ЛАБОРАТОРНАЯ ТЕХНИКА

A RESEARCH OF DYNAMIC COMPENSATION OF CORIOLIS MASS FLOWMETER BASED ON BP NEURAL NETWORKS

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Received May 24, 2012

As a resonate sensor, Coriolis Mass Flowmeter (CMF) provides a direct measurement of mass flow and is widely used in flow measurement field. However, defect of dynamic characteristics has become the main factor which restricts its further application in batch filling processes. Based on theoretical analysis, a dynamic compensation system, BP (Back-Propagation) neural network dynamic compensation method is designed in order to solve this problem. Adding a neural network dynamic compensation segment after the sensor's output, the method uses the gradient descent method with an additional momentum factor for neural network training. Studies have shown that this method greatly improves the dynamic characteristics of the Coriolis mass flowmeter.

DOI: 10.7868/S0032816213020183

1. INTRODUCTION

Coriolis Mass Flowmeter (CMF) is a type of mass flow meter which provides a direct and high precision measurement of mass flow. When there is fluid flowing in the pipeline, Coriolis force generated by the vibration of the pipeline will cause a change of the pipeline's vibration in phase and amplitude [1]. Because of the expansion of application fields and improvement of the measurement accuracy, not only sensors need to have good static characteristics, but also should meet the requirements of the dynamic characteristics. Therefore, at present the dynamic characteristic has became an important indicator to evaluate the CMF performance. However, weakness of dynamic characteristic constrains CMF's further development [2], hence becomes one of the bottlenecks for CMF's widely application.

Generally speaking, there are two ways to improve the dynamic characteristics of sensors [3]: one is to describe the dynamic characteristics of sensors by low-level differential equations. We can use zero-pole placement method to design dynamic compensation. The other is to design the compensated part by actual characteristics of sensors. However, designing a dynamic filter depends on the compensated structure or the mathematical modeling of the system in advance [4]. The compensated filter design becomes much more complicated when the sensor model has high-orders feature [5]. Once the mathematical model is determined, it is difficult to be changed and adapt to the continuous changing of the actual response. That is, the method lacks of self-adaptability. When the spectrum of this sensor has considerable amount in the high-frequency region [6], post-processing is required to determine the applied.

Neural network is a kind of information processing paradigm that is inspired by the biological nervous systems. It has been applied in many fields such as high performance aircraft autopilots, automobile automatic guidance, breast cancer cell analysis, exploration, recognition speech and so on [7]. In recent years, to enhance and improve the dynamic characteristics of system has become an important application area of neural network. The neural network system is essentially a highly non-linear kinetics network system, self-adaptive, self-learning, self-organizing, with a huge amount of parallelism, fault tolerance.

Compared to traditional pole-zero compensation, dynamic compensation of Coriolis mass flowmeter based on neural networks does not need the mathematical model of the sensor in advance. Instead, it relies on the actual data of the dynamic response to train the neural network, so it can track the signal immediately as well as improve the dynamic response characteristics of the sensor [8]. Hence, we designed a compensation based on Back-Propagation (BP) neural network in this paper, with its feasibility been proved by the experimental results.

2. BASIC DYNAMIC COMPENSATION PRINCIPLE OF CORIOLIS MASS FLOWMETER

Figure 1 is a schematic representation of the structure of the U-tube Coriolis mass flowmeter [9]. The basic principle of the dynamic compensation of CMF is improving the dynamic response of the equivalent system using a dynamic compensated digital filter at the end of the flow transmitter. Figure 2 is a generic compensated block diagram.

Generally, a linear dynamic compensated digital filter of the sensor can be described as a linear differential equation

$$y(k) + \sum_{i}^{n} a_i y(k-i) = \sum_{i}^{m} b_i z(k-i). \qquad (1)$$

From the equation (1), it can be seen that the compensated system's resonant frequency and damping ratio are different from the original one. When the parameters of the filter are chosen appropriately so that the damping ratio approaches the optimal, the dynamic measurement error of the CMF could be compensated in a large frequency range. However, the method must rely on the system's mathematical model. The poles and zeros of the system change as the flow changes, and so the accuracy online cannot be guaranteed.

