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Research Article

Electric Vehicle Usage Pattern Analysis Using Nonnegative Matrix Factorization in Renewable EV-Smart Charging Grid Environment

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The global utilization of electric vehicles (EVs) is exponentially increasing due to the increased availability of cost-efficient EVs and infrastructure managements for the EVs. In spite of the increasing usage of EVs, the problem of EV usage patterns' analysis and implementing sustainable infrastructure for the EV transportation is still under development. In addition to this, there is a challenging problem of long waiting hours in traffic signals. This study deals with these problems by proposing an architecture that includes EV usage pattern analysis using nonnegative matrix factorization (NMF) technique and renewable solar-powered wireless smart charging grid to effectively utilize or mitigate the long traffic signal waiting hours. The insights from the EV usage patterns are analyzed and presented showing the importance of usage pattern analysis alongside to the presented architecture of renewable solar-powered wireless EV-smart charging grid. These implementations improvise the usage of the EVs and enhancing the transportation experience, which in turn leads to the development of sustainable smart transportation.

1. Introduction

Intelligent transportation system (ITS) is one of the emerging research topics due to its latest advancements and technological developments [1–3]. There are various aspects in improvising ITS by means of implementing efficient traffic management systems, congestion and collision control mechanism, sustainable transportation, etc., [4, 5]. Sustainability is one of the important factors that need to be considered in this current scenario as it acts as the bridge between the efficient usage of advanced technological developments and pollution-free environmental welfares [6, 7]. This leads to the balanced usage of technology while maintaining the eco-friendly environment for the welfare of human life.

EVs [8] are a part of technological developments in ITS that favors sustainable transportation [9–11], especially in the field of ITS. Nowadays, the global usage of the EVs is exponentially increasing as well as there is an increase in the installation of various types of EV charging station/grids [12]. Figure 1 shows the statistics of the worldwide usage of the EVs from the year 2016 to 2020 [13]. According to these statistics, there is an exponential increase in the worldwide usage of the EVs in comparison to the previous years, i.e., only 1.2 million EVs in 2016, whereas nearly 6.8 million EVs are in movement in 2020.

Despite these developments, the problem of longer waiting time in traffic signals is also increasing in parallel [14–16]. Many people including passengers and taxi drivers are wasting time during long waiting hours in many traffic signals. Considering this problem of long traffic signal waiting hours, we propose the concept of utilizing those long waiting time for powering up the EVs using the EV charging grids installed underneath the roadway. To effectively

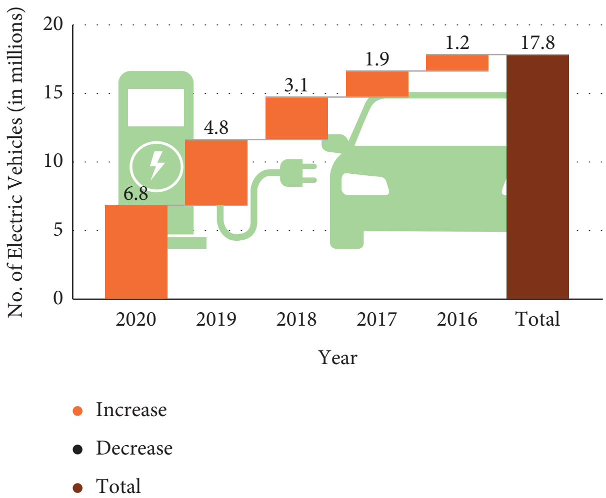

Figure 1: Worldwide usage of the EVs from 2016 to 2020.

implement the above, understanding the usage patterns of the EVs is much more important so that efficient usage of EV charging grid lines can be implemented accordingly.

Eliciting the usage patterns of the EVs helps to understand the complete usage of the EV charging patterns, car appliances usage, and number of passengers utilizing the EVs. To elicit the patterns, we apply NMF, a dimensionality reduction technique [17–20] on the EV usage dataset from the smart-grid smart-city (SGSC) project [21, 22]. This analysis helps to identify the EV usage patterns by the passengers and business people involved in the SGSC project. These usage patterns not only help in understanding various aspects such as understanding the charging patterns and appliance usage patterns but also help for efficient charging of the EVs from the grid installed underneath the road during the long waiting hours in traffic signals.

The rest of the paper is organized as follows. Section 2 contains related works. Section 3 contains the proposed architecture that includes performing EV usage pattern analysis using NMF technique and renewable solar-powered wireless smart charging grid to effectively utilize or mitigate the long traffic signal waiting hours. Section 4 contains EV pattern elicitation that incorporates dataset description, dataset representation, NMF for EV usage pattern and analysis of EV usage data, and understanding the usage patterns. Section 5 contains renewable solar-powered wireless EV-smart charging in relation to the obtained EV usage patterns during long traffic signal waiting time. Section 6 concludes the study.

