TELKOMNIKA, Vol. 11, No. 8, August 2013, pp. 4200~4207
e-ISSN: 2087-278X

Automobile Transmission Shift Control based on MAX-MIN Ant Algorithm

Chen Jianxue
Shanghai University of Engineering Science, Shanghai 201620, P.R.China
e-mail: merlyn21@126.com

Abstract

Neural networks have already been applied to transmission shift control, with its nonlinear fitting feature. To solve the problem that the network parameters highly depend on human prior knowledge, ant colony algorithm is often chosen to optimize the parameters. In order to achieve the global optimization with better performance, the MAX-MIN ant system (MMAS) is applied in BP neural network control model of automobile automatic transmission, which makes the optimum shift decision based on the vehicle velocity, the vehicle acceleration and the throttle opening, namingly three-parameter model in shift control domain. MMAS is used to search the optimal initial weights and thresholds of back-propagation (BP) neural networks. Results on field data show that the automatic transmission shift control system based on MMAS and BP networks, comparing to the system based on traditional ant coolly optimization algorithm and BP, can accelerate convergence and better network performance.

Keywords: *automated mechanical transmission, back propagation (BP), ant colony optimization (ACO), MAX-MIN ant system (MMAS)*

1. Introduction

Automated Mechanical Transmission (AMT) becomes important high-tech product in automobile industry, with good competence and large scale application in automated transmission domain. And shift control plays key role in automated transmission technology. As a popular multiple layer neural network, back-propagation (BP) neural network is widely applied in various industrial areas, particularly for pattern recognition problem, which have good self-learning, self-adaptive, associative memory function, and a high degree of parallelism, good fault tolerance, non-linear pattern recognition ability. With the help of neural networks, the drivers' experience and knowledge can be accessed by learning machines, so that the AMT decision process is similar to human behaviour. However, BP algorithm, which adopts gradient descent algorithm, may easily get trapped in local minima especially for those non-linearly separable pattern classification problems or complex function approximation problem and have slow convergence speed [1]. Ant Colony Optimization (ACO) [2-4] algorithm proposed by M. Dorigo in 1990s is a new meta-heuristic searching algorithm for solving hard combinatorial optimization problems, after simulated annealing algorithm, genetic algorithm, tabu search and evolutionary computation. ACO algorithm [5-10] has not only the feature of intelligent search and global optimization, but also of robustness, positive feedback, distributed computing, and easily combined with other algorithms. Previous application of ACO-BP is demonstrated in the AMT field [11], where the ACO algorithm is used to determinate the BP network parameters for automatic transmission decision problem. However, in AMT research, along with the parameters number increased, the complexity of ACO-BP training becomes a serious problem. It is somehow a bit difficult to balance the computational intelligence algorithm and the domain parameters. There is a requirement to improve ACO-BP algorithm while applying to AMT, with a deeper exploration of shift control model.

Over the years, the MMAS (MAX-MIN Ant System) [12-16] algorithm achieves a strong exploitation of the search history by allowing only the best solutions to add pheromone during the pheromone trail update. Also, the use of a rather simple mechanism for limiting the strengths of the pheromone trails effectively avoids premature convergence of the search. Moreover, MMAS can easily be extended by adding local search algorithms. In fact, the best performing ACO algorithms for many different combinatorial optimization problems improve the

Received February 15, 2013; Revised May 6, 2013; Accepted May 16, 2013

solutions generated by the ants with local search algorithms. As Thomas already shown, MMAS is currently one of the best performing ACO algorithms for the TSP and the Quadratic Assignment Problem (QAP). And many researchers developed various methods to improve the global search capability of computational intelligence, less or more, discovered the strategy of the improvements on genetic algorithm, paticle swarm optimization, ant system, or other evolution algorithms [17, 18]. By applying the-state-of-the-art ACO algorithm, in this paper, the AMT shift rule is analyzed and MMAS algorithm is introduced into the training of BP neural networks, then the automatic Transmission shift control is implemented, with the comparative result to previous ACO-BP algorithm.

2. MMAS and BP Networks

BP network is multi-layer single-directional propagation network, which has two key rules: (1) For regular pattern recognition, three layer network can solve most problem. (2) In three layer network, the number of hidden layer nodes and the number of input layer nodes, respectively n_1 and n_2, following the rule: $n_2=2n_1+1$. The learning algorithm of BP network is back-propagation, which is easily dropped in local minimization, hard to convergence or with long iteration time.

