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Research Article

Energy Storage Configuration Optimization Strategy for Islanded Microgrid Interconnection Based on Energy Consumption Characteristics

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As a result of distributed energy development, the demand for energy storage grows more rapidly. The optimization of energy storage allocation is urgently needed. The economic benefits and characteristics of storage allocation have been thoroughly explored, and a mathematical model of economy was established. The centralized configuration of energy storage can make the best use of surplus electricity and reduce charging loss. The peak cutting and valley filling effect is quite obvious. Furthermore, some allocation strategies of storage were proposed. Based on the data of a user-side transformer and photovoltaic power generation, the cost under different strategies and the configuration scheme with the lowest cost is calculated. The example was used to analyze and compare the benefits under various strategies, and the results show it works in cost-saving. The strategy of similarity storage allocation has a positive effect on energy and cost-saving.

1. Introduction

With the development of new energy technology and energy interconnection technology, distributed power supply has gradually become the main development direction of the energy sector. The design of distributed power supply is widely used in the construction of isolated island microgrids such as communities, islands, and remote mountainous areas. The islanded microgrid interconnection is a network that has plural electric generation nodes, and different users have their corresponding power supply. In the distributed power supply network, the large use of new energy generation technology can provide clean energy, but it also has intermittent, periodicity, and other deficiencies. Users have a variety of electricity needs. It is not consistent with the space and time distribution characteristics of power generation. This may lead to excessive peak power consumption or insufficient power supply and affect the overall normal work and reliability.

Energy storage technology is the basic support of new energy technology. It can cut the peak and fill the valley of the power supply relationship and make up the profit and loss. Advanced energy storage technology can effectively improve the energy utilization efficiency of the system, protect the system to be stable and reliable, and reduce the construction cost of the power generation.

Accordingly, researchers have proposed some methods to solve the problem of co-optimization of energy systems morphology. Research [1] has proposed a novel methodology to optimize urban energy systems as interconnected urban infrastructures affected by urban morphology. It can reduce the Levelized cost for energy infrastructure by up to 30%. Another research [2] has established a comprehensive benefit model of energy storage. And an investment decision model of the shared ES capacity configuration is proposed. These methods can achieve a greater economic benefit. Research [3] proposes a novel approach to determine the optimal local energy trading strategy for customers using the Hotelling game. It also establishes optimal trading strategies for a user to minimize their energy bill. To sum up, these research studies all consider about the configuration of storages or loads to save the cost. In this paper, a strategy of storages investment is proposed.

The main contributions of this paper are summarized as follows:

(1) Instead of configuring energy storage for each load individually, an optimization model of energy storage investment is proposed to improve the benefit.

(2) According to the investment benefit model of energy storage and optimization strategy based on power consumption similarity, an intelligent optimization algorithm is utilized to solve the proposed model.

(3) An example is used to prove the validity of the model and algorithm. The result shows the strategies of intelligent optimization of allocation can reduce the cost by 22%.

This paper is organized as follows. In Section 1, the research background and literature review of the relevant theory are summarized. In order to simplify the process of analysis, a model of distributed power supply network is proposed in Section 2. In Section 3, the benefits model of storage investment is proposed. It explains how to calculate the economic profit of the storage. Section 4 depicts an optimization algorithm and its process to solve the question. Then give an example and work out the results in Section 5. Finally, the summary and future works are concluded in Section 6.

2. Mathematical Modeling of Distributed Power Supply Network Structure of Isolated Island

In the isolated island distributed power supply network dominated by solar power generation and wind power generation, there is a one-to-one or one-to-many relationship between power generation and power consumption. Solar power stations and wind power stations form interrelated energy nodes with loads and energy storage, as shown in Figure 1. The energy nodes connect in a topological structure. In an energy node, the generation and consumption power do not match in time distribution. Solar power generation has obvious daily periodicity, as shown in Figure 2. The energy storage can be charged during the peak period of power generation in the daytime and discharged at night. It improves the utilization rate of electric energy and reduces the power supply pressure.

