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MODELING AND ALLOCATION OF VIRTUAL DEMAND SIDE MANAGEMENT RESOURCES FOR RELIABILITY IMPROVEMENT AND COST REDUCTION USING ELECTRE METHOD

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Abstract- Demand side management programs in the restructured power system environment have been divided into two categories namely energy efficiency and demand response programs. The energy efficiency method improves efficiency and performance of the equipment. Demand response programs which were presented as multi-tariff system before restructuring, get more valuable in the competitive environment the exact modeling of these programs helps the market regulator for evaluating the impact of price responsive loads on electricity market conditions. It should be noted that demand response allocation is also very important in the power system studies. In this paper, according to the price elasticity of demand and customer benefit function, the non-linear economic models of responsive load are achieved. Moreover, in order to select the most suitable bus and the optimum scenario for minimizing the operation cost, total loss, Expected Energy not served (EENS), peak-to-valley distance and power factor improvement, multi-attribute decision making (MADM) method, so-called elimination and (et) choice translating reality (ELECTRE), is used. Numerical study is performed on the IEEE-RTS 24-bus.

Keywords: Demand Response, ELECTRE, Elastic Load, Non-Linear and Economic Load Model, Costumer Benefit.

I. INTRODUCTION

DSM is a word which includes some concepts including demand side management, energy efficiency, and even increasing the consumed energy by electrified some non-electric systems [1]. In the restructured power system, demand side programs management are divided into two groups [2]:
1- Energy efficiency programs
2- Demand response programs

Restructuring in the power systems lead to the invention of some new words beside DSM. For instance, demand response (DR), which includes some methods of DSM, can result in changing the energy consumption according to the energy price. Although these programs were applied in the conventional environments in term of multi-tariff meters, in the restructured environment demand side programs (DSP) became more important and many researchers were attracted to study in this filed. The global energy agency, presented a 5-year strategy to improve the demand side management methods in the conventional environments.

The agency introduced 15 important projects (programs) that each of them can encourage the customers to participate in the electricity market and DR programs. The 13th program is related to the importance of using demand response resources [3]. Demand response programs are divided into two groups:
1- Incentive-based programs (IBP)
2- Tariff-base rate (TBR)

The sub-branch of the aforementioned programs are given in follows:
1- Tariff-based programs
✓ Time of use programs (TOU)
✓ Real time pricing programs (RTP)
✓ Critical peak pricing programs (CPP)
2- Incentive-based programs
✓ Direct load control (DLC) programs
✓ Interruptible/Curtailable loads (I/C)
✓ Demand side bidding (DSB)
✓ Emergency demand response program (EDRP)
✓ Capacity market programs (CAP)
The details of these DR programs can be found in [4].

In this paper, the time of use (TOU) programs are considered which are briefly explained. In these programs, the energy price is calculated for at least three times in a day including peak-load, base load and valley load times. This tariff can be calculated for different hours of a day or different days of a week or different times of a year. To evaluate the effects of DR programs on the operation and load profile attributes, modeling of the DR programs is a very important issue. In [5], some linear economic models of elastic loads have been presented. Since the customer benefit function is non-linear, it is better to use the non-linear DR program models to evaluate the loads behavior more accurately. Maximizing the Dis Co's benefit function in presence of non-linear customer benefit function has been studied in [6].

In this paper, three non-linear models of elastic loads including power, exponential and logarithmic models, made based on the elasticity and customer benefit function, have been considered. Using the non-linear models has some positive effects on the power system operation attributes including operation cost, peak to valley distance, system loss, power factor, reliability indices, etc. Therefore, using ELECTRE determines the most appropriate scenario and the optimum model and bus to achieve the aforementioned effects. The rest of the paper is organized as follow. In section II, the non-linear modeling of demand response programs is explained. In section III, the system operation and load profile attributes are described. The performance of ELECTRE method and its algorithm in a decision-making problem is discussed in section IV. The results of this study and the conclusions are given in sections V and VI, respectively.

II. NON-LINEAR MODELING OF DEMAND RESPONSE PROGRAMS

To model the DR programs, the demand which is denoted with $d(i)$, depends on the electricity price and tariffs. As mentioned in the previous section, there are different models for demand response programs modeling, where, in this paper, all three models including, power, exponential and logarithmic methods are implemented.

