Acoustic Diagnosis of a Pump by Using Neural Network

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A fundamental study for developing a fault diagnosis system of a pump is performed by using neural network. Acoustic signals were obtained and converted to frequency domain for normal products and artificially deformed products. The neural network model used in this study was 3-layer type composed of input, hidden, and output layer. The normalized amplitudes at the multiples of real driving frequency were chosen as units of input layer. And the codes of pump malfunctions were selected as units of output layer. Various sets of teach signals made from original data by eliminating some random cases were used in the training. The average errors were approximately proportional to the number of untaught data. Neural network trained by acoustic signals can detect malfunction or diagnose fault of a given machine from the results.

Key Words : Acoustic Diagnosis, Pump, Neural Network, Deformed Cases, Frequency Domain

1. Introduction

In order to decrease losses caused by failures of production facilities, it is required to maintain their maximum operation capacity and find out the fault of equipments rapidly (Asakura et al., 2000 ; Staroswiecki, 2000). Many studies have been performed in order to diagnose machines or structures and prevent their mal-function (Danai and Chin, 1991 ; Staszewski, 1998 ; Lin and Qu, 2000; Zang and Imregun, 2001; Chen and Mechefske, 2002 ; Chung et al., 2001). Vibration signals such as acceleration have been widely used in diagnosis of a machine as they have useful information of target machines (Lin and Qu, 2000 ; Chung et al., 2001).

The most common health monitoring method for structures is visual inspection (Zimmerman et al., 1996). This method is costly, time-consuming, and in many cases difficult to perform due to the inaccessibility of major portions of the structure. In addition, visual inspection does not give a quantitative value for remaining strength of the structure.

A general method of machine diagnosis is a series of acquisition and analysis of signals that are generated from a machine while it works. The type of signal has been selected and then sensor is attached as nearly to the position where the signal is generated as possible. For many reasons the diagnostic signal is deformed during transfer to an analyzer. It is a key in the fault diagnosis how to extract the original features from these deformed signals. The processing methods are various and have different efficiencies for different cases. Asakura et al. (2000) and Zang et al. (2001) performed fault diagnosis by using neural network theory. Bae and Lee (1998) applied a modular artificial neural network to a reactor system. Staszewski (1998) and Lin et al. (2000) used wavelet transform and extracted information on the fault diagnosis of machines from mixed signals.

The problem of structural health monitoring is best viewed in the context of a statistical pattern recognition paradigm (Duffey et al., 2001). This paradigm can be described as a four-part process : 1) operational evaluation, 2) data acquisi-

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tion & cleansing, 3) feature extraction & data reduction, and 4) statistical model development. Operational evaluation begins to define why the monitoring is to be done and to tailor the monitoring to unique aspects of the system and unique features of the damage. The data acquisition portion of the monitoring process involves selecting (1) the types of sensors to be used, (2) the locations where the sensors should be placed, (3) the number of sensors to be used, and (4) the data acquisition hardware. The area of the structural monitoring that receives the most attention is feature extraction. Feature extraction is the process of identifying damage-sensitive properties, which are derived from the measured response, and it allows one to distinguish between the undamaged and damaged structure.

Neural networks have been used for system identification. In the most common application, the neural network is taught to behave like the dynamic system of interest. These networks are typically of the recurrent or feed-forward type and are trained with gradient based learning algorithms. They have the advantage of being able to learn nonlinear systems; however, the learning algorithm is difficult to implement in real time and tends to converge to a solution very slowly. Also, the resulting model tends to be a black box that does not give much insight into the physical system being modeled (Stech, 1994; Kirkegaard and Rytter, 1994).

Acoustic signals from machines as well as vibration signals always present the dynamic information of machines while operating. These signals are believed to be very useful for feature extraction and fault diagnosis. Acoustic emission analysis was used to the evaluation of fracture behavior of steel welds (Na et al., 2006).

