An Electric Power Consumption Analysis System for the Installation of Electric Vehicle Charging Stations

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Received: 31 August 2017; Accepted: 29 September 2017; Published: 3 October 2017

Abstract: With the rising demand for electric vehicles, the number of electric vehicle charging stations is increasing. Therefore, real-time monitoring of how the power consumption by charging stations affects the load on the peripheral power grid is important. However, related organizations generally do not provide actual power consumption data in real time, and only limited information, such as the charging time, is provided. Therefore, it is difficult to calculate and predict the power load in real time. In this paper, we propose a new model for estimating the electric power consumption from the supplied information, i.e., the charging time and the number of charging involved. The experimental results show that by displaying this information on a map, it is possible to visually monitor the electric power consumption of the charging stations with an accuracy rate of about 86%. Finally, the proposed system can be used to relocate and select the location of vehicle charging stations.

Keywords: electric power consumption estimation; regression model; electric charging station

1. Introduction

Over the past decade, with the development of electric vehicle battery technology, the demand for electric vehicles has been rising rapidly in developed countries [1]. Therefore, it has become very important to choose optimal locations for charging stations [2], and maintain the load balance of the peripheral electric power supplies. If the stations are installed according to a certain distance, it is difficult to operate them efficiently. Therefore, an analysis system for electric power consumption is needed for cost reduction and the efficient operation of the charging stations. Moreover, the utilization rate and electric power consumption of the existing stations need to be analyzed to find underutilized and overutilized charging stations. Using this information, the existing stations need to be relocated or additional installation needs to be performed. For this purpose, we propose a novel system that can check the electric power consumption of each charging station in real time.

It is best to obtain the actual data of electric power consumption for the charging stations, but the real-time data provided by the related organizations are extremely limited. In the case of Korea power exchange (KPX) [3], the electric power organization in Korea, it is possible to check the real-time power supply and demand status for specific regions. However, it is difficult to verify detailed information, such as electric power consumption, at electric vehicle charging stations. The charger management organization does not have a system that can directly receive information about electric power consumption in real time. Therefore, it is necessary to estimate electric power consumption using the supplied data. In general, the electric power consumption of an electric vehicle depends on the initial state of charge (SOC) of the battery and the charging time [4], i.e., power consumption can be estimated using the charging time, initial SOC, and the data related to charging power. In particular, the operating states of the charging stations and location information can be obtained from real-time data. Hence, it is necessary to calculate the electric power consumption by generating an estimation model.
Carlos Gomez and Morcos [5] used ambient temperature and charge duration to determine the power load due to the battery charging of electric vehicles. This method was conducted under the assumption that all electric vehicle batteries were completely discharged, i.e., the initial SOC states were not considered. However, as charging time and the initial SOC of the battery have random values in a real environment, it is difficult to apply this method in a realistic situation. Cheng and Hui-mei [6] used Monte Carlo Simulation to randomly generate the initial SOC and charging time of an electric vehicle, and thereby calculated the electric power consumption. Here, the initial SOC is useful information to determine the maximum power consumption of the charging station that can be consumed in a single charge. This method calculates the charging power using a new SOC curve obtained by simply averaging the battery capacity and SOC curve values of the currently commercialized electric vehicle. However, the actual values of these two parameters (battery capacity and SOC curve) are important for calculating the power consumption of the charging stations. Therefore, this method is not suitable for calculating actual power consumption. Qiang et al. [7] calculated a battery’s SOC by measuring the change in the charging current. However, in this method, sensors must be attached to vehicles that are currently in operation so that relevant information can be received. As a result, it is not a cost-efficient method. Cauwer et al. [8] developed a model to estimate an electric vehicle’s power consumption using the kinematic parameters of the electric vehicle (EV) or the trip data as inputs. We cannot know the amount of power consumption of charging stations in a certain area. This is because, in general, a charging station is shared and used by more than one vehicle. In other words, it is hard to find out how much the charging stations load the peripheral electric power grid in a certain area. Sun et al. [9] developed a predictive model of charging load based on past power load data. The model predicted the power load of the stations using time series data, such as weather, week property, and temperature, as input variables.

In order to overcome the above-mentioned problems, we propose a new system for analyzing the electric power consumption of electric vehicle charging stations by using real-time data that reflect the actual electric vehicle information. This system can not only be used in a real environment, but also is efficient in terms of cost and accuracy as compared to existing methods.

