COMPUTER IMAGE PROCESSING AND NEURAL NETWORK TECHNOLOGY FOR THERMAL ENERGY DIAGNOSIS OF BOILER PLANTS

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Abstract: *Objective: The computer image processing and neural network technology are applied to diagnose the thermal energy of boiler plants, i.e., the flame combustion diagnosis, to verify their effectiveness and superiority. Methods: First, the YD-NQ type endoscopic high-temperature video acquisition system is used to collect the images of flame combustion. Second, the images are pre-processed by the gray-scale method and the median filtering method. Then the flame combustion parameter features are extracted. The neural network algorithm is improved, and the boiler combustion model based on the improved neural network algorithm is established; therefore, the combustion decision base is obtained. Finally, the improved neural network model is compared with the traditional neural network model and the 5-4 model to verify its validity. Results: The experiments have found that the improved neural network model is superior to the traditional neural network model. Meanwhile, its accuracy rate and confidence are relatively higher than those of the traditional model. In addition, a single sample also consumes shorter running time, which is 0.0075 s. Comparing with the 5-4 model, the improved neural network model has certain advantages, i.e., its accuracy rate and confidence are relatively higher, which are respectively 91.28% and 96.69%; however, a single sample consumes longer running time than the 5-4 model. Conclusion: The experimental research has found that the application of computer image processing and neural network technology to the thermal energy diagnosis of boiler plants can effectively determine the stability of flame combustion, timely understand the state of flame combustion, and thus diagnose the thermal energy. Therefore, they have values for applications.*

Key words: *computer image processing; neural network; flame combustion; thermal energy*

1. Introduction

With the adjustment of China's economic structure, energy conservation, emission reduction, and clean energy sources have been gradually developing. However, as far as the power generation industry is concerned, the major form of electricity production in China is still dominated by thermal power generation. Currently, the data have shown that in China, the coal-fired thermal power generation still accounts for more than 60% [1-3]. The boiler is one of the three major devices of the thermal power plant. The single-unit capacity of the boilers in power plants is constantly rising, and the boilers are developing toward large capacity and high parameters [4, 5]. For large or very large coal-fired boilers (supercritical units), if the combustion instability occurs during combustion, the thermal efficiency of boiler combustion will directly decrease, and a large number of pollution by-products will be generated, even some extreme situations may occur, such as furnace cavity extinction and major furnace safety accidents [6, 7]. The safe and stable operation of the boilers often determines the safe and environmentally friendly operation of the entire unit. The most direct indication of the stability of combustion is the combustion flame. Therefore, it is necessary to monitor the combustion state of the flame in the furnace chamber in real-time to ensure the safe and economic operation of the boilers. The way to establish a safe and reliable energy-saving furnace coal combustion system has become a critical issue [8, 9].

Over the years, the IT industry and image processing technology have been continuously advanced and developed. Image recognition-based monitoring systems are gradually being used in the boiler systems of large-scale power plants, mainly for real-time observation of flame conditions in boilers [10, 11]. However, so far, the monitoring system has only stayed in the stage of monitoring whether the coal fines are in the state of on-fire or out-fire. Although the boiler flame image monitoring system can be introduced to provide technical supports for automatic monitoring and determination of combustion stability, the monitoring of flame stability requires relevant personnel to conduct on-site observations. Therefore, the stabilization of the flame image has always been one of the urgent problems to be solved in the automatic monitoring of the combustion state of the boilers. The scientific and effective solution to this problem is significant for ensuring the safe and economic operation of boilers.

In this study, computer image processing and neural network technology are applied to the thermal energy diagnosis of boiler plants to collect images of boiler flame combustion. The grayscale processing and median filtering are used to avoid the effects of noise and other interference factors. Afterward, the feature parameters of flame combustion are effectively extracted, and a combustion model based on an improved neural network is established. Through simulation experiments, it is found that the model established in this study has excellent validity, stability, and accuracy. It can monitor the state of flame combustion in real-time and diagnose the thermal energy, which is of great significance for ensuring the normal and safe operation of the boilers.