A fundamental study was performed for developing a system of fault diagnosis of a pump by using neural network. Acoustic signals were obtained by using a microphone and a amplifier. The signals were converted to frequency domain, analyzed and compared for normal products and artificially deformed products. The deformed cases used in this study included three types of deformed shaft, unequally ground blade, and deformed bearing. The signals were obtained in various driving frequencies in order to obtain many types of data from a limited number of pumps. The acoustic data in frequency domain were managed to multiples of real driving frequency with the aim of easy comparison. The neural network model used in this study was 3-layer type composed of input, hidden, and output layer. The normalized amplitudes at the multiples of real driving frequency were chosen as units of input layer. And the codes of pump malfunctions were selected as units of output layer. Various sets of teach signals made from original data by eliminating some random cases were used in the training. The average errors were approximately proportional to the number of untaught data. The results showed that neural network trained by acoustic signals can be used as a simple method for detection of malfunction or fault diagnosis of a given machine.

2. Experimental Apparatus and Method

The pumps LG PU-250M shown in Fig. 1 were used in this study because they have rotating shafts which can be observed easily at outside while working and they are simple structure, small size, and low price. DP104 FFT analyzer of Data Physics was used as an analyzer, GRAS probe microphones were used as sensors. For references, accelerations were measured and Dytran 3136 accelerometers were used. The acoustic signal was

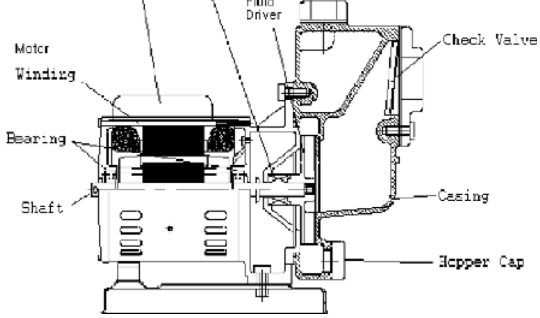

Fig. 1 PU-250M pump

measured at the upper position, amplified by an amplifier, and transformed by a FFT analyzer.

The mal-function types used in this study included three types of (1) deformed shaft by bending one or more cooling fins, (2) unevenly ground blade, and (3) damaged bearing. The acoustic signals were obtained in various driving frequencies from 54 to 64 Hz in order to obtain many types of data from a limited number of pumps. A probe microphone was installed at the 0.25 m over in the upper direction of the center of pump cover. The acoustic signals were Fourier transformed by using a FFT analyzer. The acoustic data in frequency domain were managed to multiples of real driving frequency with the aim of easy comparison.

