

Monitoring of solenoid parameters based on neural networks and optical fiber squeezer for smart preventive maintenance

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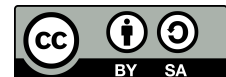
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ABSTRACT

Solenoids, also called electromagnetic actuator driven by nonlinear magnetic forces, are widely used in many applications. However, fluctuations on the performances of solenoid are a major problem, particularly in industrial applications. These fluctuations are essentially due to changes in the spring constant, in the coefficient of friction, in the inductance and the resistance of the coil. Preventive maintenance by identification and controlling of these parameters is necessary to avoid eventual effect of the parameters variation on the responses of these actuators. This paper proposes a new methodology for monitoring these parameters. Artificial neural networks algorithm coupled to optical fiber polarization squeezer based on solenoid for polarization scrambling is used for solenoid parameters monitoring. First at all, the Matlab /Simulink model has been proposed to train the Neural Network, then a simulation is proposed using Neural Net fitting toolbox to determine the solenoid parameters from the coefficients of the transfer function, determined from the time response of the squeezer fiber. The results of the simulation show the validity for predicting and monitoring the solenoid parameters.

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1. INTRODUCTION

In the solenoid, also called electromagnetic actuator, the armature is positioned by balancing the electromagnetic force against that of a return spring. The inductance and the generated force varies with displacement. These electromagnetic actuators are used in wide range of modern industrial equipment such as digital actuator arrays [1], vehicle vibration control systems [2], gas valve [3] and robotic manipulators [4]. They are simple, robust and relatively inexpensive construction [5]. However, the problem of parameters changes of these devices must be studied [6, 7]. This parametric variation may be due to changes in the spring constant, the coefficient of friction, variations in the inductance and the resistance of the coil. Other studies have shown a deterioration of the performance in presence of parametric variation [8, 9] even for the best control solutions [10], in addition, in dynamic systems like electromagnetic actuators, the unknown parameters is the main reason to reduce the control quality [11]. To improve the performance of the solenoid, one of the options is to obtain accurate modeling of this actuator by identifying and monitoring its parameters. With this solution, an accurate prediction can be made for future action of the solenoid based system and

ensure Predictive maintenance by avoiding eventual effect of the parameters changes on the responses of these actuators. Currently, most control approaches are using signals such as the coil current or voltage of solenoid to identify the parameters, but the main problems in such approach are that the detected signals are prone to interference and difficult to obtain [12]. Other works have been limited to the estimation and identification of a single solenoid parameter [7]. This paper proposes a new method using optical fiber polarization controller signal feedback coupled to artificial neural networks model (ANN) for monitoring the solenoid parameters and prediction of its performances. NN has the advantages of controlling complex and non-linear systems [11, 13] and has high accuracy of prediction capability [14]. Moreover et recently, one of the major topic of research in the involvement of the intelligence artificial is the control system[15]. In the proposed structure, the optical fiber polarization controller is based on a solenoid used as mechanical actuator to exert pressure on an optical fiber to induce an optical birefringence that modifies the polarization of the light [16]. The variation of the polarization of the light is reflected by the variation of the light intensity detected by a photodiode placed at the output of the optical fiber, In a first step, a mathematical model is proposed to obtain the response of the system, then this model is identified from this response using function tfest of Malab/Simulink [17] to determinate transfer function coefficients of the system. In second step, we will analyze the effect of solenoid parameters variation on the transfer function coefficients. This method use simulation electromagnetic fiber squeezer based polarization controller with function tfest and the simulation results are stored in a text file that will be used for neural networks training. In the last step, the neural networks model is proposed to determine the solenoid parameters from the coefficients of the transfer function, determined from the step response of the squeezer fiber. Finally, to check the efficiency of the proposed model, a prediction error is calculated.. The result of the simulation shows that this optical fiber squeezer coupled to the neural network model is very efficient to predict the performance of the solenoid by monitoring its parameters, and ensure an adequate preventive maintenance.

2. BUILDING THE SIMULINK MODEL

2.1. Structure and equations of electromagnetic squeezer fiber

The solenoid is the electromagnetic actuator exerts the pressure on the fiber. Its structure is shown in Figure 1.

