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Tuning ANFIS Using a Simplified Sparrow Search Algorithm

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Abstract. The objective of this paper is to develop an enhanced metaheuristic algorithm to train ANFIS on solving nonlinear regression problems. Firstly, we improved the sparrow search algorithm and then proposed a simplified sparrow search algorithm (SSSA). Secondly, the SSSA was hence employed to train the parameters of an initial raw ANFIS structure for a nonlinear regression problem. In order to evaluate the performance of SSSA on the tuning of (Adaptive neuro fuzzy inference system) ANFIS, we use PSO, (gray wolf optimization) GWO and basic SSA for comparison. Finally, the results of simulations indicate that, training ANFIS by SSSA reduce the root of mean of squared error in a more effective pattern. Therefore, the proposed technique increases the way to solve nonlinear regression problems.

Keywords. ANFIS, metaheuristic, simplified sparrow search algorithm (SSSA)

1. Introduction

Adaptive neuro fuzzy inference system (ANFIS) is commendably integrates the advantages of artificial neural network (ANN) and Takagi-Sugeno type fuzzy inference system (FIS) [1]. It has since been broadly employed in the application of decision making problems and nonlinear regression problems.

Queen, Kumar and Aurtherson employed ANFIS network to the control of robot manipulators with external disturbances [2]. Duka applied ANFIS method to solve the inverse kinematics problem of robot manipulators [3]. Chaudhary, Panwar, Sukavanam, et al. combined ANFIS and PID technique on the compliance control robot manipulators [4]. Hamouda, Babes, Kahla, et al. applied ANFIS technique for MPPT of Solar PV System by using PSO Algorithm [5]. Mousavi, Mirinezhad and Lyashenko integrated ACO learning algorithm and ANFIS for the family counselling for the aim of divorce rate reduction [6]. Wali used PSO and ANFIS model for the predictions of scroll chaos patterns [7].

Since the initial ANFIS before train always has lots of unknown parameters need to determine, for various problems researchers combine many different metaheuristic algorithms into ANFIS such as PSO, artificial bee colony (ABC) [8], genetic algorithm (GA), satin bowerbird optimizer (SBO) [9], whale optimization algorithm (WOA) [10], pigeon-inspired optimization (PIO)[11], gray wolf optimization (GWO) [12]and so on .

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Lately, Xue and Shen proposed a sparrow search algorithm (SSA) which was proven of the state-of-the-art performance in benchmark functions [13-14]. The objective of this study is to develop a simplified sparrow search algorithm (SSSA) and employed it to train the ANFIS and get the optimal fuzzy rule parameters thereafter.

2. SSA and Anfis Theory

2.1. Basic Sparrow Search Algorithm (Ssa)

The SSA begins with random spatial coordinates of the entire sparrow population, which mainly play three different roles in their forging activities, i.e., producers, followers and reconnoiters. Through the multiple changes and iterations of the entire population in solution space, the optimal solution of the system will be achieved eventually.

The updating pattern of producers is as follows:

$$X_{ij}^{t+1} = \begin{cases} X_{ij}^{t} \cdot \exp\left(-\dfrac{i}{R_1 \cdot It_{\max}}\right), & \text{if } R_2 < ST \\ X_{ij}^{t} + Q \cdot L, & \text{if } R_2 \geq ST \end{cases} \tag{1}$$

where d and n signify the dimension of the decision variables and the number of sparrows, respectively. Xnd is the position of the nth sparrow in dimension d. R1 and R2 are independent random numbers in the range of (0,1) and ST (belongs to [0.5,1]) means a switch of the searching pattern. Q is a random number that obeys the standard normal distribution. L is a 1×d vector in which each element is one.

Besides producer sparrows, all the rest sparrows play the role of followers. The updating pattern of followers is as follows:

$$X_{ij}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^{t} - X_{ij}^{t}}{i^2}\right), & \text{while } i > \dfrac{n}{2} \\ X_{P}^{t+1} + \left|X_{ij}^{t} - X_{P}^{t+1}\right| \cdot A^{+} \cdot L, & \text{o.w.} \end{cases} \tag{2}$$

where X_P originates from the optimal solution reached by producers and X_{worst} is the worst solution by producers. A is a 1×d vector in which each element is set to 1 or -1 randomly, and $A^+ = A^T(AA^T)^{-1}$.