Figures 2~6 show samples of acoustic data

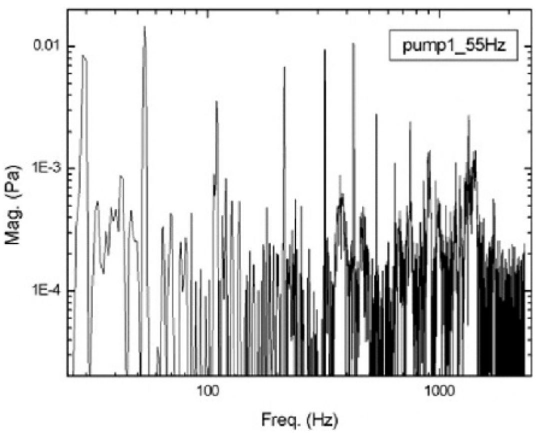

Fig. 2 Noise of normal pump A driving at 55 Hz

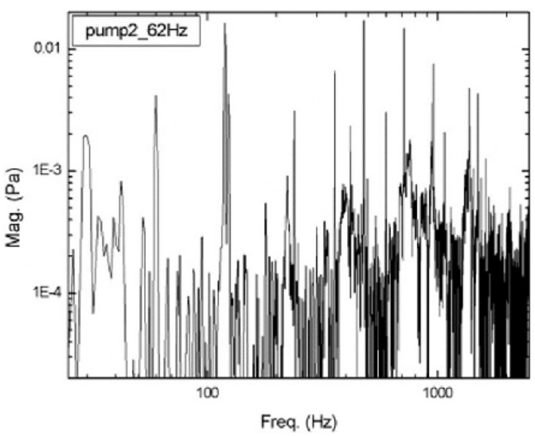

Fig. 3 Noise of normal pump B driving at 62 Hz

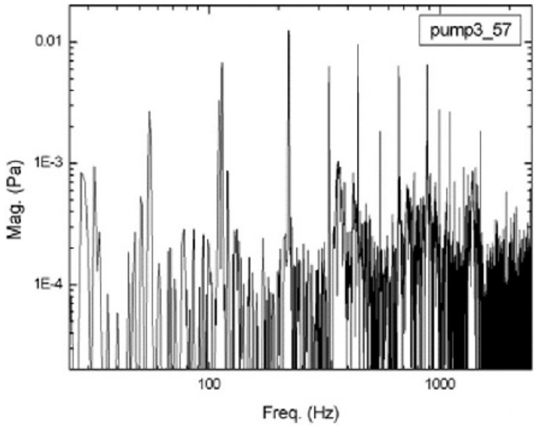

Fig. 4 Noise of pump C with bended cooling fins driving at 57 Hz

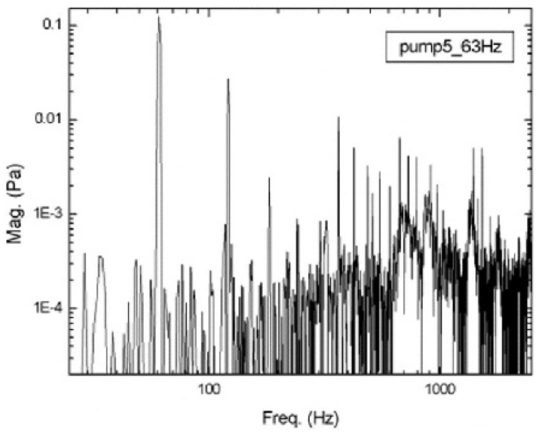

Fig. 5 Noise of pump E with unevenly ground blade driving at 63 Hz

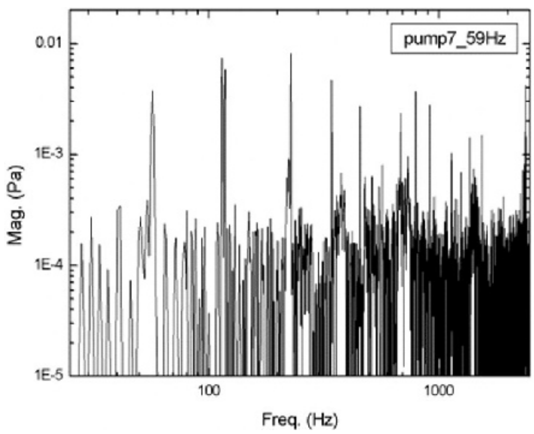

Fig. 6 Noise of pump G with damaged bearing driving at 59 Hz

transformed to frequency range for the case of pumps A and B which are normal, pump C with a bended cooling fin, pump E with unevenly ground blade, and pump G with damaged bearing balls. In the case shown in Fig. 2, the peaks were located at 1, 8, 6, 4, 2 multiples of the driving frequency in order. In the case of Fig. 4, the peaks were located at 4, 8, 2, 6, 16 multiples in order.

3. Neural Network

A multi-layered perceptron network belongs to a class of layered feed-forward nets with supervised learning. It is composed of one or more hidden layers which are placed between the input and the output layers. Each layer consists of a number of units which are connected in the structure of a layered network. The typical architecture is fully interconnected. During the training phase activation flows are only allowed in one direction, from the input layer to the output layer through the hidden layers. That is called a feed-forward process. The input vector is fed into each of the first layer units, the outputs of this layer are fed into each of the second layer units and so on (Kirkegaard and Rytter, 1994).

The internal state U_i^n and output Q_i^n of the i-th neuron in the n-th layer are expressed by using weighting factor $W_{j,i}^{n-1,n}$ and threshold θ_i^n as in equation (1).

$$U_i^n=\sum_{j=1}^{k} W_{ji}^{n-1,n} O_j^{n-1}+\theta_i^n \tag{1}$$

$$O_i^n=f(U_i^n) \tag{2}$$

In this paper a deformed sigmoid function was used as activating function $f(x)$ as shown in equation (3).

$$f(x)=\frac{2}{1+\exp(-x/a)}-1 \tag{3}$$

where a is the constant which shows the gradient of a activating function.