2. Methods

2.1. Flame image preprocessing and parameter extraction

In this experiment, the CCD camera is used to obtain the flame combustion video inside the boiler. Then, the video is used to understand the flame combustion conditions, and the stability of the flame combustion is analyzed. However, the combustion of the flame is affected by various factors, such as sensor position velocity, illumination, and random noise, which will destroy the stability and certainty of the flame combustion. Moreover, it will affect the accuracy of the acquired image parameters. Therefore, this experiment needs to obtain flame parameters based on the correct and appropriate method.

2.1.1 The acquisition of boiler flame images

The following figure shows the video acquisition system that obtains the boiler flame video used in this study. The video acquisition system of a power plant applied in this study is the YD-NQ type endoscopic high-temperature video acquisition system, which is essential equipment in the process of flame monitoring. Through the application of this system, the operating staff can accurately and timely understand the combustion state of the flame, which is of great significance for monitoring thermal energy and ensuring the safe operation of the entire power plant. The system consists of seven structural components, as shown in the following figure:

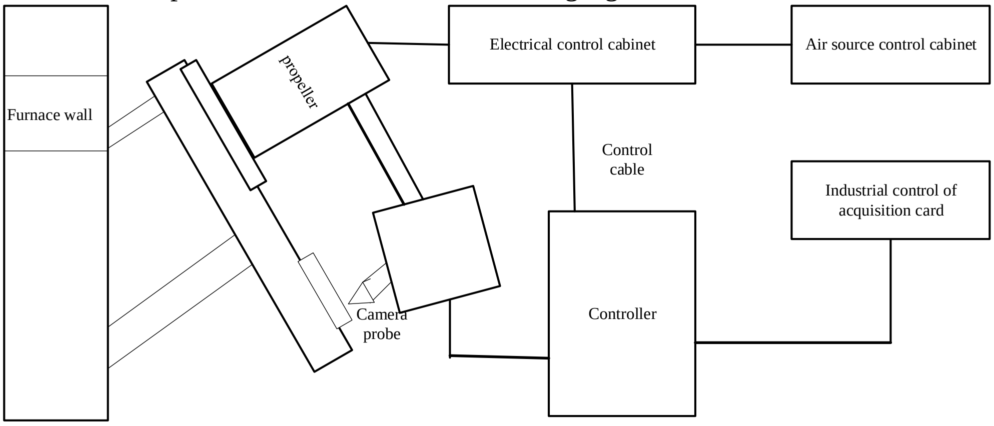

Figure 1 The high-temperature video acquisition system

The first component is the camera probe, which is the core of the entire system. The camera probe is composed of a CCD camera, an isolation cover, and the optical lenses. The most important component is the camera. The major function of the camera probe is to use its photosensitive characteristics to image the objects, output the unit signals, and then further convert them into video signals. The major function of the optical lenses is to ensure that the object is imaged with clear pixels to avoid affecting the pixels due to radiation problems. The major function of the isolation cover is to prevent the camera probe from coming into contact with other objects, thus affecting its performance work. Also, it can cool the camera and the excessive temperature of the CCD to ensure normal operation. The major function of the propeller is to protect the probe from radiation that is too high in the furnace. The major function of the controller is to control the switch, keep the camera probe stable, prevent it from being pulled in and out during operation, and control the air compression.

2.1.2 The preprocessing of boiler flame images

First, the image is processed by the method of graying. Since the color space of the color image can be divided into three components, i.e., the first component is R (Red), the second component is G (Green), and the third component is B (Blue). Meanwhile, the gray value of the color space is represented by Y. Therefore, the relationship between these components and the gray value can be expressed as:

$$Y = 0.3R + 0.59G + 0.11B \tag{1}$$

The second is to obtain a sequence of digitized images. First, space is sampled. Space sampling is the grayscale flame image after the image passes and is treated. In the computer, the gray value is stored in the NL×NS sequence. The description function of the degree image is assumed to be F(x, y), then the equation of the sampling function is as follows:

$$g(\mathrm{x,y}) = \mathrm{F(x,y)} \bullet \mathrm{h(x,y)} \tag{2}$$

The equation for calculating the space sampling function h(x,y) is as follows:

$$h(x,y) = \sum_{i=0}^{NL-1} \sum_{j=0}^{NS-1} \delta(x - i\Delta x, y - j\Delta y) \tag{3}$$