The paper consists of the following sections. Section 2 describes an overview of the proposed system and a detailed description of each module. Section 3 describes the evaluation of the estimation model and experimental results for each of the 48 charging stations in Jeju island in Korea. Section 4 draws conclusions.

2. Proposed System

Figure 1 shows the block diagram of the proposed system. The system consists mainly of data preprocessing, data modeling, and data analysis units. The data preprocessing section processes the input data for creating the estimation model. The data modeling unit generates the model that can estimate electric power consumption using only the charging time and the number of charging. The database system section creates the database that estimates electric power consumption by receiving the information related to the vehicle charging stations in real time. By mapping real-time data to a map along with location information, the proposed system monitors electric power consumption for each charging station.
2.1. Data Preprocessing

The actual charging station data may be deformed due to a failure of the charger or error that may occur during data storage and transmission. These may lead to fatal problems in generating the estimation model of electric power consumption. Therefore, in this step, before the electric power consumption estimation is modeled with raw data, the preprocessing step removes the errors to make the data correct for use in the estimation model.

2.1.1. Data Filtering

Considering the battery capacity of the current commercial electric car (Korea standard), charging takes up to a maximum of 40 minutes to complete while using a generic fast charger, because the maximum power consumption no longer increases beyond 40 minutes in charging time as shown in Figure 2. Figure 3 shows that when a battery’s SOC reaches a certain level, the charging power consumption approaches zero. This indicates that there is little change in electric power consumption after a certain time (in this case, 40 minutes). Therefore, if the entirety of the charging time is used without the data filtering process, an incorrect power consumption estimation model would be obtained; therefore, the data beyond 40 minutes are excluded from the dataset.
2.1.2. Data Selection

The next step is to select data from the whole data range received from organizations related to the vehicle charging stations. The data include location information, start and end time of charging, and charging time. In other words, the data in real time is not data of the actual electric power consumption. So, data that can estimate power consumption is needed. Equation (1) is used to calculate the electric power consumption when electric vehicles are charged [10].

\[
P_{\text{consumption}} = \int_{t_0}^{t_0+T} P(t) dt = (1 - \text{SOC}_{\text{ini}})Q_r,
\]

where \( P_{\text{consumption}} \) is the electric power consumption during time \( T \), \( \text{SOC}_{\text{ini}} \) is the initial SOC of an EV’s battery, \( Q_r \) is the rated capacity of the EV’s battery, \( t_0 \) is the starting time of charging, \( T \) is the charging duration, and \( P(t) \) is the charging power at time \( t \).

According to Equation (1), the charging time is an important factor in calculating the electric power consumption of vehicle charging stations. Moreover, the battery SOC information of the electric vehicle at the beginning of charging is important for estimating the power consumption. This is because, even if the same charging duration is used, the electric power consumption can be different depending on the initial SOC of the battery. However, this is not real-time information that may be received by the related organization, and hence other related data are necessary to replace it. Therefore, the number of charging that is performed for a specific period is used.

As shown in Figure 2, the power consumption data distribution of an actual charging station shows several power consumption values despite the same charging time. This indicates the presence of different battery SOC levels at the beginning of charging, which supports our logic that using this data directly to create a data model is not appropriate. In order to solve this problem, all of the data of the charging station during a certain period are integrated. The distribution of the integrated data is shown in Figure 4. In the distribution, the variance of the electric power consumption for the same charging time is significantly reduced. This means that when the data are integrated, the influence of battery SOC is significantly reduced.

![Figure 3](image-url) Charge curve of a lithium-ion battery equipped in a Nissan Altra EV. SOC: state of charge.

![Figure 4](image-url) New electric power consumption distribution obtained by integrating the data of Figure 2 for a specific period (units: charging time (sec), power consumption (kWh)).
Therefore, the number of charging for a specific period is used to estimate the electric power consumption of each vehicle charging station instead of the SOC value, which is highly influenced by a user’s pattern. In short, charging time and the number of charging for a specific period are selected as the prediction variables (input variables).

2.2. Data Modeling

Figure 5 describes the detailed data modeling process. This process creates the estimation model using the preprocessed data described in Section 2.1. In short, we propose an electric vehicle (EV) charging power consumption regression model to estimate the electric power consumption of each vehicle charging station. A regression model is one of the techniques used for multifactor data analysis [11]. It is a statistical technique for modeling the relationship between variables [12]. The following section provides the detailed description.

