3 Goodness-of-Fit Probabilistic Models for EV Charging in Caribbean Small Island States

L. M. Addison, G. A. Hosein, S. Bahadoorsingh and C. Sharma

in:

Towards Sustainable Transport and Mobility

Perspectives on Travelling and Commuting in Small Island States

Edited by Julia R. Kotzebue

pp. 47–63

Hamburg University Press
Verlag der Staats- und Universitätsbibliothek Hamburg
Carl von Ossietzky

Imprint

Bibliographic information published by the Deutsche Nationalbibliothek

The Deutsche Nationalbibliothek (German National Library) lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at https://portal.dnb.de abrufbar.

ONLINE VERSION

The online version is available online for free on the website of Hamburg University Press (open access).The Deutsche Nationalbibliothek stores this online publication on its Archive Server. The Archive Server is part of the deposit system for long-term availability of digital publications (https://portal.dnb.de).

DOI https://doi.org/10.15460/hup.261.1999

ISBN

Print: 978-3-943423-96-9

Book typsetting Hamburg University Press

Cover design Hamburg University Press using a photo by Florian Göttsche (2022)

Printing house Books on Demand (Norderstedt)

Publisher

Hamburg University Press, publishing house of the State and University Library Hamburg Carl von Ossietzky, Hamburg (Germany), 2022

https://hup.sub.uni-hamburg.de

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Globally, the impact of fossil fuel consumption on climate change has been an important topic of discussion in recent times. According to the IPCC (2019), the transportation sector accounted for 14 % of the global greenhouse emissions in 2014. In addition, the Energy Information Administration (EIA) (2019) reported that 28 % of the United States energy consumption was used for transportation, with 92 % of that being supplied by petroleum, while nearly 81 % of the energy supply of Caribbean states comes from oil products (FOCUS, 2016). Some estimates suggest Small Island Developing States (SIDS) globally would save around $3.3 billion annually if they switched all energy to renewable sources, especially in the Pacific and Indian Oceans (Atteridge & Savvidou, 2019). As a result, the use of electric vehicles (EVs) in communities is seen as a viable alternative in many regions worldwide, including the Caribbean.

Small islands are a prime market for EVs with limited road networks, high fuel costs and the need for direct grid storage solutions (Gay, Rogers, & Shirley, 2018). Many SISs also have favourable renewable energy resources, and renewable energy transition roadmaps are emerging. For instance, with minimal modifications to its infrastructure, the Caribbean island of Barbados can accommodate at least 20 % renewable energy penetration onto its grid (Gay et al., 2018). Since 2018, Barbados has been a regional leader in EV deployment in the Caribbean, where 1.28 % of their new car sales were electric, greater than in some higher-income countries, such as Canada (Prado, 2019).

Consequently, this reflects the need to adequately prepare electrical grids in SISs, based on driving patterns related to EVs. There are different types of EVs, classified by the amount of electricity used as the energy source. Battery Electric Vehicles (BEVs or most commonly EVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are two main classifications of Plug-in Electric Vehicles (PEVs). In general, PEVs have been identified as the main future alternative to conventional automobiles powered by Internal Combustion Engines

(Almutairi, Alotaibi, & Salama, 2018). This is due to the fact that they are environmentally friendly and economically efficient, since they emit significantly fewer greenhouse gases (GHGs) per kilometre driven, as well as being less costly to operate (Almutairi et al., 2018).

Despite these advantages, the electrical power system would be directly impacted by the integration of such vehicles on the grid (Darabi & Ferdowsi, 2011). Power and energy consumed by these vehicles can be variable, and frequency of connection onto the grid depends on certain characteristics associated with driving behaviour and journey requirements. In order to analyse the impact of the EVs on the power system, models of charging curves are integral to the process. It is important to consider the aggregate effects of charging EVs on the electric power system infrastructure (Louie, 2015). As such, integration of EVs within the smart grid framework requires careful analysis.

SISs endeavouring to reduce their carbon footprints would need to extensively analyse the effects of EV charging as these grids are inherently small, and small disturbances can wreak havoc on the electricity supply quality. In the first instance, since there are no available data, the use of probabilistic models of charging station loads can assist greatly in this process and predict the expected impacts on the network's asset utilisation, health of the grid and overall success of the introduction of EVs.

As such, charging management is crucial since an increase in the number of EVs increases the additional loads. This can lead to a change in SISs daily load profiles and, subsequently, an increase in the demand peak. Any change in the daily load profile can subsequently affect a utility's ability to manage generation, supply and distribution, with respect to time and grid constraints, while increasing peak demand can put a strain on existing generating capacity (Dyke, Schofield, & Barnes, 2010). The uncoordinated charging of many EVs can compromise the grid in a number of ways. Hence, there is a need to assess the strategies to coordinate EV charging using available variables.