3. Investment Benefit Model of Energy Storage

The income from investment in energy storage configuration is related to the number of energy storage configurations, configuration cost, voltage stability effect, peak shaving, and valley filling effect. The cost of energy storage configuration is related to the number of energy storage configurations, the maximum capacity of energy storage, the maximum power demand of energy storage, and the average working life of energy storage. The goal of energy storage optimal allocation is to solve the energy supply contradiction between the user side and the generation side and to spend as little cost as possible. There are differences in power consumption characteristics between users, and the possibility of peak valley complementary exists. Using these complementary peaks and valleys as much as possible can effectively reduce the charging and discharging times, charging and discharging depth, and the demand for the maximum energy storage capacity.

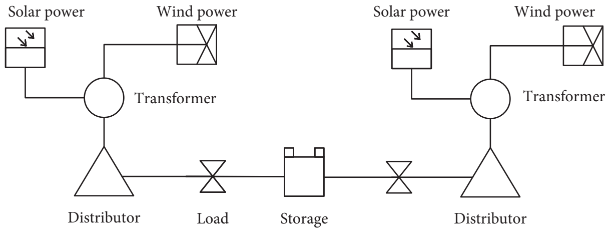

Figure 1: Energy node of DG.

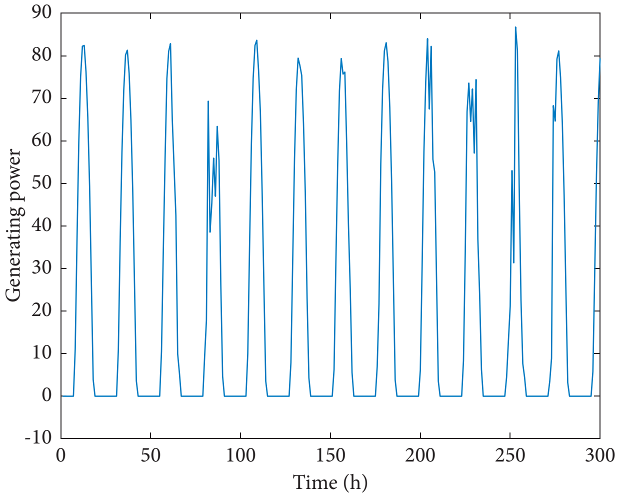

Figure 2: Solar energy feature.

3.1. Comprehensive Benefit Analysis of Energy Storage

3.1.1. Analysis on Investment Benefit of Power Generation Company. The comprehensive benefit of energy storage for the generation comes from the collection and utilization of surplus generation. In the islanded autonomous energy supply network, the total power generation on the generation side should be higher than that on the consumption side without considering the external power purchase. The total power generation of photovoltaic power generation in the daytime is far greater than the power demand of the user side. This part of power will charge the energy storage battery and discharge at night to supply the user with normal work.

$$W_{\text{power}} = \sum_{t \in T} \left(P_{t,\text{power}} - P_{t,\text{load}} \right) \Delta t, \tag{1}$$

$$C_{\text{power}} = \beta_k \xi_{\text{lost}} W_{\text{power}}. \tag{2}$$

In equations (1) and (2), W_{power} is the total power of generating surplus and $P_{t,\text{power}}$ and $P_{t,\text{load}}$ are the power of generation and consumption at time t. C_{power} is investment benefits for power generation. b_k and x_{lost} are electricity price coefficient and charging efficiency coefficient.

3.1.2. Benefit Analysis of User Side. The benefit of energy storage investment on the user side is the power supply supplement of peak power consumption and the power supply guarantee at night. Different from the generators, the demand for electricity from users presents greater randomness and volatility. Solar power generation has obvious periodicity and regularity. But in addition to the periodic electricity consumption, there will be sudden centralized electricity demand.

$$\begin{aligned} W_{\text{load}} &= \sum_{t \in T'} P_{t,\text{load}}, \\ C_{\text{load}} &= b_k x_{\text{use}} W_{\text{load}}, \end{aligned} \tag{3}$$

where W_{load} is total power consumption, C_{load} is the benefit of users' consumption, and x_{use} is the conversion efficiency coefficient of energy storage converted to electricity consumption.

