Automobile Transmission Shift Control based on MAX-MIN Ant Algorithm

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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)

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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
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, particle 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 $I_{p_i}$, and choose unique element in set $I_{p_i}$ 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 $[\tau_{\text{min}}, \tau_{\text{max}}]$.

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 $[\tau_{\text{min}}, \tau_{\text{max}}]$, and during updating, if pheromone over the range, then apply the following rules:

\[
\text{If } \tau_j \geq \tau_{\text{max}}, \text{ then let } \tau_j = \tau_{\text{max}}. 
\]
If \( \tau_j \geq \tau_{\min} \), then let \( \tau_j = \tau_{\min} \).

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

\[
\tau_{\max} = \left((1/(1-\rho)) \cdot q/e^{\text{best}}\right)
\]

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

\[
\tau_{\min} = \tau_{\max}/1000
\]

But when \( NC > 2 \), we have \( \tau_{\min} \):

\[
\tau_{\min} = \tau_{\max} \cdot (1 - NC/P_{\text{best}}) \cdot \sqrt{NC/P_{\text{best}}} / (\text{avg} - 1)
\]

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

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 \( p_1, p_2, \ldots, p_m \). 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 \( I_{pi} \) marked as \( \tau_j(I_{pi}) \) is initialized to the constant \( C > 0 \).

Step 2: 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:

\[
\text{prob} \left( \tau_j^k(I_{pi}) = \left( \tau_j(I_{pi}) / \sum_{j=1}^{N} \tau_j(I_{pi}) \right) \right)
\]

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 \( \| O_q - O_\alpha \| \), where \( O_\alpha \) 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.

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

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.

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

\[
\tau_j(I_{pi})(t + m) = (1 - \rho) \tau_j(I_{pi})(t) + \Delta \tau_j^k(I_{pi}) \quad \text{(7)}
\]

The parameter \( \rho \) (0 \leq \rho \leq 1) is called the evaporation rate of pheromone, used to avoid too rapid convergence of algorithm toward a sub-optimal region. \( \Delta \tau_j^k(I_{pi}) \) means the pheromone
on element \( j \) in set \( I_p \) left by ant \( k \) in current iteration. \( Q \) is the constant for adjusting the updating speed of pheromone. And if the pheromone of current iteration is not in range \([\tau_{\text{min}}, \tau_{\text{max}}]\), change it to \( \tau_{\text{min}} \) or \( \tau_{\text{max}} \) accordingly, where \( \tau_{\text{min}} \) and \( \tau_{\text{max}} \) 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.

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:

\[ X = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

(8)

Where \( x \) is numerical value before the normalization, \( X \) is numerical value after the normalization, \( x_{\text{min}} \) is the minimum value of the samples, and \( x_{\text{max}} \) 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].

<table>
<thead>
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<th>throttle opening</th>
<th>velocity</th>
<th>acceleration</th>
<th>Shifting point</th>
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As in ACO-BP algorithm, in MMAS it is assumed the range of network parameter \( p_i(1\leq i\leq m) \) as [−5,5], and it is supposed that set \( I_p \) contains 30 elements, ant colony size \( S \) is 32, pheromone evaporation rate \( \rho \) is 0.1, maximum iteration is 30.
Automobile Transmission Shift Control based on MAX-MIN Ant Algorithm (Chen Jianxue)
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 described in [11].

Figure 3 shows regular BP network performance, in which the network parameters are randomly initialized 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 result of algorithm convergence performance.

<table>
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<th>Ant counts</th>
<th>Optimal value</th>
<th>Algorithm convergence time</th>
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<td>MMAS</td>
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<tr>
<td></td>
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<td>6.4550e-009</td>
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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.

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 decision 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, namely 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