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A robust support vector algorithm for harmonic and interharmonic analysis of electric power system

Yong Zhan*, Haozhong Cheng

Department of Electrical Engineering, Shanghai Jiaotong University, 200240 Shanghai, PR China

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Abstract

A novel robust algorithm to harmonic and interharmonic analysis based on support vector machines (SVM) and solved by iterative reweighted least squares (IRWLS) algorithm to overcome the difficulty of exponential computation complexity, is proposed in the paper. It has a good precision for analyzing harmonics and interharmonics without synchronized sampling that is essential for fast Fourier transform (FFT). By introducing a specific loss function, the method can mitigate the infection of outliers and noises and exhibits robustness characteristics. Its IRWLS-based implementation makes it efficient and suitable for harmonic and interharmonic analysis of electric power system. The case studies showed its high precision and robustness of the SVM spectral analysis algorithm.

Keywords: Electric power system; Power quality; Harmonic and interharmonic analysis; Signal processing; Robustness; Support vector machines

1. Introduction

With the increasing use of power electronics devices and proliferation of nonlinear loads in electric power system, the issue of harmonics pollution is becoming more and more severe. For example, modern frequency power converters generate a wide spectrum of harmonics components comprising not only characteristic harmonics typical for the ideal converter operation but also considerable amount of noncharacteristic harmonics and interharmonics which may strongly deteriorate the quality of the power supply voltage. It is of great importance to accurately estimate these harmonics component for the reliable and economical operation of power system since it is the foundation to track and solve this problem.

There are many different approaches for measuring harmonics, including FFT [1], application of adaptive filters [2], artificial neural networks [3], simulated annealing optimization [4], Fuzzy linear regression [5], singular value decomposition [6], modern spectrum estimation [7], etc. Most of them operate adequately only in the narrow range of frequencies and at moderate noise levels. The FFT method suffers from the major problem such as resolution, spectrum leakage and picket-fence effects. Because of some invalid assumptions (zero data or repetitive data outside the duration of observation) made in these methods, the estimated spectrum can be a smeared version of the true spectrum. These methods usually assume the only harmonics are present and the periodicity intervals are fixed, while periodicity intervals in the presence of interharmonics are variable and very long [8]. It is very important to develop better tools of interharmonics estimation to avoid possible damages due to its influence. Modern spectrum estimation methods, such as Prony and min-norm, using high-resolution methods and the estimation accuracy in most cases is better than when using the Fourier algorithm, but it is sensitive to noise and its computation is much more complex than FFT. So it is significant to seek a harmonics analysis method that is not only precise and robust (insensitive to noise) but also has proper computation complexity.

A new method of harmonics analysis is drawn from support vector machines (SVM), which was first suggested

* Corresponding author.
E-mail address: zhanyong@sjtu.edu.cn (Y. Zhan).

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to obtain maximum margin by separating hyperplanes in classification [9], and it has been extended to the general learning theory [10]. SVM provides efficient and powerful classification algorithms that are capable of dealing with high dimensional input features and with theoretical bounds on the generalization error and sparseness of the solution provided by statistical learning theory [9]. SVM has few free parameters requiring tuning, is simple to implement, and are trained through optimization of a convex quadratic cost function, which ensures the uniqueness of the SVM solution. Furthermore, SVM-based solutions are sparse in the training date and are defined only by the most “informative” training points. SVM has been originally put forward for pattern recognition, by the introduction of an alternative loss function, it can also be applied to the linear, nonlinear regression problems. In [11], the standard SVM regression algorithm is modified to provide an adequate approach to nonparametric spectral analysis, which is called the SVM-Spec formulation. SVM-Spec algorithms are solved via quadratic programming (QP), whose time demand grows exponentially with the length of the time series, making them useless for most of the practical application. An iterative reweighted least squares (IRWLS) formulation that overcomes this limitation is proposed in [12].

In the paper, this robust support vector (SV) algorithm is introduced to analyze the harmonics and interharmonics in electric power system. Case studies indicated its high precision and robustness.

