Magnetic Remanence Prediction of NdFeB Magnets Based on a Novel Machine Learning Intelligence Approach Using a Particle Swarm Optimization Support Vector Regression

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ABSTRACT

Studies have shown that the chemical compositions affecting the magnetic properties of NdFeB magnets. In order to get the right NdFeB magnets, it is advantageous to have an accurate model with which one can predict the magnetic properties with different components. In this paper, according to an experimental dataset on the magnetic remanence of NdFeB, a predicting and optimizing model using support vector regression (SVR) combined with particle swarm optimization (PSO) was developed. The estimated result of SVR agreed well with the experimental data. Test results of leave-one-out cross validation show that the mean absolute error does not exceed 0.0036, the mean absolute percentage error is solely 0.53%, and the correlation coefficient ($R^2$) is as high as 0.839. This implies that one can estimate an available combination of different proportion components by using support vector regression model to get suitable magnetic remanence of NdFeB.

Keywords: NdFeB Magnets, Magnetic Remanence, Prediction, Regression Analysis, Support Vector Regression

1. INTRODUCTION

The rare earth permanent material NdFeB with low rare earth content, high magnetic remanence, relatively high coercivity and high maximum magnetic energy product has become a research focus in recent years(Kneller, & Hawig, 1991; Skomski, & Coey,1993; Schrefl, Fidler, & Kro-
The magnetic remanence of NdFeB is closely related to the alloying element content. Usually the magnetic remanence can be improved through optimization of alloying compositions (Jakubowicz, & Jurczyk, 2000; Jakubowicz, & Szlaferek, 1999; Rieger, Seeger, Li, & Kronmuller, 1995). But the common method is to change a kind of element content while keep the other alloying element unchanged, and then to find the change trend between this element and the magnetic remanence, and then by using the same method study how the other elements affect the magnetic remanence. But in this method the experimental work is heavy, and that the effect of interaction between various components on magnetic remanence cannot be considered at the same time. The relationship between the interaction of various components and the magnetic remanence is very complex and nonlinear. It is difficult to build an accurate theoretical method to predict the magnetic remanence. Support vector regression (SVR), proposed by Vapnik and coworker in 1995, is a new powerful machine learning theory based on structural risk minimization principle (Vapnik, 1995, 1999). Due to its excellent performance such as fast-learning, global optimization and excellent generalization ability for small-sample, SVR has been developed to solve nonlinear regression issues (Cai, Han, Ji, & Chen, 2003; Cai, Han, Ji, & Chen, 2004; Cai, Wang, & Chen, 2003; Cai, Wang, Sun, & Chen, 2003; Cai, Xiao, Tang, & Huang, 2013; Cai, Zhu, Wen, Pei, Wang, & Zhuang, 2010; Firat, Ozay, Onal, Oztekin, & Yarman Vural, 2013; Kharrat, Gasmi, Ben Messaoud, Benamrane, & Abid, 2011; Lin, & Pai, 2001; Pei, Cai, Zhu, & Yan, 2013; Tang, Cai, & Zhao, 2012; Wen, Cai, Liu, Pei, Zhu, & Xiao, 2009; Xiao, Cai, Tang, & Huang, 2013; Yi, Peng, & Li, 2012). In this paper the SVR model integrating leave-one-out cross validation (LOOCV) was build to predict the magnetic remanence of the NdFeB magnet combined with particle swarm optimization algorithm for its parameter optimization.

2. METHODS AND MATERIALS

2.1 Theory of Support Vector Regression

Suppose \((x, y)\) represents a sample, where \(x\) stands for the independent variables and \(y\) the dependent variable. In SVR, the basic idea is to map \(x\) from input space into a high dimensional feature space \(F\) by a nonlinear projecting function \(\Phi(x)\), and then to conduct liner regression in \(F\) space. So the work of SVR is to find out a linear equation (1) dependent on a given training dataset \((x_1, y_1), \ldots, (x_n, y_n)\).

\[
f(x) = W \cdot \Phi(x) + b \quad \Phi : \mathbb{R}^n \rightarrow F, \quad w \in F
\]

where \(W\) is a vector for regression coefficients, \(b\) is a bias. They are estimated by minimizing the regularization risk function \(R(C)\), namely:

\[
\text{minimize } \, R(C) = \frac{1}{2} \| W \|^2 + C \sum_{i=1}^{n} L_\varepsilon (f(x_i) - y_i)
\]

\[
L_\varepsilon (f(x_i) - y_i) = \begin{cases} 
0, & \text{if } |f(x_i) - y_i| < \varepsilon \\
|f(x_i) - y_i| - \varepsilon, & \text{if } |f(x_i) - y_i| \geq \varepsilon
\end{cases}
\]
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