Harmonic emission level evaluation method of photovoltaic system based on relevant vector machine

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Abstract. With the increasing connecting of photovoltaic systems, the harmonic pollution in power grid is deteriorated. The evaluation of the harmonic emission levels for photovoltaic system is significant for harmonic mitigation. However, when the background harmonics are unstable, traditional evaluation methods have large calculation errors. To solve this problem, a method based on the relevant vector machine is proposed in this paper. Compared with the traditional vector machine based method, the novel one can reach a high calculation accuracy, even when the background harmonics is relatively unstable. The validity for our proposed method is verified by simulation analysis.

1. Introduction

With the developing of the power system, a large number of photovoltaic (PV) systems are connected into the grid, which significantly worsens the harmonic pollution \cite{1,2}. Besides, many nonlinear customers are also existed in the utility side of the power grid. Thus, the harmonic voltages at the point of common coupling (PCC) are generated by the harmonic sources in both the PV system and the utility sides. To divide the harmonic responsibility and release the harmonic pollutions, it is crucial to evaluate the harmonic emissions for the PV system.

According to the international standard of IEC61000-3-6, the key step for the evaluation for harmonic emissions is calculating the harmonic impedance for the utility side. The existing calculation methods are including the fluctuation method \cite{3,4}, the linear regression based method \cite{5,6}, and the covariance based method \cite{7}, etc. According to the sign of the ratio for the fluctuation parts of the measured harmonic voltage and current, the fluctuation method can calculate the harmonic impedance of the utility side. This method is one of the most classical one in this researching field, however, it is only suitable for the situations where the background harmonics are stable. Based on the linear regression based method, we can obtain the impedance by calculating the regression coefficient. Yet, the regression method is still on the basis of the conditions that the background harmonic is stable. The covariance method is based on the fact that the correlation between the harmonic currents measured at the PCC and the background harmonics is weak. The impacts from the background harmonics are thus released in a certain degree. However, in the utility side of the modern power system, a large number of power electronic devices are connected in, which greatly enhance the fluctuation of the background harmonics. Thus, the covariance method still has large calculation errors in this situation.
In comparison, the support vector machine (SVM) based method has a relatively high calculation accuracy, yet, in the process of parameter setting, the impacts from the differences among the input data are usually ignored. Thereby, the calculation accuracy is still unacceptable.

To overcome the weaknesses for the existing SVM method, and to evaluate the harmonic emissions for PV system, an improved relevant vector based method is proposed in this paper. First, the equivalent circuit is built, and the harmonic voltages and currents are measured at the PCC. Then, the harmonic impedance of the utility side is calculated by the improved relevant vector based method, and the harmonic emissions are thus obtained. Compared with the conventional SVM based method, the proposed method has high calculation accuracy even when the background harmonic fluctuates heavily. The effectiveness of the proposed method is verified by simulation analysis.

2. The modal of the PV system

The structure for the PV system is shown in Figure 1. The converters, as the main harmonic source in this system, inject harmonics into the power grid. The power grid is divided into the PV system side and the utility side. In the utility side, a great number of electronic devices are connected in, which enhance the background harmonics.

![Figure 1. The structure of the PV system.](image)

The equivalent circuit of PV system is presented in Figure 2.

![Figure 2. The equivalent circuit of the PV system.](image)

Where \( U_{\text{PCC}} \) and \( I_{\text{PCC}} \) represent the measured harmonic voltages and currents, respectively. \( U_{u} \) and \( I_{c} \) respectively represent the harmonic source in the utility side and the PV system side. \( Z_{u} \) and \( Z_{c} \) respectively represent the harmonic impedances at the utility side and the PV system side.

According to Figure 2, we have

\[
U_{\text{PCC}} = \frac{Z_{u} U_{u} + Z_{c} I_{c}}{Z_{u} + Z_{c}}
\]

and

\[
I_{\text{PCC}} = \frac{Z_{u} U_{u} + Z_{c} I_{c}}{Z_{u} V_{c}}
\]
Based on the international standard of IEC61000-3-6, the harmonic emissions for the PV system can be defined as

$$U_{c-pcc} = I_{pcc}Z_U$$  \hspace{1cm} (3)

Therefore, the calculation of $Z_U$ is the key step for the evaluation of the harmonic emissions.