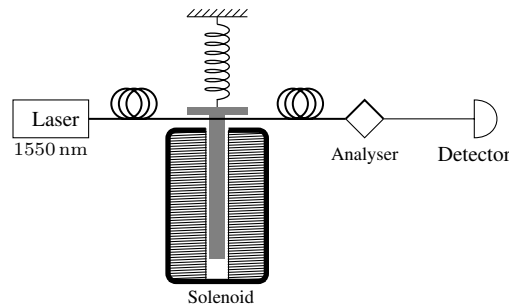


Figure 1. Scheme of using the electromagnetic squeezer fiber

The magnitude of the phase difference of two polarized light along the squeezing axis and its orthogonal axis can be expressed as [18]:

$$\delta = 6 \cdot 10^{-5} \frac{F}{\lambda d} \quad (1)$$

And the light power P_s at the output of the polarization analyzer according to scheme of Figure 1.

$$P_s = E^2 \quad (2)$$

Where

$$E = A \cdot \frac{1}{2} \cdot E \quad (3)$$

$$A = \begin{pmatrix} e^{j(\phi_m + \frac{\delta}{2})} & 0 \\ 0 & e^{j(\phi_m - \frac{\delta}{2})} \end{pmatrix} \quad (4)$$

$$P_s = E^2 = \frac{P_0}{2}(1 + \cos \delta) \quad (5)$$

Where P_0 is the input light intensity.

2.2. Mathematical model of solenoid

The solenoid is the electromagnetic actuator. It is used to exert pressure on the fiber. Its structure is shown in Figure 2.

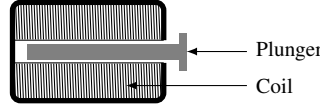


Figure 2. Cross section of solenoid

The mathematical model of solenoid is given [19] by the following expression

$$m \frac{d^2 x(t)}{dt^2} + B \frac{dx(t)}{dt} + Kx(t) = \frac{\mu_0 \mu_r N^2 A I^2(t)}{2(x_0 - x(t))^2} \quad (6)$$

Where: $x(t)$: Displacement of the armature, $I(t)$: The electromagnet coil current, A : the cross sectional area of the coil, N : the number of the turns of the coil, μ_0 : Permeability of the free space, μ_r : Relative Permeability of the dielectric material between the coil and armature, x_0 : The initial air gap between the armature and the backside of the frame, m : Masse of the armature, K : is the stiffness of the spring and B : System damping coefficient.

The equation of the electrical circuit is as follows

$$u = Ri(t) + \frac{d}{dt} [L(x).i(t)] \quad (7)$$

$$u = Ri(t) + L(x) \frac{di(t)}{dt} + i(t) \frac{dL(x)}{dt} \quad (8)$$

R is the series resistance of the solenoid coil and $L(x)$ is the inductance of the coil that depends of the air gap [19]:

$$L(x) = \frac{\mu_0 \mu_r}{x_0 - x(t)} \quad (9)$$

The balance equation of the force acting on the fiber is expressed as follow [20]

$$m \frac{d^2 x(t)}{dt^2} = F - K(x(t) - x_0) - B \frac{dx(t)}{dt} \quad (10)$$

F is the force produced by the magnetic field and it be derived knowing that magnetic system is linear and that current was kept constant

$$F = \frac{dw_t}{dx} = \frac{i^2}{2} \frac{dL(x)}{dx} = \frac{i^2}{2} \frac{aL'}{(a+x)^2} \quad (11)$$

Where $L' = \frac{\mu_0 \pi a d N^2}{g}$ and a, d, g parameters depending on the solenoid. From Equation 8 we can write

$$\frac{di}{dt} = \frac{1}{L(x)} \left(u - Ri - i \frac{dL(x)}{dx} \frac{dx}{dt} \right) \quad (12)$$

From Equation 10 we can write

$$\frac{d^2 x}{dt^2} = \frac{1}{m} \left(F - K(x - x_0) - B \frac{dx}{dt} \right) \quad (13)$$

Both Equations 1 and 5 are used to write:

$$P_s = \frac{P_0}{2} \left(1 + \cos(6 \cdot 10^{-5} \frac{F}{\lambda d}) \right) \quad (14)$$

2.3. Simulink model

The system model has been implemented in versatile software MATLAB which is widely used in control engineering around the world. This simulation is used to effectively determine the best performance of the dynamic response in the output light intensity. The electrical model Simulink which models equation 12 is represented in Figure 3(a) while the Simulink mechanical model for equation 13 is illustrated in Figure 3(b). This model depends on the intrinsic parameters of the solenoid: the mass m of the armature, the coefficient of friction B , the stiffness of the ressort K , the resistance and the inductance of the coil (R , L). The Figure 3(c) represents the optical Simulink model for Equation 14.