Management of EV penetration is necessary, since uncoordinated charging can produce an unbalanced distribution network of loads, possible overloads of distribution transformers, and cables/conductors, and sudden variations in the power quality of supply. Uncoordinated charging refers to the scenario where there is no control over when EVs are charged. This scenario significantly increases the peak demand and will require upgrades to the distribution grid, especially the upgrading of the distribution transformers. It can also lead to an increase in load imbalances, possible outages, as well as current and voltage variations. The research by Calearo, Thingvad, Suzuki, and Marinelli (2019) highlights how uncontrolled distribution of single-phase charging could be responsible for local voltage disturbances. These negative effects will increase if there are no Demand Side Management (DSM) schemes (Bahadoorsingh, Meetoo, Sharma, & Hosein, 2018) to reduce or shift energy consumption from peak hours to leaner demand periods.

On the other hand, a properly designed and well coordinated Time of Use (ToU) charging scheme can provide better flexibility and reliability to the entire electrical system (Flammini et al., 2019). According to Green, Wang, and Alam (2010), factors such as driving patterns, charging characteristics (vehicle demand profiles), charging timing (the magnitude and duration of charging cycle) and vehicle penetration impact the electric network. To demonstrate the capabilities of a coordination scheme, actual data and driver behaviours need to be available to perform simulations.

However, the scarcity of available real data regarding EVs and charging stations has forced researchers to first develop probability distributions for a number of variables (Flammini et al., 2019). Further to this, Almutairi et al. (2018) expressed the need to conduct a statistical evaluation among a wide range of available theoretical probability density functions (PDFs), in order to find the best model, to reflect the random characteristics of each driver behaviour variable. It should be noted that the driving behaviour of a typical SIS citizen is not necessarily the same as a driver resident in a metropolitan area. A metropolitan area has a significantly more complex and expansive transportation network. In a metropolitan area, driving patterns on the weekdays may include journeys from residences to transportation hubs before using mass transportation to commute into cities.

In some cases, residents may choose to commute daily with their own vehicles from their suburban residence to city workplace. In the metropolitan area, weekend journeys may be longer for leisure trips or shorter on domestic errands. In SISs, such as those in the Caribbean, citizens may have limited transportation options and so may have to rely on their own transportation for the convenience of all journeys. The total distance travelled by commuters in their vehicles in these different environments can vary from location to location and the peculiarities of the local transportation landscape.

With these nuances in mind, in an effort to derive variables for a probabilistic model, one must then consider the available data. Driving range of a typical domestic user can be treated as an estimation since the only data available are the sales of fuel. Fuel sales only may translate into an estimate of total distance travelled and it is very challenging to obtain driving route (freeways vs collector roads) and times (weekdays vs weekends, day vs night) as well as modes (eco-mode vs sport-mode) which are indicators of the energy consumed for individual users. In order to disaggregate this into the range of a typical driver, this can only be done in the first instance by using statistical inferences to determine when recharging should be required. Also, with the "novelty" of EVs in the market, it is postulated that most users would, in the first instance, plug on to recharge their EV once the user arrives home. As such, Louie (2015) and Flammini et al. (2019) use real transaction data, with probabilistic and statistical ideas, in order to assess the impact on the grids.

According to Ul-Haq, Azhar, Mahmoud, Perwaiz, and Al-Ammar (2017), addition of EVs would affect the overall load pattern of distribution networks, leading to power quality concerns such as voltage imbalances, depending on EV charging patterns over a day. The research in Ul-Haq et al. (2017) also discusses the complications in attempting to provide a deterministic quantification of the number of EV charging events per day and the associated load on the grid. The complete mobility pattern of the EV driver is an important factor, which is not always known. Hence, Yilmaz and Krein (2012) expressed that there is a need to develop a probabilistic model of EV charging to estimate an expected load in the system, leading to a power index, through which utilities can upgrade their infrastructure to support large penetration of EVs.

However, estimates of variables related to driver behaviour, such as arrival, departure times, daily mileage and so on, to characterise the PEV charging process are a challenge. Currently, there is a lack of sufficient actual data for this purpose, particularly in SISs. Therefore, the idea supported in larger countries is to use samples from transportation mobility data to estimate a PDF. The research by Almutairi et al. (2018) explains that the purpose is to not only preserve the characteristics of each variable, but to generate simulated data for further comparison. Hence, the use of PDFs is a useful way to reflect driver behaviour.

