PEV Charging Profile Prediction and Analysis Based on Vehicle Usage Data

Ali Ashtari, *Member, IEEE*, Eric Bibeau, *Member, IEEE*, Soheil Shahidinejad, *Member, IEEE*, and Tom Molinski, *Member, IEEE*

***Abstract*—Present-day urban vehicle usage data recorded on a per second basis over a one-year period using GPS devices installed in 76 representative vehicles in the city of Winnipeg, Canada, allow predicting the electric load profiles onto the grid as a function of time for future plug-in electric vehicles. For each parking occurrence, load profile predictions properly take into account important factors, including actual state-of-charge of the battery, parking duration, parking type, and vehicle powertrain. Thus, the deterministic simulations capture the time history of vehicle driving and parking patterns using an equivalent 10 000 urban driving and parking days for the city of Winnipeg. These deterministic results are then compared to stochastic methods that differ in their treatment of how they model vehicle driving and charging habits. The new stochastic method introduced in this study more accurately captures the relationship of vehicle departure, arrival, and travel time compared to two previously used stochastic methods. It outperforms previous stochastic methods, having the lowest error at 3.4% when compared to the deterministic method for an electric sedan with a 24-kWhr battery pack. For regions where vehicle usage data is not available to predict plug-in electric vehicle load, the proposed stochastic method is recommended. In addition, using a combination of home, work, and commercial changing locales, and Level 1 versus Level 2 charging rates, deterministic simulations for urban run-out-of-charge events vary by less than 4% for seven charging scenarios selected. Using the vehicle usage data, charging scenarios simulated have no significant effect on urban run-out-of-charge events when the battery size for the electric sedan is increased. These results contribute towards utilities achieve a more optimal cost balance between: 1) charging infrastructure; 2) power transmission upgrades; 3) vehicle battery size; and 4) the addition of new renewable generation to address new electric vehicle loads for addressing energy drivers.**

***Index Terms*—Plug-in electric vehicles, power generation peaking capacity, power generation planning, signal analysis.**

I. Introduction

RECENT technological developments in the battery industry, the growing pressure from energy drivers—peak oil, greenhouse gas emissions leading to climate change, energy security, and emission reduction [7], [19], [22]—have prompted the emergence of plug–in electric vehicles (PEVs). PEVs refer to pure electric and plug–in hybrid electric vehicles. With the increased adoption of PEVs, electric utilities are involved in transportation in an unprecedented way [15], [20] which will mean new challenges, infrastructure costs, and opportunities for them. Understanding PEV load profiles helps utilities to mitigate its impacts and optimize this new load into their system [9], [17].

Utilities are interested in alleviating impacts of PEVs on power supply, on the need for upgrades to distribution systems, and on the installation of charging infrastructure. Moreover, electric mobility addresses energy drivers effectively when utilities match new PEV loads with new renewable generation—independent of the generation mix. Thereby, utilities also need to understand additional restrictions imposed on marginal power generation. Thus, PEVs translate to increased infrastructure costs for utilities, which requires optimization. However, new PEV loads can potentially improve utilities system by providing opportunities for load shaving, load shifting, demand response, storage, and ancillary services for distributed generations [11], [16], [24], [25]. In [6] and [8], the impact of PEVs on generation systems are assessed by studying dispatch, operational reserves, and wind generation integration in the presence of PEVs. Other studies focus on the impact of PEVs on the generation mix and emission reductions [1], [2]. Impacts of PEVs on distribution systems are studied addressed in [5], [11]–[14], [24]. New renewable generation to address the new load remains the optimal strategy to address energy drivers simultaneously [21].

Studies on PEV–utility issues provide recommendations for utilities on how to better optimize the integration of PEVs into their system. For optimization to be effective, they require realistic PEV charging profiles. PEV–related decisions by utilities without reasonably accurate information on PEV charging patterns can lead to implementation issues and over expenditures. Deterministic and stochastic approaches can be used to predict the charging patterns of PEVs. Our study addresses gaps in the literature: predicting PEV charging behavior based on vehicle usage habits using a relatively large database of driver behavior. Previous studies on PEV load impacts do not use such extensive high-resolution database. However, our proposed approach still samples driving behavior in a particular city using gasoline vehicles. Furthermore, all simulations currently neglect air-conditioning loads and charging restrictions imposed by controllers, as these can be added later and can vary considerably.

Currently, some PEV–utility studies in the literature assume PEV charging profiles dictated by utilities [2]. Those studies commonly use an arbitrary ideal charging profile optimized

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A. Ashtari is with the Department of Mechanical and Manufacturing Engineering, University of Manitoba, Winnipeg, MB R3T 5V6 Canada (e-mail: ashtari@cc.umanitoba.ca).

E. Bibeau and S. D. Shahidinejad are with the Department of Mechanical and Manufacturing Engineering, University of Manitoba, Winnipeg, MB R3T 5V6 Canada.

T. Molinski is with Manitoba Hydro, Winnipeg, MB R3C 2P4, Canada.

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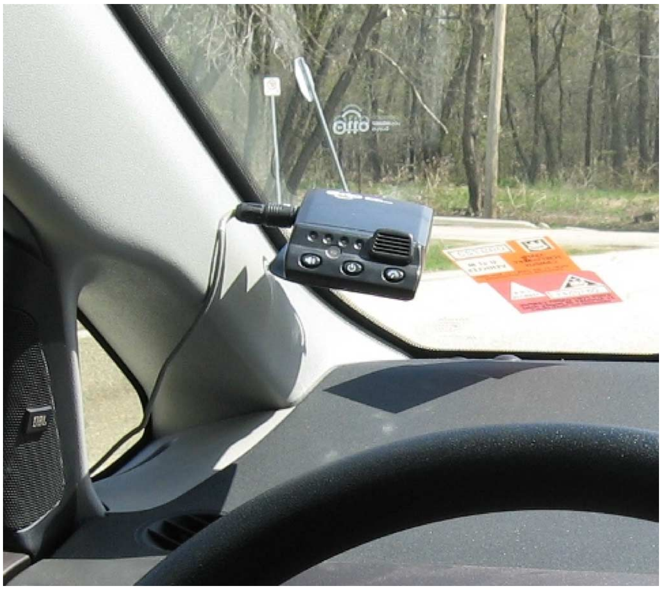

Fig. 1. GPS recording system.

from the utilities' perspective. Moreover, any controlled PEV charging profile requires to first know the uncontrolled charging profiles. Recent PEV studies try to address this issue by using travel survey data [10], [14]. This study demonstrates that accurate prediction of PEV charging profiles requires more sophisticated stochastic modeling than available literature models. Lack of proper stochastic modeling can hinder optimized integration of PEVs into electrical grid and lead to excess infrastructure. Electrification of the transportation sector will achieve the original goal to address energy drivers by the minimization of infrastructure costs and substituting the displaced oil with new renewable generation.

