Potential Evaluation Method for Aggregated Demand Response Resources Based on User Pattern Recognition

Qiang Chen, Ya Zhang, Chen Chen, Kai Dai, Jiaqi Li and Lixiao Wang

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Qiang Chen
Yunnan Power Grid Co. LTD
Kunming, China
7237366@qq.com

Ya Zhang
Yunnan Power Grid Co. LTD
Kunming, China
Zhangya@im.yn.csg

Chen Chen
Yunnan Power Grid Co. LTD
Kunming, China
654689833@qq.com

Kai Dai
Yunnan Power Grid Co. LTD
Kunming, China
281140244@qq.com

Jiaqi Li
School of Electrical Engineering
Guangzhou City University of Technology
Guangzhou, China
jackli99@foxmail.com

Lixiao Wang*
School of Electrical Engineering
Guangzhou City University of Technology
Guangzhou, China
wlixiao00@163.com

***Abstract*—Demand Response is an effective method to reduce peak load of the grid and relieve the power supply pressure. Accurate area demand response potential evaluation for power companies is the basic for demand response implementation. Therefore, this paper proposes a potential evaluation method for aggregated response resources based on user pattern recognition. This method obtains typical resource types in the resource pool by clustering massive users' electricity consumption characteristics and analyzing their response willingness. Through this method, users with high response potential are identified and the overall potential of the aggregated resource pool is evaluated. Simulation results show that the proposed algorithm can successfully recognize user patterns and obtain the aggregated potential of the resource pool. The results can provide scientific guidance for resource expansion planning.**

Keywords—response potential evaluation, aggregated demand response, user pattern recognition

I. INTRODUCTION

Demand Response (DR) plays an important part in exploring the potential of flexibility resources, reducing the peak loads and save additional investments of the grid. The demand response strategy mainly refers to the operation mechanism to guide users to transfer part of the peak loads to the valley period of time, so as to ensure the power balance between energy generation and consumption. The duration of peak load time is generally short. In China, the time interval is only 1.6% of the total hours within a year [1]. However, the economic benefits of completing demand response program are significant. A pilot project for a fully automated demand response program presented for air conditioners reduces energy consumption by 53.5% [2].

Multiple resources are considered to be effective resources which can participate in demand response. An active time-based demand response strategy for industrial consumer considering best behavioral scheme model and consumers' attitude model was implemented in [3]. Similarly, the optimal synchronized process of industrial consumers was considered in [4]. The results show that with proper demand response strategy, the profit is maximized for all customers with their satisfaction guaranteed. In [5], a new regression model is presented for demand reduction, which employed load sensitivity to outside air temperature and representative load pattern derived from cluster analysis of customer baseline load as explanatory variables. An architecture was formulated in [6], which is used for choosing the optimal set of energy consuming devices to be powered off during peak hours while respecting the energy consumer's energy saving preferences and minimizing the negative impact. Different demand response strategies are designed for several resources, such as renewable energy [7], electrical vehicle charging stations [8], energy storage systems [9], and residential loads [10].

However, due to the large number of power users and the huge amount of data involved in demand response markets, there is still a lack of a unified scheduling approach that works for all user types [11]. Clustering is an effective method to deal with multiple users with different electrical consumption characteristics and demand response characteristics. A novel load profile clustering method is proposed in [12] for residential and commercial load data classification based on the information entropy.

An adaptive clustering-based customer segmentation framework is proposed in [13] to categorize customers into different groups to enable the effective identification of usage patterns. Based on a large quantity of history data, the adjustable resources can be clustered and aggregated for further needs [14]. The general process in electric load clustering was summarized in [15] and the applications and future trends was discussed in detail.

After consumers are dynamically classified, the responsive ability of the whole market can be perceived according to the response characteristics of different type of users [16]. A

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* Corresponding author.

demand response potential evaluation method was discussed in [17] for industrial users with large power consumption and strong load regularity based on Gaussian process regression. The authors compared the actual demand response data of a local industrial user with the proposed method and verified that the method can more accurately evaluate the demand response potential. Compared to industrial users, it is more difficult to evaluate the DR potential of residential customers due to the diversity and volatility of customers' electricity consumption behaviors [18]. A DR potential evaluation for residential customers was proposed in [19] based on machine learning algorithms. Similarly, Ref. [20] presented a strategy to quantify the potential of DR of households. The strategy takes both completion rate and user experience into account, and it improves the enthusiasm of users to participate in demand response.

