The scroll flow and torque prediction with the wavelet neural network optimized by PSOA and BP

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Abstract

A new Compressed Air Energy Storage(CAES) with scroll was proposed to promote the storage efficiency, which can be acquired by the scroll efficiency tracking control with the timely evaluation, but the flow and torque is not easy acquired because the sensors possessed the merits of high price, lower life-span and subjection to the disturbance, so a torque and flow prediction algorithm based on Wavelet Neural Network (WNN) is proposed adopting a hybrid learning algorithm combining Particle Swarm Optimization (PSO) with BP. Through the comparison between predictive and the experimental data and the scroll efficiency experiment, the proposed prediction method is validated and can be successfully used to improve Pneumatic conversion efficiency.

Keywords: Compressed Air Energy Storage, Scroll, Particle Swarm Optimization (PSO), Wavelet Neural Network

1 Introduction

With the increasing depletion of conventional energy and the worsening environmental pollution, wind energy and solar energy have become the new driving force for the global economic growth, but the intermittent and the fluctuation seriously affect the power quality. Many researches show that the storage is the effective way to solve the above the problem.

Due to long span life and non-pollution, CAES is a promising storage way to stabilize the power fluctuation [1], however the lower storage efficiency seriously limits the real application of the CAES. Efficiency tracking is an effective method to enhance storage efficiency, but must real-timely evaluate the scroll performance by the flow and torque, but the flow sensor is vulnerable to environmental disturbance making the measured data deviate from the actual value. Furthermore, adding flow sensor and corresponding filter increases pressure loss and reduces storage efficiency. In addition, Surge is harmful and easily to occur at smaller flow, so it is important to real-timely monitor the flow and torque. In addition, torque sensor is all expensive and easy to be destroyed. Therefore, it is not advisable to measure the flow and torque by sensors, which make it necessary to find a new effective approach to acquire the flow and torque.

As the literatures [2, 3] described, scroll models are so complicated that could not be used to predict the flow and torque, which all modelled for performance analysis. In view of effective nonlinear modelling and prediction ability of WNN [4, 5], WNN can be applied to predict the scroll flow and torque. WNN originated from the decomposition in signal processing, which has become more popular lately [5, 6]. Zhang [6] proposed a new notation of wavelet network as an alternative to feed-forward neural networks for approximating arbitrary nonlinear functions based on wavelet transform theory. However, the architecture and the learning algorithm of WNN severely affect the ability of predicting and modelling, so many researchers have been studying on the parameters optimization of WNN, but all were focused on adjusting the initial parameters. Kuok proposed the PSOA for optimizing feed-forward neural networks, which acquired excellent performance because of rapid global search ability of PSOA [7]. Meanwhile Back Propagation Network (BP) owns the faster local optimization ability, which can compensate little local optimization ability of the PSOA. For above reason, the WNN optimized by the PSOA and BP is proposed for predicting the scroll flow and torque [6-8].

2 Scroll Performance Analysis

As shown in Figure 1, the new compress air storage system with scroll is proposed to solve wind power fluctuations at front of the generator. Scroll can be operating in the compressor mode and expander mode. The scroll can be running in the compressor mode when wind capture power is more than the load power, and the excess power will be stored in the storage vessel.

While the wind power could not supply for the load, the scroll will be working on the expander mode to supply the deficient power. High efficiency of the scroll is important for the real application of the compressed air storage system, but the scroll efficiency is affected by the

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speed and the discharge pressure, so the maximum efficiency tracking is important to make the scroll run the highest efficiency under any conditions.

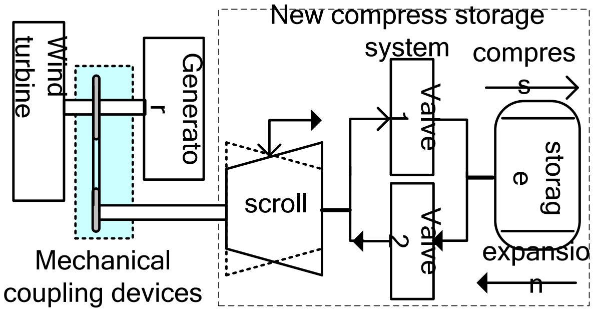

FIGURE 1 New Compressed Air Energy Storage system with scroll

But the scroll maximum efficiency tracking must be finished by the SC efficiency evaluation timely, through which to optimize control scroll. The scroll efficiency can be evaluated by Equation (1).

$$\eta_{scroll} = \frac{p_{\mathrm{d}} Q_{\mathrm{d}} \ln\left(\frac{p_{\mathrm{d}}}{p_{\mathrm{atm}}}\right)}{T_{\mathrm{in}}\omega}, \quad (1)$$

where p_{d} is the discharge pressure; Q_{d} is the discharge flow; T_{in} is diriving torque, and ω is angular speed.