This study analyzes vehicle usage data of 76 vehicles over a one–year period using data obtained by GPS recording devices on a secondly basis in the city of Winnipeg, Canada. Availability of the 44 million data points accurately predicts PEV charging profiles. Such data is not commonly available in most regions, with survey data available [10] instead. We therefore also introduce a stochastic method to use driver-surveyed data to predict PEV charging profiles in different regions and validate the new method using deterministic results obtained from actual vehicle usage data from a large database. Once proper PEV charging profile prediction methods are developed, the study compares different charging scenarios, such as home, work, and commercial locales using Level 1 and Level 2 charging rates. These simulations provide useful information for optimized investments in PEV charging infrastructure to achieve sustainable transportation.

II. Data Collection

This study uses vehicle data collected by the University of Winnipeg [4]. Data logging devices, equipped with Global Positioning System (GPS) manufactured by PERSENTECH Inc., collect vehicle displacement data with commercial parking and road elements each having property attributes identified. Fig. 1 shows a picture of the data logging system installed in the vehicles.

To best represent vehicle use patterns in the city of Winnipeg, 100 volunteers' vehicles were randomly selected according to socioeconomic attributes and data loggers were installed in their vehicles. After a period of two months, 76 volunteer drivers interested in the research continued their collaboration for another ten months. Therefore, the current study uses the movements of a fleet of 76 vehicles recorded on a per second basis over a period of one year. The volunteers were selected from different income brackets, education levels, and gender and from different areas of the city to create a statistical population best representing the drivers within the city of Winnipeg. The fleet of participating vehicles consists of sedans, both full and midsize (67%), and sport utility vehicles and pickup trucks (33%). The collected data are representative for the activities such as commuting, shopping, and socializing. Such representativeness is ensured in this study by the relatively large number of vehicles in the fleet and the long period of data collection.

The database consists of more than 44 million data points and over 150 000 parking events. The collected data required significant postprocessing due to weather, buildings, and underground parking effects on GPS signals and categorizing parking locals as home, work, commercial, or other types of parking like roadside parking. Details of the data reduction techniques are available in [4], including remapping of longitude and latitudes to protect confidentiality of drivers. This database has been previously used to construct driving cycles representative of people's driving behavior in Winnipeg [3], [21], [23]. The current study uses trips' beginnings, ends, and distance in addition to charging time, duration, and location to predict PEV charging behavior. The processed dataset used in this study can be downloaded from [4].

III. Methods

This section has three parts. Section III-A explains the assumptions used in the model. Section III-B focuses on developing a stochastic PEV charging profile prediction method, and Section III-C compares different PEV charging infrastructure with respect to PEV electric range.

A. System Model

In order to predict the impact of PEVs on electricity load, one has to identify key parameters and determine their contributions which statistically is a challenging task. Such parameters include PEV powertrain (pure electric or plug-in hybrid), the daily usage profile of PEVs, the battery capacity of the vehicles, and seasonal climate effects on the charging load. Accurate assessment of all these parameters will not be possible until the technology is widely adopted. However, it is required to make assumptions as the information is required now by utilities. Furthermore, previous scientific methods developed to obtain duty cycles, like the car chasing technique, are concerned more with vehicle emissions that do not apply to PEVs in the same manner. As an example, a PHEV engine is decoupled from the accelerator and vehicle acceleration has less of a direct impact on vehicle emissions but affects the vehicle driving range instead. This section describes the assumptions used in simulating the impact of PEVs on the electrical grid and explains why they can meet the requirements of this study. The present analysis aims at providing the utilities a better insight to predict the forthcoming PEVs electrical loads now and help to recognize the grounds in which investments are optimized.

Several studies have attempted to predict charging load impact on the grid using stochastic methods making general assumptions on the daily vehicle usage and charging availability profile [1]. The present study uses a comprehensive database of driving behavior in the city of Winnipeg that makes the results more representative and more deterministic. This study aims at providing utilities like Manitoba Hydro, the provincial utility, with better information for decision-making. However, the methodology developed herein and the results of the case study for the city of Winnipeg are of interest to other North American utilities. This is somewhat similar to previous duty cycles developed for vehicle emission in a particular city where, although a very small representative measurement sample is used, these cycles are used extensively in many jurisdictions. The assumptions used as part of the development of the simulation algorithm shown in Fig. 2 to predict load profiles are:

- Only an EV sedan is presently considered. This EV sedan is assumed to have similar characteristics as a Nissan Leaf [18]. Nissan Leaf has a relatively large battery pack (24 kWh) compared to the PEVs currently in the market. However, this situation is most likely to change in future. For the purpose of this study, using the characteristics of a typical full electric sedan, Nissan Leaf, is of interest to utilities as it potentially represents an extreme PEV configuration that demands the most charging infrastructure. The next step will be to implement a PEV penetration model that accounts for various powertrains and includes weather impacts.
- The battery pack has a capacity of 24 kWh. However, different battery sizes are also simulated to assess the sensitivity to the PEV battery size.
- Full charging takes 20 h on Level 1 charger and 8 h on Level 2 charger [18]. Note that not all charging events during vehicle simulations require a full charge as the state of charge (SOC) is tracked.
- Electric drive efficiency is 6.7 kilometers per kWh [18]. A more accurate simulation would include a range of efficiency values. However, the forecast of how different PEV technologies having varied gas engine efficiencies are going to be adopted is beyond the scope of the present study. Thus, this value is chosen for the simulations.
- Drivers start charging immediately after they arrive at home and at work. This is expected as because of extreme cold winters in Manitoba, people currently plug in their block heaters immediately upon home and work arrival. However, time of day pricing of electricity can influence charging profiles. It is hard to predict how different electricity rate patterns would affect PEV charging profile: this aspect can be investigated separately for different jurisdictions by modifying the simulation. Because Manitoba currently has a single-tariff pricing system is in effect, this is not an issue. More important, controllers can modify the PEV charging profile. This aspect should not be attempted until a clear picture of the uncontrolled charge profile is established using a deterministic or stochastic analysis, as presented in this study.
- PEV driving habits will be the same as current gasoline vehicles as PEVs need to deliver a comparable service as ICE vehicles. This assumption allows predicting the PEV battery state of the charge during simulations. However, it is important to highlight that reduction in acceleration rates improves electric driving range. Thus, driver feedbacks by manufactures or third party products for PEVs may affect driving behavior in the future. Furthermore, implementation of sensors, both in the vehicle and on roads (e.g., onboard over speed indicators and photo radar), may further affect driver behavior.

