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Load Profile Modeling of Plug-In Electric Vehicles: Realistic and Ready-to-Use Benchmark Test Data

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ABSTRACT The penetration of plug-in electric vehicles (PEVs) has increased in the transportation sector in the last few years and it has increased the uncertain load in the power sector. In order to analyze the impact on the power grid and plan infrastructure, modeling of PEV load profiles is required. Determining realistic PEV load profiles is challenging due to the involvement of serval uncertainties and complex interdependencies among different factors and to date, there are no benchmark load profiles of PEVs. In this paper, realistic and ready-to-use load profiles for PEVs are developed by considering vehicle mobility, charging infrastructure, and the market share of PEVs. Firstly, the U.S. National Household Travel Survey (NHTS) data is filtered to remove vehicles with unrealistic, duplicate, and missing data. Secondly, a set of relevant parameters is extracted to estimate different features of PEVs, such as arrival time, departure time, and daily mileage. Then, all the commercially available PEVs are grouped into four clusters using the K-means algorithm. Finally, the per unit (per PEV) load profiles are estimated using the information of the available PEVs in the market, charging levels in the residential sector, and features extracted in the previous step. A large set of scenarios are considered for each PEV cluster in determining the load profiles. The pre-unit profiles estimated in this study are ready-to-use for researchers and planners in the PEV industry and are realistic due to consideration of different relevant factors and a large traveling database of vehicles. The developed per-unit load profiles are used to estimate and analyze the PEV load profiles of the top four countries with the highest penetration percentage of PEVs.

INDEX TERMS Load profile, peak demand estimation, PEV demand estimation, PEV load, PEV policy-makers, plug-in electric vehicles, test data.

I. INTRODUCTION

A. CHALLENGES AND OPPORTUNITIES IN TRANSPORTATION ELECTRIFICATION

Transportation electrification is considered a viable solution to reduce the emissions of greenhouse gases and enhance energy security simultaneously. The former can be achieved by reducing the reliance on fossil fuels while the latter can be achieved by shifting demand to locally available renewable energy sources [1]. The penetration of plug-in electric vehicles (PEVs) has seen a dramatic increase in the last few years due to advances in battery technologies, interest in sustainable energy, and reduction in the costs of PEVs [2], [3]. The global PEV ownership has increased by 64% in 2018 as compared to the previous year, 2017 and the global PEV fleet has reached 2,264,400 in 2019 [4]. However, there are still several technical and social barriers, which need to be addressed for the widespread adoption of PEVs [5].

Various studies can be found in the literature about the potential problems due to PEVs [6] and technical challenges associated with PEVs [7]. Among several other issues, the uncertain load introduced by PEVs is considered a major problem, which may result in power quality and reliability issues in distribution systems [8]. Therefore, several studies have proposed smart charging methods, including demand response (DR) programs, to mitigate the peak load introduced by PEVs [9]–[11].

An interesting finding regarding the resilient growth of PEVs during the COVID-19 pandemic has been reported by IEA [12]. It has been reported that despite the 15% decline in the purchase of vehicles during the year 2020, the purchase of PEVs has increased in 2020 as compared to the previous

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year. This further emphasizes that a unified model for PEV load estimation is required.

B. RELATED WORK

Load modeling is required to achieve the aforementioned targets. Several studies have been conducted on the modeling of EV loads, such as agent-based modeling [13], [14], neural network-based modeling [15], [16], and stochastic modeling [17]. In addition, several studies have modeled loads for analyzing specific objectives such as the impact on grid-loading [18], [19], the impact of ownership changes [20], impact of drivers [21], and impact on the system reliability [22]. Several studies have also emphasized the importance of coordinated and controlled charging techniques, i.e. enhancement of power quality via coordinated charging is discussed in [23], [24], and impact assessment of controlled and uncontrolled charging on user waiting time is carried out in [25]. Similarly, a mechanism for sharing power among PEVs during system outages is proposed in [26], where probabilistic load models of EVs based on historical data are utilized.

All of these studies discussed in the previous paragraph have used different models, data sets, and complexity levels for estimating EV loads. This diversification results in the inability to reproduce the results effectively and hence makes it difficult for the researchers to verify/validate a proposed method or to compare different approaches. It can also be observed that PEV load profiles are modeled in all of the studies related to PEVs, i.e. planning of charging stations [3], assessment of grid impacts [18], [19], and future aspects of PEV penetration [20]. Therefore, a comprehensive yet easy and ready-to-use profile modeling of PEVs is required to save the time and efforts of researchers and planners related to the PEVs industry.

In addition, estimation of EV load is a non-trivial task. The difficulty in estimation of PEV load profiles arises from several complex factors involved in the process such as the preferences of customers, different product types, social dynamics, and policy factors [13]. In order to capture all these aspects, a huge data set is required and all the underlying uncertainties and stochastic processes need to be captured. The U.S. National Household Travel Survey (NHTS) [27] data is considered reliable and useful in determining the behavior of different vehicle owners. This survey data comprises 1,048,576 households and 309,164 vehicles and provides information on the driving pattern of different vehicle owners. Similarly, different commercially available charging stations, their charging ratings, and other technical aspects need to be incorporated. None of the existing studies have considered the modeling of PEV loads with an objective of reusability and availability for other researchers or policymakers. Instead, the objective of most of these studies to emphasize the impact of PEVs on different aspects of power systems, such as system overload, peak load, and system contingency. In addition, the load estimation procedure and per-unit load profiles are not readily available.

C. RESEARCH GAPS AND CONTRIBUTIONS

It can be observed from the literature survey that plenty of literature is available on the estimation/forecasting of the PEV load profiles. However, different methods are used in different studies and a unified benchmark model is missing. Realistic, generalized, and ready-to-use load profiles of PEVs are required to plan different aspects of PEVs and they are also required by the researcher in analyzing any newly developed model for PEVs. In addition, the different aspects of EVs analyzed in these studies generally have different underlying assumptions, thus the load profiles themselves need to be as realistic as possible. Therefore, a comprehensive yet easy and ready-to-use profile modeling of PEVs is required to save the time and efforts of researchers and planners related to the PEVs industry. Specifically, realistic load profiles of PEVs are required upon which the research community, planners, and operators can rely on and utilize them without the need of knowing the inside details of the model. To the best of the authors' knowledge, there is no such study on the modeling of benchmark PEV load profiles using comprehensive data focusing on reusability.

Given the above needs, this paper developed benchmark PEV load profiles to save the time of researchers, policymakers, and planners associated with the PEV industry. A probabilistic model for PEV charging loads is developed which includes realistic estimates of the elements characterizing the charging process and explicitly takes into account the underlying uncertainties of the random variables. The research data are drawn and analyzed from four main sources: 1) Vehicle mobility data to precisely capture driver behaviors that are essential in characterizing the charging process (e.g., mileage driven, arrival times, and departure times); 2) market sales data to extract information pertinent to PEV types and their market share; 3) manufacturers' data to obtain data pertinent to battery technologies in terms of capacities and PEV ranges; 4) SAE J1772 standards to obtain data pertinent to charging levels. A Monte Carlo simulation-based probabilistic method is developed to simulate the input variables needed to generate the PEV charging loads given the underlying uncertainty of the random variables. The major contributions of this study are as follows.

