Modeling and Predicting Structure Insensitive Properties of NiZn Ferrites by Using Support Vector Regression

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Abstract

According to the experimental dataset on the structure insensitive properties of 21 different ferrites of the doping NiZn system, support vector regression (SVR) combined with particle swarm optimization (PSO) for its parameter optimization was employed to construct mathematical model for prediction of the structure insensitive properties of the NiZn ferrites. The accuracy and reliability of the constructed support vector regression model are validated by leave-one-out cross validation (LOOCV). Test results show that for Curie temperature (*T*c), saturation magnetization (*M*s) and dielectric constant (ε) the maximum absolute percentage error does not exceed 10%, the mean absolute percentage error are 0.73%, 0.28%, 2.44%, and the correlation coefficient (R^2) is as high as 0.999, 1 and 0.994 respectively. This investigation suggests that one can optimize designing or controlling the experimental process by using support vector regression model to get suitable properties of NiZn ferrites.

Keywords

NiZn Ferrites; Support Vector Regression; Regression Analysis; Modeling.

1. Introduction

The ferrite material NiZn which have high electrical resistivity, low loss, and good high-frequency characteristics has become a research focus in recent years.[1-3] But the sintering temperature of the NiZn ferrite is about 1300 ^{0}C by using traditional ceramic technology, there is a certain gap compare with the sintered target of below 1000 ^{0}C. So more research is focused the low temperature sintering technology of ferrites at present. Another research focus is to improve the electromagnetic properties of ferrite by various methods in order to adapt to the application and miniaturization of anti EMI. [4-6] But the electromagnetic properties of ferrite are affected by many factors such as formula, processing parameters and microstructure and so on. These factors are mutually affecting and restricted, the relationship between factors and the electromagnetic properties is very complex and nonlinear. The Curie temperature (*T*c), saturation magnetization (*M*s) and dielectric loss (ε) are important intrinsic parameters of ferrite, mainly depends on the chemical composition. Usually the structure insensitive properties can be improved through optimization of chemical composition.[7,8] Based on the conventional method it is very difficult to build an accurate and complete mathematical model to predict the structure insensitive properties. Support vector regression (SVR) combined with particle swarm optimization algorithm for its parameter optimization and integrating leave-one-out cross-validation (LOOCV) is an effective method to solve this problem. In this paper, the SVR-LOOCV model was built to predict the structure insensitive properties of the NiZn ferrites and the predicted values are in good agreement with the experimental results.

2. Methods and materials

2.1 The brief theory of support vector regression

Support vector machine (SVM), proposed by Vapnik and co-workers[9] in 1995 is a statistical machine learning theory based on structural risk minimization principle. Due to its excellent performance such as fast-learning, global optimization and excellent generalization ability for small-

sample, SVM has been successfully applied to solve classification and regression problems in many areas. [10-20] It is called SVR when SVM was employed to solve the regression problems. The basic idea of SVR is to map the input vector $\boldsymbol{x}$ into a high dimensional feature space $\boldsymbol{F}$ using a nonlinear projecting function $\Phi(x)$, and then to conduct a liner regression in $\boldsymbol{F}$ space. The final regression function of SVR is as follows:

$$f(\boldsymbol{x}) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k(\boldsymbol{x}, \boldsymbol{x}_i) + b, \quad (1)$$

Where l is the number of support vector, α_i and α_i^* are Lagrange multipliers, $k(x, x_i) = \Phi(x) \cdot \Phi(x_i)$ is a kernel function, b is a bias. In this paper, radial basis kernel was adopted as the kernel function, and it is formulated as Eq. (2). The detailed principle of SVR can be referred to Refs. [9, 11].

$$k(\boldsymbol{x}, \boldsymbol{x}_i) = exp(-\gamma||\boldsymbol{x} - \boldsymbol{x}_i||^2) \quad (2)$$

2.2 Choosing of SVR parameters with PSO

The PSO method proposed by Kennedy and Eberhart in 1995 was motivated by social behavior of organisms, such as fish schooling and bird flocking. [21,22] which can be used to search the best parameter subset (ε, C, γ) that entirely decide SVR generalization. In this study, root mean square error (REMS), which directly influences the regression performance of SVR, is chosen as the fitness function:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \quad (3)$$

Where n is the number of training samples, $\hat{y}_i$ represents estimated value for the ith training sample and y_i stands for the ith actual measured values.

