A Stepping out Prevention Strategy For Permanent Magnet Linear Motor Based on Genetic and Fuzzy Neural Network Algorithm

Fuzhong Wang
School of Electronic Engineering & Automation, Henan Polytechnic University, Jiaozuo, China
Email: wangfzh@hpu.edu.cn

Caixia Gao[1] and Zhan Zhang [2]
[1,2]School of Electronic Engineering & Automation, Henan Polytechnic University, Jiaozuo, China
Email: gcx@hpu.edu.cn, gcx81@126.com

***Abstract*— For the problem of vertical-moved and discontinuous stator resulting from disturbance, this paper proposes an dual mode composite control structure for permanent magnet linear motor to prevent stepping out. The composite controller is designed containing fuzzy control, neural network control and genetic algorithm. The mechanism of the control and parameter optimization method for fuzzy neural network is given. It is shown that the proposed control strategy is effective for enhancing stability and safety of the vertical-moved, discontinuous stator winding permanent magnet linear motor and drive systems.**

***Index Terms*—discontinuous stator winding permanent magnet linear motor, stepping out prevention strategy, genetic algorithm, fuzzy neural network**

I. INTRODUCTION

Permanent Magnet Linear Synchronous Motor for Vertical Movement with discontinuous stator winding has the advantage of big thrust force, low loss, small time constant and fast response, it has been widely used in mine, hoist, transportation, warehouse and other fields. However, due to the effect of disturbances such as stator armature winding frequent switching, uniform air gap, magnetic detent force, winding inter-turn short circuit in running a course, the thrust ripple and out-of-step of motor often occurs. It will bring serious safety accident.

On the other hand, Permanent Magnet Linear Synchronous Motor for Vertical Movement with discontinuous stator winding and its servo system is a nonlinear system with time-varying parameters. In the literature, the problem has been widely studied and many approaches have been reported, such as, disturbance compensation control, adaptive control, robust control, neural network control, etc. However, the abovementioned approaches cannot solve the stepping out. For disturbance compensation control, the disturbance estimator is difficult to be designed and the stability analyze is also complicated. For adaptive control, it is difficult to design the identified algorithm for load, and the large computation and slow parameter tuning also results in rapid response. For fuzzy control and neural network model, they need either comprehensive understanding of the controlled system in order to establish fuzzy rules, or mass operation data of the system to train neural network. Besides, their controller design depends on the fuzzy rules or the neural network model.

In this paper, we propose a dual mode composite controller for permanent magnet linear motor to prevent stepping out. The controller contains fuzzy control, neural network control and genetic algorithm. In this mechanism, the global parameters of fuzzy neural network are optimized by genetic algorithm, and the local parameters are tuned by BP algorithm. Hence, the composite algorithm can change control strategy according to disturbance, and the better performance can be obtained.

II. MODEL OF OUT-OF-STEP FAULT PREVENTIVE CONTROL FOR PERMANENT MAGNET LINEAR MOTOR

A. The Determination of Controlled Variables and The Manipulated Variables

According to the theory of electric motor, the relationship between the thrust of permanent magnet linear motor and power angle is given as follow:

$$F_x = \frac{3E_0U_s}{v_sZ}\sin(\theta+\alpha) - \frac{3E_0^2R_s}{v_sZ^2} \quad (1)$$

In Equ. (1), v_s is the speed of linear motor rotor; θ is the power angle of linear motor rotor, namely the electrical angle between primary armature voltage U_s and the no-load electromotive force E_0; α=arctanR_s/X_T.

Manuscript received January 1, 2013; revised June 1, 2013; accepted July 1, 2013.
This work is supported by the Program of National Natural Science Foundation of China (NO. 61240049, NO.61074095), Henan Outstanding Person Plan (NO. 104200510021).

© 2013 ACADEMY PUBLISHER
doi:10.4304/jcp.8.9.2421-2428

According to Equ. (1), when the no-load electromotive force E_0 and power supply voltage U_s are both constant, electromagnetic repulsion F_x is the Sine function of the power angle θ, i.e. $F_x = f(\theta)$, it is also called “Force angle Characteristic”, and its curve is shown in Figure 1.

In Figure 1, θm is critical stability power angle; the corresponding working point *m* is the critical stable working point. The calculation of critical stability power angle θm is given by

$$\theta_m = \arctan KX_T / R_s \tag{2}$$

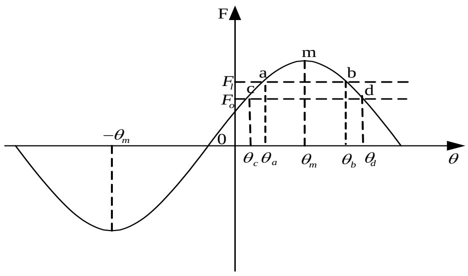

Figure 1. Force angle Characteristic curve and its working point diagram of Permanent magnet linear motor.