And neural network uses neuron model as cascade network as shown in Fig. 7. Error back propagation method (Asakura et al., 2000) was used in the learning of weighting factors and thresholds. If a neural network of N layers as shown in

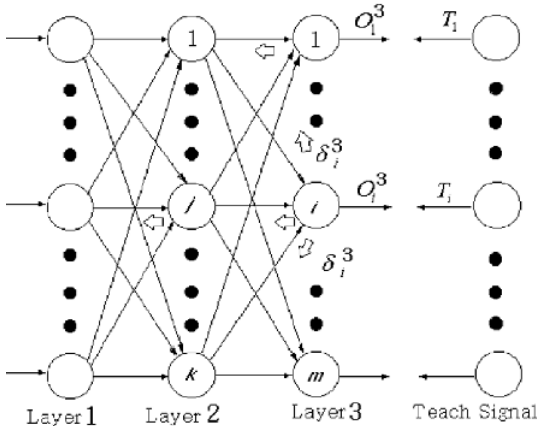

Fig. 7 3-layer neural network

Fig. 7 is considered, the internal state and output of i-th neuron in N-th layer are as following equations (4) and (5) respectively.

$$U_i^N=\sum_{j=1}^{k} W_{j,i}^{N-1,N} O_j^{N-1}+\theta_i^N \tag{4}$$

$$O_i^N=f(U_i^N) \tag{5}$$

An evaluation function J was decided as in equation (6).

$$J=\sum_{i=1}^{m}(T_i-O_i^N)^2/2 \tag{6}$$

where T_i is called a teach signal and an expected output for given input signals. By the error back propagation method, modifications of weighting factors and thresholds between the n-th layer and $(n-1)$-th layer are like equation (7) and (8) respectively.

$$W_{ji}^{n-1,n}(new)=W_{j,i}^{n-1,n}(old)+\Delta W_{j,i}^{n-1,n} \tag{7}$$

$$\theta_i^n(new)=\theta_i^n(old)+\Delta\theta_i^n \tag{8}$$

where

$$\Delta W_{ji}^{n-1,n}=-\varepsilon\frac{\partial J}{\partial W_{ji}^{n-1,n}} \text{ and} \tag{9}$$

$$\Delta\theta_i^n=-\varepsilon\frac{\partial J}{\partial\theta_i^n} \tag{10}$$

ε is a small positive number given in learning stage.

The neural network model used in this study was a 3-layer type network as shown in Fig. 7. The normalized amplitudes at the multiples of a

Table 1 Samples of peak frequencies in noise

Pump	Driving speed (Hz)	Peak frequencies (multiples)
A	52.7	6X - 8X -14X - 12X - 9X
A	59.1	2X - 1X - 8X - 6X - 12X
B	53.6	8X - 4X - 6X - 14X -2X
B	60.6	8X - 12X - 2X - 6X - 1X
C	58.1	2X - 6X - 8X - 4X - 12X
C	61.4	2X - 6X - 8X - 1X - 10X
D	57.2	2X - 6X - 4X - 8X - 12X
D	60.5	2X - 12X - 6X - 8X -16X
E	56.5	1X - 2X - 4X - 7X - 8X
E	58.2	1X - 2X - 3X - 5X - 7X
F	59.4	1X - 2X - 6X - 4X - 11X
F	61.2	1X - 2X - 11X - 6X - 4X
G	53.6	8X - 6X - 10X - 14X - 16X
G	59.8	8X - 6X - 12X - 1X - 2X
H	52.7	8X - 1X - 10X - 12X - 14X
H	59.8	6X - 2X - 8X - 1X - 10X

real driving frequency such as 1X, 2X, and 8X, where the amplitudes were relatively larger than at other multiples of a driving frequency, were chosen as units of the input layer. Table 1 shows the samples of peak frequencies in noise. Input elements were selected from the research of the peak frequencies. The multiples of a driving frequency selected as input elements in this study were 1, 2, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 16, 18, 20, 23, 25. And the codes of pump malfunctions, such as 1-0-0 for deformed shaft case, were selected as units of output layer as shown in Table 2. The number of units of the input and the output layers were 17 and 3 respectively. The number of units in the hidden layer was varied from 3 to 56. Each neural network was composed by random number generation technique. Weighting factors, thresholds and gradients of activating functions between input layer units and hidden layer units and those between hidden layer units and output layer units of each network were trained by back propagation method. The evaluation function was decided as the sum of squares of errors in the output layer, which were the differences between the teach signals and the output signals. The weighting factors

Table 2 Codes of output-layer units

Case	Code
Normal	0, 0, 0
Bended cooling fin	1, 0, 0
Unevenly ground blade	0, 1, 0
Damaged bearing	0, 0, 1

and thresholds were modified by the deepest gradient method.