2.3 Dataset and Modeling

The dataset used in this study was selected from Ref. [23]. This dataset includes 21 samples under different alloying element content which were listed in table 1. *NiO*, *ZnO*, *MnO*, GeO_2, SiO_2 represents mole percent content respectively. *T*c is the Curie temperature, *M*s is the saturation magnetization and ε is the dielectric constant. In this modeling process, mole percent content of *NiO*, *ZnO*, *MnO*, GeO_2, SiO_2 act as five input variables. The *T*c, *M*s and ε of NiZn are as the output variables. The modeling and prediction were conducted by using the 21 samples based on Support Vector Regression. After 10000 times iteration, the final SVR model successfully gets a higher accuracy for fitting each sample poit.

Table 1. Dataset

No.	*NiO*	*ZnO*	*MnO*	GeO_2	SiO_2	*T*c	*M*s	ε
1	26.67	17.78	8.88	4.00	9.33	200	2200	1
2	26.67	17.78	11.11	8.88	2.22	190	2100	2
3	26.90	17.94	4.93	2.24	13.45	200	2500	5
4	26.90	17.94	4.48	0	16.14	210	2500	4
5	26.90	17.94	4.48	16.14	0	230	2700	1
6	26.90	17.94	4.93	13.45	2.24	240	2700	1
7	27.45	18.30	5.03	5.95	5.95	250	3100	5
8	27.90	18.60	4.65	4.65	4.65	280	3500	9
9	24.40	19.50	4.88	4.88	4.88	350	2300	2
10	26.44	21.63	2.88	2.40	2.40	100	2500	4
11	33.65	14.42	2.88	2.40	2.40	250	3100	9
12	28.84	19.23	2.88	2.40	2.40	370	4400	9
13	29.12	19.42	2.43	0	3.40	340	4700	60
14	29.12	19.42	2.43	3.40	0	350	4700	50
15	29.41	19.60	0.98	1.47	1.47	370	4800	40
16	29.56	19.70	2.46	0	0.50	360	4000	30
17	29.56	19.70	2.46	0.50	0	370	4000	20
18	29.97	19.98	0.05	0.05	0.05	440	5200	80
19	29.98	19.98	0.025	0.05	0.05	440	5200	100
20	29.98	19.99	0.05	0.025	0.025	440	5200	200
21	30	20	0	0	0	450	5250	100

2.4 Evaluation of Model's Generalization Performance

Three parameters, i.e, the mean absolute error (MAE), mean absolute percentage error (MAPE) and correlation coefficient (R^2), were adopted for generalization performance evaluation:

$$MAE = \frac{1}{m}\sum_{j=1}^{m}\left|\hat{y}_j - y_j\right| \quad (4)$$

$$MAPE = \frac{1}{m}\sum_{j=1}^{m}\left|\frac{\hat{y}_j - y_j}{y_j}\right| \quad (5)$$

$$R^2 = \frac{\left[\sum_{j=1}^{m}(y_j-\bar{y})(\hat{y}_j-\bar{\hat{y}})\right]^2}{\sum_{j=1}^{m}(y_j-\bar{y})^2\sum_{j=1}^{m}(\hat{y}_j-\bar{\hat{y}})^2} \quad (6)$$

Where m means the number of test samples, y_j is the jth target value, $\hat{y}_j$ stands for predicted value for the jth test sample and $\bar{y}$ is the mean target value for all test samples.

3. Results and discussions

Table 2 gives a comparison between the experimental values and estimated values predicted by SVR. From Table 2, it can be viewed that the prediction results of majority samples for *T*c (13/21=61.9%) estimated by SVR are equal to zero. The maximum absolute percentage error predicted by SVR is only 8.88% (No. 10). The other's samples absolute percentage errors do not exceed 1.5%. For *M*s, all of the absolute percentage error are small for each sample except No. 14. The others lie within the range of 0%~1% mostly. For ε the absolute percentage errors of nineteen samples are near to experimental values among all 21 samples. Table 3 shows that for the predicted values of 21 samples the MAE of *T*c, *M*s and ε comes up to 1.70, 12.83 and 4.80, the MAPE is 0.73%, 0.28% and 2.44%, and the $R^2$is as high as 0.999, 1.000, 0.994 respectively. All these results indicate that the prediction of SVR is excellent and SVR is an effective and powerful technique for forecasting the structure insensitive properties of the NiZn ferrites.