Additionally, Ul-Haq et al. (2017) develops a probabilistic model of the charging pattern for EVs associated with residential load profiles. The probabilistic model provides the activity for the residential load profiles and EV charging patterns over a period of twenty-four (24) hours. Other studies, such as Wang and Karki (2016) and Wang et al. (2015) use a theoretical PDF to provide a fit for the sample data. This gives a snapshot of the intrinsic randomness of driver behaviour variables, which is then used to generate synthetic data from the fitted PDFs. Thus, Normal and Lognormal PDFs are assumed for the variables arrival time and daily travel mileage respectively (Wang & Karki, 2016). Alternatively, Chi-square and Power law PDF are assumed for the aforementioned variables in other research (Wang, et al., 2015).

While many papers have fit PDFs for individual driver behaviour variables as previously indicated, most have not considered weekday load profiles. In order to assess the true impact of EV charging load on the local power grid, building these EV load profiles is crucial. Since the typical SIS distribution system is fed via pole-mounted transformers, the typical SIS utility maintenance procedure is to only upgrade the pole-mounted transformer after customers have complained of regular low voltage problems or if the transformer has failed. This has led to the norm being that most pole-mounted transformers are usually operating close to their nominal kVA ratings. So any step increase in loading (EV charging) would most likely drive the distribution transformer beyond its rating.

Therefore, different EV load profiles based on driver's behaviour and flexible EV charging needs can be used to analyse the effects of charging EVs on both the power grid's loading limits and voltage fluctuations. In addition, empirical load profiles for EVs using electric mobility data can provide a genuine depiction of EV loading for future planning mechanisms. This work attempts to assess which theoretical PDFs provide the best fit for weekday load curves based on aggregate residential and EV charging profiles. It provides a template for constructing and describing PDFs based on driver variables, which can be adopted in SISs. Following this overview of the current research, a brief methodology for such a scheme is also outlined.

Then, suitable Goodness-of-Fit (GoF) statistics and PDFs based on each of the load curves by day of the week are discussed. GoF implies a comparison of the observed data with the data expected under the model, using some fit statistic, or discrepancy measure, such as residuals, Chi-square or deviance (Kéry & Royle, 2016). GoF testing is a crucial element of this analysis since it assesses if the model "fits" the data in a statistical sense. These tests are used to select the best fit PDF from a list of candidate probability distributions, in order to describe the EV weekly charging data scenarios. Subsequently, the importance of such analysis for charging behaviour is discussed, followed by preliminary conclusions and recommendations. Overall, this research serves as a benchmark for future models, which can use these PDFs to assist with the implementation of EV charging control strategies for SISs, particularly in the Caribbean.

Method

The lack of actual databases of EV charging data in many regions, particularly in SISs, has been the motivation to start the first phase of a larger predictive model, for constructing various driving behaviour variable distributions from relevant travel data. This work is a PDF fitting case study using in-home plug-in EV recharging profiles for 348 vehicles. These are associated with 200 households randomly selected among those available in the 2009 Residential Consumption Survey (RECS, 2019) data for the Midwest region of the United States.

This probability sample survey enables statistical selection of households to collect energy-related data. The publicly available dataset accounts for user activity and appliance usage statistics from more than 12,000 households across the United States. These were statistically chosen to represent over 110 million household units, which included energy consumption details from each residence. Due to the lack of charging data for many SISs in the Caribbean, this methodology provides an experimental framework to generalise the weekly load scenarios, using previously existing data in the United States. This lays the groundwork for further studies in SISs to be conducted using their unique travel mobility data.

Power profiles which depict energy consumption patterns can fluctuate, and due to this randomness, the prediction of energy demand can be difficult. For these reasons, according to the work of Muratori, Moran, Serra, and Rizzoni (2013) and Muratori (2017), residential demand profiles are variable since individual household behaviour is stochastic in nature. Each PEV starts charging as soon as it is connected to the grid and remains a sink until the battery is fully charged. Therefore, there is no coordination scheme applied to the dataset. Simulation of the amount of electricity required to fully charge the battery depends on the previous trips and charging events, which are simulated using a personal energy consumption model (Muratori et al., 2013).

The profiles proposed realistic patterns of residential power consumption. These were validated using metered data, with a resolution of 10 minutes. This research also simulated various scenarios considering different PEV market shares (Muratori, 2017). In this dataset, vehicles were assumed to be 60 % BEVs with a 200-mile range and 40 % plug-in hybrid EVs PHEVs with a 40-mile all-electric range based on market trends. Both Level 1 charging (1.92 kW) and Level 2 charging (6.60 kW) were assumed in the aforementioned dataset, and the profiles represented total PEV charging demand.