- Per-unit load profiles of PEVs are estimated considering different realistic factors and underlying uncertainties.
- The developed profiles are utilized to analyze the PEV peak load in four countries with the highest percentage of PEVs.
- The obtained PEV load profiles are ready-to-use and compact for analysis and planning of PEVs across different time horizons for researchers and policymakers.

II. ESTIMATION OF PEV LOAD PROFILES

In this section, the proposed method for determining the load profile of PEVs is discussed. The proposed method comprises three steps, which are feature extraction, pre-processing, and estimation of PEV load profiles. Determining realistic PEV

TABLE 1. Extracted relevant features from NHTS data.

Parameter ID	Explanation	Parameter ID	Explanation
#1	Household ID	#6	Trip mileage
#2	Vehicle ID	#7	Trip start time
#3	Vehicle type	#8	Trip end time
#4	Number of trips	#9	Type of starting place (where from)
#5	Day type	#10	Type of destination (where to)

load profiles is challenging due to the involvement of serval uncertainties and complex interdependencies among different factors [28]–[30]. In order to estimate realistic PEV load profiles, a set of reliable and real data is required. The NHTS data is considered reliable and useful in determining the behavior of different vehicle owners. This survey data comprises 1,048,576 households and 309,164 vehicles and provides information on the driving pattern of different vehicle owners [27]. This study also uses the NHTS data for estimating the load profile of PEVs. However, the data need to be preprocessed before using it to avoid erroneous results. Although this study has utilized the NHTS data (large and reliable set of data), per-unit profiles of other localities can also be obtained by using the proposed model, if such data is available.

A. FEATURE EXTRACTION AND PRE-PROCESSING

The NHTS data contains several parameters and several types of vehicles were considered in the survey. After careful analysis, ten features from the data were selected for this study, which are listed in Table 1. These features are used to calculate different parameters for estimating power density functions for arrival time, departure time, and mileage of PEVs, which are discussed in the following paragraph. Similarly, the most commonly used four classes of vehicles, such as passenger cars, pickup trucks, sport utility vehicles, and vans are considered in this study. Motorcycle, bicycle, and public transit vehicles were removed from the data set. Besides, code was developed to remove duplicate trips and other unrealistic data. The following are a few examples of data filtering. 1) Removal of PEVs with unrealistic traveling profiles by comparing the trip duration and the distance reported to cover in that time; 2) removal of PEVs with at least one of the features missing (unreported); 3) removal of the duplicate trips, if same data were reported for all the features of two or more trips.

After the selection of different relevant parameters and filtering of irrelevant/erroneous data, the data is pre-processed to determine useful parameters for determining the load profiles of PEVs, as shown in Algorithm I. The first step in Algorithm I is to determine the total number of PEVs with useable data. The total number of PEVs is determined using the information of household ID and vehicle ID. Then,

Algorithm 1: Pre-Processing of Extracted Data

```
Count total number of PEVs (NV) using extracted data:
  (#1 household ID and #2 vehicles ID).
for all v ∈ NV do
    Count total number of trips (NT): (#4 number of
      trips)
    for all tr ∈ NT do
        Accumulate daily driven mileage: (#6 trip
          mileage)
        If tr = 1 then
            Record first departure time (FDT): (#7 trip
              start time)
        else If tr = NT then
            Analyze the destination: (#10 type of
              destination)
            If destination is home then
                Record last arrival time (LAT): (#8 trip
                  end time)
            end if
        end if
    end for
end for
```

the total number of trips traveled by each PEV are determined and assigned to the *number of trip* feature. The number of miles traveled by each PEV is recorded for each trip and the nature of the trip is examined for detailed feature estimation. For example, the first departure time (FDT) is then computed from the first trip of each PEV. Similarly, the last arrival time (LAT) is determined from the last trip of the PEV, where the destination of the PEV was set to home. The information of each PEV extracted in this step is utilized to estimate the load profiles, which is discussed in the next section.

B. ESTIMATION OF PEV LOAD PROFILE

The input data utilized for determining the PEV load is divided into two types, i.e. data related to PEV driver behavior and data related to PEVs themselves. The data related to PEV driver behavior are the probability density functions (PDFs) of arrival time, departure time, and daily mileage. The data related to PEVs are the capacity and efficiency of the PEV

TABLE 2. Data related to four clusters of PEVs.

Cluster Number	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	1	0.000	0.000	0.000
Cluster2	4	13737.500	52.024	89.809
Cluster3	60	119375.871	37.907	80.653
Cluster4	35	98077.573	43.687	121.507

TABLE 3. Parameters of centroids determined by the algorithm for different clusters.

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Grand centroid
kWh	200.0000	106.2500	75.2475	36.6543	64.3366
km	750.0000	561.2500	381.8033	214.8571	334.7030

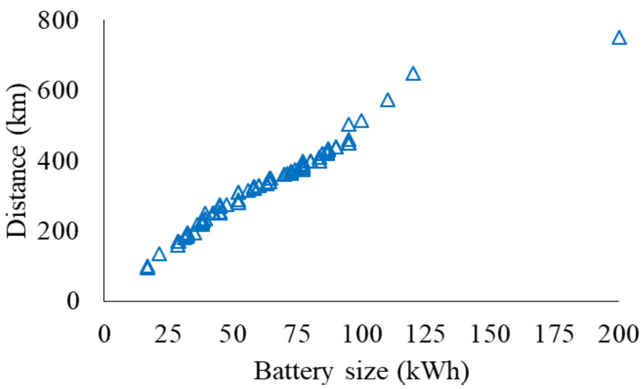

FIGURE 1. Information of battery size vs distance travelled by commercially available PEVs.

battery, the operation range of SoC, the driving range, and the total number of PEVs. Besides, data related to the market share of PEVs and the charging level of the charging stations are also considered. Information about currently available PEV at the commercial level [31], [32] is utilized and there were about 101 PEVs available, as of September 2020. It is not possible to analyze individual PEVs. Besides, several PEVs share similar features in terms of battery size and energy required to drive a distance of 1km (mileage per km), as shown in Fig. 1. After analyzing the data of Fig. 1, it can be concluded that four clusters will be sufficient to group different PEVs without losing the generality. Therefore, the PEVs are divided into four clusters (C1, C2, C3, and C4) using the K-means clustering algorithm. The data generated using the K-means algorithm for each cluster are shown in Table 2. A summary of the K-means algorithm is presented as following, details can be found in [33].

