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The improved quantum genetic algorithm with its application in fault diagnosis

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Abstract. In this paper, by analyzing the characteristics of the simulated annealing algorithm (SA) and the real double-chain coding target gradient quantum genetic algorithm (DCQGA), the real double-chain coding target gradient quantum genetic simulated annealing algorithm (DCQGSAA) is proposed. Because the performance of LSSVR is extraordinarily sensitive to its key parameters, the proposed algorithm is used to optimize these parameters, then a hybrid non-parametric prediction model is put forward. This model is used in fault prediction of liquid rocket engine thrust. The simulation results show that the proposed model is effective for small samples and multi-dimensional fault prediction.

1. Introduction

At present, artificial neural networks have been widely applied in the field of engineering [1-3]. The effect of artificial neural networks in practical applications is affected subject to the number of samples. The support vector machine (SVM) [4-5] is born to solve the disadvantages of neural networks, so it has obtained widespread applications [6]. However, the performance of SVM is very sensitive to its key parameters. In [7-10], variant intelligent algorithms are used to optimize these parameters. In [10], the genetic simulated annealing algorithm (GSAA) is introduced. In [7], DCQGA is proposed. In this paper, the real double-chain coding target gradient quantum genetic simulated annealing algorithm (DCQGSAA) is proposed based on DCQGA and GSAA. Then DCQGSAA is applied for optimizing the parameters of LSSVR, and a hybrid model is proposed. This model is used in the failure prediction of liquid rocket engine thrust. The prediction results show that this model works well.

2. DCQGSAA Algorithm

In [7], the DCQGA Algorithm is presented.

The idea of DCQGSAA is that: in each loop of DCQGSAA, DCQGA is first implemented, then so does GSAA.

3. The Proposed Model

The performance of LSSVR is associated with the type of kernel function, the corresponding kernel parameters, and the penalty item coefficient C. In this paper, the radial basis function (RBF) is selected as the kernel function. The expression of RBF is defined as:

$$K(x,x_i)=\exp\left[-\frac{\|x-x_i\|^2}{2\sigma^2}\right]$$

where σ is the width of RBF. The above proposed DCQGSAA algorithm is used to optimize the parameters of LSSVR, and the flowchart of this model is shown in Figure 1.