This thesis adopts the approach of artificial neural network to accomplish the dynamic compensation of the CMF. In this method, the normalization and linearization of the sensor system can be realized without the specific sensor model and its parameters, and then achieve the purpose of dynamic compensation. Using this method, the application is easy to realize and the dynamic characteristics of the sensor will be improved significantly.

The method of training the neural network with the parameters caught by the sensor's dynamic response is using a dynamic compensation at the end of the output. In this way, there is an error $e(k)$ between the output with the compensation and the expected output, shown in Fig. 3. Therefore, the design of the dynamic compensation turns to be the optimization of reducing the error between the compensated output and the expected one.

The system's block diagram is shown as follows. In Fig. 3, $u(k)$ is the input, $z(k)$ is the original uncompensated output, $y(k)$ is the output which is compensated. The reference modeling is the optimal second-order system (damping ratio is 0.707), and $y_d(k)$ is the output of the reference. With the continuous learning of the neural network (NN), the compensated output gradually approaches the output of the reference model. When the error $e(k) = y_d(k) - y(k)$ tends to zero, the optimal state of the system is acquired, the dynamic response time is greatly reduced, and the dynamic compensation is realized.

3. BACK-PROPAGATION NEURAL NETWORKS

In 1980s, David Rumelhart, Geoffrey Hinton and Ronald Williams, David Parker, and Yannn Le Cun invented the BP algorithm independently [10]. BP learning algorithm is described as follows: the operating signal propagates forward, error signal propagates oppositely. Figure 4 is a basic structural diagram of BP neural network.

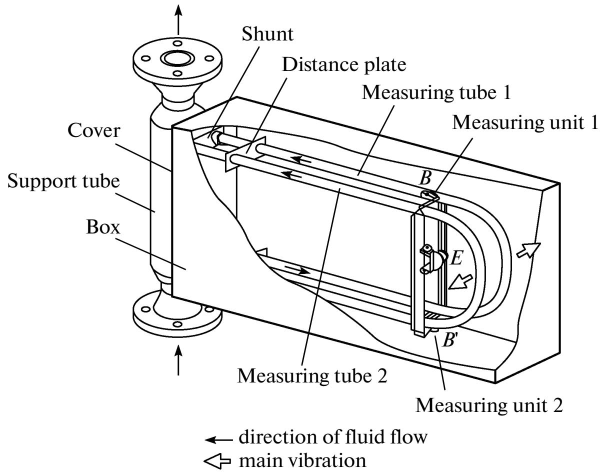

Fig. 1. The structure of the U-tube CMF.

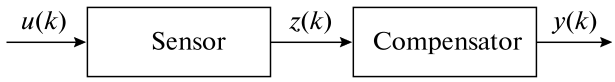

Fig. 2. Generic compensated block diagram.

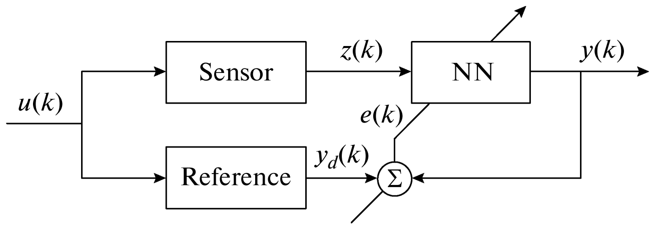

Fig. 3. NN compensated block diagram.

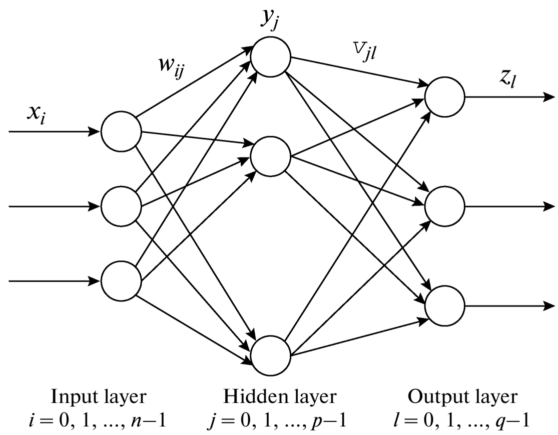

Fig. 4. The structure of BP neural network.