**Figure 5.** Overall process of data modeling.

**EV Charging Power Consumption Regression Model**

The EV charging power consumption regression model is a new estimation model of electric power consumption using the relationship between charging time and the number of charging. This model is an analytical method to find the most suitable model that can estimate the relationship between the predicted variables. The proposed model is described by Equation (2).

\[
P(X_{CT}, X_{NTC}) = w + w_{CT}X_{CT} + w_{NTC}X_{NTC} + e
\]  

(2)

where \( P(X_{CT}, X_{NTC}) \) is the charging power, \( CT \) is the charging time, \( NTC \) is the number of charging, \( X_{CT} \) and \( X_{NTC} \) are predictor variables, \( w_{CT} \) and \( w_{NTC} \) are weights for the predictor variables, and \( e \) is the error (or residual), which is the discrepancy between the real and predicted power. It can be represented by rearranging Equation (3) as:

\[
e = P(X_{CT}, X_{NTC}) - w - w_{CT}X_{CT} - w_{NTC}X_{NTC}.
\]  

(3)

When the value of ‘e’ in Equation (3) is minimal, an optimal power estimation model that can estimate the relationship between the variables can be obtained. In order to do this, the optimal values of \( w, w_{CT}, \) and \( w_{NTC} \), which are the weights of preprocessed data related to the electric power consumption (charging time and the number of charging) are obtained by the least square method [13,14]. Using these values, the proposed model that minimizes the prediction error is created.

The least square method determines the weights from the condition that minimizes the sum of the square of the probability error (Equation (4)) [14], which is the difference between the actual and predicted data for the entire data. When the square of the probability error is minimized, the partial derivatives from Equations (5)–(7) are zero. The equations are summarized and expressed in the form of a matrix in Equation (8) [15].
where $S_r$, $P_{\text{real}}$, and $P_{\text{prediction}}$ are the squared error, real power, and predicted power, respectively.

All optimal weights $(w_{\text{CT}}, w_{\text{NTC}})$ are determined from Equation (8). Using these weights, the final EV charging power consumption regression model is produced. An evaluation of this model will be discussed in Section 3.

2.3. Database System

Figure 6 shows the overall structure of the database system. This system uses a database for monitoring the electric power consumption of vehicle charging stations in real time. The real-time information provided by the related organizations is the operating state of the charging station (being charged, available, checking), and location. The charging time and the number of charging for a specific period are calculated from the operating state of the charging station. This is called the data handling process. The calculated data is stored in the database and used as the input data for the regression model. The predicted electric power consumption, charge time, and the number of charging obtained from the above process are stored in the database along with the location information, and are updated periodically. Using stored data in the database, it is possible to monitor the electric power consumption during a specific period for each charging station in real time.

![Figure 6. Overall structure of the database system. PC: personal computer.](image-url)
3. Experimental Results

Experiments were conducted on Jeju island, which has the most active EV charging stations in Korea. As shown in Figure 7, a total of 48 currently operating EV fast charging stations were selected. We use integrated data on a monthly unit to create a model. The training set and the test set were divided by a 8:2 ratio from the whole dataset. The detailed characteristics of the data used in the experiment are listed in Table 1.

Table 1. Period and the number of samples for the data on electric charging stations

<table>
<thead>
<tr>
<th>Period</th>
<th>The Number of Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>January 2015–May 2017</td>
</tr>
<tr>
<td>Train</td>
<td>January 2015–December 2016</td>
</tr>
<tr>
<td>Test</td>
<td>January 2017–May 2017</td>
</tr>
</tbody>
</table>

![Figure 7. Electric vehicle charging stations on Jeju island used for the experiments.](image)

3.1. System Implementation

We implemented the proposed system using the Python language. There are two important algorithms (data preprocessing and data modeling) in our system. We wrote the procedure of the algorithms in pseudo code as follows.

The pseudo code in Figure 8 represents the data preprocessing part. To summarize Figure 8, first, it filters data whose charging time or power consumption is 0 or null. Then, it integrates the data into a specific interval (here, one month). Through this process, we can get integrated data such as charging time, power consumption, and the number of charging.

```
for \( t_{\text{ct}} = 0; t_{\text{ct}} < \text{length(data}_{\text{ct}}); t_{\text{ct}} ++ \)
for \( t_{\text{pc}} = 0; t_{\text{pc}} < \text{length(data}_{\text{pc}}); t_{\text{pc}} ++ \)
  if (data_{\text{ct}} [t_{\text{ct}}] = \text{null or 0})
    elseif (data_{\text{P}} [t_{\text{pc}}] = \text{null or 0})
      else
        data_{\text{preprocessing}} [t_{\text{ct}}][t_{\text{pc}}]
        = data_{\text{CT}} [t_{\text{ct}}][t_{\text{pc}}] \text{ data}_{\text{PC}} [t_{\text{ct}}][t_{\text{pc}}]

data_{\text{integration}} = data_{\text{merge(data}_{\text{preprocessing}}, \text{month})}
```