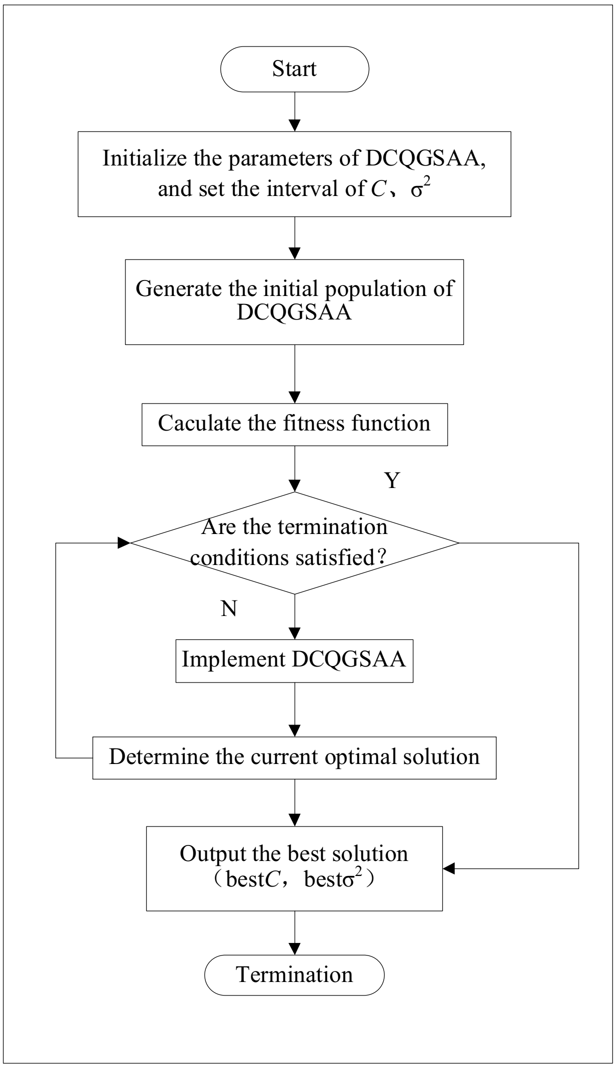

Figure 1. The flowchart of the proposed model

4. Application

The thrust of a liquid rocket engine is an important factor. It is closely related to the oxidant flow $\dot{m}_o$, the combustion flow $\dot{m}_f$, the pressure of the combustion chamber p_c, the sampling time t, and other factors. There exists a high complexity and non-linearity between these parameters and the thrust, and this relationship can be summarized as the function $F = f(\dot{m}_o, \dot{m}_f, p_c, t, \ldots)$. Therefore, the proposed model can be used to establish the failure prediction model of liquid rocket engine thrust.

The training and testing samples of the model from the firing test data, shown in Table 1 [8], are scaled. From Table 1, the number of samples is 25, and the sampling time is 0.1 s. In this study, the first 13 rows are used of the table as training samples for modelling, and the rest 12 rows are for testing samples to validate the effect of prediction.

Table 1. The table of firing test data

Sampling Time t (s)	Combustion flow ($\dot{m}_f$)	Oxidant flow ($\dot{m}_o$)	Pressure of combustion chamber (p_c)	Thrust (F)
0.0	0.3179	0.4011	0.0098	0.0000
0.1	0.3931	0.4661	0.0559	0.0496
0.2	0.5780	0.5339	0.2238	0.1418
0.3	0.6532	0.5935	0.4643	0.3262
0.4	0.6012	0.5658	0.6170	0.4113
0.5	0.6012	0.5572	0.7049	0.4681
0.6	0.6763	0.6374	0.7832	0.5674
0.7	0.7746	0.6721	0.8447	0.6596
0.8	0.8555	0.8238	0.8951	0.7730
0.9	0.9017	0.8753	0.9301	0.8440
1.0	0.9306	0.9149	0.9580	0.8865
1.1	0.9526	0.9420	0.9790	0.9163
1.2	0.9665	0.9593	0.9874	0.9362
1.3	0.9769	0.9702	0.9930	0.9504
1.4	0.9827	0.9810	0.9944	0.9574
1.5	0.9884	0.9864	0.9951	0.9716
1.6	0.9442	0.9919	0.9972	0.9787
1.7	0.9965	0.9957	0.9986	0.9858
1.8	0.9977	0.9973	1.0000	0.9929
1.9	0.9988	0.9995	1.0000	0.9986
2.0	1.0000	1.0000	1.0000	1.0000
2.1	1.0000	1.0000	1.0000	1.0000
2.2	1.0000	1.0000	1.0000	1.0000
2.3	1.0000	1.0000	1.0000	1.0000
2.4	1.0000	1.0000	1.0000	1.0000

In this experiment, the parameters of DCQGSAA are set as follows: the population size 20, the number of iterations 100, the mutation probability 0.05, the step size of rotation angle 0.001*pi, the initial temperature $t_0=f(p_g)/\ln 5$ and the annealing constant 0.7. In [9-10], the ranges of σ^2 and C are set as [0.01, 1000] and [0.01, 10000], respectively. First, the training samples are used to train LSSVR; then, the test samples are input to the trained LSSVR to obtain the predicted values of themself; the negative value of the root mean squared error between the predicted values of the test samples and their true values, -RMSE, is used as the fitness function of DCQGSAA. The key parameters of LSSVR are globally optimized to obtain the best σ^2 and best C; then the LSSVR uses the best σ^2 and best C to train the training samples and obtain the fitted values. At the same time, the consumption time in this training process is recorded; furthermore, the testing samples are input into the trained LSSVR with these best parameters to obtain the forecasted values. The fitted curve of the training samples, the forecasted curve of the testing samples, and the varying curve of the fitness function are obtained, respectively. The prediction results on the testing samples are given in Table 2.

