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Constraint-Aware Electricity Consumption Estimation for Prevention of Overload by Electric Vehicle Charging Station

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Received: 29 January 2019; Accepted: 11 March 2019; Published: 14 March 2019

Abstract: An increase in the number of electrical vehicles has resulted in an increase in the number of electrical vehicle charging stations. As a result, the electricity load consumed by charging stations has become large enough to de-stabilize the electricity supply system. Therefore, real-time monitoring of how much electricity each charging station is consuming has become very much important. However, only limited information such as charging time is available from the operators of electric vehicle charging stations. The actual electricity consumption data is not provided in real time. Conventional methods estimate the accumulated electricity consumption of charging stations using a linear regression curve. However, an estimate of the electricity consumption for each charge is needed. In this paper, we propose an advanced electricity estimation system which predicts the energy consumption for each charge. The proposed method uses a constraint-aware non-linear regression curve, and performs additional data selection processes. The experimental results show that the proposed system achieves about 73% regression accuracy. In addition, the proposed system can display the energy consumption per hour and visualize this information on a map. This makes it possible to monitor the electricity consumption of the charging stations in real-time and by location, which helps to select appropriate locations where new vehicle charging stations need to be installed.

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

1. Introduction

Electric-driven vehicles have been attracting much attention due to their efficient reduction of carbon dioxide emission [1]. Electric vehicles (EVs) operate on electricity stored in batteries, fuel cells (FCs), and ultra-capacitors (UCs), and the plug-in charged storage is used for charging. The top priority factor for the efficient and rapid diffusion of EVs is the support for charging facilities such as fast charging stations. A charging station can be installed at home, but it has the problem of longer charging time because of the low voltage of the charger. Therefore, charging stations with high voltage should be arranged so that they can be used conveniently by the users. However, the high load of the charging station can cause increased peak load demand resulting in voltage instability and reliability problems [2]. To avoid this problem, it is necessary to know real-time energy consumption by the EV charging stations. By estimating the energy consumption, we can determine how much electricity should be generated at power plants. In addition, the distribution of charging stations is the most important factor [3] since improper charging station distribution can cause concentration of the users to specific charging stations. In other words, the improper location and size of the charging station can have a negative impact on the development of EVs, the layout of the urban transportation network, and the convenience of the driver [4]. For this purpose, an electricity consumption analysis system is important as well. Analysis of the frequency of use and energy consumption of the existing charging stations can identify under- or over- utilized charging stations. This information can be used for relocating existing stations or installing new stations. Hence, a system that can check electricity consumption of each charging station in real time is needed.

It is best to know the actual electricity consumption data of the charging station for its efficient operation and installation, but it is difficult to obtain this data from the relevant organization [5]. In the case of Korea power exchange (KPX) [6], the electric power supply organization in Korea, it provides information on the real-time power supply and demand situation in a specific area. However, in general, it is impossible to obtain details such as the electricity consumption of EV charging stations in real time. Therefore, it is necessary to estimate electricity consumption from the provided information. The electricity demand of the EV charging load depends on the number of EVs, the charging characteristics of EV batteries, the charging time from switch-on to switch-off, and the initial state-of-charge (SOC) at the beginning of the charging process [7]. Practically, it is not possible to use all of this information for each charge cycle, so the values will always involve randomness. To know this actual information, additional sensors attached to EVs or chargers are required. Consequently, there is a need for a method that can estimate the energy consumption in real-time from only the charging time information.

In recent years, the methods to properly determine the distribution of EV charging stations has been investigated by a number of researchers. Wu et al. [8] proposed a method for selecting the optimal EV charging station location through a preference ranking organization-based decision system combined with the cloud model. This method recommended the distribution of charging stations in terms of price. Deb et al. [2] considered VRP index to determine the distribution network of EV charging stations. VRP index represents Voltage stability, Reliability, and Power loss. This method used a simulation system and found optimal distribution networks by using VRP index. Csiszár et al. [9] proposed a method using a greedy algorithm and land-use information. However, all these methods do not estimate the actual electricity consumption and consider the overload situation by EV charging stations. Our system estimates the actual electricity consumption and displays the information to prevent electricity overload by charging station.

Several studies have been conducted previously to estimate the electricity consumption of the EV charging load. Qian et al. [10] simulated four battery charging scenarios for uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging, and uncontrolled public charging to model and analyze EV charging loads in a distributed system. They also described the stochastic nature of the charging time and the initial SOC. This method needs to know the traffic information for estimating the start time of battery recharging. De Cauwer et al. [11] developed a model for estimating the electricity consumption of EVs using kinematic parameters or travel data as inputs. It needs an authority to get the information from the car owner, and we also cannot know the amount of electricity consumption in a specific area. Li et al. [12] suggested a method to forecast the electricity consumption using convolutional neural network (CNN) and lion algorithm (LA). It used seasonal category, maximum and minimum temperature, weather condition, day type, and the loads at the same moment in the previous five days as input. Cheon et al. [5] proposed a regression model that estimates the energy consumption using the charging time and the number of charge cycles. However, this method uses a linear regression curve to estimate the monthly cumulative electricity consumption rather than the electricity consunmption per charge. The electricity consumption per charge, not the cumulative electricity consumption, is important information for estimating real-time electricity load to prevent an overload situation. All these methods require use of additional information to estimate energy consumption, which can cause unexpected costs and efforts. In this paper, we propose a novel constraint-aware method based on a non-linear regression curve for estimating the electricity consumption per charge from the charging time without any supplementary information.

The main contribution of this paper can be summarized as follows:

(1) The proposed system can estimate electricity consumption of EV charging stations for each charge. It only needs the charging time, which will not cause additional costs and effects. The system can display the estimated energy consumption and visualize this information on a map. As a result, it can be used to prevent electricity overload by charging station and select location of newly installed stations.
(2) A non-linear regression curve is used to generate an estimated electricity consumption model for each charge using the charging time. Experimental results show that the relationship between charging time and electricity consumption is non-linear in the process of estimating the electricity consumption per charge.
(3) We limit the minimum electricity consumption to eliminate the outliers that impede the appropriate estimation curve. This is in line with the process of predicting the peak load demand due to the electricity load of the charging station, which is the purpose of monitoring the electricity consumption per charging station.
(4) The data selection process is performed to select the near-term data considering the fact that the usage patterns of the charging station users have temporal characteristics. This process helps to generate a more appropriate estimation curve.

2. Proposed System

The proposed system aims at extracting charging time information from real-time operating data of EV charging station and using it to estimate the energy consumption. Figure 1 shows the block diagram of the proposed system. The system consists of a training phase which generates an electricity consumption estimation model for each charging station, and an operating phase, which estimates the electricity consumption from the real-time operating data of charging stations based on the learned model.