Reconnoiters are not new sparrows but randomly generated from the entire population, accounting for 10% ~ 20% of the entire population. During the whole foraging activities, reconnoiters are aware of predators, even if they are eating. The updating pattern of reconnoiters is as follows:

$$X_{ij}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left| X_{ij}^{t} - X_{best}^{t} \right|, & \text{while } f_i > f_g \\ X_{ij}^{t} + K \cdot \left(\dfrac{\left| X_{ij}^{t} - X_{worst}^{t} \right|}{\left(f_i - f_w \right) + \varepsilon} \right), & \text{while } f_i = f_g \end{cases} \tag{3}$$

where X_{best} is the global best position found, β is also a random number obeying a standard normal distribution, and K is a random number in the range of [-1,1]. f_i is the fitness value of the sparrow in the current iteration, and f_g and f_w are the global best and worst fitness values, respectively. ε is an arbitrary minimal constant to avoid zero-division errors in the calculation process.

2.2. Simplified Sparrow Search Algorithm (Sssa)

Although SSA has good performance, it still has room to improve. We made these improvements and simplifications for followers and reconnoiters:

In SSSA, we adjusted the switching factor of the search pattern and simplified the search rules of follows; the updating pattern of producers is replaced by

$$X_{ij}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^{t} - X_{ij}^{t}}{i^2} \right), & i > \dfrac{n}{4} \\ X_{p}^{t+1} + \left| X_{ij}^{t} - X_{P}^{t+1} \right| \cdot \dfrac{A^{\mathrm{T}}}{d} \cdot L, & \text{o.w.} \end{cases} \tag{4}$$

In addition, the updating pattern of producers in SSSA is simplified as

$$X_{ij}^{t+1} = \begin{cases} X_{best}^{t} + Q \cdot \left(X_{ij}^{t} - X_{best}^{t} \right), & \text{while } f_i > f_g \\ X_{ij}^{t} + Q \cdot \left(X_{worst}^{t} - X_{best}^{t} \right), & \text{while } f_i = f_g \end{cases} \tag{5}$$

Compared with the basic SSA, SSSA significantly reduces the amount of calculation.

2.3. Adaptive Neuro Fuzzy Inference System (Anfis)

ANFIS is commendably integrates the advantages of artificial neural network and Takagi-Sugeno type fuzzy inference system. It has been widely applied in decision making problems and nonlinear regression problems in the last decade.

Assume a two input channels X and Y and one output channel Z. Then the fuzzy rules can be described by

- Rule 1: If X is x_1 and Y is y_1;
  then $Z = p_1X + q_1Y + c_1$.
- Rule 2: If X is x_2 and Y is y_2;
  then $Z = p_2X + q_2Y + c_2$.

The Schematic of ANFIS structures has five layers in total, which are described in figure 1.

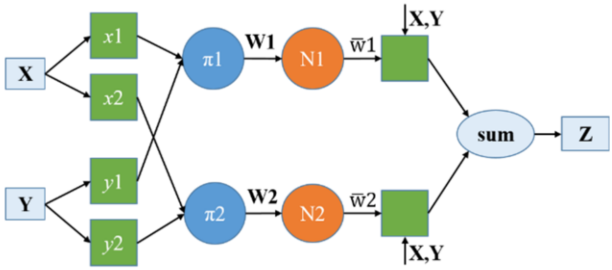
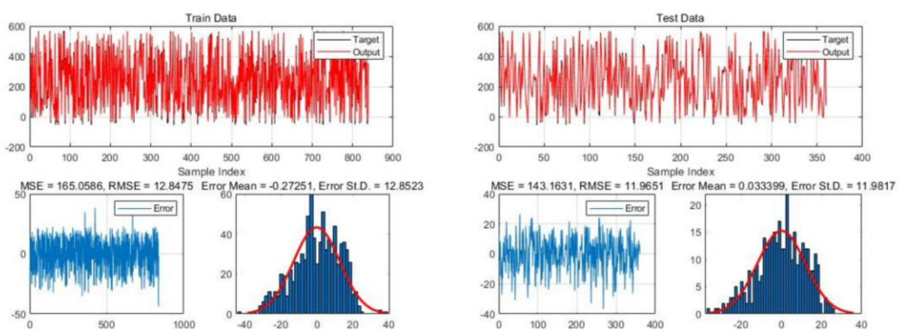


Figure 1. Schematic of ANFIS.