2. Related Works

As usage of the EVs is exponentially increasing, the importance of eliciting the usage patterns is much needed for effective implementation of various user benefitable traffic enhancement measures. In one of the recent works, the authors proposed the methodology to carry out the driving pattern analysis in the Nordic region [23]. Their analysis is more likely to be concentrated only on the driving patterns of the vehicles on the weekdays and weekends in the Nordic region. In another research work, the authors presented the study on the various factors that affect the intention of the consumer to use the EVs in Malaysia [24]. Their study is focused on providing the directions for the various policymakers and automotive manufacturers. However, these existing works did not focus on providing the architecture that facilitates the behavioral analysis and sustainable characteristics of the EV usage. In another research work, the authors presented the report on impact analysis of EV integration on the component and system levels [25]. Their work mainly focused on the EV load distribution. However, in order to effectively perform the load distribution, it is important to analyse the EV usage patterns. Authors of another recent work investigated the impact of ambient temperature to increase the EV energy consumption during cold weather conditions [26]. The outcome of their study reveals the efficient utilization of the EVs in the urban regions based on the ambient temperature. However, irrespective of the ambient temperature, efficient infrastructure is needed to encourage the usage of the EVs in the roadways for balancing the sustainable environment. In another research work, authors performed the sensitivity analysis on EVs and its impact on low-voltage distribution systems [27]. In this work, the authors analyzed the impacts of modeling of the load of EVs influencing flows and voltages in the grid using transformer and line loadings, and highest sensitivities are observed for the vehicles in the grid. However, people's charging behavior plays minor roles. In order to overcome the above-mentioned challenges, in this study, we performed the EV usage pattern elicitation and analysis using one of the dimensionality reduction techniques such as NMF to thoroughly analyze the EV usage patterns and people's charging and other behaviors and proposed the architecture of renewable solar-powered wireless smart charging grid in relation to the usage pattern analysis to improve the usage of EVs with the thought of achieving the sustainable smart transportation.

3. Proposed Architecture

The proposed architecture is shown in Figure 2, which includes EV usage pattern analysis using NMF technique and renewable solar-powered wireless smart charging grid to effectively utilize or mitigate the long traffic signal waiting hours. The architecture begins with the data processing layer in which preprocessing on the EV usage data is performed. Following the data processing layer, matrix generation and normalization are performed on the normalization layer. Once the matrix is normalized, NMF is performed on the normalized data matrix in the dimensionality reduction layer. Based on the NMF outputs, the similar data points are clustered and different patterns are analyzed in the pattern analysis layer. The analyzed patterns and the pattern insights are sent to the control hub of the traffic control monitoring center to perform various traffic control measures related to the EV based on the pattern analysis. Application of the solar-powered wireless EV-smart charging is elaborated in Figure 2.

