Analyzing the Impacts of Plug-in Electric Vehicles on Distribution Networks in British Columbia

L. Kelly, A. Rowe and P. Wild

Abstract –**The impact of uncontrolled charging of plug-in electric vehicles (PEVs) on distribution networks is investigated using a probabilistic approach based on Monte Carlo simulations. A model simulating daily residential and commercial electrical demand estimates the existing demand on the networks. A PEV operator model simulates the actions of drivers throughout a typical day to estimate the demand for vehicle charging. Three networks are studied that are typical of suburban, urban and rural networks, respectively. The analysis is focused on peak demand increases, secondary transformer overloading and voltage drops in the networks. PEV charging significantly increases the peak demand on all networks causing larger voltage drops and increasing the probability of transformer overloading.**

Index Terms **– distribution network, Monte Carlo simulations, plug-in electric vehicles, probabilistic load flow.**

I. INTRODUCTION

Recent worldwide attention to the issue of human induced global warming has led governments and automobile manufacturers to explore electric vehicle technologies in an attempt to decrease greenhouse gas (GHG) emissions from passenger vehicles and reduce reliance on fossil fuels. In Canada, a recent greenhouse gas inventory estimated that nearly 12% of the total annual emissions come from the use of passenger vehicles [1]. The vast majority of these vehicles derived their energy from gasoline or diesel fuel.

Plug-in Electric Vehicles (PEVs) represent a promising future direction for the personal transportation sector by potentially decreasing the reliance on fossil fuels while simultaneously decreasing emissions [2]. A PEV is any vehicle that obtains some or all of its energy for driving from the grid. Currently, most of the major automobile manufacturers are either developing or contemplating development of a PEV.

Advantages of PEVs will be reduced fuel costs and emissions as driving on electricity has been found to be less expensive per mile and typically produces less emissions than a conventional vehicle, even where electricity generation is dominated by fossil fuels [3]. The wide availability of existing charging infrastructure in the form of 120/240V outlets at homes and offices provides a strong advantage for PEVs, over other alternative vehicle technologies, such as fuel cells.

Despite these potential benefits, reconciliation will be needed between vehicle owners and grid operators [4]. For example, there is a natural coincidence between peak electricity demand and vehicles returning to a residence after a daily commute. This natural coincidence is the main near-term concern from the utility point of view.

As PEVs begin to penetrate the vehicle market, the number of these vehicles in a given transmission system may be relatively low. However, small neighbourhoods or areas could have higher local penetration rates. Such an effect has been seen with the local aggregation of hybrid electric vehicles in some jurisdictions [6]. Thus, the impact of PEVs on the grid will likely occur first at the level of distribution networks.

An analogy can be drawn between PEVs and distributed energy resources (DERs), such as distributed generation. For example, PEVs will be distributed in a random fashion and will connect to the customer side of the meter. The action of PEV drivers connecting to the grid will be somewhat predictable, but will contain an element of randomness much like most distributed renewable energy generation. Thus, the factors to be considered when connecting PEVs and other DERs to a distribution network are similar and will be subject to the same technical, economic and regulatory challenges.

This study uses a probabilistic model based on Monte Carlo simulations (MCS) to investigate the impacts of PEV charging on distribution networks in the British Columbia (BC) electricity system. The model uses a simulation of daily residential and commercial loads on three-phase distribution networks representing suburban, urban and rural areas. A PEV operator model simulates individual vehicles charging in an uncontrolled manner. The objective of this study is to estimate the impacts on specific power quality issues occurring in distribution networks, such as peak network demand, voltage drop and transformer overloading. These impacts are investigated by considering scenarios of increasing PEV penetration and technology advancement.

II. PROBABILISTIC LOAD FLOW ANALYSIS

A load flow (or power flow) algorithm solves the non-linear relationships between power demand, line currents, bus

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voltages and angles with the constants provided in terms of circuit parameters such as impedance and network structure [7]. Traditionally, distribution networks are radial, passively operated systems that were designed in a deterministic manner using load flow studies to capture the critical or high demand cases.

The deterministic load flow has been shown to be inadequate when considering the connection of DERs in distribution networks [8] because it does not take into account random fluctuations in loads or output of renewable distributed generators. Thus, a probabilistic approach is commonly used to capture the stochastic nature of loads and distributed energy resources.