In this chapter, the Level I charging dataset (PEV-L1) was used, since it is expected that most households would charge at this level. This data represented an uncoordinated charging scheme, where no control strategy was applied to deal with daily demand. The electricity demand profiles for the 200 households (without EV charging) were mapped to the total EV demand within the corresponding households (since some residences have more than one EV). Then, the aggregate household load was computed using the sum of the base load and the total EV load per household. The equation for this computation is expressed as:

$$PW_{Total\,Load,i} = PW_{Resid,i} + PW_{PEV,i} \tag{1}$$

where $PW_{Total\,Load,i}$ represents the total power demand for residential load, i, and $PW_{Resid,i}$ represents the power demand associated with the residential load, i and $PW_{PEV,i}$ is the corresponding total PEV-L1 load, for that household $(i = 1,2, \dots, 200)$. The models applied here ignore seasonal variations, considering only weekday and weekend profiles.

These load profiles were used to construct weekday demand curves by time of day. Then, daily load curves were fitted using polynomial curves for each day of the week. In each case, a non-linear equation was obtained.

The form of this equation is:

$$f(x)_{fitted} = a_n x^n + \dots + a_2 x^2 + a_1 x + a_0 \qquad (2)$$

where a_k represents the fitted model co-efficient of x_k, the variable ‘time of day (hrs.)’, for $k = 0,1, \dots , n$. In this work, a 5th order polynom‘al is used $(k = 5)$ ’or the best fit.

For each day of the week, GoF statistics‘were generated to ’escribe the overall fit of the model to the original data based on differences between observed and predicted values. The coefficient of determination, R^2, provides a measure of how well the fit explains the variation in the data. Root Mean Squared Error (RMSE) provides a relative measure of the fit, that is, how concentrated the data is around the line or curve of best fit. Let y_i be the true response for the i^{th} observation and $\hat{y}_i$ be the corresponding predicted response. The RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (3)$$

Lower values of the RMSE closer to 0 indicate a better fit.

Then, aggregate load curves categorised by weekday and weekend were examined in a probabilistic sense. Polynomial curve fitting was used to generate an estimated PDF for each load curve. XLSTAT 2019, the add-in package for Microsoft Excel, which uses maximum likelihood estimation (MLE) to derive the parameters of the probability distribution, provides the best-fitting theoretical PDF for each scenario. It should be noted that these distributions were chosen from a preset database of PDFs, but there may be others which can provide a better fit.

It is necessary to conduct a GoF test to check whether the observed data follows the specified distribution. The Kolmogorov-Smirnov (K-S) test is a nonparametric test which compares the empirical (actual) cumulative distribution function (CDF), say $G(x)$ to the theoretical CDF, say $F(x)$. The K-S Statistic (D) computes the largest difference between the two functions for all sample values x_i, $i = 1,2, \dots n$, using the equation:

$$D = max[G(x) - F(x)] \qquad (4)$$

This statistic was used to determine if the hypothesis of interest “the observed data follow a specified distribution” was true when compared to a critical value. The significance level or p-value of this test was set to 0.05 or 5 %, and the original assertion was rejected if $p < 0.05$.

Results

The R Statistical Software (R Core Team, 2019) environment for statistical computing and graphics was used to match EVs to households to obtain the total load. Descriptive statistics, GoF, and probability plots were generated to reflect the load profiles by day of the week. These provide developers with tools for aggregate comparisons and to visualise the differences between datasets, respectively. Figure 3.1 shows the residential load without EV charging, classified by time of day and day of the week. Ignoring seasonal variations, the general trends for the days of the week were similar. Subsequently, load curves were generated to include EV charging and the GoF of these curves analysed.

