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An Evaluation Method for Harmonic Emission Level Based on Principal Component Regression

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ABSTRACT

To identify the responsible party of harmonic pollution, this paper puts forward a novel estimation method for harmonic emission level based on principal component regression (PCR). After introducing the principles of the PCR, the author set up a regression equation based on the complex relationship between harmonic voltage, harmonic current and harmonic impedance of the supply system at the point of common coupling (PCC). Then, the PCR was introduced to estimate the harmonic emission levels of the supply system and the consumer at the PCC. The validity of our method was verified through both simulation and field test. The results show that our method can accurately estimate the harmonic emission level, while overcoming the multicollinearity of independent variables and retaining important information in regression.

1. INTRODUCTION

With the growing application of nonlinear loads and distributed generators, the power system is faced with an increasingly severe harmonic pollution [1-2]. To solve the problem, it is imperative to clarify the responsibilities for the pollution and differentiate the harmonic emission levels between the supply system and the consumer [3-6].

In relevant studies, the harmonic emission level is mainly evaluated based on the harmonic contributions of the supply system and the consumer at the point of common coupling (PCC) [7-10]. Many evaluation methods have emerged, including Kalman filter [11-12], harmonic state estimation [13], k-nearest neighbors (kNN) algorithm [14], empirical mode decomposition [15] and distributed measurements [6]. In practice, however, the harmonic emission level is generally evaluated by statistical methods [16].

The fluctuation method and its variants are the earliest statistical evaluation approaches for harmonic emission level [17-18]. By this method, the harmonic impedance of the power system is calculated as the ratio of voltage and current measured at the PCC, and used to identify the responsibilities for harmonic pollution between the power system and the consumer. Despite its simplicity, the fluctuation method may be inaccurate if the voltage and current are not measured accurately.

Later, Zhang and Yang [19] proposed the binary linear regression method, which estimates the resistance component of the harmonic impedance. However, this method performs poorly if the measured voltage and current at the PCC contain singular values. Che and Yang [20] reduced the influence of the singular values through weighting by the robust regression method, but this strategy overlooks the correlation between independent variables in statistical analysis. Then, Huang and Xu [21] introduced the partial least squares (PLS) regression to evaluate harmonic emission level. Compared to the robust regression method, the LS regression identifies information and noise in the power system accurately, and determines the correlation between variables based on statistical features.

The above methods improve the estimation accuracy of harmonic emission level to different degrees. Nevertheless, there are two common problems with these strategies. First, there are too many independent variables in these methods, increasing the modelling complexity. Second, some important data may get lost due to the correlation between independent variables. Because of the two problems, the existing estimation methods for harmonic emission level may be inefficient in extracting the information from dependent variables that has powerful explanatory ability. In severe cases, this type of information is entirely lost.

This paper proposes a method to estimate harmonic emission level based on principal component regression (PCR). In this method, the principal components are selected according to the amount of the information contained, thus overcoming multicollinearity of the independent variables. Moreover, this method can retain as much information of important independent variables as possible. In this way, the harmonic emission level of both supply system and the consumer can be estimated at a high accuracy.

2. THE PCR

The PRC is a statistical method that expresses the information as the linear combination of the least variables [22]. Let by $\{x_1, x_2,...,x_p\}$ be p independent variables in the problem. Then, the dataset of n samples can be described as:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix} = (X_1, X_2, \cdots, X_p) \quad (1)$$

The PCR is a linear transform between the p independent variables:

$$\begin{cases} F_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \\ F_2 = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \\ \cdots \\ F_p = a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p \end{cases} \quad (2)$$

where, $a_{\_ij}$ is the principal component coefficient. Equation (2) can be rewritten as

$$F = AX \quad (3)$$

where, $F=(F_1, F_2,\ldots, F_p)^T$; $X=(X_1, X_2,\ldots, X_p)^T$; A is the score matrix.

Let $\lambda_1, \lambda_2,\ldots, \lambda_P$ be the p eigenvalues of the score matrix A that satisfy $\lambda_1 \geq \lambda_2 \ldots \geq \lambda_n$, and a_j be the corresponding eigenvectors. Then, the variance of F_1 can be expressed as

$$Var(F_1) = a_1 X X^T a_1^T = \lambda_1 \quad (4)$$

Similarly, it can be derived that $Var(F_i)=\lambda_i$. Thus, the variances of principal components decrease in turn. Besides, the covariances of the principal components can be computed by:

$$\begin{aligned} Cov(a_i^T X^T, a_j X) &= a_i^T (\sum_{k=1}^{p} \lambda_k a_k a_i^T) a_j \qquad (i \neq j) \\ &= \sum_{k=1}^{p} \lambda_k (a_i^T a_k)(a_k^T a_j) = 0 \end{aligned} \quad (5)$$

Through the above transform, the independent variables $\{x_1, x_2,...,x_p\}$ become a new set of variables $\{F_1, F_2, \ldots, F_p\}$, whose variances decrease in turn.

