Strategies to Assess the Analog Circuit Performance of Multicore Adaptive Iterative LSSVR

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Abstract. In order to obtain accurate and fast fault information from circuit vibration signals, a method of extracting fault functions based on degradation conditions under limited and improved bandwidth experimental conditions is proposed. The fault analysis of the circuit fault is carried out through the multi-carrier conveyor relationship.

Keywords: Improved Empirical Mode Decomposition for Limited Bandwidth, Fault Diagnosis, Multi-core Correlation Vector Machine

I. Bayesian Network

1.1 Bayesian Network Structure
Bayesian networks were proposed by Judia Pearl in the 1980s. This is an uncertain model, which relies on the possibility of processing and simulating human thinking in the past, and its network structure can be comparable to sharp directed graphics. As shown in Figure 1, Bayes contains nodes, and there are many nodes, each node represents an uncertain variable.[1] These nodes can be reflected in sharp vectors, such as the direction of line segments connected by vectors through vector lines, the causal relationship between contracts, and accurate feedback of abstract problems, which promotes the relationship between network nodes and structures easily and clearly. Relationships between any chart structures can be expressed, and information can be expressed in a variety of ways. Even the dynamic changes of the model, such as the relationship between lead and exit, node relationships, etc., will not affect the accuracy of the model, and the model can be evaluated and predicted.
For a given set of random variables \( X = \{X_1, X_2, ..., X_n\} \), its Bayesian network should have the following two points:

1. Each variable in the set represents a separation of \( X \) sections.
2. If the variable \( x \) represents the variable \( V \), then \( x \) is the original node of \( V \) and a probability is used to determine the interaction between the contracts.

One part of a Bayesian network router can be thought of as consisting of contracts, and the other part can be thought of as a strong influence between contracts represented by probability distribution.[2]

For the variables in group \( X \), the common probability distribution formula is:

\[
p(x) = \sum_{i=1}^{n} p(x|pa_i)
\]

In which, \( x \) refers to different node variable, and \( pa_i \) refers to the father node of \( X_i \).

\((S, P)\) refers to the joint probability distribution \( p(x) \), the construction of the Bayesian network, is analyzed from different angles, and produces different results. If Bayesian networks are built from previous possibilities, they are often subjective. If the Bayesian network is established based on actual field data, it is objective.[3] In order to build a Bayesian network, we first need to collect fault information about the object, analyze causal defects with the contract. In the first step, the layout of the Bayesian network is established. In the second step, the probability distribution of node conditions is determined. As shown below:
1. Knowledge Acquisition of Bayesian Network

The acquisition of the Bayesian network enables some known knowledge and understanding of errors in the rules, and then the actual problem is solved by the computer. There are many ways to understand Bayesian networks, such as understanding the experience of experts, failure and impact analysis, forming a tree of knowledge and understanding errors.

The way to acquire knowledge, especially expert experience, refers to experts in a certain field based on their rich work experience and rich professional knowledge. After participating in the research for a certain period of time, they can gain experience and systematic knowledge in the field and deal with specific problems flexibly. These problems have reference and guidance value for solving problems. Some knowledge structures are clear and rich, but some structures have inevitable disturbances, errors, and omissions, which will affect the diagnosis.

There are different classifications of knowledge and experience in diagnosing intelligent errors. If distinguished according to the function of knowledge, it is usually divided into generating practical knowledge, descriptive knowledge, and judicial knowledge. The classification of processes mainly uses existing diagnostic rules to explain knowledge, which is a problem-solving strategy; descriptive knowledge depends on the fact that it uses the characteristics of the object. Clarification of concepts, relationships, and other understandings of judgment are certain standards of governance, ways of thinking, etc. that are used to motivate the resolution of problems that need to be addressed. In order to understand the experience of experts, the representativeness of the production base is mainly used in the field of artificial intelligence.

Failure mode and impact analysis is a method to analyze the bottom-up error of the system. FMEA analyzes errors in the early stages of device design, reduces hidden system error issues, and improves reliability. Therefore, it is broken down into primitive units. Based on their functions and
characteristics, they analyze potential failure situations one by one. Experts in this field will then analyze the impact of various failure scenarios on the system and even the system, and describe the failure scenarios according to the degree of impact, the degree of damage, and the possibility of failure modes.[6] The FMEA model is considered more suitable for judging and interrogating equipment errors at a later stage. The steps to analyze FMEA failure are as follows:

![FMEA Failure Analysis Process](image)

**Figure 3** FMEA Failure Analysis Process

Fault tree analysis is a decision model for diagnosing faults and it is often used in the engineering field. However, this type of fault tree model has been fixed and is not suitable for post-creation. New diagnostic information cannot be introduced into model diagnostics, which is a discount on the effectiveness of the diagnostics.[7] However, in general, free trade agreements are more comprehensive and suitable for judging problems. According to the shape of the tree, analyze the cause of the system failure step by step, and then analyze the cause of the system failure and the probability of each failure. This is a logical approach, depending on cause and effect. By analyzing the hierarchical structure of the system, the failure status and impact of each layer, and then the cause of each layer for all wrong basic events.

