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On-line Tuning PID Parameters in Idle-speed Engine based on Modified BP Neural Network by Particle Swarm Optimization

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Abstract: PID control systems are widely used in many fields, and many methods to tune parameters of PID controller are known. When the characteristics of the object are changed, the traditional PID control should be adjusted by empiri cal knowledge. It may bring a worse performance to the system. In this paper, a new method to tune PID parameters cal led as the modified back propagate network by Particle swarm optimization is proposed. This algorithm combines the c onventional PID control with the back propagate neural network (BPNN) and the particle swarm optimization (PSO). T his method is demonstrated in the engine idle-speed control problem; the proposed method provides prominent perform ance benefits over the traditional controller in this simulation.

Keywords: BP neural network, Particle swarm optimization; PID control; Engine idle-speed control.

I. INTRODUCTION

Vehicle is a symbol of modern civilization. It doesn't only bring comfortable life to people, but also promotes the economic and social progress. For whole automobile, the engine system is the most important component of the vehicle. Following statistics of some research, the spark ignition engine spends a large percentage of their operation in the idle-speed region. In this condition the engine management system aims to maintain a constant idle speed in the presence of alterable situation. The engines are inherently nonlinear, incorporating variable, time delays, and discontinuity which make to model to be difficult. Because of this reason, some researches, for example neural network approach, are well known to fit for the engine control system. Neural network is well fit for engine control system.

In the last decades, the conventional PID control has been largely applied to many fields. Because of its versatility, PID strategy still remains the most common control algorithm in modern industry. When the idle-speed engine system occupies in the alterable situation, the rapid and accurate response of the controller is necessary. In this research, a learning type PID control system using modified BP network by particle swarm optimization is designed which will bring prominent performance benefits over a traditional controller in this application.

II. Modified BP network by Particle Swarm Optimization

1. Back Propagate Neural Network

BP network is widely used in many fields. It is proposed by Rumelhart in 1986. The BPNN is a multi-layers network that consists of the input layer, the hidden layer, and the output layer. The standard structure will be shown in Fig 2.1.

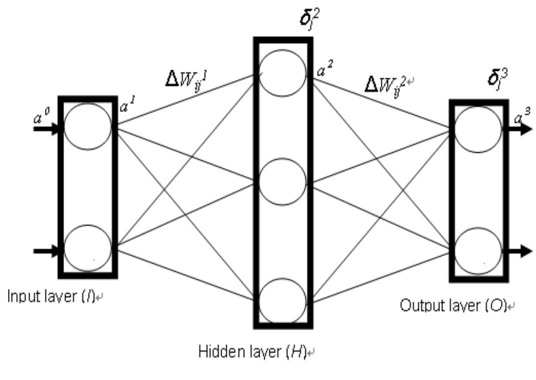


Fig 2.1.Structure of BP network

BP algorithm step:

Firstly, the actual output of BPNN will obtain from the actual outputs as eq. (2.1). It is forward progress.

$$a^{m+1} = f^{m+1}(w^{m+1} * a^m + b^m),m = 0,1,\ldots,M-1 \quad (2.1)$$

a: output of each layer
w: weight value
b: bias value
m: number of layer

Secondly, the error will be generated at the output layer by comparing between the actual output and the target output. The error function at output layer is defined as

$$Ep = \frac{1}{2}\sum_{k=1}^{M}(T_k - A_k)^2 \quad (2.2)$$

T_k : reference output

A_k : actual output

The total error function of neural network is shown in eq. (2.3).

$$E = \sum_{p=1}^{p} Ep \quad (2.3)$$

P: total numbers of pattern

Thirdly, the gradient descent method is utilized to calculate the weight of network and adjusts the weight of interconnections to minimize the output error. The gradient descent algorithm adopts the weights according to the gradient error, which is given by eq. (2.4).

$$\Delta W_{ij} = -\eta \times \frac{\partial E}{\partial W_{ij}} \quad (2.4)$$

η : Learning rate

The general form of ∂E/ ∂W is expressed as the following eq. (2.5).

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n \times A_i^{n-1} \quad (2.5)$$

A: output value of each layer

W: connective weight

δ: error signal

n: layer number of BP network

Substituting (2.4) into (2.5), the gradient error is expressed as

$$\Delta W_{ij} = \eta \times \delta_j^n \times A_i^{n-1} \quad (2.6)$$

ΔW adjusts the weight value between the input layer nodes to the output layer nodes from output layer to the input layer. This is known as the back propagates progress. According to these adjustments, the error will decrease until the small set point. However, there are some disadvantages in BP algorithm. It is easy to converge to local minimum point; and it means the long time to convergence and training are needed.

