Transfer Function Analysis to Evaluate Drying Quality of Power Transformers by Support Vector Machine

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ABSTRACT

For many years, an increasing interest existed in application of transfer functions (TF) method as a measure for detection of winding mechanical faults in transformers. However, this paper aims to change the application of TF method in order to evaluation of drying quality of power transformers during manufacturing process. For this purpose, support vector machine (SVM) is used. The required data for training and testing of SVM are carried out on 50MVA 132KV/33KV power transformer when the active part is placed in the drying chamber. Three different features extracted from the measured TFs are then used as the inputs to SVM to give an estimate for required time in drying process. The accuracy of proposed method is compared with the existing work in this field. This comparison shows the superior capabilities of this proposed method.

Keywords: Transformer, Drying Process, Transfer Function, Support Vector Machine.

1. INTRODUCTION

The strategically role and economical importance of power transformers in the electrical networks does not need to be discussed. Due to the existence of a strong competition in the electrical power supply industry, the importance of the transformer monitoring systems application has increased over the time. Therefore, many techniques in monitoring and diagnosing the faults have been considered by electrical energy suppliers. Each technique can be applied for a specific type of problem and has its own merits. In this regard, transfer function (TF) method which is generally known frequency response analysis (FRA), is increasingly being used to detect winding mechanical damages [1]-[5].

The FRA technique is basically a comparative method, in which one performs the frequency measurements over a wide frequency range and compares the result with a fingerprint measurement of mentioned unit or with other reference responses (from a sister unit or another phase of the same transformer). This method follows from the fact that the TF of any RLC network, change as a function of frequency. Any power transformer may be represented by a complex network of resistances, inductances and capacitances. These electrical elements are a function of mechanical geometry inside the transformer, as well as the electrical properties of the insulating materials used in the construction. Any change in these values will result in a measurable shift in the frequency response of transformer in comparison to reference response.

The past researches [6]-[9] show that some common faults such as windings or core deformation, winding axial displacement, turn-to-turn fault, re-clamping pressure; earth loosing and etc, can be diagnosed by use of FRA technique. However, this paper represents a new application of TF which is used to evaluate the quality of transformer drying process during manufacturing stages. Because the electrical elements of windings in their equivalent circuits are affected by moisture content, this idea is occurring to the mind that the changes in the form of TF in high frequency ranges can be used as an index for degree of insulation dryness. As a result, TF analysis based on SVM is used as a reliable method to evaluate drying quality of power transformers.

In [10] a method based on application of FRA technique and artificial neural network (ANN) is introduced for comparison of TFs to evaluate drying quality of transformers. Although the mentioned study gave important results, such results are not efficient to evaluate drying quality of power transformers without performing additional investigations. To address these shortcomings, an intelligent based method of TF analysis is proposed for evaluation of drying quality in power transformers.

2. PROBLEM DESCRIPTION

Drying process is one of the most important stages in transformers manufacturing stages which its quality is directly proportional with transformer lifetime. If drying process is done well, the failure of this equipments will also greatly reduced. At the manufacturing site of power transformers when the complete active part is formed, it must be dried in drying chamber under high vacuum and temperature. Its takes even a few days depend on the voltage level and the required insulation quality of the transformer. So, this stage of manufacturing is a bottleneck in the

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production line. During the drying process the released water are collected and according to the rate of absorbed water the sufficiency of drying and consequently the time period that the active part must remains in the furnace is controlled. This open-loop control strategy has some disadvantages and causes the drying process to last more than the time actually required or before a sufficient dryness due to a failure in drying procedure, the process being terminated. To solve the problem a direct measurement of insulation dryness is needed while the active part is in the drying chamber. It is evident that measurement of moisture content of the active part insulation particularly under the environmental condition of the furnace is not a simple task.

Based on above discussion, with respect to long time duration in drying stage and furnaces limitation in factory, obtaining an estimation of required time in drying process can be very valuable and economical.

In this contribution, drying process has been evaluated by use of TF method. TF method is a comparative method; in this method the results of a new measurement is compared with the referential measurement [1]. The measured TF at the end of drying process, is considered as a reference TF and the other TFs (in different time intervals) are compared against the reference one.