Taking Equ. (2) into Equ. (1), we can get the maximal electromagnetic thrust of permanent magnet linear synchronous motor as follows:

$$F_m = \frac{3E_0}{\upsilon_s Z'^2}[U_s Z' - KE_0 R_s] \tag{3}$$

According to the operation stability analysis theory of synchronous motor, -θm ~+θm is the steady work area of permanent magnet linear synchronous motor. The out-of-step fault of permanent magnet linear synchronous motor is mainly caused due to the electromagnetic force less than the weight of the load and makes the motor deviate from the stable working area after the disturbance in the operation process (power angle $|\theta|$ is beyond 73^0). Therefore, out-of-step fault can be prevented by examining the changes of power angle. If the tendence of the power angle is possible to exceed the stable working range appears, it should be increase the electromagnetic force rapidly and make the power angle stay in the stable region to prevent the out-of-step fault of permanent magnet linear synchronous motor. In order to ensure the working point not excess the critical stable working point *m* and enter the unstable region when the motor is disturbed, then the operating power angle |θ| should be less than |θm| with an enough error, i.e. stability margin. Therefore, the power angle stability margin $\Delta\theta$ is selected as the controlled variable.

From Equ. (1), it is shown that electromagnetic thrust is approximately direct proportional to power supply voltage and inverse proportional to the speed of the motor, Therefore, the power supply voltage and the running speed of the motor can be used as manipulated variable. The power angle can be controlled into a stable region to prevent the out-of-step faults of the permanent magnet linear synchronous motor through the comprehensive regulation of motor power supply voltage and the running speed of the motor and increase the electromagnetic force of motor.

B. The Basic Theory of The Mode to Prevent The Out-of-step Fault of PermanentMmagnet Linear Motor

According to the above analysis and combined with the fuzzy control theory, the building of the control and prevention model for permanent magnet linear synchronous motor is shown in Figure 2. The basic idea is: regard the difference between critical stability power angle θ_{m} and the moving power angle θ, (namely the stability margin) as the control of the volume, by changing the voltage of power supply or changing the running speed of motor to prevent the out-of-step faults appearing. The out of step faults preventive control model using dual mode control structure and consists of modal identification device, fuzzy control module of power supply voltage (fuzzy controller 1), fuzzy control module of motor speed (fuzzy controller 2).

From Equ. (2) and (3) we can obtain that the electromagnetic force of linear motor can be increased by improving the power supply voltage, which ensures the stable operation of motor, and keeps the running speed of motor not change. This is the main reason for choosing of dual mode control algorithm. However, the rise of power supply voltage will be limited by the working current of permanent magnet linear synchronous motor, if the working current of the motor exceeds its rated working current, the motor will be burned down. Hence, the proposed method is feasible for the current case. Although reducing the running speed (frequency) of permanent magnet linear synchronous motor can increase the electromagnetic force of permanent magnetic linear synchronous motor and control the power angle into the stabile work area, the running speed (frequency) reduction will affect the efficiency of system. Therefore, this paper uses the double mode control structure and integrated regulate the power supply voltage and running speed of the motor.

The basic idea of out-of-step prevention model for Permanent magnet linear synchronous motor is given as follow: firstly, according to the given speed of permanent magnet linear synchronous motor, and using the Equ. (2) to calculates the critical stability power angle θ_m, and conduct real-time detection of the operation power angle θ of the motor and get the stability margin permanent magnet linear synchronous motor. and then according to the working current of permanent magnet linear synchronous motor, using online switching module (modal identification device) to select different fuzzy controller, finally, by changing the power supply voltage or the operation speed of the motor to realize the stable control of motor. Every fuzzy controller selects the appropriate fuzzy rule and infers to get the output based on the size of stable margin and the changing rate, eventually make permanent magnet linear motor can keep stable operation. In Figure 2, *e* is the stability margin (difference) between critical stability power angle θm and operating power angle θ of permanent magnet linear synchronous motor, and e_c is the stability margin rate.

© 2013 ACADEMY PUBLISHER

The effect of modal identification device is to choose different fuzzy controller based on the armature winding current size of permanent magnet linear synchronous motor. The algorithm modal identification device is given as follow:

When the armature winding current of phase A I_a is less than or equal to the rated armature current I_{amax}, namely $I_a \le I_{amax}$, fuzzy controller 1 (the supply voltage fuzzy control module) is selected.

When $I_a > I_{amax}$, fuzzy controller 2 (the motor running speed fuzzy control module) is selected.