In the above equation, the number of pixels of the flame grayscale image matrix in the horizontal direction is represented by NL, the number of pixels in the vertical direction is represented by NS, and the interval in the space of the sampling function array is expressed by Δx and Δy. After applying Eq. (1) to preprocess the image, the corresponding digitized image sequence is obtained, which is as shown below:

$$g(x,y) = \begin{cases} g(0,0) & g(0,1) & \ldots & g(0,NS-1) \\ g(1,0) & g(1,1) & \ldots & g(0,NS-1) \\ \ldots & \ldots & \ldots & \ldots \\ g(\mathrm{NL}-1,0) & g(\mathrm{NL}-1,1) & \ldots & g(\mathrm{NL}-1,\mathrm{NS}-1) \end{cases} \tag{4}$$

In the equation, the specific gray value at the position (i, j) is represented by g(i, j), wherein the gray value of the corresponding pixel is determined by the relative position of row and column positioning image pixel and the two-dimensional matrix specific value.

To remove the noise when collecting the flame combustion images, after the images are subjected to grayscale processing, they are also subjected to de-noising processing. The de-processing method applied in this experiment is the median filtering method. First, a set of the digitized image sequence is selected, which is defined as x_1, x_2, x_3, x_4, ..., x_n. Then, the sequence is rehearsed in descending order, i.e., $x_{i1} \le x_{i2} \le x_{i3} \le x_{in}$, which is represented as $\{x_i, i \in I\}$. Therefore, the equation for calculating the median filter output is as follows:

$$y = Med\{x_1, x_2, x_3, .., x_n\} = \begin{cases} \frac{1}{2}[x,(\frac{n}{2}) + x_i(\frac{n}{2}+1)] \\ x_i(\frac{n+1}{2}) \end{cases} \tag{5}$$

The median filtering method applied in this study is mainly based on the filtering window of one type of two-dimensional digital image sequence and its correct selection, which can be used for representation. Therefore, the equation of the median filtering method is:

$$y_i = \underset{A}{Med}\{x_{ij}\} = Med\{x_{i+r,j+s}, (r,s) \in A(i,j) \in I^2\} \tag{6}$$

By applying the median filtering method to process the flame image, the processed flame images can be obtained, which can well avoid the influence of high-frequency noises. Moreover, the pulse doping body existing in the image can also be effectively removed. In addition, there is no adverse effect on the spectral characteristics of the image and the flame edge characteristics.

2.1.3 Feature extraction of flame combustion parameters

There is a linear relationship between temperature and grayscale, which is a proportional relationship, i.e., the higher the temperature is, the larger the gray value is. Conversely, the lower the temperature is, the smaller the gray value is. If the amount of changes in the gray value of the image is obvious, it means that the flame combustion is intense; on the contrary, when the amount of changes is not that obvious, the flame combustion is relatively stable. However, due to the difference in the size and load of boilers, the combustion of the burner flame will be affected, leading to interference. Even if the combustion is normal, the overall brightness of the image will be smaller than the background brightness.

According to Wien Radiation Law, the monochromatic radiance L_λ of the flame that can be seen with the eyes has a certain relationship with the flame temperature T, which is as follows:

$$L_\lambda = \varepsilon(\lambda)\frac{C_1}{\lambda\pi^5}e^{-\frac{C2}{\lambda T}} \tag{7}$$

In the above equation, the wavelength application of the flame is expressed by λ, and the radiant energy generated by the flame of the wavelength λ is expressed by L, wherein the first radiation constant is represented by C_1, and the second radiation constant is represented by C_2. T is the thermodynamic temperature symbol. The gradation of the monochrome images can be further obtained by calculating the radiance of the images, which is represented by g, and the calculation equation is as follows:

$$g = \frac{1}{\mu_{\max} - \mu_{\min}}(2^a - 1)2^b \bullet \eta_3$$
$$\bullet[\frac{\tau}{4}\pi L_\lambda (D/f)^2 At\eta_1 \bullet \eta_2 - \mu_{\min}] \tag{8}$$