Probabilistic load flow (PLF) analysis is often based on Monte Carlo Simulations (MCS) [9], a modelling technique in which repetitive solutions of a load flow algorithm provides a set of values defining the random variables of interest. In the case of distribution networks, these variables are usually consumer loads and DER production. However, in this study, the probabilistic (random) elements are consumer loads and PEV loads.

In a MCS, the random variables are sampled at each repetition from a probability density function and used as inputs to the load flow program. The output from a PLF estimates the frequency of occurrence of adverse events such as voltage drop and line current overloading. For this study, a forward/backward sweep algorithm is used to solve the load flow, as described by Kersting [10].

A. Customer Load Modelling

An efficient method to predict the 24-hour demand on a distribution network is to sum the load curves corresponding to the various types of customers supplied by the substation [11]. These customer load curves show a small variation around a mean value and it is common when performing probabilistic load flow studies to assume a normal distribution of load within an hour for each load bus and customer class on the network [8, 11, 12].

In this study, three unique customer classes are simulated: residences, offices and retail stores. The load for each group of customers was estimated from normalized customer load curves and it is assumed that the load (P_i) within an hour follows a normal distribution:

$$f(P_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \cdot e^{\frac{-(P_i - \overline{P}_i)}{2\sigma^2}} \qquad (1)$$

where $\overline{P}_i$ is the mean value and σ_i is the standard deviation. Given an average hourly load profile and a standard deviation, the probability density function (PDF) of equation (1) can be used to generate load data. A PDF is also used for the reactive power portion of the demand.

A PDF for each group of customers connected to a secondary transformer at each half-hour of a 24 hour period is used to estimate the demand at all locations. To determine the parameters of these PDFs, the following method is used:

- The complex peak network demand (MVA) for the previous year is separated into real and reactive components assuming a power factor equal to 94.
- The recorded peak real and reactive power throughout the network is allocated to each transformer. The allocation is based on the customer energy demands at each transformer, penalizing those customers with higher energy consumption.
- Using a normalized mean and standard deviation for each customer type at half hour intervals, the peak demand is scaled to match the peak of the normalized means

This method ensures that the PLF is simulating a worst case scenario of customer loads for a high demand period. It also ensures that demand on transformers is not based on capacity of the transformers but on the consumption of the customers connected, leading to a more realistic investigation.

B. PEV Simulation Model

Many difficulties arise when attempting to predict both the temporal charging demand and technological aspects of PEVs in the future. First and most importantly, there are currently no PEVs or EVs in production leading to a wide uncertainty in the types of technologies and market penetration that will be seen in the coming years. Second, the scale of distribution networks may not warrant an aggregated charging demand modelling approach due to the small number of PEVs on the networks, especially when examining low PEV market penetration scenarios. Third, the assumptions for vehicle charging within residential or commercial customer classes will be inherently different. In order to reconcile these concerns, a novel approach to modelling individual PEV driver's actions in a stochastic manner is identified. The approach described here segregates the vehicle simulation model by customer class and considers the uncertainties in PEV technology.

Three methods of simulating PEVs loads are used simultaneously to determine PEV loads at office, retail and residential locations. For office and retail locations, work station chargers are "installed" during model initialization. Each office charger is operated at the 1.4 kW level. One PEV per installed office charger arrives at the office location in the morning randomly between 07:00 and 09:00 with a random battery state of charge that is uniformly distributed between empty and half of its capacity. The vehicles begin charging immediately and continue until their batteries are full. The demand is tracked through the day to ensure individual batteries are not overfilled.

Simulations for retail locations use traffic volume data [13] to calculate a probability of vehicles arriving at a charging location at each half hour throughout a day. Vehicles connect only for one hour at a time with an assumed power demand of 7.6 kW.

For residential PEVs, a vehicle travel simulation models the stochastic actions of vehicle operators as they commute to work and make trips away from their home. The model assumes that all PEV owners commute to work every day. Other trips can occur during work hours, during the evening commute and during the evening.

Each vehicle is simulated and tracked throughout the MCS for the dual purpose of predicting the temporal charging demand of these PEVs and estimating the gasoline and electricity consumption of individual PEVs. It is assumed that

30% of the PEVs have the ability to charge while at the workplace. All PEVs are assumed to charge from the grid in an uncontrolled manner and to begin charging immediately when returning home from a trip. Battery state of charge is tracked to ensure that batteries are not overcharged or under drawn and to determine the timing and amount of charging load from each individual PEV during each hour. The residential PEV simulation model uses data from the US National Personal Transportation Survey [14] and survey data presented by Bhat and Singh [15].