CT: Charging Time, PC: Power consumption

Figure 8. Pseudo code of data preprocessing (data filtering and integration).
The pseudo code in Figure 9 represents the data modeling part. The algorithm of Figure 9 is summarized as follows. For the whole data, this method first calculates the square of the difference between the actual power consumption and the power consumption obtained by Equation (4). Then, values that minimize the sum of the data are obtained.

\[
\text{Load } \text{dataIntegration}
\]
\[
\text{for } (i_{\text{long}} = 0; i_{\text{long}} < \text{length(dataIntegration)}; i_{\text{long}}++)
\]
\[
\text{for } (i_{\text{short}} = 0; i_{\text{short}} < \text{length(dataIntegration)}; i_{\text{short}}++)
\]
\[
\text{Error} =
\]
\[
\text{data}_{\text{PCIntegration}}[i_{\text{long}}][i_{\text{short}}] -
\]
\[
\text{w}_{\text{CT}}[i_{\text{long}}][i_{\text{short}}] \times \text{data}_{\text{CTIntegration}}[i_{\text{long}}][i_{\text{short}}] -
\]
\[
\text{w}_{\text{NC}}[i_{\text{long}}][i_{\text{short}}] \times \text{data}_{\text{NCIntegration}}[i_{\text{long}}][i_{\text{short}}] -
\]
\[
w_0[i_{\text{long}}][i_{\text{short}}]
\]
\[
\text{squared_error}[i_{\text{long}}][i_{\text{short}}] +=
\]
\[
nerror^2[i_{\text{long}}][i_{\text{short}}]
\]
\[
\frac{\partial (\text{squared_error})}{\partial w_{\text{CT}}} \rightarrow 0
\]
\[
\frac{\partial (\text{squared_error})}{\partial w_{\text{NC}}} \rightarrow 0
\]
\[
\frac{\partial (\text{squared_error})}{\partial w_0} \rightarrow 0
\]
\[
\text{for } (i_{\text{tot}} = 0; i_{\text{tot}} < \text{length(data)}; i_{\text{tot}}++)
\]
\[
\text{if } (\text{data}_{\text{CT}}[i_{\text{tot}}][i_{\text{tot}}] = \text{NULL or } 0)
\]
\[
\text{elseif } (\text{data}_{\text{PC}}[i_{\text{tot}}][i_{\text{tot}}] = \text{NULL or } 0)
\]
\[
\text{else}
\]
\[
\text{data}_{\text{primary}}[i_{\text{tot}}]
\]
\[
= \text{data}_{\text{CT}}[i_{\text{tot}}][i_{\text{tot}}] \times \text{data}_{\text{PC}}[i_{\text{tot}}][i_{\text{tot}}]
\]
\[
\text{Solve the above partial differential equations,}
\]
\[
\text{Get the weights } (w, w_{\text{CT}}, \text{and } w_{\text{NC}}) \text{ & model function for power consumption of EV stations}
\]
\[
\text{data}_{\text{PCIntegration estimate}} = \text{model(data}_{\text{CTIntegration}} \times \text{data}_{\text{NCIntegration}})
\]
\[
\text{NC: the Number of Charging}
\]

Figure 9. Pseudo code of data modeling.

In Section 3.2, we evaluate the power consumption estimation model as obtained above.

3.2. Evaluation of EV Charging Power Consumption Regression Model

The accuracy of the EV charging power consumption regression model was evaluated by using two metrics: Mean Absolute Percentage Error (MAPE) [16] and Normalized Root Mean Square Error (NRMSE) [17]. Both of these metrics had features that were independent of the data scale.

3.2.1. Evaluation Metrics

MAPE is a widely used metric for comparing the prediction performance of different data by measuring the percentage error, and it can be expressed by Equation (9). The percentage error is the ratio of the real power value to the error, and it is expressed by Equation (10).

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{p_i}{p_i} \right| = \frac{1}{n} \sum_{i=1}^{n} |p_i|
\]  \hspace{1cm} (9)
where $p_i$ is the percentage error, $e_i$ is the forecast error, $P_{i,prediction}$ is the $i$th predicted power value for the constituent being evaluated, and $P_{i,real}$ is the real power value for the constituent.