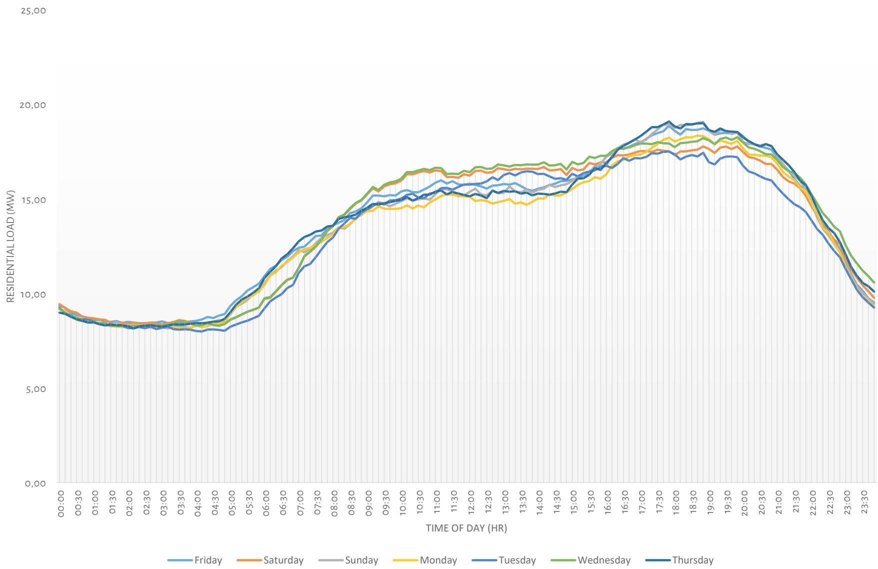

Figure 3.1 Residential Load Curves by Time of Day and Day of the Week (no EV Charging)
Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein, Addison, Bahadoorsingh, and Sharma, 2020, Caribbean Electric Industry Journal, 16, 36–39. DOI:10.47412/QZWP9167, and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison, Hosein, and Bahadoorsingh, 2020, International Conference on Emerging Trends in Engineering and Technology, (http://conferences.sta.uwi.edu/iconetech2020/index.php)

Hourly Load Curves by Day of the Week

Load curves were generated for the original uncoordinated charging scheme by day of the week, in contrast to seasonal load variations, which are most commonly examined in the literature. In order to determine the charging behaviour on a weekly basis, total load curves based on the residential consumption and additional load from daily EV charging were constructed graphically.

These are shown in Figure 3.2 where, upon initial inspection, the peak demand occurred mainly between the hours of 4 p. m. (16:00 hrs) and 10 p. m. (22:00 hrs) daily. Descriptive statistics were generated as shown in Table 3.1. The mean, ***M*** (average) and standard deviation, ***SD*** (spread of data points about the mean) can later be used as estimates of shape and scale parameters in certain PDFs. Tuesdays experienced the highest average load (19.47 MW) while Thursdays experienced the lowest (18.35 MW). The standard deviations were similar for each day, ranging from 5.32 MW to 6.07 MW.

Each load curve was best fit to a polynomial to the 5th degree. The overall fit for each curve was quite good based on the correlation coefficients, R^2 values (all close to 1) while the RMSE value was the lowest for Thursday (0.65), indicating this particular day had the best relative fit. Since the demand by day of the week was fairly similar, aggregate weekday and weekend load curves were generated and validated. The mean weekday load was 19.04 MW, slightly less than that of the weekend (19.12 MW). These load curves were examined further to find suitable theoretical PDFs to represent them.

Goodness-of-Fit to Polynomial Functions and Known PDFs

Non-linear polynomial equations were used to fit aggregate weekday and weekend load curves for this dataset. These can be used to estimate the probability of daily demand at a particular time of day. The weekend and weekday scenarios are both displayed in Figure 3.3. The PDFs of the load curves were best fit to polynomials to the 5th degree. The coefficients of the two equations were close, which indicated that the demand for weekday and weekend, even with inclusion of the use of EVs on the grid, was quite similar for this particular region. The differences in demand here were reflective of their daily residential and EV charging behaviours.

Subsequently, standard PDFs were also used to determine the distributions with the best fit. EasyFit 5.6 Professional, an add-in package in Microsoft Excel, performs GoF tests and is used to evaluate the most appropriate distribution based on the smallest K-S value compared to the critical value, which is the best fit for the data. Figure 3.4 shows the best three PDFs for the weekday load curves. The histogram represents the spread of daily load over 24 hours. The PDF known as Johnson SB (System of Distributions) was found to be the best fit (K-S = 0.0162, $p > 0.05$), followed by the Generalised Gamma (K-S =0.0277, $p > 0.05$) and then the Dagum distribution (K-S = 0.0282, $p > 0.05$), as shown in Table 3.2.