A framework for establishing models was proposed to reveal buildings' dynamic demand response potential under different meteorological conditions and control strategies in [21]. A power load shifting potential of secondary sectors was studied in [22] through the questionnaires investigation and face-to-face interviews. Optimal scheduling and decomposition of the regional demand response reserve target was designed in [23], [24] to guarantee the balance of supply and demand and mitigate power grid investment.

In this paper, we propose a potential evaluation method for aggregated demand response resources based on user pattern recognition. Firstly, multiple clustering methods are applied to process massive user electricity consumption data, then the method with the best performance is selected to recognize the user pattern. Based on different patterns and their response willingness, the aggregated response potential of the resource pool is evaluated, which can provide guidance for further expansion planning of the resource pool.

This paper is organized as follows: Section 2 introduces the logic of potential evaluation method for aggregated demand response resources based on user pattern recognition. Simulation studies and results analysis are carried out in Section 3. Section 4 presents the conclusions.

II. Potential Evaluation Method

A. Method description

The flowchart of potential evaluation method for aggregated demand response resources based on user pattern recognition is shown in Fig.1. Firstly, the user's daily electricity consumption curve is standardized ， then Normalized cut method (N-cut) method, K-means method, Gaussian Mixture Model method (GMM) and Nearest Descent methods (ND) are applied to recognize user's electricity consumption pattern. Davies-Bouldin index, Silhouette Coefficient are used to evaluate the recognition performance. The optimal clustering result is obtained to analyze user clusters. Additionally, the user's willingness and economic value are statistically analyzed based on the questionnaire data, and the response characteristics of each cluster is obtained. According to the actual load levels, the clusters with high response potential are identified. Finally, all kinds of response resources are aggregated to form a highly responsive resource pool. Based on the evaluation of response potential of various resources, the response potential of the resource pool in the electricity supply region can be obtained. This can provide suggestions for further expansion planning of the pool.

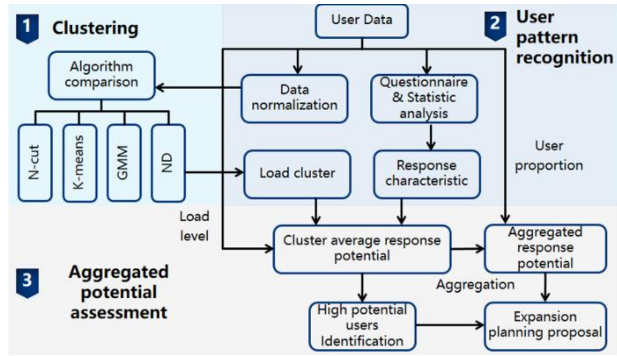

Fig. 1. Flowchart of potential evaluation method for aggregated demand response resources based on user pattern recognition

B. Clustering

1) Standardization

Maximum and minimum standardization, also known as deviation standardization, is a linear transformation of the original data so that the resulting values are mapped between [0-1]. The maximum and minimum standardized formula is as follows：

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where x' is the normalized data, x is original data, $x_{\max}$ is maximum value of the sample data, and $x_{\min}$ is minimum value of the sample data.

2) Clustering algorithm

Clustering is used for data mining, which belongs to unsupervised learning. The goal of clustering is to divide many unlabeled sample data sets into several different subsets according to their similarity, to ensure that the similarity of data objects in the same cluster is as large as possible, and the differences between data objects that do not belong to the same cluster are as large as possible. In practical applications, there is no clustering method that can be applied to various data samples, so scholars have proposed different clustering analysis methods based on the characteristics of different data samples. The commonly used clustering analysis methods are：

a) k-means method: The k-means method performs an initial division of the data set and then enters a loop. The objective function is to minimize distance of elements in the same cluster, so that the similarity of elements of one cluster can be maximized, and the similarity of elements between the clusters can be minimized. The distance of two elements in one cluster is as follows [25]：

$$E_{\text{k-means}} = \sum_{k}^{K} \sum_{x \in C_i}^{N} (x - \mu_i)^2 \tag{2}$$

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x \tag{3}$$

Where x is a sample. N is the number of objects. K is the number of clusters. The smaller the E value, the better the clustering effect.

