Regional Nonintrusive Electric Vehicle Monitoring Based on Graph Signal Processing

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Abstract: Electricity network is leading to a low carbon future with high penetration of plug-in electric vehicles (EVs). However, it is extraordinarily difficult to acquire detailed information on regional EV electrification with an incomplete monitoring system for network operators. In this paper, a flexible graph signal processing (GSP)-based non-intrusive monitoring on aggregated EVs is proposed to enhance the EVs visibility for operating power system safely and cost-efficiently. It can deduce the individual EV charging status with the highest possibility iteratively from the limited dataset using a GSP-based possibility calculation after processing a daytime EV characteristic charging patterns. The experiment is developed with realistic EV charging datasets collected in London, and the results show the daily EVs number in a specific region of 500 EVs daily aggregation can be estimated efficiently with an around 4.77% value of relative mean absolute deviation (RMAD) applying the proposed method.

1. Introduction

With the UK government support to facilitate decarbonization transport including ultra-low emission vehicles in policy and funding [1], the growth of EVs (36 million EVs demand by 2040 [2]) is implicating demand and supply balance since the grid is not originally designed to accommodate the temporal-spatial uncertainty of EVs. Meanwhile, the load monitoring systems in the distributed network are under development with huge investment £30 million [3]. The electrification of transportation is of great potential to deliver smart energy system operations such as smart charging and demand-side response to release network capacities and to reduce the total energy cost [4][5][6]. To enable these smart schemes, it is critical to visualise the detailed EV charging information i.e. location, plug-in charging time and capacity [7]. However, it is extremely difficult to install intrusive sensors to record each EV in real-time due to the economy and privacy issues.

Many researchers have explored the non-intrusive load monitoring (NILM) method in the household level. It decodes the aggregated home energy into power-consumption of individual appliances by applying sophisticated algorithms. The disaggregation approaches can be divided in term of mathematical strategies [8]: 1) states-based optimizing states of each appliance behaviour model to aggregate the end-use observation such as probabilistic Hidden Markov Model [9] and sparse coding [10]; 2) the events-based methods detecting the significant changes of the aggregated signal and analysing the changes with each appliance feature such as clustering active and reactive power change [11].

It is an interesting idea to leverage this method further in regional EVs aggregated level for system operators– regional non-intrusive EV monitoring [12] with the development of EV measurement systems. Different from the traditional NILM technology in household level, which decomposes different appliances, the regional non-intrusive EV monitoring aims to disaggregate different EV charging patterns. It is hard to distinguish individual EV charging features due to the countless combinations of EV types, EV state of charging (SoC), EV owner charging behaviours affected by contextual information such as weather and traffic. Another challenge is the incomplete EV monitoring data at a low rate, which limits the charging features granularity. Previous non-intrusive EV monitoring research work has been explored primarily with limited activation matching pursuit (LAMP) in [7], which is a greedy algorithm decomposing individual EV profiles of high correlation with the aggregated signal.

In this paper, a novel regional EV disaggregation based on graph signal processing flexible framework is proposed: 1) the development of EV characteristic charging patterns [5], which are clustered from realistic historical monitoring in Low Carbon London project [13] and Customer Led Network Revolution project [14]; 2) an iterating disaggregation of each EV charging information contributing to the aggregated charging profile with most possibility calculated by graph signal processing (GSP) tool. Graph signal processing provides a flexible framework with a graph indexed by nodes for processing data of irregular graph domains, and it can deal with the massive datasets with complex structures [15]. The possibility distribution of all the charging patterns existing in the aggregated profile in each disaggregation is generated in day size applying GSP classification function [16] with piecewise smoothness minimization.

The following sections of the article are: Section 2 describes the EV disaggregation problem formulation including generation of EV characteristic charging patterns from historical datasets. And a disaggregation algorithm based on possibility calculation using GSP variation classifier is introduced in Section 3; the experimental results and conclusions are in Section 4 and 5.