ACO algorithm is originated from the observation and research of ant colony behaviour. Collectively a colony of ants can perform useful tasks such as building nests, and foraging (searching for food). The most important is that ants are able to discover the shortest path to a food source and to share that information with other ants through stigmergy which is a form of indirect communication used by ants in nature to coordinate their problem-solving activities. Ants achieve this kind of communication by laying a chemical substance called pheromone that induces changes in the environment which can be sensed by other ants. The inspiring source of ACO is the pheromone trail laying and following behavior of real ants which use pheromones as a communication medium. The most important feature of ACO is its distributed computing capability, which leads to global optimization and excellent nonlinear problem solution.

The basic idea of ACO is: given m parameters to optimize, including all weight and threshold of neural network, marked as $p_1,p_2,...p_m$. For each $p_i(1\leq i\leq m)$, assume that its possible numerical value set is I_{pi}. Defining the number of ant is S, all ants search for food from nest. Each ant go from set I_{p1}, and choose unique element in set I_{pi} according to specific probability determined by the pheromone of the set elements. Once the ant finish choosing element in all sets, it can access the food. By iteratively adjusting the pheromone of the elements, the process is going on until the global optimization result is found. By combining the ACO with the BP, a new algorithm referred to as ACO-BP hybrid algorithm is adopted in the ACO-BP neural network [19]. The main idea for this hybrid algorithm is using ACO algorithm to train all weights and threshold of BP network, in order to find the optimal initial weight and threshold of BP network by minimizing the training error norm. Finally the BP algorithm is used to search around the global optimum. In this way, this hybrid algorithm may find an optimum more quickly.

Now, to avoid local minimization, the ACO-BP can be improved by introducing MMAS algorithm. In the history of searching algorithm, greedier search methods potentially aggravates the problem of premature stagnation of the search. MMAS algorithm, which has been specifically developed to avoid local minimization, differs in several key aspects from AS [5]. One is to exploit the best solutions found during an iteration or during the run of the algorithm, after each iteration only one single ant adds pheromone. This ant may be the one which found the best solution in the current iteration (iteration-best ant) or the one which found the best solution from the beginning of the trial (global-best ant). And to avoid stagnation of the search the range of possible pheromone trails on each solution component is limited to an interval [min, max]. Additionally, MMAS deliberately initialize the pheromone trails to max, achieving in this way a higher exploration of solutions at the start of the algorithm. Normally in MMAS algorithm, there will be two modifications. One is for the update of pheromone, that is, in MMAS, only the optimal solution of the iteration will update the pheromone, not like in the traditional AS, all ants' path will update the pheromone. The other is the constraint of pheromone. That is, to avoid convergence stagnation in iterations, limit the pheromone in range[τ_{min}, τ_{max}], and during updating, if pheromone over the range, then apply the following rules:

If $\tau_j \geq \tau_{\max}$, then let $\tau_j = \tau_{\max}$.

If $\tau_j \geq \tau_{\min}$, then let $\tau_j = \tau_{\min}$

In this paper, τ_{min} and τ_{max} can be set by the equation (1) and (2).

$$\tau_{\max} = \left(\left(1/(1-\rho) \right) \cdot Q/e^{best} \right) \quad (1)$$

Where e^{best} is the optimal solution of current iteration, assume currently there are NC iterations, and when NC≤2, we have:

$$\tau_{\min} = \tau_{\max}/1000 \quad (2)$$

But when NC>2, we have τ_{min}:

$$\tau_{\min} = \tau_{\max} \cdot \left(1 - \sqrt[NC]{P_{best}}\right) \cdot \sqrt[NC]{P_{best}} \Big/ (avg - 1) \quad (3)$$

Over experimental results, MMAS is not sensitive to P_{best} value, normally $avg=NC/2$, and P_{best} =0.5.

The procedure for this MMAS-BP algorithm can be summarized as follows:

Step 1: Initial condition: given m parameters to optimize, including all weight and threshold of BP network, marked as $p_1,p_2,...p_m$. For each $p_i(1\leq i\leq m)$, initialize its possible value randomly in the given range, which form a finite set I_{pi}. The pheromone value for element j in set I_{pi} $(1\leq i\leq m)$ marked as $\tau_j(I_{pi})(1\leq j\leq N)$ is initialized to the constant $C>0$.

