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Markov Chain-Based Modeling of Electric Vehicle Power Consumption

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Abstract

The power consumed by recharging Electric Vehicles (EVs) can significantly impact the electric grid. EV charging can potentially cause a sharp increase in electricity demand at the end of every workday as EV owners begin charging their cars upon returning home. Having an accurate short-term forecast of EV power consumption can mitigate some of these impacts. One way of improving forecast accuracy is to develop a Markov Chain model of the underlying process. This research develops a Markov Chain model of hourly aggregate EV power consumption based on EV charging data from the Puget Sound region in Washington State during the year 2012. A Markov Chain model is a discrete time stochastic process where the future evolution of the process is conditionally independent of the past given the present. Aggregate EV charging power consumption exhibits strong diurnal trends—low in morning and increasing over the evening as drivers return home to recharge their vehicles. To represent these characteristics, the Markov Chain model was partitioned into three segments based upon the time of day. Within each segment, there are four distinct states, each corresponding to a range of power consumption. Transition probabilities between the states within each segment were computed. This model was used to simulate aggregate EV power consumption over a 24-hour period.

Keywords: Electric Vehicles, Load Profiles, Load Forecasting and Markov Simulation

1. Introduction

Today's transportation system predominantly relies on fossil fuels such as petroleum. Internal combustion engines (ICEs) have been a dominant source of vehicle propulsion for the last 100 years. However, ICEs create harmful emissions and noise pollution. When assessing alternatives to ICEs, it is important to consider Electric Vehicles (EVs). Credible research has shown that the majority of the vehicle's carbon production is during operation rather than production. EVs consume only a third as much energy in operation as ICEs, no matter what fuel is used to generate the electricity they use[1]. Sources of electricity range from wind, solar, hydro, biofuel, natural gas, nuclear, and fossil fuels, most of which are domestically available. Thus, EVs have the potential to support the United States's economy and reduce dependence on imported oil. The electric power industry expects a 400% growth in annual sales of plug-in electric vehicles by 2023, which substantially increases the load demand and electricity usage[2]. Understanding EV charging patterns can help utilities plan and operate the power grid in order to account for large vehicle charging loads.

This paper develops a Markov chain model of EV power consumption based on the 2012 Seattle EV charging data set provided by ECOtality[3]. Markov Chain models are beneficial when modeling a probabilistic patterned time-series. Markov Chains are useful in modeling a process that changes from one state to another over time. In this research, the states are the different ranges of EV power consumption. This paper is organized as follows. In Section II, the data set, load profile and an introduction to Markov Chains are provided. In Section III, the methodology for developing the model segments and states are explained. The Markov simulation methodology is explained in Section IV. Section V explains the results and analysis of the simulation and conclusions follow in Section VI.

2. Background

2.1. load profile

The data used in this research comes from ECOtality's "EV Project." The EV Project collects EV charging station data for registered Nissan LEAF and Chevrolet Volt vehicles. The EV Project collects information on the vehicle model, energy used and time duration of charger use. This research focuses on the Washington State, specifically in Seattle, for the year 2012. There are about 1,200 EVs that were analyzed in the data set[3].

The data set containd aggregated EV charging station demand values sampled at 15-minute intervals during 2012 (35,136 total samples). However, this research focuses on the converted the 15-minutely samples to hourly-averages of these samples in order to easily examine a 24-hour load profile[4].

Figure 1 shows the hourly average consumption load profile for Seattle in the year 2012. A trend is apparent. There is a moderate increase in power consumption from 4:00 to 12:00, a significant increase from 12:00 to 20:00, and then a general decrease from 20:00 to 4:00.

