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OPTIMIZATION OF HYDROGEN-FUELED ENGINE IGNITION TIMING BASED ON THE PARTICLE SWARM OPTIMIZED FUZZY NEURAL NETWORK

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ОПТИМІЗАЦІЯ ВИПЕРЕДЖЕННЯ ЗАПАЛЕННЯ ДВИГУНА НА ВОДНЕВОМУ ПАЛИВІ НА ОСНОВІ НЕЙРОННОЇ МЕРЕЖІ З НЕЧІТКОЮ ЛОГІКОЮ, ОПТИМІЗОВАНОЮ МЕТОДОМ РОЮ ЧАСТОК

Purpose. In order to solve the increasingly serious energy crisis and environmental pollution problems, to find a clean and renewable alternative fuel for vehicle engines becomes the only way. In this paper, a hydrogen-fueled engine experiment system has been established. And because of some combustion characteristics of hydrogen, abnormal combustion such as pre-ignition and backfire usually happens. Ignition timing optimization is very helpful for the suppression of abnormal combustion.

Methodology. On the basis of ignition timing data calibrated on hydrogen-fueled engine experiment system, an ignition timing optimization model, which is the function of rotating speed and loading of the engine, is established by the fuzzy neural network (FNN) combined with the particle swarm optimization (PSO). A simulation experiment has been carried out on the model.

Findings. The experiment results show that the mean absolute error of the prediction is 0.704 and the mean relative error is 2.2%. The algorithm is capable of fast, accurate forecasts on the best ignition timing of the hydrogen fueled-engine.

Originality. In this paper, a PSO-FNN model was firstly used in the hydrogen-fueled engine experiment system and it promotes the application of artificial intelligence algorithm in Engineering.

Practical value. The PSO-FNN model was proved to be a very effective approach to optimize the ignition timing, because it avoids a large number of engine calibration tests and greatly reduces the workload of the experiment and improves the efficiency.

Keywords: *fuzzy neural network, particle swarm optimization, hydrogen-fueled engine, ignition timing, optimize*

Introduction. Nowadays, the energy and resources are increasingly strained and the living environment is gradually deteriorated. Countries around the world are aware of the importance of the search for cleaner and sustainable fuel instead of traditional fossil fuels. For this purpose, people carried out further experiments and research. As a clean, renewable energy, the hydrogen fuel provides an ideal direction to solve the energy crisis because of its advantages of high heating value, less pollution, etc. Hydrogen has many unique advantages as an engine fuel, but compared to fossil fuels, hydrogen fuel trends to generate pre-ignition, backfire and other abnormal combustion in the combustion process. The volume power is low and the engine produces large amounts of NO_x at high loads. Ignition timing optimization of hydrogen fueled-engine is the key technology to improve engine performance and avoid abnormal combustion, which is the current focus of research. The traditional ignition timing control method is measuring the parameter data points under different operating conditions (speed, load), which conforms to the optimization thought. The collection of the-se points forms a three-dimensional MAP, and the data is stored in the ROM of the ECU. In actual engine operation process, ECU transfers out the best ignition timing data from the ROM based on the information provided by load and speed sensors. Then the program does some appropriate amendments, the revised data is passed to the actuators to control the engine running. But its control law (namely MAP) needs a lot of engine pre-test to calibrate, whose workload is voluminous, and it is impossible to take all conditions into account [1].

Junfa Duan [2] has concerned on the optimizing of the hydrogen injection timing and pressure to control the backfire. Tien Ho and Vishy Karria [3] has built a suite of neural network models to predict accurately the effect of different engine operating conditions. Anuj Pal and Avinash Kumar Agarwal [4] have done a study of laser ignition in a hydrogen-fueled engine. Kaname Naganuma and Toru Honda [5] have researched on the high-pressure direct injection hydrogen engine. However, these studies have not solved the problem of the optimization of the ignition timing of the intake port injection hydrogen-fueled engine to solve abnormal combustion in nature. And these researches have not solved the problem of weak convergence speed and the weak ability of processing nonlinear data of neural network. This paper solves these problems by PSO-FNN and can be used to get the ignition MAP of the hydrogen-fueled engine to avoid abnormal combustion.