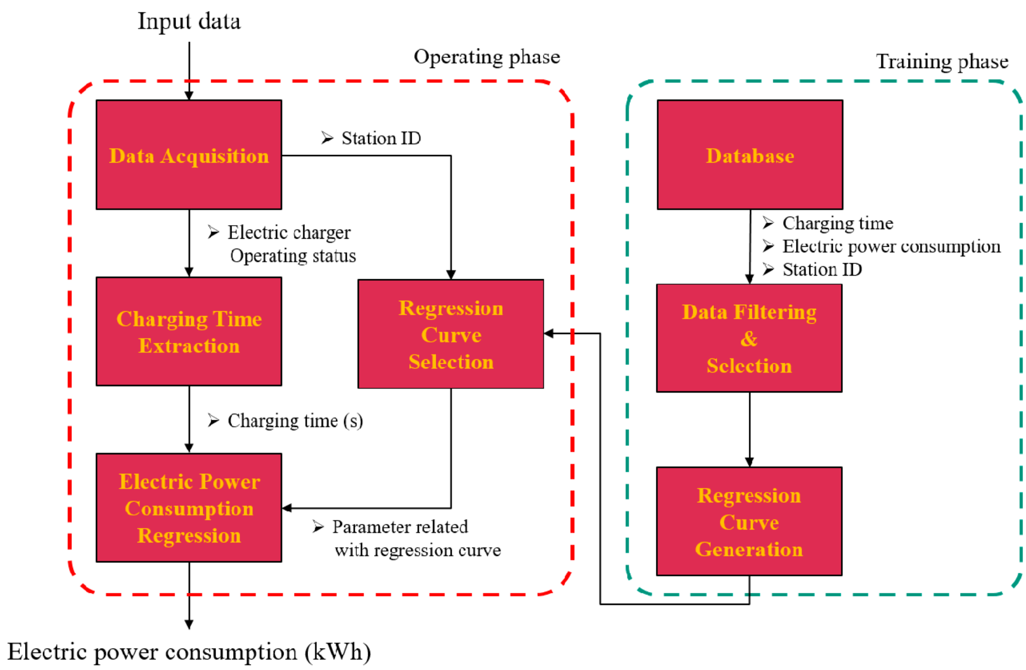


Figure 1. Block diagram of the proposed system. Station IDs are the numbers determined by the electric charger operating organizations to discriminate each station.

2.1. Training Phase

The training phase, which is the process of generating an estimation curve for the energy consumption, consists of data filtering, data selection, and regression curve generation. In the process of generating the estimation curve, past data acquired from EV charging stations are used. Since the corresponding data includes invalid data, a filtering process is required. In addition, the data selection process (minimum electricity consumption limitation process and near-term data selection) is required for more accurate estimations of model learning. We will discuss the data filtering and selection process in Section 3. Based on the selected data, regression curve fitting using the non-linear regression curve is performed.

Regression Curve Generation

From the selected data, a regression curve is generated to estimate the energy consumption by electric charging stations. However, the charging time data provided by operators of the charging station is invalid. It doesn't mean the actual charging time, but the connection time between charger and car, including the time when no current flows into the car. Therefore, the relation between the charging time and energy consumption is not one-to-one. A specific value of charging time can be mapped to multiple energy consumption values. To solve this problem, Cheon at el. [5] accumulated the energy consumption by month and applied a linear regression curve to estimate the monthly accumulated energy consumption. However, to prevent electricity overload by EV charging stations, we should be able to estimate the energy consumption for each use of the charger. Hence, this paper proposes a method estimating the electricity consumption for each use of the charger by using non-linear regression curve with several preprocessing. We will discuss the preprocessing details in Section 3. Figure 2 shows heat maps related to the estimated probability functions of the electricity consumption distributions in relation to charging time. It can be acquired by using kernel density estimation based on Gaussian function [13,14]. The dark regions are regions that have high probability value. From the heat maps, it can be argued that the relation between charging time and energy consumption is non-linear. (It is because the line crossing the darkest regions for each charging time is curved.) Hence, we use a non-linear curve as a regression curve.

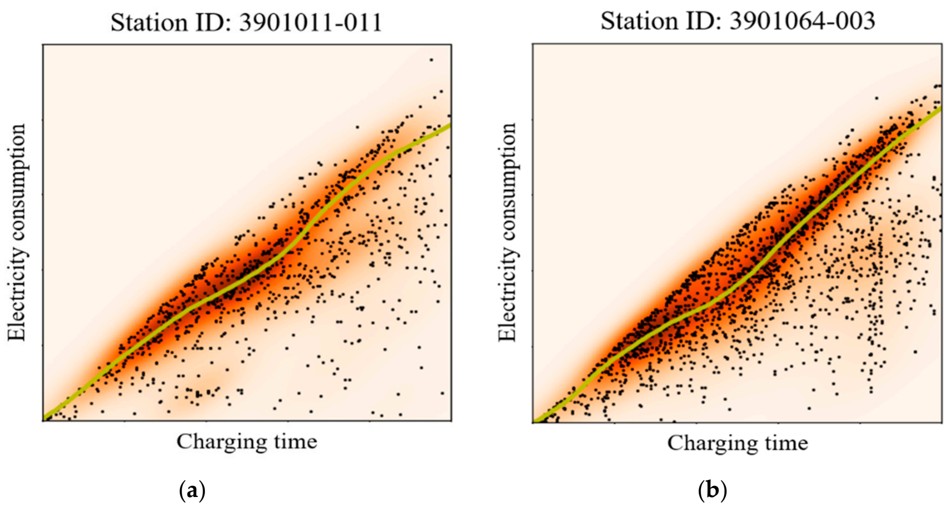


Figure 2. Heat maps related to the estimated probability function of electricity consumption distribution in a relation to charging time for sample stations. Station ID: (**a**) 3901011-011; (**b**) 3901064-003.

The proposed method fits the regression curve statistically using the past data consisting of charging time and energy consumption. A polynomial regression curve [15,16] is used because the relation between charging time and electricity consumption is non-linear. The proposed regression curve can be represented by Equation (1).

$$P(X_{CT}) = a_0 + a_1 X_{CT} + a_2 X_{CT}^2 + a_3 X_{CT}^3 + e \quad (1)$$

$P(X_{CT})$ is the electricity consumption, X_{CT} is the charging time. a_0, a_1, a_2 and a_3 are parameters representing the regression curve, and e is estimation error. This equation can be rewritten to Equation (2).

$$e = P(X_{CT}) - a_0 - a_1 X_{CT} - a_2 X_{CT}^2 - a_3 X_{CT}^3 \tag{2}$$

By minimizing the estimation error e, an optimal regression curve can be generated for electricity consumption estimation. The least square method [17,18] is used to find the values of a_0, a_1, a_2 and a_3. This method determines the parameters by minimizing the sum of squared of estimation error e. The optimal points can be reached when the partial derivatives of Equations (3)–(7) become zero. To summarize the equation, we can represent them by a matrix in Equation (8).

$$S_r = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left(P_{i,real} - P_{i,prediction}\right)^2 = \sum_{i=1}^{n} (P_{i,real} - a_0 - a_1 X_{i,CT} - a_2 X_{i,CT}^2 - a_3 X_{i,CT}^3)^2 \tag{3}$$

$$\frac{\partial S_r}{\partial a_0} = -2 \sum_{i=1}^{n} (P_{i,real} - a_0 - a_1 X_{i,CT} - a_2 X_{i,CT}^2 - a_3 X_{i,CT}^3) \tag{4}$$

$$\frac{\partial S_r}{\partial a_1} = -2 \sum_{i=1}^{n} X_{CT}(P_{i,real} - a_0 - a_1 X_{i,CT} - a_2 X_{i,CT}^2 - a_3 X_{i,CT}^3) \tag{5}$$

$$\frac{\partial S_r}{\partial a_2} = -2 \sum_{i=1}^{n} X_{CT}^2(P_{i,real} - a_0 - a_1 X_{i,CT} - a_2 X_{i,CT}^2 - a_3 X_{i,CT}^3) \tag{6}$$

$$\frac{\partial S_r}{\partial a_3} = -2 \sum_{i=1}^{n} X_{CT}^3(P_{i,real} - a_0 - a_1 X_{i,CT} - a_2 X_{i,CT}^2 - a_3 X_{i,CT}^3) \tag{7}$$

$$\begin{bmatrix} n & \sum_{i=1}^{n} X_{i,CT} & \sum_{i=1}^{n} X_{i,CT}^2 & \sum_{i=1}^{n} X_{i,CT}^3 \\ \sum_{i=1}^{n} X_{i,CT} & \sum_{i=1}^{n} X_{i,CT}^2 & \sum_{i=1}^{n} X_{i,CT}^3 & \sum_{i=1}^{n} X_{i,CT}^4 \\ \sum_{i=1}^{n} X_{i,CT}^2 & \sum_{i=1}^{n} X_{i,CT}^3 & \sum_{i=1}^{n} X_{i,CT}^4 & \sum_{i=1}^{n} X_{i,CT}^5 \\ \sum_{i=1}^{n} X_{i,CT}^3 & \sum_{i=1}^{n} X_{i,CT}^4 & \sum_{i=1}^{n} X_{i,CT}^5 & \sum_{i=1}^{n} X_{i,CT}^6 \end{bmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{n} P_{i,\,real} \\ \sum_{i=1}^{n} X_{i,CT} P_{i,\,real} \\ \sum_{i=1}^{n} X_{i,CT}^2 P_{i,\,real} \\ \sum_{i=1}^{n} X_{i,CT}^3 P_{i,\,real} \end{pmatrix} \tag{8}$$