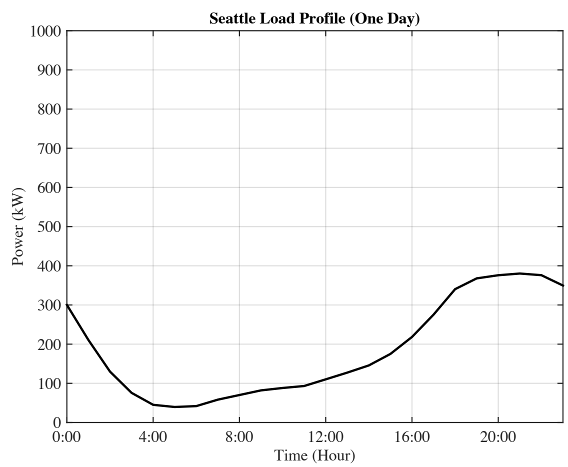

Figure 1. Seattle EV Charging Load Profile

The nighttime peak is expected because EV drivers usually come home in the early evening to charge their EVs. The power consumption continues to increase throughout the early evening until approximately 23:00. By this time, drivers have returned home and many EVs have become fully charged. The load steadily decreases until 4:00 then increases as commuters drive to work, some of them charging their EVs at their workplace.

2.2. Markov chain

Markov Chains are used to probabilistically model a pattern that progresses over time. Since the load profile in Figure 1 follows a pattern, a Markov chain is an appropriate modeling approach. A Markov chain is a mathematical model of a sequence of random variables that evolves over time in a probabilistic manner. The behavior at the next point in time depends only on the current state and does not depend on what happened before. In other words, the next state of the system depends only on the present state and not on preceding states. The Markov chain equation explains this property:

$$\Pr(X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, ..., X_n = x_n) = \Pr(X_{n+1} = x \mid X_n = x_n) \quad (1)$$

where, X_{n+1} is the next hour, x is the possible next state, X_n is the current hour and x_n is the current state[5]. Informally this can be interpreted as the probability of transitioning into a certain state in the next hour, given the present state in the current hour. Given the present, the future is conditionally independent of the past.

Figure 2 shows an example of the Markov chain model. In hour $n = 1$, the state is x_3. The probability of transitioning into each state in hour $n = 2$ is displayed. Using the Markov definition, we can demonstrate the probability transition of state x_3 to state x_1. Given equation (1), the probability of transitioning into state x_1 in the next hour $(n = 2)$, given the process is in state x_3 during the first hour $(n = 1)$ is 30%. Therefore, $\Pr(X_2 = x_1 \mid X_1 = x_3) = 30\%$. In this research, we use the Markov chain to model the hourly transitions from different states of EV power consumption.

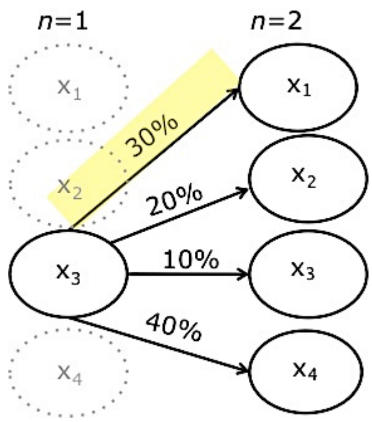

Figure 2. Markov Chain Model Example

3. Methodology

This research investigated EV power consumption by modeling the 2012 Seattle data set using a Markov chain. To do this, the average load profile of the daily EV consumption was partitioned into three time segments, referred to as Alpha, Beta, and Gamma. Each segment corresponds to a trend in the load profile. A separate Markov chain model was developed for each segment.

Markov Chains use discrete states to model the underlying process, but the EV data are continuous values. Therefore, the EV data in each segment were quantized into four states such that 25 percent of the data mapped into each state. A 24-hour period was then simulated and compared to the actual data.

3.1. Model Segments

Let $\boldsymbol{P}$ be a matrix whose elements correspond to a specific hourly aggregate EV load in the data set. The data are arranged such that each row in $\boldsymbol{P}$ corresponds to a specific day and each column is a specific hour of the day. Therefore $\boldsymbol{P}$ has 366 rows (2012 is a leap year) and 24 columns. Let $P_{d,h}$ be the power consumption of hour h of day d. Let P_α, P_β, P_γ be sub-matrices of $\boldsymbol{P}$, where $P_\alpha = \{P_{d,h} : 4 \le h < 11\}$, $P_\beta = \{P_{d,h} : 12 \le h < 19\}$, $P_\gamma = \{P_{d,h} : 20 \le h < 3\}$ represent the Alpha, Beta, and Gamma model segments, respectively.