Fuzzy Neural Network (FNN) has been widespread concerned in different applications for its good abilities of nonlinear function approximation, adapting and learning, and parallel information processing. It is the subject that scholars are willing to study now. Using neural network technology to deal with fuzzy information can effectively solve the problem of obtaining the fuzzy rules and generating membership functions. The introduction of the fuzzy logic technology, which has the ability of logical inference and high order information processing, can greatly broaden the scope and ability of processing information for neural networks. It combines fuzzy logic with neural networks, cannot only represent qualitative knowledge, but also has the ability of self-learning and processing quantitative data [6]. However, the network has the shortcomings of a complex learning process on network structure and parameters, slow convergence and easy to fall into local optimum, which has limited its application.

As a stochastic optimization algorithm based on the theory of swarm intelligence, Particle Swarm Optimization (PSO) guides optimized search based on the swarm intelligence which is produced by cooperation and competition among the particles of the swarm. As a new optimization algorithm, PSO [7] has the characters of fast convergence speed, high robustness, strong global search ability, and without the aid of the characteristic information of the problem itself (such as gradient). Combining PSO with neural networks, optimizing the connection weights of the neural network based on the PSO algorithm, can overcome above problems of the neural network better.

In this paper, on the basis of previous studies, a fuzzy neural network optimization model on the engine ignition timing was proposed for the issues of complicated calibration on hydrogen engine ignition timing. And the network was trained through PSO algorithm to find the right value and the corresponding optimal fitness, which improved its shortcomings of slow convergence and easy to fall into local extreme value. And predict the best ignition timing from the known data.

Particle swarm optimized fuzzy neural network (PSO -FNN). ***Fuzzy neural network theory.*** Fuzzy Neural Network, which can handle fuzzy information, is a kind of neural network system that all or part of it is composed of fuzzy neurons. The neural network has a large number of highly connected processing elements (nodes), which demonstrates the ability to learn and generalize according to the training model or data. The decision-making of fuzzy system is based on the input which is expressed by linguistic variables. It's a kind of new idea that combine fuzzy logic system with neural networks, which exchanges the design of fuzzy logic control and decision-making system for the training and learning of the neural network, so that the neural network provides the fuzzy logic system with the connecting structure (nature of fault-tolerant, distributed represents) and learning ability.

Fuzzy neural network model. Fig. 1 shows the forward-type 4-layer fuzzy neural network [8]. Respectively, the 4 layers are the input layer, the fuzzify layer (membership function generating layer), the defuzzify layer, and the output layer, so there are n inputs and one output layer node.

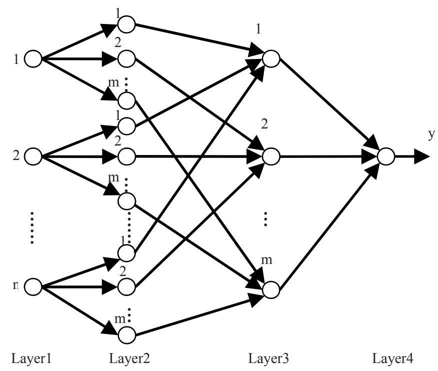

Fig. 1. Fuzzy neural network structure model

The first layer is a layer accepts external input signal, and transmits the input value to the fuzzy unit of fuzzify layer. The layer *2* and layer *3* nodes are terms nodes, they work as membership function and they, separately, convert the input values to a certain ambiguity and defuzzify these data according to the ambiguity function.

Layer *1*: input layer.

There are n inputs in this layer, the nodes in the first layer directly pass the input value to the next layer. The inputs and outputs are defined by

$$I_i^{(1)} = O_i^{(1)} = x_i, i = 1, 2, ...n \ .$$

Where the x_i is the input value of the i-th node, then we can know the input value of a certain node in the first layer. According to this equation, the connection weight of the first layer is *1*.