II. Multi-core Adaptive Iterative LSSVR Algorithm

2. 1 Basic Principles of LSSVR
LSSVR is an automatic learning mode derived from Bayesian algorithm. The tail probability of the income signal is predicted by LSSVR to achieve the classification effect.
LSSVR can quantify diagnosis with stronger differences and is more suitable for practical applications. LSSVR is actually a binary classification, which provides the possibility of attribution of test samples, and can only provide two samples. However, error diagnosis does not work, it requires classification of multiple types of data.[8] Therefore, in order to solve the problem of misclassification with LSSVR, multiple binary LSSVR series must be used. Common formulas, including: One Verse One (OVO), One Verse Rest (OVR), Binary Tree (BT), and Decision Directed Acyclic Graphs (DDAG). But there is a cumulative phenomenon; as shown in Figure 4, after drawing a ring-free graph and filtering by hierarchical filter layers, DDAG is first proposed by the plate and other parts to insert multi-level SVM bands and general DDAG mode. This method requires a small number of works, there is no overlap and no classification, so the classification effect is better. Later, Huilan et al. Suggested replacing multiple characters with two characters instead of LSSVR.

![Figure 4 Decision Directed Acyclic Graph Structure of Supporting Vector Machine](image)

2. 2 MKLSSVR Basic Theories
Kernel function plays an important role in LSSVR and largely determines the accuracy of model diagnosis. Single-core LSSVR is one of the most widely used LSSVR. This method is simple and easy to use, but only uses one basic function, which may ignore useful information during training, especially the data held by the training, thereby weakening the ability to promote the model. In order to achieve a higher diagnosis rate and better transmission ability, researchers at home and abroad have explored the best core learning methods and have achieved many successes. Multi-core learning methods are the most widely used methods.[9] In order to take advantage of the various core functions of the kernel in data processing, a variety of kernel core functions are combined to achieve better propagation capabilities and more accurate diagnosis. In literature, LSSVR has been proposed to play the core function of multiple shapes to improve the performance of the model. In view of the diversity of kernel functions, this document proposes a multi-asymmetric kernel model that combines kernel RBF functions with linear multi-boundary kernel functions and improves the operation of the model. The goal of this paper is the non-linear and non-fixed nature of the circle signal. An asymmetric multi-core method is used to build the MKLSSVR model.

Given the different advantages of different types of processing functions in data processing, it is necessary to select the appropriate transaction for each key function. For kernel core functions that play a significant role in improving model performance, the corresponding transactions must be larger, while for kernel core functions that have little effect in improving model performance, transactions must be reduced, or even controlled to zero. Obviously, it is unrealistic to determine the coefficients of each core function through manual experiments. Therefore, combined with years of working
experience, a QPSO algorithm to improve each kernel function was determined. On the basis of ensuring the operation of the model, the distributed distribution of transactions will be realized, that is, the core function of the kernel that contributes little to improving the accuracy of the model has a coefficient.

III. Simulation Experiment

3.1 Data Collection and Processing
The experimental circuit uses a typical OTL power amplifier with a bootstrap circuit in the analog electronic technology as the test circuit. Multisim 12.0 was selected as the simulation program, showing the power amplifier Figure 5. The occupant performance evaluation index mainly includes 8 indexes: adder, upper and lower frequency, rolling range, input sensitivity, noise pressure, maximum non-deformed output power and maximum non-deformed output energy.

Figure 5 OTL Power Amplifier with Bootstrap Circuit

First, for the obtained set of training samples, 100 sets of samples are randomly selected as experimental data, and 3 error values (150%) and 30% interference data (30%) are added to the 100 samples to ensure similarity between the samples obtained and actual data collected on site. Second, we can standardize 100 sets of data to [1, 1], pick 50 sets of training samples not connected to the Internet, 20 sets of prediction samples, and 30 sets of training data packages. In order to fully prove the accuracy and reliability of MKLSSVR, the traditional methods of LSSVR and ε-SVR are used to evaluate the decline performance of this data group.

3.2 Numerical Experiments
In the experiment, eight technical evaluation indexes of the tested amplifier were determined, and whether the performance evaluation of the output $y_i \in \{-\epsilon, \epsilon\}$ met the standard. The parameters of the simulated stereo model were improved by the improved PSO algorithm. At the same time, a preliminary determination of the number of sample size termination clauses carried out by the reduction process was carried out to determine the algorithm.[10] According to the training data, data
performance and errors, the auxiliary equipment training samples are compared respectively. For the evaluation results, see Table 1.3.