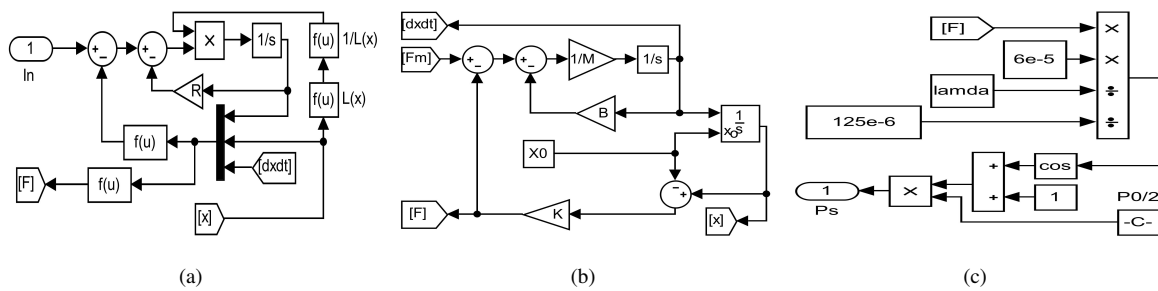


Figure 3. Simulink models: (a) Electrical model, (b) Mechanical model, (c) Optical model

3. PRINCIPLE OF SIMULATION

3.1. Monitoring process flowchart

For prediction and monitoring of the solenoid parameters, the coefficients of the transfer function obtained from the step response of the squeezer fiber based on the solenoid are used as input of the NN model. Parameters solenoid M , B and K are expected as outputs. The flowchart of monitoring process is shown in Figure 4. Figure 5 propose the architecture of the ANN model and Table 1 illustrates an example of identification result used for the ANN training.

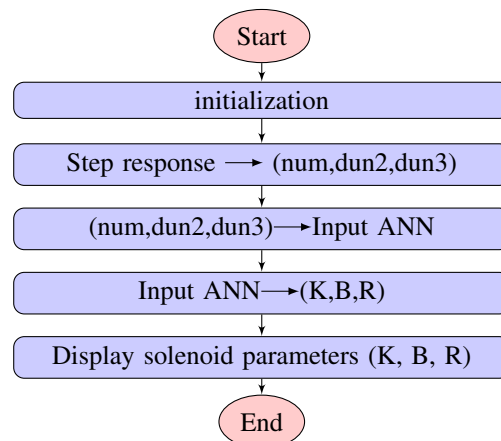


Figure 4. Monitoring process Flowchart

3.2. Neural networks architecture

The NN inputs consist of a matrix of order 10000×3 , each line represents a set of coefficients of the transfer function num , $dun2$ and $dun3$. While the outputs are the elements of a matrix of the same order as the inputs. Each line of which is a set of solenoid parameters (K , B and R), the structure also contains 10 hidden layers chosen by default with the sigmoid function as activation function and 3 output layers with a linear activation function (Figure 5).

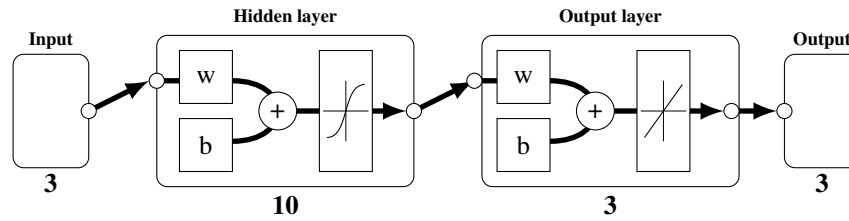


Figure 5. Monitoring process Flowchart

3.3. Neural networks training

3.3.1. Identification with variable parameters for NN trainig

First, we propose a mathematical model to obtain the response of the system, and then this model is identified from this response using identification function `ttest` whose syntax is `sys=ttest(data, np, nz)`. This function is used to estimate a transfer function containing `nz` zeros and `np` poles from the index response (`data`) of the Simulink model described in paragraph 2.3. The resulting transfer function has the coefficient (`num`, `dun2`, `dun3`). And can be expressed as the following form:

$$Tf = \frac{num}{s^2 + dun2s + dun3} \quad (15)$$

Secondly, in order to obtain the system transfer function for different values of the solenoid parameters, K , B and R are varied while keeping $m=200g$ and $L=20mH$ since they are not likely to vary during long-term operation of the solenoid. The variation interval of K is $[1000;3000]$; R : $[10,15]$ and B : $[2,4]$. The inputs of the Simulink model are a matrix of three columns and n rows of random value of solenoid parameter. The random variation between the max and min values of each of the three parameters (K , B and R) is obtained by using the function `rand(n,1)` whose syntax is as follows:

$$parameter=(max-min)*rand(n,1)+min \quad (16)$$

Where parameter is K , R or B , and $n= 10\,000$. The following Figure 6 represents the flowchart which allows to obtain the dataset and Table 1 shows an example of the text file results obtained. The results of this simulation are used as data (`num`, `dun2`, `dun3`) and target (K , B , K) for training the neural network model as shown in Section 3.3.2.

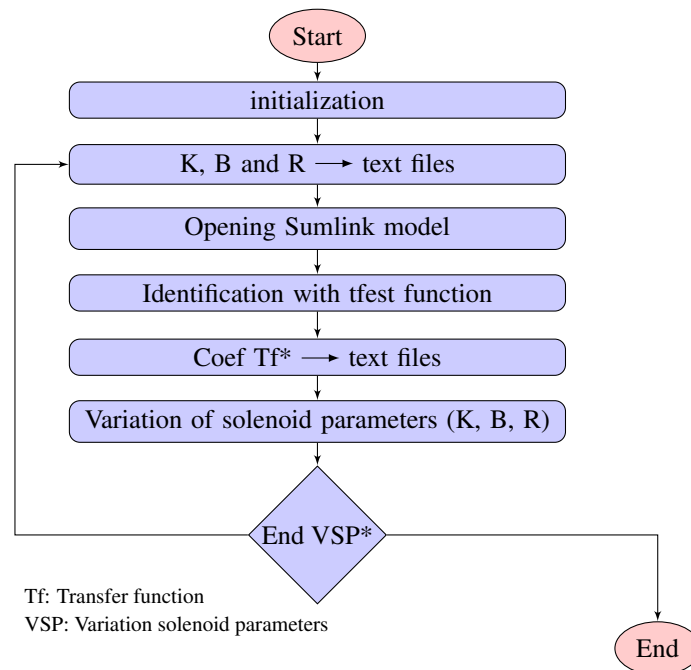


Figure 6. Identification flowchart

Table 1. . Identification result for Neural Network training

Indice	K (N/m)	B(Ns/m)	R(Ω)	Num	Dun1	Dun2	Dun3
1	2998.5692	3.2177	11.8536	114.7376	1	16.2331	15095.4567
2	2168.9635	2.3559	12.8581	70.5311	1	11.8918	10931.6472
3	2521.0054	2.1333	13.6778	72.4483	1	10.7603	12681.9928

3.3.2. Neural networks training

The target of neural network is able to identify and predict the solenoid parameters. Data from step response and neural network target are used to search weight (w) and bias (b). Weight and bias are obtained by entering data and target in Matlab program by using Neural Net fitting toolbox which offers several training functions. The updating of weight and bias values during network training is performed according to the Levenberg-Marquardt optimization which offers faster tracking of system parameter change [21]. The Levenberg-Marquardt algorithm is an efficient and popular damped least square technique. This algorithm is a combination between the steepest gradient descent and the Gauss-Newton algorithms [22]. The activation function at the output of the HNs is the sigmoid function, it delivers a continuously smoother range of values between 0 and 1 and is less expensive in terms of calculation. At the output of the network, the activation function is linear, which creates an output signal proportional to the input. During searching process weight and bias, the dataset is subdivided into three percent, 70% for training, 15% for the test and 15% for validation. The evaluation of the model is measured using three evaluation performances which are mean square error (MSE), coefficient of correlation (R) and error histogram. The optimization technique applied in the ANN model training is optimize the weights and biases of the ANN structure by minimizing the mean square error (MSE).