2. Particle Swarm Optimization

Particle swarm optimization is a stochastic population-based evolutionary computer algorithm for solving problem. It is one of intelligence algorithm based on social-psychological principles. It provides insights into social behavior, as well as contributing to engineering applications. The particle swarm optimization algorithm was firstly described in 1995.

$$v_i = w * v_i + c_1 * r_1 * (pbest_i - x_i) + c_2 * r_2 * (gbest_i - x_i) \quad (2.7)$$

$$x_i = x_i + v_i \quad (2.8)$$

x: position of particle;

v: velocity of particle;

Pest: personnel best position of particle swarm;

Gbest: global best position of particle swarm

C: learning rate;

r: random number;

w: inertial factor;

Eq. (2.7) and (2.8) are learning rule of particle swarm optimization.

Flow chart of particle swarm optimization is shown in Fig. 2.2.

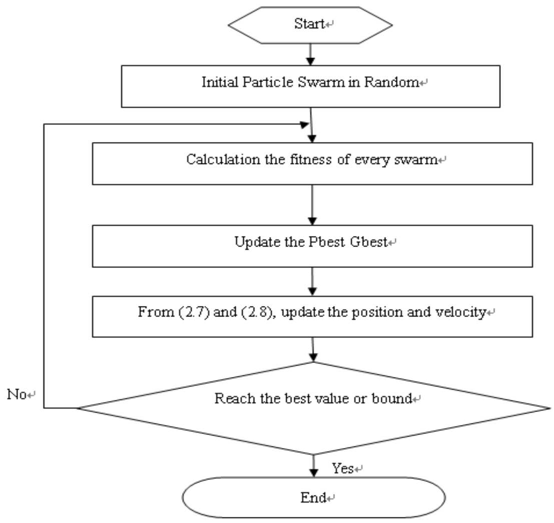


Fig 2.2.Flow Chart of Particle Swarm Optimization

There are three points why the PSO is choice to combine with BP network.

—Particle swarm optimization is a type of the global optimal method. It will find the global minimum point.

—The speed of search in PSO is much faster than the genetic algorithm.

—PSO has the simple structure to program.

3. Modified BP network by PSO

A new algorithm to combine BP network and PSO is proposed to overcome the disadvantages of BP network. The whole BP network training process consists of two Phases:

Phase 1: The global optimization procedure
(Particle swarm optimization)

- Step1.1 To design a group of swarm this represents the weight and bias of BP network.
- Step1.2 To calculate by forward progress in BP network to evaluate warm by error rate.
- Step1.3 To operate particle swarm optimization

Phase 2: Refining the learning procedure.
(Traditional BP algorithm training)

- Step2.1 To train BP network by traditional method.

In this method, some groups of particle swarm will be generated randomly. They represent the weight value and bias of BP network. Then these values will be taken into BP network and calculated in BP's forward progress. The function is shown in eq. (2.1). Comparing with actual output, the error of each group will get as eq. (2.2). Eq. (2.2) will be choice as the cost function of particle swarm optimization. After some steps, eq. (2.7) and eq. (2.8) will be used to calculate. This is the optimization process by PSO. During the many times of the optimization, Ep will reach the expected value. Then the best particle swarm will be generated. Next step is to take the optimized weight value and bias into BP network, and train BP network as traditional BP algorithm. The following figure will demonstrate the computational steps in detail for 2-3-1 structure network as an example.

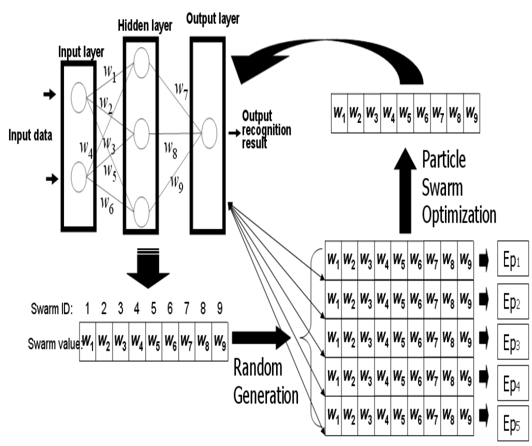


Fig 2.3.Schematic diagram of new algorithm

According to these procedures, it has proven that the new algorithm gets much faster convergence and more powerful calculation.

III. Idle-Speed Engine System

To compare with the traditional PID control scheme, the new algorithm is simulated on a simple generic engine model. The engine system changes throttle angle to keep the engine speed on fixed idle speed in alterable load demands. The following figure illustrates the model of the engine. In this simulation, 800Nm has been choice as a reference value of the idle-speed.