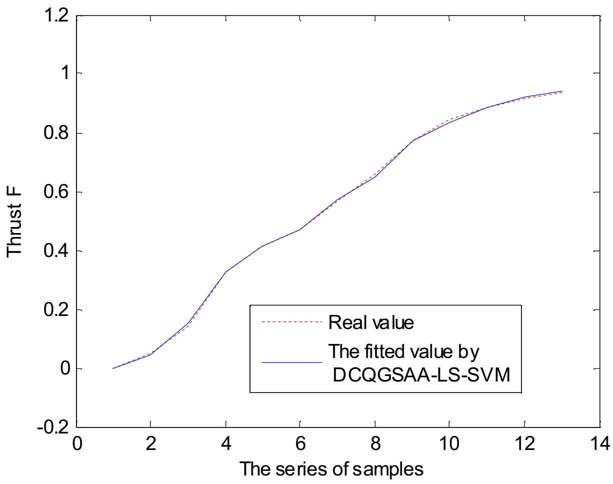

Figure 2. The fitted curve of the training samples

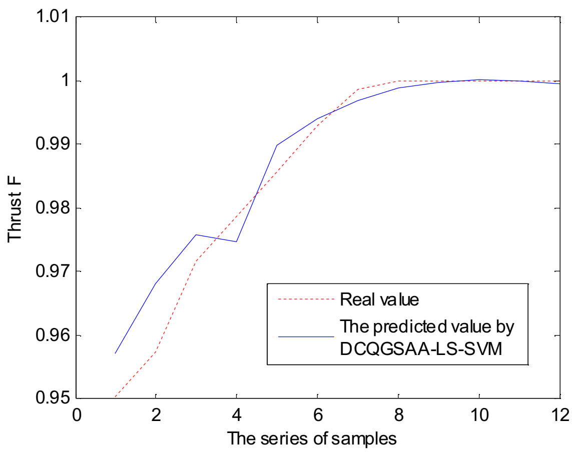

Figure 3. The predicted curve of the testing samples

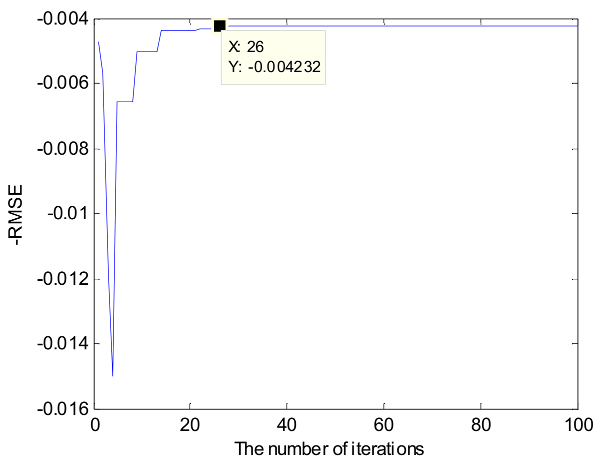

Figure 4. The changing curve of the fitness function

From Figure 2, it can be seen that the optimized LSSVR can better fit the training samples. From Figure 3, it shows that the optimized LSSVR can also better predict the values of the testing samples. From Figure 4, it can be seen that the fitness function has gone to the stable value of -0.004232 after 26 iterations. All these indicate that the proposed model has good generalization performance.

Table 2. The prediction results of the testing samples

No.	True value	The predicted value of the proposed model	The predicted value of LSSVR [8]
1	0.9504	0.9570	0.9595
2	0.9574	0.9681	0.9694
3	0.9716	0.9759	0.9745
4	0.9787	0.9748	0.9835
5	0.9858	0.9899	0.9885
6	0.9929	0.9941	0.9931
7	0.9986	0.9970	0.9976
8	1.0000	0.9988	1.0013
9	1.0000	0.9997	1.0024
10	1.0000	1.0002	1.0024
11	1.0000	1.0001	1.0024
12	1.0000	0.9995	1.0024
The average relative error (%)		0.2977%	0.37%
The time of training (s)		0 (the simulation result using MATLAB)	0.0006

5. Conclusion

In this paper, DCQGSAA is proposed combined with the advantages of DCQGA and SA. Then it is used to optimize the key parameters of LSSVR, and the hybrid non-parametric prediction model is built. This model is applied to predict the thrust of a liquid rocket engine. The simulation results show that this model is productive for fault prediction on small samples and high dimensions.

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