Layer *2*: fuzzify layer.

There are $n*m$ fuzzy nodes in the second layer, which are divided into n groups, and each group has m fuzzy nodes. The inputs and outputs of the second layer are defined by

$$I_{ij}^{(2)} = O_i^{(1)}, O_{ij}^{(2)} = \mu_{ij}(x_i) = \exp\left(-\frac{\left(I_{ij}^{(2)} - m_{ij}\right)^2}{\sigma_{ij}^{2}}\right),$$
$$1 \le i \le n; 1 \le j \le m.$$

Where m_{ij} and σ_{ij} are respectively the center (or average) and width (or mean square) of the j-th membership function of the i-th input and they can be trained. m_{ij} may be deemed to be the connection weights in the layer *2*. If a membership function is completed by using a set of nodes, the function of each node can be a standard form (such as Sigmoid function) .And the entire sub-network can be trained off-line with a learning algorithm (such as PSO algorithm), to achieve the desired membership function.

Layer *3*: defuzzify layer.

The third layer includes m nodes, the inputs and outputs are

$$I_{ij}^{(3)} = \prod_{i=1}^{n} O_{ij}^{(2)}, O_j^{(3)} = I_j^{(3)},$$
$$1 \le i \le n; 1 \le j \le m.$$

Namely, output of the node is the algebraic product of all inputs.

Layer *4*: output layer.

There is only one output node in this layer and the output is defined by

$$y = \sum_{j=1}^{m} \omega_j O_J^{(3)} \quad .$$

Where ω_j is the connection weight between the layer 4 and the j-th node of the third layer.

Compared to ordinary neural network, Fuzzy neural network constituted like this, can simplify the calculation of some of the processing unit because of the use of fuzzy math calculation method. As a result of fuzzy mechanism, fault tolerance of the system has been improved.

Above all, fuzzy neural network can expand the scope of information processing of the system to handle non-deterministic information. At the same time, it strengthens the methods of information processing of the system to make the system more flexible when processing information [6].

Particle swarm optimization. In addition to ant colony algorithm and fish swarm algorithm, particle swarm optimization is another group intelligent optimization algorithm in the field of computational intelligence. In 1995, Kennedy and Eberhart proposed PSO [9] in IEEE International Conference on Neural network. PSO algorithm derived from the study of predation behavior of birds, when the birds prey, they share the information on food location among community members. That is, searching around the bird, which is nearest to the food at present, can accelerate the speed of targets discovery. PSO algorithm was inspired by the features of biological population behavior and applied to solve optimization problems. Each particle in the algorithm represents a potential solution to the problem, and each particle corresponds to a fitness value. Velocity of the particles determines the movement direction and distance of the particle. It changes dynamically with the movement experience of its own or other particles to realize the optimization in the entire solution space. In each iteration, the particles update themselves according to the two "extreme value": one is the personal best, which is the optimal solution found currently by the particles themselves, another is global best, that is, the optimal solution found currently by the entire group. Compared to other evolutionary algorithms, PSO is a more efficient parallel-searching algorithm, simple, fewer parameters and easy to implement. It can be used to solve a large number of non-linear, non-differentiable and multimodal complex optimization problems with high computational efficiency.

Training of neural network based on PSO. When using PSO to train the neural network, the first step should be encode the connection weights among all neurons in the particular structure into an individual represented by real-number strings. Assuming that the network contains D optimized weights (threshold included), then each individual will be expressed by a D-dimensional vector $X_i = (x_{i1}, x_{i2}, \ldots x_{iD})$, which is consist of D weight parameters. Its velocity is $V_i = (v_{i1}, v_{i2}, \ldots v_{iD})$, individual extreme value is $P_i = (p_{i1}, p_{i2}, \ldots p_{iD})$, global extreme value of the swarm is $P_g = (p_{g1}, p_{g2}, \ldots p_{gD})$.

