180 feeders across

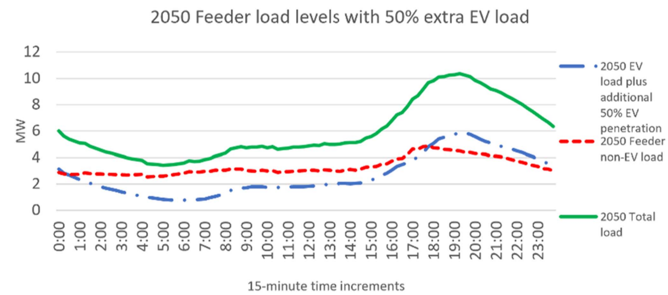

Fig. 9. Case 3 2050 feeder load levels in 15-min time increments.

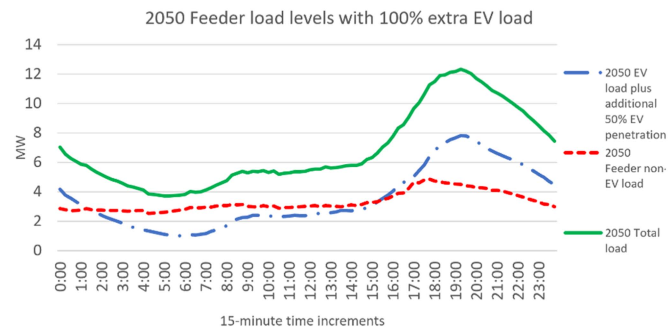

Fig. 10. Case 4 2050 feeder load levels in 15-min time increments.

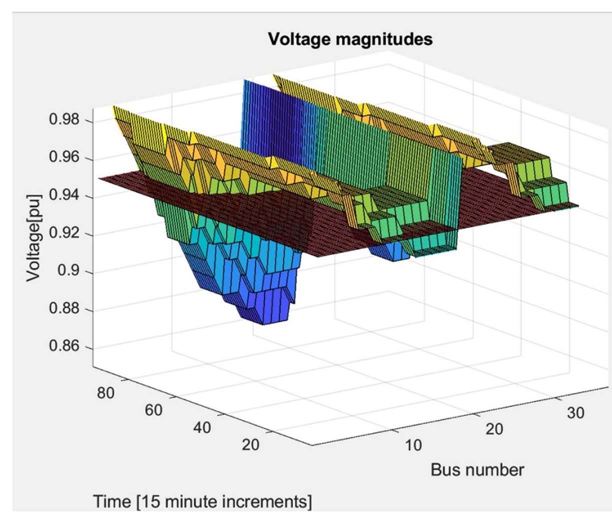

Fig. 11. Case 4 voltage magnitudes across all 33 buses.

the Colorado Springs Utility network. Afterward, the total load distribution of the feeder was obtained by adding the resulting 2030 and 2050 feeder EV load to the feeder utility non-EV load.

However, in cases 3 and 4, the total load was obtained by adding, respectively, 50% and 100% additional EV load penetration with respect to the EV load of case 2.

The results for case scenario #4 are highlighted, as it represents the most likely scenario for the feeder circuit located in an upper-middle-class residential area, where higher EV penetration is expected. For case scenario #4, Fig. 11 and Fig. 12, respectively, show the voltage magnitudes (p.u.) and line capacities (MVAR) across all 33 buses over 24 h, as computed

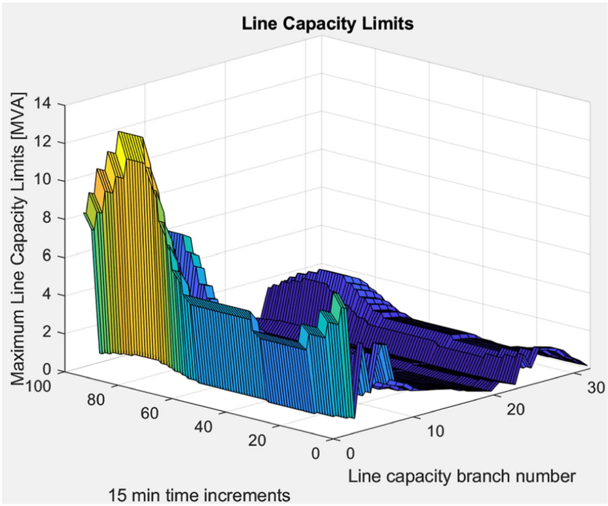

Fig. 12. Case #4 line capacity limits across all branches.