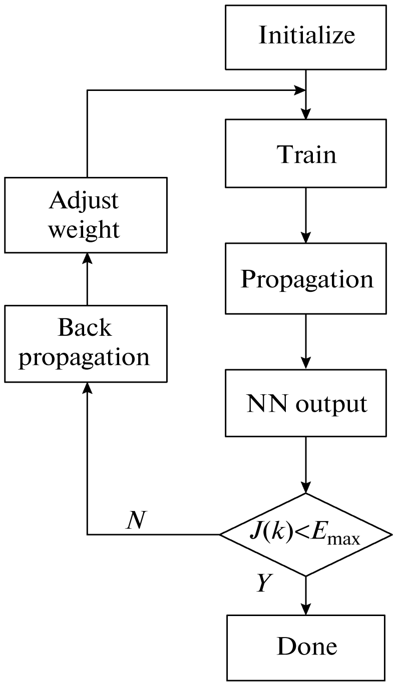

Fig. 5. The flow chart of the NN's training.

Take three layer BP neural networks for example, the input node is x_i, the hidden layer node is y_j, and the output node is z_l. The network weight values between the input layer nodes and the hidden layer nodes are w_{ij}. The network weight values between the hidden layer nodes and the output layer nodes are v_{jl}. θ_i is the neuron threshold. The expected value of the output node is y_d, the model is calculated as follows:

output of hidden layer nodes

$$y_j(k) = f\left(\sum_i w_{ij}x_i(k) - \theta_j\right) = f(net_j(k)), \tag{2}$$

$$net_j(k) = \sum_i w_{ij}x_i(k) - \theta_j, \tag{3}$$

output of output layer nodes

$$z_l(k) = f\left(\sum_i v_{jl}y_i(k) - \theta_j\right) = f(net'_j(k)), \tag{4}$$

besides,

$$net'_j(k) = \sum_j v_{jl}y_j(k) - \theta_l. \tag{5}$$

Most neural network models adopt BP neural network and variations in the field of practical application of artificial neural networks. It is also the key part of the feed-forward networks, which reflects the essence of the ideology of the neural network algorithm [10]. BP neural network is computationally intensive and can only apply to a very slow response speed sensor, so the range of applications is not widely [11]. The main advantage of using ANNs with respect to traditional methods consists of the fact that no a priori information on the model of the system is required; instead, only a set of input–output measures is used to infer a general rule that models the given sensor [12].

4. IMPROVED NETWORK TRAINING METHOD WITH ADDING MOMENTUM

For multi-layer network, BP algorithm and its variants is the most common learning algorithm. It's an algorithm based on steepest descent method, and the algorithm uses the negative gradient information as the minimization of the descent direction which has slow learning speed for its linear convergence. Figure 5 is flow chart of the NN's training. Mostly, it needs thousands of step-by-step iterations or more. Moreover, the convergence rate of the algorithm depends on parameters' selection.

Hence, one chooses the gradient descent method with an additional momentum factor for neural network training. It means that using the gradient descent method to correct the network weights with an additional momentum which makes convergence rate faster and acquisition of the global minimum easier. Let us set the learning rate as η, the momentum factor as α.

Output nodes' error:

$$J(k) = \frac{1}{2}\sum_l (y_d(k) - z_l(k))^2. \tag{6}$$

Generally, the use of these function requires special skills in the training of the networks and their commissioning into the overall control system [13]. And we select the S-shaped function $f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}$ as transfer function, its differential coefficient is:

$$f'(x) = [1 - f(x)]^2/2. \tag{7}$$

Adjust weights by Δv_{lj}, Δw_{ji}. They are proportional to the error function of along the gradient descent. When adding the momentum factor, the output layer is:

$$\begin{cases} \Delta v_{jl}(k+1) = \eta\delta_l y_j(k) + \alpha\Delta v_{jl}(k) \\ v_{jl}(k+1) = v_{jl}(k) + \Delta v_{jl}(k+1) \\ \delta_l = -(y_d(k) - z_l(k))f'(net'_l(k)) \end{cases}. \tag{8}$$