2. EV Disaggregation Problem Formulation

2.1. Disaggregation Objective

Supposed that the aggregated EV charging profile signal during a specific period T $\mathbf{y} = [y_1, y_2, \dots y_T]$ such as an EV charging station total charging profile in a distributed network is available for gird operators, EV disaggregation aims to figure out the ground truth of the aggregated signal from the historical EV charging dataset $\mathbf{X}$ with N individual representative EV charging profiles. As described in the general mathematical formulation in (1), the underlying individual charging contribution $\mathbf{x}^i \in \mathbf{X}$ with $i \in \{1, 2, \dots N\}$ activated in period $\mathbf{t} \in \{1, 2, \dots T\}$ can be deduced approximately.

$$f(\mathbf{x}_t^i) = \min || \mathbf{y} - \sum_{i}^{N} \mathbf{x}_t^i ||_2^2 \quad (1)$$

2.2. EV Characteristic Patterns

Low Carbon London [13] project provides about 60 residential EVs monitoring data [17] [18] obtained in the grid side via EV charging stations for more than one year from 2013 to 2014 delivered by UK Power Networks. However, the half-hour sampling rate of the EV charging datasets [7] means that the available realistic dataset is incomplete and disguises the underlying diversity. These individual residential EV charging profiles are highly related to distinct EV users charging behaviours, EV charging types (rapid, fast and slow charging) and some contextual factors such as regional weather, traffic, population density and different regions [17]. Therefore, EV characteristic charging patterns can be developed to represent all the EV typical profiles with different users and EV types in one targeted area such as one EV charging station.

In the pre-progress of EV characteristic patterns (shown in Figure 1), the long-term incomplete EV monitoring charging profiles from monitoring datasets is divided into day length. Firstly all the EV daily patterns are filtered with maximum amplitude and variation below some threshold (0.005 kWh in [7]) to remove some invalid patterns with low charging activities.

Then a real EV charging profile will be clustered if it is highly correlated with any existing EV day pattern. The correlation coefficient of any two daily patterns is calculated with (2) [7] where x_i x_j are two EV daily profiles with their mean value μ_i μ_j, their standard deviation value σ_i, σ_j and expectation operator E. And it will be clustered with an existing pattern when the correlation coefficient of the EV charging profile is higher than a threshold value of 0.85 [7].

$$\rho(x_i, x_j) = \frac{\mathrm{E}[(x_i - \mu_i)(x_j - \mu_j)]}{\sigma_i \sigma_j} \quad (2)$$

In the end, the 396 characteristic EV charging patterns $\mathbf{x}^i$ (i is the pattern number) in one day size are achieved after processing from the raw 60 EV charging data in Low Carbon London over one year [17]. They represent the EV charging situation with different combinations of EV types and user charging behaviours in the specific monitoring region in Low Carbon London. The visualization of the EV patterns is shown in Figure 1. Each vertical line in Figure 1 represents one kind of EV daily charging load profile with charging and non-charging information. And the different colour of each vertical line in Figure 1 shows EV active charging power (in kWh).