TABLE VIII
SUMMARY OF THE IMPACTS OF EV CHARGING FOR THE FOUR SCENARIOS OF THE CASE STUDY

Case	Voltage drop (p.u.)	Max line capacity reached	Peak time	Peak time duration
#1	0.96	54.8 %	6:30 P.M.	5:30–9:30 P.M.
#2	0.92	86.4 %	7:15 P.M.	5:45–9:15 P.M.
#3	0.898	104.7%	7:15 P.M.	5:45–9:15 P.M.
#4	0.86	131.3 %	7:15 P.M.	6:15–8:30 P.M.

in 15-min intervals. A detailed inspection of Fig. 11 shows the voltage dropping to 0.86 p.u. during peak time from buses 15 through 18. Also, an inspection of Fig. 12 shows the line capacities exceeding their limits from buses 1 to 2 to reach 131.31% and from buses 2 to 3 to reach 115.6% of their respective limit. Case #4 demonstrates having the most severe impact on the distribution grid. Table VIII summarizes the impacts of EV charging for the four case scenarios in Table VII.

E. Scenario #4 Negative Impacts Mitigation

In general, there are several ways to increase the bus voltage and mitigate negative impacts resulting from overloading a distribution grid. Selecting a technique could be influenced by many factors, such as cost and effectiveness. Some of those mitigation techniques could include adding voltage regulators, as proposed in [21]. Other mitigation techniques used involved the addition of DG resources [22], [23]. Moreover, new technologies, such as single-stage wireless inductive power transfer topology, which enables bidirectional V2G operation, could help with the grid power quality mitigation [24], [25]. As for line capacity, there are mitigation techniques that might help reduce the line congestion that can be considered, such as adding distributed energy resources in key locations in the distribution grid without compromising the power quality [26]. Based on the

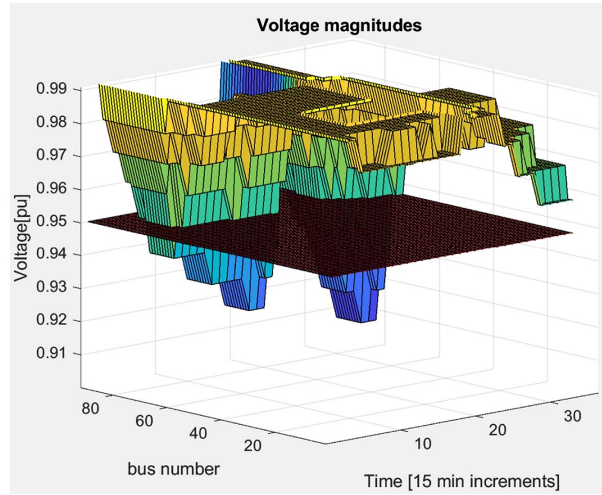

Fig. 13. Case #4 with DG, voltage magnitudes across all 33 buses.

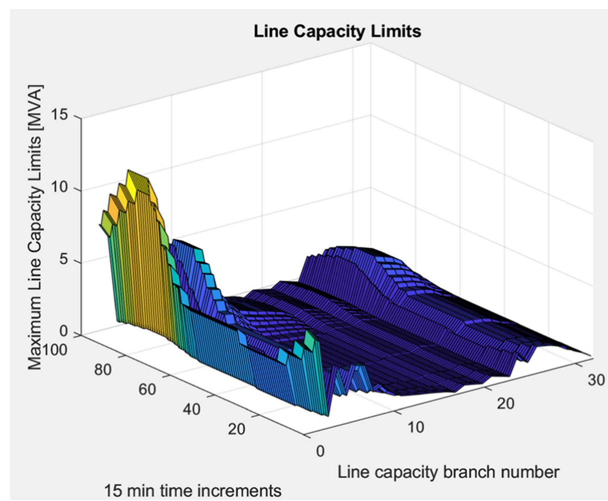

Fig. 14. Case #4 with DG, line capacity limits across all branches.