In the above equation, both a and b are quantized bits, quantum efficiency, or spectral response coefficient. The transfer efficiency and transfer coefficient are respectively represented by η_1 and η_2, where A represents the sensitive area of CCD imaging, $\mu_{\min}$ represents the minimum value of brightness level, and D/f represents the lens aperture ratio of the CCD imaging. Through the above equation, the calculation method for the average gray value can be obtained as follows:

$$g_{av} = \frac{1}{NL \times NS}\sum_{i=1}^{NL\times NS} g_i \tag{9}$$

Through the above equation, the calculation method of the average gray level of the effective area of the flame can be further inferred as follows:

$$g_{ff}\frac{\sum_{i=1}^{m}\sum_{j=1}^{n} gij \bullet L(g_{ij} - E_{th})}{\sum_{i=1}^{m}\sum_{j=1}^{n} L(g_{ij} - E_{th})} \tag{10}$$

L(x) represents the step function. When the value is greater than 1, x≥0. When the value is less than 0, x<0. The grayscale threshold of the effective average gray is represented by E_{th}. When the threshold is 180, the average light intensity of the flame in this area can be seen.

Therefore, a method for calculating the abundance of the flame can be obtained, and the equation is as follows:

$$S_{av} = \frac{\sum_{i=1}^{NL\times NS} L(g_i - g_{th})}{NL \times NS} \tag{11}$$

In the above equation, g_{th} represents the threshold of the flame abundance that has been set before, which is 180.

2.2. Neural network model establishment

The stability analysis of the system is the core content of this experimental study. First, the combustion features of the flame are taken as the major parameters of the study, i.e., the flame average grayscale, the effective average grayscale, the flame abundance, the high-temperature area ratio, and the centroid offset. Then, by using the improved neural network algorithm for modeling, since there is no data on coal quality at the time of establishment, it is assumed that the coal command will not change during the combustion process, as shown in the following figure, which is the model for boiler combustion:

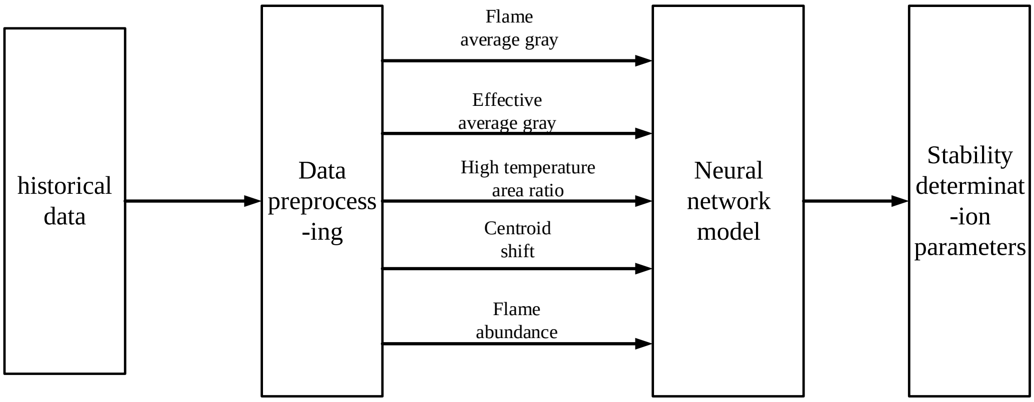

Figure 2 The boiler combustion model based on improved neural networks

This study first selects a set of combustion images. The images are grouped into a set of samples and denoted with $IS = \{S_1, S_2, ..., S_n\}$. Then, they are combined and represented by a four-tuple information system, i.e., $IS = \{S, A, V, f\}$, where A represents a set of non-empty conditional attributes consisting of m combustion parameters, and V represents the set of attribute values. Next, the previously determined maximum value of the parameter is calculated and normalized to obtain the "deviability" of the vector Ri. The equation is as follows:

$$\begin{aligned} Di = \left|Ri - R0\right| = \frac{1}{\sqrt{2}}[\omega 1((\mathrm{r}_{i1}^{L} - r_{i_0 1}^{L})^2 \\ +(\mathrm{r}_{i1}^{U} - r_{i_0 1}^{U})^2) + \omega_2((\mathrm{r}_{i2}^{L} - r_{i_0 2}^{L})^2 + (\mathrm{r}_{i2}^{U} - r_{i_0 2}^{U})^2 \\ ... + \omega_m((\mathrm{r}_{im}^{L} - r_{i_0 m}^{L})^2 + (\mathrm{r}_{im}^{U} - r_{i_0 m}^{U})^2] \end{aligned} \tag{12}$$

In the above equation, the degree of deviability is the degree of phase difference stability, which can reflect the combustion state of the flame. There is a positive correlation between the degree of deviability and combustion state; the smaller the deviability value is, the stabler the combustion state is. Conversely, a larger deviability value indicates that the combustion state of the flame is unstable.