There are many comparative algorithms introduced in the literature. These methods can be classified into four main categories as follows:

a) Algorithms based on mathematical and statistical methods [11]-[15].

b) Algorithms based on electric circuit models [16]-[19].

c) Algorithms based on estimation methods [2], [7]-[8], [20].

d) Algorithms based on artificial intelligence methods [6], [21]-[22].

Between these methods, algorithms based on artificial intelligence methods are known as one of the best methods for solving the pattern recognition problems.

Among artificial intelligence algorithms, SVM is a proper and efficient method for classification applications [6], [22]-[23]. As a result, in this paper SVM is used for estimation of required time in drying process. The most important factor required for a successful SVM based pattern recognition is the proper features selection, as input. To extract the proper features for training and testing of SVM both the mathematical and statistical methods, and the estimation algorithm are used. Since the method based on electric circuit model is not applicable to SVM as an input; therefore this method is not used.

The required data for training and testing of SVM are obtained through tests on a 50MVA 132KV/33KV power transformer. At the first step, the required measurements are carried out for the active part of power transformer while the active part had been placed in the drying chamber in different time intervals during drying process. In the next step, using mathematical based algorithms and estimation based algorithms, appropriate indices are extracted with the required accuracy. The features extracted through mentioned algorithms are used as inputs of the SVM classifier in order to predict the required time in drying process. Comparison of this classification accuracy against the past well-known method is discussed next, in detail.

3. SUMMARY OF METHODS EMPLOYED

Since in this study a combination of mathematical and statistical indices (IFR, IAR and CC) beside estimation method (VF) and SVM are employed to predict the required time in drying process, therefore these methods will be described briefly in here.

3.1 IFR and IAR Indices

In drying process, the most important changes observed in TF characteristics are in peak and trough points (This is shown in figures 2, 3). Thus, the frequency and amplitude variations in these points can be used as reliable indices to train the SVM. The variation of the i-th frequency, in peak and trough points; also referred to as the i-th index of frequency ratio (IFR) is defined as follows [6]:

$$IFR_{ti} = \frac{f_{k,ti}}{f_{o,ti}} \quad , \; IFR_{pi} = \frac{f_{k,pi}}{f_{o,pi}} \tag{1}$$

Where fk,ti and fo,ti represent the i-th frequency in trough points and fk,pi and fo,pi are the i-th frequency in peak points (k indicates reference TF and o is indication of other conditions).

Similarly, the variation of amplitude in the peak and trough points, are represented through the index of amplitude ratio (IAR) as follows:

$$IAR_{ti} = \frac{A_{k,ti}}{A_{o,ti}} \quad , \; IAR_{pi} = \frac{A_{k,pi}}{A_{o,pi}} \tag{2}$$

Where Ak,ti and Ao,ti represent the amplitude of TF at the i-th trough point, and Ak,pi and Ao,pi are the amplitude of TF at the i-th peak point, respectively.

3.2 CC Index

The correlation coefficient (CC) is a measure for the similarity of two curve progressions. For two TFs−TF1 and TF2− this factor can be determined as follows [11]-[13]:

$$CC = \frac{\sum_{i=1}^{N} [TF_1^*(f_i) \cdot TF_2^*(f_i)]}{\sqrt{\sum_{i=1}^{N} [TF_1^*(f_i)]^2 \cdot [TF_2^*(f_i)]^2}} \tag{3}$$

At which:

$$TF_1^*(f_i) = |TF_1(f_i)| - \frac{1}{N}\sum_{i=1}^{N}|TF_1(f_i)|$$
$$TF_2^*(f_i) = |TF_2(f_i)| - \frac{1}{N}\sum_{i=1}^{N}|TF_2(f_i)| \tag{4}$$

The measured TFs imply that the changes in TFs do not spread equally over the entire frequency range but are often bounded in several frequency areas. On the other hand, CC to compare the TFs devotes a numeric value that is not suitable for training the SVM. Hence, studying the TFs in smaller frequency ranges could be helpful in training of SVM. In this regard, the three ranges are called [5]: 1) low frequency (LF): 0-1 MHz; 2) medium frequency: MF: 1-2 MHz; and high frequency (HF): 2-3 MHz and the calculated CC for these ranges are CCLF, CCMF, and CCHF, respectively, for LF, MH, and HF.