A. Power Model

A.1. Single-Period Elastic Load Modeling

Elasticity which is the sensitivity of demand to the prices is defined as follows:

$$E = \frac{\rho_0(j)}{d_0(i)} \cdot \frac{\partial d(i)}{\partial \rho(j)} \tag{1}$$

where, $P_0(j)$ is the initial electricity price at hour j, and $d_0(i)$ is the initial demand at hour i.

In (1), if $i=j$ the elasticity is negative and if $i \neq j$ the elasticity is non-negative. According to (1), if the electricity price increases at ith hour, the electricity demand will decrease at hour i, and the electricity demand will increase at hour i, if the electricity price at hour j increases. When the electricity price is different for different periods of time, demand will respond to it [7].

Some loads are single-period elastic loads which cannot be served in another time period. These loads can be turned on or turned off at the specific time like lighting or they can respond to the electricity prices at the time that they have to be supplied. These loads have a self-elasticity and this value is non-positive for these loads. Another elastic loads are multi-period loads which can be supplied in the different time periods. In fact, these loads can be shifted in time from peak load times to the off-peak times like heating and cooling loads. These loads which can be shifted in time according to the electricity price of another time period, have cross elasticity. The value of cross elasticity is always non-negative, because, when the electricity price is increased in a specific period of time, the electricity demand is increased in other time periods.

A number of large loads like industrial loads may include both single-period and multi-period loads which have been considered as the combined-period loads. The customer benefit function is calculated using (2):

$$S = B(d(i)) - d(i).\rho \tag{2}$$

where, S is the customer benefit function, $B(d(i))$ is the income of the costumer at hour i, and $d(i)$ is demand at hour i. The maximum benefit is obtained using (3):

$$\frac{\partial B(d(i))}{\partial d(i)} = \rho(i) \tag{3}$$

Using the Taylor series of $B(d(i))$, the customer benefit function is obtained as follows [8]:

$$B(i) \cong B_0(i) + \frac{\rho_0(i).d(i)}{1+E(i,i)^{-1}} \{ (\frac{d(i)}{d_0(i)})^{E(i,i)^{-1}} - 1 \} \tag{4}$$

where, $B_0(i)$ is the customer benefit function at hour i for initial electricity price , p_0 is the initial electricity price, d_0 is the initial demand, and $B(i)$ is the customer benefit function at hour i for demand (d) and spot price p.

By differentiating (4) and substituting in (3) the following equation is derived:

$$\frac{\rho(i)}{\rho_0(i)} = (\frac{d(i)}{d_0(i)})^{E(i,i)^{-1}} - \frac{1}{1+E(i,i)^{-1}} \tag{5}$$

where, $E(i,i)$ is the self-elasticity.

For small value of elasticity, the second term in (5) can be ignored. In the real conditions, the elasticity has a value in a range of (-0.1,-0.2). Hence, the power model of the single-period loads is as follows:

$$d(i) = d_0(i).(\frac{\rho(i)}{\rho_0(i)})^{E(i,i)} \tag{6}$$

A.2. Modeling of Multi-Period Elastic Loads

To model the multi-period elastic loads, firstly, the concept of cross elasticity should be described [9]. Hence, considering the aforementioned Equations (1-4) the model power model of multi-period loads for a 24-hour period is as (7):

$$d(i) = d_0(i).\prod_{\substack{j=1 \\ i \neq j}}^{24} (\frac{\rho(j)}{\rho_0(j)})^{E(i,j)} \tag{7}$$

A.3. Modeling of Combined-Period Elastic Loads

As mentioned in the previous sections, some loads may include both single and multi-period loads, where, they are known as combined-period loads. The power model of the combined-period loads with constant i in a period of 24-hour is as follows:

$$d(i) = d_0(i).\prod_{\substack{j=1 \\ i \neq j}}^{24} (\frac{\rho(j)}{\rho_0(j)})^{E(i,j)} \tag{8}$$

where, $E(i,j)$ is the cross elasticity.

In general, Equation (8) determines how much electricity should be consumed by customers to maximize the benefit. It is notable that the demand response programs in this study are time-based rate (TBR). In power form, $E(i,i)$ is constant for all price and loads. Therefore, this form is known as constant elasticity model.