For the hidden layer,

$$\begin{cases} \Delta w_{ij}(k+1) = \eta\delta'_j x_i(k) + \alpha\Delta w_{ij}(k) \\ w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij}(k+1) \\ \delta'_j = f'(net_j(k))\sum_l \delta_l v_{jl} \end{cases}. \tag{9}$$

And $\sum_l \delta_l v_{jl}$ is a part of the error of hidden output node δ'_j, it represents the error which is produced by the error δ_l of output node z_l though back-propagation of weights v_{jl}.

5. DYNAMIC COMPENSATION EXPERIMENT OF CMF

For experimental study of the dynamic characteristics of the CMF, we must establish a specialized device to provide reliable traceability and foundation for dynamic measurement and compensation. The experimental system is shown in Fig. 6. According to its function, the system consists of two parts: flow piping systems and electrical control system. It can be used for static calibration and step response dynamic experiments of CMF.

During dynamic experiments, when the switch of the fast solenoid in main pipeline and branch pipeline valve is closed, step flow signal is produced. The solenoid valve is controlled by a special calibration controller. The system also contains signal acquisition equipments and devices to record the step response data of checked flowmeter and reference flowmeter.

The input of the compensation neural networks consists of an actual output data of the sensor and a delay signal of the compensated output. So we train the neural networks based on the experimental data, and normalize the actual step response data as the sample data of the training. The ideal output of the sensor is regarded as the expected output of the neural networks.

Selecting the number of neurons' nodes: the input layer, $n = 5$, the hidden layer $p = 20$, the output layer $q = 1$. What is more, $\mathbf{x} = [z(k), z(k-1), z(k-2), y(k-1), y(k-2)]$, is the input of the input layer, $z = y(k)$ is the output of the output layer. The reference model is the best second-order system (damping ratio is 0.707), $y_d(k)$ is the reference model step response output. $\eta = 0.02$ is the learning rate, $\alpha = 0.01$ is the momentum factor, $E_{\max} = 0.01$ is the maximum index error. It takes 138 steps in MATLAB to converge at the

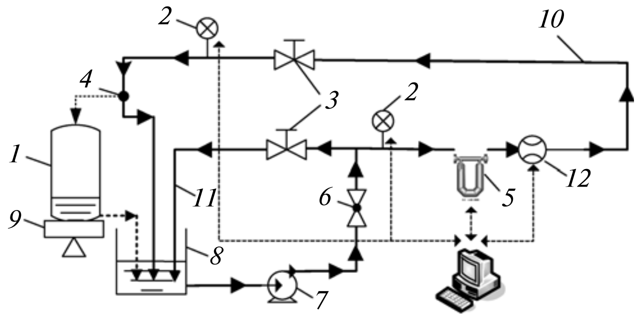

Fig. 6. Experimental system's schematic of CMF. *1* – weighing tank; *2* – pressure gauge; *3* – solenoid valve; *4* – commutator; *5* – CMF; *6* – ball valves; *7* – variable frequency pump; *8* – tank; *9* – electronic scales; *10* – main pipeline; *11* – branch pipeline; *12* – turbine flowmeter.

point where the accuracy is satisfied. At this time, we can gain all the weights of each layer is shown in Table 1 and Table 2.

Figure 7a shows the dynamic response curve of Coriolis mass flowmeter. There are four curves in Fig.7a: the reference output, the actual input before compensation, the output after pole-zero compensation and the output after neural network compensation. Figure 7b shows that it reduces the system dynamic response time from about 2 s to 40 ms. Meanwhile, the dynamic performance improvement is shown in Table 3.

To do the experiment, the step response of flow is picked every one tenth of the whole span. Comparing with zero-pole compensation, the neural network compensation makes the time of system response less. No matter how much the flow modeling changes, it can make the system work in the optimal states since it is self-adaptive. Hence, the dynamic characteristic is improved significantly.