Dynamic block of components are taken as

$$Gi(s) = \frac{9000}{(0.05s+1)} \qquad Ga(s) = 0.85e^{-0.1s}$$

$$Gr(s) = \frac{20}{(3.5s+1)} \qquad Kn = 1*10^{-4}$$

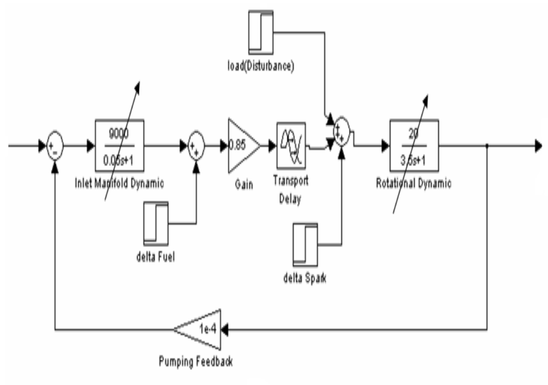


Fig 3.1.Engine idle-speed model

IV. Simulation and Comparison

1. Experiment Settings

In this section, the new algorithm will be compared with the traditional PID control scheme and PID control with BPNN control scheme in the idle-speed engine system. There are two cases of the experiment for the idle-speed engine. The one is to increase the gain of Gi. Gi represents the inlet manifold dynamic block. Because of the carbon deposition and dust, it will make the gain of Gi to be increased. The other is to increase the gain of Gr. Gr represents the power-train rotational dynamic block. When the loads are increased, the gain of Gr will follow the increment. In these two situations, three algorithms are adopted to keep the idle speed of engine to be stable.

The three methods of PID control law adopt the increment PID form shown in eq. (4.1).

$$u(k) = u(k-1) + Kp[e(k) - e(k-1)] + Kie(k) + Kd[e(k) + e(k-2) - 2e(k-1)] \quad (4.1)$$

2. Structure and Parameters setting

In the traditional PID control system, there are so many method to determine the PID parameters, including Ziegler Nicolas Method, pole placement, Nyquist based design, and so on. The parameters of PID controller are determined here by Ziegler-Nicolas method.

In modified BP network by PSO control system, the structure of the modified BP network by PSO control system is shown in Fig.4.1.

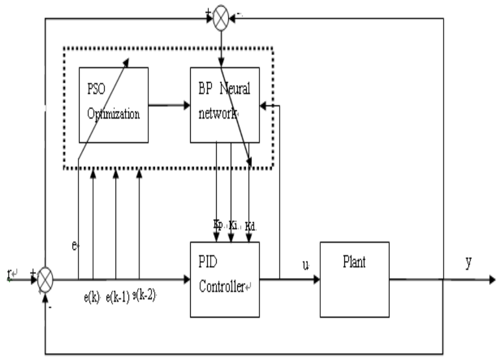


Fig 4.1.Structure of new self-tuning PID control system

It consists of four parties: the conventional PID controller, BP neural network, the particle swarm optimization and plant, where Kp, Ki, Kd are the coefficients of the proportion, the integral and the differential.

The learning algorithm of the new PID control system is as that:

—For the BPNN, there are 4 nodes in the input layer, 4 nodes in the hidden layer, and 3 nodes in the output layer. $\eta = 0.5$;

—Observe y(k) and r(k), e(k)=y(k)-r(k)

—Generate the groups of the particle randomly, the PSO optimizes the initial weights of BPNN and gets the initial value of parameters.

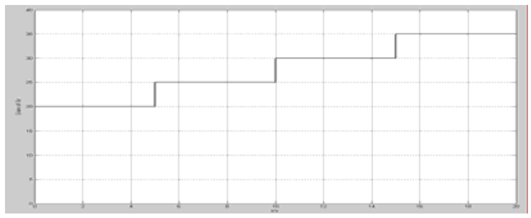
—Inputs and outputs of each layer of BPNN are calculated and three parameters of PID will be obtained.

—Calculate the output of the controller from eq. (4.1).

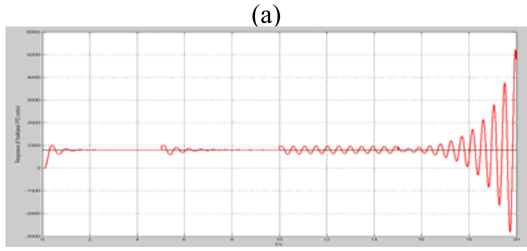
In the BPNN with PID control system, the structure of BPNN is same with the new method, and the difference is calculated just only BPNN without PSO optimization. In next section, the advantages of the new algorithm will be shown by the simulation.