- A target number k is decided, which refers to the number of centroids in the dataset and is also equal to the number of desired clusters.
- The sum of squares (distance) is calculated for every data point and is allocated to each of the clusters in such a way that the distance is minimized.
- The K-means algorithm allocates every data point to the nearest cluster while keeping the centroids as small as possible.

The two variables used for the clustering of PEVs are the energy of the PEV battery (kWh) and the mileage of the PEVs (km). The centroids of the four clusters and the grand cluster for these two variables are shown in Table 3.

It has been noted in [34]–[36] that majority of the vehicle owners prefer to charge their PEVs in the home rather than in public charging stations. In the residential sector, generally, level 1 and level 2 charging stations are used (SAE J1772 standard). Therefore, in this study also, these two charging levels are considered to estimate the load profiles of PEVs, details about power, voltage, and current of each level are given in [35]. An overview of the proposed scheme for determining the per unit PEV load profiles is shown in Fig. 2.

After receiving the input data related to PEV owners and data related to PEVs, load profiles of individual PEVs are determined, according to Algorithm II, which is discussed in the next paragraph. Using the load profile of individual PEVs (P_t^v), the load demand of the PEV fleet (P_t^{fleet}) is determined using the following equation. This equation can be used to compute the hourly load of the entire PEV fleet.

$$P_t^{fleet} = \sum_{v \in NV} P_t^v \quad \forall t \in T \tag{1}$$

This process is repeated for each scenario (s) and convergence in the load profile is computed using the recorded (stored) profile of PEVs till scenario s. If the addition of a new scenario does not change the estimated profile (the error is lesser than a pre-defined threshold (ε)), the process is terminated and the final profile for unit PEV is determined. Otherwise, the process is repeated by adding a new scenario.

The load profile of individual PEVs is determined as explained in Algorithm II. After getting the information on the total number of PEVs, a random number in the range of 0 and 1 is generated and daily mileage is determined using the driven mileage cumulative distribution function (CDF). The SoC of vth PEV (SoC^v) is determined using Equation (2). Where (R^v) is the range of vth vehicle and (M^v)

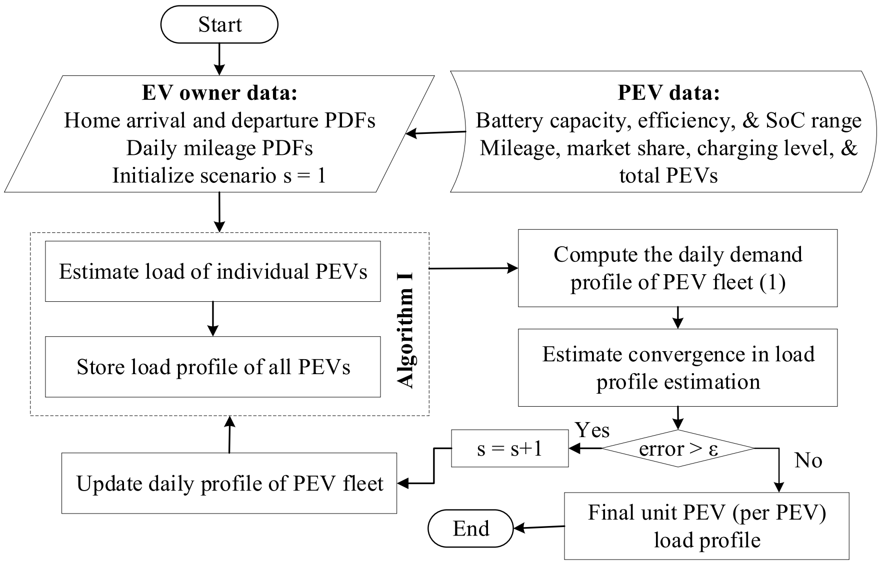

FIGURE 2. Flowchart for estimation of unit (per PEV) load profile.

is the daily miles driven by each PEV. It implies that SoC linearly decreases with an increase in the daily miles driven by the vehicle.

$$SoC^v = \begin{cases} 20\% \\ \left(\dfrac{R^v - M^v}{M^v}\right) \cdot 100 \end{cases} \quad \forall v \in NV \tag{2}$$

If the SoC is within the defined bounds, the required charging energy (E^v) and charging duration (D^v) of PEV is determined using Equations (3) and (4), respectively. Initially, the required energy is computed using (3) and then based on the required energy, the number of intervals required for charging that energy is computed using (4).

In Equation (3), B^{cap} is the capacity of the PEV battery in kWh. In Equation (4), η^v is the efficiency of the PEV battery and L^{ch} is the charging level of the charging station.

$$E^v = \left(SoC^{\max} - SoC^v\right) \cdot B^{cap} \quad \forall v \in NV \tag{3}$$

$$D^v = \frac{E^v}{\eta^v \cdot L^{ch}} \quad \forall v \in NV, ch \in [1,2] \tag{4}$$

Then, two random numbers in the range of 0 and 1 are generated, one each for the arrival and departure time of PEV. Arrival time is estimated using the arrival time CDF and departure time is estimated using the departure time CDF. By using the arrival and departure time information, the stay duration (SD) of PEV is computed in the next step.

If stay time is longer than the charging duration, the PEV is charged until its SoC reaches the upper limit at the charging rate of the charging station, as given by (5). If the stay time is lesser than the charging duration, PEV is charged until its departure, as given by (6). In these equations AT represents arrival time, DT represents departure time, and DV represents the total number of intervals required for fully charging the EV.

$$P_t^v = L^{ch} \quad \forall t \in [AT, \ldots AT + D_v\text{-}1] \tag{5}$$

$$P_t^v = L^{ch} \quad \forall t \in [AT, \ldots AT + DT\text{-}1] \tag{6}$$

III. RESULTS AND ANALYSIS

A. TEST DATA

The input data utilized for determining the PEV load in this study is the NHTS survey data [27], which comprises 1,048,576 households and 309,164 vehicles and provide information on the driving pattern of different vehicle owners. The data is pre-processed to remove erroneous and unrealistic results by filtering PEVs with incomplete information or duplicate results. Similarly, the data were filtered to include only four classes of vehicles: passenger cars (light, compact, medium, heavy); sport utility vehicles; pickup trucks; and vans. Hence, the resulting data group comprises approximately 350,000 usable households and 150,000 vehicles. The two commonly used charging levels used in the residential sector, i.e. level 1 (120V, 12A, 1.44kW) and level 2 (240V, 30A, 7.2kW) are used in this study. Similarly, the four clusters of PEVs, as described in section II, are considered in this study for simulations.

B. ESTIMATION OF TRAVELING PARAMETERS

In this section, parameters related to the daily traveling of PEVs are estimated using the filtered data of NHTS, as discussed in the previous section. The parameters discussed in this section are the arrival time, departure time, and the daily mileage traveled by PEVs. These parameters are used to estimate the per unit load profile of PEVs considering different charging levels and different types of vehicles, which are discussed in the next section.