Various sets of teach signals, which were made from original data by eliminating some random cases, were used in the training. The number of cases in the original data set was 88 and that of teach signals was varied from 56 to 84. When a neural network has been trained correctly, its output represents the same code given in Table 2 for each set of signals. When a neural network has error, some elements of its output codes are different with the expected codes. An error of each neural network was calculated for the original data as a percentage of the cases at which the network failed to show the same type of deformation as teach signal data.

$$Error = \frac{\textit{No. of data set failed to identify}}{\textit{No. of total data set}} \times 100(\%) \qquad (11)$$

For example, if the expected output of a neural network for eleventh set of data is (1,0,0) and the obtained output is (0,0,0), and if the output codes for all other data set are same with the expected output codes, then the neural network has an error $1\times100\%/88=1.14\%$. And the errors of learning for various types of acoustic signals were compared according to the number of untaught cases and the number of units in hidden layer. The average errors were approximately proportional to the number of untaught data, but they did not show consistent trends for the number of units in the hidden layer.

4. Results

The errors of failure in identifying the type of malfunction were calculated for various cases and various numbers of units in the hidden layer. In each case random addresses of the given number in the learning data were excluded by random number generation method. The number of cases was 12 and in each case the number of the hidden layer units were 3 and, 4, 8, 12～56. The numbers of untaught data were 4, 8, 12～36.

Figure 8 shows the errors as a function of untaught data when the number of units in the hidden layer was 12 as a sample. Figures 9～13 show the averages and standard deviations of errors for the given number of units in the hidden layer as the number of untaught data changes.

Figures 9～13 are the states where the numbers of units in the hidden layer were 4, 16, 28, 40, 52 respectively as examples. The average errors of twelve cases increased generally as the number of