B. *PEV Charging Profile Prediction*

In this section, a deterministic and three stochastic methods predict the charge profile using a simulation model implemented in Matlab. The deterministic approach is novel and uses the vehicle data directly. The three stochastic approaches use the driver data indirectly using a statistical approach. Stochastic methods do not require accessing the complete vehicle usage data and are presented for regions where vehicle usage data are not available. Stochastic approaches only have access to distributions of home departure time, daily traveled distance, and home arrival time, similar to the data found in [10]. The first two of the stochastic approaches modeled are from previous studies. The third stochastic method is developed in this study and is shown to adhere to the deterministic exact results more closely compared to previous stochastic methods. Implementation of these different methods of calculations in Matlab using assumption presented earlier and methods summarized in Table I are now presented. Fig. 2 details the algorithm for the various mathematical transformation required to produce the charging profiles, with some of these transformations already explained in previous publications.

It should be noted that all three stochastic approaches use numerically obtained probability density functions (pdf's). Pdf's used in the simulations are not fit to explicit functions. Rather, they are used numerically to avoid unnecessary errors. This means these pdf's are reproducible by simply obtaining the histograms of the data. All the driving data and the code is made available publically to help the readers understand and replicate the method.

1) Deterministic Method: Daily traveled distances, home arrival times, and home departure times extracted from the vehicle usage database is the basis of the deterministic approach, which for the purpose of this study requires processing 44 million data points. Vehicles are first charged in the simulation using a Level 1 charger at home (120 V) and without utility charge control. For each car in the first iteration of the SOC simulations, the SOC is assumed to be 100% when leaving home on the first day. SOC values for each car are iteratively calculated for the duration of the vehicle usage data over one-year duration. On occasions when the vehicle is out of charge, its charge is set to zero when charging begins. During the simulation, tabulated occurrences when vehicles are out of charge reflect the necessity of charging

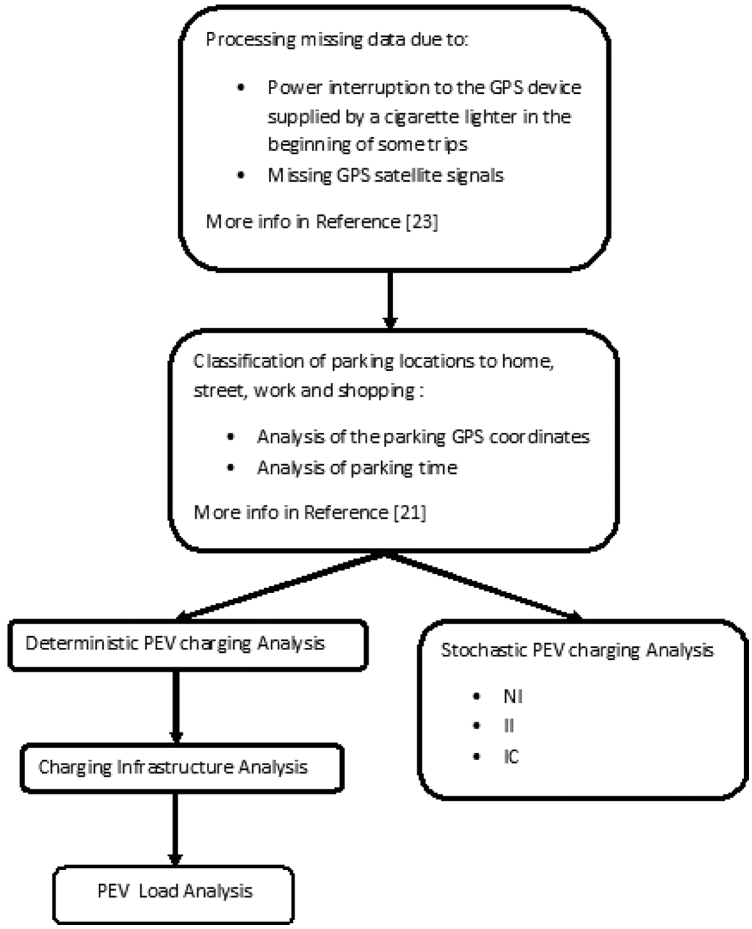

Fig. 2. Simulation algorithm from the GPS data recoded by the OTTO system in each vehicle to the load impact profile calculations using a deterministic and stochastic approach presented in this study.

TABLE I
PEV CHARGING PROFILE PREDICTION METHODS

Type	Name	Section explained
Deterministic	Deterministic	III-B1
Stochastic	NI	III-B2
Stochastic	II	III-B3
Stochastic	IC	III-B4

infrastructure and impose a restriction on utility control possibilities. Section III-C addresses this important aspect.