The deviability of the flame combustion is determined within the interval. In addition, other factors, such as noise, will result in a large difference between the stable output and the sample. For example, "1" and "3" are two combustion states that are quite different, which respectively belong to the "stable" and "unstable" states. At this time, the model output is not confident. Therefore, the confidence of the model needs to be set:

$$R = \sum_{k=1}^{n} \gamma_k \times 100\% / n \tag{13}$$

In the above equation, the brush of the test sample is represented by n, the confidence factor of the k-th sample is represented by γ_k, the accuracy rate of the model is represented by P, and the model output is rounded to the same degree of deviability as the sample. The deviability/total number of samples×100% is the accuracy rate of the model.

3. Simulation result of combustion stability determination

In this study, the MATLAB software is used to simulate the established model. The previously established stability determination model is divided into two stages, i.e., the training stage and the test stage. During the training stage, the sample needs to be input to the simulation model according to the previously established format. The major purpose is to test the validity and accuracy of the model. By comparing the improved neural network model with the traditional neural network model and the T-S (Tagaki-Sugeno) fuzzy neural network combustion stability model, i.e., the 5-4 model, the superiority of the improved model is verified.

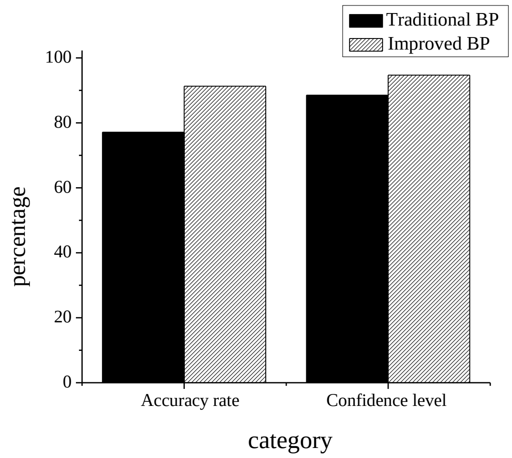

Figure 3 The comparison of accuracy rate and confidence of the traditional neural network model and the improved neural network model

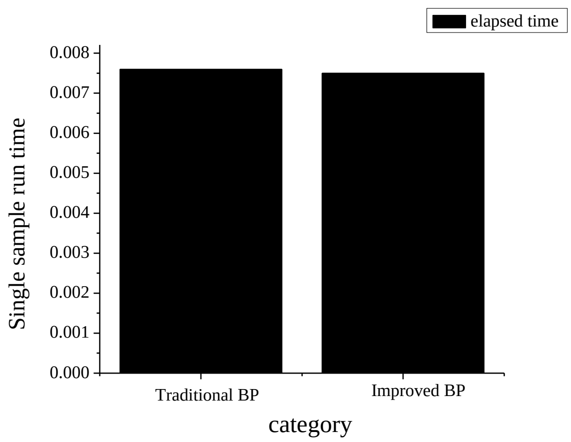

Figure 4 The running time of a single sample of the traditional neural network model and the improved neural network model

As shown in the above figures, by comparing the two models, it is found that the improved neural network model is more superior to the traditional neural network model. Meanwhile, the accuracy rate and confidence of the improved model are relatively higher than those of the traditional neural network model. In addition, the running time of a single sample also consumes a shorter time. It can be seen that the improved neural network model can effectively extract the parameters of the flame combustion, and can automatically diagnose the flame combustion state.