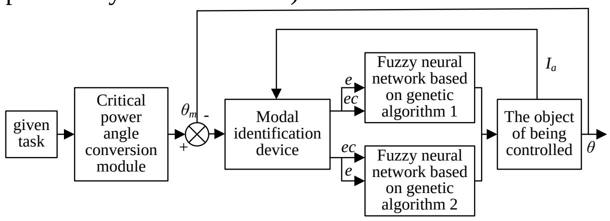

Figure 2. The out-of-step prevention control model for permanent magnet linear motor.

III. Fuzzy Neural Network Design Based On Genetic Algorithm

This paper considers fuzzy neural network based on genetic algorithm to achieve the out-of-step fault prevention of permanent magnet linear synchronous motor, that is using genetic algorithm to learn the attached function parameters of fuzzy neural network, namely uses three-step hybrid training method to train the network to get the application of Internet which is used to optimized the control parameters of out-of-step fault prevention, and then use this network to prevent and control the out-of-step faults of motor and ensure the safe operation.

A. Construction of Fuzzy Neural Network

The fuzzy neural network for out-of-step fault prevention and control of permanent magnet linear synchronous motor is a feed-forward multi-layer structure, is shown in Figure 3. The fuzzy reasoning can be realized through the analysis of the input and output data. Fuzzy neural network controller mainly consists of 5 layers, they are the input layer, fuzzy layer, fuzzy rule layer, fuzzy decision layer, defuzzification layer (the output layer). Each layer has its unique weights between neurons, learning to find the optimal weight to minimize the error between the ideal output and actual output as much as possible through continuous on-line back propagation in the fuzzy neural network. The front four layers is used to complete the fuzzification, establish the fuzzy rules, reasoning out suitable fuzzy output when fuzzy control volume is put in, reasoning. The fifth layer uses for on-line reconstruction defuzzification and complete fuzzy solution to get actual control volume.

The structure of fuzzy neural network is shown in Figure 3.

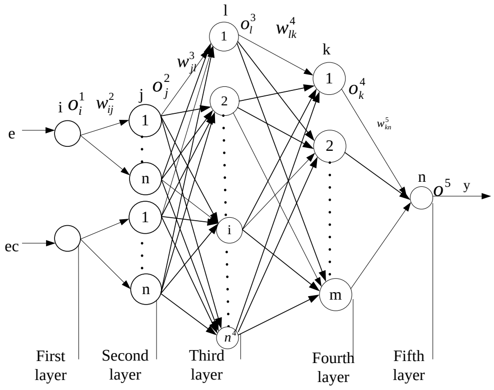

Figure 3. Structure of fuzzy neural network.

The analysis fuzzy neural network and the input and output relationship between each layer of neurons is given as follow:

(1) the first layer is the input layer, the input nodes are the stability margin (difference) e(k) between the critical stability power angle θm and operating power angle e(k) of permanent magnet linear synchronous motor and the stability margin rate ec(k). For each neuron, the input layer is as follow:

$$o_i^1 = I_i^1 = x_i \, , \, x_i = e(k) \;\; or \;\; ec(k) \tag{4}$$

In Equ. (4), the deviation of liquid level $e(k)=\theta_m-\theta(k)$, stability margin rate $e_c(k) = e(k)-(k-1)$, $k=0,1,\ldots n$. T is sampling time.

(2) the second layer is fuzzy layer: each node output corresponding membership values and use the Gauss type membership function.

$$I_j^2 = w_{ij}^2 o_i^1 \tag{5}$$

$$o_j^2 = \exp[-(\frac{I_j^2 - m_k}{\sigma_k})^2] \tag{6}$$

In Equ. (6), m_k, α_k are the mean and variance of Gauss membership function. Because the basic universe of stability margin $e(k)$ is [5^0, 30^o], fuzzy language groups are {PT, PL, PS, PM, PB, PV}, the universe is divided into 11 grades which are {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. The basic universe of stability margin rate $E_c(k)$ is [-5^o + 5^o], fuzzy language groups are {NB, NM, NS, PS, PM, PB}, and its universe as divided into 11 grades which are {-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5}. From the above analysis, the value of K is 22.

(3) the third layer is the fuzzy rule layer:

$$I_l^3 = \prod_j w_{jl}^3 o_j^2 \tag{6}$$

$$o_l^3 = I_l^3 \tag{7}$$

The initialization value of the hidden layer node number of third layers shall be equal to the number of fuzzy rules, in this paper the number of fuzzy rule is n^2, which is decided by both input variables and the number

© 2013 ACADEMY PUBLISHER

of fuzzy subset, and a total of 36 rules[11], as table Ⅰ, table Ⅱ shown. Then the specific number can be determined through optimizing by optimization algorithm. The expression of fuzzy control rule is as follow:

$$\begin{aligned} &R_j : IF\ e\ is\ A_1^j\ and\ ec\, is\ A_2^j \\ &THEN\ \ y\ is\ B_1^j \qquad j = 1,2.....n^2 \end{aligned} \tag{8}$$

where, A_i^j and B_i^j are the fuzzy sets of input and output variable, respectively representing the errors and its rate of change and the motor power supply voltage or the speed of the motor.

