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A novel online performance evaluation strategy to analog circuit

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ABSTRACT

An analog circuit performance online evaluation approach is presented subject to the inevitable actualities of the fault value caused during the data collection process. The multi-model with the corresponding features is modeled via fuzzy clustering based data features firstly. And then the developed scheme relies on a weighted combination of normal least square support vector regression (LSSVR) and particle swarm optimization (PSO) to realize the active suppression for the wrong value and disturbance parameters. Furthermore, another problem should be considered; namely, the traditional offline evaluation approach could not realize the model's timely adjustment with the sample increasing or decreasing. Focusing on this issue, the increase and decrease interaction update idea is imported to the modified performance evaluation scheme. The developed model can be updated quickly online. Numerical testing data information supported by the college analog circuit experiments adopted eight performance indexes of the traditional OTL amplifier to establish training set. This data information had been obtained via precision instrument evaluation in two years. Numerical simulations are preformed to verify the performance of the proposed approach.

1. Introduction

Fault diagnosis about analog circuit can be dated to 1962 [1], R. S. Berkowitz discussed the network element value solvability and its importance in the establishment of methods of automatic trouble shooting of electronic equipment. And based on this issue, amount of researchers, such as Duhamel et al. [2], and You et al. [3], pay attention to this topic because of advent of modern, complex integrated analog circuits and systems. The corresponding fault diagnosis scheme had also been presented. Two basic analog circuit approaches, simulation before test and simulation after test, are proposed [4]. Whatever the approach, the fault diagnosis is closely related to the data information [5,6]. In both the approaches, the complexity involved and computation time required usually place limit on their applicability. Focusing this issue, symbolic analysis [7], observer/residual generator [8], sensitivity computation [9–13], and data driven [14,15] have been employed to reduce the computational cost, and some achievements have been approved.

A growing number of researchers pay attention to this issue of analog circuit fault diagnosis, especially analog circuit performance evaluation. Actually, the performance evaluation of analog circuit is especially important when it is working in a system. Zhao et al. [16] proposed a robust control of continuous-time systems with state-dependent uncertainties and its application to electronic circuits. Moreover, robust control has also been applied in this field. Aiming to the data information uncertainty, system robustness was employed to deal with it. The literature [17] proposed an evaluation method of amplifier performance based on SVR which has the merit of higher evaluation precision, portable, lower cost, while this design procession ignored the wrong value and disturbance value. Focusing on the defect, the literature [18] proposed a sample error weighted LSSVM scheme to reduce singular point impact. And the literature [19] combines the fuzzy clustering idea with LSSVM, considers the advantage of weighted simultaneously, to be weighted for every sample point, and which guarantees the robustness of LSSVM. Although Refs. [18,19] have obtained the robust via weighted to reduce the effect of singular value, the weighted value selection, of the proposed two approaches, is constant. Moreover the weighted value is easy to be affected by parameters of LSSVM. Based on this, the literature [20] imports the robust RBF to robust LSSVR (RLSSVR) to avoid the LSSVM parameter effect to this weighted value determination. However, another difficult problem, initial weighted and structure determination, is still on.

For the fact discussed above, fuzzy clustering with LSSVR is combined firstly to realize analog circuit performance evaluation. The fuzzy clustering method (FCM) is high efficiency soft clustering algorithm which permits one sample to belong the different classes in a disparate membership degree. The membership degree, deduced via FCM, is directly related to every sample that means that the value of the membership degree is not a constant. Therefore, the FCM not only can be used to generate n LSSVR sub-

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models, but also can be used to update the weight for the new generation sub-model. Then the model precision can be improved via the combination predication. Although the regression precision of the training samples can be improved, the amount of calculation could not be reduced. PSO will be employed to optimize the penalty factor and kernel parameter of LSSVR model because of the capacity of rapid convergence and global optimization about PSO. At the same time, considering the factor, the number of the samples, affected computation speed, increased and decrement interactive learning algorithm is employed.

The remainder of this paper is organized as follows: Section 2 introduces the fuzzy clustering algorithm. Section 3 presents the main results about the PSO–FCLSSVR prediction model, and PSO–FCLSSVR increased and decrement interactive learning algorithm is presented in Section 4. In Section 5, simulation results with the application of the proposed performance evaluation approach for analog circuit are presented. Conclusions and future work are given in Section 6.