Step2: Each ant start with the first set I_{p1} to search for food, choose one element from each set, until all ants reach the last set I_{pm}. The choice of an element $j\in I_{pi}$ is, at each construction step, done probabilistically with respect to the pheromone model. The probability for ant $k(1\leq k\leq S)$ to choose element j in set I_{pi} is defined as follows:

$$prob\left(\tau_j^k(I_{pi})\right) = \left(\tau_j(I_{pi})\right) \Big/ \sum_{\mu=1}^{N} \tau_\mu(I_{pi}) \quad (4)$$

Step 3: Now ant K needs to choose elements in the whole set. After initializing the weights and threshold of BP network by the elements chose by ant $k(1\leq k\leq S)$, use BP algorithm to train the network, calculate the training error norm e^k defined as norm(O_n-O_q), where O_n is the actual output of training samples, O_q is the expected output of training samples. And the obtained BP network training loss error e^k needs to be examined whether it is optimal value so far in current iteration. If it is, calculate the delta of the pheromone values of all elements in set I_{pi} by Equation (5). Either, let the delta be zero.

$$\Delta\tau_j^k(I_{pi}) = \begin{cases} Q/e^k, if\ \ ant\ k\ choose\ \ element\ \ \ j\ in\ set\ \ I_{pi}\ \ in\ current\ \ iteration \\ 0, else \end{cases} \quad (5)$$

Step 4: If all ants complete choosing elements in set, then the current iteration is done and all pheromone of the elements in set I_{pi} need to update following Equation (6) and (7). Either, we return to step 3.

$$\Delta\tau_j(I_{pi}) = \sum_{k=1}^{S} \Delta\tau_j^k(I_{pi}) \quad (6)$$

$$\tau_j(I_{pi})(t+m) = (1-\rho)\tau_j(I_{pi})(t) + \Delta\tau_j(I_{pi}) \quad (7)$$

The parameter ρ $(0\leqslant\rho\leqslant1)$ is called the evaporation rate of pheromone, used to avoid too rapid convergence of algorithm toward a sub-optimal region. $\Delta_j^k(I_{pi})$ means the pheromone on element *j* in set I_{pi} left by ant *k* in current iteration. *Q* is the constant for adjusting the updating speed of pheromone. And if the pheromone of currrent iteratioin is not in range [τ_{min}, τ_{max}], change it to τ_{min} or τ_{max} accordingly, whereτ_{min} and τ_{max} is defined by Equation (1), (2) and Equation (3).

Step 5: Continue step 2, 3 and 4, *NC*=*NC*+1, until the algorithm converges to a state in which all the ants construct the optimal solution or the maximum iteration is reached. Output the optimal result, which means optimal initial weights and threshold of BP network.

3. Automatic Transmission Shift Control Model

Shift rule is the important problem in AMT control, which directly impact the power, energy of the vehicles, and adaptive capability to environment. The shift rule mainly means the relationship between gear and control parameters while shifting. Traditionally the shift rule can be divided into three types according to the control parameters. Usually single parameter is the speed, and two parameters are speed and throttle opening, and three parameters are speed, throttle opening, and acceleration [20].

For the two parameters shift rule, it is simplified to use steady state data of throttle opening and speed to determine transmission shifting which belong to static parameters, however both acceleration and deceleration is dynamic process, when the vehicle starts, or the transmission shifts, or the driving environment changes. To secure the shifting quality, it is necessary to introduce the third parameter into the AMT parameters, which is the acceleration of the vehicle, in order to construct the dynamic three parameters shift rule. Three parameters shift rule include optimal power shift schedule and optimal fuel economy shift schedule. Overall, compared with two parameters shift rule, three parameters shift rule has better acceleration performance, more economic benefit, better dynamical performance and higher shifting quality. Furthermore, it has extra advantages of smooth shifting, low shift impact, high degree of riding comfort, and better durability of automotive products [21]. Figure 1 shows the whole neural network shifting control system framework.