b) N-cut method: N-cut can identify sample spaces of any shape. This method is based on graph theory. It defines that the edge weight value between farther points is lower and that between closer points is higher. N-cut method classifies the graph composed of massive data points to minimize the edge weights between the subgraphs and maximize the edge weights in the subgraphs. The similarity between clusters is as follows[26]:

$$E_{\text{N-cut}(A,B)} = \frac{\text{cut}(A,B)}{\text{assoc}(A,V)} + \frac{\text{cut}(A,B)}{\text{assoc}(B,V)} \tag{4}$$

$$\text{cut}(A,B) = \sum_{\mu \in A, \nu \in B} \omega(\mu,\nu) \tag{5}$$

$$\text{assoc}(A,V) = \sum_{\beta \in A, \lambda \in V} \omega(\beta,\lambda) \tag{6}$$

Where A, B are sample points. V is the entire graph. $\text{cut}(A,B)$ is the sum of the weights of A and B. $\omega(\mu,\nu)$ is the edge weight of μ and ν. $\text{assoc}(A,V)$ is the sum of weights of A and V. The smaller the value of $E_{\text{N-cut}(A,B)}$, the better the clustering performance.

c) GMM method: GMM is a commonly used probability distribution model, which has a wide range of applications in the field of mathematical statistics. The cluster presents an oval shape, which is better than the circle of k-means. The Gaussian hybrid model iterates to maximize the probability of the sample point to the center of the Gaussian distribution. The probability density function of GMM is as follows[27]:

$$P(k) = \sum_{k=1}^{K} \pi_k N(x|\mu_k, \sum k) \ , \quad \sum_{k=1}^{K} \pi_k = 1 \tag{7}$$

Where x is a sample, and its mean vector is μ_k. Σk is the covariance matrix. K is the number of clusters, π_k is the probability of the sample belonging to the k-th Gaussian distribution, which is greater than 0. $N(\text{x}|\mu_k, \Sigma \text{k})$ is the probability density of the k-th Gaussian.

d) ND method: ND method organizes the data set into a sparse graph and allocates clusters by removing irrelevant edges in the graph. The ND method is simple, efficient, and stable. ND can organize data sets with different shapes and attributes. The probability density of ND is the following formula[28]:

$$P(i) = -\sum_{n=1}^{N} e^{-\frac{d(x_i, \text{x}_j)}{\sigma}} \tag{8}$$

Where N is the number of all samples, x_i and x_j are the two samples. σ is the core bandwidth parameter. $d(x_i, x_j)$ represents the distance between x_i and x_j, which can be expressed using Euclidean distance, as the formula $d(x_i, x_j) = \|x_i - x_j\|_2$.

C. Clustering effect evaluation method

Davies-Bouldin index (DBI) comprehensively considers the similarity of samples within the class and the difference of samples between the clusters. The smaller the value, the higher the effectiveness of clustering. Suppose we have m samples and are clustered into n categories. The specific definition of DBI is as follows:

$$BDI = \frac{1}{N} \sum_{i=1}^{N} \max_{j \neq i} \frac{\overline{S_i} + \overline{S_j}}{\|w_i - w_j\|_2} \tag{9}$$

Where: DBI represents the index value. $\overline{S_i}$ is the average Euclidean distance from the i-th sample to its class center. $\|w_i - w_j\|_2$ is the Euclidean distance from the class center of i-th and j-th clusters. Different classifications can lead to different values. The smaller the DBI value, the lower the degree of dispersion and the better the classification performance.

Silhouette Coefficient (SC) is also applicable in situations where the actual category information is unknown. SC measures whether the current sample point is close to other sample points of the same cluster and far enough from the other clusters. The specific definition of SC is as follows:

$$SC = \frac{b-a}{\max(a,b)} \tag{10}$$

Where: a is the average distance between the current sample point and other sample points of the same cluster. b is the average distance between the current sample point and the closest other sample point of another cluster. The contour coefficient of a sample set is the average value of that of all samples. The value range of contour coefficient is [-1, 1]. The closer the distance between samples of the same cluster, the higher the SC score.