3.3 Vector Fitting (VF)

In principle, a TF approximation (of a given order) can be found by fitting it with a function which is made of the ratio of the two polynomials as shown in equation (5):

$$f(s) = \frac{a_m s^m + \cdots + a_1 s + a_0}{b_n s^n + \cdots + b_1 s + b_0} \tag{5}$$

Where m and n are the number of numerator and denominator coefficients, a_i and b_i are the values of i-th coefficient for the numerator and denominator, respectively.

However, generally the TF of a passive system can be approximated by a rational function f(s) in the form [24] shown by equation (6):

$$f(s) = \frac{N(s)}{D(s)} = \sum_{i=1}^{n}\frac{r_i}{s - \overline{p}_i} + d.s + e \tag{6}$$

The residues ri and poles pi are either real quantities or appear in complex conjugate pairs, while d and e are real. The problem at hand is to estimate all of the coefficients in equation (6), so that a least squares approximation of f(s) is obtained over a given frequency interval. It should be noted that equation (6), represents a nonlinear problem in terms of the unknowns, because the unknowns pi appear in the denominator.

VF solves the problem of equation (6), sequentially as a linear problem in two stages, as has been showed in [24]. After achieving a good approximation of f(s) in equation (6), coefficients of and bi in equation (5) can be calculated using ri, pi, d and e [2].

3.4 Support Vector Machine (SVM)

The SVM introduced by Vapnik [25] was firstly proposed for classification problems of two classes but was found to be useful to deal with nonlinearly separable cases too. The details of relevant theory have been discussed in [25]-[26]. Here a brief discussion has been provided.

SVM is recognized as one of the standard tools for machine learning and data mining, which is based on advances in statistical learning theory. Originally developed to solve binary classification problems, SVM determines a number of support vectors from training samples and converts them into a feature space using various kernel functions, among which the most commonly used are radial basis function (RBF), polynomial basis function, and sigmoid function. Hence, by solving a quadratic optimization problem, the optimalseparating hyper-plane with a maximal margin between two classes is defined [26].

For the purpose of multi-category classification, various different binary classification methods are implemented, such as 'one-against-al', 'one-against-one', 'binary tree', etc [27]. The SVM used in this work is a 'one-against-one' having been approved as one of the appropriate binary methods for multi-category classification [27] with a RBF kernel employed and defined by the following equation:

$$K(x,y) = exp\left(-\frac{(x-y)^2}{2\sigma^2}\right) \tag{7}$$

Where x and y denote support vectors and σ is a RBF kernel parameter to be determined. In order to control the SVM generalization capability a misclassification parameter C should also be defined [23].

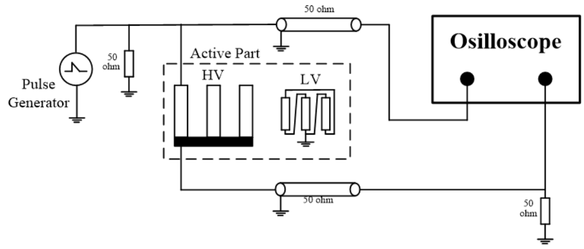
4. TEST OBJECTS AND MEASUREMENTS

One of methods to measure the TF of transformer windings is impulse voltage method. This method is based on the fact that a steep impulse or step voltage is applied to the winding as input and simultaneously the voltage or current at the other terminal be measured as output. If the input signal involves enough frequency components to excite all desired oscillatory modes of the winding, the frequency behavior or TF can be extracted accurately [28].

In this paper, TF measurements have been performed for the active part of a 50MVA 132KV/33KV power transformer while the active part had been placed in the drying chamber in different time intervals during drying process [10].

Figure 1.a and Figure 1.b show a view of implemented instrumentation system and its schematic diagram, respectively. Using the pulse generator, a suitable step pulse with a rise-time of 100 nsec and the amplitude of 140 V is applied to the high voltage winding of a phase and the current is measured at the end of coil via a pure 50Ω resistor shunt. The input and output signals were sampled with 500 Msps using a digital storage oscilloscope. These two time domain signals stored were converted into ASCII data and transferred to the computer for further processing.