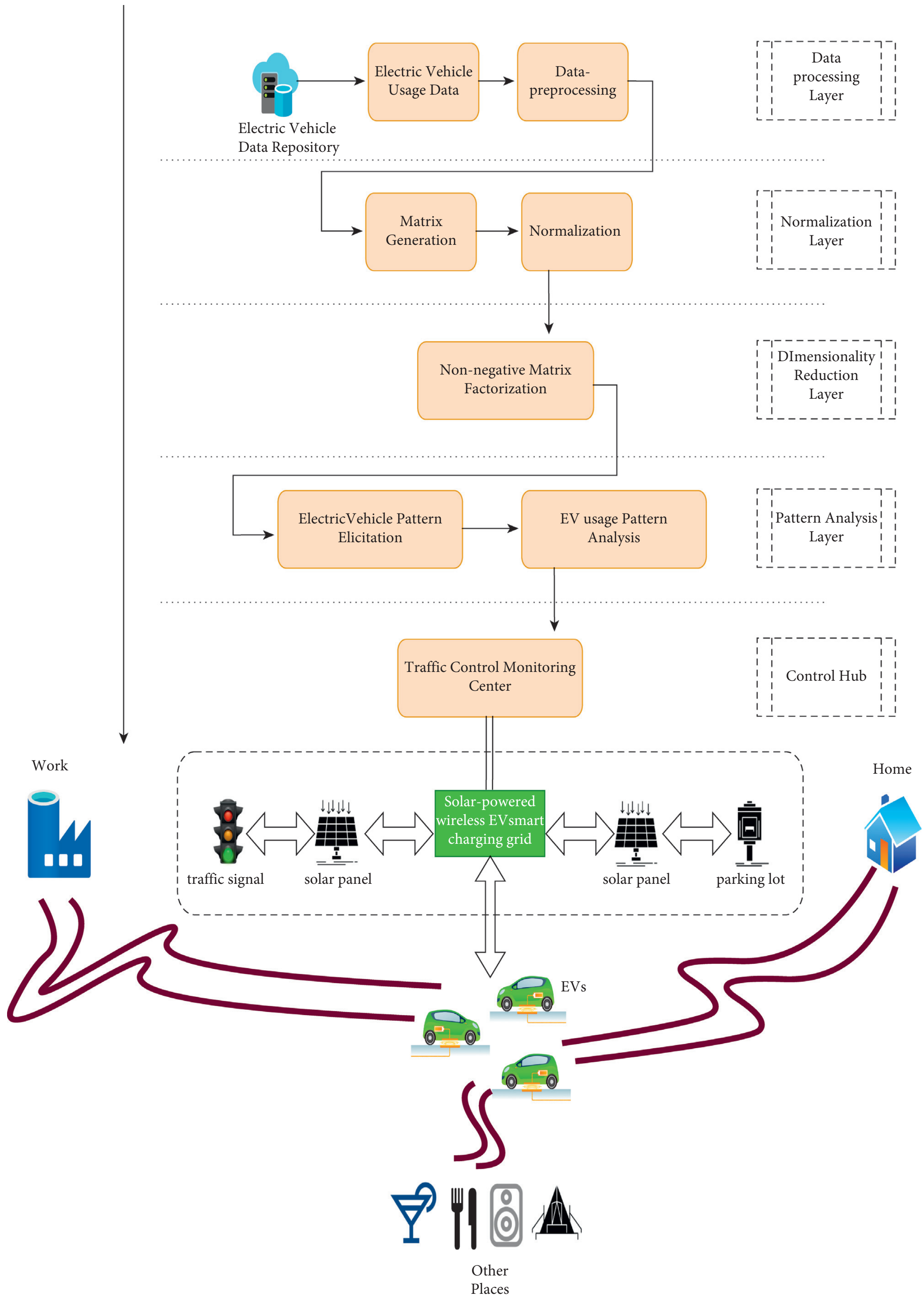

Figure 2: Proposed architecture of renewable EV charging during traffic signal waiting time based on EV usage patterns.

4. EV Pattern Elicitation

4.1. Dataset. The analysis is performed on the dataset which is downloaded from the data repository in the Australian Government's Department of Industry, Science, Energy, and Resources data archive. The dataset includes the usage of the EV by households and businesses in which the EV usage data is a part of the smart-grid smart-city (SGSC) project [21]. This project involves the trial of 20 Mitsubishi iMiEV cars of the 2010 model and the trips' details including the usage of car appliances such as headlamp, air-conditioning, and state of the battery charge during beginning and end of each trip. The entire data were collected during the period of August 2011 to May 2013.

4.2. Dataset Representation. The EV dataset that records the overall vehicle trips alongside to the record of trip duration, state of charging during start and end of the trip, average velocity, AC 'On' duration, headlamp 'On' duration, distance travelled from source to destination, and number of passengers occupied on the EV. Let us consider $\mathbf{X} \in \mathbb{R}^{\mathbf{M}\times\mathbf{N}}$ is the data matrix consisting of the above records. This matrix can be factorized into two lower-dimensional factor matrices, say, $\mathbf{U} \in \mathbb{R}^{\mathbf{M}\times\mathbf{r}}$ and $\mathbf{V} \in \mathbb{R}^{\mathbf{N}\times\mathbf{r}}$ using nonnegative matrix factorization technique. Equation (1) represents the factorization of the matrix:

$$\begin{gathered} X \approx UV^T \\ s.t,\ U \geq 0 \text{ and } V \geq 0, \end{gathered} \tag{1}$$

whereas,

$$U \in \mathbb{R}^{M\times r}, \tag{1a}$$

$$V \in \mathbb{R}^{N\times r}. \tag{1b}$$

4.3. Nonnegative Matrix Factorization (NMF). In this scenario of EV data, trip-feature matrix $X \in \mathbb{R}^{M\times N}$ is the representation of the count of the vehicle trips with respect to the feature records. M is the total number of trips by the EV, i.e., 26150 trips, and N is the feature records, i.e., 8 features ranging from trip duration, state of charging during start and end of the trip, average velocity, AC 'On' duration, headlamp 'On' duration, distance travelled from source to destination, and number of passengers occupied by the vehicle. Implementation of NMF on this dataset is much useful in separately extracting the usage patterns by the representation of lower-dimensional factor matrices U (trips × patterns) and V (features × patterns). As defined in Equations 1(a) and 1(b), "r" distinctive patterns can be obtained from X matrix during the factorization process based on the rank "r." Optimization problem is formulated, in Equation (2), which is the minimization problem with Euclidean distance as the cost function:

$$\min_{U\geq 0,\, V\geq 0} f(U, V) = X - UV^{T2}. \tag{2}$$

The cost function as defined in Equation (2) is a nonconvex optimization problem that can be solved using factorization algorithms such as alternating least squares (ALS), multiplicative update (MU) rule, and stochastic gradient descent. In this study, we used MU rule to solve Equation (2). Due to the nonconvex nature, we must fix U to learn V and fix V to learn U. The NMF starts with randomly initialized values for the factor matrices U and V. The MU rules will then be applied to update the factor matrices using gradient calculation. The MU rules will take the following form:

$$U \leftarrow U - \mu_U.\nabla_U f(U, V), \tag{3a}$$

$$V \leftarrow V - \mu_V.\nabla_V f(U, V), \tag{3b}$$

where μ_U and μ_V indicate the learning rates for updating U and V, respectively, and $\nabla_U f(U, V)$ and $\nabla_V f(U, V)$ represent the gradients (derivatives) of $f(U, V)$ with respect to U and V, respectively.