S_r, $P_{i,\,real}$, and $P_{i,\,prediction}$ are squared error, real electricity consumption, and estimated electricity consumption. The values of a_0, a_1, a_2 and a_3 can be obtained from Equation (8). Finally, by using the regression curve defined by those parameters, the electricity consumption of electric charging stations can be estimated.

The proposed system statistically generates regression curve from Equation (8) by using past data of charging time and electricity consumption. The statistical property can be different for each charging station. From this point of view, this method separately fits the regression curve for each station by using each past data. The evaluation of the proposed system is described in Section 3.

2.2. Operating Phase

In the operating phase, the system estimates electricity consumption in real-time using the regression curve generated in training phase. First, the system gets the operating status and the station IDs. The station IDs are the numbers assigned to each station for distinguishing stations by management organizations. The operating status is used to extract the charging time, and the station IDs are used to select regression curve parameters. The proposed monitoring system acquires the regression curve parameters from a server using station IDs. Those parameters are generated and stored in the server during the training phase. The selected parameters are applied in Equation (1), except estimation error term like Equation (9), to estimate the electricity consumption using extracted charging time.

$$P\left(X_{CT,op}\right) = a_0 + a_1 X_{CT,op} + a_2 X^2_{CT,op} + a_3 X^3_{CT,op} \tag{9}$$

$X_{CT,op}$ is the charging time acquired during the operating phase, a_0, a_1, a_2 and a_3 are parameters representing the regression curve of each charging station. And, it can be summarized using Equation (8) in Equation (10).

$$\begin{aligned} P\left(X_{CT,op}\right) &= \left(1\ X_{CT,op}\ X^2_{CT,op}\ X^3_{CT,op}\right)\begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} \\ &= (1\ X_{CT,op}\ X^2_{CT,op}\ X^3_{CT,op}) \begin{bmatrix} n & \sum_{i=1}^{n} X_{i,CT} & \sum_{i=1}^{n} X^2_{i,CT} & \sum_{i=1}^{n} X^3_{i,CT} \\ \sum_{i=1}^{n} X_{i,CT} & \sum_{i=1}^{n} X^2_{i,CT} & \sum_{i=1}^{n} X^3_{i,CT} & \sum_{i=1}^{n} X^4_{i,CT} \\ \sum_{i=1}^{n} X^2_{i,CT} & \sum_{i=1}^{n} X^3_{i,CT} & \sum_{i=1}^{n} X^4_{i,CT} & \sum_{i=1}^{n} X^5_{i,CT} \\ \sum_{i=1}^{n} X^3_{i,CT} & \sum_{i=1}^{n} X^4_{i,CT} & \sum_{i=1}^{n} X^5_{i,CT} & \sum_{i=1}^{n} X^6_{i,CT} \end{bmatrix}^{-1} \begin{pmatrix} \sum_{i=1}^{n} P_{i,\ real} \\ \sum_{i=1}^{n} X_{i,CT} P_{i,\ real} \\ \sum_{i=1}^{n} X^2_{i,CT} P_{i,\ real} \\ \sum_{i=1}^{n} X^3_{i,CT} P_{i,\ real} \end{pmatrix} \end{aligned} \tag{10}$$

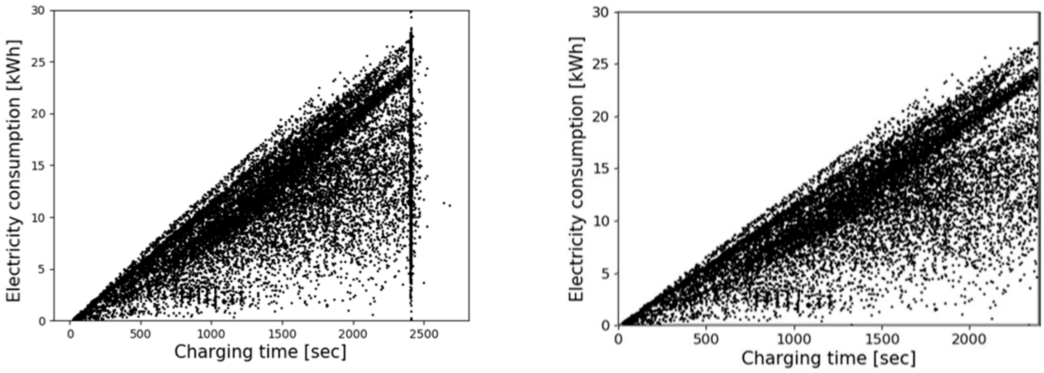
$X_{i,CT}$, $P_{i,\ real}$, and $P_{i,\ prediction}$ are charging time, real electricity consumption, and estimated electricity consumption in training phase and n is the number of training data. From Equation (10), we can estimate electricity consumption of each station. The estimated electricity consumption data are stored in the database and can be used for the real-time monitoring of electricity demands.

3. System Implementation

As we mentioned in Section 2, the total system consists of training phase and operating phase. In the training phase, the system generates regression curves to estimate the electricity consumption of EV charging stations from charging time. The training phase consists of data filtering, data selection, and regression curve generation. In this section, we will describe more details about data filtering and the selection process. The past data acquired from operators of the charging stations contains a lot of error data. In the data filtering process, the system eliminates the error data. In addition, the charging time data provided by the charging stations is invalid. Hence, it is difficult to generate the regression curve directly. In the data selection process, we select valid charging time data to generate a more accurate regression curve. In the operating phase, the system estimates the energy consumption of EV charging station by using a generated non-linear regression curve.

3.1. Data Filtering

In the estimation curve generation process for electricity consumption, past charging time and corresponding electricity consumption data from EV charging stations are used. However, there is a lot of invalid data. When charging an EV, it takes up to 40 minutes to fully charge a battery with a rapid charger [19]. However, the data received from the charging station operating agency includes a charging time of 40 minutes or more, and this is due to the errors that occur during the data acquisition process. Since the data whose charging time is more than 40 minutes is invalid data, the proposed system removes the corresponding data through an appropriate filtering process. Figure 3 shows the distribution of charging time and electricity consumption data before and after filtering. Data distribution before the filtering process shows that non-ideal data distribution appears near the charging time of 40 minutes (2400 seconds).