3. The basic theory of the relevant vector based method

To calculate $Z_U$, in this paper, an improved relevant vector based method is proposed. The basic theory of this method is introduced as the following.

For the training sample set $\{x_n, t_n\}_{n=1}^N$, the input and output vectors, defined as $x_n$ and $t_n$ are independent from each other. The output vectors $t_n$ are the regression function of $x_n$, and we have

$$t_n = y(x_n) + \varepsilon_n$$  \hspace{1cm} (4)

where the noise signal $\varepsilon_n$ satisfies $\varepsilon_n \sim N(0, \sigma^2)$, the symbol $\sigma^2$ represents variance.

The regression function of the relevant vector is

$$y(x, \omega) = \sum_{i=1}^N \omega_i K(x, x_i) + \omega_0$$  \hspace{1cm} (5)

where $K(x, x_i)$ is the kernel function, $\omega_i$ is the weight coefficient, and $\omega_0$ is the deviation. The likelihood function of the training sample set is

$$p(t | \omega, \sigma^2) = \left(2\pi\sigma^2\right)^{-N/2} \exp\left\{ -\frac{1}{2\sigma^2} \|t - \Phi \omega\|^2 \right\}$$  \hspace{1cm} (6)

where $t = (t_1, t_2, \cdots, t_N)^T$ represent the output vector, $\Phi$ is a $N \times (N+1)$ matrix, where $\Phi = [\phi(x_1), \phi(x_2), \cdots, \phi(x_N)]^T$ and $\phi(x_n) = [1, K(x_n, x_1), \cdots, K(x_n, x_N)]^T$.

To avoid overfitting, the prior distribution of $\omega$ is obtained by Bayes theorem as

$$p(\omega | \alpha) = \prod_{i=0}^N N(\omega_i | 0, \alpha_i^{-1})$$  \hspace{1cm} (7)

where $\alpha_i (i=0, 1, \cdots, N)$ is the hyperparameter.

By assuming the prior distributions of hyperparameter $\alpha_i$ and the variance of the noise signal $\sigma^2$ are Gamma distributions, based on the Bayes theorem, we have

$$p(\omega, \alpha, \sigma^2 | t) = \frac{p(t | \omega, \sigma^2)p(\omega, \alpha, \sigma^2)}{p(t)}$$  \hspace{1cm} (8)

The posterior distribution of the weight vector $\omega$ is

$$p(\omega | t, \alpha, \sigma^2) = \frac{p(t | \omega, \sigma^2)p(\omega | \alpha)}{p(t | \alpha, \sigma^2)}$$  \hspace{1cm} (9)

$$= \left(2\pi\sigma^2\right)^{-(N+1)/2} \exp\left\{ -\frac{1}{2} (\omega - \mu)^T \Sigma^{-1} (\omega - \mu) \right\}$$

Where $\Sigma$ and $\mu$ are respectively represent the variance and mean values of this posterior distribution, and we have

$$\Sigma = (\sigma^2 \Phi^T \Phi + A)^{-1}$$  \hspace{1cm} (10)
To obtain the posterior distribution of the weight vector, the optimal value of \( \alpha \) and \( \sigma^2 \) should be calculated based on

\[
\alpha_i^{\text{new}} = \frac{1 - \alpha_i \Sigma_{ii}}{\mu_i}
\]

(13)

\[
\left(\sigma^2\right)^{\text{new}} = \frac{\left\| t - \Phi \mu \right\|^2}{N - \sum_{i=1}^N \left(1 - \alpha_i \Sigma_{ii}\right)}
\]

(14)

Thus, the optimal values, \( \alpha_{\text{MP}} \) and \( \sigma^2_{\text{MP}} \), are obtained. During the iteration, most of the hyperparameters tend to be infinite; thus, the corresponding weight parameters tend to zero. Therefore, in the calculation process, many elements in the kernel function matrix can be ignored and the matrix is sparse. For a new input \( x_\ast \), the variance and expectation of the regression prediction are

\[
\sigma_*^2 = \sigma^2_{\text{MP}} + \phi(x_\ast)^T \Sigma \phi(x_\ast)
\]

(15)

\[
y_* = \mu^T \phi(x_\ast)
\]

(16)

where \( y_* \) is the output of \( x_\ast \).