3.2. Average Cost Model of Energy Storage. The life cycle cost of energy storage consists of construction cost and operation and maintenance cost [4, 5]. The construction cost of energy storage should be shared equally in the working life. The construction cost of energy storage depends on the energy storage capacity and maximum working power, as well as the infrastructure cost [6, 7]. Charging and discharging lead to the consumption of energy storage life. The daily average charge-discharge depth is inversely proportional to the storage life. The concrete expression is as follows:

$$\begin{aligned} S_e &= x_c C_{\max} + x_p P_{\max} + s, \\ S_k &= x_k N, \\ N &= N_0 \left(1 - r_k \overline{P}\right). \end{aligned} \tag{4}$$

In the equation, x_c, x_p, and x_k are cost coefficient of energy storage capacity, energy storage working power, and management expenses. The values of these parameters are shown in Table 1. $C_{\max}$ and $P_{\max}$ are maximum energy storage capacity and maximum working power. s is the cost per unit of energy storage infrastructure. N and N_0 are actual working life and initial working life. r_k is charge and discharge power loss coefficient. $\overline{P}$ is average daily charge and discharge power. The average cost of storage can be expressed as

$$\overline{S} = \frac{x_c C_{\max} + x_p P_{\max} + s + x_k N_0 \left(1 - r_k \overline{P}\right)}{N_0 \left(1 - r_k \overline{P}\right)}. \tag{5}$$

4. Optimization Model of Energy Storage Investment

Considering the objective feasibility of sharing energy storage resources between specific users, we want to establish a shared energy storage system between some adjacent users. The existing method to solve this kind of problem is to select the combination with similar power consumption characteristics among users [8–11] and complement each other in peak valley. This method can reduce the total peak demand of users to a certain extent and make full use of power generation. On the basis of this method, the intelligent optimization algorithm can be used to transform the problem into a pairing optimization problem, so as to further reduce the construction cost of energy storage.

Table 1: Parameters.

Reference	Value
x_c (yuan/MWh)	1173000
x_p (yuan/MW)	2234000
x_k (yuan/MWh)	9700

4.1. Energy Storage Optimization Strategy Based on Power Consumption Similarity. The similarity of power consumption indicates whether the time distribution of power consumption is consistent or not [12]. Users with high similarity in electricity consumption have the same peak valley time with each other, which has the advantage of reducing the charging and discharging times of energy storage and reducing the loss. The disadvantage is that the peak value is consistent, the voltage supply is sometimes insufficient, and the maximum capacity and power supply of energy storage are highly demanded [13]. Users with low similarity of electricity consumption complement each other in peak valley, which has the advantage of reducing the maximum peak value, evenly distributing each other's power to each time period, and reducing the construction cost of energy storage. The disadvantage is that the energy storage will charge and discharge frequently, which may bring loss to storage. In the face of different user characteristics and energy storage construction costs, here are some optimization strategies.

The similarity characteristics of power consumption of users are related to the slope. The slope correlation degree is a correlation analysis method, which can highlight the correlation between the fluctuation and rise of the curves. As shown in Figure 3, there are 4 user curves. Taking user i and user j as examples, the power supply characteristic curve $L_{i,t}$ and $L_{j,t}$ have a slope correlation degree $j(t)$ in time t as

$$j(t) = \frac{1}{1 + \left| \left(1/s_i\right)\left(\Delta L_{i,t}/\Delta t\right) - \left(1/s_j\right)\left(\Delta L_{j,t}/\Delta t\right) \right|}, \tag{6}$$

$$\begin{cases} s_i = \sqrt{\dfrac{1}{T} \displaystyle\sum_{t=1}^{T} \left[L_{i,t} - \overline{L_{i,t}}\right]^2}, \\ s_j = \sqrt{\dfrac{1}{T} \displaystyle\sum_{t=1}^{T} \left[L_{j,t} - \overline{L_{j,t}}\right]^2}. \end{cases} \tag{7}$$

In equation (6), s_i and s_j express load standard deviation of user i and user j. $\overline{L_{i,t}}$ and $\overline{L_{j,t}}$ express the average load of user i and user j. Simplify to