By substituting the derivatives of U and V in Equations 3(a) and 3(b), the MU rules will become

$$\begin{aligned} U &\leftarrow U - \mu_U.\left(XV - UVV^T\right), \\ V &\leftarrow V - \mu_V.\left(U^T X - U^T UV\right). \end{aligned} \tag{4}$$

The simplest form of update rule avoids subtractions by defining the learning rates μ_U and μ_V as (U/UVV^T) and (V^T/U^TUV). In this form, the positive component and negative component of the derivatives are used as numerator and denominator, respectively:

$$\begin{aligned} U &\leftarrow U.\frac{XV}{UVV^T}, \\ V &\leftarrow V.\frac{U^T X}{U^T UV}. \end{aligned} \tag{5}$$

4.4. Evaluation Measures. As Equation (2) is a nonconvex optimization problem, the choice of "r" is not straightforward. Therefore, the rank "r" in Equations 1(a) and 1(b) is determined using the various evaluation measures such as within-cluster dispersion and between-cluster dispersion. Based on the abovementioned evaluation measures, optimal rank is determined on the clusters and data points, whereas cluster is nothing but patterns. The determination of within-cluster dispersion and between-cluster dispersion is to prove that the clusters are well separated from the other data points and clusters as well as the data points are grouped together within the cluster, respectively. Figure 3 shows the rank evaluation measures for the EV dataset, whereas 1e6 in Figure 3(b) represents the unit of Y-axis in exponential notation (1e6 is equivalent of 1 million). Equations (6) and (7) show the within-cluster dispersion and between-cluster dispersion, respectively:where B_d and W_d are between-cluster and within-cluster dispersions, S shows the set of data, clusters are represented as g, and the set of points in the cluster are represented as C_g. c_g and c_s are the center of cluster and center of data, respectively, while n_g indicates the number of points in the cluster.

$$W_d = \sum_{g=1}^{m} \sum_{x\in C_g} \left(x - c_g\right)\left(x - c_g\right)^T, \tag{6}$$

$$B_d = \sum_{g=1}^{m} n_g\left(c_g - c_S\right)\left(c_g - c_S\right)^T. \tag{7}$$

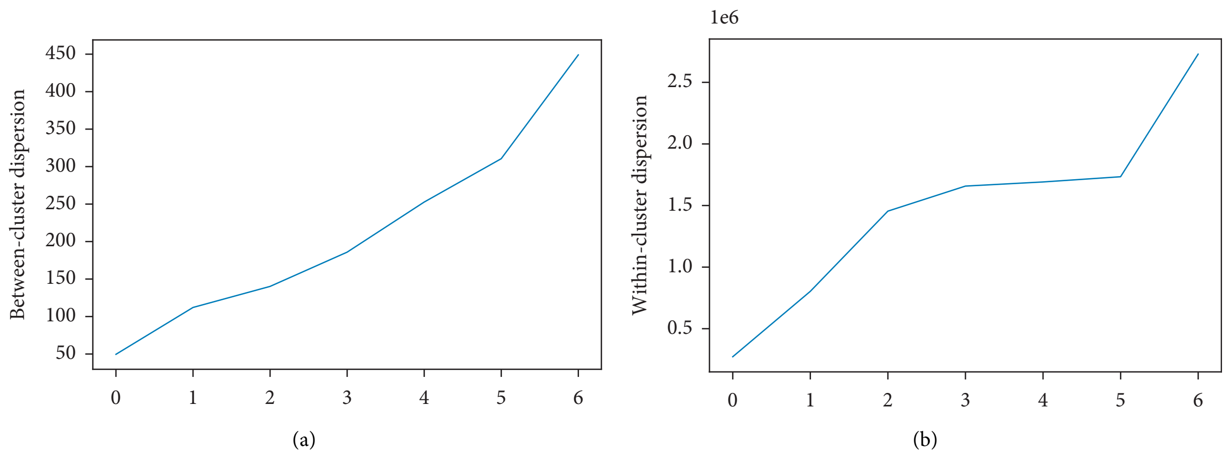

FIGURE 3: Rank evaluation measures: (a) between-cluster dispersion; (b) within-cluster dispersion.

4.5. Analysis on EV Data. Elicitation of patterns from the EV usage data helps to understand the EV usage patterns based on the various features including trip duration, state of charging during start and end of the trip, average velocity, AC 'On' duration, headlamp 'On' duration, distance travelled from source to destination, and number of passengers occupied by the vehicle.