**Table 1** Data Characteristics and Error Comparison Results of Training Samples

| Number of training sample groups | Evaluation method | Training MAE | Training MSE |
|----------------------------------|-------------------|--------------|--------------|
|                                  |                   | A_u | U_om | U_s | U_N | A_u | U_om | U_s | U_N |
| 50                               | MKAILSS VR        | 0.0 | 0.1  | 0.0 | 0.1 | 0.0 | 0.0  | 0.0 | 0.0 |
|                                  |                   | 584 | 104  | 724 | 357 | 129 | 603  | 121 | 688 |
| 50                               | LSSVR             | 0.0 | 0.3  | 0.3 | 0.7 | 0.0 | 0.0  | 0.0 | 0.3 |
|                                  |                   | 906 | 128  | 072 | 602 | 780 | 938  | 734 | 083 |
| 50                               | ε-SVR             | 0.6 | 0.2  | 0.2 | 0.6 | 0.2 | 0.2  | 0.2 | 0.2 |
|                                  |                   | 132 | 768  | 681 | 877 | 934 | 712  | 528 | 744 |

**Table 2** Data Characteristics and Error Comparison Results of Training Samples

| Number of training sample groups | Evaluation method | Training MAE | Training MSE |
|----------------------------------|-------------------|--------------|--------------|
|                                  |                   | A_u | U_om | U_s | U_N | A_u | U_om | U_s | U_N |
| 50                               | MKAILSS VR        | 0.0 | 0.0  | 0.0 | 0.1 | 0.0 | 0.0  | 0.0 | 0.0 |
|                                  |                   | 466 | 997  | 989 | 436 | 092 | 624  | 106 | 745 |
| 50                               | LSSVR             | 0.5 | 0.2  | 0.1 | 0.5 | 0.2 | 0.1  | 0.0 | 0.3 |
|                                  |                   | 453 | 508  | 293 | 794 | 402 | 599  | 765 | 594 |
| 50                               | ε-SVR             | 0.1 | 0.3  | 0.1 | 0.6 | 0.2 | 0.2  | 0.2 | 0.3 |
|                                  |                   | 301 | 284  | 421 | 039 | 605 | 676  | 492 | 052 |

**Table 3** Comparison of Evaluation Results

| Evaluation method | A_u | f_{lw}/M_{Hz} | f_{l}/M_{Hz} | f_{s}/M_{Hz} | U_{m} | P_{lw}/mW | U_{l}/mW | U_{N}/pV | CP U Averag e time/s |
|-------------------|-----|---------------|--------------|--------------|-------|-----------|-----------|----------|---------------------|
| MKAILS VR         | 46.0263 | 3.8 | 199.8 | 3.7 | 0.4 | 24.9 | 10.0 | 68.0 | 100 | 83 |
| LSSVR             | 51.4757 | 3.9 | 173.9 | 3.9 | 0.4 | 20.3 | 10.0 | 6661 | 60 | 68 |
| ε-SVR             | 56.3644 | 2.2 | 336.2 | 2.2 | 0.6 | 51.0 | 16.0 | 16.0 | 52 | 96 |
| Experimental value | 46.0000 | 3.7 | 203.7 | 3.7 | 0.4 | 25.8 | 10.0 | 6.3 | 1840 | - |

Figure 6 and Figure 7 show the speed response curve and local regression curve under the three algorithms, respectively. This point is the support vector. In Figure 2, we compare the detection time of LSSVR in one cycle, while making a sharp comparison of the detection times of the other two methods, which shows that MKLSSVR runs much faster than other algorithms. It can be seen from Fig. 3 that the density of the MKLSSVR support vector is at a relatively large curvature change position, and the relative position is relatively stable.
The experimental results show that compared with the traditional $\varepsilon$-SVR method, LSSVR method and precision instrument estimation results, the measurement results of MKAILSSVR are not significantly different from the latter three, but the operating speed has increased dramatically. At the same time, due to the use of multi-core RBF and adaptive iterative methods, the number of auxiliary vectors in the training set is greatly increased.

**IV. Conclusion**

In view of the insufficient performance evaluation methods of traditional simulated circles in dealing with extreme values, it is recommended to use complex weighted network performance evaluation methods based on network simulation circles. The advantages of improved particle swarm optimization algorithm combined with pvr and FCM method are used to combine the predicted weights with the circular model, which can effectively deal with the data set containing wrong values.
In addition, considering the traditional indirect evaluation strategy of changing the sample set, issues such as models cannot be adjusted in a timely manner. Therefore, the increase and decrease of interactive updates in the performance evaluation strategy are presented in a single document. In practice, the evaluation method of MKAILSSVR has the characteristics of excellent accuracy, high calculation speed, low development cost, and easy implementation. Therefore, evaluation strategies are worthy of research and development.

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