The training result are illustrated in Figure 7(a) which represents the convergent curve of the MSE according to the epochs, error histogram and coefficient of the correlation between the output and the target are respectively illustrated in Figure 7(b) a and Figure 7(c).

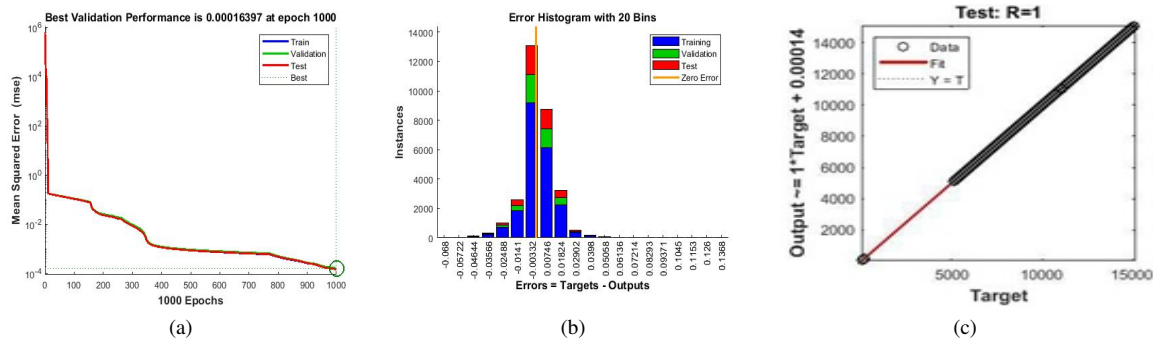


Figure 7. Training performance: (a) The convergent curve of the MSE, (b) Training error histogram, (c) Training coefficient of correlation

3.4. Monitoring result and prediction error

The prediction and monitoring, of the solenoid parameters are achieved through the data acquisition (num, dun2, dun3) from the step response of optical fiber polarization controller based on solenoid. These data are used as inputs the NN model in order to find the parameters. The predicted solenoid parameters M, B and K obtained from the transfer function coefficient are illustrated in the Table 2. Figure 8 shows the structure of monitoring process.

Table 2. Predicted parameters testing result

	NN input			Solenoid parameter		
	num	dun2	dun3	K(N/m)	B(Ns/m)	R(Ω)
Test1	74.23	18.28	5683	1101.8	3.60	8.90
Test2	137.86	14.03	14010	2775.5	2.76	10.40
Test3	59.12	16.21	10871	2159.5	3.22	14.03

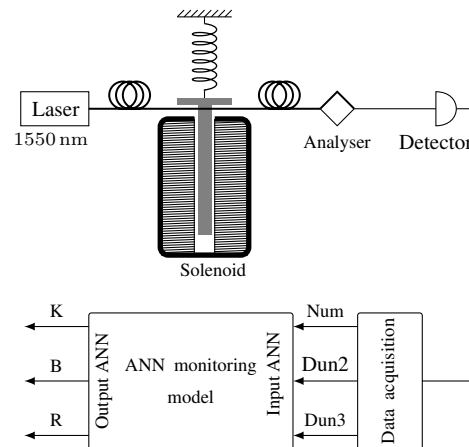


Figure 8. The model architecture for monitoring and prediction of solenoid parameters

3.5. Model performance testing

The evaluation of the model performance is done according to the flowchart of the Figure 9 by using data not utilized for the model training. The parameters found are used as inputs of the simulink model to find the predicted value of transfer function coefficients. These values are compared with the current values :num, dun2 and dun3 to finally calculate the prediction error . The model performance testing structure is illustrated in Figure 10.