Figure 4 shows the heatmap representation of the EV usage patterns based on various features. The heatmap representation shows that there are 7 different patterns such as P1 to P7, on the EV usage data with corresponding feature representations. If we consider pattern P1, trip duration has more dominance in comparison to other features. In pattern P2, passenger occupancy is more. In pattern P3, there is no dominance of trip duration and passenger occupancy; however, distance travelled shows its dominance in P3 pattern. Likewise, pattern P4 shows average velocity is dominating than other features. Pattern P5 is quite interesting as this shows the dominance of AC Power-On duration compared to others. Also, the state of charge during the end of the trip is dominating in the P6 pattern while there are no moderate changes in the P7 pattern.

The above pattern analysis is very difficult to obtain from the initial preanalysis of the dataset. Here comes the usage of NMF technique in eliciting these latent pattern behaviors in the EV usage dataset.

4.6. Understanding the EV Usage Patterns Based on Source/Destination. As discussed in Section 4.5, it is important to analysis the impact of the pattern variations based on the source and destination of the EV. Figure 5 shows the pattern analysis of the EV trips based on the origin (source) of the trip. In Figure 5, *X*-axis shows the representation of cluster IDs, which are the patterns ranging from P1 to P7, and *Y*-axis shows the count of the total number of trips by the EV based on the source such as home, work, or other locations.

The analysis on Figure 5 shows that patterns P1 and P6 have the huge impact based on the EV trip origin, whereas there is a moderate impact of patterns P3 and P7. On considering pattern P6, it is very clear pattern P6 is more concentrated to the other places as the origin of the trip such that the usage of the EV from other places to either home or work is preferred. This applies to almost all the patters ranging from P1, P2, P3, and P7, whereas only moderate usage of the EVs travelling from home to work or other locations.

Figure 6 shows the pattern analysis of the EV trips based on the trip end, i.e., destination. As discussed in Figure 5, patterns P1 and P6 have more records of the EV usage based on the trip destination. As similar to the trip source, the usage of the EV from either home or work to other places is more preferred. However, pattern P7 is quite different such that the usage of vehicle is more preferred to home as the destination irrespective of the trip origin which is either from work or other places. From the analysis based on Figure 4, Figure 5, and Figure 6, pattern P6 is more dominating in which the EV users are travelling from home/work to other places and vice versa. Also, on considering the heatmap representation in Figure 4, pattern P6 is corresponding to the high dominance of state of charge of EV during trip end.

5. Renewable Solar-Powered Wireless EV Charging during Traffic Signal Waiting Time

One of the problems identified from the analysis of the EV usage patterns is that a greater number of EV travelling from home/work to other places or vice versa are undergoing the charging pattern during the end of most of the trips. This can be addressed using the proposed architecture in which the solar-powered wireless EV charging grid installed underneath the roadway nearby to the traffic signal areas provides the electric power needed to the EV during long traffic signal waiting time. The power to the smart grid is obtained using the solar panels installed alongside to the roadways. However, the length of the solar-powered wireless EV-smart charging grid varies according to the respective landscape of the regions.

Application of the solar-powered wireless EV-smart charging is elaborated in Figure 7, which shows the schematic representation of the implementation of the solar-