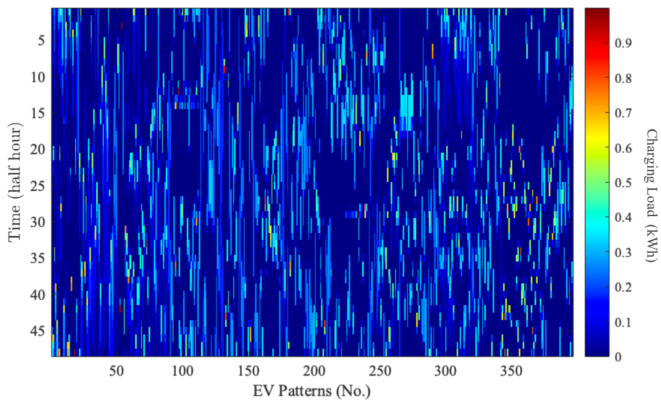


Fig. 1. *EV characteristic patterns of Low Carbon London*

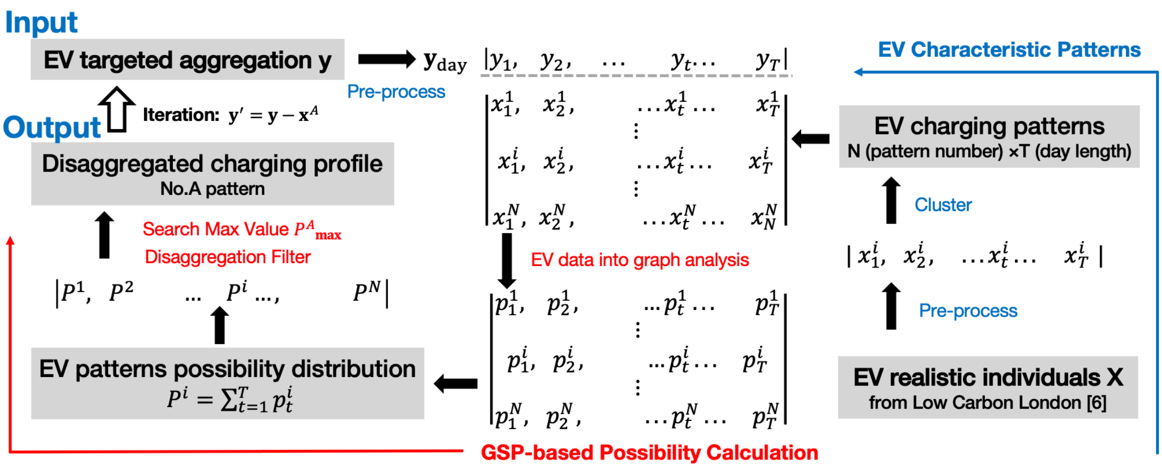


Fig. 2. *An overview flowchart of GSP-based disaggregation*

3. GSP-based Disaggregation Algorithm

Graph signal processing provides a great compact format of a graph consisting of vertices, edges and signals, which has been developed for processing data of irregular graph domains [15] to use the tools in traditional signal processing. It can represent and deal with massive datasets with complex structure [19], which owns the reliable power to connect the practical and theoretical research with flexible data framework and fast data processing. Therefore, it is of great perspectives to develop the GSP-based tool to analyse the existing mathematics problems.

EV disaggregation is a hard optimization problem since the high aggregated data level, i.e. many EVs charging at the same time in one region and the incomplete feature of low monitoring resolution. Here a GSP-based possibility distribution calculation with aggregated data and EV characteristic patterns is proposed in one day size to utilise the limited datasets. The aim is to decompose the aggregate charging load profile and match the component with individual EV patterns. The matching criterion is assumed to be the similarity calculated by GSP between the features of EV patterns (as depicted in Figure 1) and the aggregation features, which are the normalised load profiles at each sampling point. And it is assumed that individual EV pattern with the most feature similarity owns the highest possibility existing in the integrated charging profile.

An overview flowchart of GSP-based disaggregation algorithm including the EV characteristic pattern development in Section 2 from the available datasets and GSP-based possibility calculation is shown in Figure 2. $\mathbf{y}_{\text{day}}$ is the aggregated charging profile split in day size T (48 measurements with half-hour sampling rate) to be decomposed. P^i is the possibility distribution of EV characteristic charging patterns contributing to the aggregated EV charging profile signal, which is acquired applying GSP variation classification tool [16]. And in each disaggregation, the charging pattern in $\mathbf{X}$ with maximum P value meaning the highest possibility is subtracted from the aggregated profile and the residual aggregated profile is the input in the next loop. The iteration will stop until the residual aggregated charging EV cannot be subtracted.

3.1. Graph Signal Processing

3.1.1. Graph Signal Processing Framework

Graph signal processing can be applied in the implementation of a large dataset with the features that components are related in dependency and similarity. It can be represented with a typical mathematics graph framework:

Nodes or vertices $\mathbf{v}$ represent the component cells of the graph system v_n. And a dataset $\mathbf{X}$ is mapping each cell in the graph.

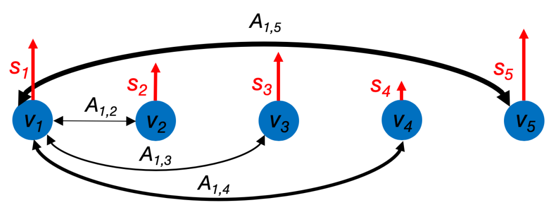


Fig. 3. Graph signal processing framework

Edges or links $\mathbf{A}$ describe the connections or interactions between the component cells with possible directions. Each element $A_{i,j}$ of the weighted adjacency matrix is a measurement between the i^{th} and j^{th} node connection (x_i and x_j). It can be calculated via the similarity of them using a Gaussian Kernel weighting function known as Gaussian similarity (REF kernel) in (3), where σ is the scaling factor that influences the similarity comparison refinement.

$$A_{i,j} = \exp\left\{-\frac{(x_i - x_j)^2}{\sigma}\right\} \quad (3)$$

Graph signal $\mathbf{s}$ [s_1, s_2, s_3, s_4, s_5] carries the signal information of the graph system and is defined as a mapping relationship with each node (red arrow in Figure 3). And particularly in our application, $\mathbf{s}$ can be the classification label of each node based on dataset $\mathbf{X}$ [16].