above, mitigation techniques are considered for scenario #4 of Table VIII. In this case, the voltage was at 0.86 across buses 10–18 during peak load hours, and the line capacity limit was 131.3% between buses 1 and 2, and 115.6% between buses 2 and 3. As such, the first mitigation technique considered in this work is to add a DG resource at a specific location of the 33-bus system to increase the voltage to a minimum of 0.9 during peak loads and help reduce line capacity limits to below their limit. The power flow simulation was performed using PowerWorld simulation software on case #4 when adding 0.5 MW of DG at bus 15. The results are shown in the three-dimensional (3-D) model of Fig. 13. After implementing this mitigation technique, the voltage was brought back up to above 0.90 p.u. from bus 15 to bus 18 during peak time. In addition, Fig. 14 shows the line capacity limits across all branches with EV load after adding DG at bus 15. An inspection of Fig. 14 for the total load profile shows that a maximum line capacity of 12.48 MVA from bus 1 to bus 2 was reached during peak time between 6:15 P.M. and 8:30 P.M. This represents almost 124.8% of the line capacity limit and an improvement of 6.5% of the line capacity decrease. Similarly, a maximum line capacity of 10.93 MVA from bus 2 to bus 3 was reached during the same peak time. This represents almost 109.3% of the line capacity limit and an improvement of 6.3% of the line capacity decrease. As such, it can be concluded that adding a DG resource in this case mitigated the negative impacts on the voltage levels. However, it did not improve the line capacity to an acceptable level. Therefore, an increase in line capacity is considered to keep the line capacities below their limits. In this case, the capacity limit of branch 1 was increased by 2.5–12.5 MVA and the capacity of branch 2 was increased by 1—11 MVA. Next, the impact of implementing the mitigation technique is evaluated using the line overload index J_{OL} and voltage deviation index V_{DI} [27].

During peak time, it is useful to get a numerical indication of the total line overload before and after applying mitigation techniques in case #4. For that purpose, the overload J_{OL} index is utilized [27]

$$J_{\mathrm{OL}} = \sum_{k=1}^{32} \left(\frac{P\left(k\right)}{P(k)_{\max}} \right)^2 \tag{1}$$

where k is the number of branches across the 33-bus distribution system, k is the branch number, $P(k)$ is the amount of power (MVAR) at each branch, and $P(k)_{\max}$ is the maximum amount of power that the branch can carry. In this case, J_{OL} (summed over all lines) has a value of 8.963 before applying the mitigation technique and a value of 6.97 after applying it, a decrease of 1.992. This decrease proves the effectiveness of the employed mitigation techniques in reducing the total line overload [27].

In addition, the voltage deviation index V_{DI} during peak time was calculated before and after applying mitigation techniques in case #4 as follows [27]:

$$V_{\mathrm{DI}} = \sum_{i=1}^{33} \left| \frac{v_i - v_{i,0}}{v_{i,0}} \right| \tag{2}$$

where $V_{i,o}$ represents the nominal voltage under normal conditions and is assumed to be 1 p.u. and V_i is the actual voltage at each bus from buses 1 to 33. The total voltage deviation was found to be 2.5 before applying mitigation techniques and decreased by 0.76 to 1.74 after applying it. Again, the decrease proves the effectiveness of the employed mitigation techniques in reducing the total voltage deviation.

IV. Sensitivity Analysis Scenarios With Respect to EV Charging Speed and Strategy

In this section, a sensitivity analysis is conducted for case #4 in order to study the impact of EV charging access and speed as well as charging strategy on the power quality at the distribution nodes. This is achieved by considering different levels of access to home charging and the home charging strategy. As a result, a significant change in EV load is observed. The configurations considered are as follows.