The assumed specifications of PEV battery and charging technology are based on the battery requirements set forth by the USABC and NREL [16]. Two extended-range electric vehicle (E-REV) technologies are selected to represent near-term PEV technology. Two battery sizes are considered: A PEV-10 (i.e 10 mile electric range) with a 4.85 kWh battery and a PEV-40 with a 16.6 kWh battery. Two possible charging levels are also considered for home charging: 1.4 kW at 120V, and 7.6 kW at 240V. The vehicle parameters are determined probabilistically at the start of the model when assigning PEVs to locations throughout the network.

Three scenarios define increasing levels of PEV market penetration. The "low", "medium" and "high" scenarios represent vehicle penetrations of 5%, 15% and 25%. Here, penetration is calculated for the percentage of residences in the network that have a PEV. Vehicle locations are selected at random. As the scenario changes from low to high, the number of installed chargers at office and retail locations increases, as do the numbers of installed residential chargers at the 240V level. The scenarios are outlined in Table I.

TABLE I
SCENARIO DEFINITION

Parameter	Low scenario	Medium scenario	High scenario
PEV penetration rate	5%	15%	25%
Percentage of home charging at 240V	25%	75%	90%
Percentage of offices and retailers charging PEVs	20%	50%	75%
Percentage of 16.6 kWh batteries	50%	50%	50%

C. Implementation of the Probabilistic Load Flow

The probabilistic load flow algorithm was implemented entirely in Matlab software. A model algorithm is presented in Fig. 1. A single 24 hour period is examined at half hour intervals using a total of 350 iterations for each simulation. The value of 350 iterations was chosen based on a convergence analysis.

Three three-phase networks are modelled that represent topologically and demographically distinct network types: suburban, urban and rural. A summary of the defining characteristics of each network is shown in Table II. These networks are real networks from locations in BC, taken from the BC Hydro interconnected grid.

The urban network is very short and 35% of its demand is residential, with 65% from and office and retail. The suburban network is medium length and 98% of its demand is residential with only 2% from office and retail. The rural network is extremely long and 93% of its demand is residential, with 7% from office and retail. The total connected capacity of each network, as shown in Table II, is the sum of the rated capacities of all secondary transformers in a network.

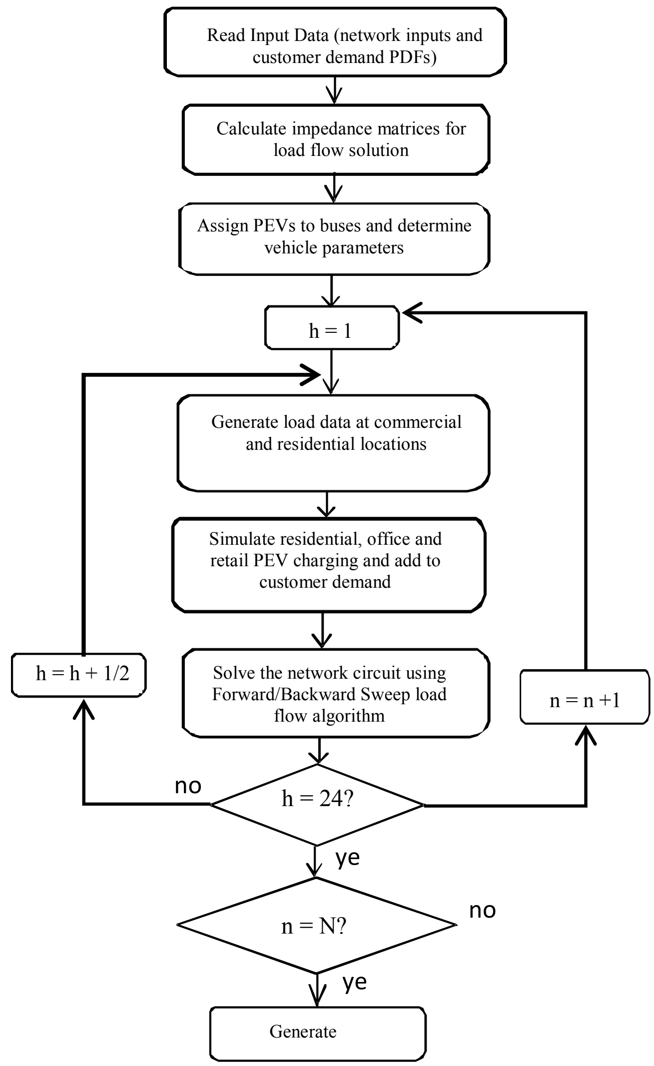

Fig. 1. MCS algorithm flow chart (h, hours; n, iterations)