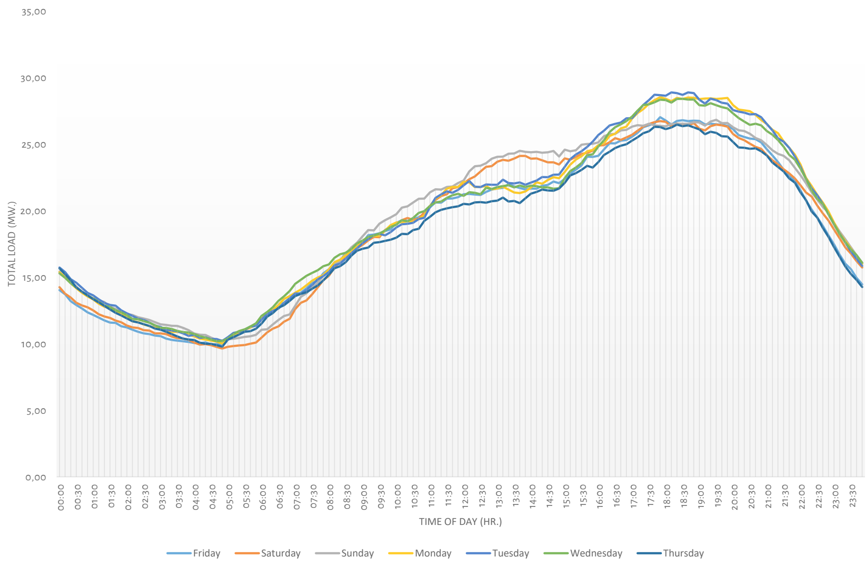

Figure 3.2 Total Load Curves by Time of Day and Day of the Week
Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein et al., 2020, Caribbean Electric Industry Journal, 16, 36–39. DOI:10.47412/QZWP9167, and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison et al., 2020, International Conference on Emerging Trends in Engineering and Technology, (http://conferences.sta.uwi.edu/iconetech2020/index.php)

In Figure 3.4, the values of the parameters are $\gamma=-0.441, \delta=0.758, \lambda=26.639$ and $\xi=-2.564$ for the Johnson SB distribution. The corresponding parameters for the Generalised Gamma are $k=146.71, \alpha=0.00917$ and $\beta=23.824$, while those for the Dagum distribution are $k=0.0068, \alpha=198.62$ and $\beta=23.766$. The shape parameters in the aforementioned distributions allow for flexibility which allows them to fit various real-life scenarios. This enables the realistic stochastic dynamics of EV charging profiles to be showcased.

Table 3.1 Descriptive and Goodness-of-Fit Statistics for Total Load Curves (MW) by Day of the Week

	MON	TUES	WED	THURS	FRI	SAT	SUN	WEEKDAY	WEEKEND
Mean	19.38	19.47	19.33	18.35	18.59	18.82	19.40	19.04	19.12
SD	6.03	6.07	5.84	5.32	5.67	5.94	5.83	5.76	5.87
Min	10.01	10.2	10.17	9.78	9.94	9.63	10.23	10.03	9.93
Max	28.50	28.86	28.37	26.44	27.00	26.70	26.80	27.75	26.62
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
RMSE	0.83	0.76	0.86	0.65	0.69	0.72	0.75	0.74	0.74
Total	0.83	0.76	0.86	0.65	0.69	0.72	0.75	0.74	0.74

Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein et al., 2020, Caribbean Electric Industry Journal, 16, 36–39. DOI:10.47412/QZWP9167, and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison et al., 2020, International Conference on Emerging Trends in Engineering and Technology, (http://conferences.sta.uwi.edu/iconetech2020/index.php)

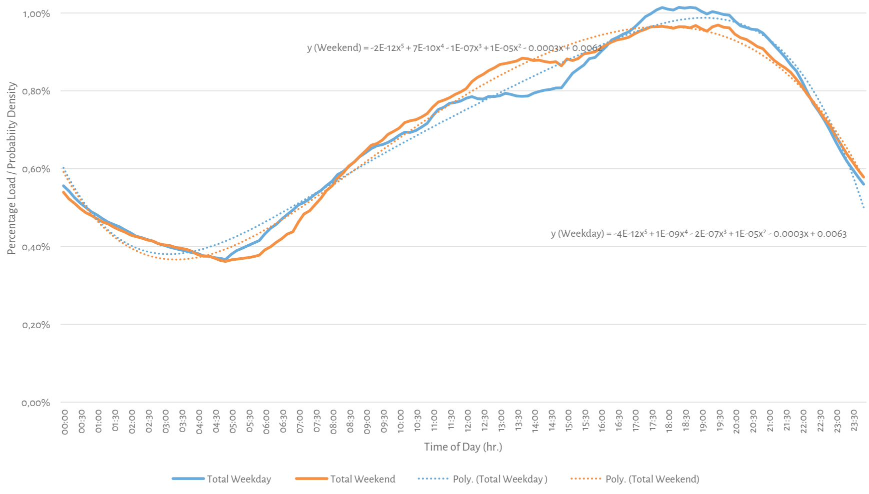

Figure 3.3 Probability Density Functions for Power Demand Curves by Weekday and Weekend
Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein et al., 2020, Caribbean Electric Industry Journal, 16, 36–39. DOI:10.47412/QZWP9167, and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison et al., 2020, International Conference on Emerging Trends in Engineering and Technology, (http://conferences.sta.uwi.edu/iconetech2020/index.php)

The PDFs in Table 3.2 can be used to generate the uncoordinated charging power demand, ***f(x)***, at a certain charging time, ***x***. The advantage of these 'best' fitting PDFs is the additional shape parameters which provide a more realistic fit than popular PDFs such as the Normal and Weibull. This can be repeated for the weekend scenario also. In this way, random characteristics of the data can be preserved and EV charging load profiles can be easily estimated using these equations. Although known PDFs can be fitted as shown, polynomial curve fitting also provides a feasible technique to provide a close fit for such analysis. This flexibility is essential for further predictive demand analysis.