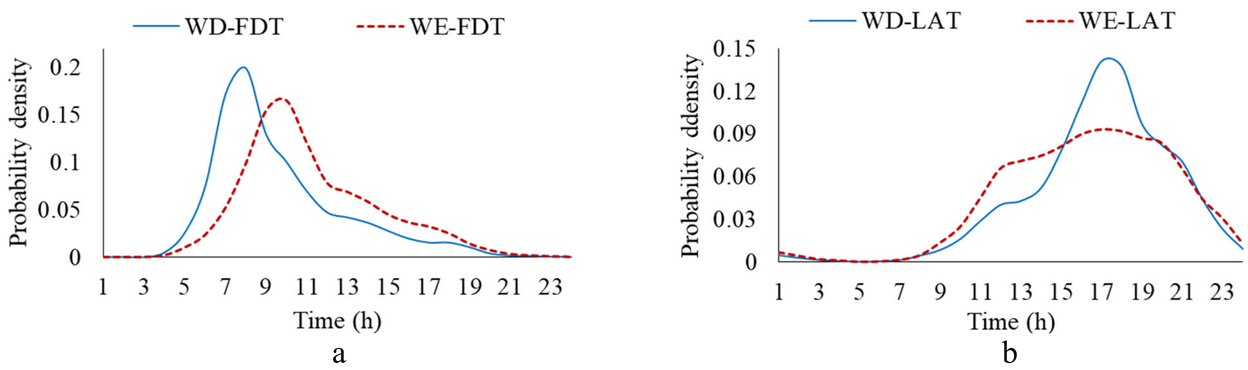

FIGURE 3. The probability density function of PEVs: a) first departure time; b) last arrival time.

Algorithm 2: Load Profile Estimation for Each Scenario

1: Get information on the total number of PEVs (NV).
2: **for all** $v \in NV$ **do**
3: Generate a random number in the range [0,1]
4: Estimate daily mileage using driven mileage CDF
5: Compute SoC using (2)
6: **If** $SoC^{\min} \leq SoC^{v} \leq SoC^{\max}$ **then**
7: Compute charging energy (E^{v}) using (3)
8: Compute charging duration (D^{v}) using (4)
9: Generate a random number [0,1] and estimate arrival time of PEV using arrival time CDF
10: Generate a random number [0,1] and estimate the departure time of PEV using departure time CDF
11: Calculate stay duration (SD): arrival & departure time
12: **If** $SD \geq CD$ **then 1**
13: Estimate load profile using (5)
14: **else**
15: Estimate load profile using (6)
16: **end if**
17: Send load profile information of PEV to figure 2
18: **else**
19: v=v+1, repeat from step 3.
20: **end if**
21: **end for**

1) ESTIMATION OF ARRIVAL AND DEPARTURE TIMES

Fig. 3 shows the probability density functions of FDT and LAT of PEVs on weekdays (WD) and weekends (WE). It can be observed from Fig. 3a that the first departure time of PEVs from home is concentrated around 7 am, which is reasonable since most of the vehicles leave home at that time for work. Similarly, the FDT for weekends is shifted towards 10 am, which is also realistic, as most people tend to go out late on weekends as compared to the weekdays. Fig. 3b shows that most of the vehicles return home around 4 to 7 pm on weekdays while return time on weekends is dispersed between 12 pm to 9 pm. This result is also realistic since most of the people start arriving home from work between 4 pm to 7 pm on weekdays. Similarly, on weekends some people tend to stay outside till late while others tend to come back home early. In order to assure the reproducibility of results, the numerical data related to LAT and FDT of vehicles during weekdays and weekends are tabulated in Appendix (Table 6).

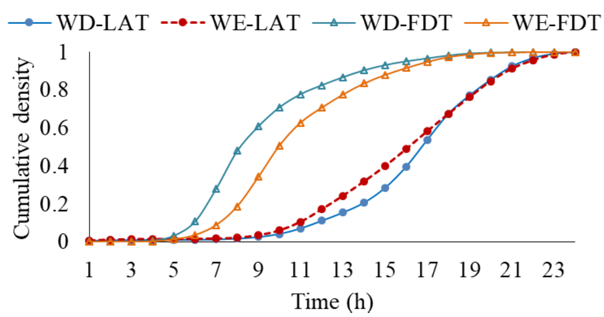

FIGURE 4. The cumulative density function of PEVs arrival and departure times.

The CDF of all four parameters is shown in Fig. 4 and it can be observed that about 80% of the vehicles leave their homes till 11 am on weekdays and a steep increase can be observed between 7 am and 9 am. In the case of weekends, the steepness of the departure curve is lower as compared to the weekdays and the rise starts later and reaches 80% around 1 pm. In the case of arrival time, the steepness of the weekend curve is higher than the weekdays between 11 am and 5 pm. The lower steepness of the weekdays' curve is due to the lesser number of people returning home during noon or afternoon on weekdays as compared to the weekends. From 6 pm onwards, both the curves follow a similar pattern and 80% of the vehicles return to their home around 9 pm.

2) ESTIMATION OF DAILY MILEAGE

Fig. 5 shows the histograms of daily mileages (in percentage) traveled by PEVs during weekdays and weekends. It can be observed that most of the vehicles travel in the range of 5 to 30km and is the same for both weekdays and weekends. It is

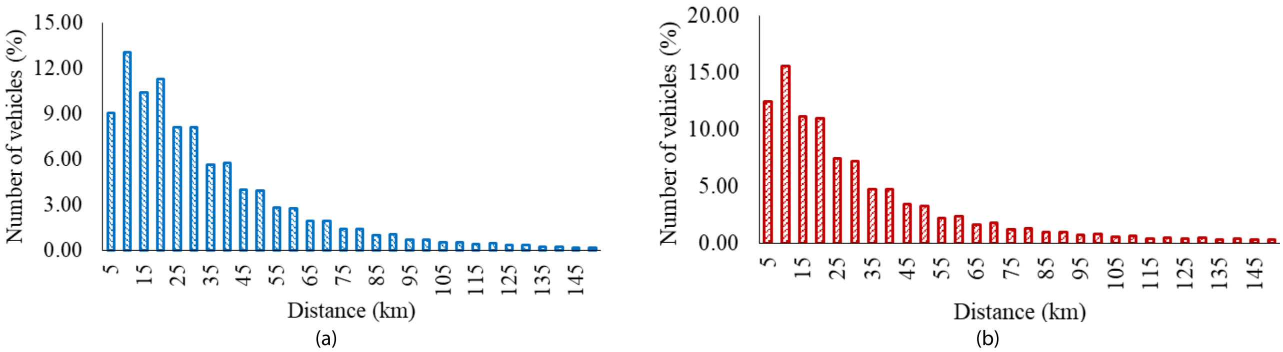

FIGURE 5. Daily mileage histograms of PEVs: a) weekdays; b) weekends.