2. Fuzzy clustering

Let $X=\{x_1,x_2,\cdots,x_n\}$ denotes a training sample, and $X\subseteq R^p$. For illustration purposes, we define c to be class number, $v_i(1\le i\le c)$ denotes the ith class center, $u_{ik}(1\le i\le c, 1\le k\le n)$ denotes the ith membership function. Then the objective function of FCM can be defined by

$$J_m(U,v)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^m\|x_k-v_i\|^2 \tag{1}$$

where $0\le u_{ik}\le 1$, $0<\sum_{k=1}^{n}u_{ik}<n$, $U=\{u_{ik}\}$a, $v=(v_1,v_2,\cdots,v_c)$ and $m>1$ is membership degree weight coefficient, its constraints are

$$\sum_{i=1}^{c}u_{ik}=1, 1\le k\le n \tag{2}$$

Then combined Eq. (1) with Eq. (2), the following Eqs. can be obtained:

$$u_{ik}=\frac{(1/\|x_k-v_i\|^2)^{1/(m-1)}}{\sum_{j=1}^{c}(1/\|x_k-v_j\|^2)^{1/(m-1)}}, 1\le i\le c, 1\le k\le n \tag{3}$$

$$v_i=\frac{\sum_{k=1}^{n}u_{ik}^m x_k}{\sum_{k=1}^{n}u_{ik}^m}, 1\le i\le c \tag{4}$$

FCM algorithm can be done based on square error and objective function criterion. Initial scheme should be given out firstly, and then the objective function (2) would reach the minimum via the multi-iterative with Eqs. (3) and (4).

3. PSO–LSSVR prediction model

3.1. LSSVR theory

Let record data sample $S=\{s_i|s_i=(x_i,y_i)\}$, where $x_i\in R^n$ is the ith input value, $y_i\in R$ is the corresponding output value. For the regression problem about the given sample set $S=\{s_1,\cdots,s_n\}$, the input value is mapped from low dimension space to high dimension feature space via $\varphi(x):R^d\to R\bar{d}$. The regression function of the feature space can be defined by

$$y(x)=\omega\varphi(x)+b \tag{5}$$

where $\varphi(\cdot)$ denotes the feature function, ω and b are the regression parameters. Then the minimization risk function is defined by

$$R(r)=\frac{1}{2}\|\omega\|^2+\frac{1}{2}\gamma\sum_{i=1}^{N}L(y_i,y(x_i)) \tag{6}$$

Sum of the squares is selected as the form of loss function, and the inequality constrains is transformed to equation constrains. Then the optimization problem [21] of LSSVR can be expressed by

$$\min J(\omega,e)=\tfrac{1}{2}\|\omega\|^2+\tfrac{1}{2}\gamma\sum_{i=1}^{N}e_i^2$$
$$s.t.\, y_i=\omega\cdot\varphi(x_i)+b+e_i \quad i=1,\cdots,N \tag{7}$$

where $J(\omega,e)$ is the objective function, γ is the factor coefficient and $e=(e_1,e_2,\cdots,e_N)^T$ is the evaluated error vector of the samples. To facilitate analysis and calculation, the lagrangian multiplier and matrix transformation are employed to overcome the complexity about determination feature function $\varphi(x_i)$. Therefore, the optimization problem (7) can be converted to be

$$\begin{bmatrix}0 & 1^T\\ 1 & A\end{bmatrix}\begin{bmatrix}b\\ a\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \tag{8}$$

where $A\equiv\Omega+\gamma^{-1}I$, $\Omega_{ij}=k(x_i,x_j)$, $1=[1,\cdots,1]^T$, $y=[y_1,\cdots,y_N]^T$ is the output vector, and $a=[a_1,\cdots,a_N]^T$ is the lagrangian multiplier vector. Then the LSSVR model can be obtained via solving b,a

$$\hat{y}=\sum_{i=1}^{n}a_ik(x_i,x_j)+b \tag{9}$$

where $k(\cdot,\cdot)$ expresses the kernel function with the Mercer condition. Here Gaussian radial bases function (RBF) is adopted

$$k(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right) \tag{10}$$

where σ denotes the width of kernel function. The two parameters σ and γ have the strong influence to the learning ability and generalization ability of LSSVR model [22]. As to get the optimal parameters, modified PSO algorithm [23] is employed.

3.2. Modified PSO optimal algorithm

In PSO algorithm, $u_i=(u_{i1},u_{i2},\cdots,u_{im})$ expresses the position vector of the ith particle, $p_i=(p_{i1},p_{i2},\cdots,p_{im})$ expresses the best position that the$i$th particle has been through and $v_i=(v_{i1},v_{i2},\cdots,v_{im})$ expresses the velocity vector of the ith particle, $p_g=(p_{g1},p_{g2},\cdots,p_{gm})$ expresses the best position that all the particles have been through. The equations of updated velocity and position are defined by

$$\begin{cases} v_{im}^{k+1}=wv_{im}^k+c_1r_1(p_{im}-u_{im}^k)+c_2r_2(p_{gm}-u_{im}^k)\\ u_{im}^{k+1}=u_{im}^k+v_{im}^{k+1}\end{cases} \tag{11}$$

where r_1, r_2 are the random number of [0,1] and w is the initial weight. w is the key parameter which can balance the global search ability and local search ability of the PSO algorithm. We employ the following initial weight to update:

$$w=w_{\max}-(w_{\max}-w_{\min})\frac{iter}{iter_{\max}} \tag{12}$$

where $iter$ denotes present iterations, $iter_{\max}$ denotes the maximum iterations, and $w_{\min}$, and $w_{\max}$ denote the maximum and minimum of the initial weight respectively.

Another two important parameters are self-learning factor c_1 and social learning factor c_2 which directly affect the PSO algorithm convergence performance. The c_1 and c_2 with dynamic