However, in the case of MAPE, if the data is close to zero, the percentage error may have an extremely skewed distribution. As a result, it is difficult to use it for zero or very small electric power consumption. In order to compensate for this problem, NRMSE is additionally used for the model’s evaluation.

NRMSE is a metric that normalizes the root mean square error. This is expressed by the percentage of how much the predicted data deviates from the line, and is expressed by Equation (11).

$$\text{NRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_{i,\text{prediction}} - P_{i,\text{real}})^2} \times \frac{100}{M},$$  

where $M$ is the average of predicted power values.

3.2.2. Evaluation Results for EV Charging Power Consumption Regression Model

The EV charging power consumption regression model mentioned in Equation (2) was used to evaluate how well the electric power consumption of each charging station was estimated. The results are listed in Table 2.

Table 2. Results from charging stations on Jeju island applying the EV charging power consumption regression model.

<table>
<thead>
<tr>
<th>Charging Station</th>
<th>MAPE(%)</th>
<th>NRMSE(%)</th>
<th>RMSE(kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15.451</td>
<td>15.599</td>
<td>179.676</td>
</tr>
<tr>
<td>2</td>
<td>13.936</td>
<td>15.710</td>
<td>114.085</td>
</tr>
<tr>
<td>3</td>
<td>16.519</td>
<td>20.603</td>
<td>296.552</td>
</tr>
<tr>
<td>4</td>
<td>10.711</td>
<td>12.931</td>
<td>342.108</td>
</tr>
<tr>
<td>5</td>
<td>13.410</td>
<td>13.471</td>
<td>303.040</td>
</tr>
<tr>
<td>6</td>
<td>8.158</td>
<td>8.707</td>
<td>291.095</td>
</tr>
<tr>
<td>7</td>
<td>16.241</td>
<td>17.632</td>
<td>458.939</td>
</tr>
<tr>
<td>8</td>
<td>12.995</td>
<td>13.213</td>
<td>584.086</td>
</tr>
<tr>
<td>9</td>
<td>9.157</td>
<td>8.707</td>
<td>451.650</td>
</tr>
<tr>
<td>10</td>
<td>11.025</td>
<td>11.295</td>
<td>234.659</td>
</tr>
<tr>
<td>11</td>
<td>12.490</td>
<td>13.368</td>
<td>158.394</td>
</tr>
<tr>
<td>12</td>
<td>6.981</td>
<td>8.243</td>
<td>158.525</td>
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<td>13</td>
<td>18.238</td>
<td>15.828</td>
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<td>14</td>
<td>12.195</td>
<td>12.090</td>
<td>159.809</td>
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<tr>
<td>15</td>
<td>16.389</td>
<td>16.546</td>
<td>449.747</td>
</tr>
<tr>
<td>16</td>
<td>20.904</td>
<td>22.016</td>
<td>498.520</td>
</tr>
<tr>
<td>17</td>
<td>19.034</td>
<td>19.229</td>
<td>739.039</td>
</tr>
<tr>
<td>18</td>
<td>18.772</td>
<td>19.359</td>
<td>481.611</td>
</tr>
<tr>
<td>19</td>
<td>9.510</td>
<td>11.430</td>
<td>178.609</td>
</tr>
<tr>
<td>20</td>
<td>15.430</td>
<td>15.538</td>
<td>542.412</td>
</tr>
<tr>
<td>21</td>
<td>15.762</td>
<td>16.100</td>
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</tr>
<tr>
<td>22</td>
<td>15.980</td>
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<td>1057.214</td>
</tr>
<tr>
<td>23</td>
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<td>19.650</td>
<td>411.719</td>
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<td>24</td>
<td>9.258</td>
<td>9.635</td>
<td>308.196</td>
</tr>
<tr>
<td>25</td>
<td>24.049</td>
<td>26.018</td>
<td>303.870</td>
</tr>
<tr>
<td>26</td>
<td>17.216</td>
<td>22.498</td>
<td>253.966</td>
</tr>
<tr>
<td>27</td>
<td>7.355</td>
<td>7.819</td>
<td>694.061</td>
</tr>
<tr>
<td>28</td>
<td>12.582</td>
<td>13.151</td>
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<td>19.009</td>
<td>19.630</td>
<td>490.568</td>
</tr>
<tr>
<td>30</td>
<td>14.519</td>
<td>14.941</td>
<td>224.324</td>
</tr>
<tr>
<td>31</td>
<td>6.115</td>
<td>6.601</td>
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</tr>
<tr>
<td>32</td>
<td>11.511</td>
<td>11.729</td>
<td>134.658</td>
</tr>
<tr>
<td>33</td>
<td>12.917</td>
<td>13.896</td>
<td>236.226</td>
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<td>8.983</td>
<td>8.603</td>
<td>196.159</td>
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<tr>
<td>35</td>
<td>7.897</td>
<td>8.562</td>
<td>373.645</td>
</tr>
</tbody>
</table>
Table 3 shows the results of estimating the electric power consumption of the EV charging stations from January to May 2017 using the proposed regression model. Figure 10 is a graph showing how the result of Table 3 differs from the actual power consumption. The y-axis of the graph represents the power consumption of the charging station. The x-axis represents the name of the station (1 to 48). Figure 11 shows the electric power consumption data of May 2017 (from Table 3) on a map.