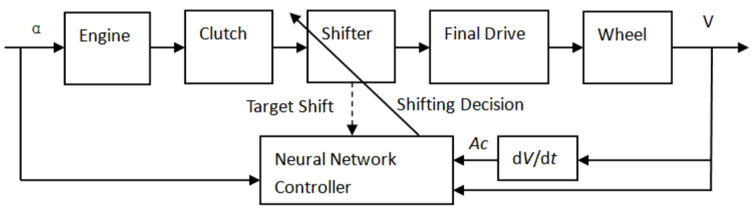

Figure 1. Neural Network Shifting Control System

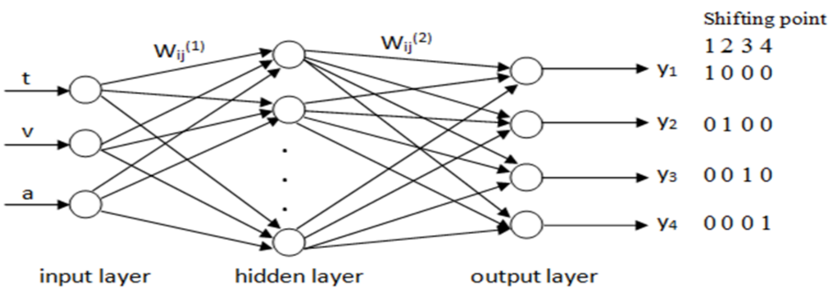

Figure 2. BP Neural Network Model of Three-parameter Automatic Shift Control

Based on three parameters shift rule, the BP network gear shift decision model is presented which has three inputs and one output. The input of gear shift decision model is the vehicle velocity, the vehicle acceleration and the throttle opening. The output of gear shift decision model is the optimal shifting point, namely the vehicle gears [22]. For the presence of speed gap when shifting, which cause the curves of up-shifting and down-shifting to be different, there are two BP networks for respectively identifying up-shifting and down-shifting processes. In this paper, only up-shifting process is studied. Figure 2 shows the proposed BP network structure, in which there are 3 nodes in input layer and 4 nodes in output layer.

4. Result and Discussion

Normalization is a common phase for pre-processing the input data before the training. For neural networks, normalized data is better for training and learning.

Thus:

$$X = (x - x_{\min})/(x_{\max} - x_{\min}) \tag{8}$$

Where x is numerical value before the normalization, X is numerical value after the normalization, x_{min} is the minimum value of the samples. and x_{max} is the maximum value of the samples.

Here gives the design rules of neural networks, including 3 input layer nodes, 7 hidden layer nodes, 4 output layer nodes, the excitation function of hidden layer is Tansig, and the excitation function of output layer is Logsig.

In the experimental setup, 20 samples are constructed for each shifting point, totally 80 samples. After pre-processing, 40 samples are chosen as training samples, while other 40 samples as test samples.

Table 1. Training samples of three parameters gear shifting model. The input includes the throttle opening, the velocity, and the acceleration. The output is the shifting point. The basic unit is 1% for throttle opening, 1Km/h for velocity, and 1m/s2 for acceleration. For the numerical value of shifting points, 1,2,3 and 4 represent shifting between gear 1-to-2,2-to-3,3-to-4,and 4-to-5 respectively [23].

sample number	throttle opening	velocity	accelera-tion	Shifting point	sample number	throttle opening	velocity	accelera-tion	Shifting point
1	1.0	6.89	1.65	1	21	1.2	15.53	1.12	2
2	3.5	12.06	2.00	1	22	2.4	21.75	1.27	2
3	7.7	20.68	2.23	1	23	5.7	27.96	1.35	2
4	9.5	22.4	2.27	1	24	8.2	34.17	1.39	2
5	11.3	27.54	2.34	1	25	11.3	46.6	1.43	2
6	13	31.01	2.39	1	26	13.7	49.71	1.45	2
7	14.5	34.46	2.35	1	27	15.7	55.9	1.47	2
8	15.3	36.18	2.31	1	28	17.9	62.13	1.433	2
9	16.8	39.63	2.20	1	29	20	68.3	1.35	2
10	17.6	41.35	2.13	1	30	22	74.56	1.25	2
11	1.3	18.39	0.828	3	31	2.0	25.75	0.438	4
12	3.9	27.58	0.935	3	32	5.4	38.63	0.502	4
13	5.5	36.8	1.00	3	33	8.8	51.5	0.54	4
14	9.3	45.16	1.032	3	34	15.8	77.3	0.5	4
15	11.6	55.16	1.037	3	35	19.6	90.13	0.462	4
16	16.4	73.55	1.030	3	36	24.2	103	0.418	4
17	18.8	82.74	1.016	3	37	29.3	115.9	0.361	4
18	22.5	91.94	0.964	3	38	35.5	128.8	0.271	4
19	26.2	101.1	0.875	3	39	42.5	141.6	0.147	4
20	29.2	110.3	0.771	3	40	54	148	0.07	4

As in ACO-BP algorithm, in MMAS it is assumed the range of network parameter $p_i(1 \le i \le m)$ as [-5,5], and it is supposed that set I_{pi} contains 30 elements, ant colony size S is 32, pheromone evaporation rate ρ is 0.1, maximum iteration is 30.