(4) the fourth layer is the fuzzy decision layer:

$$I_k^4 = \sum_k w_{lk}^4 o_l^3 \tag{9}$$

$$o_k^4 = \min(1, I_k^4) \tag{10}$$

(5) the fifth layer is the defuzzification layer:

$$I^5 = \sum_k w_{kl}^5 o_k^4 = \sum_k (m_k \sigma_k) o_k^4 \tag{11}$$

$$u = o^5 = \frac{I^5}{\sum_k \sigma_k o_k^4} \tag{12}$$

TABLE I.
FUZZY RULERS 0F SUPPLY VOLTAGE

E	EC					
	NB	NM	NS	PS	PM	PB
PT	STOP	STOP	STOP	STOP	PB	PB
PL	STOP	STOP	PB	PB	PB	PM
PS	PB	PB	PM	PM	PM	PS
PM	PM	PM	PS	PS	PS	ZO
PB	PS	PS	ZO	ZO	NS	NS

TABLE Ⅱ.
FUZZY RULERS 0F THE RUNING SPEED OF MOTOR

E	EC					
	NB	NM	NS	PS	PM	PB
PT	STOP	STOP	STOP	STOP	NB	NB
PL	STOP	STOP	NB	NB	NB	NM
PS	NB	NB	NM	NM	NM	NS
PM	NM	NM	NS	NS	NS	ZO
PB	NS	NS	ZO	ZO	PS	PS
PV	ZO	PS	PM	PM	PM	PB

In Equ. (9)~(12), n=7, m=7, n^4=74, I_i^k and O_i^k are the input and output of the i neurons in layer k in the fuzzy neural network ; W_{ij}^k is the weights from the node i of layer k-1 to the node j of layer k. The initial weight value of the first four layers is chosen for 1 in this network.

The m is the maximum of output variable fuzzy subset, the output are voltage increment ΔU_1 and output frequency increment ΔU_2 in the prevention control of out-of-step fault. Their basic universe is [-6, +6], the fuzzy language subset is {NB, NM, NS, ZO, PS, PM, PB}. The universe is divided into 13 grades which are {-6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6}. The membership function is Gauss function as the Equ. (6) shows.

B. The Parameter Optimization of Fuzzy Neural Network

This paper proposes the genetic algorithm to optimize the parameters of fuzzy neural network. Genetic Algorithm (GA) is a kind of method with random search and global optimization which is based on biological evolution process, therefore, the global network parameters in the fuzzy neural network are optimized through genetic algorithms, and the local parameters are optimized though BP algorithm. Thus the genetic algorithm is used as an off-line training fuzzy neural network controller (rough adjustment), and the BP algorithm is used to adjust the parameters of neural networks (fine adjustment), if this two kinds of method is used integratedly, the self learning performance and robustness of the fuzzy neural network control system can be greatly improved.

For the fuzzy neural network to control and prevent out-of-step fault of permanent magnet linear synchronous motor, the premise and conclusion part adopt Gauss membership function, its center parameters m_k and width parameter σ are global parameters, and can be adjusted and optimized through genetic algorithm, however, the weights of the inference rules mainly are local parameters, and can be adjusted and optimized through BP algorithm.

(1) The step to train the membership function using a genetic algorithm[12]:

First step: firstly, encoded the center and width of fuzzy subset membership function which is belonging to the genetic fuzzy neural network fuzzy layer (the second layer) and the output layer (the third layer). Chromosome string is shown in Table Ⅲ. $M2_j$ is the fuzzy subset membership function centre of fuzzy layer fuzzy, $\sigma 2_j$ is the fuzzy subset membership function width of fuzzy layer, j=input number x input number fuzzy subset number; $M5_n$ is the fuzzy subset membership function centre of output layer, $\sigma 5_n$ is the fuzzy subset membership function width of output layer, n=output number x output fuzzy subset number.