(a) *A view of test object in high voltage laboratory*



(b) *Schematic of measurement circuit*

Fig.1: *Transformer under test in high voltage laboratory*

The converted sampled data are zero padded to avoid spectral leakage. Also in order to obtain lower frequency range in the frequency response curves, exponential window is applied to the new time domain data before transforming in the frequency domain. Finally, the TF between applied voltage and response current is computed by dividing their spectra in the frequency domain employing Fast Fourier Transform (FFT) technique. Using the established setup, 30 measurements are performed while the active part was under drying process in drying chamber for about 66 hours. Note that because of low vacuum degree in furnace, the maximum applied voltage should not be more than 300 V.

The measured results in this contribution show that the enhancement of drying time affects the TFs and modify them, differently. Variations of measured TF for different times during early hours of process is significant rather than last hours of drying process. For instance, Figure 2 indicates the variations of TF for three different time intervals during early hours of process. Also, Figure 3 shows the variations of TF for three different time intervals during end hours of drying process. The measured TF at the end of drying process, is considered as a reference TF and the other TFs (in different time intervals) are compared against the reference one. Sound features extracted from these TFs can easily lead to valid time estimation.

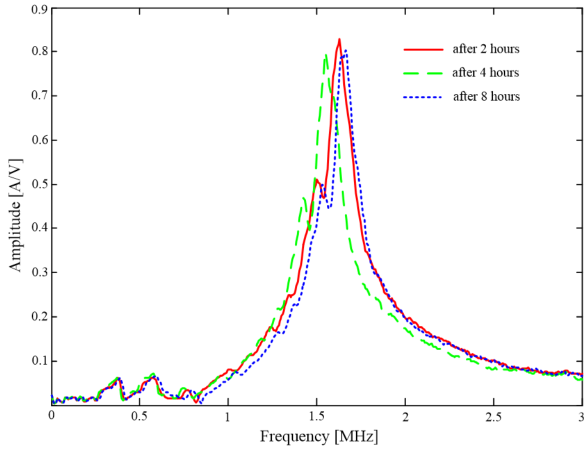


Fig.2: *The measured TFs for three different time intervals (2, 4, and 8 hours) during early hours of process*

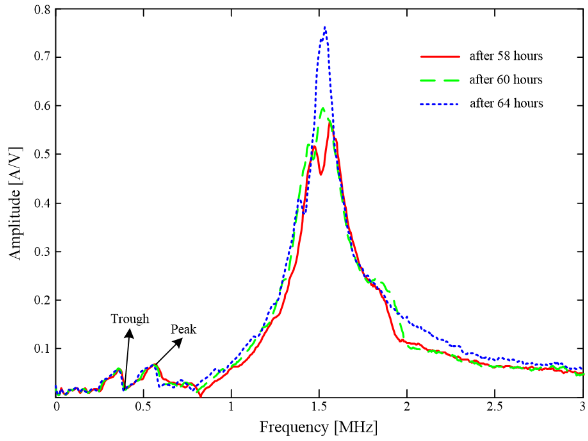


Fig.3: *The measured TFs for three different time intervals (58, 60, and 64 hours) during end hours of process*

5. ESTIMATION OF THE REQUIRED TIME TO DRYING

In this work, the SVM is used to estimate the required time for drying process in power transformers. In general, an SVM process is formed from three steps: in the first step measurements should be carried out to acquire TFs needed. The second step is related to feature extraction, in which the most proper features found for prediction. In the third step, using features found in the prior step, the prediction will be done. Extracted features in previous items are used for training SVM. Then, using trained SVM decision will be made on new data.

5.1 Feature Extraction

In this paper, features extraction is based on using the information of TFs. The measured TF at the end of drying process is considered as a reference TF and the other TFs (in different time intervals) are compared against the reference one.

One of the methods for comparison of TFs versus the reference TF is developed by application of the mathematical indices such as IFR and IAR. Therefore, the defined indices in (1), (2) can be applied as an input to SVM. On the other hand, the CC between two measured TFs in the three frequency ranges is change due to drying process. So, these coefficients are used as another efficient index for training of SVM.