III. RESULTS

A. Network demand

The average network (total) demand including PEV charging, for each simulated 24 hour period, is shown in Fig. 2 (a-c). The three networks exhibit a high PEV demand during the hours of 16:00 to 20:00 due to the arrival of vehicles after their commute home which increases the existing peak demand, especially for the high scenario. The urban network shows a large demand increase in the daytime hours (9:00 – 15:00) due to the charging of vehicles at office and retail locations. The maximum network demand for the high scenario is 10.5 MVA, 3.9 MVA and 12.6 MVA for the suburban, urban and rural networks, respectively. The average demand exceeds the network capacity in the rural network in the high scenario.

TABLE II
THREE PHASE NETWORK CHARACTERISTICS

Parameter	Suburban	Urban	Rural
Total length (km)	26.1	10.1	114.6
Length of three phase sections (km)	6.3	8.1	18.3
Length of single phase sections (km)	19.8	2.0	96.3
Line-to-line voltage (kV)	25.2	12.6	25.2
Network rated capacity (MVA)	12	6	12
Recorded peak network demand (MVA)	9.4	3.8	11.8
Total connected capacity (kVA)	14, 735	7,375	24,900
Amount of residential demand (%)	98%	35%	93%
Amount of office demand (%)	1%	51%	4%

The average daily energy supplied to the network is calculated for each network and scenario with and without PEV charging. The calculated energy is then used to estimate the average percent increase in energy supplied to each network and compared to the case without PEV charging. The average percent increase in energy is compared with the average percent increase in peak demand as shown in
Fig. 3.
An important consequence of charging PEVs in an uncontrolled manner is that the peak demand increases at a higher rate than energy when adding more PEVs to a network. For example, in
Fig. 3, for the rural network, the increase in energy from PEV charging grows from 0.41% to 2.63% for the low and high scenarios, respectively. In comparison, the average percentage increase in peak demand rises from 1.13% to 8.95%, a much larger increase. The higher rate of increase in peak demand is a result of more vehicles charging at 240V during the peak period.

B. Transformer Overloading

Secondary transformers provide the voltage step-down from base network voltage to the customer voltage level (120/240V). Overloading transformers is an important issue, especially for secondary transformers, because numerous households charging a PEV on 240V simultaneously would add a load that is higher than typical household loads. When transformers are overloaded, the expected lifetime of these assets is decreased.

Secondary transformers overloaded above 20% of their capacity were counted at each time interval in the three networks. The average percentage of overloaded secondary transformers in the suburban network is shown in Fig. 4. The rural and urban networks did not have high rates of transformer overloading and PEV charging did not significantly increase the occurrence of overloads on these two networks.