Let F_1 be the first principal component to replace the original p variables. This component must contain as much information of the p variables as possible. In other words, the variance $Var(F_1)$ should be maximized. If F_1 cannot cover all the information of the p variables, the second principal component F_2 should be introduced. Note that the information already covered by F_1 should not be included in F_2, because $cov(F_1, F_2)=0$. The third, the fourth…, the pth principal components can be set up by analogy. According to Equation (5), these principal components are not correlated with each other, and their variances decrease in turn $Var(F_1)>Var(F_2),\ldots,>Var(F_p)$. With the decrease of variance, the amount of information contained in each principal component also declines.

In practice, not all the p principal components are identified. Instead, the first q principal components are selected based on their cumulative contribution rate μ, i.e. the variance ratio of a principal component to the total variance of all principal components:

$$\mu = \frac{\lambda_i}{\sum_{i=1}^{p} \lambda_i} \quad (6)$$

Studies have shown that the integrated variable can cover most information of the original variables, if its cumulative contribution rate surpasses 85% [23]. The important information of the original independent variables can be preserved by selecting the principal components based on the contribution rate. In addition, if the F_i value is close to zero, the corresponding independent variables show an approximate linear correlation. After neglecting the relatively small principal components, it is possible to overcome the collinearity between independent variables.

Once the expression of principal components and sub-variables are obtained by the PCR, the dependent variables can be regressed to sub-variables of each principal component. Thus, the regression model can be obtained between dependent variables and sub-variables of each principal component. The expression of principal components facilitates the regression modeling between the standardized independent variables and the dependent variables. Finally, the standardized independent variables can be transformed to the original independent variables, completing the regression modeling between original independent variables and dependent variables.

3. PCR-BASED ESTIMATION OF HARMONIC EMISSION LEVEL

The equivalent circuit of the supply system and the consumer at the PCC is shown in Figure 1, where U_{sh} is the harmonic voltage source of the supply system, I_{ch} is the equivalent harmonic current source of the consumer, Z_{sh} and Z_{ch} are the harmonic impedances of the supply system and the consumer, respectively, and I_{pcch} and U_{pcch} are the harmonic current and harmonic voltage measured at the PCC, respectively. According to the circuit principle, the following equation can be derived:

$$\dot{U}_{pcch} = \dot{U}_{sh} - \dot{I}_{pcch} \dot{Z}_{sh} \quad (7)$$

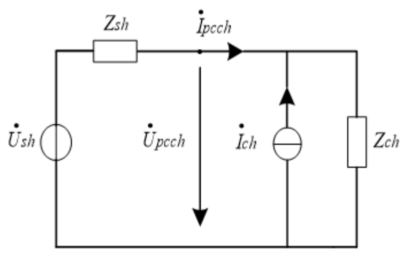


Figure 1. The equivalent circuit of the supply system and the consumer

The real part and the imaginary part can be expressed as multiple linear regression equations, respectively:

$$U_{pcchx} = U_{shx} - I_{pcchx} Z_{shx} + I_{pcchy} Z_{shy} \quad (8)$$

$$U_{pcchy} = U_{shy} - I_{pcchx} Z_{shy} - I_{pcchy} Z_{shx} \quad (9)$$

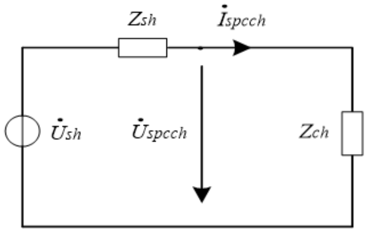
where, I_{pcchx} and I_{pcchy} are the real part and the imaginary part of the harmonic current I_{pcch} measured at the PCC, respectively; U_{pcchx} and U_{pcchy} are the real part and the imaginary part of the harmonic voltage U_{pcch} measured at the PCC, respectively. In multiple linear regression, I_{pcchx} and I_{pcchy} are independent variables, while U_{pcchx} and U_{pcchy} are dependent variables. The regression coefficients Z_{shx}, Z_{shy}, U_{shx} and U_{shy} can be obtained by solving Equations (8) and (9) by the PCR.