Let d_{mn}, l_{mn} and a_{mn} be the home departure time, daily traveled distance and home arrival time, respectively for the m^{th} car on the n^{th} day. Range of m varies between 1 and 76 and n between 1 and 365 in this study. The following equation describes the battery discharge:

$$\mathrm{SOC}_a(m,n) = \mathrm{SOC}_d(m,n) - \frac{d_{mn}}{Eff \times C} \times 100 \qquad (1)$$

where $\mathrm{SOC}_a(m,n)$ and $\mathrm{SOC}_d(m,n)$ denote the percentage of SOC when arriving at home and when departing home respectively; C is the battery capacity and is 24 kWh in this study, and Eff is the overall electrical drive efficiency assumes 6.7 km/kWh which takes into account both charge and discharge efficiencies. If (1) yields a negative value for $\mathrm{SOC}_a(m,n)$, this value is set to zero. Tabulated number of days the battery does not have enough charge is a measure of the PEV electrical range and availability of public charging infrastructure requirements. Because the focus of the research is on the methodology, using various powertrains and including air conditioning loads is outside the scope of simulations.

The following equation describes the charge cycle:

$$\mathrm{SOC}_d(m,n) = \mathrm{SOC}_a(m,n-1) + \frac{t_{mn} \times R}{C} \times 100 \qquad (2)$$

where t_{mn} is the charging time in hours and R is the charging rate in kW. Charging time is the minimum of the parking time and the required time for full charging considering the SOC at the beginning of the charging. With respect to charging rate, R, Level 1 charging is used in this Section. In Section III-C, Level 2 (240 *V*) charging is also simulated.

2) NI Stochastic Method: This section describes the NI stochastic method using non-iterative and independent probability density functions (pdf's). Assume $f_a(a)$ and $f_l(l)$ denote the pdf's of home arrival time and the length of daily traveled distances. These pdf's are obtained from the home arrival and daily traveled distance data points in the GPS records regardless of the vehicles. A Monte Carlo simulation with 10 000 points is conducted. For each point, charging times are calculated as follows. Home arrival time t_a is selected from $f_a(a)$ and daily traveled distance d is selected from $f_l(l)$. Charging begins at t_a. Charging end time t_e is calculated as

$$t_e = \frac{C - \frac{d}{Eff}}{R}. \qquad (3)$$

Note that in this stochastic method, $f_a(a)$ and $f_l(l)$ are assumed to be independent from each other which is not statistically accurate. In addition, assuming the vehicle is always fully charged when leaving home which is also not accurate. Home departure time and home departure SOC are not included during the simulations to reflect the assumptions made when applying the NI stochastic method. [14] is an example where the NI stochastic method used in previous studies.

3) II Method: This section describes the iterative and independent pdf II method used in the literature. For this method, assume $f_d(d)$ denotes the pdf of home departure time. Charging starts at t_a like the NI method. The charging end time on day n, $t_e(n)$, is then calculated as

$$t_e(n) = \min\left\{t_d(n+1), \frac{C - \frac{d(n)}{Eff}}{R}\right\} \tag{4}$$

where $t_d(n+1)$ is the home departure time in day $n+1$ picked from $f_d(d)$ and $d(n)$ is the distance traveled in day n picked from $f_l(l)$. Note that unlike the NI method, home departure time is now included in the calculations. Another difference between the II method and the NI method is that the II method is iterative, i.e., the order of days affects the simulations. However, $f_a(a)$, $f_l(l)$ and $f_d(d)$ are still assumed to be independent pdf's. The independence of the pdf's is the similarity of the NI and II methods.

4) Proposed IC Stochastic Method: This section describes the iterative and conditional pdf IC stochastic method introduced by this study. We assume that $t_d(n)$ is the home departure time on day n and is selected from $f_d(d)$. Traveled distance in day n, $d(n)$, is then chosen from pdf $f_d(d|t_d(n))$ where $f_d(d|t_d(n))$ is the pdf of the daily distance traveled of the days where home departure time is within 5 min of $t_d(n)$. Home arrival time on day n, $t_a(n)$ is obtained from pdf $f_a(a|t_d(n), d(n))$ where $f_a(a|t_d(n), d(n))$ is the pdf of the home arrival times of those days where home departure time is within 30 minutes of $t_d(n)$ and daily traveled distance is within 5 km of $d(n)$ used in the II method. Charging beginning will then be $t_a(n)$ and charging end time is obtained from (4). Note that the charging end time is calculated from the same equation for both II and IC stochastic methods. However, the values of $t_a(n)$, $t_d(n)$, and $d(n)$ are selected from conditional pdf's in the proposed IC method and independent pdf's are used in the II method. There are no previous studies that have used this method.

C. Simulated Charging Infrastructure Scenarios

Table II shows the various scenarios simulated in this study. Two charging rates, Level 1 and Level 2, and three charging locals previously extracted from the database [23]—home, work, and shopping—are included in the simulations. Utility–imposed charging control strategies are currently not included in this study. Table II shows the different charging scenarios simulated in this study.

H1 method assumed that charging is done only at home using a Level 1 charger. It is currently possible to implement this scenario in Winnipeg at low cost. H1W1 assumes that the work place provides Level 1 charging as well. This scenario can also be implemented in Winnipeg with relatively low cost. Because of Winnipeg's extreme cold winters, many public parking places are equipped with block heater chargers which can also be used for charging PEV batteries. However, many of these outlets are being cycled on and off to save power and would require to be modified. H1W1S1 scenario includes charging at shopping places as well as charging at home and wile at work. H2W1 uses Level 2 charging at home and Level 1 charging at work. H2W2 applies Level 2 charging both at home and at work. H2W1Box is the same as H2W1 except that it excludes trips that travel more than 150 km from Winnipeg.

TABLE II
SIMULATED CHARGING SCENARIOS

Name	H Home	W Work	S Shopping	Distance Restriction
H1	Level 1	–	–	–
H1W1	Level 1	Level 1	–	–
H1W1S1	Level 1	Level 1	Level 1	–
H2W1	Level 2	Level 1	–	–
H2W2	Level 2	Level 2	–	–
H2W1Box	Level 2	Level 1	–	Yes

IV. RESULTS

We first present results for NI, II, and IC stochastic charging prediction methods for comparisons. Results depicting the effect of charging infrastructure on utility load and on PEV electric range is then presented. These results are based on analysis methods described in Section III, the dataset reviewed in Section II, and the algorithm depicted in Fig. 2.