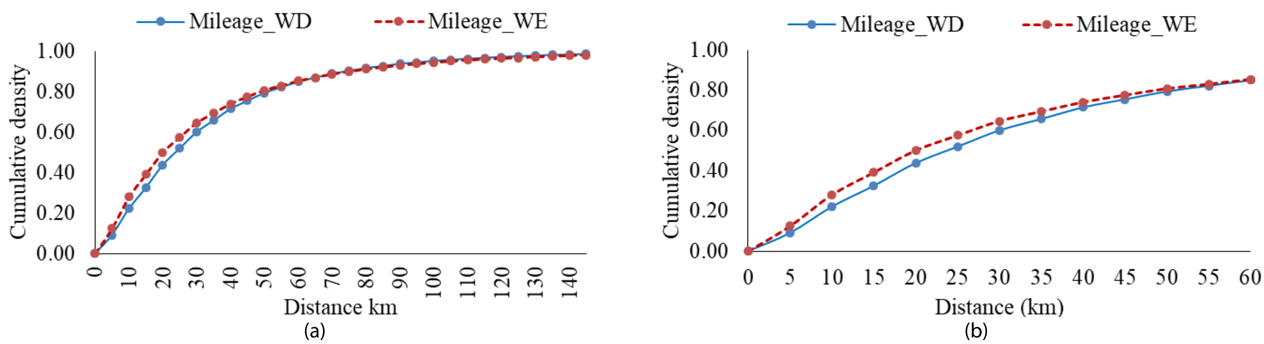

FIGURE 6. Cumulative density function of PEVs daily mileage: a) total range; b) truncated range.

interesting to note that on weekends a larger fraction of vehicles travels lesser than 20km as compared to weekdays. This might be due to the traveling of more commercial vehicles during weekdays, which tend to travel more as compared to private vehicles. Similarly, in both cases, a minute number of vehicles travel more than 70km, which implies that most of the vehicles do not need a recharge during the same day. Since the size of the batteries in most of the PEVs is sufficient to travel up to 100km with a full recharge. This also supports the fact that most vehicle owners prefer to recharge their PEV at their homes as compared to commercial charging stations.

Fig. 6 shows the cumulative distribution of daily distance covered by vehicles during a day. It can be observed from Fig. 6a that less than 1% of the vehicles travel more than 100km in a day. In order to show the difference in traveling patterns during weekdays and weekends, the lower range (0 to 60km) is truncated and shown in Fig. 6b. Fig. 6b shows that more than 85% of the vehicles travel lesser than 60km per day. The average mileage of PEVs is about 189W/km [33] considering different PEV models available in the market in 2020. It implies that PEVs with a useable energy capacity of 11.34kWh could fall into 85% of PEVs that travel less than 60km and still do not need a second recharge on the same day. Similarly, PEVs with a usable energy capacity of 18.9kWh or higher can travel about 100km a day without a second recharge, which comprises 99% of the vehicles, according to the data of NHTS. In order to assure the reproducibility of results, the numerical data related to the daily traveling distance of vehicles during weekdays and weekends are tabulated in Appendix (Table 7).

3) ESTIMATION OF PER-UNIT LOAD PROFILES

The load profiles of all the four clusters of PEVs (C1, C2, C3, C4) considered in this study with different charging levels (level 1 (L1) and level 2 (L2)) are shown in Table 4 and Table 5. It can be observed from Table 4 that the load increases from noon onwards and reaches a peak around 6 pm to 9 pm for all the vehicles during weekdays while the peak on weekends is around 7 pm to 10 pm. This behavior is reasonable since most of the PEVs return home early evening on weekdays and the return time tends to be elongated on weekends. In the case of level 1 charging, PEVs keep charging for several hours due to the lower power rating of the charger. Therefore, the load profiles in this case (Table 4) are more flattened, and charging continues till early morning on the following day.

Table 5 shows the load profiles of all the four clusters (C1, C2, C3, C4), considered in this study, with level 2 charging stations. It can be observed from Table 5 that the load increases from 3 pm onwards and reaches a peak around 6 pm weekdays while the peak on weekends is between 2 pm to 10 pm. In contrast to the level 1 charging profiles, the level 2 charging profiles are more concentrated in the late evening hours and the load during early morning hours is

TABLE 4. Per unit load profiles of PEVs with level 1 charging stations in kW.

Time interval	Weekdays				Weekends			
	C1	C2	C3	C4	C1	C2	C3	C4
1	0.501771	0.326282	0.343869	0.285355	0.440181	0.298216	0.312821	0.265253
2	0.432523	0.265971	0.282091	0.228301	0.382917	0.248272	0.261783	0.218195
3	0.371318	0.215963	0.230975	0.182097	0.331595	0.206412	0.21867	0.178945
4	0.318149	0.175433	0.188881	0.145456	0.288033	0.171994	0.183024	0.147126
5	0.271972	0.142514	0.153974	0.116048	0.250064	0.143203	0.153171	0.1208
6	0.233532	0.116612	0.126786	0.093623	0.218543	0.120299	0.129545	0.100066
7	0.202468	0.097134	0.106058	0.077272	0.193546	0.103101	0.111742	0.084566
8	0.180632	0.086001	0.093945	0.068479	0.176422	0.093509	0.101353	0.076561
9	0.168056	0.082651	0.090059	0.067271	0.173881	0.097513	0.104779	0.081997
10	0.168255	0.091109	0.097756	0.077295	0.187269	0.115705	0.121955	0.100871
11	0.186932	0.116412	0.12244	0.103314	0.226647	0.157805	0.164354	0.142691
12	0.219388	0.152878	0.158962	0.140172	0.289158	0.21969	0.226117	0.204061
13	0.253236	0.186534	0.192883	0.173246	0.349052	0.275698	0.281861	0.25776
14	0.294105	0.226837	0.233371	0.211985	0.40474	0.324248	0.330495	0.303749
15	0.366083	0.295307	0.30289	0.278837	0.459011	0.370508	0.378647	0.347984
16	0.475527	0.398277	0.407181	0.379485	0.516082	0.419933	0.428968	0.394419
17	0.615054	0.524891	0.53526	0.502191	0.569569	0.464316	0.475486	0.435568
18	0.731825	0.623791	0.63565	0.594917	0.614408	0.498222	0.510297	0.466405
19	0.774675	0.645968	0.660591	0.610789	0.644542	0.519034	0.531082	0.484186
20	0.786432	0.638496	0.655782	0.598275	0.664739	0.529797	0.543612	0.494005
21	0.77827	0.615105	0.633193	0.571198	0.657741	0.514574	0.529789	0.47699
22	0.73231	0.558531	0.577384	0.511947	0.621284	0.473455	0.489335	0.435356
23	0.661841	0.481507	0.500979	0.436162	0.571043	0.421803	0.437826	0.384748
24	0.579503	0.398941	0.417697	0.355732	0.504442	0.357444	0.372689	0.321903
Total	10.30386	7.463145	7.748656	6.809449	9.734907	7.144751	7.399402	6.52421