It is known that learning online will cost time, neural networks training and calculation also takes time, the output response often lags the input when using sensor to measure dynamic signal, which cannot accu-

Table 1. Weights between input layer and hidden layer

w_{ij}	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	w_{ij}	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$
$j = 1$	0.665	0.730	0.407	0.492	0.026	$j = 11$	0.466	0.225	0.080	0.191	0.638
$j = 2$	0.964	0.217	0.296	0.888	0.589	$j = 12$	0.153	0.242	0.382	–0.004	0.672
$j = 3$	0.700	0.332	0.212	–0.347	0.487	$j = 13$	0.337	0.921	0.344	0.316	–0.009
$j = 4$	0.404	0.429	0.589	–0.007	0.348	$j = 14$	0.396	0.176	0.773	0.904	0.397
$j = 5$	0.404	0.429	0.589	–0.007	0.348	$j = 15$	0.597	0.209	0.449	0.408	0.262
$j = 6$	–0.022	0.394	0.628	0.558	0.411	$j = 16$	0.288	0.256	0.412	0.203	0.264
$j = 7$	0.047	0.573	0.071	0.139	0.232	$j = 17$	0.529	0.716	0.400	0.310	0.104
$j = 8$	0.133	0.160	0.189	0.291	0.321	$j = 18$	0.033	0.299	0.326	0.674	0.984
$j = 9$	0.136	0.173	0.818	0.285	0.252	$j = 19$	0.954	0.476	0.259	0.805	0.816
$j = 10$	2.818	2.82	2.664	2.543	2.664	$j = 20$	0.695	0.700	0.064	0.438	0.289

Table 2. Weights between hidden layer and output layer

$v_{jl}(l = 1)$							
$j = 1$	0.798	$j = 6$	0.622	$j = 11$	0.806	$j = 16$	1.041
$j = 2$	0.414	$j = 7$	0.999	$j = 12$	0.563	$j = 17$	0.845
$j = 3$	1.167	$j = 8$	0.334	$j = 13$	1.152	$j = 18$	0.344
$j = 4$	0.707	$j = 9$	1.020	$j = 14$	0.418	$j = 19$	0.497
$j = 5$	0.898	$j = 10$	1.253	$j = 15$	0.907	$j = 20$	0.759

rately reflect the changes of the input signal [14]. So the convergence rate of the network itself may not catch the continuous changing error. If a neural network without training is added to the system directly, the compensation may be failed due to the algorithm of large complexity and the iterations of numerous times. To solve this problem, we need to train the neural network offline to obtain a compensation neural