The process of PSO is as follows:

Step *1*: Particle swarm initialization.

According to particle swarm size Z and the above-mentioned individual structures, a number of individuals (particles), generated randomly, is formed into a swarm. Different individuals re-present one set of different weights in neural networks. Meanwhile, the initial position X, the initial velocity V, personal best $pBest$ and global best $gBest$ are initialized. To prevent particles searching blindly, generally their position and speed are limited in a certain interval $[-X_{\max}, X_{\max}], [-V_{\max}, V_{\max}]$.

Step *2*: Build the network.

Each component of an individual in the particle swarm is mapped to the weights in the network. Inertia weight constant w (interval [0.4, 0.9]), non-negative constants c_1 and c_2 and other parameters are set to build a network.

Step*3*: Extract training sample randomly.

Step*4*: Calculate the fitness of each particle.

The mean squared error (MSE), which is produced in the training set of each network, is calculated to serve as the target function, that is, the fitness

$$f = \frac{1}{K} \sum_{i=1}^{K} \left(y_i - \bar{y} \right)^2 .$$

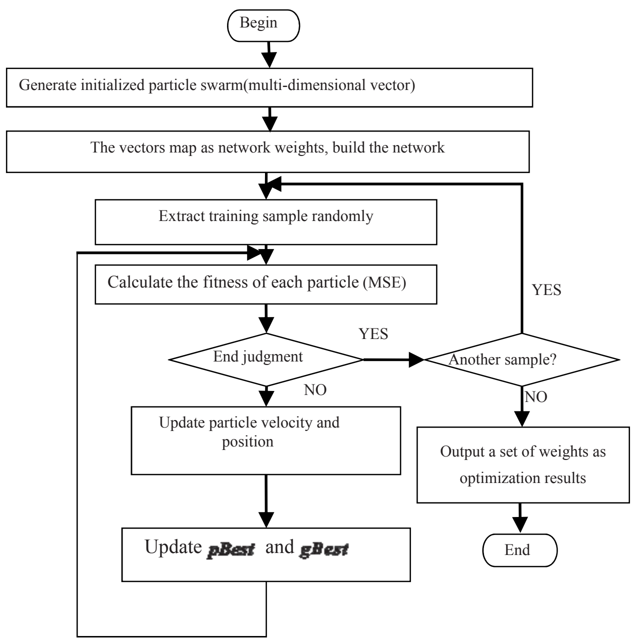

Fig. 2. Training flow chart

Where y_i is the predicted output value of the network, $\overline{y}$ is the actual output of the network, K is the number of training data pairs of each iteration.

Step *5*: End judgment.

It can be judged whether an individual meets the termination condition, if it is, switch into step *7*, if not, switch into step *6* to continue iterating.

Step *6*: Update particle velocity and position, Update $pBest$ and $gBest$, switch to step *4*.

The update of particle velocity and position are respectively based on the formula (1, 2)

$$V_{id}^{k+1} = \omega V_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k} \right) + c_2 r_2 \left(p_{gd}^{k} - x_{gd}^{k} \right); \qquad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}, d = 1, 2, ...D, i = 1, 2, ...n . \qquad (2)$$

Where r_1, r_2 is the random number between (0,1), k is the number of iteration.

The method to update personal best and global best is as following:

The value is compared with the current personal best $gBest$, if the current value is smaller than the $gBest$, then current value is assigned as $gBest$, otherwise not be assigned. The update of global best $gBest$ is in the same way.

Step *7*: It can be judged whether there is another sample, if it is, switch to step *3*, if not, a set of weights (global best) are outputted as the optimization results, and the training ends.