Table 2. Comparison between experimental values and simulated results

	$Tc(^0C)$			$Ms(\times 10^{-4}T)$			$\varepsilon(\times 10^{-4})$		
No.	Exp.	SVR	Error (%)	Exp.	SVR	Error (%)	Exp.	SVR	Error (%)
1	200	200.00	0.00	2200	2199.99	0.00	1	1.00	0.39
2	190	190.00	0.00	2100	2094.12	0.28	2	2.00	0.00
3	200	200.00	0.00	2500	2500.02	0.00	5	5.00	0.05
4	210	210.00	0.00	2500	2498.65	0.05	4	4.00	0.01
5	230	230.00	0.00	2700	2700.23	0.01	1	1.00	0.06
6	240	240.00	0.00	2700	2700.53	0.02	1	1.00	0.00
7	250	250.00	0.00	3100	3099.58	0.01	5	5.00	0.00
8	280	280.05	0.02	3500	3499.95	0.00	9	9.00	0.00
9	350	353.26	0.93	2300	2299.99	0.00	2	2.00	0.00
10	100	91.12	8.88	2500	2500.00	0.00	4	4.00	0.01
11	250	250.00	0.00	3100	3100.00	0.00	9	9.00	0.01
12	370	370.00	0.00	4400	4400.00	0.00	9	9.03	0.28
13	340	340.00	0.00	4700	4656.83	0.92	60	59.97	0.05
14	350	350.01	0.00	4700	4555.02	3.08	50	49.99	0.02
15	370	370.00	0.00	4800	4804.68	0.10	40	40.00	0.00
16	360	360.00	0.00	4000	3997.34	0.07	30	30.00	0.00
17	370	366.81	0.86	4000	3997.33	0.07	20	21.96	9.78
18	440	436.44	0.81	5200	5185.45	0.28	80	80.00	0.00
19	440	445.25	1.19	5200	5216.54	0.32	100	100.07	0.07
20	440	445.12	1.16	5200	5212.34	0.24	200	199.37	0.63
21	450	443.60	1.42	5250	5230.60	0.37	100	100.00	0.00

Table 3. Prediction performance of SVR model

Response	MAE	MAPE (%)	R^2
$Tc(^0C)$	1.70	0.73	0.999
$Ms(T)$	12.83	0.28	1
ε	4.80	2.44	1

The Fig. 1 is the comparison between the experimental values and results predicted by SVR. From Fig. 1 one can see that the most points lie on or very close to the straight-line with slop 1 (except No. 20 for ε). This demonstrates that the predicted values are in quite good agreement with the measured values, and also illustrates that the constructed SVR model possess good generalization ability.