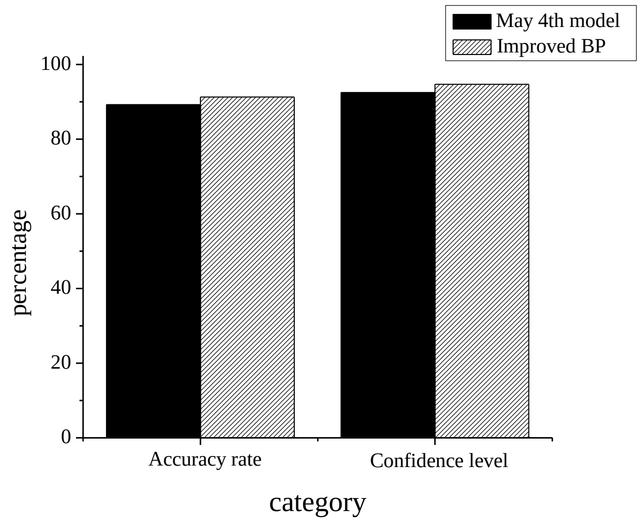

Figure 5 The comparison of accuracy rate and confidence of the 5-4 model and the improved neural network model

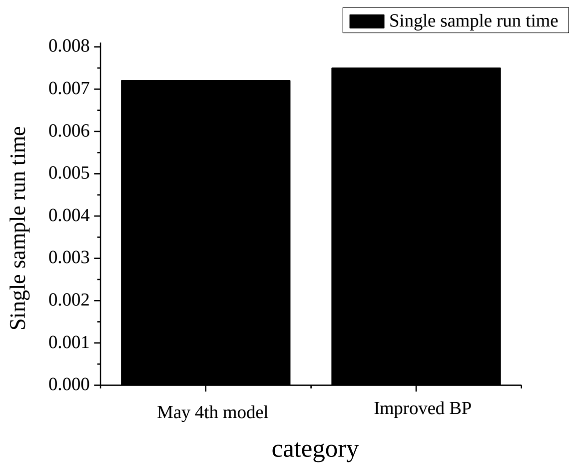

Figure 6 The running time of a single sample of the 5-4 model and the improved neural network model

As shown in the above figures, by comparing the 5-4 model with the improved neural network model, it is found that the improved neural network model still has certain advantages; its accuracy rate and confidence are relatively higher although the single sample runs relatively longer. The advantage in accuracy is particularly obvious, which has a strong approximation ability.

4. Discussion

More stringent requirements are imposed on coal-fired power station boilers that are important equipment for energy production. Especially for large-capacity coal-fired power station boilers, stricter control requirements are imposed on their emission targets such as nitrogen oxides, sulfur oxides, and carbon dioxide. Due to the diversity of coal-firing types, the combustion state is becoming more and more complicated. There is a close relationship between the combustion state and thermal energy. Therefore, the state of thermal energy is also very unstable, which has a great negative impact on people. Therefore, it is vital and necessary for the boiler thermal energy diagnosis.

This experiment is carried out by applying computer image processing and neural network technology to the thermal energy diagnosis of boiler plants. First, the combustion images are collected. Then, the images are preprocessed by grayscale processing and the median filtering method. Next, the feature parameters of flame combustion are extracted to establish a combustion model based on an improved neural network. The comparisons and simulation experiments show that the improved neural network model is superior to the traditional neural network model. Meanwhile, its accuracy rate and confidence are relatively higher. In addition, a single sample also consumes shorter running time, which is 0.0075 s. Comparing with the 5-4 model, the improved neural network model has certain advantages, i.e., its accuracy rate and confidence are relatively higher, which are respectively 91.28% and 96.69%; however, a single sample consumes longer running time than the 5-4 model. The experimental results indicate that computer image processing and neural network technology have great effectiveness for the thermal energy diagnosis of boiler plants. Computer image processing technology can extract feature parameters of combustion images, and the improved neural network model is stable. The flame combustion condition can be determined according to the obtained feature parameters, thereby ensuring the stability of the thermal energy state.

5. Conclusions

Computer image processing and neural network technology have good values for applications in thermal energy diagnosis for boilers. By inputting image feature parameters into the combustion model based on improved neural network algorithm, the state of flame combustion can be known in real-time. Meanwhile, its stability can be determined and its thermal energy can be analyzed. By understanding the state of thermal energy, timely solutions can be made to protect the safe and orderly operation of the boilers. However, when selecting and extracting feature parameters, this study only refers to the relevant documents and references. The influence of each parameter on the flame combustion stability is not proved by specific data. Meanwhile, the selection of parameters lacks emphasis. Therefore, the subsequent study will clarify these issues further.

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Project: Image Segmentation Technology Research Based on Graph Division Theory, Subject No.: J61 630, Project leader: Zhang Junzhen.

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