3. Simulation Process

In order to estimate the effectiveness of SSSA on the tuning of ANFIS, the PSO and basic SSA are employed for comparison. In the tuning process of ANFIS by all these metaheuristic algorithms, the population is set to 30 and iterations is set to 20. In both SSA and MSSA, producers account for 30% of the entire population and the switch threshold *ST* of produces is set to 0.6. In the basic SSA, reconnoiters account for 20% (the same as the original literature), but account for 60% in SSSA. Moreover, in the PSO method, the learning factors are set to 1.2 and 1.5, and the weight coefficient decreases linearly from 1 to 0.1.

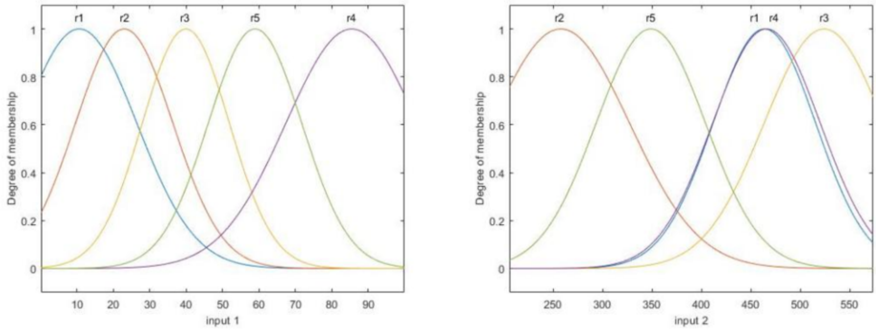
All the metaheuristic methods were trained by real engine data, were divided into training group and test group according to the proportion of 3:1. After the tuning process, the simulation results on the train data and the test data by SSSA are shown in figure 2.



(a) (b)

Figure 2. Simulation results on (a) train data and (b) test data by SSSA.

Overall, the output data in figure 2 (a) and (b) is in good agreement with the target data. The RMSE of train data obtained by SSSA is 12.8475 and that of test data is 11.9651. Meanwhile, the RMSE of train data obtained by PSO is 13.5933 and that of test data is 13.0517. The RMSE of train data obtained by the basic SSA is 12.9577 and that of test data is 13.1397. The performance of tuning ANFIS using SSA is better than the other metaheuristic algorithms.



(a) (b)

Figure 3. Membership functions of (a) input 1 and (b) input 2 after tuning by SSSA.

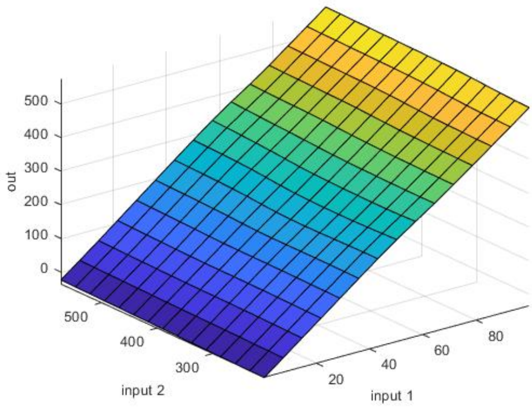


Figure 4. The Fuzzy rule surface after tuning by SSSA.

The membership function and fuzzy rule surface trained by SSSA are shown in figure 3 and figure 4, respectively. From the two figures, we can see that although the trained membership function shows high irregularity, the solution space based on the membership function shows good linear characteristics, indicating that the method is reasonable and has good convergence performance.

4. Conclusions

In this work, the SSSA was proposed and employed for the tuning the fuzzy rule parameters of ANFIS. The antecedent and consequent parameters in the initial raw ANFIS are trained and optimized by the SSSA. To estimate the effectiveness of SSSA, PSO and the basic SSA are utilized for comparison. Results suggest that the SSSA has the lowest error of the metaheuristic algorithms. In summary, The SSSA is demonstrated to be another effective means of tuning the ANFIS parameters.

Acknowledgements

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