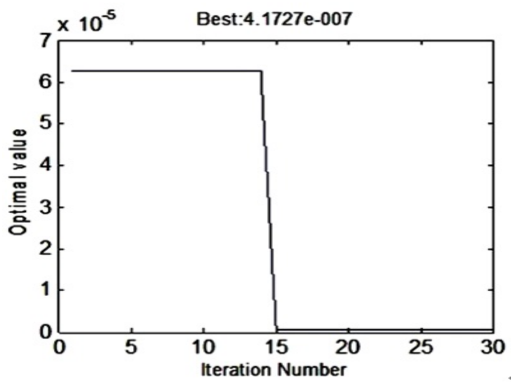

Figure 1. Optimal Curve of ACO-BP

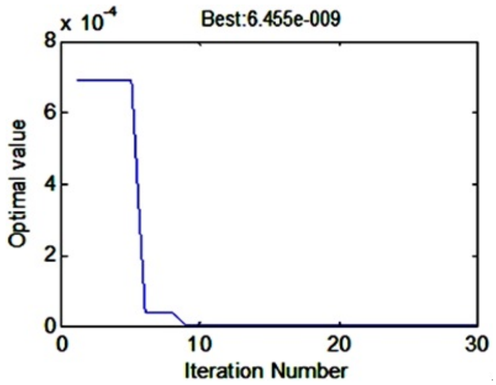

Figure 2. Optimal Curve of MMAS

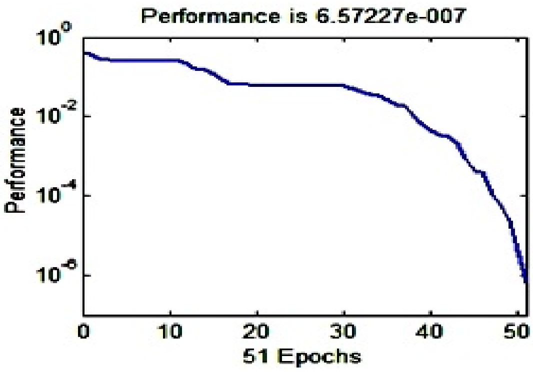

Figure 3. Performance of BP Networks

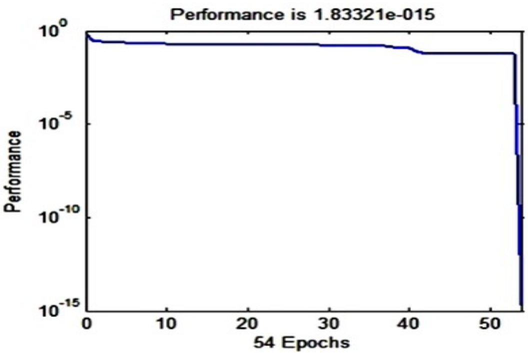

Figure 4. Performance of ACO-BP network

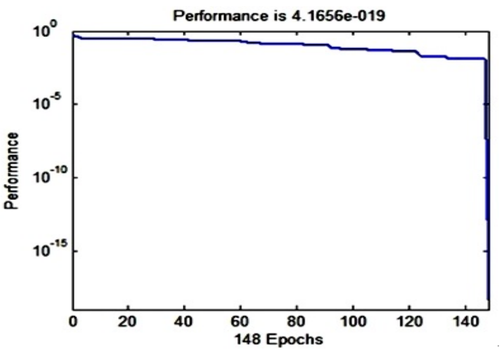

Figure 5. Performance of MMAS

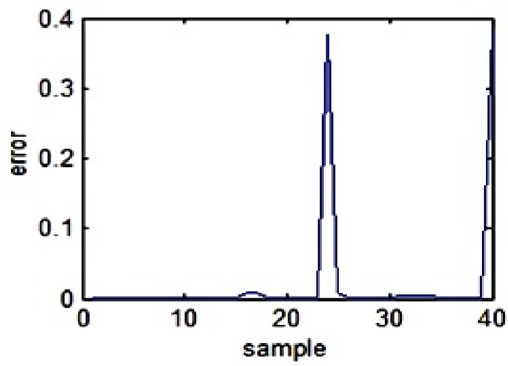

Figure 6. Test error of BP Networks

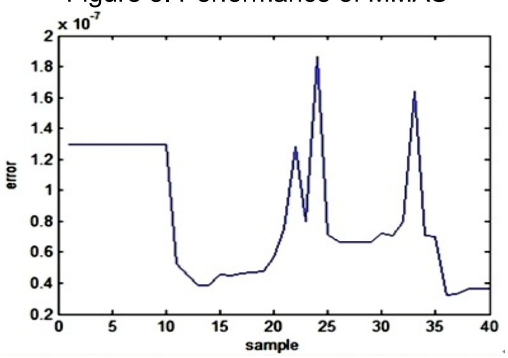

Figure 7. Test error of ACO-BP network

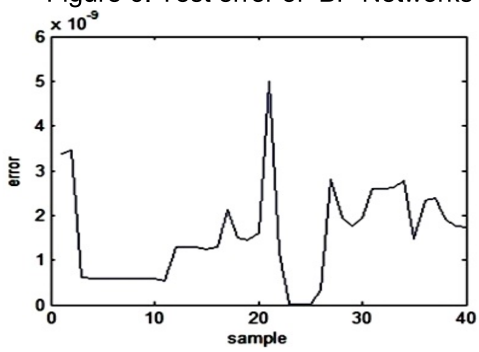

Figure 8. Test error of MMAS

Figure 1 and Figure 2 demonstrate the convergence capability gap of MMAS and ACO-BP. Comparing to ACO-BP, MMAS has higher convergence speed, just as descripted in [11].

Figure 3 shows regular BP network performance, in which the network parameters are randomly initilized as a benchmark reference. Figure 4 shows the proposed ACO-BP algorithm performance, as well as Figure 5 for MMAS performance. Figure 5~Figure 8 show the test error of regular BP network, ACO-BP network, and MMAS-BP network, respectively. By introducing MMAS algorithm, both the network generalization capability and shift decision precision are improved. Compared with BP network, the error norm of training samples decreases from 0.0077 to 6.4550e-009, and the error norm of the test samples decreases from 0.5247 to 7.1280e-009, with 100% diagnosis precision based on MMAS-BP network. Compared with ACO-BP algorithm,The error norm of training samples decreases from 4.1727e-007 to 6.4550e-009, and the error norm of the test samples decreases from 4.1729e-007 to 7.1280e-009, with 100% diagnosis precision based on MMAS-BP network. And Table 2 gives the comparative reuslt of algorithm convergence performance.