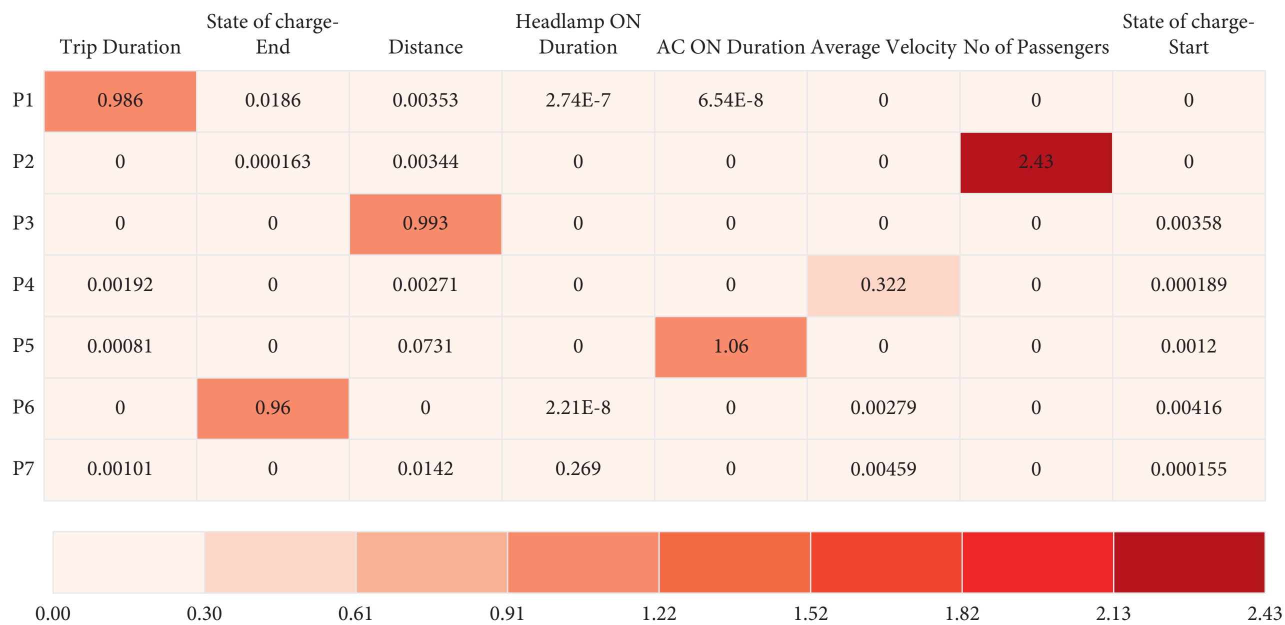

Figure 4: Heatmap representation of EV usage patterns based on various features.

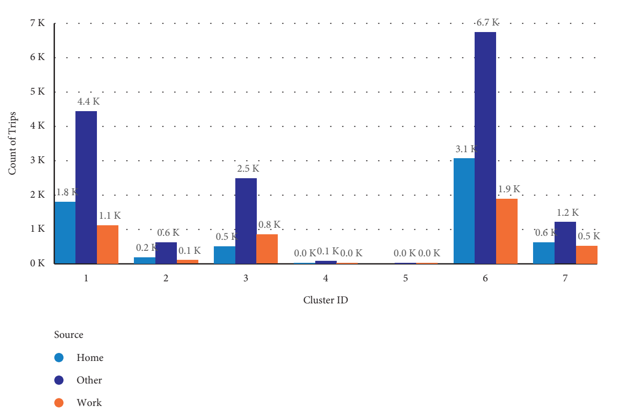

Figure 5: Pattern analysis of EV trips based on trip origin (source).

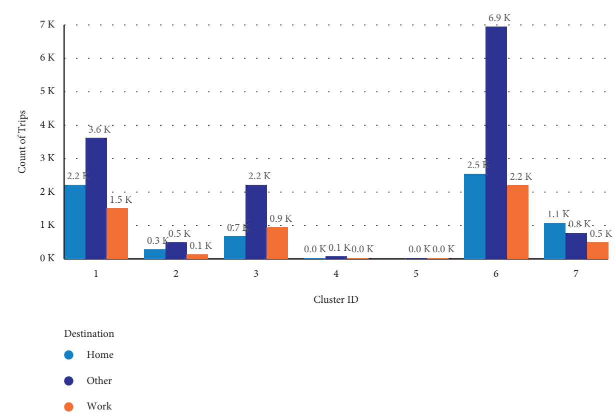

Figure 6: Pattern analysis of EV trips based on trip end (destination).

powered wireless EV-smart charging grids installed underneath the roadway of the traffic signal areas where there is a long waiting time due to the heavy traffic scenarios. By this implementation, it is very easy to tackle the problem of state of charge of the EV during trip end from the dataset analyzed in this study while utilizing the renewable resources as the power source for efficiently powering up the smart grid (Figure 7).

Alongside to the above analysis, additional dataset [28, 29] consisting of 24 hours traffic signal volume data recorded on traffic signals in various places of Victoria is analyzed.

Traffic signal volume data are recorded by utilizing the detectors and installed into the road surface, which is activated once the vehicle passes over it. The detector sends the pulse signal to the traffic signal in this manner. The analysis is conducted on the quarter Q1 of 2020 traffic signal volume count data to get the insights of traffic signal volume data. Figure 8 shows the pie-chart representation of the total traffic signal volume counts data recorded during the Q1 of 2020, i.e., traffic signal volume count data from January to April 2020. The representation shows that nearly 20 billion of vehicles crossed the traffic signals per month in the Q1 of 2020.

Figure 9 shows the graphical representation of traffic signal volume counts recorded on the respective regions of Victoria location, whereas BBN, Blackburn, BEN, Bendigo, BRI, Brighton, CA1, Carlton 1, CA2, Carlton 2, CRN, Croydon, DIO, Dialin/Dialout, DON, Doncaster, ES2, Essendon 2, ESS, Essendon, FR2, Frankston 2, FRA, Frankston, FT1, Footscray 1, FT2, Footscray 2, FT3, Footscray 3, GE2, Geelong2, GEE, Geelong, GLI, Glen Iris, GR2, Greensborough 2, GRE, Greensborough, KEW, Kew, MC1, Melbourne City 1, MC2, Melbourne City 2, MC3, Melbourne City 3, MEN, Mentone, MNP, Moonee Ponds, PR2, Preston 2, PRS, Preston, SK1, St Kilda 1, SK2, St Kilda 2, SP2, Springvale 2, SPR, Springvale, VI2, regional Victoria 2, VIC,