Moreover, the results of the estimated TFs show that the coefficients of numerator and denominator of rational functions (equation 5) change due to drying. Therefore, indirectly TFs are compared through examination of these coefficients which can be detected easily by VF method [24]. Absolute ratio of these coefficients in numerator and denominator of transformer TF in different time intervals with respect to those parameters related to the reference TF are used as an efficient index for estimation of drying time. Following relations show the way of calculating these indices:

$$Ra_i = \left|\frac{a_{oi}}{a_{ki}}\right| \tag{8}$$

$$Rb_i = \left|\frac{b_{oi}}{b_{ki}}\right| \tag{9}$$

a_{ki} and b_{ki} are the values of i-th coefficient for the reference TF, a_{oi} and b_{oi} are the values of i-th coefficient for other conditions, respectively.

5.2 Training Procedure

To train SVM first of all, its structure (input/output data) should be determined. In order to improve the prediction performance, three different conditions of extracted features have been tried.

In first state, the defined indices in equations (1), (2) have been used for training of SVM. Therefore, input matrix in this case (feature 1) can be defined as follow:

$$input_{featurel} = \begin{pmatrix} IFR_{t1,ti_1} & \cdots & IFR_{t1,ti_s} \\ \vdots & \vdots & \vdots \\ IFR_{tj,ti_1} & \cdots & IFR_{tj,ti_s} \\ IFR_{p1,ti_1} & \cdots & IFR_{p1,ti_s} \\ \vdots & \vdots & \vdots \\ IFR_{pk,ti_1} & \cdots & IFR_{pk,ti_s} \\ IAR_{t1,ti_1} & \cdots & IAR_{t1,ti_s} \\ \vdots & \vdots & \vdots \\ IAR_{tj,ti_1} & \cdots & IAR_{tj,ti_s} \\ IAR_{p1,ti_1} & \cdots & IAR_{p1,ti_s} \\ \vdots & \vdots & \vdots \\ IAR_{pk,ti_1} & \cdots & IAR_{pk,ti_s} \end{pmatrix} \tag{10}$$

Where:

ti: is abbreviation of time interval,

s: show the number of time intervals that TF is measured, and

j, k: represent the number of trough and peak points in TFs, respectively.

In second state, the defined index in equations (3) is used for training of SVM. Equation (11) shows the input matrix in this case (feature 2):

$$input_{feature2} = \begin{pmatrix} CC_{LF,ti_1} & \cdots & CC_{LF,ti_s} \\ CC_{MF,ti_1} & \cdots & CC_{MF,ti_s} \\ CC_{HF,ti_1} & \cdots & CC_{HF,ti_s} \end{pmatrix} \tag{11}$$

In third state, the defined indices in equations (8), (9) are used for training of SVM. Equation (12) shows the input matrix in this case (feature 3):

$$input_{feature3} = \begin{pmatrix} Ra_{1,1} & \cdots & Ra_{1,s} \\ \vdots & \vdots & \vdots \\ Ra_{m,1} & \cdots & Ra_{m,s} \\ Rb_{1,1} & \cdots & Rb_{1,s} \\ \vdots & \vdots & \vdots \\ Rb_{n,1} & \cdots & Rb_{n,s} \end{pmatrix} \tag{12}$$

Where:

m, n: represent the number of numerator and denominator coefficients in estimated TFs, respectively.

Output of SVM in each of three states can have different classes (according to different time intervals). As a result, the output of SVM is single dimension vector that shows the required time in drying process.

After finding features 1, 2, 3, results of these calculations are applied to SVM as an input. The input matrixes sizes for features 1, 2 and 3 are 20×20, 3×20, and 40×20, respectively.

It should be noted that in order to obtain a suitable measure for comparison, the features extracted (equations 10, 11 and 12) should be normalized using the following equation:

$$X = \frac{x - \mu}{sd} \tag{13}$$

Where x stands for each of the matrix rows (in equations 10, 11 and 12), μ and sd denote the mean value and standard deviation of x, and X is the normalized vector of x.

5.3 Results and Discussion

Accidentally two-thirds of measured data are used for training of SVM and one-third is used for its validations. Since thirty samples extracted from one power transformer employed in this work, therefore twenty and ten samples is used for training and testing of SVM, respectively.

After training, data related to validation is applied to the SVM as a testing input for prediction of time to drying. In this case, the sizes of the input matrixes are 20×10, 3×10, and 40×10 for features 1, 2 and 3, respectively.