3.2. States

Discrete states of EV charging power need to be defined so that a Markov model can be used. In this research, four states are defined for each segment, as described in Table 1. There are several approaches to defining the states. In this research, the distribution of continuous values in each segment (Alpha, Beta and Gamma) was used to determine the range of continuous value that map to a specific discrete state. The boundaries of the continuous values associated with each state in each segment were determined as follows.

Table 1. Markov Chain Time Segments

Segment	**Hours**	**States**
Alpha (α)	4:00-11:00	$\alpha_1, \alpha_2, \alpha_3, \alpha_4$
Beta (β)	12:00-19:00	$\beta_1, \beta_2, \beta_3, \beta_4$
Gamma (γ)	20:00-3:00	$\gamma_1, \gamma_2, \gamma_3, \gamma_4$

Consider segment Alpha. Since there are four states needed for each segment, the quartiles of P_α are used to define the boundaries of the continuous values that map to each state. This is visualized in Figure 3. The quartiles are computed from the empirical inverse cumulative distribution function $F_\alpha^{-1}(x)$ of P_α.

The EV charging values, in kilowatts, associated with the state α_1 range from zero to F_α^{-1} (0.25), that is [0, 39.72). The ranges for α_1 are F_α^{-1} (0.25) to F_α^{-1} (0.50) or [0.3972, 58.49) and so on. The process is repeated to determine the ranges for the four states in Beta and Gamma, as shown in Figure 4 and Figure 5. Table 2 summarizes the state boundaries for each segment.

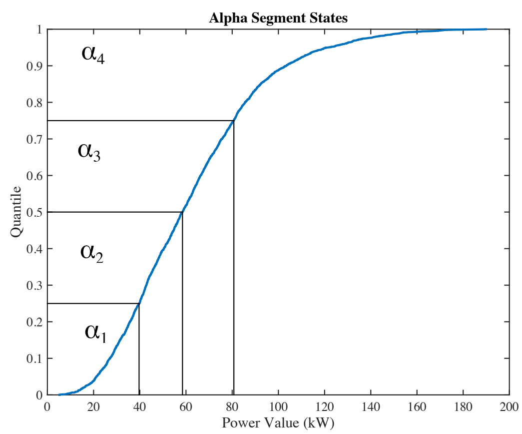

Figure 3. Empirical cumulative distribution function of Alpha Segment

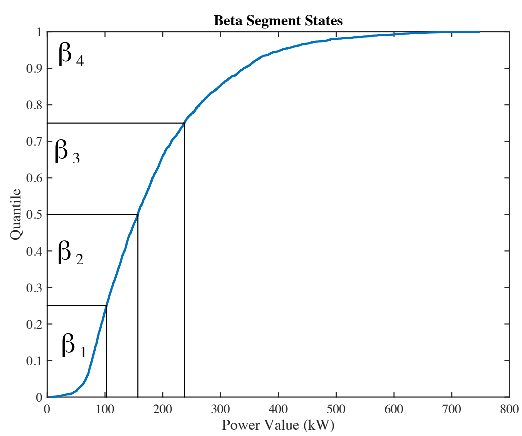

Figure 4. Empirical cumulative distribution function of Beta Segment

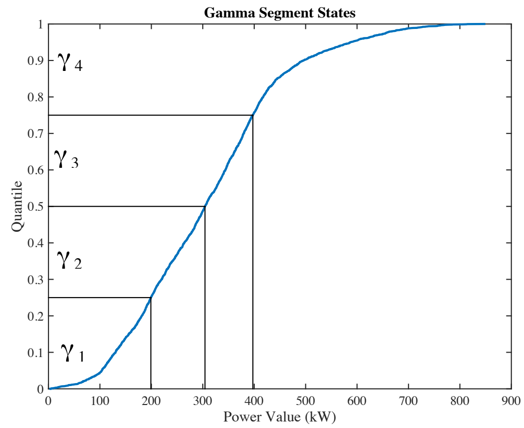

Figure 5. Empirical cumulative distribution function of Gamma Segment

Table 1. state boundaries

Alpha Segment: 4:00-11:00				
	α_1	α_2	α_3	α_4
α (kW)	[0, 39.72)	[39.72, 58.49)	[58.49, 80.72)	[80.72, ∞)

Beta Segment: 12:00-19:00				
	β_1	β_2	β_3	β_4
β (kW)	[0, 102.77)	[102.77, 156.87)	[156.87, 237.32)	[237.32, ∞)