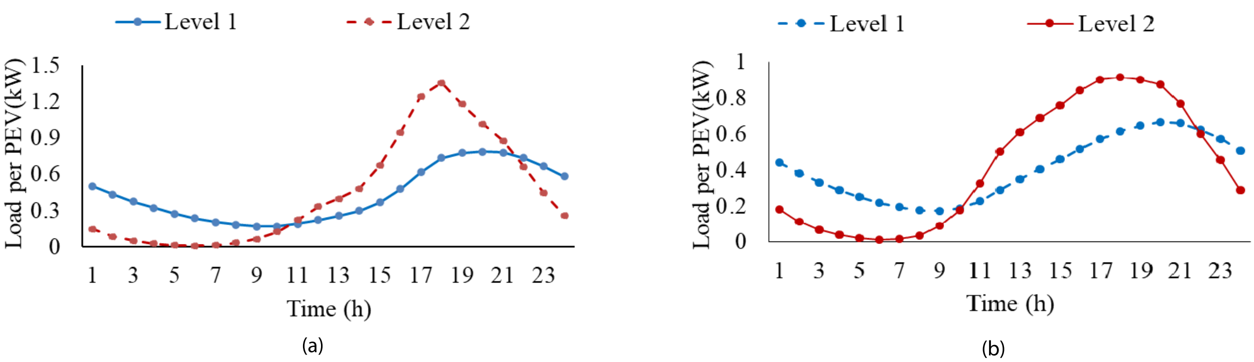

FIGURE 7. Per unit load profile of C1 vehicles with different day types: a) weekday1; b) weekend 2.

negligible. The same effect can be observed for both weekdays and weekends and this is due to the higher rating of level 2 chargers. Due to the higher rating of level 2 chargers, PEVs are charged just after they arrive and require lesser time as compared to the level 1 charging stations.

It is interesting to notice that in both the cases (L1 and L2), the total daily load of C3 vehicles is higher than the C2 vehicles, even though the battery size of C2 vehicles is higher than the C3 vehicles. This difference is due to the mileage efficiency of PEVs, i.e. the energy required to travel one km of distance in C2 (0.197) is higher than that of C3 (0.187). Due to this difference, the amount of energy consumed by C3 vehicles is higher than those of C2 vehicles and thus needs more energy. In addition, as it is evident from the daily mileage profile that most of the PEVs do not travel more than 60km daily. Therefore, the energy required by PEVs (on daily basis) will be more influenced by per km mileage efficiency. It implies that only battery size is not the deciding factor in determining the load, which could be general thinking.

In the following section, the estimated per-unit PEV load profiles are utilized to estimate the peak PEV load of the top four countries with the highest penetration of PEVs. The peak load is estimated for both weekdays and weekends considering the future outlook of PEV penetration.

TABLE 5. Per unit load profiles of PEVs with level 2 charging stations in kW.

Time interval	Weekdays				Weekends			
	C1	C2	C3	C4	C1	C2	C3	C4
1	0.146913	0.068186	0.074535	0.055485	0.180609	0.091025	0.09974	0.075894
2	0.08421	0.037382	0.041036	0.029586	0.113195	0.052548	0.057907	0.043373
3	0.047272	0.019089	0.020752	0.015093	0.066451	0.026691	0.029942	0.02205
4	0.025847	0.009877	0.0107	0.008164	0.037979	0.014047	0.015956	0.011719
5	0.011792	0.003719	0.004242	0.002878	0.018834	0.005947	0.006677	0.004704
6	0.007848	0.003678	0.004107	0.003145	0.010767	0.004288	0.00471	0.003117
7	0.010958	0.008122	0.00831	0.007598	0.013119	0.008611	0.008909	0.007533
8	0.030727	0.02527	0.025958	0.024038	0.032463	0.025059	0.026075	0.023281
9	0.062668	0.050986	0.052107	0.047854	0.087449	0.072165	0.073632	0.066911
10	0.121562	0.097971	0.101306	0.091569	0.175184	0.138719	0.144124	0.13196
11	0.220723	0.179019	0.180666	0.166318	0.324202	0.258625	0.26551	0.243713
12	0.330996	0.261363	0.267243	0.240084	0.499896	0.396086	0.407267	0.369497
13	0.397714	0.303612	0.310562	0.277671	0.608725	0.467702	0.481381	0.435013
14	0.47972	0.362412	0.37097	0.329896	0.684679	0.513417	0.531587	0.471819
15	0.669082	0.512657	0.528154	0.472966	0.757374	0.560603	0.580346	0.512931
16	0.944397	0.731979	0.751629	0.676308	0.838381	0.616634	0.638874	0.562725
17	1.242667	0.948913	0.980407	0.875772	0.898527	0.65162	0.674519	0.594685
18	1.353642	1.000437	1.041274	0.917127	0.915047	0.657153	0.683696	0.600529
19	1.179015	0.820711	0.857136	0.738249	0.900882	0.637286	0.664433	0.579199
20	1.0145	0.684401	0.716657	0.616764	0.872562	0.614433	0.63983	0.556917
21	0.874129	0.58361	0.60786	0.519745	0.765266	0.525095	0.545514	0.471949
22	0.659733	0.418005	0.434677	0.366073	0.600247	0.394596	0.412333	0.351526
23	0.44235	0.255781	0.269327	0.220981	0.452872	0.285846	0.301869	0.250931
24	0.257863	0.133295	0.142942	0.111021	0.289826	0.163914	0.177043	0.139177
Total	10.61633	7.520475	7.802558	6.814385	10.14453	7.18211	7.471874	6.531152

In order to visualize the per unit load profile of PEVs, the profile of the C1 is shown in Fig. 7 as an example for both level 1 and level 2 chargers. It can be observed from Fig. 7 that the load profile starts increasing from 11 am and also that the load profile starts increasing from 11 am and also the load from the previous day can be seen in the early hours (1 am to 5 am) for level 1 charger. In the case of the level 2 charger, the load profiles resemble the arrival time PDF, which is shown in Fig. 7a for weekdays and Fig. 7b for weekends. Due to the higher power rating of the charger, the load profiles in the case of level 2 follow the vehicle arrival time for both weekdays and weekends. However, in the case of level 1 charging, the load is distributed throughout different intervals of the day due to the requirement of more time for charging.