As the Figure 2 described, scroll machine consists of two intermeshed identical scrolls, which form many closed chambers, and chamber air will be pressuring successively with the Chambers volumes change gradually. When orbit angle revolves to the discharge angle, the compressed air can be discharged to the storage. Driving Torque has strong relation with the discharge pressure p_{d}. In view of the fixed volumetric machine of the scroll, scroll flow depends on the speed and the inlet volume. Hence the speed and storage pressure are the key influence factor on flow and torque, which will be taken as the principal input for the prediction.

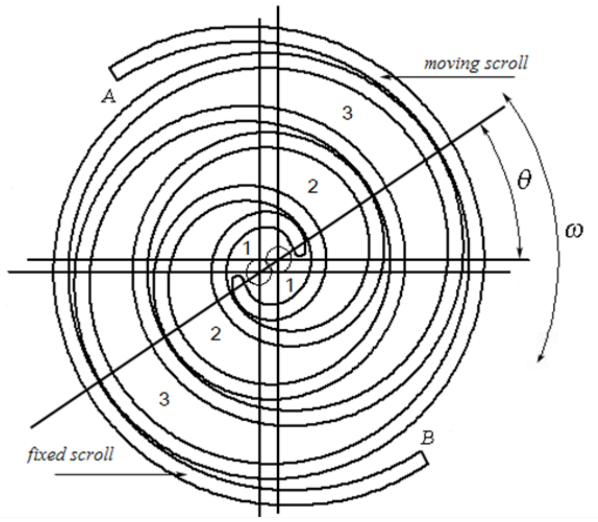

FIGURE 2 Scroll machine structure

3 Scroll flow and torque prediction algorithm

The WNN optimized by the hybrid learning algorithm combining the PSO with the BP algorithm is applied to predict the flow and torque of the scroll. For sake of quickly acquiring optimal result, this algorithm uses the PSO to do global search in the beginning, and then uses the BP to do local search around the global optimum.

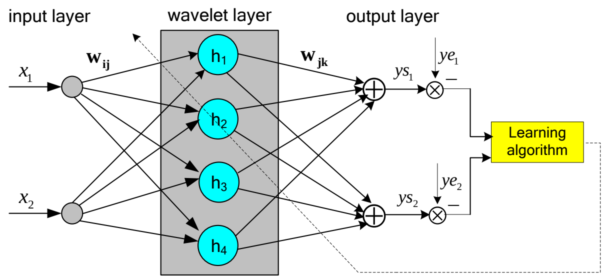

FIGURE 3 Three-layer WNN structure

3.1 THE STRUCTURE OF THE WNN

As the key factor influencing the flow and torque of the scroll, the speed and discharge pressure was taken as the input variable (x_1 and x_2), while the flow and torque acted as the output variable (ys_1 and ys_2). The structure of the WNN model is shown in Figure 3. It is designed as a three-layer structure of 2-4-2, which comprised of an input layer, a wavelet layer, and an output layer. For the discrete wavelet transform, the mother wavelet $\varphi(x)$ describes the dilation a and the translation b as follow:

$$\varphi_{a,b}(x) = \varphi\left(\frac{x-b}{a}\right). \quad (2)$$

In this paper, we use the Morlet wavelet as the wavelet function which can be controlled and expressed as follow:

$$\varphi(t) = \cos\left(\frac{7}{4}t\right)\mathrm{e}^{-\frac{t^2}{2}} \quad (3)$$

Therefore, the activation function of the jth wavelet node connected with the two input data is represented as:

$$h(\mathrm{j}) = \cos\left(\frac{7}{4}\sum_{\mathrm{i}=1}^{2}\frac{\mathrm{w}_{\mathrm{ij}}x_{\mathrm{i}} - b_{\mathrm{j}}}{a_{\mathrm{j}}}\right)\mathrm{e}^{-\frac{1}{2}\left(\sum_{\mathrm{i}=1}^{2}\frac{\mathrm{w}_{\mathrm{ij}}x_{\mathrm{i}} - b_{\mathrm{j}}}{a_{\mathrm{j}}}\right)^2} \quad \mathrm{j} = 1 \sim 4 \quad (4)$$

According to the theory of multi-resolution analysis, output can be regarded as a linear combination of wavelets, so it can be expressed as:

$$\mathrm{ys} = \sum_{\mathrm{j}=1}^{4}\mathrm{w}_{\mathrm{jk}}h(\mathrm{j}), \quad (5)$$

where w_{ij} and w_{jk} are the input-wavelet layer and wavelet-output layer adjustable weighting parameters, a_j and b_j are the dilation and translation factors, which all are optimized to improve the performance of the WNN.