1) *Access to Home Charging:*

Conducted a sensitivity analysis assuming that drivers have access to home charging for the following cases.

TABLE IX
SENSITIVITY ANALYSIS SCENARIOS

Sensitivity analysis scenarios	Access to home charging	Home charging strategy
A.	80% Level 1 and 20% Level 2	Delayed−finish by departure
B.	50% Level 1 and 50% Level 2	Delayed−finish by departure
C.	20% Level 1 and 80% Level 2	Delayed−finish by departure
D.	80% Level 1 and 20% Level 2	Delayed, and start at midnight
E.	50% Level 1 and 50% Level 2	Delayed, and start at midnight
F.	20% Level 1 and 80% Level 2	Delayed, and start at midnight
G.	80% Level 1 and 20% Level 2	Immediate–as slow as possible
H.	50% Level 1 and 50% Level 2	Immediate–as slow as possible
I.	20% Level 1 and 80% Level 2	Immediate–as slow as possible
J.	80% Level 1 and 20% Level 2	Immediate, as fast as possible
K.	50% Level 1 and 50% Level 2	Immediate, as fast as possible
L.	20% Level 1 and 80% Level 2	Immediate, as fast as possible

a) 20% Level 1 and 80% Level 2.
b) 50% Level 1 and 50% Level 2.
c) 80% Level 1 and 20% Level 2.

where Level 1 charging having the slowest charging speed and Level 2 having the faster charging speed.

2) *Home Charging Strategy:*

The following four options for home charging strategies are considered:

a) immediate, as fast as possible;
b) immediate, as slow as possible;
c) delayed, and finish by departure;
d) delayed, and start at midnight.

A. *Sensitivity Analysis Scenarios*

As previously noted, since both the access to home charging speed levels and the home charging strategy have notable impacts on the total amount of EV load penetration on the distribution grid, a total of 12 combinations of those parameters are considered in this study. The sensitivity analysis scenarios are shown in Table IX, which represents the different possible outcomes of access to home charging and home charging strategies as defined earlier. Also, Table X and Fig. 15 show the total peak load from EV charging across all 180 feeders (MW) for CSUs electric distribution network for each scenario, as well as the peak time of EV charging. Scenario “F” shows the highest peak EV load, while scenario “G” results in the lowest peak EV load. A detailed power flow simulation is conducted for the two

TABLE X
SENSITIVITY ANALYSIS SCENARIOS EV CHARGING LOAD LEVELS

Sensitivity analysis scenarios	Total peak load from EV charging for 180 feeders (MW)	Peak time
A.	631.149	6:30 A.M.
B.	842.868	7:00 A.M.
C.	1036.921	7:00 A.M.
D.	1250.47	12:15 A.M.
E.	2110.873	12:15 A.M.
F.	2981.741	12:15 A.M.
G.	375.451	7:30 P.M.
H.	410.472	12:00 A.M.
I.	452.249	12:00 A.M.
J.	598.775	7:30 P.M.
K.	703.784	7:15 P.M.
L.	800.538	6:45 P.M.

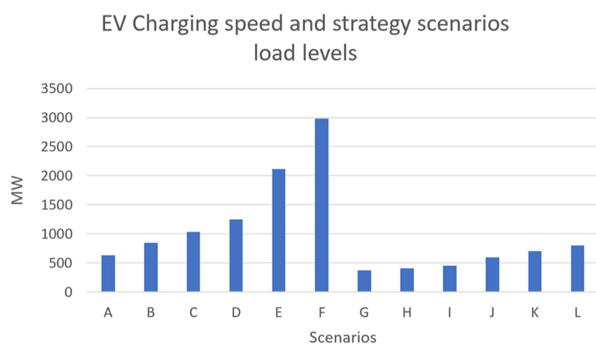

Fig. 15. EV charging speed and strategy scenarios load levels.