Table 2. Comparative results of optimal value for both ACO-BP and MMAS algorithms show MMAS has a magnificent accuracy improvement. And also MMAS has minor improved convergence performance than ACO-BP algorithm.

Ant counts	Optimal value		Algorithm convergence time	
	ACO-BP	MMAS	ACP-BP	MMAS
37	4.1727e-007	6.4550e-009	1077.318496	928.255755
32	6.1105e-007	2.0297e-008	923.413172	839.027283
27	7.3951e-007	2.5955e-008	877.390355	784.354389

On both convergence time and optimal value, MMAS beats ACO-BP. It brings over 10% convergence speed improvement and about 60% accuracy improvement, compared with the reported result in [4].

5. Conclusion

Recent research in AMT has strongly focused on improving the performance of optimization algorithms, mostly refer to computational intellegence, e.g. neural networks and ant systems. In this paper we have presented MMAS based AMT system, an improved ant system algorithm system for shift control, which aim (i) to exploit more strongly the best solutions found during the search comparing to traditional randomly parameterized BP network or ACO-BP network, and (ii) to avoid premature convergence of the ants search for AMT dicision rules. The shift control model is also discussed, mainly on the choice of the parameters of automobile transmission. In the shift control model, the vehicle velocity, the vehicle acceleration and the throttle opening are chosen as the input of the neural network, namingly three-parameter model. And our results on field data demonstrate that MMAS-BP network can get better shift decision precision and better convergence performance than both traditional BP network and ACO-BP algorithm in AMT shift control.