III. SIMULATION STUDIES AND RESULTS

A. Data Description

More than 1500 users of various building types include factories, office buildings, schools, and hospitals are investigated in this paper. The original electricity consumption data of the users are shown in Fig.2. Fig.3 illustrates the hourly electricity consumption of the users. The figure shows the randomness and irregularity of electricity consumption in this area, which causes the problem of load management and aggregated potential evaluation for grid company.

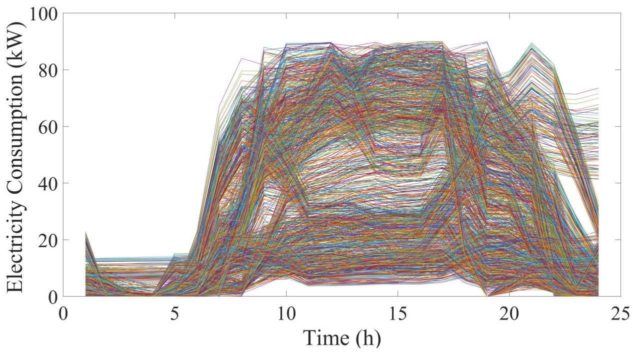

Fig.2 Original electricity consumption curves

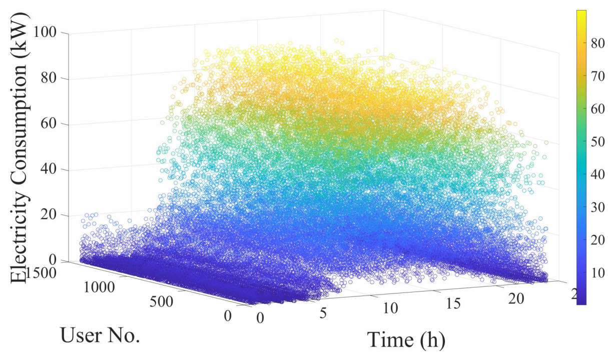

Fig.3 Hourly electricity consumption of 1500 users

B. Clustering performance

In this paper, N-cut, K-means, GMM and ND are applied to recognize the user's electricity consumption pattern. The recognition performance is evaluated by DBI, SC and overall score. The overall score is calculated by SC/DBI. Table 1 shows the recognition performances by different methods. The better the recognition performance, the smaller the DBI value, the greater the SC value, and the greater the overall score. As can be seen in the table, N-cut clustering method has the worst classification performance, which means that the method is not suitable for clustering the electricity consumption data in this area. ND clustering method has the best clustering performance with the overall evaluation of 0.9787, which is higher than K-means of 0.9182, and GMM of 0.8623. Therefore, ND clustering method is chosen for recognize the user's pattern in this paper.

Table.1 Recognition performance by different methods

Clustering methods / Recognition performance	N-cut	K-means	GMM	ND
DBI	1.6669	0.7645	0.724	0.6323
SC	0.0152	0.7020	0.6243	0.6189
Overall score	0.0091	0.9182	0.8623	**0.9787**

C. User pattern recognition

In this section, user pattern recognition results obtained by ND clustering method are compared to the results obtained by building type classification. When users are connected to the grid, they are divided into 16 categories according to their building types, which can be seen in Fig.4. Building type classification method do not consider user's electricity consumption characteristics, and so many categories are not conducive to the unified management of the grid.

By ND clustering method, the users are divided into 5 clusters, the typical electricity consumption of which are shown in Fig. 5. Typical load of Cluster 1 reaches its peak at 8h, 13h and 19h, respectively. The three peaks are basically the same. Therefore Cluster 1 shows three-peak feature. Typical load of Cluster 2 increases gradually from 6 h to 17 h, then decreases slowly, showing single-peak feature. Typical load of Cluster 3 reaches its peak at 10-11 h and 14-17 h, and then drops sharply at 17 h. At 22 h, there is another peak. Therefore, Cluster 3 shows multi-peak feature. Typical load of Cluster 4 reaches its peak at 8h and 21h, and power consumption in the evening was significantly higher than that in the morning. Therefore, Cluster 4 shows double-peak feature. Typical load of Cluster 5 increases from 4 hours, reaches its peak and basically remains unchanged from 9 to 17 hours, and then decreases steadily. Therefore, Cluster 5 shows single-peak and flat-top feature.