3. Simulation Result

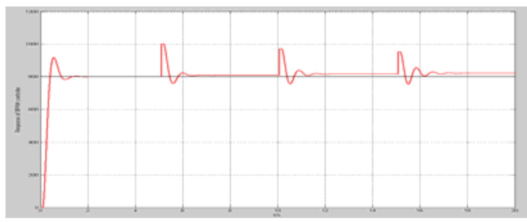
In the experiment 1, the gain of Gr is changed from 20 to 35 in 20 seconds shown in Fig.4.2 (a). The responses of the control systems are shown as follows. Fig.4.2 (b) is the result of the traditional PID control. When the gain of Gr increases up to 30, the divergence response is shown. Obviously, it is unexpected. In the Fig.4.2(c), the response of BP network control system is shown. It has improved but the steady state error is remained. When PSO is adopted to optimize the BP network in control system, the response is shown in Fig.4.2 (d). The output of the control system has improved dramatically. The state error has eliminated. Fig.4.3. (e) shows the update of Kp, Ki and Kd. The solid line is for the new algorithm and the dashed line is for the BP network. The red curve is the parameter Kp; The green curve is the parameter Ki; The blue curve is the parameter Kd.



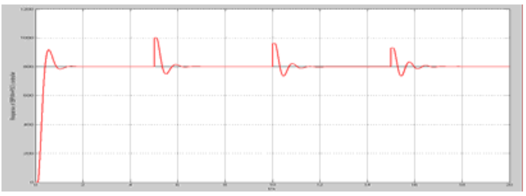
(a)



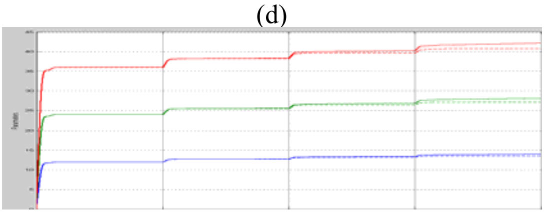
(b)



(c)

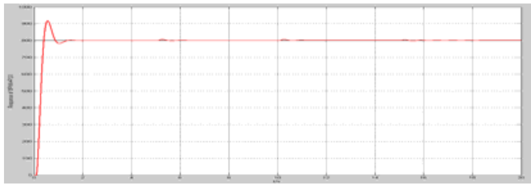


(d)

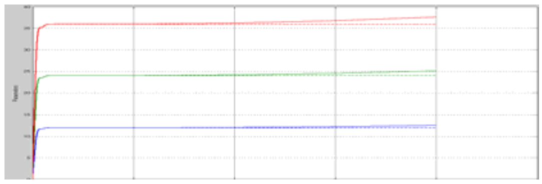


(e)

Fig 4.2.Experiment for the increment of Gr



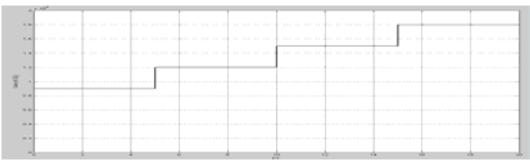
(d)



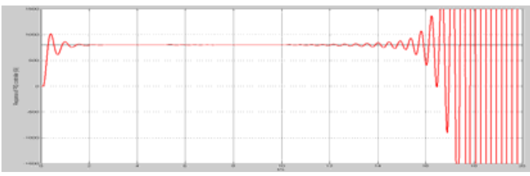
(e)

Fig 4.3.Experiment for the increment of Gi

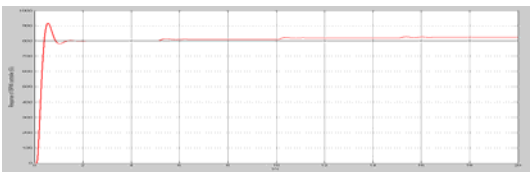
In the experiment 2, the gain of Gi is changed from 9000 to 18000 in 20 seconds shown in Fig. 4.3(a). The responses of the control systems are shown as follows. Fig.4.3 (b) shows the response of traditional PID control. When the gain of Gi increases up to 15000, output of system is unstable. In Fig.4.3(c), it is response of BP network control system. It has improved greatly, but there is steady state error. In Fig.4.3 (d), the output of modified BP network by PSO control system is shown, and the state error is eliminated. Meanwhile, the response of the control system is much faster and higher accuracy. Fig4.3. (e) shows the update of parameters of BP network and BP with PSO method. Because of combining with PSO, the modified BP network is more effective for the update of the parameters.



(a)



(b)



(c)

V. Conclusion

In this paper, an effective approach to tune PID parameters by on line is proposed. The PID controller based on BPNN and PSO improves the level of intelligent decision making and can adapt to various working requirements. PSO will improve BP network greatly, and it makes BP network faster convergence, and avoid local minimum point. According to procedure proposed in this paper, the new algorithm has shown not only powerful calculation but also strong robustness. The satisfactory simulation result has proven that the proposed algorithm is effective for the idle-speed control problem.

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