TABLEⅢ.
THE CHROMOSOME STRING WHICH SHOWS THE CENTER AND WIDTH OF FUZZY NEURAL NETWORK FUZZY SUBSET MEMBERSHIP FUNCTION

Fuzzy layer				Output		
X	X	…	X	X	X	…	X
$M2_1$	$M2_2$	…	$M2_j$	$m5_1$	$m5_2$	…	$M5_n$
X	X	…	X	X	X	…	X
$\sigma 2_1$	$\sigma 2_2$	…	$\sigma 2j$	$\sigma 5_1$	$\sigma 5_2$	…	$\sigma 5_n$

Encoding method adopts tandem binary mapping encoding method, each parameter is shown with 10-bit unsigned binary code. The lower limit and upper limit of

© 2013 ACADEMY PUBLISHER

the range of parameter value are set as $p_{max.j}$ and $p_{min.j}$, thus, the relationship between the value of parameter string representation and the value of actual parameters is as follow:

$$p_j = p_{\min.j} + \frac{(p_{\max.j} - p_{\min.j})R}{2^{i-1} - 1} = p_{\min.j} + \frac{(p_{\max.j} - p_{\min.j})R}{2^3 - 1} \quad (13)$$

The values of $M2_j$ and $\sigma 2_j$ range from 0 to 20 in this paper.

Second step: the determination of crossover probability and mutation probability.

The choice of crossover probability P_c and mutation probability P_m in the parameters of genetic algorithm has a very important influence in genetic behavior and performance, directly affects the convergence of the algorithm. The bigger P_c is, the faster new individual is produced; however, if P_c is too big, the genetic models may be destroyed easily, and this makes individuals which have highly adaptive structure will be destroyed soon. If P_c is too small, the search process will be too slow and even remain stagnant. It's difficult to produce new individual structure, if the probability of mutation Pm is too small; If the P_m value is too large, the genetic algorithm will change into a purely random search algorithm. For different optimization problems, the P_c and P_m need to be determined through repeated tests, which is very complicated, and it is difficult to find the best value which is suitable for every problem.

Aiming at this problem, an adaptive genetic operators is introduced, P_c and P_m can automatically change with the fitness. When the various fitness of population tends to be consistent or regional local optimum, so that P_c and P_m increased; and when the population fitness is more dispersive, decrease P_c and P_m. At the same time, if the sufficiency of individual is higher than average individual fitness, it corresponds to the lower P_c and P_m so that the solution can protect access to the next generation; but lower than the average fitness of individual and combining the situation that Individual constraint violation, P_c and P_m should be relatively high to eliminate the solution. Therefore, adaptive P_c and P_m can provide the optimal P_c and P_m for a solution. the algorithm can keep the population diversity, at the same time, to ensure the convergence of genetic algorithm through the adaptive genetic operator.

$$\begin{aligned} P_c &= P_{c1} - \frac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{\max} - f_{\min}} & (f' \geq f_{avg}) \\ P_c &= P_{c2}(1 + kc) & (f' < f_{avg}) \end{aligned} \quad (14)$$

$$\begin{aligned} P_m &= P_{m1} - \frac{(P_{m1} - P_{m2})(f_{avg} - f)}{f_{\max} - f_{\min}} & (f \geq f_{avg}) \\ P_m &= P_{m1}(1 + kc) & (f < f_{avg}) \end{aligned} \quad (15)$$

where $f_{\max}$ is the maximum volume of fitness value in population; f_{avg} is the average fitness value of each generation population; f' is the larger fitness value in the two individuals which are to cross; f is the fitness value of the individual which is to create variation; c, k is the punishment coefficient (constant), and its value should be determined by the importance of the constraint conditions.

Tthird step: calculation of moderate function value.

The quality of fitness function directly affects the evolution process of genetic algorithm, and related to the quality of optimization result. Because the design of system must to meet the overall performance indicator (the transition time, rise time, overshoot, steady state error) of system and these indicators are associated with transient error of system, the performance of the controller is evaluated through the discrete objective function as is shown in Equ. (16)

$$\min E = \frac{1}{2}\sum_{i=1}^{m}(u_i - u_i^*)^2 \quad (15)$$

where U_i is the expected sample output value; U_i is the output value of fuzzy neural network; m is the number of samples. Therefore, the fitness function value should be calculated based on the Equ. (16).

$$f_i = C_m - E \quad (16)$$

where $C_{\max}$ is an appropriate and relatively large constant.

Fourth step: using the niche sharing function method, let the individual in genetic algorithm create evolution in a particular environment to find out the more optimal solution. In this paper, the fitness of each antibody is changed combining the niche sharing function to clone each antibody based on the changed fitness, and to better keep the diversity of population and create a niche evolution environment.

Sharing function $sh(i, j)$ is used to show the close degree between two individuals in the population, its Equ. is as follow:

$$sh(i,j) = \begin{cases} 1 - \dfrac{d(i,j)}{\sigma_{sh}} & d(i,j) < \sigma_{sh} \\ 0 & d(i,j) \geq \sigma_{sh} \end{cases} \quad (17)$$

$d(i, j)$ is the Euclidean distance between antibody I and j. σ_{sh} is the designated peak radius.