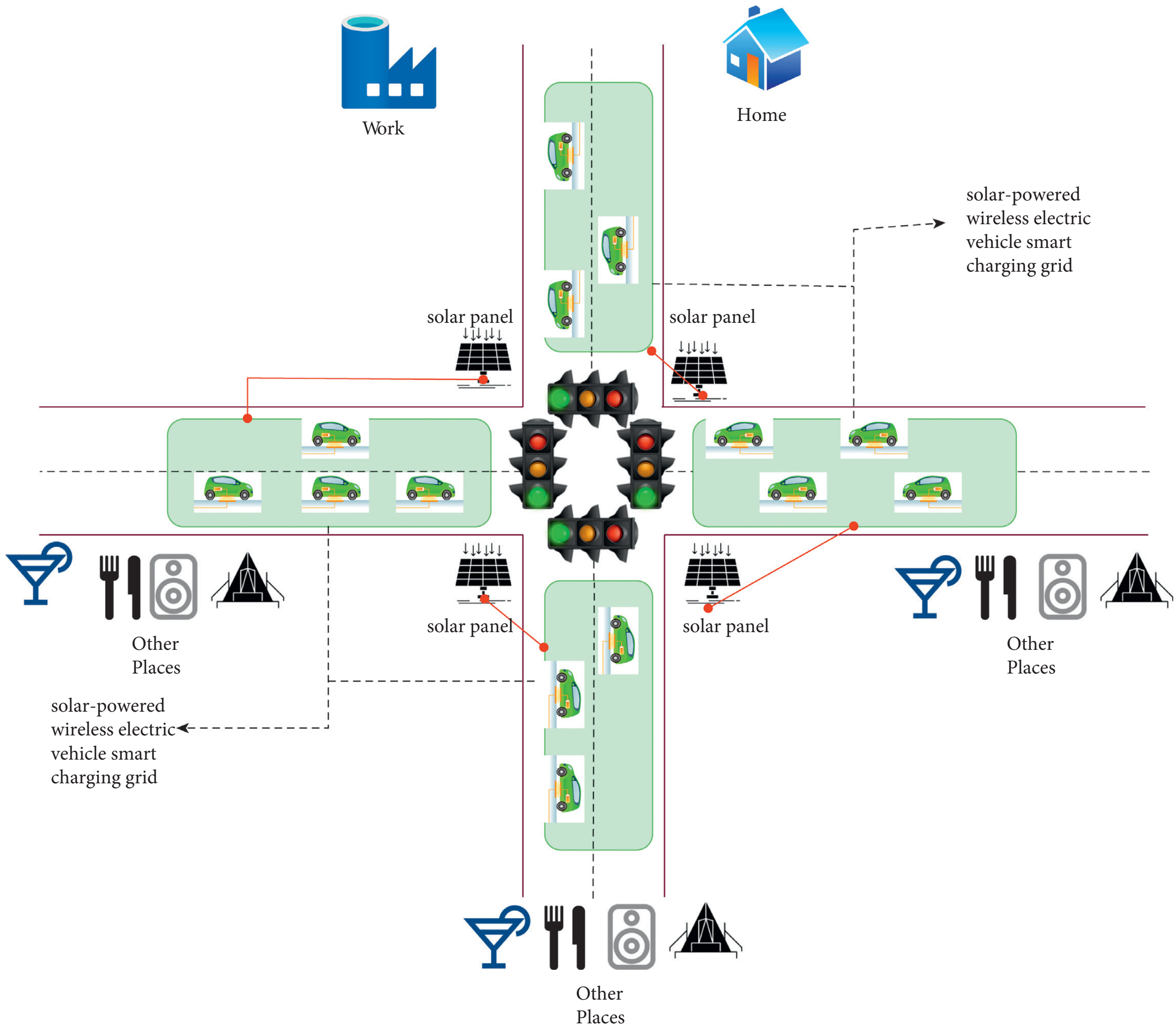

Figure 7: Schematic representation of solar-powered wireless EV-smart charging grid.

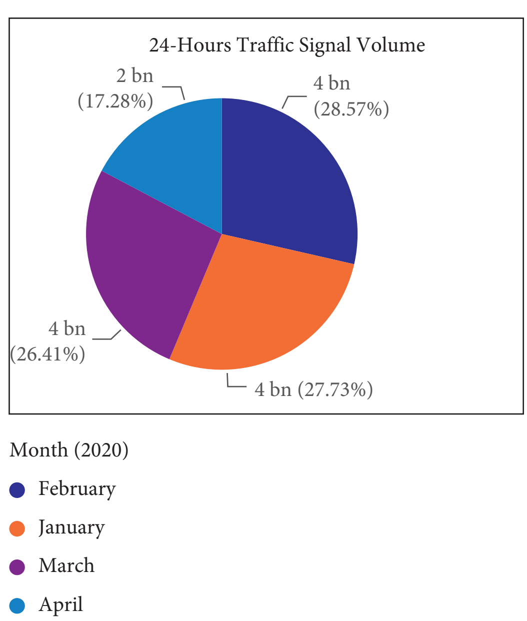

Figure 8: Pie-chart representation of 24-hours traffic signal volume data.