Table 3.2 Top Three Best Fitting PDFs for Weekday Load Curve

PROBABILITY DISTRIBUTION	PDF	K-S STATISTIC	P-VALUE
Johnson SB	$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}z(1-z)} \exp\left(-\frac{1}{2}\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)^2\right)$, $\xi < x < \xi + \lambda; \quad -\infty < \gamma, \xi < \infty; \delta > 0, \lambda > 0$	0.0162	1.0
Generalised Gamma	$f(x) = \frac{kx^{k\alpha-1}}{\beta^{k\alpha}\Gamma(\alpha)} \exp\left(-\left(\frac{x}{\beta}\right)^k\right)$, $x > 0, k > 0, \alpha > 0, \beta > 0, \Gamma(\alpha)$ is the Gamma function	0.0277	0.99
Dagum	$f(x) = \frac{\alpha k \left(\frac{x}{\beta}\right)^{k\alpha-1}}{\beta\left(1+\left(\frac{x}{\beta}\right)^{\alpha}\right)^{k+1}}$, $x > 0, k > 0, \alpha > 0, \beta > 0$	0.02821	0.99

*Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein et al., 2020, Caribbean Electric Industry Journal, 16, 36–39. DOI:*10.47412/QZWP9167, *and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison et al., 2020, International Conference on Emerging Trends in Engineering and Technology,* (http://conferences.sta.uwi.edu/iconetech2020/index.php)

Discussion

It is evident that descriptive statistics and goodness-of-fit metrics are useful tools to investigate the nature of large datasets. In particular, maximum daily peak values are of significance to distribution grid protection schemes to predict system disturbances. The mean values can be used to demonstrate the percentage increase of daily demand compared to lower EV penetration scenarios, thereby considering suitable EV charging scheduling schemes.

In particular, the existing daily load pattern obtained can be used to estimate the coincidental demand with vehicle(s) charging. This can now be used to predict if distribution transformers will become overloaded, using the generated PDFs as a guide for predicted demand at a certain time in the week. In addition, this supports the development of a "rule of thumb" guide for the utility related to the maximum number of EVs that can be added to a circuit, before power quality issues would be experienced.

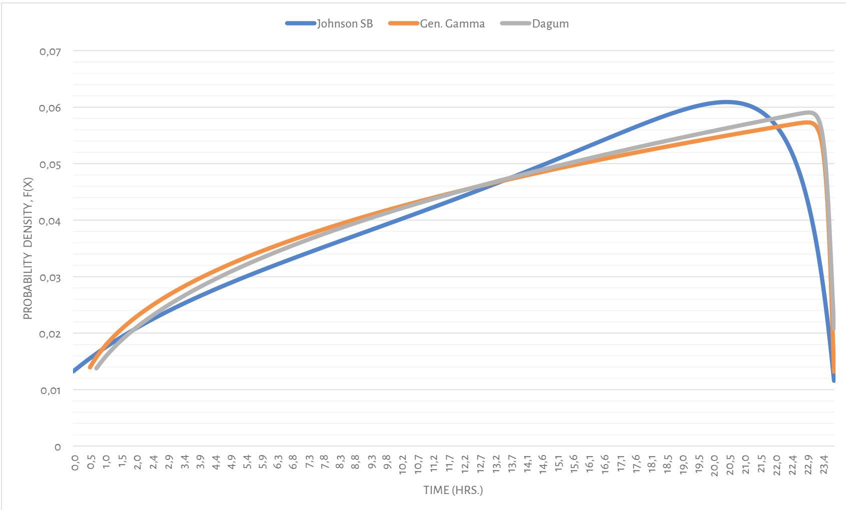

Figure 3.4 Probability Density Functions for the Weekday Load Curve
Note. From "Probabilistic Assessment of Electric Vehicle Charging Behaviour," by Hosein et al., 2020, *Caribbean Electric Industry Journal, 16*, 36–39. DOI:10.47412/QZWP9167, and "Goodness of Fit of Probabilistic Models for Electric Vehicle Charging Behaviour," by Addison et al., 2020, *International Conference on Emerging Trends in Engineering and Technology*, (http://conferences.sta.uwi.edu/iconetech2020/index.php)

In most SISs in the Caribbean, there is a need for a strategic EV infrastructure planning and likely upgrading of the supporting power system assets. This would also inform the utility/fleet owners as to where are the best location(s) to install public chargers and the expected impacts of those chargers on the grid. If these are not done concurrently, EV penetration can cause stability and power quality issues on these small island power systems. In this regard, GoF statistics can also provide key parameters which can encourage a more measured approach to compute the expected demand on the power system.