Table 3. Results of electric power consumption estimation of charging stations on Jeju island applying the EV charging power consumption regression model.

<table>
<thead>
<tr>
<th>Charging Stations</th>
<th>Results of Electric Power Consumption Estimation (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2017.01</td>
</tr>
<tr>
<td>1</td>
<td>976.213</td>
</tr>
<tr>
<td>2</td>
<td>590.121</td>
</tr>
<tr>
<td>3</td>
<td>552.208</td>
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<tr>
<td>4</td>
<td>2602.497</td>
</tr>
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<td>5</td>
<td>2289.288</td>
</tr>
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<td>6</td>
<td>5828.593</td>
</tr>
<tr>
<td>7</td>
<td>2251.293</td>
</tr>
<tr>
<td>8</td>
<td>3726.512</td>
</tr>
<tr>
<td>9</td>
<td>1457.333</td>
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<td>10</td>
<td>2279.002</td>
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<td>11</td>
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<td>3875.569</td>
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MAPE: mean absolute percentage error; NRMSE: normalized root mean square error; RMSE: root mean square error
Figure 10. Comparison of real and predicted power consumption for EV charging stations: (a) January 2017; (b) February 2017; (c) March 2017; (d) April 2017; (e) May 2017.
Figure 11. Visualization of the distribution of the estimated electric power consumption for charging electric vehicles on Jeju island using the proposed system in May 2017.

As shown in Figure 11, the map-based analysis system can check and analyze the electric power consumption of each charging station for a specific period in real time. The radius of the circle indicates the amount of electric power consumption at each charging station: the higher the electric power consumption, the larger the size of the circle. It is also possible to visually understand the power load level easily by dividing the power consumption into four levels and using different colors for them. By using this, it is also possible to monitor the load contribution by vehicle charging stations in the peripheral electric power grid in real time. This can be used to relocate the electric vehicle charging stations for a homogeneous distribution of electric power loads in specific areas.

4. Conclusions

The proposed system can measure and analyze the electric power consumption for each electric vehicle charging station during a specific period in real time. The proposed EV power consumption regression model estimated the electric power consumption using only the charging time and the number of charging. As a result of the evaluation, the model showed a high accuracy of about 86%.

The overall system consists of data processing, data modeling, and database systems. The data preprocessing section preprocesses the data to be used as the input of the EV power consumption regression model. We received data of actual charging time and power consumption for two years from the related organization. The data was integrated at a specific period unit to create integrated charge time and power data. We can also get a new variable, the number of charging, which is related to EV power consumption. In the data modeling part, we made a regression model that can obtain the amount of power consumption as output by using the input data created in the data preprocessing part. As a result of the evaluation using MAPE and NRMSE, the model showed a high accuracy of about 86%. Finally, in the database system part, the charging status information (charging, waiting, checking) received in real time is converted into charging time and the number of charging and stored in the database. If the power consumption for a specific period is requested, the power consumption can be estimated through the proposed regression model using the charging time and the number of charging during the corresponding period as input.

In addition, by displaying the estimated electric power consumption on a map, it was possible to identify the areas with high power consumption. So, it is expected that the proposed model can be used effectively for relocating and selecting the locations of electric vehicle charging stations.

Acknowledgments: This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry, and Energy (MOTIE) of the Republic of Korea (No. 20161210200560).

Author Contributions: Seongpil Cheon and Suk-Ju Kang conceived and designed the experiments; Seongpil Cheon and Suk-Ju Kang performed the experiments and analyzed the data; Seongpil Cheon and Suk-Ju Kang contributed to the system’s development; and Seongpil Cheon and Suk-Ju Kang wrote the paper.
Conflicts of Interest: The authors declare no conflict of interest.

References


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