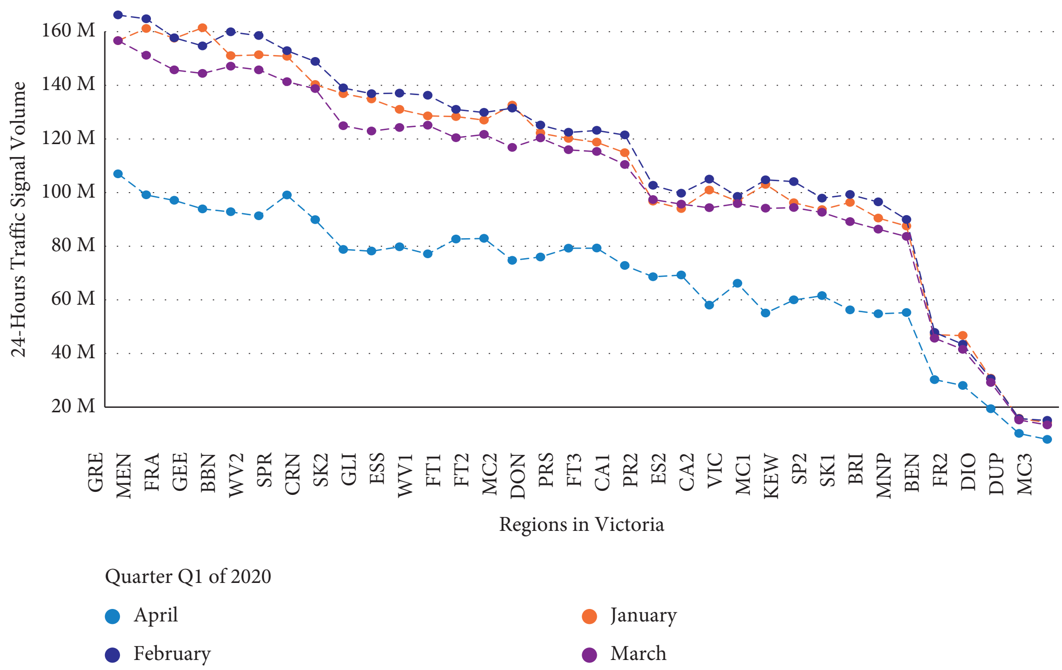

Figure 9: Twenty-four hours' traffic signal volume data by regions in Victoria during Q1 of 2020.

regional Victoria, WV1, Waverly 1, and WV2, Waverly 2. This analysis shows that passengers are spending long times on traffic signals based on the traffic signal volume records. In Figure 9, except few regions of Victoria, almost all the regions are experiencing a greater number of traffic signal volumes, which leads to long waiting hours in the traffic signals. The similar pattern can be expected on the EV usage as the growth of the EV usage is exponentially increasing. The proposed architecture of implementation of the solar-powered wireless EV-smart charging grids installed underneath the roadway of the traffic signal areas can be efficiently utilized on these kinds of use cases based on the historical traffic signal volume records alongside to the initial analysis of the EV usage patterns. In this manner, the proposed architecture improves urban planning. Initial installation cost of the wireless solar-powered EV charging smart grids may seem to be challenging; however, the overall usage is very effective which leads to the efficient utilization of the traffic signal waiting time and improves the passenger's or driver's overall transportation experience.

6. Conclusion

This study analyses the usage patterns of the EV trips that were recorded on the smart-grid smart-city EV trial data project which utilizes 20 EVs used by households and businesses. Also, the importance of NMF to elicit the latent usage patterns of the EV trips from the outputs of NMF is discussed. Alongside to this pattern analysis, impact of the pattern variations based on the EV's source and destination is analyzed to have a clear picture on how the variation in the patterns impacting the overall mobility. In addition, we proposed the architecture that explains the usage of implementing solar-powered wireless EV-smart charging grid installed underneath the roadway of the traffic signal area to mitigate the problems in traffic signal long waiting time in relation to the obtained usage patterns. This implementation also helps to encourage the use of a greater number of EVs in the near future which leads to the development of efficient and sustainable transportation to the mankind.

Data Availability

The datasets used in the study are openly available to the readers. Readers can access EV usage data and traffic signal volume count data used in this paper at https://data.gov.au/data/dataset/smart-grid-smart-city-electric-vehicle-trial-data and https://discover.data.vic.gov.au/dataset/traffic-signal-volume-data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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