Gamma Segment: 20:00-3:00				
	γ_1	γ_2	γ_3	γ_4
γ (kW)	[0, 199.23)	[199.23, 304.29)	[304.29, 397.09)	[397.09, ∞)

Using the state boundaries, the transition matrices for Alpha and Beta, Gamma were created. Transition matrices compactly describe the probability of transitioning between states within the same segment. Let T_k generically represent the transition matrix for matrix for segment k. Let the elements of T_k be

$$T_k = \begin{bmatrix} t_{i,j} & t_{i,j+1} & \cdots & t_{i,4} \\ t_{i+1,j} & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ t_{4,1} & \cdots & \cdots & t_{4,4} \end{bmatrix} \tag{2}$$

where $t_{i,j} = \Pr\left\{X_{n+1} = j \middle| X_n = i\right\}$. As an example, $t_{3,4}$ of T_β is the probability of transitioning from state 3 to state 4 in the Beta segment (12:00-19:00). Transition matrices $T_{\alpha\beta}$, $T_{\beta\gamma}$, $T_{\gamma\alpha}$ are also needed to handle the transition between the last hour of one segment to the beginning of the next segment. For example, $T_{\alpha\beta}$ is used to determine the probability of transitioning from a given state in Alpha at hour 11:00 to a state in Beta at hour 12:00.

A transition matrix is populated by analyzing the data in the corresponding sub-matrix. For example, to determine element $t_{1,3}$ of matrix T_α (time period 4:00-11:00), P_α is analyzed. First, the number of occurrences N of elements in the range of 0 to 39.72 kW (state α_1) is computed. Then, the number of occurrences *M* of a value in the range of 0 to 39.72 kW (state α_1) followed by a value in the range of [58.49, 80.72) (state α_3) is computed. The value M divided by N is $t_{1,3}$. This is the probability of transitioning from state α_1 to state α_3 in the time period 4:00 to 11:00.

Figure 6 shows an alternative way to visualize the first row of transition matrix T_α. The probability of transitioning from state α_1 in one hour to state α_2 in the next hour is $t_{1,2} = \Pr\{X_2 = 2 | X_1 = 1\} = 28.46\%$. The probability of transitioning to state α_3 in the next hour from state α_1 in the current hour is $t_{1,3} = \Pr\{X_2 = 3 | X_1 = 1\} = 6.48\%$. The probability of transitioning to state α_4 from state α_1 is $t_{1,4} = \Pr\{X_2 = 4 | X_1 = 1\} = 0\%$ (there is never an α_1 to α_4 transition in the data set). The probability of staying in state α_1 in the next hour, given being in state α_1 in the current hour is $t_{1,1} = \Pr\{X_2 = 1 | X_1 = 1\} = 65.06\%$.

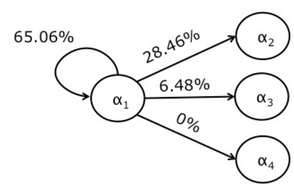

Figure 6. State α_1 Markov Model

The same method was used to calculate the Markov transition probabilities for the remaining matrices. Table 3 shows the probability transitions for $T_\alpha, T_{\alpha\beta}, T_\beta, T_{\beta\gamma}, T_\gamma$ and $T_{\gamma\alpha}$. Note that segment-to-segment transition matrices such as $T_{\alpha\beta}, T_{\beta\gamma}$ and $T_{\gamma\alpha}$ in Table 3 show a majority of 0% probabilities. For example, in the $T_{\alpha\beta}$ matrix, the probability transition from state α_1 to states β_2, β_3, or β_4 is 0%. This is because state α_1 corresponds to very low power values. From Table 2, a transition from α_1 to β_1, requires a minimum change in power value from 39.72 kW to 102.77 kW. Such a rapid change never occurred from 11:00 to 12:00 in the data set. Also note that the Gamma segment never ended in γ_4, so the transition probability is not calculated.