The fitness function of the k[th] training sample can be defined as follows:

$$finess(k) = \frac{1}{2}\sum_{i=1}^{2}(ys_i(k) - ye_i(k))^2 , \quad (6)$$

here i is the number of the output node; k is number of the sampling data; $ys_i(k)$ is the model prediction output, while $ye_i(k)$ is the actual output, $e(k)$ is the learning error.

3.2 THE PARAMETER OPTIMIZATION ALGORITHM FOR THE WNN

Based on these considerations of the relative merits analysis of PSO and BP, the project adopts a hybrid algorithm combing with PSO and BP to optimize parameters of WNN for flow and torque prediction. As shown in Figure 4, the WNN key parameters is optimized including three steps, I) PSO algorithm is used to find the optimum region for the initialization of the BP algorithm; II) BP algorithm is applied to find turn optimum solution; III) optimal result is determined by the comparison of the PSO and BP result.

3.2.1 PSO optimization process

This project, PSO algorithm is initialized with a group of random particles including weights, translation factor and dilation factor. Each particle can be represented as:
Particle(i)=[w_{11} w_{12} w_{13} w_{14} w_{21} w_{22} w_{23} w_{24} w_{31} w_{32} w_{33} w_{34} w_{41} w_{42} w_{43} w_{44} a b],

$$\text{Particles matrix} = [\text{Particle}(1);\text{Particle}(2);\ldots\ \text{Particle}(n)] ,$$

here m is the total particles, and this project set the particles as 200.

Every particle holds its velocity $v_{id}(t)$ and poison $x_{id}(t)$, which can be dynamically adjusted by

$$\begin{aligned} v_{id}(t+1) = w v_{id}(t) + c_1 \cdot r_1 \cdot [pb_{id}(t) - x_{id}(t)] + \\ c_2 \cdot r_2 \cdot [pg_d(t) - x_{id}(t)] \end{aligned} , \quad (7)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) , \quad (8)$$

$$w(t) = w_0 - (w_0 - w_{end})(t / \text{maxgen1})^2 , \quad (9)$$

where, $pb_{id}(t)$ is the best-found location of i[th] particle at the time; $pg_d(t)$ is the global best position among all particles up to time; c_1 and c_2 are two positive constants, while r_1 and r_2 are two random parameters; w is the inertia weight to balance between global and local explorations, which can be adjusted according to the Eq. (9), and w_0 and wend are the initial and the end inertia weights; maxgen1 is the maximal iterative times of the PSO, and this project set it as 500.

As shown in Fig.4, PSO optimization is repeated until the convergence criterion or stop conditions are satisfied, which can be set as $finess(k) \le 0.001$ and $maxgen1$=500. Or else, the velocity, poison and w are renewed repeatedly, and then performance criterion is evaluated according to Equation (6). Then, best position and group best position can be updated repeatedly until the predefined convergence criterion is satisfied, which can be set as the initialisation for the BP algorithm.

3.2.2 BP optimization process

BP will start to search the optimum around the pg that the PSO acquired until the stop conditions are met. The optimal stop condition sets as $maxgen2$=1500, and the best optimal solution can be adjusted by the Equation (10) [9] repeatedly.

$$\begin{cases} W_{ij}(t+1) = W_{ij}(t) + \eta\Delta W_{ij}(t) = W_{ij}(t) - \frac{\eta}{2}\sum_{h=1}^{2}\frac{\partial ys_h}{\partial W_{ij}}e \\ W_{jk}(t+1) = W_{jk}(t) + \eta\Delta W_{jk}(t) = W_{jk}(t) - \frac{\eta}{2}\sum_{h=1}^{2}\frac{\partial ys_h}{\partial W_{jk}}e \\ a(t+1) = a(t) + \eta\Delta a(t) = a(t) - \frac{\eta}{2}\sum_{h=1}^{2}\frac{\partial ys_h}{\partial a}e \\ b(t+1) = b(t) + \eta b(t) = b(t) - \frac{\eta}{2}\sum_{h=1}^{2}\frac{\partial ys_h}{\partial b}e \end{cases} , \quad (10)$$

where η is the learning rate, and the $e = ys(t) - ye(t)$.