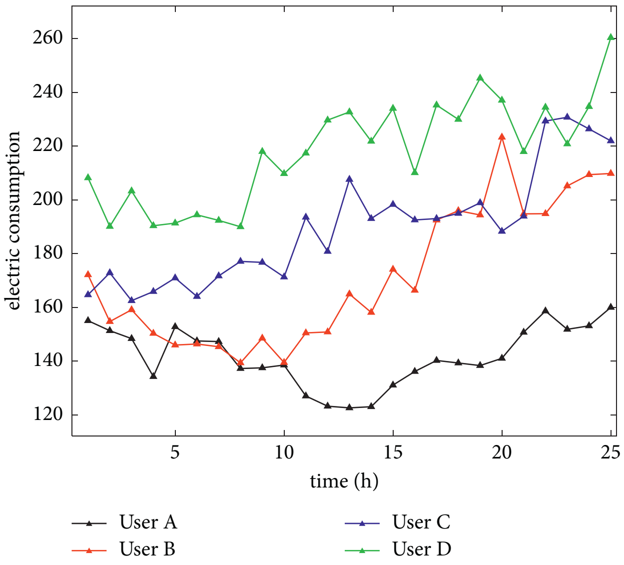

Figure 3: Users' transformer data.

$$j(t) = \frac{1}{1+\left|\left(\Delta L_{i,t}/s_i\right) - \left(\Delta L_{i,t}/s_j\right)\right|}. \tag{8}$$

In a certain period, the similarity of power consumption characteristics of user i and user j can be expressed as follows:

$$l = \frac{1}{T}\sum_{t=1}^{T} j(t). \tag{9}$$

Energy storage investment is a long-term process. In principle, here should use the maximum periodic power consumption characteristics of the user as the measurement basis [14]. The basic unit of user power consumption characteristics is days according to these data.

4.1.1. Electricity Similarity Screening. When selecting users with high similarity, here are the steps: first, calculate the similarity among all users according to formula (8), for example, the similarity matrix of user A–D is formula (10). Second, select C and D with the highest similarity, remove C and D from the matrix, then select A and B with the highest similarity, and so on.

$$j = \begin{bmatrix} 1 & 0.6649 & 0.6385 & 0.6192 \\ 0.6649 & 1 & 0.6735 & 0.7164 \\ 0.6385 & 0.6735 & 1 & 0.6025 \\ 0.6192 & 0.7164 & 0.6025 & 1 \end{bmatrix}. \tag{10}$$

4.1.2. Users' Combination Strategy Based on Low Electricity Similarity. Here are some examples to show the effect of pairing configuration to storages. The electric consumption data of users A to D are displayed in Figure 3. And the similarity indicators are recorded in formula (10). The lowest similarity indicator is 0.6025 of C and D. Then we strike out C and D, and A and B will be left. So according to the low similarity strategy, we should make A and B in pair and C and D in pair. After allocation of users, the cost and benefit of pairs are calculated in Table 2.

The effect of storage configuration can be reflected by the peak power consumption ratio of individuals and combinations, as well as the maximum storage ratio. They are all recorded in Table 3.

In Table 3, the peak power ratio expresses the quotient of the sum of A and B power peak and A & B power peak. The energy storage capacity ratio expresses the quotient of the sum of A and B storage capacity and A & B storage capacity.

Theoretically, the combination of users with low power consumption similarity can cut peak and fill the valley, effectively reduce the requirements of energy storage power and capacity, and achieve greater economic benefits.

4.1.3. Users' Combination Strategy Based on High Electricity Similarity. The high similarity indicator is 0.7164 of B and D, and the left combination is A and C. Other progress is the same to low similarity strategy, and the result is recorded in Tables 4 and 5.

According to the statistical results of this example, the combination of users with low similarity achieves greater benefits. The users with low power consumption similarity have less benefits. It shows that the low similarity strategy has a better positive effect on cost reduction.

4.2. Energy Storage Configuration Strategy Based on Intelligent Algorithm and User Electricity Consumption Characteristics. Based on the basic configuration strategy of pairwise combination, the energy storage configuration optimization problem is essentially a combinatorial optimization problem [15, 16]. This target is to find the best matching scheme in a group of users with the lowest cost. If all the combination schemes are evaluated directly, there are $C_N^2, C_{N-2}^2, \ldots, C_4^2$ schemes to be calculated. The scheme base is large and the calculation cost is too high. Therefore, the problem is transformed into a sequence scheduling problem and uses an intelligent optimization algorithm to solve the scheduling problem. As shown in Figure 4, the basic processes are as follows:

(i) Objective: after pairwise combination, find the lowest total average daily cost.