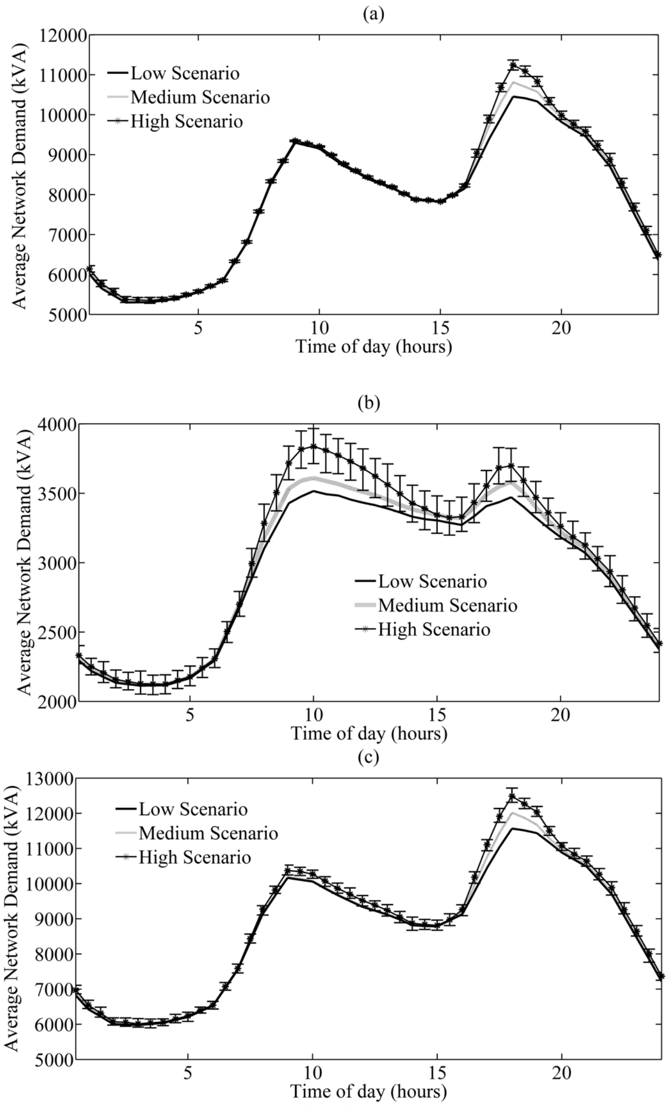

Fig. 2. Average network demand for all three scenarios in the (a) suburban network, (b) urban network and (c) rural network. Error bars represent the maximum and minimum demand values.

C. Voltage drop

Voltage drop is of concern for rural distribution networks due to the lengths of these networks. The generally accepted standard is that bus voltage should be maintained between 95% and 105% of the base network voltage [17]. A *tolerable zone* is also defined in which bus voltage is between 91% and 95% of the base network voltage. For these cases, attempts should be made to improve the voltage through the use of voltage regulating equipment [17].

The voltage histogram shown in Fig. 5 is based on data from the most highly loaded bus on the rural network at the peak time (18:00). In the absence of PEV charging, the voltage is below the favourable zone. When PEV charging is considered, the voltage shifts further away from the favourable zone. These results show that this network may require some form of voltage regulation in the future, especially if PEV charging becomes prevalent.

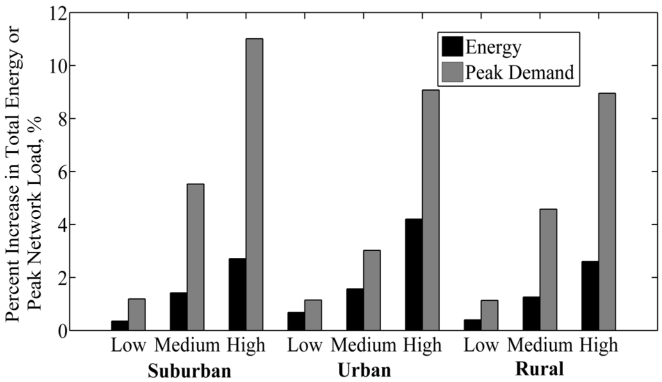

Fig. 3. Percentage increases in energy and peak load for each network in the low, medium and high scenarios

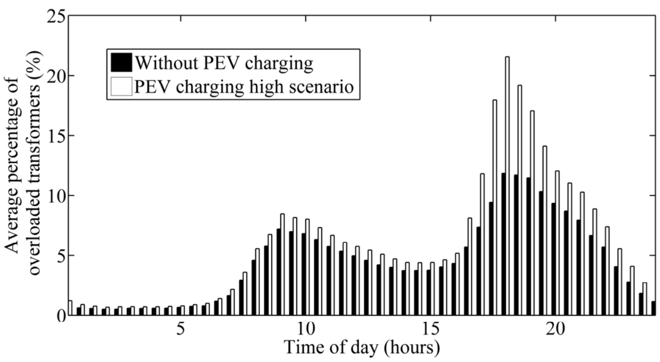

Fig. 4. Percentage of overloaded transformers for the suburban network.

IV. Discussion

A. Network Demand

PEVs charging in an uncontrolled manner caused large increases in the peak demand for each of the networks considered. In the urban network, PEV charging at the office locations added a significant amount to the load during the late morning and early afternoon. As customers upgrade their home charging to 240V, the peak network demand will increase significantly if no charging control is in place. This increase in peak load is undesirable from a distribution operation point of view as investment to reinforce the networks may be needed. Reinforcements may need to be done to increase the capacity of networks and also to increase capacity of secondary transformers.