There is room for further work to generate more accurate PDFs for corresponding load curves, in order to subsequently predict EV demand, as well as feed into more complexed schemes. A limitation of typical theoretical PDFs used to model mobility data in larger countries is the inability to accurately describe the weekday demand at particular hours in the day for SISs, where climate and demand may also be vastly different. This may affect the accuracy of performance indicators and estimates at certain times. However, without actual local data, analogues of these PDFs modified to fit the location situation, are excellent starting points in the prediction of the effects of EV penetration on the health of the local grid.

Development of realistic PEV load profiles is essential for accurate determination of impacts on power system planning and operation applications (Almutairi et al., 2018). The aim is for system operators to have tools to evaluate uncoordinated systems properly in order to build coordination charging schemes based on EV demand. The outputs of this assessment can also be fed into DSM programmes to improve power consumption efficiencies. DSM plays an important role in the development of smart grids. This study provides key insights into estimation of PDFs based on EV charging behaviours, in order to build and assess models associated with transportation mobility data for SISs.

Hence, the real value in the methodology is the ability of the selected probabilistic model to provide the statistical representation of the power consumption at a particular time and location, based on the local users' driving behaviour and corresponding charging patterns. This can be superimposed on the existing power consumption requirements to determine the distribution network's transformers and cables capacity utilisation. Thus, any SIS can adopt a probabilistic approach to enhance the uniqueness of their EV demand, in contrast to larger countries.

Recommendations and Conclusion

This work presented an assessment of EV charging using goodness-of-fit of PDFs. These can then be utilised to build suitable PDFs to estimate country-specific metrics and enable forecasting models to be created for EV charging, using data-driven approaches. As EV penetration increases and charging coordination schemes are developed, power system planning is critical and generation expansion must continue to be ahead of the load growth. The adoption of renewable energy technology can play a role to potentially delay capital investment for power system upgrades at the transmission and distribution levels while developing prosumers that approach the adoption boundaries of various V2X options.

Undoubtedly, this data-driven approach will inform decisions suitable for the local landscape. Market readiness and progressive adoption in SISs, especially in the Caribbean, are faced with numerous unique policy, technical, infrastructural, legislative, and financial challenges, which may have stymied EV adoption. The holistic assessment using accurate and applicable transportation data of the existing state of play in any SIS must be performed. This will include public and private sector analyses to identify an all-inclusive path for EV adoption. This path must be made transparent and accessible to all stakeholders identifying the surrounding industries, which can be developed and sustained. There are many players and actors (public, private and non-profit) that need to participate and actively contribute for successful EV adoption. Stakeholder consultation is, therefore, critical and public awareness paramount.

Consideration of the importation process, applicable standards, standard development, tax exemptions and tariff considerations, suitable EV selections, licensing and insurance considerations, dealer, customer and utility responsibilities, safety aspects and vehicle-to-grid considerations have been documented (Meetoo et al., 2018). The reduction of GHGs and opportunities for improved health of the citizenry, linked to the sustainable development goals. National commitments will also influence policy development and possibly accelerate policy implementation. The development of an implementation plan requires a careful technical review of the technology available, ensuring applicability to the proposed plan.

Review of compliance, with existing local electrical and communication codes and standards is critical, especially if there is a long(er) term aspiration of integrating smart city measures. This can also initiate reviews of codes and standards. EVs can also provide an abundant supply of user data, and this introduces measures for privacy for big data collection and processing. Another such data-driven approach can also foster confidence for emerging urban mobility and ride sharing services, third party EV charging applications utilising Fintech and cryptocurrencies.

Therefore, it is recommended that the next step be to improve the goodness-of-fit of these probabilistic models for EV charging behaviour using real local transportation data. This can be extracted ideally from an EV pilot study or another hybrid approach, leveraging real local landscape commute data to produce revised probabilistic models. Future work should involve use of Monte Carlo simulation modelling techniques using predetermined PDFs for other mobility survey data variables such as home arrival times, home departure times, and daily mileage.

These models can then be incorporated into the real local power system models to perform sensitivity analyses and adequacy assessments at various penetration levels at strategic locations in the island power system. Such technical studies will further enhance the power system planning exercises. This is particularly important for SISs to maintain the integrity of the quality of the electricity supply, minimise outages, optimise the utilisation of the ageing electricity distribution networks and possibly delay capital asset investment(s).

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