Experiment system of a hydrogen-fueled engine. Experiment system of a hydrogen-fueled engine [10] consists of eddy current engine test system of DDM series, bus-type hydrogen supply system, electronic control unit (ECU) and the hydrogen injection system, etc. The hydrogen-fueled engine was converted by the Jialing JH600, a water-cooled four-valve single-cylinder four-stroke gasoline engine. The hydrogen of the experiment system is provided by the hydrogen bottle by using special bus. The inlet and outlet pressure of the bus are 15Mpa (without reducing valve). Hydrogen flows through the valve and then flows into the speed switching valves of electro-hydraulic control. The electronic control unit controls the open time and duration of the speed switching valve according to engine operating conditions. Via the special injection, hydrogen is injected into the combustion chamber at the end of the compression stroke. Air flows through the stable pressure box and then flows into the intake manifold. Ignition timing is also controlled in accordance with the engine operating conditions by the electronic control unit. The experiment system of the hydrogen-fueled engine is shown in fig. 3. And the functional block diagram of the system is shown in fig. 4.

The optimization model of IGNI-TION TIMING BA-SED on PSO-FNN. ***Algorithm principle.*** Engine ignition timing (ignition advance angle) θ_s has a big impact on the engine power, economic efficiency, emissions and combustion processes [11]. Besides, θ_s is a complex non-linear function of the various engine operating parameters (Speed n_z, load ρ, coolant temperature T_W, intake pressure P_a, etc.)

$$\theta_{opt} = f\left(n_z, \rho, T_W, P_a, ... \right).$$

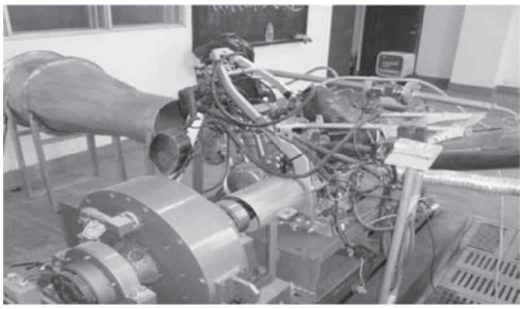

Fig. 3. The experiment system of the hydrogen-fueled engine

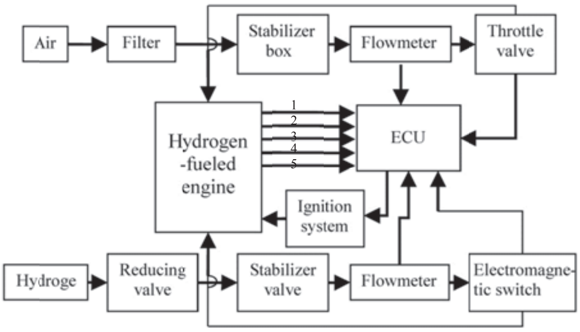

Fig. 4. The functional block diagram of the system: 1 – speed signal; 2 – throttle valve signal; 3 – air mass flow signal; 4 – hydrogen mass flow signal; 5 – detonation signal

Its optimization process is complex. This study depends on the modeling and simulation experiment based on fuzzy neural network, which has the ability of handling uncertain systems that have no precise mathematical model, such as complex nonlinear and multivariable systems. Meanwhile, in order to simplify the workload, modeling process only takes the speed n_z ($r/\min$) and load ρ, the two parameters, into account. The fuzzy neural network has a total of four layers as previously shown. The input layer has two nodes, that is, the speed n_z and load ρ, and the output layer has only one node, ignition advance angle θ_s, namely. The fuzzy neural network is trained and tested based on the ignition timing data calibrated on hydrogen-fueled engine experiment. The selected data is fully taken the engine optimization indicators in different conditions into account. The connection weights in the network can be calculated by the function of self-learning of the neural network combined with the particle swarm optimization algorithm. Then the trained network can be used to predict the ignition advance angle. Some of the ignition advance angle training samples of the hydrogen-fueled engines are shown in the table.