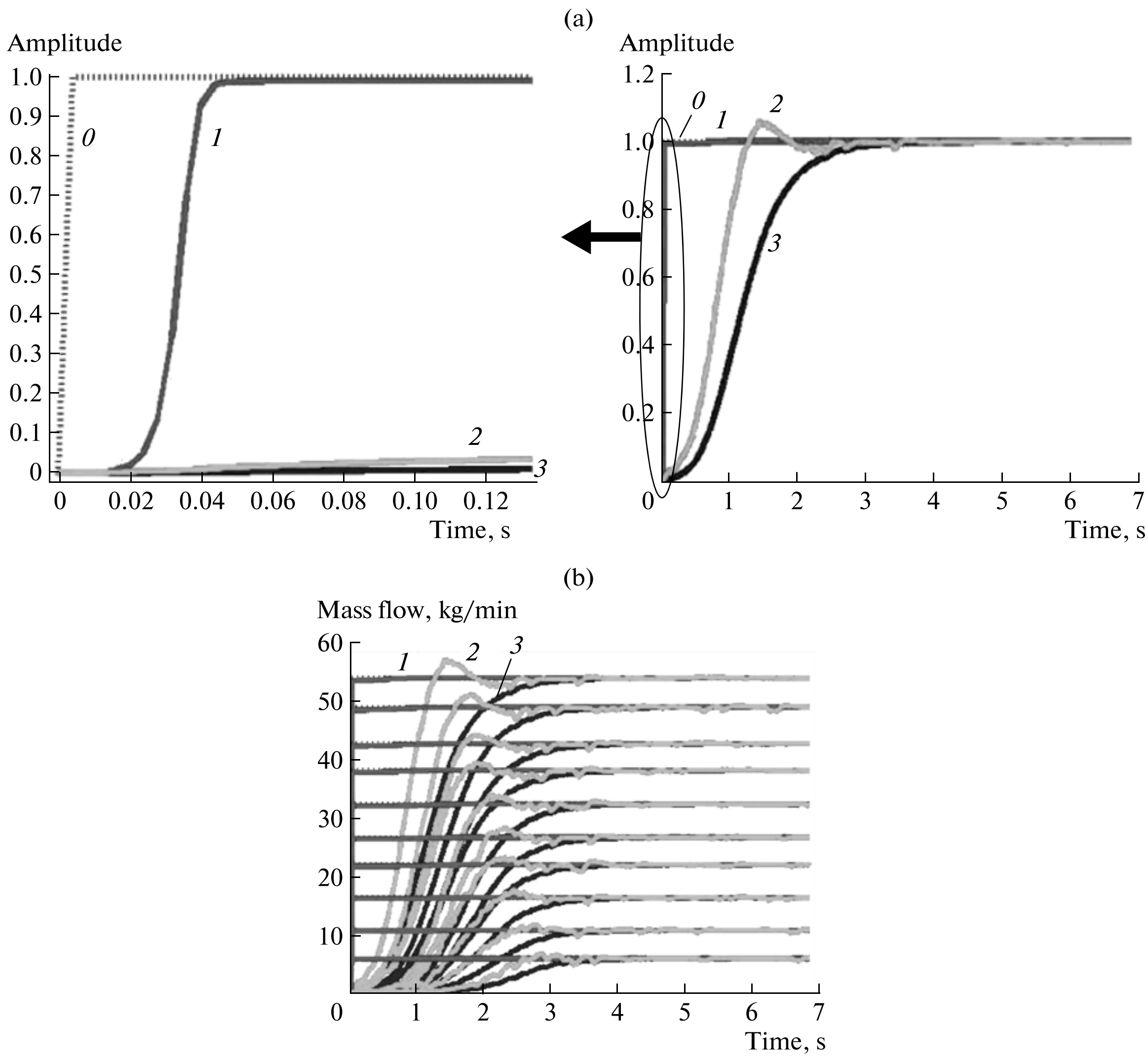

Fig. 7. The compensated output of CMF (a) and outputs of various flow (b). *0* – reference (a), *1* – NN compensation, *2* – zero and pole compensation, *3* – before compensation.

Table 3. Main characters of dynamic performance in whole-span

Main characters of dynamic performance in whole-span (55 kg/min)			
Character	Before compensation	After the zero-pole point compensation	After NN compensation
Rise time, s	2.368	1.176	0.040
Peak time, s	–	1.418	–
Overshoot	–	5.5%	–

network which can reflect the compensation system originally, make weights and parameters of the network work in the vicinity of the global minimum [15]. Then, add the trained neural network to the system to improve the efficiency of learning online.

6. CONCLUSION

(1) In this paper, the BP neural networks is designed to connect in series to the CMF's output port as dynamic compensator, which works for improving system's dynamic characteristics. Compared with general method, it only need to know the actual input and expected output of the sensor, instead of depending on the mathematical modeling of the system. Experiments have shown that the method overcome the complexity in modeling and the error produced by modeling simplification. Therefore, it greatly improves the dynamic characteristics of the Coriolis mass flowmeter.

(2) During the research, we found that the more hidden layer nodes there are the higher accuracy we can gain. But, accordingly the training time becomes longer. On the contrary, reducing hidden layer nodes will reduce the training time, but may result in the system oscillation and convergence which making it difficult to carry out multiple iterations. Hence, it is a critical issue for different systems to determine the number of hidden layers and hidden layer nodes in each layer. However, there exists no good method or criteria to determine the number at present, which is worth further research.

ACKNOWLEDGMENTS

This study is supported by the National Natural Science Foundation of China with grant No.60904094.

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