The sharing degree of antibody i is as follow:

$$sh_i = \sum_{j=1}^{N} sh(i,j) \qquad (i = 1,2,3,\cdots N) \quad (18)$$

N is the size of the current population. Assuming fi is the fitness of antibody i before sharing, then the modified fitness is as follow:

$$f_i^{'} = \frac{f_i}{sh_i} \quad (19)$$

The fifth step: genetic evolution and finding the best individual solution.

(2) The extraction of fuzzy rules

After the preliminary adjustment of parameters of fuzzy membership function in first phase, and then input the input/output training data from the opposite ends of the network. The input training data first reaches the

© 2013 ACADEMY PUBLISHER

interval nodes of second layer, at the same time O_i^2 is got through calculating, and then the activation strength O_i^3 of third layers rule node can be calculated through the connection weights and O_i^2 of third layers. The output training data can reach the interval nodes of the fourth layer according the transmission mode which is from top to bottom, at the same time, X_j^4 can be got through calculating. Now the task is to find the correct mapping relationship with the output interval node for each regular node, namely is $N1 \times N2$ rules. In order to accomplish this task, this paper adopts the minimum-maximum matching algorithm and its steps are as follow:

Step 1. Put all the training data into the calculate network in order and calculate the connection weights of fourth layer, (the initial value is 0, i=1, 2, ⋯ , $N1 \times N2$, j=1，2,⋯ , $N3$). For each pair of input/output training data, W_{ij} is updated follow the next Equ.:

$$W_{ij\max}^{'} = W_{ij\max} + o_i^3 \times X_{j\max}^4 \tag{20}$$

In the Equ., j_{max} is the node with largest intensity of activation in every activated interval node in the fourth layer by output training data, and the connection weights of other interval nodes do not update[13].

Step 2: Extract and optimize fuzzy rule from W_{ij} and respectively compare the $N3$ connection weights connected with each ruled node in the third layers with a given threshold. If all the weights are less than a given threshold, then the ruled node and its connection weights will be deleted. Conversely, if all the weights are more than a given threshold, the biggest one in the $N3$ connection weights will be set to 1; this determines the mapping relationship between the rule node and an output interval node, at the same time, the rest of the connection weight will be set to 0.

After second stages of learning, $N1 \times N2$ fuzzy rules can be got at most. The deleted rule nodes are considered to have little or no effect to any output interval nodes. The selection of threshold can reference experience and accuracy requirement.

(3) Optimization of parameters based on a supervised learning

After the extraction of fuzzy rules, which determine the mapping relationship between the third and fourth layer of network, the whole neural fuzzy inference network structure is completely determined. The learning task of this stage is to optimize the fuzzy membership function parameters and further improve the accuracy of fuzzy identification[14-17].

This paper adopts improved BP algorithm to train fuzzy neural network with teacher, and get further optimization and adjustment to the input and output variable membership function.

III. Simulation Experiment

In this paper, simulation experiment is performed in the Matlab/Simulink, the simulation parameters are selected as: Polar distance τ_n=51mm; Direct-axis & quadrature axis electrical inductance L_d=L_q=154.2mH; Active cell quantity M=270kg; Armature resistance R_s=2.985Ω，Rated current I_{amax}=25A.

A. Simulation Experiment Procedure

(1) Network Formation & Sample Selection

If the original state is 0, the stability margin $e(k)$ varies in (5°, 30°), then the rate of stability margin change $e_c(k)$ varies in (-5° +5°). Under the Rated operating speed, when the running current is less than the rated current, by changing the load, 30 voltage data imposed on the motor take place(distributed in (0, 180V). Under rated running current, by changing the load, 30 speed data output by the frequency converter take place (distributed in (0, 6Hz). Altogether, there are 30 pairs of input and output training data for the next step of network training.

(2) Select the well-trained network (basing on the genetic algorithm's fuzzy neural network) [15] and perform the simulation experiment to get the optimized control result.

And then, separately perform the methods of changing the service voltage and motor speed.

B. Change Service Voltage

The datum speed is v_s=1m/s, and its relative biggest Power-angle is around: θ_m=70°. The Loading Shock is 200kg, and the curve chart of permanent magnet linear synchronous motor (SPMLSM) is as below:

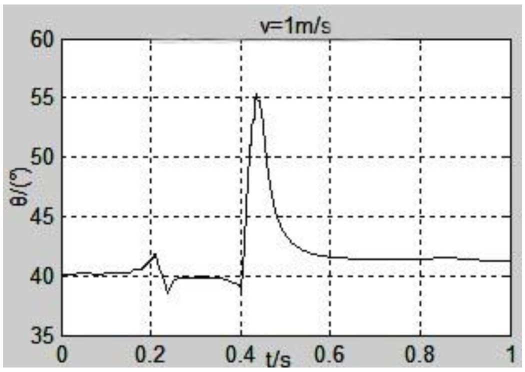

Figure 4. Power-angle change curve under the velocity 1m/s.