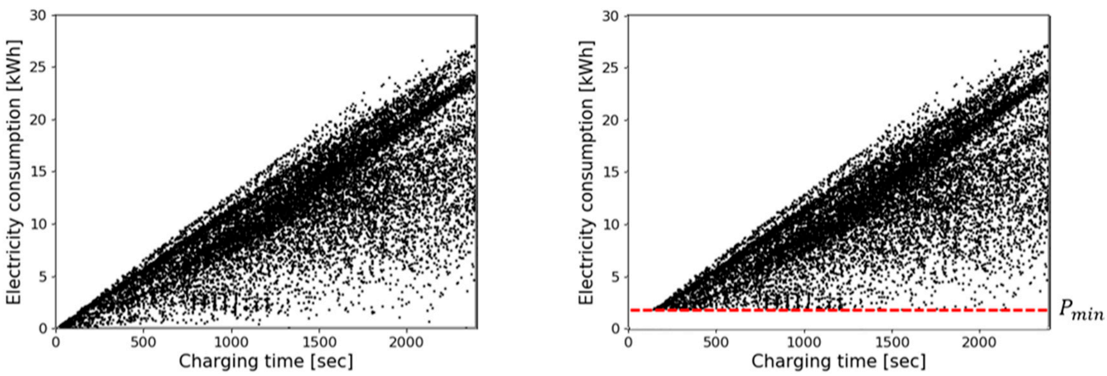


(**a**) (**b**)

Figure 3. Actual electricity consumption distribution of a fast charger according to charging time (units: charging time (sec), electricity consumption (kWh)). (**a**) before filtering, (**b**) after filtering.

3.2. Data Selection

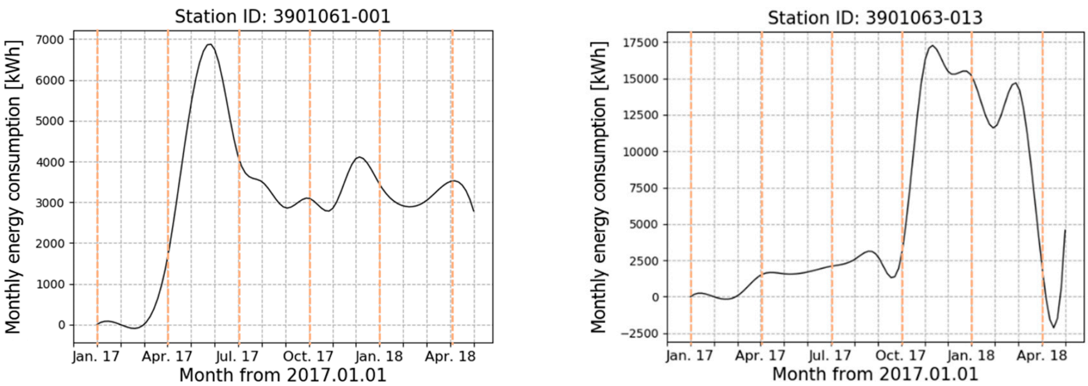
The curve for estimating electricity consumption of the EV charging station should be a one-to-one relationship between the charging time and the electricity consumption. However, as shown in Figure 3b, the distribution of electricity consumption according to charging time is somewhat widespread due to the invalid charging time, making it difficult to find an appropriate estimation curve. Therefore, it is necessary to eliminate outliers that impede the accurate estimation curve. The proposed system removes outlier data through the minimum electricity consumption limitation process. This process removes data having a value smaller than a specific electricity consumption in the learning data. The low electricity consumption data is removed because there are more outliers in the data. It can be seen that the distribution of low electricity consumption data is sparser than that of high electricity consumption data in Figure 3b. From this point of view, the process of eliminating data below a specific electricity consumption increases the accuracy of the electricity consumption estimation model. Figure 4 shows the proposed minimum electricity consumption limitation technique.



(**a**) (**b**)

Figure 4. A proposed technique considering the minimum electricity consumption. Data with a lower electricity consumption value based on the minimum electricity consumption value defined by Pmin is removed. Graphs (**a**) before applying the proposed method and (**b**) after applying the proposed method.

In addition to the minimum electricity consumption limitation technique, the period-based data selection process is performed to generate high performance electricity consumption estimation curve. The usage pattern of each EV charging station depends on the period. For example, there are some periods when the number of tourists drastically increases. During this period, the amount of energy consumption of charging stations increases and the usage pattern of each EV charging station changes. Additionally, depending on the arrangement change of charging station, the usage pattern of each charging station can change. As the demand for electrical vehicles increases, the number of electrical vehicle charging stations increases simultaneously. Newly installed charging stations diminish the charging load of nearby charging stations, which then results in the change of usage pattern of the charging station. On the other hand, the broken charging stations affect the usage pattern of nearby charging stations as well. It weighs more load to the stations located in adjacent regions. Therefore, it is possible to generate a more accurate estimation model when considering the change over time. Therefore, the proposed system does not use all the past data in the process of generating the estimation model, but uses only the data in the period close to the estimation period. Figure 4 shows a graph of monthly electricity consumption change over time for two sample EV charging stations. Figure 5a,b shows that electricity consumption changes according to month. Consequently, it can be confirmed usage of the charging station differs from one period to another, and a data selection process according to the period is necessary.



(**a**) (**b**)

Figure 5. A graph of monthly electricity consumption change over time. Station ID: (**a**) 3901061-001; (**b**) 3901063-013.

4. Experiment Results

The proposed system was evaluated using the real datasets of electrical chargers which are currently under operation. The number of stations we used for experiments were 175, which are located in Jeju island in Korea. We collected datasets from three organizations. The datasets were collected from January 2017 to June 2018. We used data from January 2017 to March 2018 for training and from April 2017 to June 2018 for testing. The accuracy of the EV charging electricity consumption regression model was evaluated using two metrics: mean absolute percentage error (MAPE) [20–22] and normalized root mean square error (NRMSE) [21–23]. These metrics have features that are independent of the data scale.

4.1. Evaluation of EV Charging Electricity Consumption Regression Model

The EV charging electricity consumption regression model in Equation (2) was used to evaluate how well the electricity consumption of each charging station was estimated. The results are listed in Table 1. Since it is difficult to show the evaluation results for all 175 stations, we have clustered the stations into 20 groups. We grouped them by considering the locations and averaged the evaluation errors by clusters. As a result, most of the clusters achieved the estimation errors of 20–30%, and the total average errors are MAPE of 27.175% and NRMSE of 27.622%. The locations of stations and which clusters they belong to are shown in Figure 6.

Table 1. Results from charging stations on Jeju island applying the EV charging electricity consumption regression model.

Cluster	MAPE(%)	NRMSE(%)
1	26.09	26.92
2	26.42	27.28
3	30.94	30.34
4	29.06	28.28
5	27.27	27.42
6	28.40	27.95
7	21.77	22.15
8	27.83	27.96
9	22.87	25.41
10	25.41	25.54
11	26.51	27.26
12	21.86	24.55
13	32.62	30.46
14	22.39	23.86
15	25.00	26.99
16	25.34	27.44
17	25.59	26.86
18	26.34	26.97
19	27.82	28.14
20	32.96	34.12
Average	27.18	27.62

MAPE: mean absolute percentage error; NRMSE: normalized root mean square error.

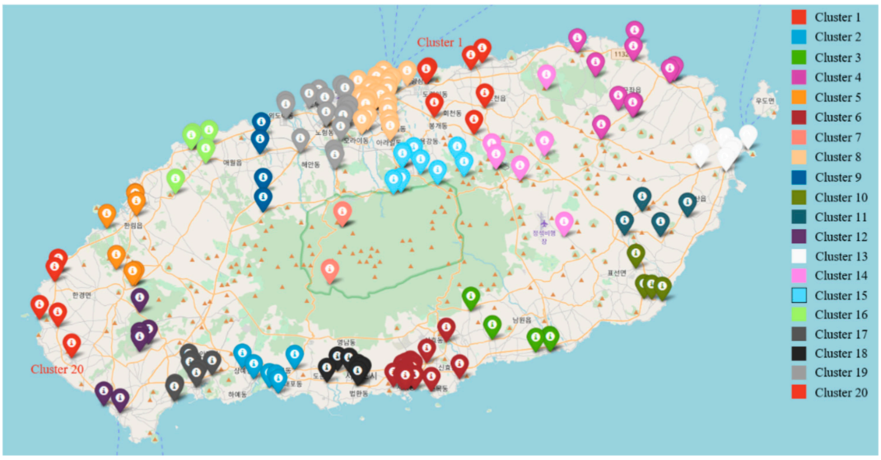


Figure 6. Electric vehicle charging stations on Jeju island clustered by the location of stations. Each color represents each cluster.