3.1.2. Graph Signal Processing Classifier

Smoothness is an important and foundational feature of the graph signal s in signal progressing. It means the adjacency components are likely to own similar values, which is called bandlimitedness in spectral-domain [15]. And the smoothness of the graph signal $\mathbf{s}$ with M vertices can be calculated from a graph signal's Laplacian quadratic form [20] in (4) defined with a total variation of the signal referred to the graph [21] together with the similarity matrix $\mathbf{A}$. $\mathbf{L}_{M\times M}$ is another expression of the weighted adjacency matrix $\mathbf{A}$ with the Equation $\mathbf{L} = \mathbf{D} - \mathbf{A}$ and $\mathbf{D}$ is a diagonal matrix where $D_{k,k} = \sum_{j=1}^{M} A_{j,k}$ with k = $\{1, 2, \ldots, M\}$. The measurement of smoothness can be rearranged in (4) $\mathbf{s}^T\mathbf{L}\mathbf{s}$, which should be small if $\mathbf{s}$ is pricewise smooth. This property can be used as a objective function to minimize the variation of the graph signal $\mathbf{s}$ weighted by $\mathbf{A}$ [22].

$$\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} A_{i,j}\left(s_i - s_j\right)^2 = \mathbf{s}^T\mathbf{L}\mathbf{s} \quad (4)$$

The smoothness feature above in GSP can be used as a total graph variation classifier [16]. And the goal of this classification is that nodes of the graph with the same value with the set node (v_1) are going to be classified with the same label signal. The global smoothness minimization can be generated to achieve the smallest smoothest of the graph with N vertices, which is the objective function with $\mathbf{s}$ (M-length) and $\mathbf{s}_{2:M}$ the variables.

Since the signal s_1 of the first node with aggregated information is known (labelled 1 in advance) and $\mathbf{L}$ is a diagonally symmetric matrix, the smoothness minimization function can be simplified in (5).

$$\begin{aligned} &\arg\min \ \ ||\mathbf{s}^T\mathbf{L}\mathbf{s}||_2^2 \\ &= \arg\min\left\{2\mathbf{s}_1^T\mathbf{L}_{1,2:M}\mathbf{s}_{2:M} + \mathbf{s}_{2:M}^T\mathbf{L}_{2:M,2:M}\mathbf{s}_{2:M}\right\} \quad (5)\end{aligned}$$

Thus, this optimization problem is an unconstrained quadratic programming problem and the solution of the graph signals $\mathbf{s}_{2:N}$ which is the classification labels of $\mathbf{v}_{2:M}$ compared with the first node v_1 can be obtained with the closed-form formula [20]: ($\mathbf{L}^{\#}$ and $\mathbf{L}^T$ are pseudo-inverse and transpose of matrix $\mathbf{L}$)

$$\mathbf{s}_{2:M}{}^* = \mathbf{L}^{\#}_{2:M,2:M}(-s_1)\mathbf{L}^{T}_{1,2:M} \qquad (6)$$

The similarity label distribution of the $\mathbf{v}_{2:M}$ nodes compared with the first node can be obtained in (6), where nodes with s approaching 1 are in the same class pre-defined with the first node and vice versa.

3.2. EV Data into Graph Analysis

3.2.1. Data processing

The obvious different scales of targeted aggregated EV load profile and the individual EV charging patterns make it complicated to analyse by comparing the load profile value. Therefore, it is applied with a common method in data processing– *Normalisation*. Each realistic charging profile is progressed with different normalisation methods depending on the dataset **X** carried by vertex. Moreover, a plus difference ΔP of load profiles means an increase and the normalised method "scaled" can keep the increase information after processing the realistic data:

- max-min normalisation: $\mathbf{x}' = \frac{\mathbf{x} - x_{min}}{x_{max} - x_{min}}$
- scaled by max and min difference: $\mathbf{x}' = \frac{\mathbf{x}}{x_{max} - x_{min}}$
- z-score normalisation: $\mathbf{x}' = \frac{\mathbf{x} - \mu}{\sigma}$ where μ and σ are the mean value and standard deviation of **x**.