Table

Ignition Advance Angle of Training Samples

Load $\rho/\%$	**Speed** 650	**Speed** 950	**Speed** 1250	**Speed** 1550
19.40	48.55	48.60	48.65	48.70
32.30	42.95	43.75	44.55	45.15
45.20	34.60	35.30	36.60	37.90
51.60	30.20	3030	30.60	31.10
77.40	20.40	20.40	20.50	20.70
87.10	20.10	20.20	20.20	20.35
100.00	19.80	19.90	19.95	20.05

Load $\rho/\%$	**Speed** 2150	**Speed** 2300	**Speed** 2750	**Speed** 3050
19.40	48.80	48.81	48.95	49.50
32.30	46.15	46.35	47.00	47.15
45.20	40.50	41.10	42.50	42.70
51.60	34.20	35.50	38.30	38.90
77.40	22.20	24.80	28.50	28.60
87.10	21.60	23.25	25.50	25.50
100.00	20.30	20.50	20.90	21.00

Load $\rho/\%$	**Speed** 3350	**Speed** 3650	**Speed** 4250	**Speed** 4550
19.40	49.10	49.15	49.25	49.35
32.30	47.25	47.35	47.50	47.65
45.20	42.90	43.00	43.30	43.40
51.60	39.40	39.60	39.80	40.00
77.40	28.60	28.60	28.70	28.70
87.10	25.60	25.60	25.70	25.70
100.00	21.05	21.10	21.20	21.30

Simulation test. In this study, a fuzzy neural network based on particle swarm optimization (PSO-FNN) is set up and the simulation operation is conducted on the MATLAB software. The fuzzy neural network adopts the pattern of 2–6– 3–1, that is, the number of nodes in each layer are: 2, 6, 3, 1 ($n = 2$, $m = 3$). The parameters of the fuzzy neural network are: the number of weights (dimension of the vector) $D = 2*m*n + m = 15$, the termination condition is iterating 100 times, the number of training data pairs of each iteration K is 84. The parameters of particle swarm algorithm, chosen for the fuzzy neural network weights optimization, are: swarm size Z = 40, inertia weight constant ω = 0.7, $c_1 = c_2 = 1.49$, iteration number is 100, maximum speed $V_{\max} = 2$, maximum position $X_{\max} = 10$.

Results. In order to verify the optimization effects of PSO-FNN algorithm for hydrogen-fueled engine ignition advance angle, the training samples are inputted to the neural network and trained, part of the test samples are used to verification. The results show that the modeling and simulation of the engine ignition timing using PSO-FNN have achieved the desired effect. Fig. 5 shows the convergence curve of the error (MSE) by using PSO-FNN. When the number of iterations only reaches 16, the error precision is 0.007233, and the convergence rate gradually slows down. When reaching 100 iterations, the error precision is 0.003939, which is the desired result.

The results of the calculated value and the actual calibration value of the test samples are as shown in fig. 6. It is clear in the figure that in the 42 test samples, the result of each calculated value is very close to the corresponding actual value, which means the ignition timing prediction satisfies the expectations under different conditions. The mean absolute error between the calculated value and the actual value of PSO-FNN is 0.704, the mean relative error is 2.2%, the maximum absolute error is 1.412 and the maximum relative error is 6.1%.