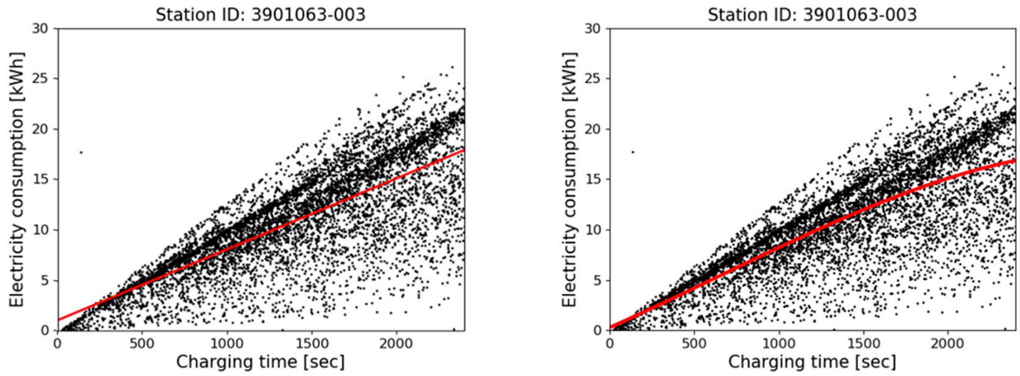
4.2. Ablation Study and Analysis

To evaluate the effects of each process we used in the training phase, we conducted ablation studies. We compared the estimation error distributions for each process. Cheon et al. [5], the most recent method, was used as the benchmark method. We compared the distributions of estimation errors of stations for each method with the distribution of the benchmark method. In addition, we compared the results of all the processes we applied. The methods we compared were the usage of non-linear regression curve, minimum electricity constraints, and near-term data selection.

4.2.1. Effects of Non-Linear Regression

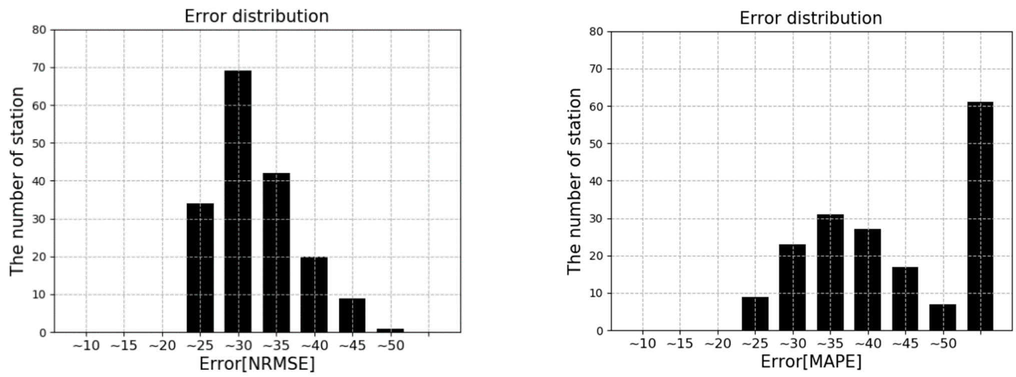
In this work, we argued that the relation between charging time and electricity consumption was non-linear when we did not estimate energy consumption accumulated during some periods.

From this point of view, we used a 3rd–order polynomial curve and common non-linear curve as the estimation curve. Figure 7 shows each regression curve using non-linear and linear regression curve each for the sample station. The linear regression curve passes through sparser regions than the non-linear regression curve. In addition, Table 2 shows the distributions of estimation errors of stations for the cases of linear and non-linear regression. The numbers in Table 2 represent the number of stations which have the estimation error in the range. The graphs of the distributions are in Figure 8. Since the relation between charging time and energy consumption was non-linear, the distribution of errors improved when we applied the non-linear regression curve.

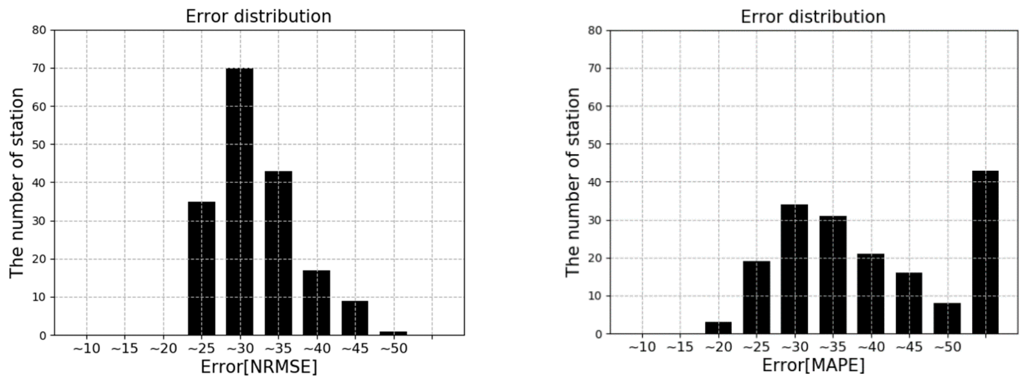


(**a**) (**b**)

Figure 7. Generated regression curves for the sample station using (**a**) conventional linear regression curve and (**b**) the proposed non-linear regression curve.



(**a**)



(**b**)

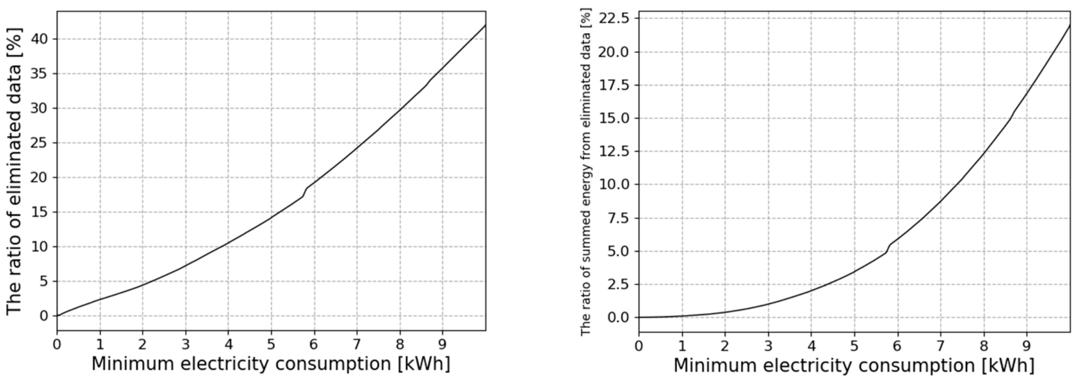
Figure 8. Graphs of electricity consumption estimation error distribution when using (**a**) the conventional linear curve and (**b**) the proposed non-linear curve.

Table 2. The distributions of estimation errors of stations for the cases of linear and non-linear regression.