B. Exponential Model

B.1. Single-Period Elastic Load Modeling

In the exponential form, the costumer benefit function is obtained by extending the Taylor series of $B(d(i))$ as follows [19]:

$$B(i) \cong B_0(i) + \rho_0(i).d(i).\{1 + \frac{1}{E(i,i)}[\ln(\frac{d(i)}{d_0(i)} - 1]\} \quad (9)$$

The above equation is not defined for zero-loads and zero-elasticity loads. By differentiating the above equation and substituting in (3), the exponential form of single-period elastic load is obtained:

$$d(i) = d_0(i).\exp\{E(i,i).\frac{\rho(i) - \rho_0(i)}{\rho_0(i)}\} \quad (10)$$

B.2. Multi-Period Elastic Load Modeling

According to what was explained in modeling of power form of multi-period elastic loads, (11) is derived:

$$d(i) = d_0(i).\exp\{\sum_{j=1, i\neq j}^{24} E(i,j).\frac{\rho(j) - \rho_0(j)}{\rho_0(j)}\} \quad (11)$$

B.3. Combined-Period Elastic Load Modeling

In the exponential model, the combined-period load model, considering the constant i and a 24-hour period, is obtained from (10), (11) as follows:

$$d(i) = d_0(i).\exp\{\sum_{j=1}^{24} E(i,j).\frac{\rho(j) - \rho_0(j)}{\rho_0(j)}\} \quad (12)$$

C. Logarithmic Model

C.1. Single-Period Elastic Load Modeling

For the logarithmic model, the customer benefit function can be obtained using (13) [10]:

$$B(i) \cong B_0(i) + \rho_0(i).d_0(i).E(i,i)\{\exp[(\frac{d(i) - d_0(i)}{E(i,i).d_0(i)}) - 1]\} \quad (13)$$

By differentiating the above equation, and substituting in (3), the logarithmic model of single-period elastic load is derived:

$$d(i) = d_0(i)\{1 + E(i,i).\ln(\frac{\rho(i)}{\rho_0(i)})\} \quad (14)$$

C.2. Multi-Period Elastic Load Modeling

Using the definition of self-elasticity and cross elasticity and using (1), the logarithmic model of multi-period elastic load can be calculated by (15):

$$d(i) = d_0(i).\{1 + \sum_{j=1, i\neq j}^{24} E(i,j).\ln(\frac{\rho(j)}{\rho_0(j)})\} \quad (15)$$

C.3. Combined-Period Elastic Load Modeling

In the exponential model, the combined-period load model, considering the constant i and a 24-hour period, is obtained from (14), (15) as follows:

$$d(i) = d_0(i).\{1 + \sum_{j=1}^{24} E(i,j).\ln(\frac{\rho(j)}{\rho_0(j)})\} \quad (16)$$

III. THE UTILIZED ATTRIBUTE AND INDICES

A. Operation Cost Attribute

This attribute is obtained by solving the power flow equations in a 24-hour period, where, for each time, the operation cost is calculated and the total cost is the sum of costs in the whole time period.

B. Loss Index

Another index which is very important in the power system operation is loss index, and, loss reduction has always been one of the system operator concerns. Any changes in the power flow through the system can affect the system loss considerably. The mathematical model of loss index used in this study, is as follows:

$$\min\ F = P_{totloss}$$

$$\text{s.t.} \begin{cases} P_{totloss} = \sum_{t=1}^{24} p_t \\ p_t = \sum_{l=1}^{N_L} (R_{pu}.p_{l,t}^2) \end{cases} \quad (17)$$

where, R_{pu} is lth line's resistance, and $p_{l,t}$ is the power flow through line l at time t.

C. Load Factor

The power factor (PF) index is calculated using the load curve in a 24-hour period. This factor is the most important factor from the viewpoint of the customer and its mathematical model is as (18):

$$LF = \sum_{t=1}^{24} (\frac{d(i)}{24.peak}).100 \quad (18)$$

where, $peak$ is maximum demand during a 4-hour period.

D. Peak to Valley-Load Distance Attribute

The DR programs in the most times reduce the peak to valley distance. This attribute is also calculated according to the 24-hour load curve.