Compare Fig.5 with Fig.4, the users are not classified precisely using the building type classification method. In the case of Cluster 4, it includes type3, type6, and type11 obtained by the building type classification method. Even though the load levels and peak times are slightly different from each other, all of the three types show the same double-peak feature, and should be recognized as the same pattern.

Table 2 shows the features of the 5 clusters. As can be seen in this table, the maximum values of all clusters are close to 1, and the minimum values are close to 0. The average value of Cluster 1 is the highest, reaching to 0.6269; In terms of standard deviation, variance and root mean square, Cluster 4 has the lowest degree of dispersion and is relatively stable. The peak factor and pulse factor of Cluster 4 are higher than others, which means that its peak value is extremely high compared to its average value. From the perspective of load level, the peak duration ratio of Cluster 5 is the highest, which means it runs at the peak for the longest period. By contrast, Cluster 3 runs at low load for most of the time.

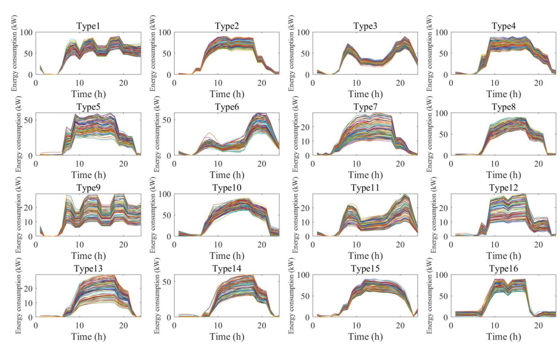

Fig.4 User categories obtained by building type classification

Table2 Electricity consumption features of 5 clusters

Trait / No.	maximum value	Minimum value	Average value	Standard deviation	Variance	Root mean square	Peak factor	Pulse factor	Fluctuation range	Minimum load rate	Peak -valley difference ratio	Average load rate	Load Fluctuation rate	Peak duration ratio	Valley duration ratio
1	**0.9918**	0	**0.6269**	0.3413	0.1165	**0.7104**	1.3961	8.5145	**0.9917**	0	**0.9999**	**0.6321**	0.5444	0.3750	0.1667
2	**0.9823**	0.0065	0.4804	**0.4039**	**0.1632**	0.6222	1.5698	5.9867	0.9768	0.0056	0.9944	0.4891	0.8408	0.3333	0.4167
3	0.9874	0.0519	0.4358	0.4018	0.1615	0.5871	1.5935	5.7937	0.9355	**0.0526**	0.9474	0.4414	**0.9221**	0.3333	**0.4167**
4	0.9878	0	0.4333	0.2986	0.0892	0.5227	**1.8895**	**11.075**	0.9877	0	**0.9999**	0.4387	0.6892	0.1667	0.2500
5	0.9757	0.0030	0.5218	0.4009	0.1607	0.6529	1.4897	6.0531	0.9726	0.0031	0.9969	0.5348	0.7682	**0.4167**	0.3333

Peak factor = (maximum value - minimum value) / root mean square; Pulse factor = (maximum value - minimum value) / variance; Minimum load rate = minimum value / average value; Peak-valley difference ratio = (maximum value - minimum value) / average value; Average load rate = average value / maximum value; Load fluctuation = standard deviation / average value; Peak duration ratio = the proportion of load values during periods of high system load (≥ 80%*max) in a given period; Valley duration ratio = proportion of load values during periods of low system load (≤ 20%*max) in a given period