A. Results of PEV Charging Profile Prediction Methods

Section III-B presented NI and II methods and the proposed IC method. The purpose of these methods is to provide predictions of PEV charging patterns for regions where vehicle usage data is not available. This section compares these three stochastic methods with respect to the more exact deterministic method which uses actual driving and parking information of the vehicles infrom the database. The results are also analyzed to explain which method is most more accurate with respect to the sampled driving data.

Fig. 3 compares the power profiles produced by the three stochastic methods with the deterministic method as obtained from simulations (Fig. 2). All three stochastic methods are able to reproduce the trends when compared in the deterministic exact profile. It can be observed that the new IC method produces the closest results to the exact deterministic profile. However, the ICnew IC method compares better with the produces the closest results to the exact deterministic profile while the NI method has the worst prediction. Table III provides tabulates the numerical values of the prediction errors of the three stochastic methods as compared to the deterministic profile. Results in this table illustrate that the modifications in the stochastic modeling of the PEV charging profile prediction methods, can result in 12% improvements in the accuracy of the results when compared to the deterministic method which itself is an approximation of the actual load profile. In addition to improved accuracy, an important advantage of the IC method over the NI and II methods is its ability to more accurately estimate the peak load, an important

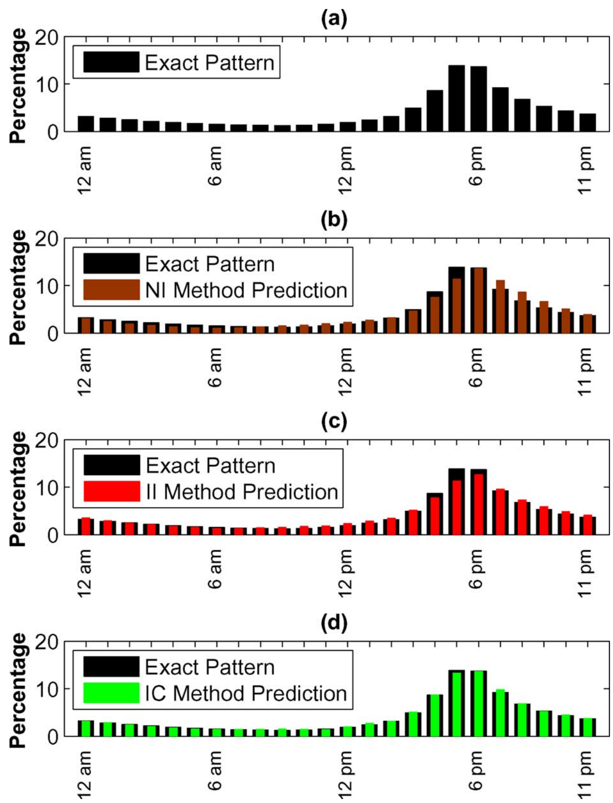

Fig. 3. Comparing the PEV charging profile prediction of different stochastic methods.

TABLE III
PREDICTION ERRORS OF THE STOCHASTIC METHODS

Method	Error
NI	15.4%
II	10.7%
IC	3.4%

aspect for utilities. It can be seen from Fig. 3 that the NI and II methods yield the highest errors at 5 P.M. when PEV charging load peak. However, the IC method yields a reasonable accuracy at 5 P.M.. Considering that the peak load is an important factor for utilities wanting to reduce infrastructure cost, the IC method is therefore recommended. The sources of error will are now be quantified below.

Fig. 4 shows the histogram of the home departure time extracted from the for the vehicles in the database using the mathematical simulation depicted in Fig. 2. A relatively high considerable percentage of the vehicles leave home in the early in the hours of the morning. This suggests that in some days, some vehicles might may not be fully charged when departing home. The NI method ignores this fact, i.e., it does not include home departure time in the PEV charging profile calculations. Implicitly, the NI method assumes that the vehicles are 100% charged when leaving home. This is the main source of error in the NI method compared to the II method. Because the II method is iterative, it effectively simulates the SOC of the vehicle taking into account the home departure time.

Figs. 5 and 6 demonstrate why the IC method is more accurate compared to the II method. Fig. 5 shows the change in daily traveled distance histogram versus departure time. Results show

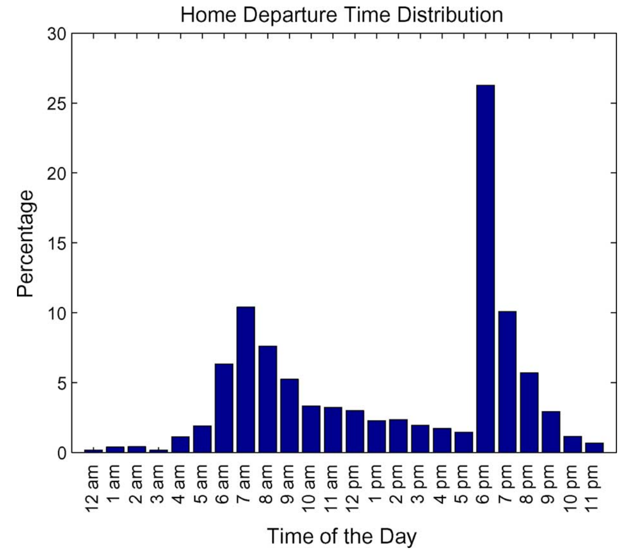

Fig. 4. Home departure time histogram.

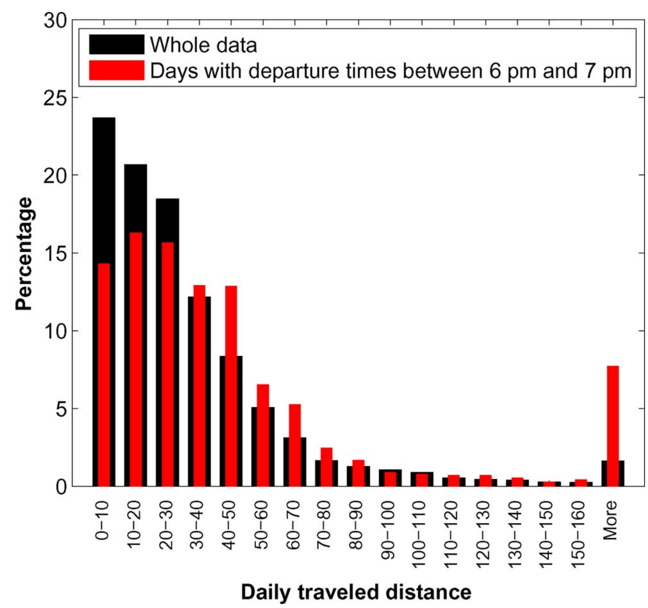

Fig. 5. Change in daily traveled distance histogram versus departure time.

that daily traveled distance correlates with the departure time. Therefore, it is not correct for a stochastic method to select numbers from independent distributions of daily traveled distance and home departure time. Fig. 6 demonstrates the correlation between the daily traveled distance and home arrival time distributions. This figure demonstrates that these two variables are indeed correlated and cannot be selected from independent distributions. Using conditional pdf's as in IC method incorporates the correlation between home departure time, home arrival time, and daily traveled distance. This approach results in 7.3% improvements in the accuracy of PEV charging profile prediction.