E. Reliability Index (Expected Energy Not Served)

Expected energy not served ($EENS$) is considered as a reliability index in this study. This index refers to the amount of energy that the customers did not receive from the system due to the lack of power generation. This index can be calculated using (19):

$$EENS = \sum (C_{out} - Reserve).P_{individual}(Reserve).t \quad (19)$$

where, C_{out} is the amount of power out of the whole system power, which is not supplied during the contingencies, maintenance, etc. and $P_{individual}$ ($Reserve$) is the reserve probability.

IV. ELECTRE METHOD

In this method, all alternatives are evaluated using the outranking comparisons and the ineffective alternatives will be ignored. A pairwise comparison is done based on the degree of agreement (W_j) and degree of disagreement compared to the weighed values and it is used to test the alternatives. Since, all of these stages are done based on the concordance and discordance of the alternatives, this method is famous as concordance analysis.

A. ELECTRE Decision Making Algorithm

Step 1: changing the decision making matrix D to a dimensionless matrix as follows:

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}} \tag{20}$$

Step 2: Making a weighted dimensionless matrix (V) using vector (W). It is notable that the entropy method is used in this study for weighting.

Step 3: Determination of concordance and discordance sets for each pair of alternatives ($k, l = 1, 2, ..., m; l \neq k$). The available attributes are divided into two concordance (S_{kl}) and discordance (D_{kl}) sub-sets. The concordance set of A_l, A_k includes all attributes where, A_k is preferred to A_l as follows:

$$J = \{ j \mid r_{kj} \geq r_{lj} \} \tag{21}$$

where, r_{ij} is considered with the ascending benefit.

Also, the discordance set D_{kl}, includes all attributes in which (1) is satisfied.

$$D_{kl} = \{ j \mid r_{kj} \leq r_{lj} \} = J - S_{kl} \tag{22}$$

Step 4: Calculating the concordance matrix: The value of the concordance set (S_{kl}) is calculated by the available weights of the concordance attributes. In the other word, the concordance criterion is the sum of the weights (W_j) of those attributes which create the set S_{kl}. Hence, the concordance criterion ($I_{k,l}$) between A_k and A_l is as follows:

$$I_{kl} = \sum_{j \in S_{k,l}} W_j \quad , \quad \sum_{j=1}^{n} w_j = 1 \tag{23}$$

The concordance criterion ($I_{k,l}$) shows the relative importance of A_k over A_l such that $0 \leq I_{k,l} \leq 1$.

The higher value of the $I_{k,l}$, the more priority of A_k over A_l. Hence, the subsequent values of $I_{k,l}$ criterion make the asymmetric matrix (I).

Step 5: Calculating the discordance matrix: Discordance criterion (related to the set $D_{k,l}$) unlike the $I_{k,l}$ criterion, indicates how much A_k evaluation is worse than A_l. This criterion ($NI_{k,l}$), is calculated using the elements of matrix V considering the discordance set $D_{k,l}$. It is important that the information of I and NI have some obvious differences and they complement each other, so, the matrix I reflects the weights of concordance attributes and asymmetric matrix NI reflects the biggest relative difference of $V_{ij} = n_{ij}.W_j$ for discordance attributes.

Step 6: Determining the effective concordance matrix: The I_{kl} values of the concordance matrix should be evaluated by comparing them to a threshold value. This comparison is carried out to judge the priority chance of A_k over A_l more accurately. This chance will increase when I_{kl} become higher than a minimum threshold ($\bar{I}$), i.e. $I_{k,l} \geq \bar{I}$. The $\bar{I}$ can be obtained using the average of concordance criteria as follows:

$$\bar{I} = \sum_{k=1}^{m} \sum_{l=1}^{m} \frac{I_{k,l}}{m(m-1)} \tag{24}$$

According to $\bar{I}$ (minimum threshold), a Boolean matrix F is made so that:

$$f_{kl} = 1 \xrightarrow{\text{if}} I_{kl} \geq \bar{I}$$

$$f_{kl} = 0 \xrightarrow{\text{if}} I_{kl} \leq \bar{I}$$

Then, each element in matrix F with value 1 (effective concordance matrix) is an effective alternative and dominates the other ones.