(ii) Population individuals: N-digit sorting without repetition.

(iii) Selection strategy: for each individual, randomly select an individual in the population to compare with it, and select the individual with high fitness to retain.

(iv) Crossover strategy: when a group of genes in a pair of individuals meet the requirements of crossover, the genes are exchanged and the original values should be retained. The specific measures are as follows.

Table 2: Statistic of users and their combination.

	Peak power consumption	Maximum storage	Similarity characteristics
A	160	1919.10	0.6649
B	223.34	2432.61	
A & B	369.84	3993.52	
C	230.76	2600.23	0.6025
D	260.40	2921.85	
C & D	482.37	4022.01	

Table 3: Ratio of the statistic of users and their combination.

Peak power consumption ratio	Maximum storage ratio	Cost ratio
97.45	81.63	84.89

Table 4: Statistic of users and their combination.

	Peak power consumption	Maximum storage	Similarity characteristics
A	160	1919.10	0.6385
C	230.76	2600.23	
A & C	369.84	4461.20	
B	223.34	2432.61	0.7164
D	260.40	2921.85	
B & D	482.37	5354.41	

Table 5: Ratio of the statistic of users and their combination.

Peak power consumption ratio	Maximum storage ratio	Cost ratio
97.40	98.42	97.71

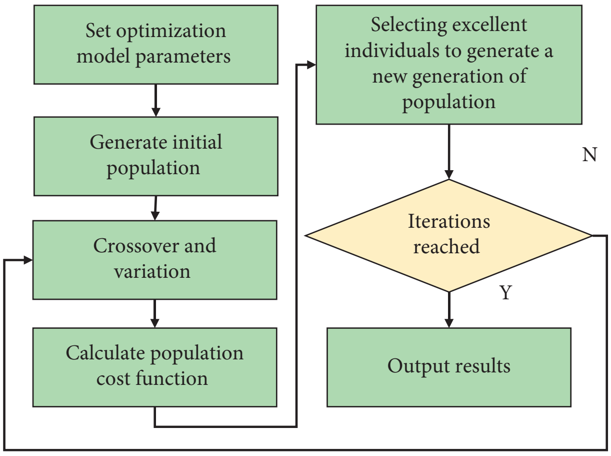

Figure 4: Optimization process.

(v) Mutation strategy: in order to mutate a gene and retain the integrity of the original sequence, the specific method is as follows.

When A and B cross, B and A in the original individual also cross, as shown in Figure 5.

When changing a to b, the original position of b should change into a, as shown in Figure 6.

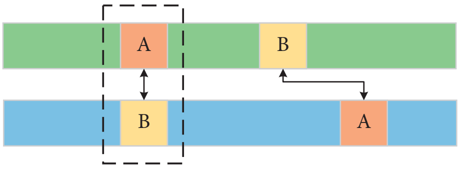

Figure 5: Mutation process.

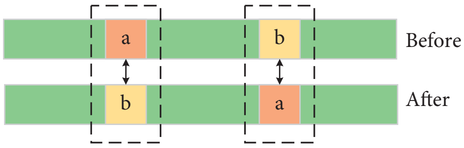

Figure 6: Cross process.

5. Example Analysis

5.1. Data Description. In order to reflect strong periodicity and peak valley complementary effect, 40 transformer data are selected for users and 40 groups of photovoltaic power generation data for power generation. By processing the data, each generation side can meet the daily power demand of the user.

5.2. Similarity Screening and Cost Calculation. After a high similarity screening of 40 users, 20 groups of energy storage configuration user combinations are formed. According to formulas (1)–(5), the daily average benefit of users is calculated, and the results are shown in Table 6.

In Figure 7, the red bar is the average daily cost when each user configures energy storage, the yellow part is the

Table 6: Cost of different schemes.