Method	NRMSE						
	0–20	**21–25**	**26–30**	**31–35**	**36–40**	**41–45**	**46~**
Linear	0	34	69	42	20	9	1
Polynomial	0	35	70	43	17	9	1
Method	**MAPE**						
	0–20	21–25	26–30	31–35	36–40	41–45	46~
Linear	0	9	23	31	27	17	68
Polynomial	3	19	34	31	21	16	51

4.2.2. Effects of Minimum Electricity Consumption Constraint

The proposed method suggested additional selection steps to generate more appropriate regression curve. The first selection step was the minimum electricity constraint. We set the minimum electricity consumption value and removed data that had electricity consumption below the minimum electricity consumption. In this experiment, we set the value as 2 kWh. Figure 9a shows the ratio of eliminated data to the total data and Figure 9b shows the ratio of summed energy of the eliminated data to that of total data in relation to minimum electricity consumption value. The ratio of eliminated data at the 2 kWh of minimum electricity value is 4.42%. On the other hand, the ratio of summed energy of eliminated data at the 2 kWh of minimum electricity value is 0.38%. From the facts, we can argue that the eliminated data hardly affects the monitoring electricity load of EV charging stations.



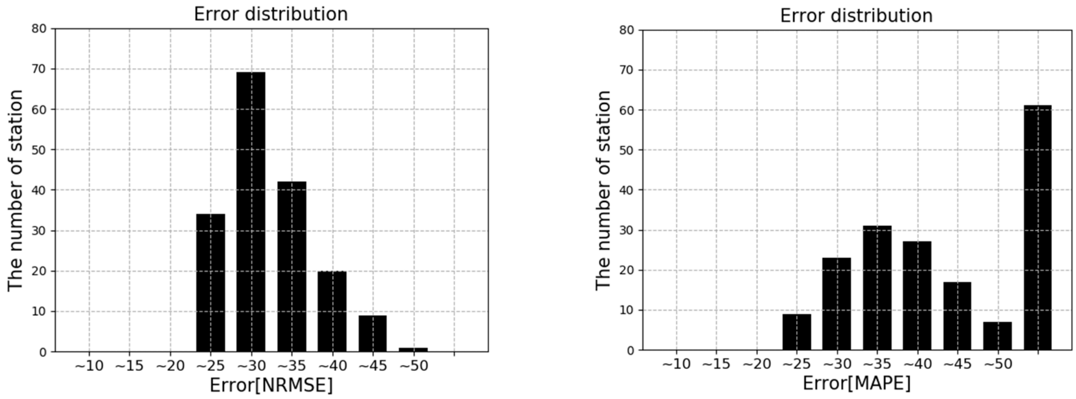
(**a**) (**b**)

Figure 9. Graphs represent the effects of eliminated data. (**a**) The ratio of eliminated data to total data and (**b**) the ratio of summed energy of the eliminated data to that of total data in a relation to minimum electricity consumption value.

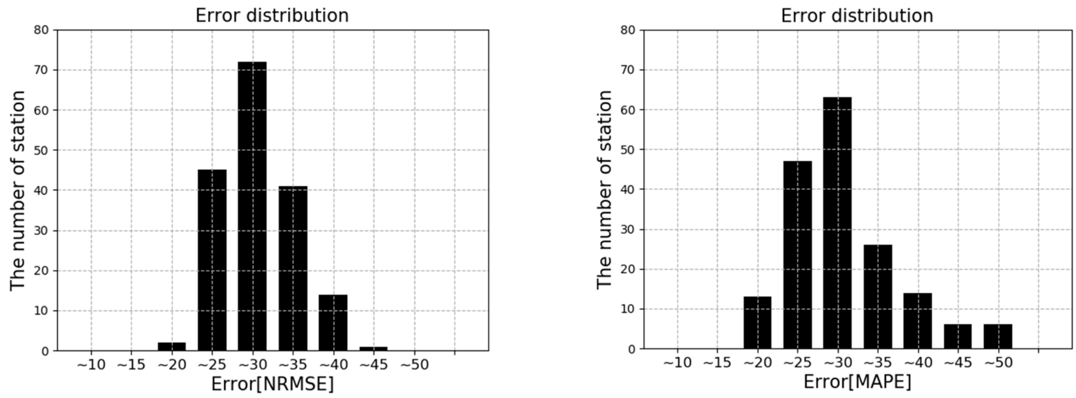
Although the eliminated data hardly changes the electricity load of EV charging stations, they drastically improve the estimation errors of stations by removing outliers. Table 3 shows the distributions of estimation errors of stations with and without the minimum electricity consumption constraint. Figure 10 shows the graphs of the distributions with and without minimum electricity consumption constraint. From the results, it is evident that we have improved the distributions of estimation errors using minimum electricity consumption. Most especially, the MAPE error was improved more than the NRMSE error.

Table 3. The distributions of estimation errors of stations with and without minimum electricity consumption constraint. 'No-constraints' represents the case without the constraints and 'Constraint' represents the case with the constraint.

Method	**NRMSE**						
	0–20	**21–25**	**26–30**	**31–35**	**36–40**	**41–45**	**46~**
No-constraint	0	34	69	42	20	9	1
Constraint	2	45	72	41	14	1	0
Method	**MAPE**						
	0–20	21–25	26–30	31–35	36–40	41–45	46~
No-constraint	0	9	23	31	27	17	68
Constraint	13	47	63	26	14	6	6



(**a**)

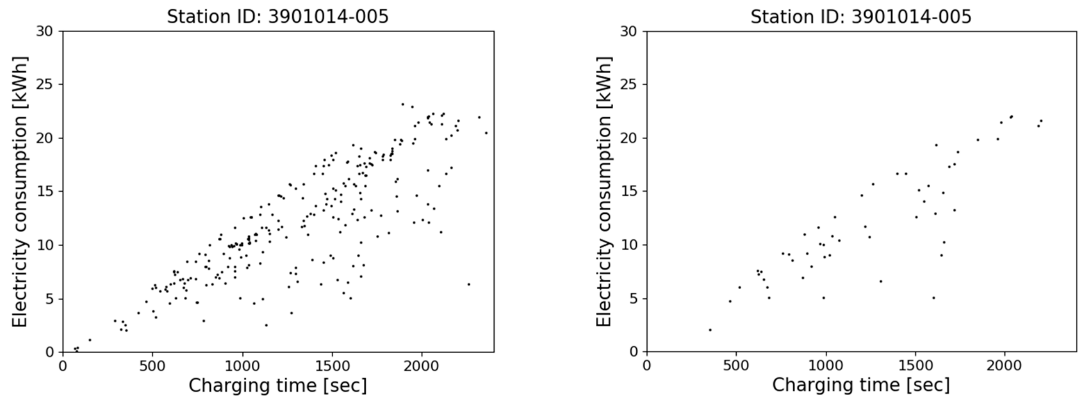


(**b**)

Figure 10. Graphs of energy consumption estimation error distribution (**a**) without constraint and (**b**) with constraint.