References

[1] Van A, Ooyen, Nienhuis B. Improving the convergence of the back-propagation algorithm. *Neural Network*. 1992: 465-471.

[2] Dorigo M, Di Caro G. The Ant Colony Optimization meta-heuristic New Ideas in Optimization. London: McGraw Hill, 1999.

[3] Dorigo M, Di Caro G, Gambardella LM. Ant algorithms for discrete optimization Artificial Life. 1999: 137-172.

[4] M Dorigo, CA Maniezzov. The ant system optimization by a colony of cooperating agents. *IEEE Transactions on System, Man and Cybernetics*. 1996; 26(1): 1-13.

[5] Dorigom, LM Gambardella. Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation*. 1997; 1(1): 53-66.

[6] M Dorigo, E Bonabeau, G Theraulaz. Ant algorithms and stigmergy. *Future Generation Computer Systems.* 2000; 16: 851-871.

[7] M Dorigo, G Di Caro. The ant colony optimization meta-heuristic. In: D. Corne, M. Dorigo, F. Glover *Editors*. New Ideas in Optimization. McGraw-Hill. London. 1999: 11-32.
[8] M Dorigo, G Di Caro, LM Gambardella. Ant algorithms for distributed discrete optimization. *Artificial Life.* 1999; 5: 137–172.
[9] M Dorigo. Optimization, learning, and natural algorithms. PhD Thesis. Dip. Elettronica, Politecnico di Milano. Italy; 1992 (in Italian).
[10] M Dorigo, V Maniezzo, A Colorni. *Positive feedback as a search strategy*. Technical Report 91-016, Dip. Elettronica, Politecnico di Milano, Italy, 1991.
[11] Chen Jianxue, Yu Shui. *Application of ACO-BP Algorithm in Automobile Automatic Transmission Shift Control*. Applied Mechanics and Materials. 2013; 263-266: 553-556.
[12] T Stützle. Local search algorithms for combinatorial problems - analysis, improvements, and new applications. PhD Thesis. Department of Computer Science, Darmstadt University of Technology, Darmstadt, Germany; 1998.
[13] T Stützle, HH Hoos. *The MAX–MIN ant system and local search for the traveling salesman problem*, In: T. Bäck, Z. Michalewicz, X. Yao. *Editors*. Proceedings of the IEEE International Conference on Evolutionary Computation (ICEC'97), IEEE Press, Piscataway, USA, 1997; 309–314.
[14] T Stutzh, H Hoos. *Improvements on the Ant System: Introducing MAX-MIN Ant System.* Proceedings of the International Conference on Artificial Neruai Networks and Genetic Algorithms. 1997; 245-249.
[15] T Stützle, H Hoos. *MAX–MIN ant system and local search for combinatorial optimization problems*. In: S. Voss, S. Martello, I.H. Osman, C. Roucairol. *Editors*. Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization, Kluwer Academic Publishers, Boston, MA. 1999; 313–329.
[16] T Stützle, H Hoos. MAX-MIN Ant System. *Future Generation Computer System*. 2000; 16(8): 889–914.
[17] Jiang Jing, Meng Lidong. The strategy of improving convergence of genetic algorithm. *Indonesian Journal of Electrical Engineering*. 2012; 10: 2063-2068.
[18] Guoqiang Zheng, Zhao Liang, Jishun Li. Optimization of an Intelligent Controller for Parallel Autonomous Parking. *Indonesian Journal of Electrical Engineering*. 2013; 11: 1069-1075.
[19] Wang Ge, Pu Peng-bo. Application of ACO-BP in Neural Network Training. *Computer Simulation*. 2009; 26: 136-141.
[20] Daekyun Kim. Math-model Based Gear-shift Control Strategy for Advanced Vehicle. *Powertrain Systems*. 2006; 5: 5-15.
[21] Yu Ronghui, Sun Dongye, Qing Datong. Study on Dynamic Gearshift Law of Automated Mechanical Transmission. *Transactions of the Chinese Society for Agricultural Machinery*. 2006; 37: 25-30.
[22] WANG LF. Research for the method determining shifting rule of automatic transmission. *Automobile Technology*. 1998; 6: 7-9.
[23] HOU Peiguo, SUN Chuanming, LU Zeyong. Neural networks in application of discriminant auto gear-shift. *China Measurement Technology*. 2007; 33: 64-70.