B. PEV Utility Load

This section provides an analysis on the effect of PEV charging profiles on Manitoba load using the deterministic method. In order to calculate the PEV load, one needs to predict the PEV adoption rate. Such predictions are beyond the

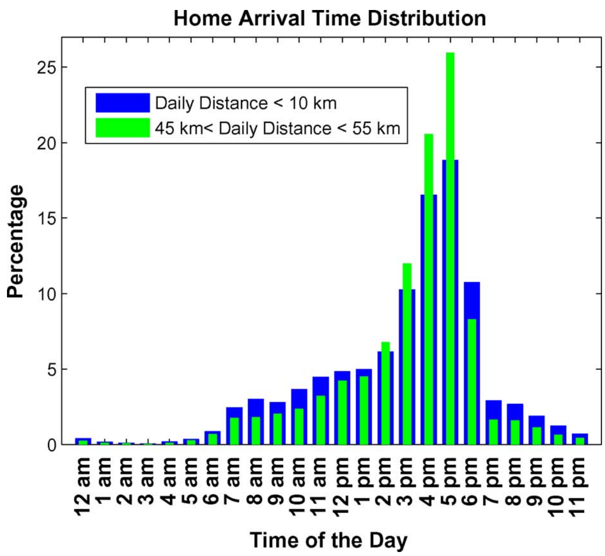

Fig. 6. Effect of daily traveled distance on home arrival time distribution.

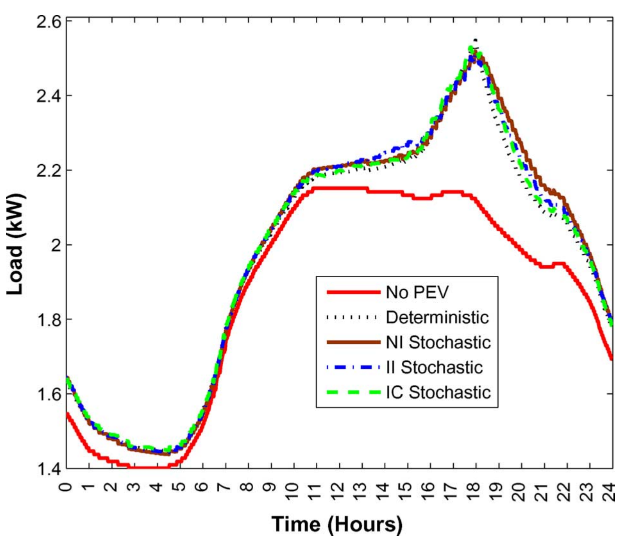

Fig. 7. Average load profile per person with 100% adoption of EV sedans in summer.

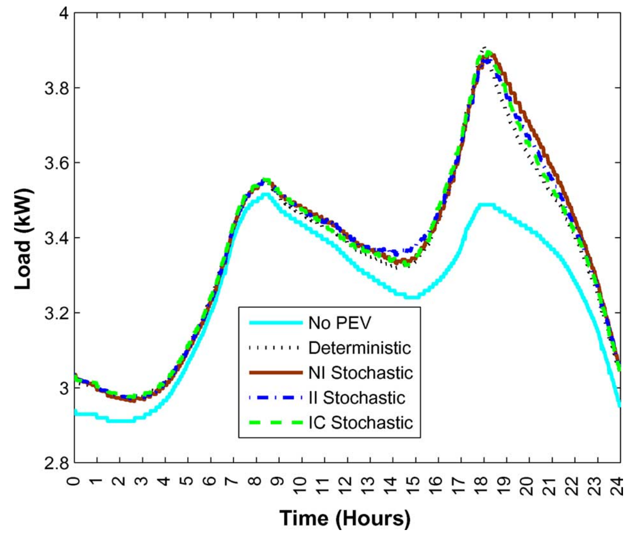

Fig. 8. Average load profile per person with 100% adoption of EV sedans in winter.

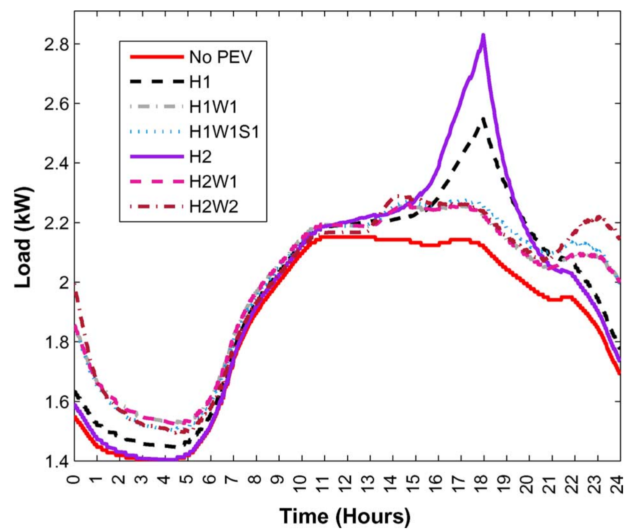

Fig. 9. Average load profile per person with 100% adoption of EV sedans under different charging scenarios in summer (H $=$ Home; W $=$ Work; S $=$ Shopping).

scope of this study and thus we chose a different approach by calculating the PEV load impacts if all the passenger vehicles in Winnipeg were EV sedans. More accurate analysis which includes variable PEV adoption rates and other PEV powertrains is ongoing. However, an upper limit analysis in the current study provides insight on the effect of large adoption of PEVs.