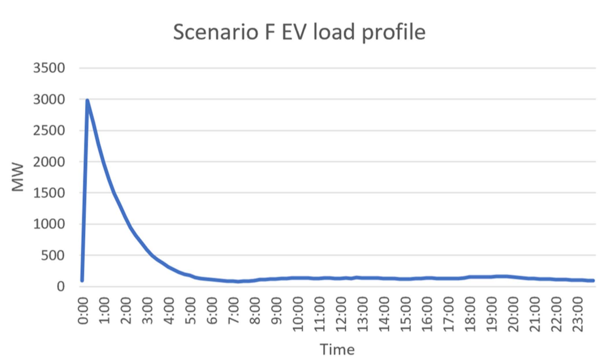

Fig. 16. Scenario "F" EV load profile across the 180 feeders in 15-min intervals.

scenarios to study the impact of EV charging speed and strategy on the distribution grid nodes. The curves of Fig. 16 and Fig. 17 show, respectively, the EV load profiles for scenarios F and G in 15-min intervals.

B. Sensitivity Analysis Power Flow Study of Scenario "F"

As can be appreciated from the results in Table X and Fig. 15, scenario "F" has the highest EV peak load of the distribution grid at a total of approximately 2981 MW at 12:15 A.M. Fig. 18 shows the feeder load levels for utility non-EV load, EV load of

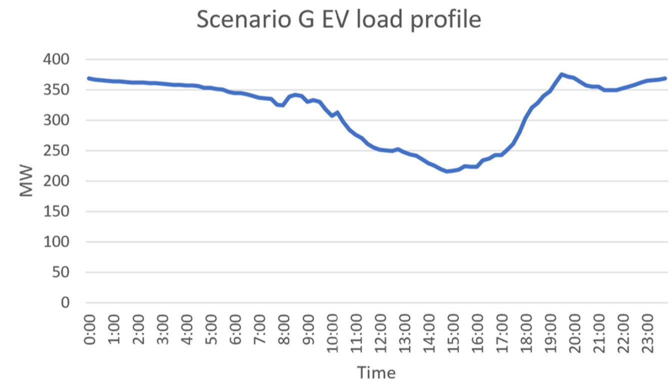

Fig. 17. Scenario "G" EV load profile across the 180 feeders in 15-min intervals.

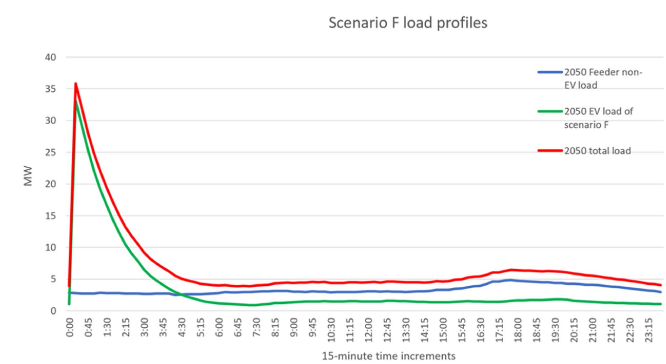

Fig. 18. Scenario "F" feeder load levels.

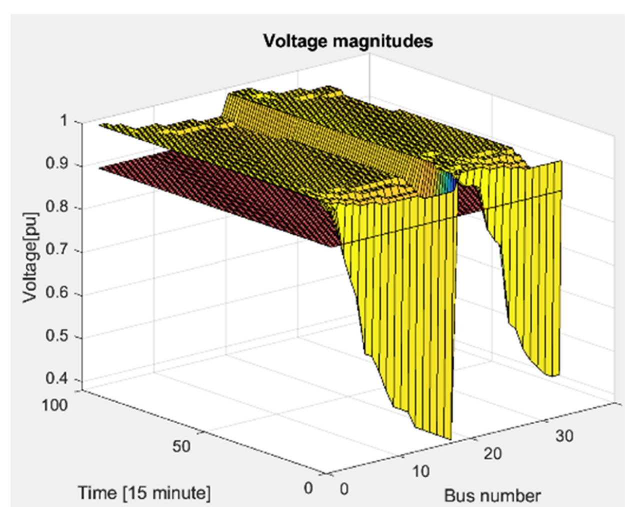

Fig. 19. Scenario "F" voltage magnitudes across all 33 buses.

sensitivity analysis scenario F, and total load. In this scenario, the EV load represents 33.1 MW (1195%) of the utility non-EV load of 2.77 MW during peak time.