3.2.3 Optimal result decision process

BP algorithm searches the optimum around Pg for some generations (1500). If the stop condition is met, the optimization must be decided by the comparision with PSO and BP result, and the smallest can be transmitted to WNN.

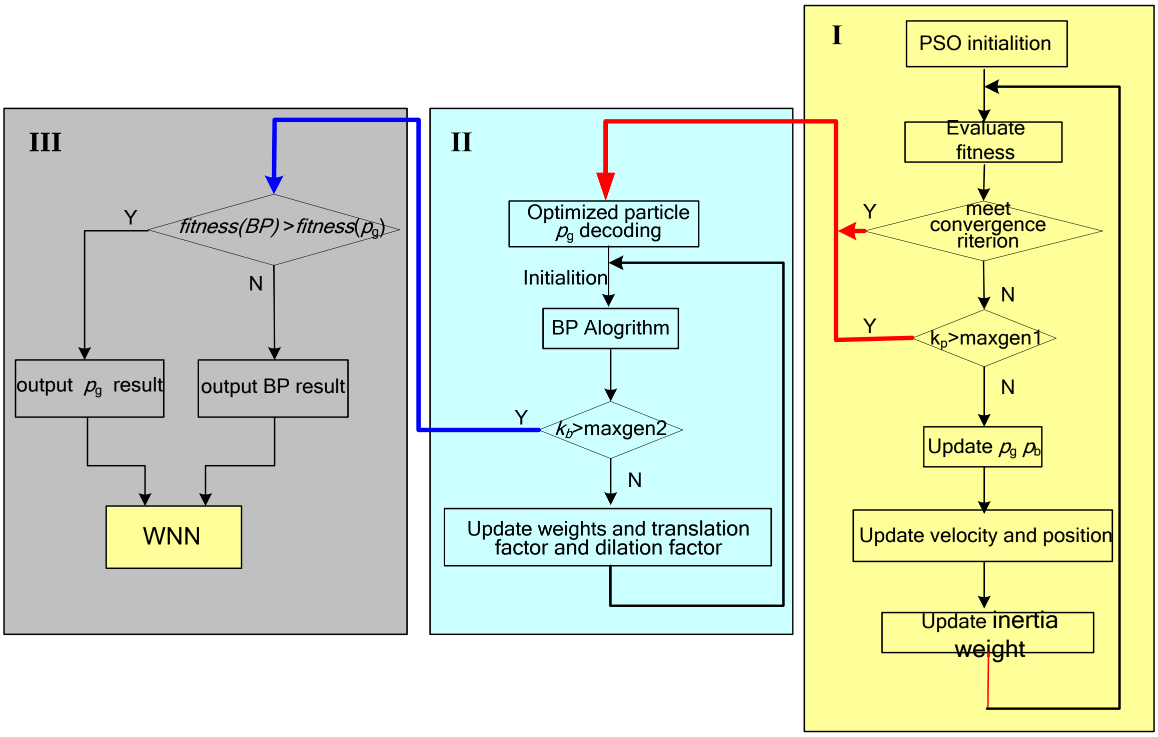

FIGURE 4 WNN key parameters optimization principle

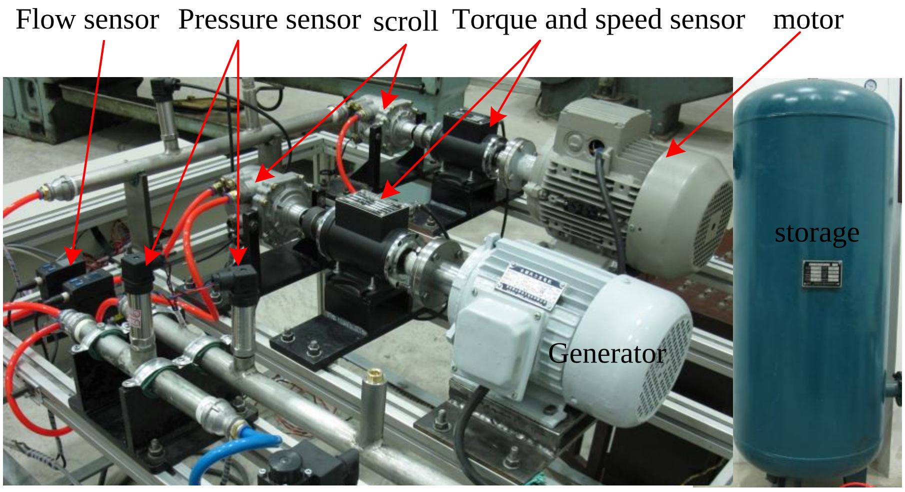

FIGURE 5 New CAES with scroll experiment test rig

4 Experiment Result Analysis

As shown in Figure 5,the new CAES experiment test rig is set up including 4kW Siemens motor, scroll machine(WHX-86,discharge pressure:0-600kpa), storage vessel(1.5m3), scroll flow and torque. Measuring and acquiring system. Multi-speed scroll experiment are performed by motor, and then 3580 groups data including speed, discharge pressure, flow and torque were collected , and 3000 groups were applied to train and optimize the WNN key parameters, while the rest were used to validate the model identified.