Table 3. Transition Matrix Values

Alpha	α_1	α_2	α_3	α_4		Alpha-Beta	β_1	β_2	β_3	β_4
α_1	65.06	28.46	6.48	0.00		α_1	100.00	0.00	0.00	0.00
α_2	21.51	36.84	34.36	7.29		α_2	100.00	0.00	0.00	0.00
α_3	8.59	16.41	35.91	39.09		α_3	93.33	0.00	0.00	6.67
α_4	0.18	1.90	5.45	92.47		α_4	49.75	31.16	6.03	13.07
Beta	β_1	β_2	β_3	β_4		Beta-Gamma	γ_1	γ_2	γ_3	γ_4
β_1	88.04	11.65	0.31	0.00		β_1	100.00	0.00	0.00	0.00
β_2	28.34	42.63	28.88	0.15		β_2	92.86	7.14	0.00	0.00
β_3	3.57	23.16	47.15	26.12		β_3	55.56	44.44	0.00	0.00
β_4	0.00	1.39	11.57	87.04		β_4	0.00	15.02	43.69	41.30
Gamma	γ_1	γ_2	γ_3	γ_4		Gamma-Alpha	α_1	α_2	α_3	α_4
γ_1	93.27	6.61	0.13	0.00		γ_1	10.68	19.29	38.28	31.75
γ_2	26.96	51.13	20.02	1.89		γ_2	0.00	0.00	0.00	100.00
γ_3	1.73	25.51	54.98	17.78		γ_3	0.00	0.00	0.00	100.00
γ_4	0.00	3.14	19.17	77.69		γ_4	--	--	--	--

4. Simulation

The Markov simulation is a two-part process. First the simulation determines the states for each hour in a 24-hour time series and store into an array, s[h]. The second part of the simulation involves probabilistically evaluating the power values for each state in s[h], which are stored into the array $\tilde{P}[h]$.

Figure 7 shows the flow chart that explains the first part of the procedure. Let h represent the hour, s[h] represent the state at hour h, r represent a random number drawn from a uniform distribution, U, and T_k represents a transition matrix, either $T_\alpha, T_{\alpha\beta}, T_\beta, T_{\beta\gamma}, T_\gamma$ or $T_{\gamma\alpha}$.

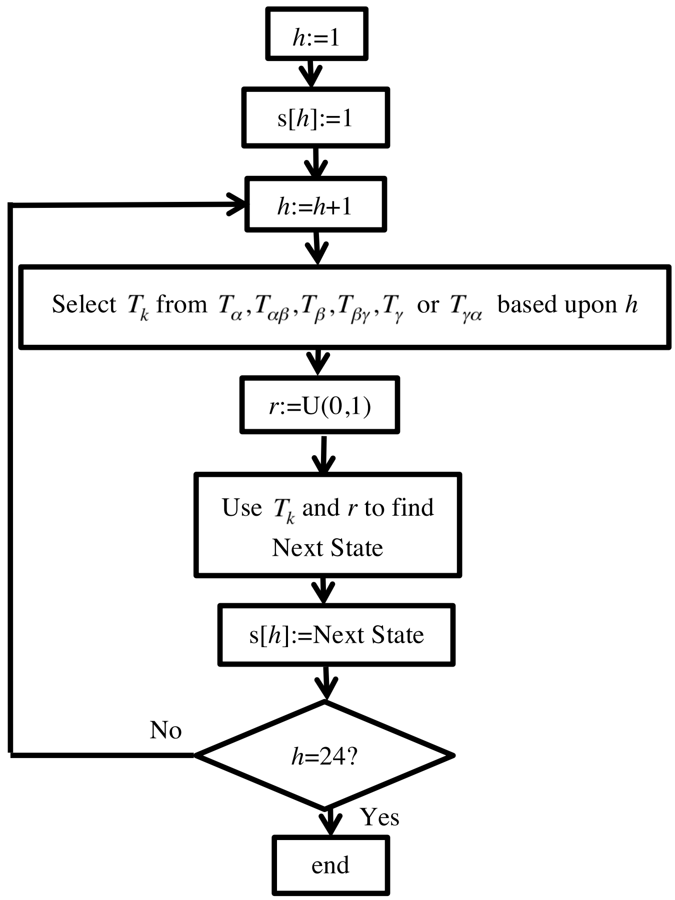

Figure 7: Flow Chart Simulation of s[h]

The simulation begins at h=1. The first state is arbitrary and is set to 1 in this example, but any other state can be selected or randomly assigned. The simulation increments to the next hour. Next, the appropriate transition matrix, T_k, is selected based upon hour h. If $4 < h < 11$ then T_α is selected for T_k. If $h = 11$ then $T_{\alpha\beta}$ is selected. If $11 < h < 12$, then T_β is selected. $T_{\beta\gamma}$ is selected if h=12, and T_γ is selected if $12 < h < 3$ and $T_{\gamma\alpha}$ is selected if $h = 3$.