The power flow simulation was performed on scenario "F" using PowerWorld simulation software. The results are shown in the 3-D model of Fig. 19 for the total load profile (including EV load). As can be appreciated from Fig. 19, the voltage

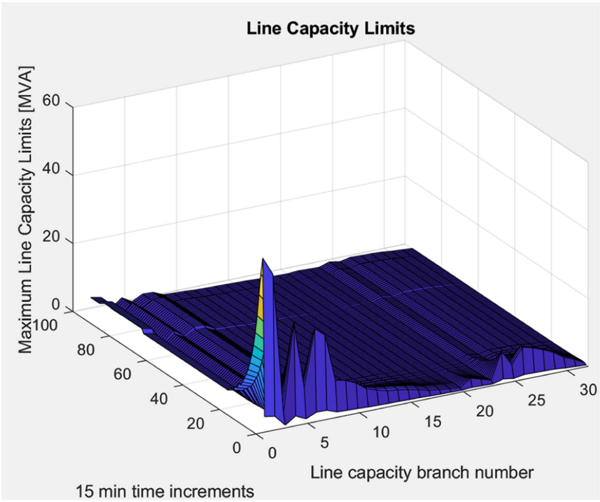

Fig. 20. Scenario “F” line capacities’ limits across all branches.

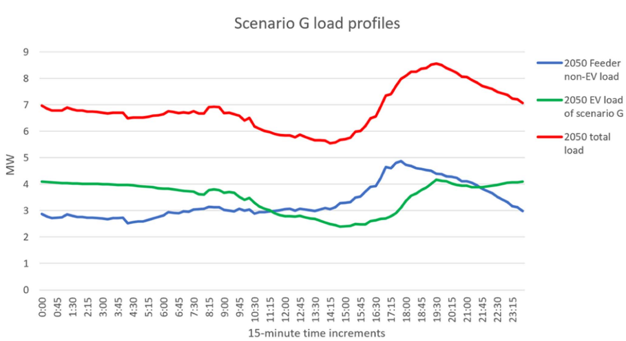

Fig. 21. Scenario “G” feeder load levels.

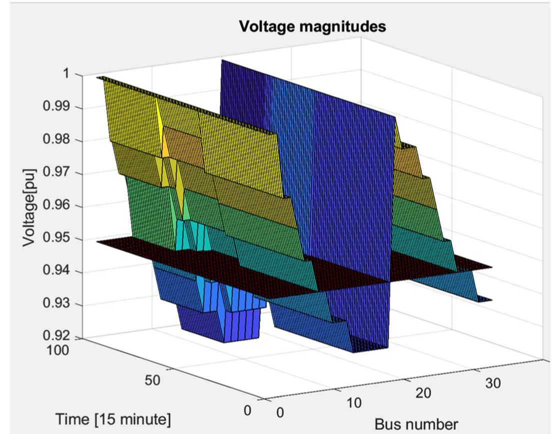

Fig. 22. Scenario “G” voltage magnitudes across all 33 buses.

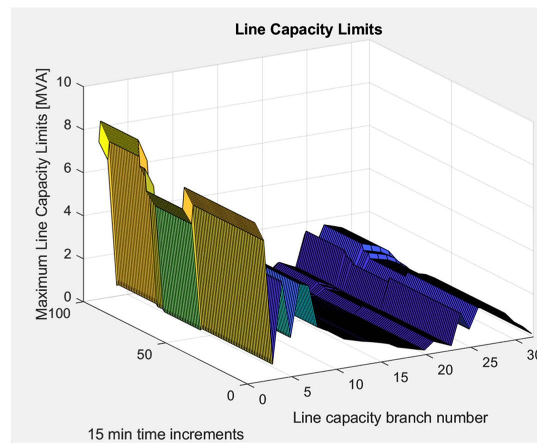

Fig. 23. Scenario G line capacities’ limits across all branches.

magnitudes significantly dropped below 0.9 p.u. across buses 3–18 and 23–33 during the peak times between 12:15 A.M. and 2:30 A.M., with the worst voltage drop of 0.38 p.u. recorded at bus 18 at 12:15 A.M. Moreover, the line capacities exceeded their limits across all branches with EV loads, as shown in Fig. 20. An inspection of Fig. 20 for the total load profile shows that a maximum line capacity of 50.45 MVA from bus 1 to bus 2 was reached at 12:15 A.M. This represents almost 505% of the line capacity limit. Similarly, the line capacities of branches 1 through 11 were also exceeded.