2. SVM regression

SVM has become very popular for learning from experimental data and solving various classification, regression and density estimation problems. Initially developed for solving classification problems, support vector techniques can be successfully applied to regression. The general regression learning problem is set as follow: the learning machine is given l training from which it attempts to learn the input–output relationship (dependency, mapping, or function) $f(\mathbf{x})$. Considering a set of training data $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l)\}$, where each $\mathbf{x}_i \subset R^n$ denotes the input space of the sample and has a corresponding target value $y_i \subset R$ for $i = 1, \ldots, l$ where l corresponds to the size of the training data. The idea of the regression problem is to determine a function that can approximate future values accurately. The generic SVR estimation function takes the form:

$$f(\mathbf{x}) = (\mathbf{w}\Phi(\mathbf{x})) + b \tag{1}$$

where $\mathbf{w} \subset R^n$, $b \subset R$ and Φ denotes a non-linear transformation from R^n to high dimensional space. The goal is to find the value of $\mathbf{w}$ and b such that values of $\mathbf{x}$ can be determined by minimizing the regression risk:

$$R_{\text{reg}}(f) = C\sum_{i=1}^{l}\Gamma(f(\mathbf{x}_i) - y_i) + \frac{1}{2}\|\mathbf{w}\|^2 \tag{2}$$

where $\Gamma(\cdot)$ is a cost function, C is a pre-specified constant which determines penalties to estimation errors. A large C assigns higher penalties to errors so that the regression is trained to minimize error with lower generalization while a small C assigns fewer penalties to errors; this allows the minimization of margin with errors, thus higher generalization ability. The ε -insensitive loss function is the most widely used cost function. The function is the form:

$$\Gamma(f(\mathbf{x}) - y) = \begin{cases} |f(\mathbf{x}) - y| - \varepsilon, & \text{for } |f(\mathbf{x}) - y| \geq \varepsilon \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Thus, the loss is equal to zero if the difference between the predicted $f(\mathbf{x})$ and the measured value is less than ε. Vapnik's ε-insensitivity loss function (3) defines an ε tube. (Typical graph of a regression problem as well as relevant mathematical objects required in learning unknown coefficients w_i are shown in Fig. 1. If the predicted value is within the tube the loss (error or cost) is zero. For all other predicted points outside the tube, the loss equals the magnitude of the difference between the predicted value and the radius ε of the tube. Note that for $\varepsilon = 0$, Vapnik's loss function equals a least modulus (a.k.a. Huber's robust loss) function.

This loss function is less sensitive to outliers than the quadratic loss function used in least squares method and enables a sparse set of support vectors to be obtained. In solving regression problem, the SVM performs linear regression in n-dimensional feature space using ε-insensitivity loss function. At the same time, it tries to reduce model capacity by minimizing $||\mathbf{w}||^2$, in order to ensure better generalization. All

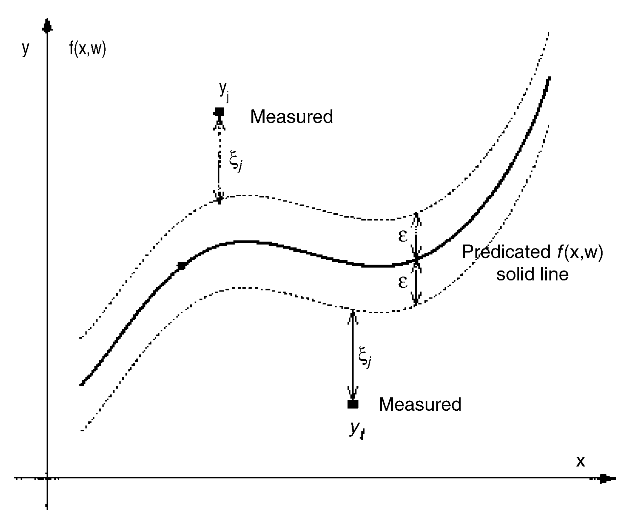

Fig. 1. Parameters used in one-dimensional (1-D) SV regression.