As shown in Figure 6, average fitness of the flow and torque are respectively 0.01 and 0.013. The model prediction output has been successful in approaching the experiment torque and flow, which validated the WNN optimized by hybrid training algorithm efficient.

As shown in Figure 7, scroll efficiency tracking is realized from the timely efficiency evaluation by the predicted flow and torque. With the increase of discharge pressure, the scroll is running with the highest efficiency all the time. When discharge pressure less than the designed pressure, the efficiency tracking is acquired by the elevate speed to accelerate the efficiency enhancement corresponding to the time from 0s to 1500s; while the time from 1500s to 3500s, the discharge pressure is larger than the designed pressure, the efficiency tracking is realized through the raising speed to prevent the efficiency reduction. The efficiency tracking experiment further validated the prediction algorithm, which can be directly used to the CAES system.

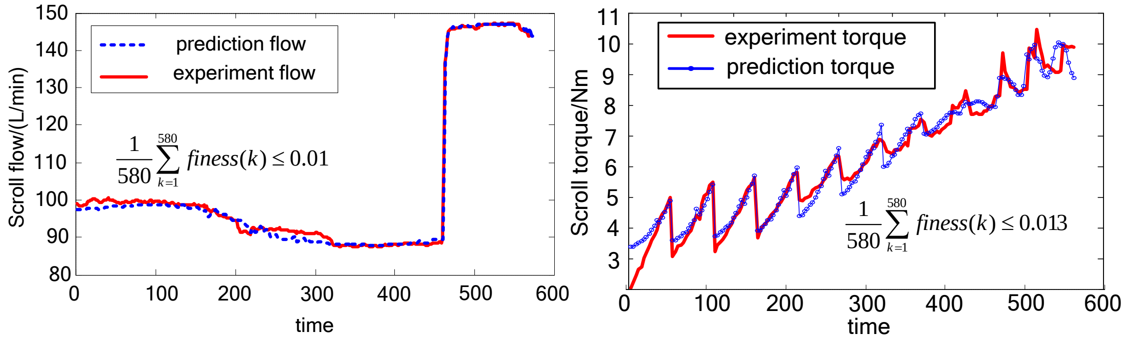

FIGURE 6 The comparison with the prediction and experiment result

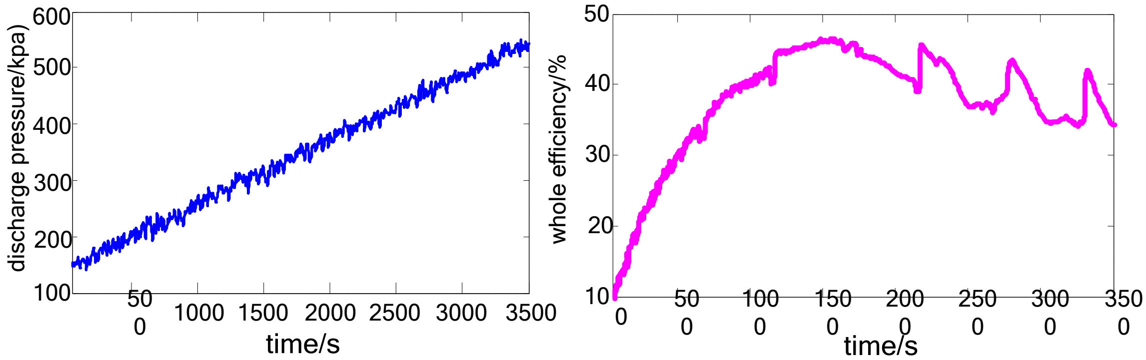

FIGURE 7 Scroll maximum efficiency tracking with the flow and torque prediction

5 Conclusion

This paper proposed a flow and torque prediction algorithm adopting WNN optimized by the PSO and BP. Key parameters of WNN is trained by the multi-speed experiment data. With comparison of the prediction and experiment data and the scroll efficiency tracking experiment, the prediction algorithm of the flow and torque is validated, which can be successfully to improve the Pneumatic conversion efficiency.

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