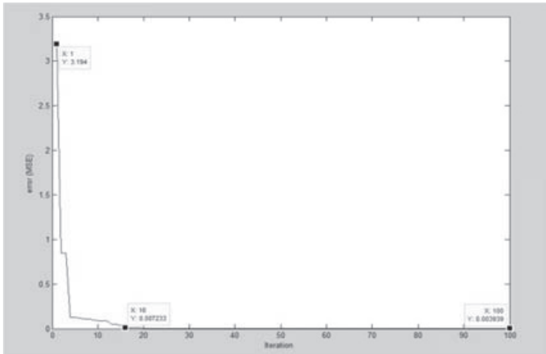

Fig. 5. The convergence curve of the error (MSE) by using PSO-FNN

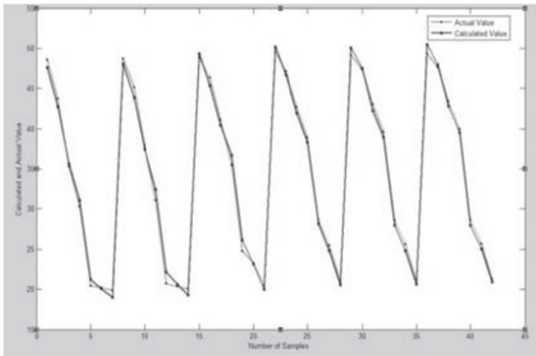

Fig. 6. Calculated values and the actual calibrated values of the test sample

Conclusions. The hydrogen-fueled engine ignition timing optimization simulation model based on particle swarm optimization-fuzzy neural network algorithm is built in this paper, it has the ability of self-learning, solving nonlinear problems of the fuzzy neural network and the advantages of high efficiency and handling multiple individuals of the particle swarm optimization algorithm. The experimental results show that the PSO-FNN model works well, with the advantages of stable, high precision and high speed, to achieve the optimal prediction of the engine ignition timing and form the best ignition MAP to avoid the abnormal combustion of the hydrogen-fueled engine, which has a strong practicability in engineering and scientific research.

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Мета. Єдиним шляхом вирішення наростаючих проблем енергетичної кризи та забруднення довкілля стає пошук екологічно чистого поновлюваного альтернативного палива для автомобільних двигунів. У роботі представлене експериментальне дослідження двигунів на водневому паливі. Зважаючи на деякі характеристики процесу горіння водню, частими є ситуації виникнення раннього запалення (передчасного займання) та зворотного спалаху (зворотного удару). Оптимізація випередження запалення сприяє запобіганню відхилень у процесі згорання.

Методика. На основі даних щодо регулювання запалення двигуна на водневому паливі, отриманих на експериментальній системі, розроблена модель оптимізації випередження запалення, що є функцією частоти обертання та навантаження двигуна. Вона ґрунтується на нейронній мережі з нечіткою логікою та оптимізації методом рою часток. Модель була експериментально протестована.

Результати. Експеримент показав, що середня абсолютна похибка розрахунків складає 0,704, а середня відносна похибка – 2,2%. Запропонований алгоритм дозволяє виробляти швидкий і точний розрахунок найкращого кута випередження запалення у двигунах на водневому паливі.

Наукова новизна. Уперше в експериментальній системі двигуна на водневому паливі використана модель на основі нейронної мережі з нечіткою логікою, оптимізованою методом рою часток, що просуває використання алгоритмів штучного інтелекту в машинобудуванні.

Практична значимість. Доведена ефективність використання моделі на основі нейронної мережі з нечіткою логікою, оптимізованою методом рою часток як підхід до оптимізації випередження запалення. Вона дозволяє обходитися без великої кількості калібрувальних випробувань, значно зменшує трудомісткість експериментів і підвищує ефективність.

Ключові слова: *нейронна мережа з нечіткою логікою, оптимізація методом рою часток, двигун на водневому паливі, випередження запалення, оптимізація*

Цель. Единственным путем решения нарастающих проблем энергетического кризиса и загрязнения окружающей среды становится поиск экологически чистого возобновляемого альтернативного топлива для автомобильных двигателей. В работе представлено экспериментальное исследование двигателей на водородном топливе. Ввиду некоторых характеристик процесса горения водорода, частыми являются ситуации возникновения раннего зажигания (преждевременного воспламенения) и обратной вспышки (обратного удара). Оптимизация опережения зажигания способствует предотвращению отклонений в процессе сгорания.

Методика. На основе данных о регулировке зажигания двигателя на водородном топливе, полученных на экспериментальной системе, разработана модель оптимизации опережения зажигания, которая является функцией частоты вращения и нагрузки двигателя. Она основывается на нейронной сети с нечёткой логикой и оптимизации методом роя частиц. Модель была экспериментально протестирована.