C. Sensitivity Analysis Power Flow Study of Scenario “G”

Scenario “G” has the lowest EV load level on the distribution grid at a total of 375.451 MW occurring at 7:30 P.M. Fig. 21 shows the feeder load levels for utility non-EV load, EV load of sensitivity analysis scenario “G”, and total load. In this scenario, the EV load represents 4.171 MW (94.98%) of the utility non-EV load of 4.391 MW during peak time at 7:30 P.M.

The power flow simulation was performed on scenario “G” and the results are shown in the 3-D model of Fig. 22. Fig. 22 shows the voltage magnitudes remaining above 0.93 p.u. at all times across all 33 buses, and thus, above the 0.9 p.u. recommended threshold for distribution networks. Moreover, all line capacities remained within their limits, as Fig. 23 shows, with the highest line capacity recorded at 8.53 MVA from bus 1 to bus 2 during peak time at 7:30 P.M. This represents almost 85.3% of the line capacity limit from bus 1 to bus 2, and all other line branches remained below their capacity limits.

D. Total Line Overload and Voltage Deviation Comparison of Case Scenarios, and Discussion of the Results

In addition to the above, the total line overload index JOL and the total voltage deviation index V_{DI} are evaluated for the two scenarios. The total line overload and voltage deviation indices were calculated for scenarios “F” and “G,” and a summary of the results is shown in Table XI. It should be noted that a decrease in the value of JOL corresponds to a lower line overload capacity level. Similarly, a decrease in the value of V_{DI} corresponds to a lower voltage deviation level. As can be appreciated from the results in Table XI, in scenario “G,” voltage and line capacities remained within their specified limits. Consequently, it is recommended that utilities prioritize and incentivize the charging program with immediate—as slow as possible for home charging and 80% Level 1 and 20% Level 2 charging, which would least impact the utility’s distribution grid.

TABLE XI
TOTAL LINE OVERLOAD AND VOLTAGE DEVIATION METRICS

Sensitivity analysis scenarios	Total line overload (J_{OL})	Total Voltage deviation Index (V_{DI})	Voltage drop (p.u.)	Max line capacity reached
Scenario F	99.44	11.82	0.38	505%
Scenario G	3.86	1.58	0.93	85.3%

V. LIMITATIONS, FUTURE WORK, AND CONTRIBUTION TO THE FIELD

The approach presented in this work has the limitation of using the IEEE 33-bus system as the model to simulate the behavior of the electric distribution grid, which inherently makes simplifying assumptions [17] due to the lack of detailed information about the grid. In future research, it would be useful to study and simulate the behavior of the actual distribution network topography at CSU. Furthermore, it is recommended to introduce ancillary services [28] to help with EV charging integration with the electric grid. This can be possibly done through the utilization of bidirectional EV operation, such as V2G, vehicle-to-home, and vehicle-to-vehicle technologies. Those newly emerging technologies are effective since EVs behave as controllable loads and can help even out demand throughout the day. Also, EVs have the capacity to act as distributed energy storage and offer the grid on-demand frequency assistance and serve as energy storage by shifting loads and providing on-demand frequency support [29]. Another future study could also include the integration of ancillary services program, such as dispatch programs and community batteries charged from renewable resources, to address issues related to load and peak time shifting in both overload and underload conditions. This could present an effective solution for remote communities that do not have access to national grids or even for areas where the reliance grid could be problematic during peak load hours [30]. Finally, it should be noted that as EV charging directly impacts the electric grid, specifically distribution networks [31], this article could be of value to utility companies and related power industries in addressing challenges due to new loads from EV charging and could contribute to the emerging topic of EV charging as related to the following.