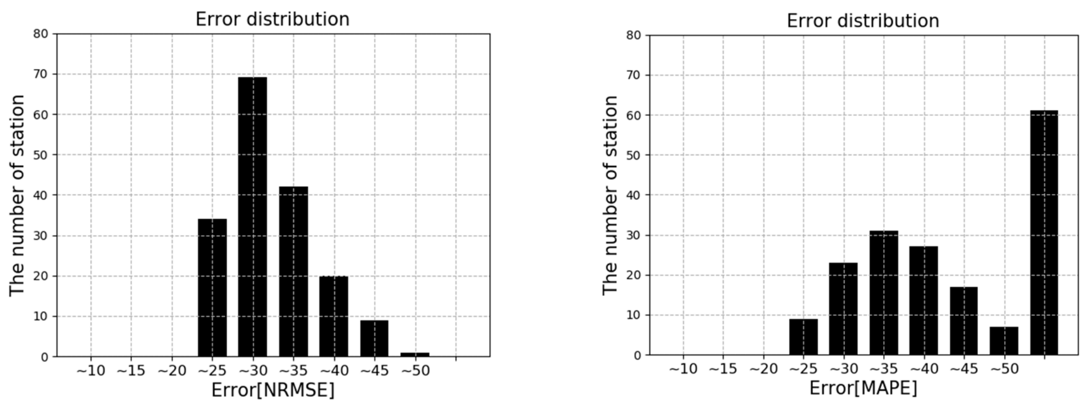
4.2.3. Effects of Recent Data Selection

The second selection step to generate appropriate regression curve was recent data selection. The usage pattern of electric charging stations depends on the period. Therefore, if we select only recent data to generate regression curve, we can estimate electricity consumption more accurately. In this experiment, we chose data until 3-months before the period we wanted to estimate energy consumption. The term was determined through experimentation. If the term was shorter than 3-months, the proposed system could use too few data if it was collected for a month. On the other hand, if the term was longer than 3-months, the strength of recent data became too weak to generate proper curve. Figure 11 shows electricity consumption distribution according to charging time for a sample charging station during a month and 3 months. We can see that there are too few data acquired during a month in Figure 11b, which makes it difficult to generate appropriate regression curve. On the other hand, if the system used data collected during over 3 months, there are too many widespread data, which generates a messy curve. Table 4 shows the distributions of estimation errors of stations with and without the recent data selection step. Figure 12 shows the graphs of the distributions with and without the recent data selection step. It is evident that the distributions of estimation errors have improved with the recent data selection step.

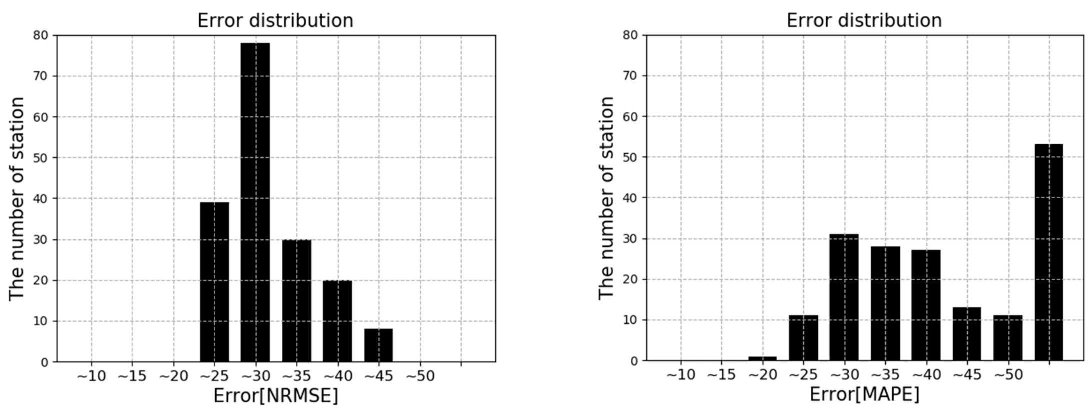


(**a**) (**b**)

Figure 11. Electricity consumption distribution according to charging time for sample charging station (**a**) from April 2017 to June 2017 and (**b**) at June 2017.



(**a**)



(**b**)

Figure 12. Graphs of energy consumption estimation error distribution (**a**) without recent data selection step and (**b**) with recent data selection step.

Table 4. The distributions of estimation errors of stations with and without recent data selection. 'All' represents the case without recent data selection and 'Recent' represents the case with recent data selection.

Method	**NRMSE**						
	0–20	**21–25**	**26–30**	**31–35**	**36–40**	**41–45**	**46~**
All	0	34	69	42	20	9	1
Recent	0	39	78	30	20	8	0
Method	**MAPE**						
	0–20	21–25	26–30	31–35	36–40	41–45	46~
All	0	9	23	31	27	17	68
Recent	1	11	31	28	27	13	64

4.2.4. Results of the Proposed Method

When we applied all methods mentioned before, we got the best result compared to when we applied only one method. The distributions of estimation errors of stations are summarized in Table 5. When we compare the proposed methods, we find that minimum electricity consumption constraint is the most effective to import error distribution than any other method. Finally, we can get the best result when we apply all methods rather than only one method.

Table 5. The distribution of estimation errors of stations when we apply the proposed methods each and all. The best result is when we apply all methods.

Method	**NRMSE**						
	0–20	**21–25**	**26–30**	**31–35**	**36–40**	**41–45**	**46~**
Linear [5]	0	34	69	42	20	9	1
Polynomial	0	35	70	43	17	9	1
Constraints	2	45	72	41	14	1	0
Recent	0	39	78	30	20	8	0
Proposed	3	51	73	30	18	0	0
Method	**MAPE**						
	0–20	21–25	26–30	31–35	36–40	41–45	46~
Linear [5]	0	9	23	31	27	17	68
Polynomial	3	19	34	31	21	16	51
Constraint	13	47	63	26	14	6	6
Recent	1	11	31	28	27	13	64
Proposed	13	56	59	25	13	6	3

4.3. Outputs of Overall Monitoring System

In this section, we will show the outputs of the overall monitoring system. As we mentioned in the introduction, we propose the electricity consumption estimation and monitoring system of EV charging station to prevent the electricity overload. For this purpose, the system should provide the estimated electricity consumption results in system display. The system can display the information by two ways. At first, our system is able to show the graphs of estimated electricity consumption value in a relation to time (hour) for each station. Figure 13 shows the example graphs for several sample stations. The black lines of the graphs represent actual electricity consumption value in relation to time (hour), and the orange lines of the graphs represents the estimated electricity consumption value in relation to time (hour). From the Figure, we can see that the proposed electricity estimation system can estimate the energy consumption of EV charging stations quite appropriately because the orange lines are quite similar to the black lines. Secondly, the proposed system can display the estimated electricity consumption results in a map. By showing the information in a map, we can check the electricity load of EV charging stations in a specific location. Figure 14 shows the example maps of estimated electricity consumption of charging stations on Jeju island. Each map represents the estimated electricity load of each charging station for sample times. It shows the electricity load of each station by colors; stations colored by black consumed energy below 5 kWh, green consumed energy below 15 kWh, orange below 25 kWh, and red over 25 kWh.