The per-unit (per PEV) load profiles estimated in this study are realistic and ready-to-use for researchers, policymakers, and planners related to PEVs. The profile data for the PEV fleet can be computed by multiplying the number of PEVs of that category with the corresponding PEV's load profile and by summing different clusters of PEVs. For example, if a fleet contains a number of C1, b number of C2, and c number of C3 vehicles, then the load profile of the fleet can be computed by using the following equation. Where, P_t^{fleet} is the load of the PEV fleet while P_t^{C1}, P_t^{C2}, P_t^{C3} are the per PEV profiles of C1, C2, and C3, respectively as given in Tables IV and V.

$$P_t^{fleet} = a.P_t^{C1} + b.P_t^{C2} + c.P_t^{C3} \tag{7}$$

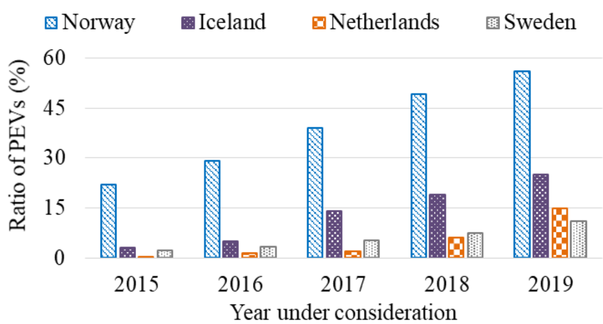

FIGURE 8. Top four counties with highest percentage of PEVs.

IV. LOAD ESTIMATION AND ANALYSIS

The developed per unit PEV load profiles can be utilized to estimate the daily loads of different countries/regions. These estimated load profiles can show the PEV peak load hours and system operators can prepare/manage the system accordingly. In this section, four countries, based on maximum PEV penetration percentages, are selected for analyzing their PEV peak loads using the PEV penetration outlook data. The top four countries with the highest penetration percentage (relative to the total number of vehicles) are Norway, Iceland, Netherlands, and Sweden [37]. The percentage of PEVs from the year 2015 to 2019 for these four counties is shown in Fig. 8. The historic data can be used to estimate the future penetration levels of PEVs in these countries.

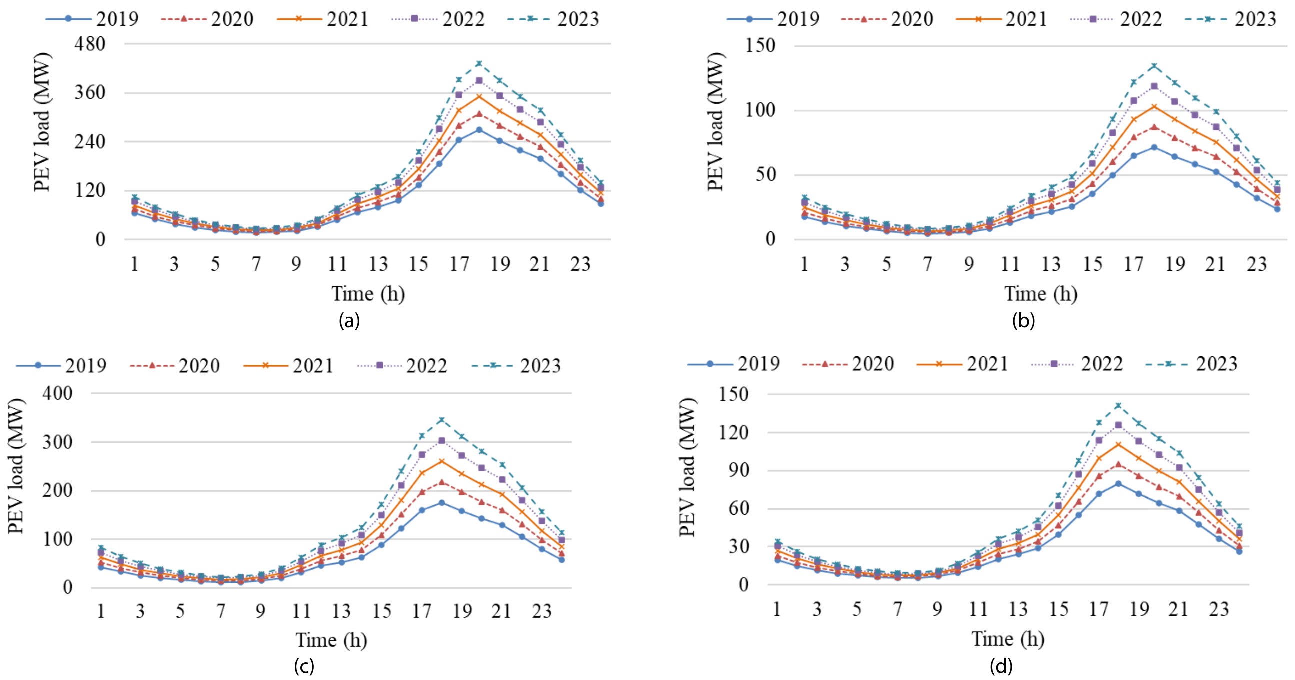

FIGURE 9. Estimated load profile of PEV load during weekdays: a) Norway; b) Iceland; c) Netherlands; d) Sweden.

Equation (7) can be utilized to estimate the hourly load of PEVs in each country during different hours of the day on weekdays and weekends. The data on the total number of PEVs in each country is taken from [12] and [37] and projections are based on the history data. The total number of PEVs is divided into four clusters as described in Table 3. For example, 1% of EVs in cluster 1, 5% in cluster 2, 60% in cluster 3, and 34% in cluster 4. It also assumed that 50% of the residential charging stations in each country are level 1 and 50% are level 2. Based on these considerations, the daily PEV load is estimated for the next 4 years for both weekdays and weekends.

Figure 9 shows the estimated load profile of PEVs in the four selected countries where data of 2019 is real load while remaining is projected load, based on the history data. It can be observed that the overall trend for all the countries is similar due to consideration of similar factors such as the percentage of EVs in different clusters and the percentage of level 1 and level 2 chargers. However, the magnitude of load in different countries is different. For example, the peak load of Norway in 2023 is projected around 430MWh while that of Iceland and Sweden is around 150MWh. It can be observed that the peak in Norway and Netherlands are similar despite a higher percentage of PEVs in Norway, which is due to the higher number of total vehicles (PEVs and internal combustion engine vehicles) in the Netherlands. The same is the case with Iceland and Sweden, where Iceland has a higher penetration of PEVs while Sweden has a higher number of total vehicles.

Figure 10 shows the daily PEV load profiles of the four selected countries. Similar to Fig. 9 the magnitude of peak load in each country is different although the overall load profile is similar, primarily due to consideration of the same factors for all four countries. It can be observed that the peak load of the weekends is lower than the peak load of weekdays in all the cases, which aligns with the normal traveling behavior of PEVs.

TABLE 6. Arrival and departure time PDFs of vehicles.