From the above chart, when the Loading Shock is 200kg, the motor power angle changes abruptly from 38° to 55.1° and stays stablely at 42° after 0.17s.

C. Change Motor Speed

The datum speed is v_s=0.6m/s, and its relative biggest Power-Angle is around: θ_m=60°, the Loading Shock is 100kg. The curve chart of permanent magnet linear synchronous motor (SPMLSM) is as below:

From the above chart, when the Loading Shock is 100kg, the motor power angle changes abruptly from 35° to 53° and stays stablely at 35° after 0.15s.

It is shown that the Stepping out Prevention strategy basing on the permanent magnet linear motor of genetic algorithm's fuzzy neural network could make sure the stable operation of the permanent magnet linear motor according to the size of the stability margin of the Power-Angle.

© 2013 ACADEMY PUBLISHER

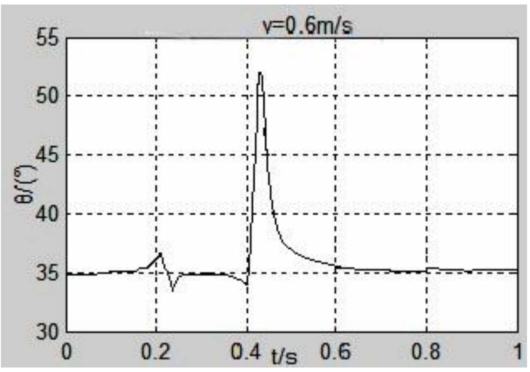

Figure 5. Power-angle change curve under the velocity 0.6m/s.

V. CONCLUSION

(1) An organic combination of genetic algorithm and fuzzy neural network generates a Stepping out Prevention strategy of permant magnet linear motor is proposed in this paper. The result of the simulation experiment shows that the control strategy is accurate and reliable, and the control method is simple. It can enhance stability and safety of the vertical –moved, discontinuous stator winding permanent magnet linear motor, and its drive system effectively.

(2) By judging the current of armature winding and selecting different controllers, adjust the service voltage and operating speed separately of the permanent magnet linear motor; and control the motor Power-angle in the stable area. It can prevent the permanent magnet linear synchronous motor (SPMLSM) from the step-out failure effectively.

(3) Using the improved genetic algorithm and the comprehensive optimization of membership function parameter and rule of inference weight, the problem of deciding the membership function parameter and rule of inference weight has been solved. The analysis of the simulation studies results shows that the fuzzy neural network controller basing on the genetic algorithm has good dynamic property, steady-state performance, anti-interference performance and robustness.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (NO. 61074095) and (No. 51277054), and Ministry of Education Scientific Research Foundation for Chinese Overseas Returnees (NO. 20071108), and 2011 year guidance of scientific and technological research projects of China Coal Industry Association (No. MTKJ2011-387), (No. MTKJ2011-391), and (No. MTKJ2011-394).

REFERENCES

[1] Xudong Wang, Kai Cao, Haichao Feng, Lili Guo, Xiaozhuo Xu, "Design and Analysis of Permanent Magnet Linear Synchronous Motor with Special Pole Shape," *Journal of Computers*, Vol.8, pp.478-484, Feb 2013.

[2] Xiaozhuo Xu, Xudong Wang, Jikai Si, Haichao Feng, Baoyu Xu, "Detent Force Analysis and Optimization for Vertical Permanent-magnet Linear Synchronous Motor with Fractional-slot Windings," *Journal of Computers,* Vol.8, pp.756-763, Mar 2013.

[3] Gao Caixia, Wang Qiaolian,Yu Lin, et., "The analysis of the out-of-step auident of the vertical-moving PMLSM", *Journal of Henna Polytechnic University* (*Natural Science*), Vol. 30, No. 3, 2011, pp. 310-315.

[4] Wang Fuzhong, Jing Penghui, Li Xiangdong, et., "Study on stability and controlling of low-speed permanent magnet linear synchronous motor", *Journal of Henna Polytechnic University* (*Natural Science*), Vol. 28, No. 2, 2009, pp. 202-206.

[5] Huijing Yang, Chunying Wang, Ning Du, "High Level Synthesis using Learning Automata Genetic Algorithm," *Journal of Computers*, Vol.7, pp.2534-2541, Oct 2012.

[6] PIIPPO A, HINKKANEN M,LUOMI J,"Analysis of an adaptive observer for sensorless control of interior permanent magnet synchronous motor," *IEEE Transactions on Industrial Eletronics*, Vol.55, pp. 570–576, Feb 2008.