In the EV GSP-based disaggregation, the EV aggregated data are divided into day size, which can be analysed with the EV characteristic patterns shown in Table 1 (T is the day size). The goal of disaggregating the total demand is to match a particular EV with the most similar charging profile features which are extracted from the EV data pool of Low Carbon London project [17]. And the graph matrix **X** is generated by combining the daily aggregated profile as the first row and the known EV characteristic patterns (i is EV typical pattern number in total pattern number N) in Table 1.

Table 1 EV data graph matrix

Data type	Graph Matrix X
EV aggregation	$\begin{vmatrix} y_1, & y_2, & \dots y_t \dots & y_T \end{vmatrix}$
EV patterns	$\begin{vmatrix} x_1^1, & x_2^1, & \dots x_t^1 \dots & x_T^1 \\ & & \vdots & \\ x_1^i, & x_2^i, & \dots x_t^i \dots & x_T^i \\ & & \vdots & \\ x_1^N, & x_2^N, & \dots x_t^N \dots & x_T^N \end{vmatrix}$

3.2.2. Discrete Similarity Generation

An EV data graph framework in one discrete sampling point t is shown in Table 2. For example, $[y_1, x_1^1, \dots x_1^i \dots, x_1^N]$ is the first sampling point measurement discrete graph. And the first vertex v_1 is the aggregation feature and the following vertices are N typical EV pattern features at the first sampling point. Each vertex can map the charging load profile value directly, and it is also worth to apply the first-order difference of the charging load to evaluate the performance of the algorism $\Delta P = P_{t+1} - P_t$, which represents the power change during the sampling time (half-hour) with the positive value of ΔP indicating an increase.

The similarity matrix **A** can be obtained via **X** of the graph via equation (3) to show the similarity level of the aggregated feature and individual pattern feature at each time point. With the first node v_1 of aggregated information labelled graph signal s_1 as 1, the following vertex label signals show the discrete similarity distribution $\mathbf{p}^{1:N} = \mathbf{s}_{2:N+1}{}^*$ (calculated via equation (6)) of all N EV characteristic patterns at the specific time t referred to the aggregated signal feature y_t.

Table 2 EV graph signal processing data framework

	EV Data	Graph		
		No. Node	**Dataset X**	**Signal s**
Data into Graph	EV aggregated	1	$\lvert y_t \rvert$	s_1=1
	EV patterns	$\begin{matrix} 2 \\ \vdots \\ i+1 \\ \vdots \\ N+1 \end{matrix}$	$\begin{vmatrix} x_t^1 \\ \vdots \\ x_t^i \\ \vdots \\ x_t^N \end{vmatrix}$	$\begin{vmatrix} p^1 \\ \vdots \\ p^i \\ \vdots \\ p^N \end{vmatrix}$

3.2.3. Daily Possibility Integration

Applied the GSP-based discrete possibility calculation $\mathbf{p}_t^{1:N}$ of N EV patterns of each time measurement t in T, the discrete possibility matrix – $\mathbf{S}_{N\times T}$ can be generated.

Table 3 GSP-based possibility distribution

	Possibility Type	Possibility Matrix
Graph into Analysis	discrete similarity matrix	$\begin{vmatrix} p_1^1, & p_2^1, & \dots p_t^1 \dots & p_T^1 \\ & & \vdots & \\ p_1^i, & p_2^i, & \dots p_t^i \dots & p_T^i \\ & & \vdots & \\ p_1^N, & p_2^N, & \dots p_t^N \dots & p_T^N \end{vmatrix}$
	P: daily possibility matrix	$\begin{vmatrix} P^1, & P^2 \dots & P^i \dots, & P^N \end{vmatrix}$

Then the daily possibility matrix of each EV pattern can be integrated with all the daytime sampling points:

$$P^i = \sum_{t=1}^{T} p_t^i \qquad (7)$$

P^i represents the daily possibility distribution of the EV typical daily charging pattern with number i. And it is expected the EV pattern with the biggest P value in **P** has the most possibility contributing to the aggregated EV charging profile with the most similar shape.