Scheme	Cost
Initial configuration scheme	438764
High similarity scheme	389980
Low similarity scheme	385987

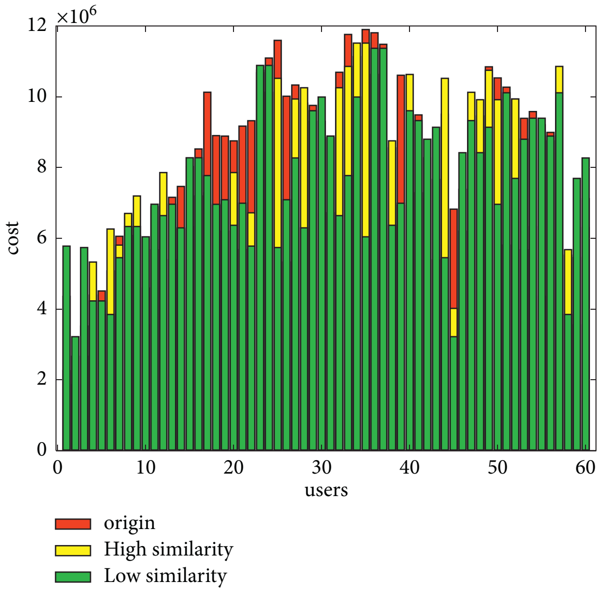

Figure 7: Cost after optimization.

average daily cost when the high similarity combination configuration is used, and the green part is the result of the low similarity combination configuration.

According to the above experimental results, it can be seen that similarity screening can somehow improve the benefit and cut down the cost. And low similarity screening does better in cost reduction. But this method is susceptible to different data, sometimes high similarity is better while sometimes low similarity.

5.3. Combination Configuration and Cost Calculation of Intelligent Optimization Algorithm. In this section, the parameters of the basic optimization model are set according to Section 4, and the number of iterations is adjusted according to the cost reduction. The values of relevant parameters are shown in Table 7.

According to Figure 8, when the number of iterations reaches 9000, the decrease of cost function is no longer obvious, and the extreme value is 340680. Through experiments, it is found that the lowest cost function can be reduced to about 340000.

5.4. Result Analysis. The optimization result is shown in Table 8. Theoretically, low similarity strategy and high similarity strategy have their own advantages and disadvantages under different user characteristics, and an intelligent optimization algorithm is suitable for any user characteristics. From the results, the low similarity strategy and the high similarity strategy are similar in this case, and the intelligent optimization algorithm is more significant.

Table 7: Optimization parameters.

Parameter	Value
Iterations	10000
Number of population	40
Mutation probability	0.1
Cross probability	0.9

Table 8: Result statistics.

Optimization strategy	Reduction rate (%)
High similarity strategy	11.12
Low similarity strategy	12.03
Intelligent strategy	22.35

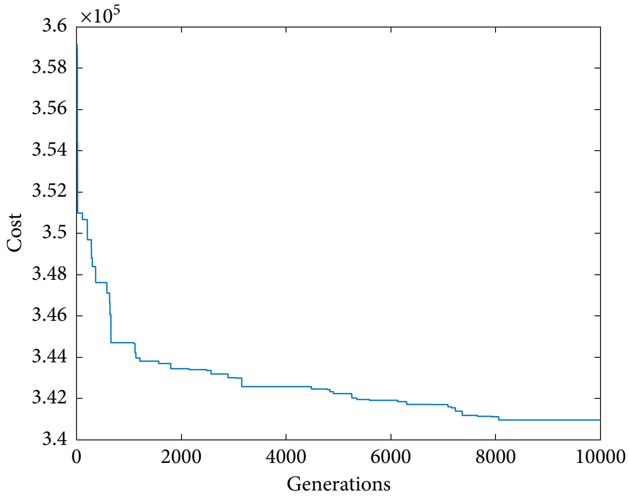

Figure 8: Optimization result.

6. Conclusion

Based on the concept of shared energy storage, this paper introduces three optimization strategies to optimize the allocation of energy storage resources. It uses 40 sets of transformer data and photovoltaic data for example analysis. The results show that sharing energy storage resources according to the characteristics of electricity consumption can effectively reduce the allocation cost and achieve greater economic benefits. Moreover, the optimization algorithm can further improve the effect of cost reduction. According to the example, the suggestions of energy storage configuration are as follows:

(1) Users with obvious peak valley characteristics can obtain greater cost-effectiveness under the shared energy storage configuration scheme.

(2) Sometimes it is difficult to plan user combinations reasonably because of making configuration strategy simply according to user characteristics. Using the intelligent algorithm can get more reasonable results and a better optimal configuration effect.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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