Close attention should be paid by utility planners to the number and location of PEVs sold within the system. Relevant policy and business models should be created in order to encourage vehicle charging during the off-peak hours where the impact to the system would be minimized. This could be achieved in a number of ways, for example, through the use of a smart metering system and real-time pricing information delivered to the customer home to allow for an automated charging scheme.

B. Transformer overloads

Overloading of secondary transformers is highest on the suburban network, while the urban and rural networks showed lower rates of transformer overloading. This is due to the suburban network having a larger number of customers connected to fewer transformers than the other networks increasing the likelihood of an overload. In urban areas, large buildings such as offices and apartments are connected to three phase transformers which are generally oversized, resulting in fewer overloads. In rural networks the customers are spread out over a larger area and more transformers are installed to avoid lengthy secondary wiring sections where losses are higher.

The overloading of transformers in suburban areas may be of significant concern, especially if a large proportion of PEV owners upgrade their existing home circuit to include a 240V vehicle charging outlet. Suburban networks may also see the highest rates of PEV penetration due to the presence of many residential commuters. To avoid the impact of increased transformer loss of life, smart metering infrastructure could be used to identify overloaded transformers.

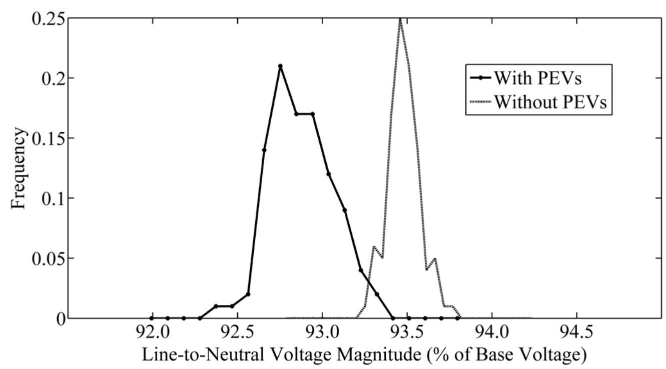

Fig. 5. Bus voltage distribution for lowest single phase bus voltage on the rural network at 18:00 hours without PEV charging and PEV charging in the high scenario.

C. Voltage drop

Voltage drop is currently a concern for rural distribution networks and PEV charging will worsen this problem. Due to the existing voltage drop issues, rural networks could be ideal locations for vehicle-to-grid pilot projects. For example, the vehicles could be used for voltage support on a network to increase the voltage by supplying power back to the network during peak times. Customers on rural networks may be more willing to be involved in vehicle-to-grid schemes if it improves the reliability of power supply to their home since these customers are more likely to have experienced outages and power quality problems in the past.

V. Conclusion

A probabilistic load flow model based on Monte Carlo simulations is presented to estimate the impacts of PEV charging on distribution networks. A probabilistic customer demand model is coupled with a probabilistic simulation of

PEV driving and charging. Three representative networks are investigated. The impacts to the networks' peak demand, energy usage, secondary transformer overloading and bus voltage drop are investigated.

The networks in this study are representative of the types of networks found within the British Columbia provincial grid and throughout most of North America. For small penetrations of PEVs, daily operation of the networks is not significantly affected. For networks that do not have peak demands near their capacity, the uncontrolled charging of vehicles does not create significant problems in terms of reliable operation of these networks. However, networks that currently have demands near their capacity are the most likely places that PEV charging could have adverse impacts.

The introduction of PEVs to a residential network where the loads on secondary transformers are already close to their capacity will increase the rate of transformer overloads decreasing their expected lifetime. This impact will be amplified if large numbers of PEV owners upgrade their home charging outlets to 240V and there is no control over when the vehicles charge or the amount of power used when charging.

Integrating PEVs with smart grid technologies will allow higher penetrations of PEVs because the charging may be shifted to the low demand hours. This can be accomplished without adding significant network infrastructure, even on already stressed networks. The variety of impacts investigated in this study shows that an integrated approach to distribution system management is needed that can incorporate real-time measurement of parameters of interest through a smart metering program and high level modelling of networks.

Further study should be undertaken to quantify the costs and benefits of integrating smart metering infrastructure in distribution networks especially in the presence of PEVs and other distributed energy resources. Studies to analyze the emissions and transmission level impacts associated with PEV charging should be undertaken to ensure the maximum environmental benefit of these vehicles can be realized while maintaining transmission and generation reliability.

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