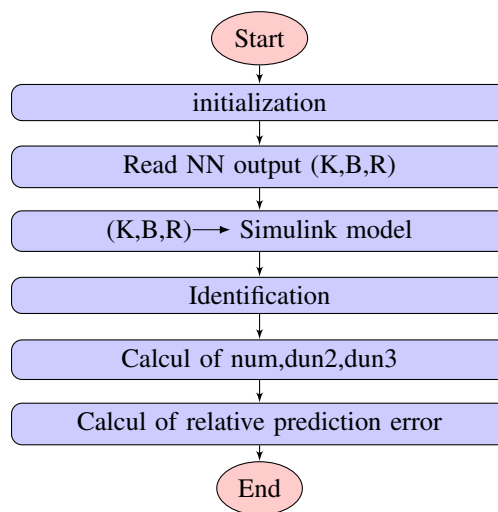


Figure 9. Performance testing flowchart

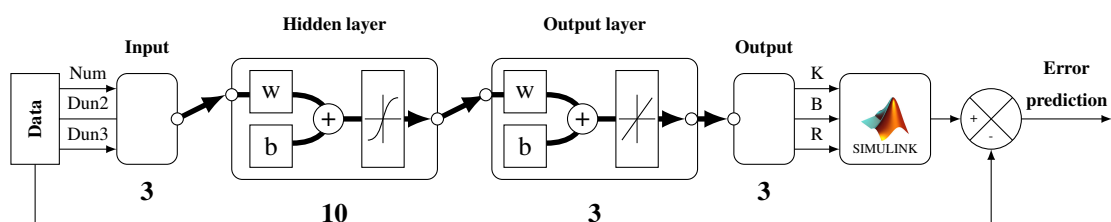


Figure 10. The detail model performance testing

Table 3. Simulink model testing result

	Solenoid parameters			Simulink model outputs		
	K(N/m)	B(Ns/m)	R(Ω)	num	dun2	dun3
Test1	1101.8	3.60	8.90	74.73	18.34	5684
Test2	2775.5	2.76	10.40	137.74	14.05	14010
Test3	2159.5	3.22	14.03	58.97	16.21	10870

Table 4. The test result prediction error

	Actual values (NN input)			Predicted values (simulink model output)			Relatif prediction error		
	num	dun2	Dun3	num	dun2	dun3	num	dun2	Dun3
Test1	74.23	18.28	5883	74.73	18.34	5684	0.67%	0.30%	0.01%
Test2	137.86	14.03	14010	137.74	14.05	14010	0.08%	0.13%	0%
Test3	59.12	16.21	10871	58.97	16.21	10870	0%	0%	0.003%

3.6. Results and discussion

Table 1 illustrates the result of the mathematical model identification of the system proposed for training using the ttest function for different values of the parameters K, B and R, it can observe from this table that if the stiffness of the spring K, the coefficient of friction B and the resistance of the solenoid coil R vary, the coefficients of the transfer function characterizing the model dun2 and dun3 also vary, however the coefficient dun1 is kept constant is equal to 1. The Figure 7(a) shows the convergence curve of MSE which illustrate the evolution of the NN training, It can be observed from this figure that suitable weights and biases of the NN model are finding in the end of the iteration with a better MSE value which is around $1,6397 \cdot 10^{-4}$. In addition, the improvment of the model performance might be realized by increasing the number of iterations (epochs) in order to minimize the MSE . The Gaussian form of the error histogram in Figure 7(b) and the value of coefficient of correlation between outputs and targets during the test illustrated in Figure 7(c) shows the high quality of training result.

On the other hand, from the results obtained on the performance test model of Figure 8 which are illustrated on the Table 2, it is clear that the predicted values of K, B and R are in clear agreement with the test values obtained by the model of the Figure 10 and which are illustrated in Table 3. Moreover and generally, the training result is less accurate compared with the training. However, from the testing performance given in the Table 3 and the relative prediction error illusted in Table 4, it is proven that the training performance of Levenberg-Marquardt algorithm is able to control and predict the solenoid parameters, and that the proposed neural network monitoring was successfully implemented .

4. CONCLUSION

In this work, we have succeeded in building a artificial neural networks model for monitoring the parameters of solenoid based on optical fiber polarization squeezer signal feedback. The results of this model have been verified through the simulation on Matlab/Simulink. The proposed neural networks model has satisfactory performance of prediction and has met the monitoring requirement. In addition, this study based on the exploitation of solenoid in the optical field is very useful in order to do prediction performance for this actuator used in others industrial or domestic system. The success of this research will be the basis for futur research. In the next step, the autors will install the neural network algorithm on the microcontroller for rmonitoring the real solenoid parametes.

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