The steps of calculating \( Z_u \) using the proposed improved relevant vector machine based method are as the following.

1) For the training sample set \( \{x_n, t_n\}_{n=1}^N \) of the relevant vector machine, the input vector \( x_n \) is consisted by the measured harmonic voltages and currents. The symbol \( t_1 \) is the initial value of \( Z_u \), \( t_n \) \( (n=2, 3, \ldots, N) \) is the calculated \( Z_u \) in the \( (n-1)\)th regression.

2) Chose the Gauss kernel function and set the bandwidth.

3) Initialize the hyperparameter \( \alpha \) and variance \( \sigma^2 \), and calculate their optimal value using Eq. (13) and Eq. (14).

4) Calculate the distributions of the weight vectors.

5) input the new harmonic voltages and currents data, and calculate \( Z_u \) using the relevant vector machine.

4. Simulation analysis

Based on the circuit in Figure 2, the simulation data are set as the following.

The amplitude of \( I_C \) is set into 100 A and we have \( |I_C| = p|I_c| \). Besides, the angle of \( I_C \) and \( I_s \) are set into 30° and 60°, respectively. In addition, ±10% random fluctuations are added into both \( |I_C| \) and \( |I_U| \) and their angles. Besides, by considering that the harmonic source signals of both sides are correlated to each other in some scenarios, 10% sinusoidal fluctuations are also added into both \( |I_C| \) and \( |I_U| \) and their angles.

The harmonic impedances of the both sides are set as \( Z_u = 0.5 + 1j \Omega \) and \( Z_c = 4.5 + 7.8j \Omega \), respectively. Meanwhile, 20% sinusoidal fluctuations are added into the real and imaginary parts of both \( Z_u \) and \( Z_c \), respectively.

Four methods, i.e. 1) linear regression method, 2) covariance method, 3) SVM based method, and 4) the proposed method, are used to calculate the harmonic impedance of the utility side. Table 1 and 2 present the average evaluation errors after repeated calculating for 100 times.
Table 1. Contrast of $|Z_u|$ calculation errors.

| $p$ | Method (1) | Method (2) | Method (3) | Method (4) |
|-----|------------|------------|------------|------------|
| 0.1 | 1.40       | 1.41       | 1.23       | 1.15       |
| 0.4 | 2.87       | 1.75       | 1.02       | 1.38       |
| 0.7 | 3.72       | 3.6        | 2.69       | 1.68       |
| 1.0 | 8.72       | 6.06       | 4.91       | 2.79       |
| 1.3 | 14.80      | 11.29      | 8.62       | 4.48       |
| 1.5 | 26.90      | 20.74      | 13.22      | 9.08       |

Table 2. Contrast of harmonic emissions level errors.

| $p$ | Method (1) | Method (2) | Method (3) | Method (4) |
|-----|------------|------------|------------|------------|
| 0.1 | 1.94       | 0.86       | 0.94       | 0.91       |
| 0.4 | -3.35      | 1.59       | 1.89       | 1.89       |
| 0.7 | 4.67       | -4.21      | 2.59       | 2.55       |
| 1.0 | -7.01      | -6.50      | -6.61      | -3.49      |
| 1.3 | -14.27     | -12.02     | -8.65      | -6.21      |
| 1.5 | -17.02     | -21.64     | -14.42     | -10.38     |

Table 1 and 2 indicate that when the background harmonics are stable, the calculation accuracy of each method is high. However, when $p$ is increased, the background harmonics are enhanced, which increases the calculation errors of method (1) and method (2). Although the evaluation accuracy for method (3) is relatively high, when the background harmonic is unstable, the evaluation errors are still large. In comparison, the proposed method has low calculation errors in each case.

5. Conclusion
An improved relevant vector machine based method is proposed in this paper for harmonic emission levels evaluation in photovoltaic system.
This method can calculate the harmonic impedance of utility side with high accuracy even when the background harmonic is unstable, thus, can evaluate the harmonic emissions for photovoltaic system accurately.

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