According to Statistics Canada, there are currently 643 580 registered passenger vehicles in Manitoba. Manitoba has a population of 1 213 815. Using these numbers, one can calculate the average load profile per person in Manitoba with 100% adoption of EV sedans. Figs. 7 and 8 shows such results using different PEV charging profile prediction methods. This is chosen as an upper limit of the impacts of PEV load, excludes ac loads and provides information on public infrastructure requirements.

The results show that PEV load can be potentially significant to Winnipeg utility system. In particular, PEV charging profiles results in sharper peaks in Winnipeg load.

C. Charging Scenarios Results

The results in Figs. 9 and 10 are obtained using Level 1 home charging (H1). The results of other strategies such as Level 2 charging (H2), charging at work or shopping (H1W1S1) are presented in Figs. 9 and 10. The results show that if charging is restricted to home, EV load has a significant peak around 6 P.M. Adding charging at work substantailly smoothens the profile.

Table IV shows the percentage of the trips that PEVs go out of charge under different charging scenarios. As expected, H1 has the highest percentage of the trips without sufficient battery charge. However, this number, 3.69% is still a considerably small number. Using Level 1 chargers at work reduces the run–out–of–charge events to 1.95% and adding Level 1 charger at shopping places further reduces that number to 1.18%. Using a Level 2 charger at home with a Level 1 charger at home and without charging while shopping, H2W1 is more effective than H1W1S1 scenario. Adding a Level 2 charger at work improves the number by only 0.21%. H2W1Box scenario which removes

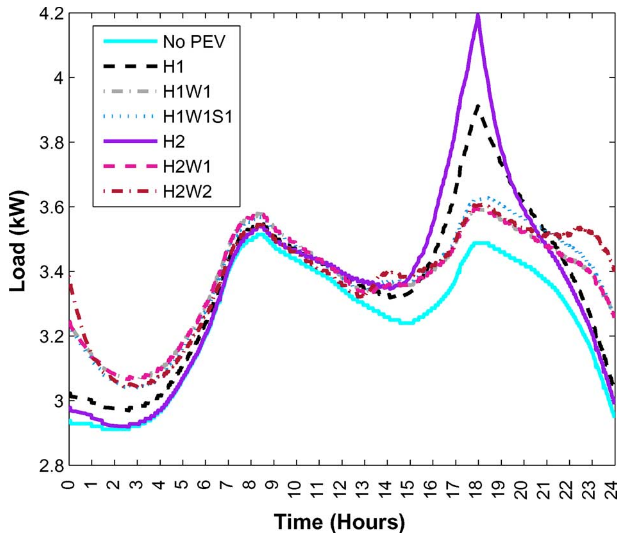

Fig. 10. Average load profile per person with 100% adoption of EV sedans under different charging scenarios in winter (H = Home; W = Work; S = Shopping).

TABLE IV
PERCENTAGE OF THE TRIPS THAT PEVS GO OUT OF CHARGE UNDER DIFFERENT CHARGING SCENARIOS

Scenario	Out of Charge (%)
H1	3.69
H1W1	1.95
H1W1S1	1.18
H2W1	0.84
H2W2	0.63
H2W1Box	0.58

the trips that are outside a 150 km circle from the center of Winnipeg results in only 0.58% of the trips with no sufficient charge. However, H2W1Box is only 0.05% more reliable than H2W2, which suggests that excluding out of town trips does not guarantee 100% reliability of the electrical range for EV sedan under the described charging scenarios.

Results in Table IV suggests that other factors such as battery size will have a greater impact on the reliability of the PEV electrical range. In order to understand the effect of battery size on PEV electrical range reliability, simulations were conducted assuming different battery sizes for an EV sedan. Fig. 11 shows the result of that simulation. For a battery size of 32 kWh, all the charging scenarios except for H1 yield relatively similar results. The effect of charging scenarios is more dramatic for smaller battery sizes. For example, a 16–kWh EV charged under H1 scenario has less range than an 8–kWh EV charged under H2W1 scenario.

Ideally, if collaboration exists between vehicle manufacturers, utilities, governments, and customers, data presented in Fig. 11 can minimize the overall costs of PEV technology and maximize its benefits. For example, such collaboration can lead to a correct policy regarding the question of whether to invest on bigger battery sizes or on charging infrastructure and make sure that new electrical loads are always match with new renewable generation to address energy drivers simultanously rather than requirements of specific driving cycles.

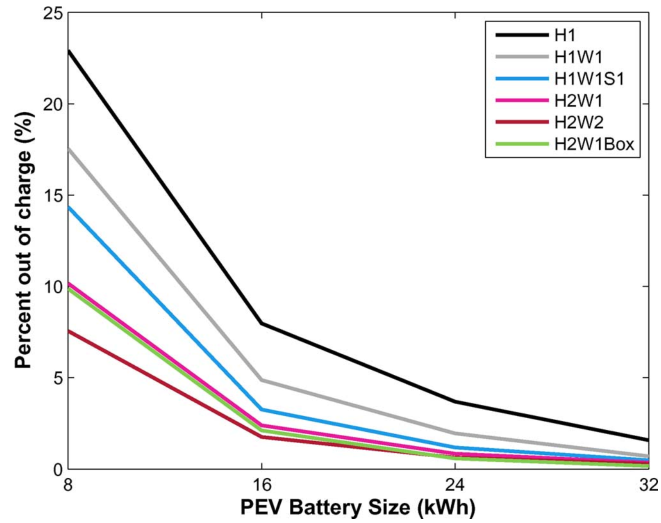

Fig. 11. Effect of battery size and charging scenario on PEV electrical range reliability (H = Home; W = Work; S = Shopping; Box = Within 150 km of Winnipeg).

D. Sensitivity Analysis

To measure the stability of the simulation results, it is desirable to show some sensitivity analysis. The sensitivity analysis can clarify how the electricity consumption changes with different input values and show the limitations of the simulation results. We used these tests for sensitivity analysis: increasing/decreasing the driving speed by 10% and delaying the arrival and departure time by 1 hour. When driving speed increases by 10%, peak power increases by 5.8% but the peak location does not change. When both departure and arrival times change by 1 h, the peak magnitude does not change. However, its location is shifted by 1 h.