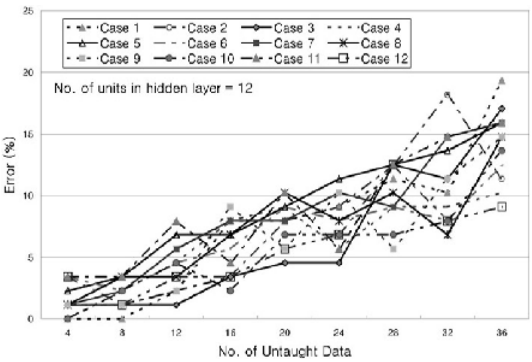

Fig. 8 Errors in the state of 12 hidden layer units

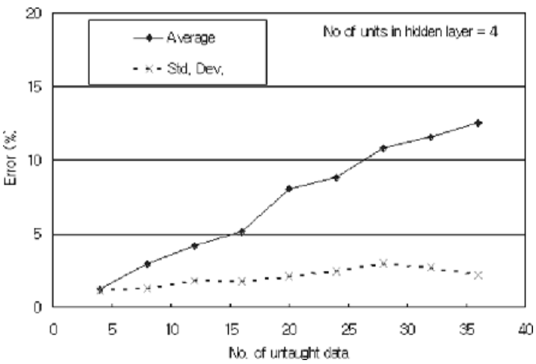

Fig. 9 Errors in the state of 4 hidden layer units

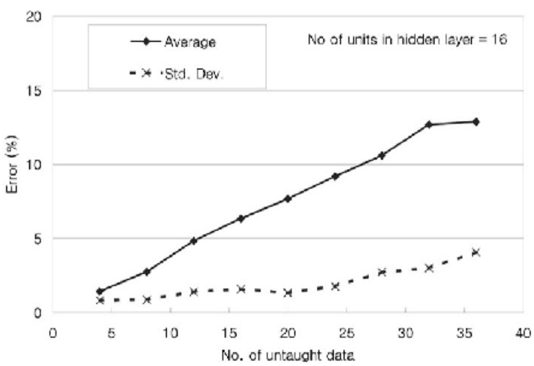

Fig. 10 Errors in the state of 16 hidden layer units

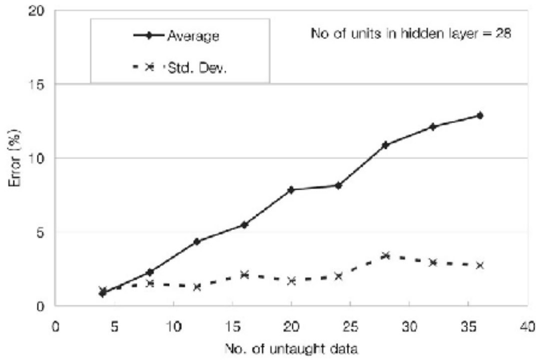

Fig. 11 Errors in the state of 28 hidden layer units

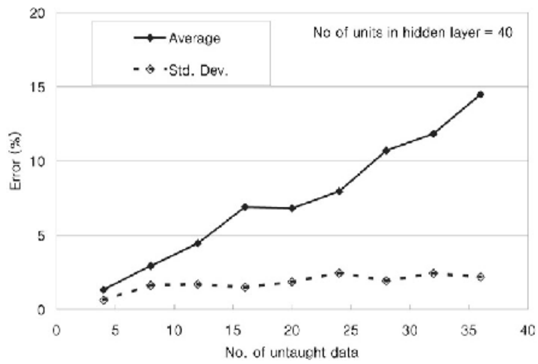

Fig. 12 Errors in the state of 40 hidden layer units

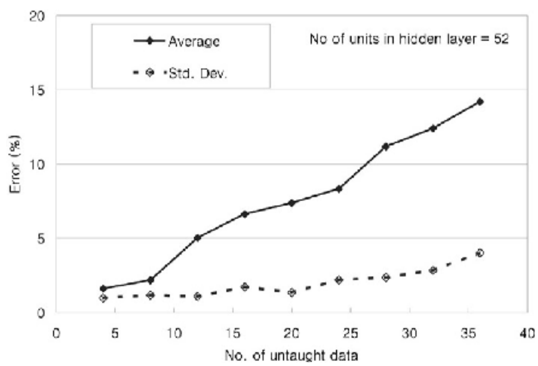

Fig. 13 Errors in the state of 52 hidden layer units

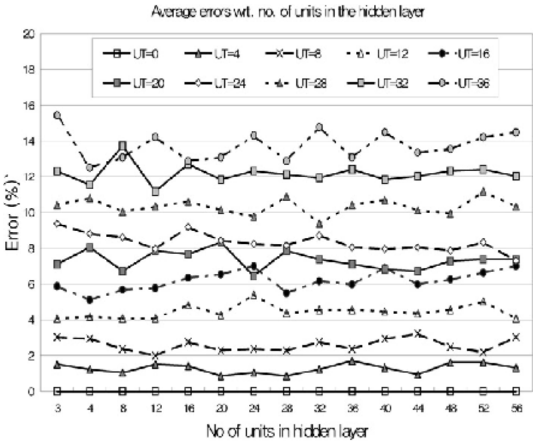

Fig. 14 Average errors versus no. of units in the hidden layer

untaught data increased. But the standard deviations of the errors did not increase uniformly. The average errors were less than 10% if the untrained data set were less than 24 set or 27%. From that, more data set is required to be used in training if the error of fault diagnosis is to be small.

The resultant average errors are shown as the number of units in the hidden layer increased in Fig. 14. They showed small errors but did not show uniform tendency in Fig. 14. Figure 14 shows lower errors when the numbers of units in the hidden layer were 4, 12, 20, and 44. These results were given by using 12 random cases where the untrained data sets were selected by random number generation method. And the results could be different more or less if other selecting schemes on the untrained data sets would be used.

5. Concluding Remarks

Acoustic signals were obtained in various driving frequencies during the operation of pumps. The acoustic data in frequency domain were managed to multiples of real driving frequency with the aim of easy comparison. The neural network model used in this study was 3-layer type and it was composed of input, hidden, and output layer. Various sets of teach signals were made from original data sets by eliminating some random cases and used in the training. The average errors were approximately proportional to the number of untaught data. The resultant average errors showed small values but did not show uniform tendency. The results showed that neural network trained by acoustic signals can be used as a simple method for a detection of machine malfunction or fault diagnosis.

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