Time interval	Last arrival time		First departure time	
	Weekday	Weekend	Weekday	Weekend
1	0.004694	0.006799	0.000130	0.000052
2	0.002865	0.004263	0.000130	0.000104
3	0.001428	0.001909	0.000174	0.000157
4	0.000784	0.001072	0.005084	0.001905
5	0.000131	0.000183	0.026150	0.010205
6	0.000496	0.000418	0.074971	0.023569
7	0.001385	0.001543	0.172240	0.052202
8	0.004529	0.004760	0.199492	0.098792
9	0.008569	0.013651	0.129284	0.154934
10	0.016286	0.024948	0.100488	0.165505
11	0.029087	0.045294	0.069453	0.120560
12	0.040252	0.066084	0.047251	0.078381
13	0.042969	0.071210	0.042071	0.068854
14	0.052192	0.074924	0.036405	0.058518
15	0.078440	0.081435	0.027694	0.044998
16	0.111760	0.090091	0.019721	0.036619
17	0.141292	0.093517	0.015461	0.032261
18	0.137277	0.092262	0.015496	0.025005
19	0.096903	0.087502	0.010568	0.014094
20	0.082011	0.083815	0.003991	0.007360
21	0.070350	0.065927	0.001709	0.003210
22	0.043962	0.044536	0.001284	0.001644
23	0.023105	0.030806	0.000547	0.000835
24	0.009231	0.013050	0.000208	0.000235

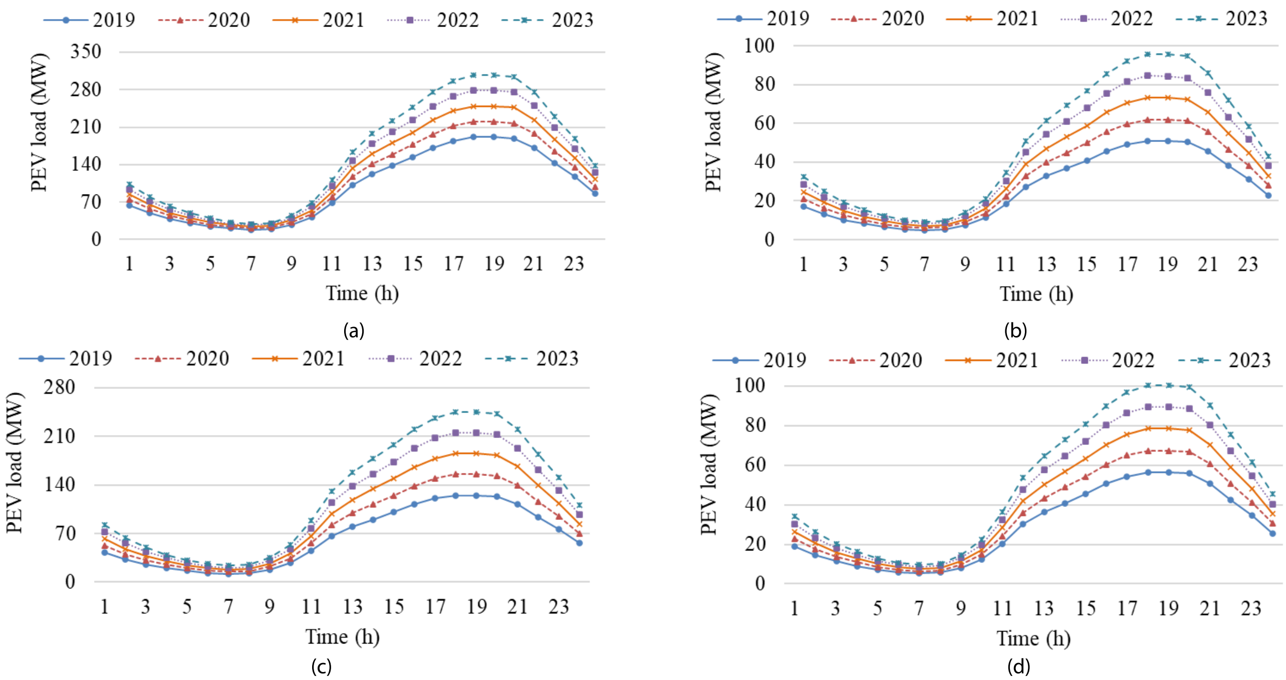

FIGURE 10. Estimated load profile of PEV load during weekends: a) Norway; b) Iceland; c) Netherlands; d) Sweden.

TABLE 7. Percentage of vehicles with corresponding daily traveling distance.

Distance (km)	5	10	15	20	25	30	35	40	45	50
Weekdays (%)	9.07	13.05	10.39	11.28	8.15	8.10	5.68	5.77	3.99	3.93
Weekend (%)	12.44	15.55	11.10	10.94	7.46	7.15	4.74	4.71	3.44	3.26
Distance (km)	55	60	65	70	75	80	85	90	95	100
Weekdays (%)	2.81	2.78	1.98	1.94	1.42	1.42	1.02	1.07	0.70	0.75
Weekend (%)	2.21	2.35	1.64	1.76	1.20	1.23	0.96	0.95	0.66	0.77
Distance (km)	105	110	115	120	125	130	135	140	145	150
Weekdays (%)	0.53	0.55	0.41	0.46	0.34	0.36	0.25	0.25	0.19	0.21
Weekend (%)	0.53	0.61	0.35	0.44	0.37	0.42	0.29	0.36	0.25	0.30
Distance (km)	155	160	165	170	175	180	185	190	195	200
Weekdays (%)	0.16	0.15	0.15	0.12	0.11	0.10	0.09	0.09	0.07	0.10
Weekend (%)	0.21	0.21	0.15	0.19	0.11	0.19	0.12	0.11	0.13	0.17

This is an example of how the estimated per-unit PEV load profiles can be utilized to analyze the present and future peak loads of PEVs in different countries and regions. Researchers and policymakers can use the local parameters to estimate more realistic load profiles. In addition, these estimates can be utilized for planning the future infrastructure related to PEVs, i.e. location, size, and type of charging stations along with up-gradation of transmission/distribution lines and transformers.

V. CONCLUSION

Per-unit PEV load profiles are estimated in this study considering different realistic factors and underlying uncertainties. The developed profiles are based on different parameters related to PEVs, charging infrastructure, and traveling pattern of vehicle drivers and a huge database (NHTS) has been utilized. The estimated load profiles are utilized to estimate the peak PEV load in the top four countries with the highest penetration percentage of PEVs. PEV future outlook data is utilized to estimate the future PEV peak loads in the four selected countries during both weekdays and weekends. Simulation results have shown that developed profiles can be easily utilized for estimating load profiles of PEV in different countries and regions with current and future penetration levels of PEVS.

It can be concluded that the developed ready-to-use load profile of PEVs estimated in this study can save the time and efforts of researchers and planners in the PEV industry. Researchers and planners can take the developed profiles and estimate the load of the whole PEV fleet by considering the number of PEVs in each category. It was observed that most of the vehicles (about 85%) travel less than 60km daily and most of the PEVs do not need a second recharge on the same day. Similarly, the per-unit hourly load profiles of all the four

PEV clusters, considered in this study, are tabulated to make them ready-to-use for researchers and planners.

APPENDIX RESULTS OF TRAVELING PARAMETERS

See Tables 6 and 7.

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