E. Economic Considerations

For electric utilities, it is of paramount importance to have an accurate estimation of the additional load resulting from large scale PEV adoption and the investments required to accustom the electrical infrastructure with new load conditions. The required investment may include potential new generation stations, transmission, distribution systems, and charging infrastructure. For example, if the PEV peak load is significant, utilities may consider investments in smart charging technologies or changes in electricity pricing system. Accurate prediction of PEV load is also necessary for proper policy making decisions. The proposed IC method is 12% more accurate than existing NI method. If a utility uses NI method instead of II method, it can mistakenly decide to build new generation stations which involve significant investments. Also, decisions regarding upgrades in distribution systems are going to need accurate PEV load prediction methods.

On the issue of charging infrastructure, different parties can be involved such as car manufacturers, utilities, and governments. The question that was risen and was partly addressed in this paper was to find the most cost effective way to increase PEV adoption. More specifically, it is of interest to know which scenario makes the most sense: building charging infrastructure with faster rates and in different places or making larger battery packs. Answer to such a question needs access to real–world high resolution driving data which is made available in this study. Moreover, the goal of such optimization should be the service to the public, i.e., increased reliability of PEVs and less gasoline consumption. A solution that is merely optimized for utilities or car manufacturers will not necessarily be optimum for the costumers or the environment.

In this section, a preliminary approach for optimizing PEV integration is proposed. We model the cost of PEV development as follows:

$$\begin{aligned}&\text{PEV Adoption Increase Cost}\\&\quad= \text{New Infrastructure Cost} + \text{Unreliability Penalty}. \quad (5)\end{aligned}$$

New infrastructure cost is a function of investments in larger battery sizes and new charging infrastructure

$$\begin{aligned}&\text{New Infrastructure Cost}\\&\quad= f_1(\text{Battery Cost}, \text{Charging Infrastructure Cost}). \quad (6)\end{aligned}$$

Function f_1 will vary in different regions. Unreliability penalty is proportional to the number of times that PEV battery is out of charge, which is shown in Fig. 11. Therefore, we can write

$$\begin{aligned}&\text{Unreliability Penalty}\\&\quad= f_2(\text{Battery Cost}, \text{Charging Infrastructure Cost}). \quad (7)\end{aligned}$$

Combining (5)–(7) results in

$$\begin{aligned}&\text{PEV Adoption Increase Cost}\\&\quad= f(\text{Battery Cost}, \text{Charging Infrastructure Cost}) \quad (8)\end{aligned}$$

where $f = f_1 + f_2$.

As an example of the application of this cost model, obtaining function f can help a municipality to decide whether to invest in charging infrastructure or to subsidize PEV batteries. The analysis given in this study is a preliminary effort to calculate f_1. Function f_2 will vary based on the application and the region.

V. Conclusion

We recorded vehicle usage data for 76 vehicles in a one–year period in the city of Winnipeg, Canada, and used this data to predict PEV charging profiles and electrical range reliability. The study shows that proper stochastic modeling, i.e., using an iterative method with conditional pdf's can improve the accuracy of the predictions by 12% compared to existing methods, which are commonly noniterative and use independent pdf's.

Combinations of charging places simulate different charging profiles; home, work, and shopping and charging rates; Level 1 and Level 2. The effect of charging scenario on electrical range reliability is more significant where battery sizes are smaller.

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Ali Ashtari earned the B.Sc. and M.Sc. degrees in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 2001 and 2004, respectively, and the Ph.D. degree in electrical engineering from the University of Manitoba, Winnipeg, MB, Canada, in 2010.

He currently holds an industrial postdoctoral fellowship at the University of Manitoba, sponsored by both Mathematics of Information Technology and Complex Systems (MITACS) and Manitoba Hydro. His current research focuses on the application of signal processing and analysis techniques in alternative energy systems.

Eric Bibeau received the B.Sc. degree from McGill University, Montreal, QC, Canada, in 1986 and the M.Sc. and Ph.D. degrees from the University of British Columbia, Vancouver, BC, Canada, in 1988 and 1993, respectively.

He is a Mechanical Engineer and is currently an Associate Professor with the University of Manitoba, Winnipeg, MB, Canada, and holds the Natural Science and Engineering Research Council of Canada/Manitoba Hydro Chair in Alternative Energy. He specializes in developing power systems using biomass feedstocks, industrial waste heat, and kinetic energy from rivers for distributed-energy applications. He is also involved in developing blade deicing mitigation strategies for wind turbines and expertise in electric vehicles and district energy systems as a means to increase the renewable energy ratio in Canada to simultaneously address climate change and peak oil energy drivers.

Dr. Bibeau is a Registered Professional Engineer in the Province of Manitoba.

Soheil Shahidinejad received the B.Sc., M.Sc., and Ph.D. (with honors) degrees from Sharif University of Technology, Tehran, Iran, in 1993, 1996 and 2002, respectively, all in mechanical engineering.

He is currently a Research Associate with the Department of Mechanical and Manufacturing Engineering, University of Manitoba, Winnipeg, MB, Canada. His research deals with the study and analysis of energy-efficient systems and renewable energies.

Dr. Shahidinejad is a member of the Society of Automotive Engineers.

Tom Molinski received the B.Sc. degree in electrical engineering and the M.S. degree in electrical engineering degree from the University of Manitoba, Winnipeg, MB, Canada.

He has worked for Manitoba Hydro, Winnipeg, for the past 36 years and is currently the Section Head of Emerging Energy Systems in the Power Planning Division. He is responsible for research, planning, concept development, and recommending emerging energy technology projects (like wind, small hydro, bioenergy, energy storage, and various solar technologies) suitable for Manitoba Hydro to implement now or in the future. He works with government, academia, various research groups, and several learned societies to determine what are the available emerging energy technologies that Manitoba Hydro can use now and in the future. He has collaborated on research projects with several professors at the University of Manitoba for his entire career (36 years in total and 8 years with Dr. Bibeau) and has given many guest lectures there and at other universities.