A random number within the range of $0 \le r \le 1$ is picked from a uniform distribution. Using the selected transition matrix, if $r < t_{(s[h-1],1)}$, then the determined state for that hour is state 1. If $t_{(s[h-1],1)} \le r < t_{(s[h-1],2)}$, then the determined state for that hour is state 2. If $t_{(s[h-1],1)} \le r < t_{(s[h-1],3)}$, then hour h is in state 3, and if $t_{(s[h-1],3)} \ge r$, then hour h is in state 4. The determined state for hour h is stored as s[h]. The simulation evaluates if hour $h = 24$. If not true, the simulation repeats itself by incrementing by one until h =24. When the simulation is complete, s[h] is an array of 24 values each in which 1, 2, 3, or 4 corresponds to a state.

The next step in the simulation is to find the continuous power values $\tilde{P}[h]$ corresponding to each discrete state in s[h]. This is done probabilistically, again using the inverse cumulative distribution function for each state and segment. Figure 8 shows the flow chart that determines the power value associated with the simulated hour.

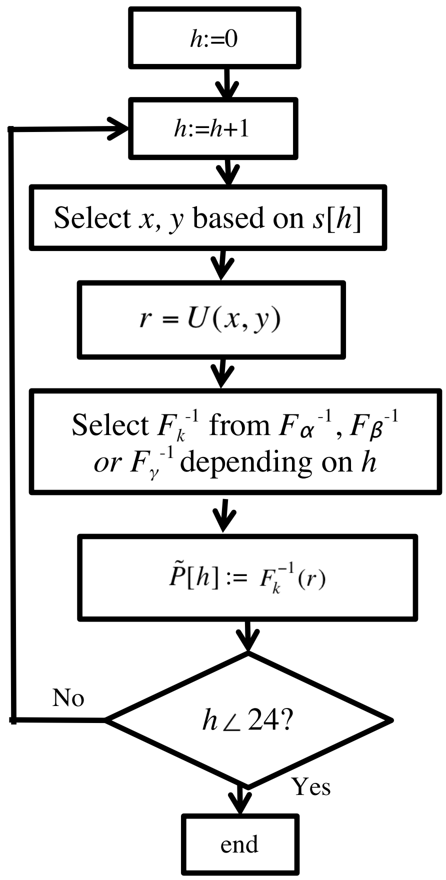

Figure 8: Flow Chart Simulation of $\tilde{P}[h]$

Using the simulated hour array, s[h], the process defines the power value with its associated state and hour. To do so, the hour is incremented to 1, and then a random number r is drawn from a Uniform distribution on the interval [x, y). The value of x and y are determined from the state $s[h]$ as follows. If $s[h]$ = 1, then the interval is [0, 0.25); for $s[h]$=2, then interval is [0.25, 0.50); if $s[h]$=3, then the interval is [0.50, 0.75); and if $s[h]$=4 then the interval is [0, 0.25). The continuous power value $\tilde{P}[h]$ is set to F_k^{-1}(r) where F_k^{-1} is the inverse empirical cumulative distribution function corresponding to the data in P_k, and k is either α, β, or γ, depending on the hour simulated.

The simulation is then asked to evaluate if hour h = 24. If not true, then the simulation repeats itself by incrementing by one, h:=h+1, until h = 24 is true. When the simulation is complete, $\tilde{P}[h]$ is an array of 24 simulated values, with the power values corresponding to each hour.

5. Results

Figure 9 and 10 shows the Markov simulation and a typical day of EV power consumption from the data set, respectively. Comparing both figures, the general shapes of the curves are similar. The general trends increase and decrease in the same areas. It is not expected that the model exactly matches the actual data, due to the probabilistic nature of the model as well as the simplifications made in the modeling process.