Step 7: Determination of the effective discordance matrix: The NI_{kl} elements of the discordance matrix are also evaluated to a threshold value like step 6. This threshold value can be calculated as follows:

$$\overline{NI} = \sum_{k=1}^{m} \sum_{l=1}^{m} \frac{NI_{k,l}}{m(m-1)} \tag{25}$$

Then a Boolean matrix G, an effective discordance matrix, is made so that:

$$g_{k,l} = 1 \xrightarrow{\text{if}} NI_{k,l} \leq \overline{NI}$$

$$g_{k,l} = 0 \xrightarrow{\text{if}} NI_{kl} \geq \overline{NI}$$

The elements of matrix G with value 1, indicate the dominance relations among the other alternatives.

Step 8: determination of the global effective matrix: The common elements ($h_{k,l}$), which create the global matrix H, are derived using the two matrixes, F and G, as (26):

$$h_{k,l} = f_{k,l} \cdot g_{k,l} \tag{26}$$

Step 9: Ignoring the non-effective alternatives: the effective alternatives can be extracted from matrix H, in the way that each column of matrix H which has one element with value 1 can be omitted because that column is dominated by one or more rows.

V. CASE STUDY AND RESULTS

The IEEE 24-bus RTS test system has been chosen to implement the proposed method. One of the importance of this system is the large scale of this system which is close to the real power systems. Hence, the results of studies on this system can be developed to the real systems [11]. The single line diagram of this system is given in Figure 1, and the data related to the elasticity is given in [12].

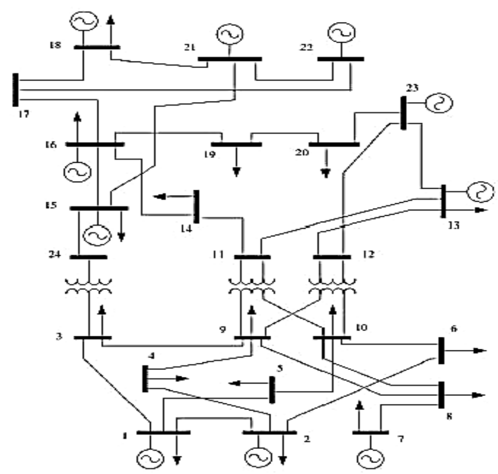

Figure 1. Single line diagram of IEEE 24-bus RTS system

As mentioned before, the considered DR programs in this study are time-based rate programs (TBR). For these programs, four scenarios have been considered and the best scenario and model and the best bus will obtained using the proposed method.

A. The First Scenario

In this scenario, the electricity spot price of each bus is related to the locational marginal price (*LMP*) of that bus, and its value is 0.5×*LMP* for valley-load times, *LMP* for base load times, and 2×*LMP* for peak-load times. The elasticity is the same as what was stated as Table 1 and the customer's participation in these programs is two percent.

Table 1. Self and cross elasticity

	Valley load	Base load	Peak load
Peak load	0.012	0.016	-0.1
Base load	0.01	-0.1	0.016
Valley load	-0.1	0.01	0.012

B. The Second Scenario

In this scenario, the spot price of each bus and the percentage of customers participation in the DR programs is the same as scenario 1, but, the elasticity is two times of that was in scenario 1.

C. The Third Scenario

In this scenario, the spot price of each bus is dependent on its *LMP* at valley, base, and peak load times. The value of spot price for valley-load time is 0.25×*LMP*, *LPM* for base-load times, and 4×*LMP* for peak-load times and the elasticity and customer participation is the same as scenario one.

D. The Forth Scenario

In this scenario, the spot price for each bus and the elasticity is the same as the first scenario, but, the customer participation in the DR programs is 4 percent.

The IEEE 24-bus RTS system has 17 load buses and for each of these buses, four scenarios should be considered and for each scenario, four models including linear, power, exponential and logarithmic models should be implemented. Finally, the optimum model and scenario and the best bus is selected. Therefore, the different priorities are obtained by implementing each scenario on each bus. Since the number of choices are very large and all of them cannot be shown in the paper, the results of bus 1 is just given here. Figures 2 to 4 show the priorities of the different scenarios including 4 models from the independent system operator (ISO), Utility, and customer viewpoints.