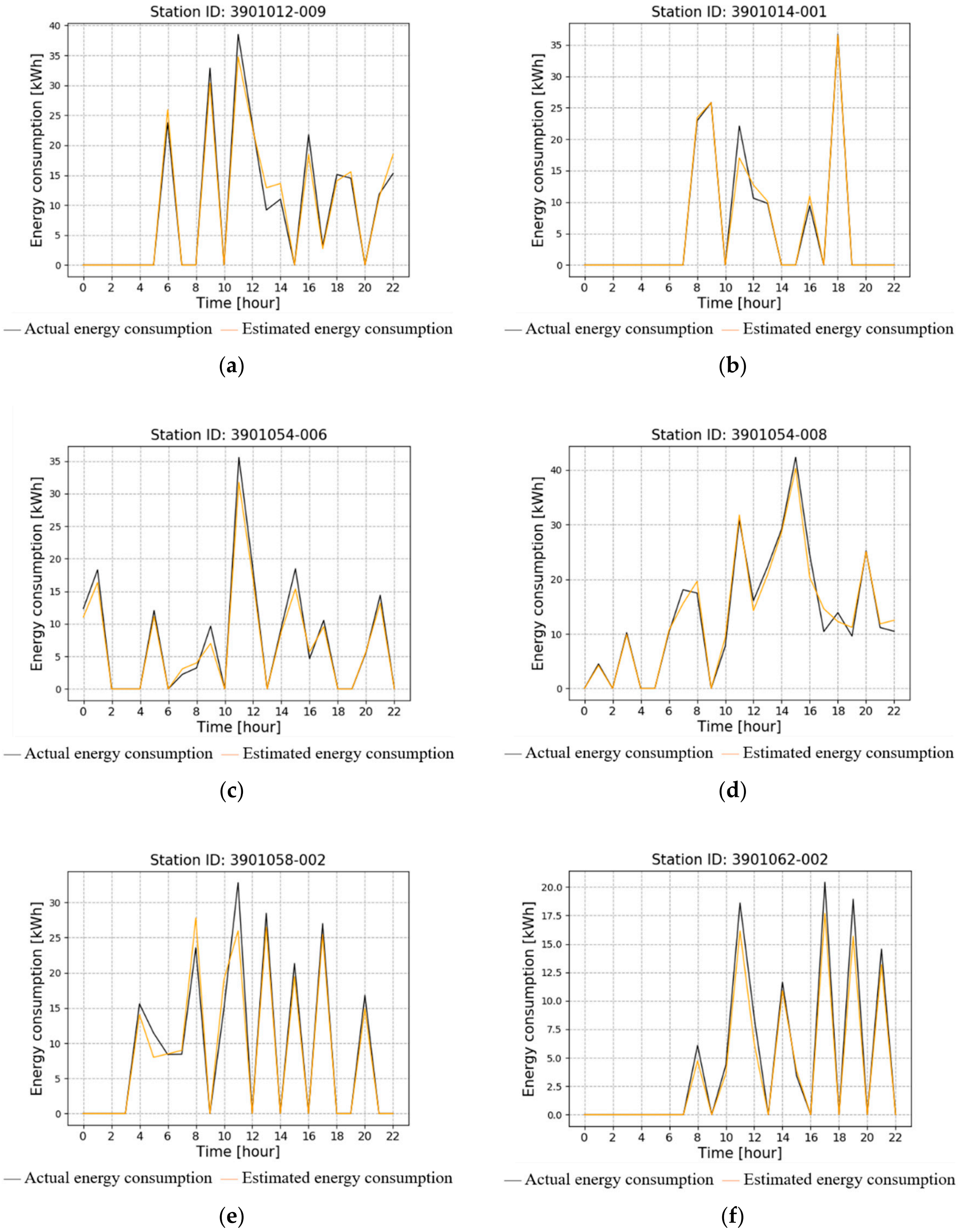


Figure 13. The first display example: graphs of estimated electricity consumption value in a relation to time (hour) for each station. Station ID: (**a**) 3901012-009; (**b**) 3901014-001; (**c**) 3901054-006; (**d**) 3901054-008; (**e**) 3901058-002; (**f**) 3901062-002.

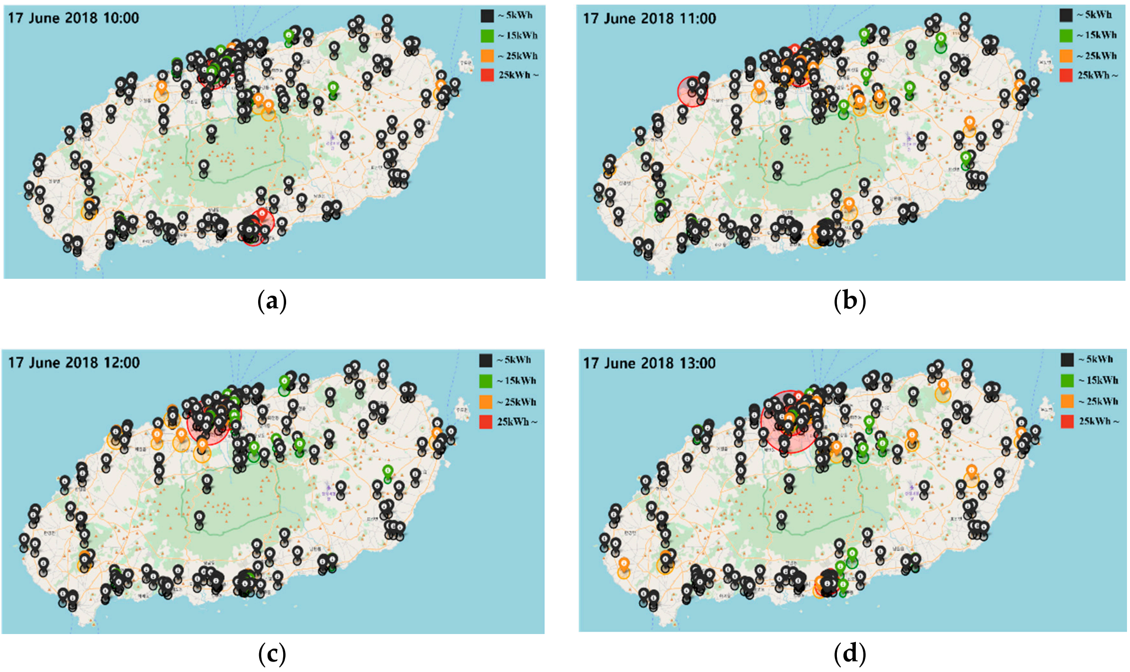


Figure 14. The first display example: maps showing estimated electricity consumption results. Time: (**a**) 17 June 2018 10:00; (**b**) 17 June 2018 11:00; (**c**) 17 June 2018 12:00; (**d**) 17 June 2018 13:00.

5. Conclusions

An increase in the number of electrical vehicles has resulted in an increase in the number of electrical vehicle charging stations. As a result, the electricity load consumed by charging stations has become large enough to de-stabilize the electricity supply system. To prevent electricity overload by EV charging stations, a monitoring system of electricity consumption in real-time is needed. The proposed system estimates the electricity consumption of EV charging stations from charging time. The proposed system generates non-linear regression curves with additional preprocessing in the training phase. The preprocessing step helps to generate more accurate curves despite the existence of invalid data. Evaluation results show that our system can estimate the electricity consumption for each station with an averaged 73% accuracy. Although previous works estimate accumulated electricity consumption, the proposed method estimates electricity consumption per charge using charging time. Furthermore, it does not require any additional information, which can cause additional costs and efforts.

The overall system we proposed can be used to stabilize the power supply system by monitoring real-time energy consumption. The system can display the estimated electricity consumption by two ways. First of all, it can display graphs of estimated electricity consumption value in a relation to time (hour) for each station. From the graphs, we can check the electricity load of charging stations per time. Consequently, if we can estimate today's electricity consumption in the form of these graphs, we can predict tomorrow's electricity consumption per time because electricity consumption is likely to be similar at the same time between today and tomorrow. By doing so, electric power supply organizations can prepare reserved energy from power plants. Secondly, the proposed system can display the estimated electricity consumption results on a map. From the map, we can see the electricity load of EV charging stations at a specific location. This information can be used to plan investment decision of operators of EV charging stations. They can make a decision about where to install new charging stations considering demands from the maps. As a result, newly installed stations can help to reduce electricity loads of nearby locations. In conclusion, our overall system can help to stabilize power supply systems.

Author Contributions: N.A., S.Y.J. and S.-J. K. conceived and designed the experiments; N.A., S.Y.J. and S.-J. K. performed the experiments and analyzed the data; N.A. and S.-J. K. contributed to the data selection process development; and S.Y.J. and S.-J. K. contributed to the non-linear regression curve adoption; N.A., S.Y.J. and S.-J. K. wrote the paper.

Funding: This research received no external funding

Acknowledgments: This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2019-2018-0-01421) supervised by the IITP(Institute for Information & communications Technology Planning & Evaluation), and by the Korea Institute of Energy Technology Evaluation and Planning(KETEP) and the Ministry of Trade, Industry & Energy(MOTIE) of the Republic of Korea (No. 20161210200560).

Conflicts of Interest: The authors declare no conflict of interest.

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