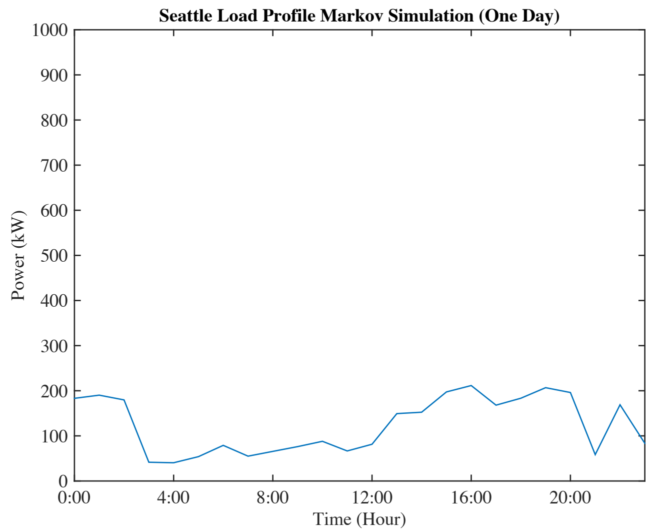

Figure 7: Markov Simulation (One Day)

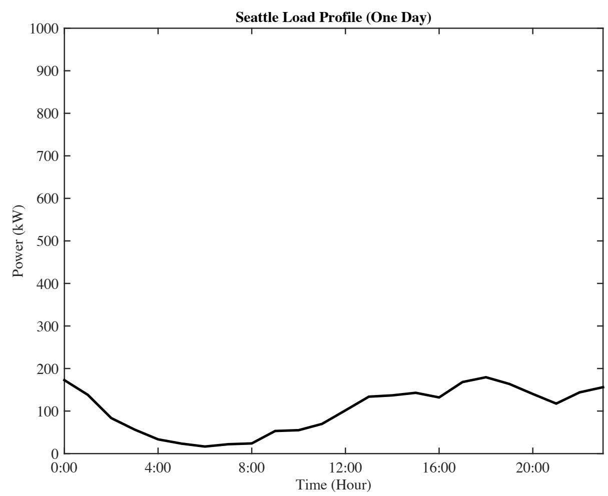

Figure 8: EV power consumption of a typical day

Figure 11 shows the results of $\tilde{P}[h]$ from the Markov simulation average of 100 days, plotted on a Time versus Power (kW) axis. Comparing this figure with the average Seattle load profile average shown in Figure 1, the general trends are similar. Both trends are increasing and decreasing in the same general, which confirms the Markov chain simulation.

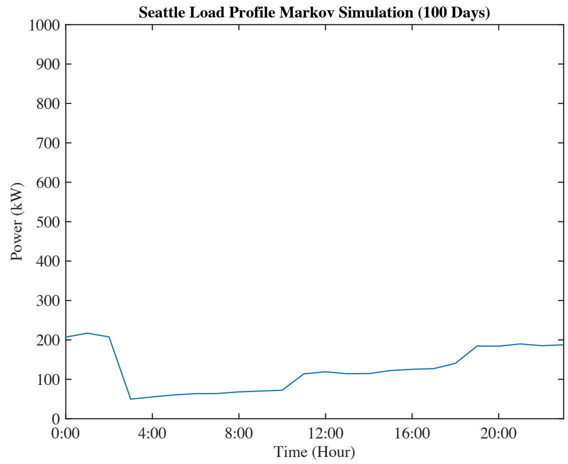

Figure 9: Markov Simulation Load Profile Average (100 Days)

6. Conclusions

This paper utilizes the Markov chain to model electric vehicle charging profiles by creating time dependent models. The 2012 Seattle EV charging data set was separated into morning, afternoon, and nighttime to model and simulate charging patterns. Analyzing the general shapes of the graphs from the original data and the Markov simulated data, we can conclude that the Markov chain model and simulation was successful.

In conclusion, this research developed a Markov Chain model with three segments and four states for electric vehicle charging consumption and developed a simulation algorithm. The model can be improved by increasing the number of segments—perhaps as high as one per hour—and increasing the number of states, for example, from four to eight.

. Weekdays and weekdays can also be separated and evaluated to improve the Markov chain model.

7. Acknowledgments

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