Результаты. Эксперимент показал, что средняя абсолютная погрешность расчетов составляет 0,704, а средняя относительная погрешность – 2,2%. Предложенный алгоритм позволяет производить быстрый и точный расчет наилучшего угла опережения зажигания в двигателях на водородном топливе.

Научная новизна. Впервые в экспериментальной системе двигателя на водородном топливе использована модель на основе нейронной сети с нечёткой логикой, оптимизированной методом роя частиц, которая продвигает использование алгоритмов искусственного интеллекта в машиностроении.

Практическая значимость. Доказана эффективность использования модели на основе нейронной сети с нечёткой логикой, оптимизированной методом роя частиц, в качестве подхода к оптимизации опережения зажигания. Она позволяет обходиться без большого количества калибровочных испытаний, значительно уменьшает трудоемкость экспериментов и повышает эффективность.

Ключевые слова: *нейронная сеть с нечёткой логикой, оптимизация методом роя частиц, двигатель на водородном топливе, опережение зажигания, оптимизация*

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IMAGE FEATURE CLASSIFICATION BASED ON PARTICLE SWARM OPTIMIZATION NEURAL NETWORK

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ОЗНАКОВА КЛАСИФІКАЦІЯ ЗОБРАЖЕННЯ НА ОСНОВІ НЕЙРОННОЇ МЕРЕЖІ ІЗ ЗАСТОСУВАННЯМ МЕТОДУ РОЮ ЧАСТОК

Purpose. The purpose of image feature classification is to divide an image into several meaningful regions according to certain features, making these features the same or similar in a certain region but significantly different in different regions. In this paper, we will investigate the role of neural network and particle swarm optimization (PSO) in the image feature classification.

Methodology. We propose the image feature classification method that combines PSO with neural network. BP neural network has been extensively applied in feature classification and it can classify specific objects or features through early learning, however, BP neural network algorithm also has many defects, including slow convergence speed and easiness to be trapped in local optimum. PSO optimized neural network fully exhibits its global search ability and parallel operation ability.

Findings. Firstly, we take the gray image with specific object as the object to be segmented, study the samples with PSO neural network and get the training network. Secondly, we take the pixel matrix of the image as the input vector and put in the well-trained network for classification. Finally, the image feature classification can be realized.

Originality. We made a study of image feature classification based on the particle swarm optimization neural network. We discussed the theory of image feature classification, basic principles of PSO and neural network.

Practical value. We have also conducted the simulation experiment to confirm that the method suggested in this paper is a feasible one. We have proved that it has higher convergence speed and stronger robustness. Through the highly-efficient processing, this method can obtain important information and achieve excellent effect when used in the segmentation of the objects in complicated scenes.

Keywords: *gray image, feature classification, particle swarm optimization, BP, neural network, segmentation*

Introduction. Image feature classification is one of the basic questions of image processing and computer vision, and it has gained more and more attention in the field of image analysis and processing in recent years. Due to gray scale, frequency spectrum, texture and so on, posed in images, it becomes a complex task to be solved [1]. Image segmentation, object separation, feature extraction and parameter measurement will transfer the original image into a more abstract and compact form, making it possible for high-level analysis and understanding. Image feature classification is the foundation of image understanding and recognition and the research on image feature classification has always been a research hotspot of digital image processing techniques, and it is also a key step of image analysis [2].

Image feature classification serves as a connecting link in the image engineering and it lies between the low- and high-level processing. Although foreign scholars have made extensive research on the techniques of image feature classification, it is still very difficult to find a reliable image feature classification method. Every segmentation algorithm performs the segmentation by using certain specific characteristics of the image. The algorithm suitable for the segmentation of a certain kind of image may not be able to do the segmentation on another kind or it is possible that different segmentation methods are required in segmenting different regions of the same image [3]. Many current techniques are not fit for real-time or approximate real-time processing. So far, an in-