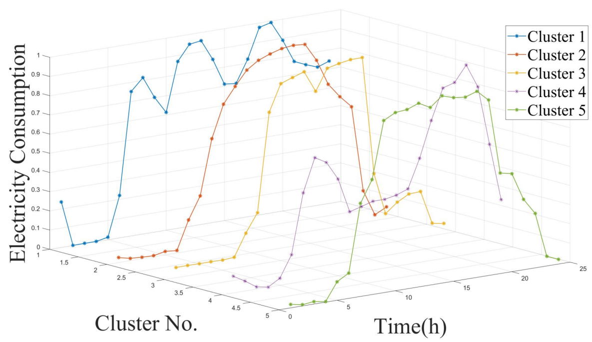

Fig.5 Electricity consumption characteristics of 5 clusters

D. Aggregate potential evaluation

Figure 6 shows the aggregated demand response potential, the potential of the resource pool is relatively high during day-time, 10-17 h. Considering that the maximum of the load in this area is 69.9615 MW and the maximum response potential is 3.5175 MW, the resource pool has formed the response potential of 5% of the maximum load now. In this pool, Cluster 2 and Cluster 5 are resources with the highest potential. It is worth noting that the potential is low in the early morning, and needs to be further strengthened.

Fig.7(a) shows the total response potential of the resource pool. As can be seen in the figure, the response potential is concentrated during 7-24 h, with the maximum response potential of 3.5175 MW in 17 h. Fig.7(b) shows response potential distribution of different clusters. As can be seen in the figure, the potential of all typical clusters is near to zero during 1-6 h, with a minimum overall potential of 0.046MW. At other times, Cluster 2 and Cluster 5 have extremely high response potential. The maximum value of the former is 1.3049 MW in 16 h and the maximum value of the latter is 1.0328 MW in 14 h. Cluster 3 has the lowest response potential, which is concentrated during 9-17 h and the maximum value of its response potential is only 0.4459MW in 16 h. Cluster 1 and Cluster 4 have continuous response potential. The former can provide response capacity during 7-24 h, and the latter can provide response capacity during 7-23 h. The performance of Cluster 4 is particularly outstanding in 21 h, with a maximum value of 0.6215 MW.

Therefore, in the future construction of the resource pool, it is necessary to enhance the potential during 1-6 h and build a more extensive resource pool. In addition, Cluster 2 and Cluster 5 are users with the highest potential, so expansion of the pool can focus on developing these kinds of users to continuously excavate the demand response potential in this area.

Table 3 User proportion of 5 clusters in the resource pool

Type	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Number of users	188	472	188	282	374
Proportion	12.5%	31.383%	12.5%	18.75%	24. 87%

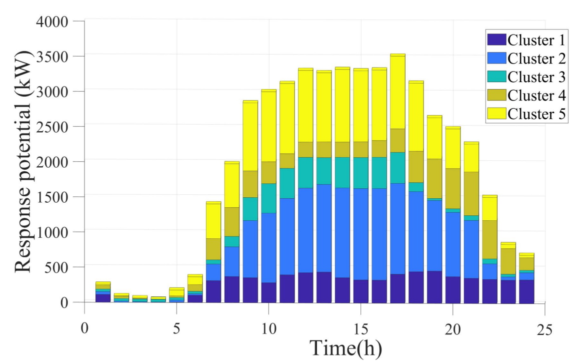

Fig.6 Demand response potential of clusters

IV. Conclusion

This paper proposes a potential evaluation method for aggregated demand response resources based on user pattern recognition. The following conclusions are drawn from the paper:

(1) ND clustering method has the best user pattern recognition performance, with the overall score of 0.9787, which is higher than K-means of 0.9182, and GMM of 0.8623.

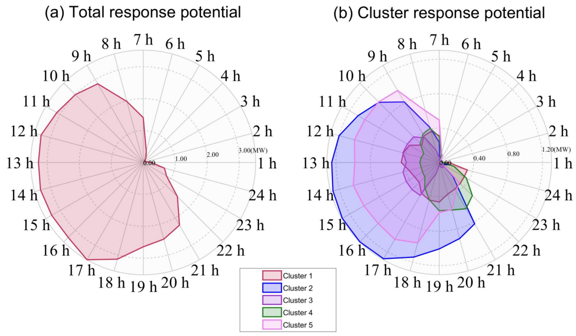

Fig.7 Aggregated and single demand response potential

（2）The 1500 users in the power supply area can be grouped into 5 clusters, in which Cluster 2 and Cluster 5 have extremely strong response potential. The maximum value of the former is 1.295 MW in 16 h and the maximum value of the latter is 1.018 MW in 14 h.

（3）The aggregated resource pool has a maximum response potential of 3.512MW, and has formed 5% response potential of the total load. However, during 1-6 h, the response potential is low and continuous excavation is needed.

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