Different scenarios have been shown in the Table 2, and the results of the optimum scenario and model and the initial weights are given in the Table 3. The indices weights from different viewpoint has been carried out using entropy method, and the related results are given in the Table 4 and the best results of modified weights from different viewpoints are given in Table 5.

VI. CONCLUSIONS

In this paper, some non-liner economic models for responsive loads based on the elasticity and the customer benefit function were implemented. By implementing these method, many attributes of the power system operation and load profiles including load curve, operation cost, system loss, power factor, valley to peak distance, and EENS may change. But, as mentioned in the results section, these variation are not always in a positive way.

Improvement of these factor and attributes depend on the appropriate allocation of DR programs, and selecting a proper model for DR programs as virtual resources in the power system. In the other words, in this paper in addition to extracting the non-linear model for the responsive loads, the importance of optimum allocation of virtual resources and choosing the optimum model has been considered. The results of this study, which carried out on the IEEE 24-bus RTS system, showed that the proposed method has some appropriate and considerable effects on the different attributes and it is favorable from different system viewpoints to be implement in the real power systems.

Table 2. The results of different scenarios including various models

Scenario	Program	Model	Elasticity	Electricity price		Participation percentage
				Price	Time	
1	TOU	Linear Power Exponential Logarithmic	Like Table 1	0.5×*LMP*	Valley load	20
				LMP	Base load	
				2×*LMP*	Peak load	
2	TOU	Linear Power Exponential Logarithmic	Two times of scenario 1	0.5×*LMP*	Valley load	20
				LMP	Base load	
				2×*LMP*	Peak load	
3	TOU	Linear Power Exponential Logarithmic	The same as scenario 1	0.25×*LMP*	Valley load	20
				LMP	Base load	
				4×*LMP*	Peak load	
4	TOU	Linear Power Exponential Logarithmic	The same as scenario 1	0.5×*LMP*	Valley load	40
				LMP	Base load	
				2×*LMP*	Peak load	

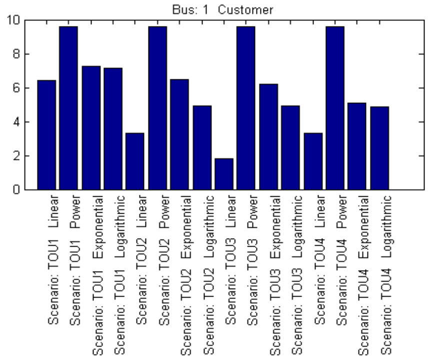

Figure 2. Priority of scenarios on the number one bus (customer point of view)

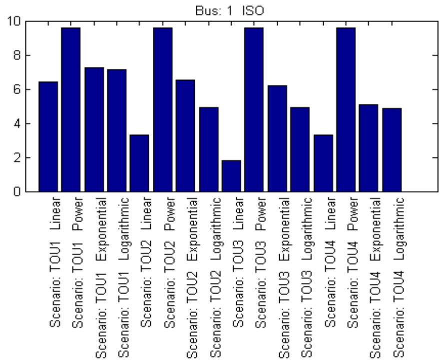

Figure 3. Priority of scenarios on the number one bus (utility point of view)

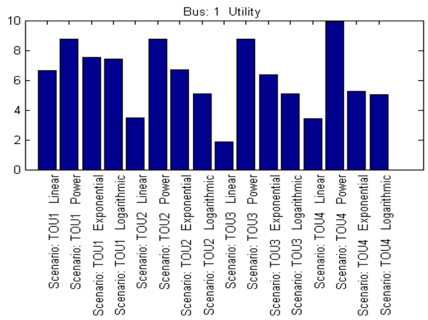

Figure 4. Priority of scenarios on the number one bus (ISO point of view)

Table 3. Initial weights

Indices	Valley-peak distance	Power Factor	Loss	Operation cost	EENS
Initial weights	0.0492	0.0029	0.0032	0.0006	0.9442

Table 4. Indices weights from different viewpoint

Viewpoint	Valley-peak distance	Power Factor	Loss	Operation cost	EENS
ISO	0.0334	0.002	0.0011	0.0004	0.9631
Utility	0.1122	0.0106	0.0073	0.0079	0.862
Customer	0.0491	0.0058	0.0016	0.0003	0.9432

Table 5. The best model from all viewpoints

Model	Scenario number	Bus number
Power	1	2

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