1) Developing and analyzing a real case study to evaluate the impact of EV charging in a utility servicing a specific geographic area up to the year 2050.
2) Providing a road map for utilities to understand the impact of the electrification of the transportation sector on their electric distribution grid in the next 20–30 years.
3) Accurately estimating EV adoption rates by technology, classes, and battery size up to the year 2050 in a specific electric utility coverage area.
4) Studying the related power quality impacts of EV charging on the distribution network.
5) Proposing effective mitigation techniques that utilities could implement to reduce the negative impact of new EV charging loads on their grid.
6) Recommending an optimum EV charging program that would minimize high peak loads from EV charging and, thus, reduce voltage drop.

VI. CONCLUSION

In this work, a methodology to assess the electricity demand due to the electrification of the transportation sector and its impact on the electric distribution network has been assessed in a given geographic area. The power flow simulation results showed that, in 2030, the electric distribution grid will not be severely impacted by the addition of EV charging loads to the utility projected 2030 non-EV loads. However, in 2050, it was noticed that the projected EV charging loads could have a severe impact on the electric distribution grid from the addition of EV charging loads. Moreover, it was shown in this study that some mitigation techniques could be implemented effectively to improve the voltage drop levels at the distributed grid nodes and to reduce the line capacities congestion levels, such as adding DG across the electric distribution network at key grid nodes and by increasing the line capacity limits at certain branches of the system. Moreover, DG proved effective in both improving voltage drop levels at the grid nodes, along with reducing the power line congestion caused by the addition of EV charging loads. This could present a promising solution for utilities in general trying to diversify their power generation resources, where more PV generation across the distribution network could help with both reducing negative power impacts on the distribution grid, along with providing a clean generation resource.

Also, it was notable that EV owners charging preferences and EV charging speed levels significantly impact the electric distribution grid, as it affects the EV charging peak load levels. Based on the above, it could be stated that the more evenly spread out the charging time is and the faster the charging levels are, the higher the EV peak load on the distribution grid will be. Consequently, the impact on the grid nodes voltage and the congestion on the power lines will be more severe. The optimum charging program that was recommended from the results of this study could be implemented by utilities to best maintain the distribution grid's power quality and achieve an overall power system-level optimization of the distribution network.

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Gerard Albadawi Abiassaf (Member, IEEE) received the M.S. degree in electrical engineering with an emphasis in power and energy systems from the Colorado School of Mines, Golden, CO, USA, in 2023.

His research focused on renewable energy integration with the electric grid and the impact on the electric distribution grid. He currently works as an Electrical Engineer with Pure Power Engineering, Hoboken, NJ, USA, which specializes in commercial, industrial, utility scale solar, and energy storage system design.

Abd A. Arkadan (Fellow, IEEE) received the B.Sc. degree from the University of Mississippi, Oxford, MS, USA, in 1980, the M.Sc. degree from Virginia Tech, Blacksburg, VA, USA, in 1981, and the Ph.D. degree in 1988, from Clarkson University, Potsdam, NY, USA, all in electrical engineering.

He joined Electrical Engineering Department, Colorado School of Mines, in 2016. Prior to that, he was a Professor with Marquette University, Milwaukee, WI, USA. Also, he served as the University President and Professor with Rafik Hariri University, Lebanon, from 2004 to 2014. His research interests include power and energy systems, electric machines, and design optimization using computational electromagnetics and AI techniques. His applications emphasize renewable and efficient energy and power systems, hybrid and electric vehicles, microgrids, and onboard aerospace and marine power systems.

Dr. Arkadan chaired and served on several IEEE Conference Editorial Boards and as an Editor-in-Chief for special issues of IEEE Transactions. Also, he served as the Chair of several IEEE conferences, including the first IEEE-IEMDC conference held in Milwaukee, WI, in 1997, and the IEEE Conference on Electromagnetic Field Computations, IEEE-CEFC, held in Denver, CO, in 2022.