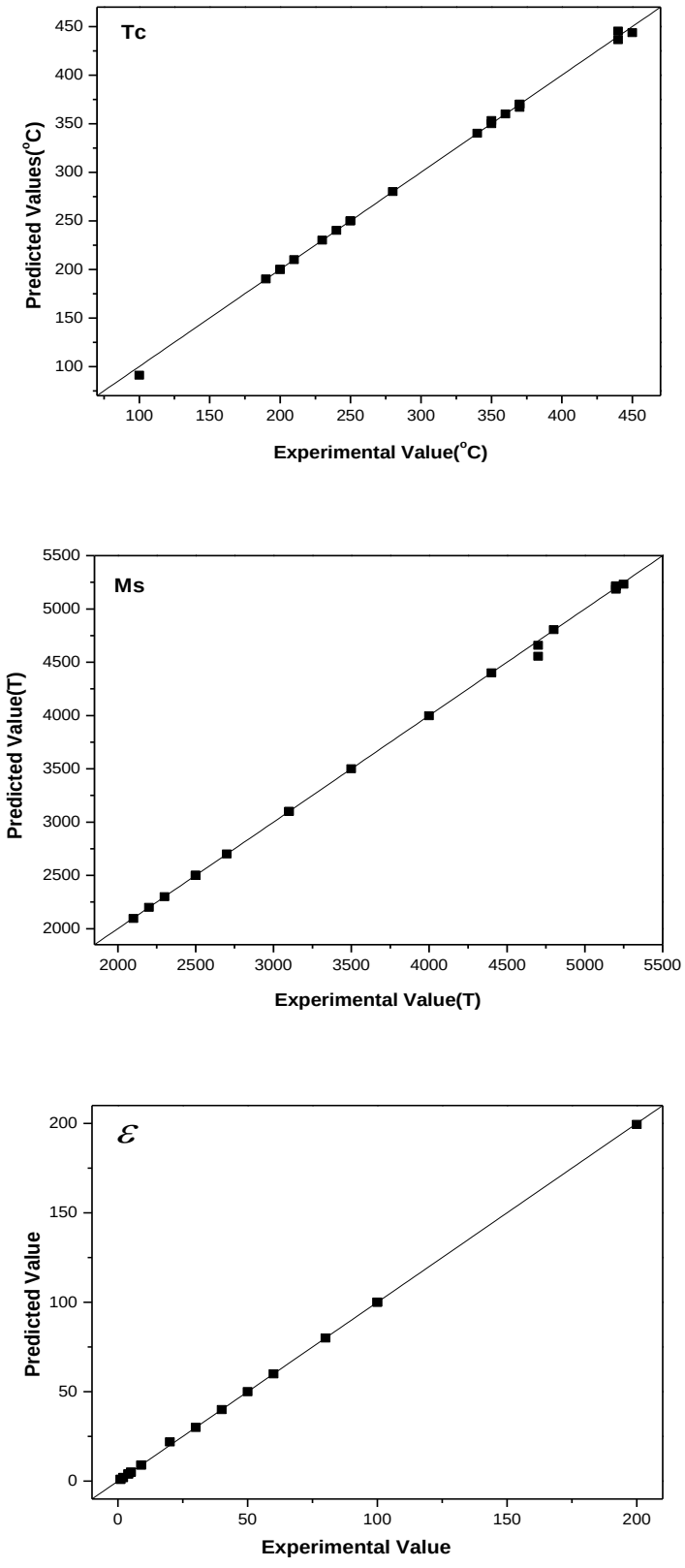

Fig. 1 Comparison of experimental values vs estimated values

Figure 2 depicts the percentage error distribution of structure insensitive properties calculated by SVR-LOOCV. From Fig. 2, it can be seen that most percentage errors of structure insensitive properties predicted by SVR are near x=0 on both sides. These demonstrate that the predicted values of SVR-LOOCV are in good agreement with the experimental values, and also illustrates that the constructed SVR-LOOCV model possess good generalization ability.

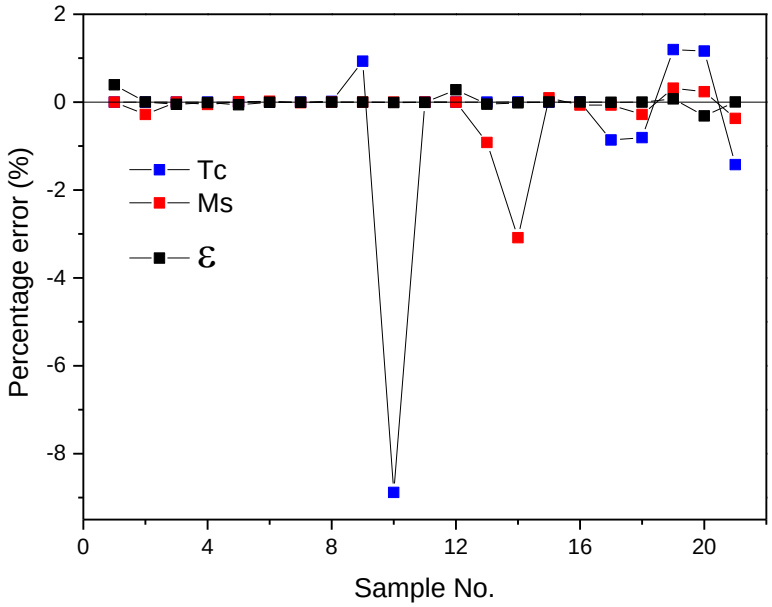

Fig. 2 Plot of the percentage error distribution of structure insensitive properties calculated by SVR-LOOCV

4. Conclusion

In this paper, the model for predicting the structure insensitive properties of NiZn ferrite under five different synthesis parameters was set up by using support vector regression approach combined with particle swarm optimization. The prediction results show that the structure insensitive properties is a multi-variable, nonlinear system. The effect of the mole percent content of chemical compositions on structure insensitive properties is very complicated. The predicted errors of SVR are small. The established model possesses strong generalization ability. The predicted values are consistent quite well with the experimental values.

Acknowledgments

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