With all P^i of each EV pattern in **P** acquired, each final disaggregation is the selection of the charging pattern with the greatest value. However, it is required to limit the selection progress with a disaggregation filter applying in **P** to avoid over-subtraction between the residual aggregated data and individual charging patterns. During one EV disaggregation, the negative difference distance of each EV pattern in day time is calculated: 1) find all the negative value **R** in the difference of $\mathbf{y}$-$\mathbf{x}^i$ aggregated load profile and each individual pattern in T period; 2) calculate the Euclidean distance $||\mathbf{R}||^2$ of the negative difference values. 3) all EV patterns are filtered by removing the EV pattern with negative difference above an adjustable disaggregation threshold value α in the process of max possibility EV pattern selection.

Therefore, the targeted aggregated charging profile can be disaggregated with individual charging profiles in EV patterns one by one until there is no biggest P can be calculated. In the end, the overview mathematical models with different vital parts of the proposed EV disaggregation tool based on graph signal processing are listed in Table 4.

Table 4 GSP daily disaggregation model comparison

Model	**Data- processing**		**Disaggrega-tion filter threshold α**
	Vertex	**Normalisation**	
Model 1	P_t	Max-min	3.5
Model 2	$\Delta P = P_{t+1} - P_t$	Scaled	4
Model 3	P_t	Z-score	3.5

3.3. Performance Estimation

The mean absolute deviation (MAD) is used to evaluate the performance of the disaggregation error and loss error between the realistic $\mathbf{y(t)}$ and the estimated value $\mathbf{x(t)}$ with sampling interval t in length T. And due to the different scales of the EV aggregated datasets, relative mean absolute deviation (RMAD) is applied which defines as MAD divided by the mean value of the realistic data **y** [7] in (8):

$$\text{RMAD} = \left(\frac{\frac{1}{T}\sum_t^T |x_t - y_t|}{\hat{\mathbf{y}}}\right) \qquad (8)$$

In our EV disaggregation, EV aggregation load profile reconstruction error with extracted EV individual patterns and the number of EVs estimation error are two main performance metrics. As for the No. of EVs estimation, the discrete charging profile for each representative EV pattern contains many low power points, and it is necessary to filter non-connecting period with a small threshold value 0.005 kWh [7] to limit individual minimum charging power. Thus, the RMAD of the EV number estimation can be gained with the ground truth (individual EV information) of the aggregated realistic signal **Y** and the disaggregation results.

4. Experimental Results

Supposed that an aggregated EV load profile in a region such as an EV charging station load profile is available, the objective of the implement is to deduce the individual EV charging information such as aggregated charging number connected to the region, which is highly related to different EV charging behaviour features. However, it is extremely difficult to disaggregate the EV charging information when many EVs are connected and aggregated at the same time. Thus, a GSP-based possibility calculation disaggregation method is proposed to extract each EV with the highest possibility underlying the aggregated load profile.

Table 5 GSP daily segmentation disaggregation case studies in Low Carbon London

Case Group	**Aggregated EV load profile**		***Model 1***		***Model 2***		***Model 3***	
	No. of EV	**Peak charging demand (kWh)**	**RMAD (%) Load**	**RMAD (%) No.of EVs**	**RMAD (%) Load**	**RMAD (%) No.of EVs**	**RMAD (%) Load**	**RMAD (%) No.of EVs**
1	30	9.6670	27.5215	21.7703	33.1180	29.6651	37.1713	35.4067
2	50	18.2390	12.8726	17.3859	31.7106	30.8261	20.7598	17.8792
3	100	25.3540	8.7386	13.1422	19.3892	16.5472	26.9317	26.1051
4	150	38.7410	5.0921	12.5516	23.4737	11.8910	16.9432	11.0239
5	200	50.9780	6.1702	9.9091	20.5041	25.0953	22.7209	13.2806
6	250	71.4860	4.5602	8.8110	20.8286	15.5255	12.8270	8.7580
7	300	67.4180	4.2743	11.5109	16.0003	14.8965	10.4487	9.4409
8	350	84.7020	3.8625	6.5424	14.2099	12.0596	12.8223	14.2032
9	400	100.4400	3.5333	6.9753	11.6285	13.5031	8.8995	7.1759
10	450	105.4630	1.6075	5.7377	18.9963	19.1303	11.7877	5.4460
11	500	119.9620	3.4615	4.7699	19.3761	10.1491	16.1083	13.6617