The choices of SVM parameters values were based on trial and error. The obtained results show that the choice of σ from 3.6 to 5.2 ($3.6 \leq \sigma \leq 5.2$) and from 80 to 110 for C ($80 \leq C \leq 110$) could provide a good performance for our tests.

Following the prediction of SVM, the best results obtained have been shown in Table 1. A close observation of this table shows that the SVM is able to identify the time of drying correctly in most of the cases.

In order to prove the capabilities of the proposed method, a comparison between SVM technique and past method based on ANN and CC [10] is carried out here (see column 2 of Table 2). Meanwhile, the results of prediction using other indices (features 1, 3) are given in Tables 2. For ANN classification, a three layer feed-forward structure with the input, hidden, and output layers based on back-propagation learning algorithm is employed as the classifier [29]. The elements of (10), (11) and (12) are used as input and the outputs of ANN are class labels. The choices of ANN parameters were based on trial and error. The best obtained result through ANN is presented in Table 2.

As displayed in Tables 1, 2 the accuracy of SVM in the prediction of required time to drying is better than ANN method. In SVM all three features (1, 2, 3) have come up with appropriate results, although the accuracy of feature 1 is higher than features 2 and 3. It can be explained that the number of training samples in SVM method is not of a great significance and the number of input data that is located in boundary regions (these data generate support vectors) are the most important factor on its accuracy. With the identification of support vectors, the border line between data is determined and SVM utilizes these vectors for pattern recognition. It is obvious that the number of training samples in feature 3 is more than in feature 1. However, some of the data in feature 3 doesn't vary in different states and are similar to each others. Therefore, it is difficult for SVM to determine support vectors in these cases and it may lead to wrong detection of SVM. Meanwhile, the figures of measured TFs are generally similar, except in location of frequencies and amplitudes in peak and trough points. Consequently, the statistical indices such as CC are the same for many TFs and therefore they are not suitable as the inputs of SVM and ANN. Therefore, it is difficult for SVM and ANN to estimate the drying time in feature 2.

While, the number of data in feature 1 is counted by the number of peak and trough points which are clearly observable in measured TFs. The major modifications appeared in measured TFs are related to those in peak and trough points and the trend of these changes for different time intervals is nearly identical and differs from other ones. Consequently, it is possible for SVM, in feature 1, to easily determine support vectors and border line between various time intervals. Consequently, an SVM based method with feature 1 produces the best results in estimation of drying time. Thus, it can be used for evaluating the drying quality in power transformers as a reliable method.

6. CONCLUSION

Estimation of the required time to dry in power transformers is an important subject for transformer manufacturers. However, a reliable method cannot be found for this purpose, in the literature. A new method for evaluation of the required time for drying process is proposed by application of SVM technique, in this paper. The proposed method is able to accurately estimate the drying time. For training and testing purposes of the SVM, the measured data related to 50MVA 132KV/33KV power transformer is employed. After extracting the features of the measured TFs by IFR and IAR indices (feature 1), CC method (feature 2) and VF method (feature 3), they are applied to SVM classifier, for its training. The validation process reveals that the proposed method, based on SVM using feature 1, has a high accuracy.

Employing the proposed method in different transformers will reveal more knowledge to evaluate drying quality. Therefore, it can be concluded that the evaluation of drying quality in power transformers will require more work and effort.

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Table 1: *Results of Prediction based on SVM using different Features (C: correct and W: wrong)*

Method / Time to dry	SVM		
	Feature 1	Feature 2	Feature 3
Class 1	C	C	C
Class 2	C	C	C
Class 3	W	W	W
Class 4	C	C	C
Class 5	C	C	C
Class 6	C	C	C
Class 7	C	C	C
Class 8	C	C	C
Class 9	C	W	C
Class 10	C	W	W
Accuracy	90%	70%	80%

Table 2: *Results of Prediction based on ANN using different Features (C: correct and W: wrong)*

Method / Time to dry	SVM		
	Feature 1	Feature 2	Feature 3
Class 1	C	C	C
Class 2	C	C	C
Class 3	W	W	W
Class 4	C	C	C
Class 5	W	W	C
Class 6	C	C	C
Class 7	C	C	C
Class 8	C	C	C
Class 9	C	W	W
Class 10	W	W	W
Accuracy	70%	60%	70%

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