[7] Lin F J,Shen P H, "Robust fuzzy neural network sliding-mode control for two-axis motion control system," *IEEE Transactions on Industrial Eletronics*, Vol.53， pp. 1209–1225,Apr 2006

[8] Li Jianing, Yi Jianqiang, Zhao Dongbin, et., "A New Fuzzy Identi6cation Approach for Complex Systems Based Oil Neural-Fuzzy Inference Network", *ACTA AUTO MATICA SINICA*, Vol. 32, No. 5, 2006, pp. 695-703.

[9] Teng Hongqiu, Li Chunhua. "An Artificial Immune Algorithm for Multimodal Optimization Based on Niche Techniques", *Computer Simulation*, Vol. 26, No. 12, 2009, pp. 148-248.

[10] Wu Life, Cheng Linhui. "An Improved BP algorithm based on cloud self-adaptive genetic algorithm", *Journal of South Central University for Nationalities* (*Nat．Sci．Edition*), Vol. 30, No. 4, 2011, pp. 98-101.

[11] Xiong Zhibin. "Credit evaluation modelling based on self-adaptive genetic fuzzy neural network". *Journal of System Simulation*, Vol. 23, No. 3, 2011, pp. 490-496.

[12] Zhang Liyi, Liu Ting, Sun Yunshan, et., "Research of genetic algorithm optimization neural network weights blind equalization algorithm based on reed number coding",*Computer Engineering and Applications*, Vol. 45, No. 11, 2009, pp. 162-164.

[13] Shi Huaji, Yin Jijun, Li Xingyi, et., "Optimization of feedforward neural network by genetic algorithm with influence factor", *Application Research of Computers*, Vol. 24, No. 11, 2007, pp. 103-105.

[14] Qiao Peili, Zheng Lin, Ma Lili. "Research on a niche genetic algorithm", *Journal of Harbin UNIVERS II Y of Science and Technology*, Vol. 16, No. 1,2011, pp. 90-93.

[15] WANG Ying-fa,XIA Chang-liang,CHEN Wei. "Startup Strategy for Brushless DC Motor Based on Fuzzy Rules", *Proceedings of the CSEE*, Vol. 29, No. 30, 2009,pp. 98-103.

[16] HUANG Hui-xian, RUAN Ting. "Application of Adaptive Fuzzy Sliding Mode Control Based on GA in Positioning Servo System of the Permanent Magnetic Linear Motors", *Natural Science Journal of Xiangtan University*, Vol. 32, No.4, 2010,pp. 94-98.

[17] Parma G,Menezes B R,Braga A P,etal. "Sliding mode neural network control of an inducton motor drive", *International Jouranal of Adaptive Control and Signal Processing*， Vol. 17, No.6, 2003,pp. 501-508.

© 2013 ACADEMY PUBLISHER

Fuzhong Wang was born in 1961 at Mengzhou in Henan province. He gained PhD in 2010 at Information and Electrical Institute of China University of Mining (Beijing).His major fields of study is Electrical automation, artificial intelligence and Industrial process control.

He has chaired or as a principal investigator to complete the National Natural Science Foundation, Natural Science Foundation of coal, Natural Science Foundation of Henan Province Torch Plan of Henan Province. He focuses on research, "addressing rural power grid failure."

Professor Wang is the senior member of Chinese Society for Electrical Engineering and China Coal Society fellow member. He also is the Henan Automation Institute director. He edited the 《Microcontroller Theory and Application of Technology》 and 《Supply and distribution Technology》.

Caixia Gao was born in 1981 at Ruichang in Jiangxi province. She gained master degree in 2008 at Henan Polytechnic University (Jiaozuo).Her major fields of study is

Ms Gao is the teacher of Henan Automation Institute. She has edited the “Modern power supply technology”.She has published articles such as “The power angle detection for non-salient pole permanent magnet linear motor based on the additional high-frequency windings of mover”, “Mover Position Detection Device for Non-Salient Pole Permanent Magnet Linear Motor Based on Additional High-Frequency Windings of Mover”,“Design and Implementation Of Active Low-frequency Filter Using MATLAB”,etc.

Zhan Zhang was born in 1976 at Xuzhou in Jiangsu province. She gained master degree in 2008 at Henan Polytechnic University

Ms Zhang is the teacher of Henan Automation Institute. She has edited the“Modern power supply technology”.She has published articles such as “Research on Calculation of Transformer’s Parameters with Modern Information Technology”,“A Manufacturing System Based on Virtual Reality”, “The approximate method of three phase short-circuit current calculation based on the per-unit value form of Ohm's law”,etc.

© 2013 ACADEMY PUBLISHER