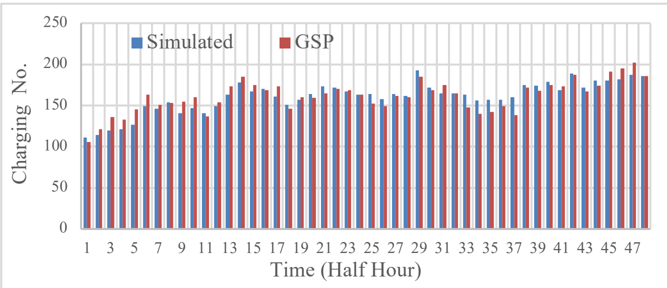
4.1. GSP-based daily disaggregation performance

A day segmentation of the EV aggregation load profile is proposed. It focuses on the truth that all EV characteristic patterns are daily EV charging behaviour combinations since there are separated from the raw datasets day by day in the development of EV patterns, which takes the realistic and limited temporal regional EV behaviour information into consideration.

The synthetic daily aggregated EV charging profiles are generated via aggregating random EV daily characteristic pattern of Section 2.2 at the start (0:00 am) of the simulated day particularly. With the same integrated synthetic EV charging load profile consisting of different EV patterns number in each case group (30, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500 EV patterns shown in Table 5), the GSP-based EV disaggregation models described in Table 4 are validated and compared.

4.1.1. Validation with Low Carbon London

The results of the EV aggregated load profile reconstruction and disaggregated EV number estimation in Low Carbon London dataset[23] are shown in Table 5 with RMAD (%) value of each model. From the overview performance of each EV GSP disaggregation model, *Model 1* behaves better in most cases with different EV simulated number, which uses the EV active power data directly with a max-min normalisation in data processing and disaggregation filter threshold 3.5 (compared with *Model 2* and *3* in Table 4). And in cases applying *Model 1*, it seems that the disaggregated error decrease with lower RMAD value in load reconstruction and number estimation when more EVs are simulated, i.e. aggregated load profile peak demand increases. Furthermore, it achieves a great result in case 11 of 500 daily EVs simulation in term of RMAD in load reconstruction 3.4615% and EV number estimation 4.7699%, which is drawn directly in Figure 4 with the blue line of simulated EV data and the red line of GSP disaggregation result.



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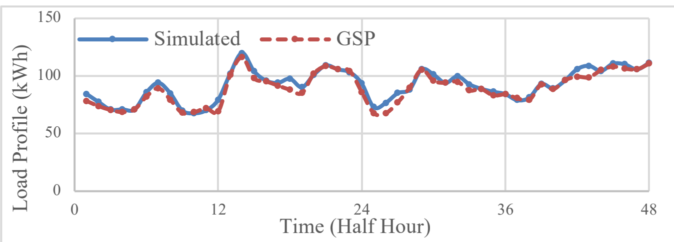

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Fig. 4. *GSP-based disaggregation day segmentation performance of 500 EVs connected **(a)** number estimation comparison **(b)** load profile reconstruction comparison*

4.1.2. Validation with Customer-Led Network Revolution (CLNR)

In addition, this GSP disaggregation method can be tested with other datasets as well. Customer-Led Network Revolution project (CLNR) [14] studies the domestic EV charging in UK to improve the understanding of current and future electricity usage patterns. It provides household electricity load data and EV charging load data generated by 143 domestic customers who own an EV and have a home charging point during six months from Feb 2014 to June 2014. It provides a 10-min measurement and it is aggregated every three active power of the sampling period into half-hour resolution since the household EV data is metered in half hour.

Table 6 GSP-based disaggregation with CLNR datasets

Case	Aggregated EV load profile		*CLND Datasets*	
	No. of EV	Peak charging demand (kWh)	RMAD (%) Load	RMAD (%) No.of EVs
1	30	18.17	11.0516	8.8567
2	50	29.13	11.9893	7.9156
3	100	55.82	9.7064	8.9902
4	150	75.84	8.0771	25.6334
5	200	96.61	8.6746	9.0960
6	250	124.64	12.5847	3.0585
7	300	148.59	6.9462	4.9470
8	350	161.89	5.1945	4.0823
9	400	189.44	7.5808	2.2602
10	450	213.16	6.5537	1.9180
11	500	229.81	8.9453	3.6089

With the CLNR dataset, the daily 608 EV patterns are generated and the GSP disaggregation with *Model 1* is tested with the synthetic aggregated EV charging profile, which applies the same method with GSP disaggregation of Low Carbon London data. The results are shown in Table 6. It can be summarised that the GSP disaggregation performs better when the peak EV charging demand is high with more simulated EVs, which is consistent with the findings in Section 4.1.1. Moreover, it can achieve a 1.92% RMAD error in EV number estimation in case 10 with 450 EVs connected in Table 6.

4.2. Comparison with LAMP disaggregation

What's more, the GSP-based disaggregation performance can be evaluated further compared with the novel limited activation matching pursuit (LAMP) method proposed in [7].

In LAMP, the test synthetic aggregated EV load profile is simulated with shifting the individual EV patterns at random and tuning the total EV pattern number during a period of nine days and the middle seven days load profile is selected to reduce the truncation effect [7]. When 500 individual EV load patterns are simulated, the weekly synthesis EV aggregated load profile fluctuates from a maximum value of 21.91 kWh to minimum value of 3.66 kWh.

Table 7 GSP-based disaggregation vs LAMP disaggregation performance comparison

Case	**Aggregated EV load profile**		**GSP**		**LAMP**	
	No. of EV	**Peak charging demand (kWh)**	**RMAD (%) Load**	**RMAD (%) No.of EVs**	**RMAD (%) Load**	**RMAD (%) No.of EVs**
1	30	4.390	58.32	98.71	42.59	76.34
2	50	9.3190	46.95	119.69	38.31	52.23
3	100	8.7940	30.35	48.40	28.74	30.49
4	150	11.4260	25.00	48.51	22.36	21.18
5	200	12.0330	25.36	29.49	22.42	21.28
6	300	15.1800	17.99	21.14	18.52	24.24
7	500	21.9100	13.18	19.16	13.25	31.73
8	600	24.6790	12.07	21.55	15.72	33.21
9	800	31.0010	12.46	17.90	26.54	45.04

To apply the proposed GSP-based disaggregation, the weekly EV aggregated load profiles in [7] are divided into day length, and each day load profile is validated to achieve the aggregated EV number separately. The GSP-based disaggregation performance with RMAD value of EV load and EV number is compared with the result of LAMP [7] in Table 7.

From Table 7, it can be seen that the presented GSP-based disaggregation behaves better as the EV pattern number increases. In particular, there is a huge improvement in the aggregated EV number estimation with GSP-based disaggregation method when decomposing more than 500 EV patterns in a week. The performance of EV number estimation is improved around 60% by GSP-based disaggregation (17.90%) in terms of RMAD value, compared to LAMP (45.04%) in case 9 with 800 EVs simulated in a long period.

Therefore, the proposed GSP-based disaggregation method can be considered by utilities to estimate aggregated EV number with better performance in a region when a large number of EVs are connected, i.e. an EV charging and parking building load profile.

5. Conclusions

In this paper, a novel implementation of a non-intrusive EV disaggregation based on limited historical datasets in Low Carbon London with half-hour resolution is introduced in detail to increase low voltage visibility in a special area for grid operators in system planning, operation and energy market. It is based on graph signal processing flexible framework and classifier application to calculate the highest possibility in the aggregated EV charging profile. The results show that the visibility of the regional daily EV charging number can be deduced accurately with an around 4.77% RMAD error in 500 EVs aggregation simulated in one day. In addition, this GSP disaggregation method is also validated with dataset in the Customer Led Network Revolution project and compared with LAMP disaggregation method. With more complete EV data acquired in the future, a more exhaustive regional EV disaggregation can be deployed with other enabling technologies.

6. Acknowledgments

This research is supported by the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (Grant No. LAPS20011) of China.

7. Reference

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