To reduce the background harmonic fluctuation, the data used to calculate Z_{sh} and U_{sh} are often divided into M sections. Then, the statistical values of Z_{sh} and U_{sh} can be respectively obtained by:

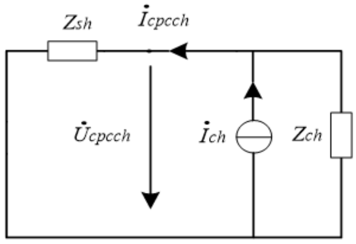
$$\bar{Z}_{sh} = \frac{1}{M}\left(\sum_{m=1}^{M} Z_{shxm} + j\sum_{m=1}^{M} Z_{shym}\right) \tag{10}$$

$$\bar{U}_{sh} = \sqrt{\left(\frac{1}{M}\sum_{m=1}^{M} U_{shxm}\right)^2 + \left(\frac{1}{M}\sum_{m=1}^{M} U_{shym}\right)^2} \tag{11}$$

Next, the harmonic emission level of the consumer can be obtained based on Z_{sh} and U_{sh}. According to the superposition principle, the equivalent circuit in Figure 1 can be split into two circuits (Figure 2).



(a) The supply system



(b) The consumer

Figure 2. The equivalent circuits of the supply system and the consumer

Then, the harmonic emission levels of the supply system and the consumer can be respectively described as:

$$\dot{U}_{spcch} = \frac{Z_{ch}}{Z_{ch} + Z_{sh}}\dot{U}_{sh} \tag{12}$$

$$\dot{U}_{cpcch} = \frac{Z_{ch}Z_{sh}}{Z_{ch} + Z_{sh}}\dot{I}_{ch} \tag{13}$$

Equations (12) and (13) can be combined into:

$$\dot{U}_{pcch} = \dot{U}_{spcch} + \dot{U}_{cpcch} \tag{14}$$

The consumer is usually a source of constant harmonic current with a large resistance Z_{ch}, while the supply system is often a source of constant harmonic voltage with a small resistance Z_{sh} [16]. Thus, it is obvious that $|Z_{ch}| \geq |Z_{sh}|$. Thus, we have:

$$|U_{spcch}| \approx |U_{sh}| \tag{15}$$

$$|U_{cpcch}| \approx |U_{pcch}| - |U_{sh}| \tag{16}$$

4. SIMULATION

The simulation was carried out on Matlab/Simulink with the circuit in Figure 3. The impedance settings and voltage amplitudes of the supply system for the fundamental and harmonic waves are listed in Tables 1 and 2, respectively. For the supply system, the fundamental frequency and fundamental initial phase were 49.9Hz and 10°, respectively. For the consumer, the harmonic current amplitudes were set as follows: I_{c3}=47A, I_{c5}=16A, I_{c7}=8A, I_{c9}=6A, and I_{c11}=3A, and the fundamental impedance was set to 2.723+j11.345Ω.

For comparison, our method, partial least squares method (PLSM), and improved fluctuation method (IFM) were all applied to estimate the harmonic impedance and the harmonic emission level of the supply system. The estimation results are recorded in Tables 1 and 2. The harmonic emission level of the supply system is listed in the form of relative error (%)

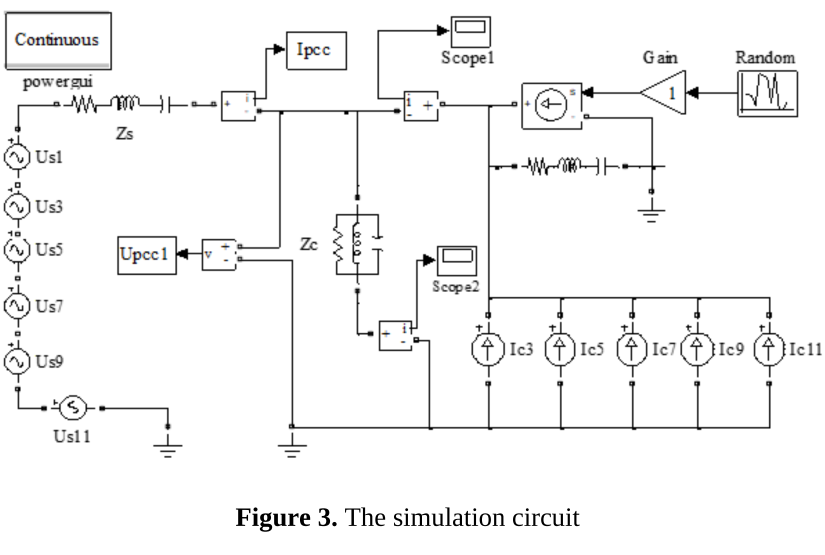


Figure 3. The simulation circuit

Table 1. Settings and estimates of harmonic impedance of the supply system

Harmonic order	Set value of Z_{sh} (Ω)	Estimated by the PLSM (Ω)	Estimated by the IFM (Ω)	Estimated by our method (Ω)
Fundamental	0.5+j1.371	0.471+j1.362	0.481+j1.389	0.5+j1.371
3	0.5+j4.146	0.486+j4.012	0.480+j4.291	0.497+j4.181
5	0.5+j6.910	0.5161+j6.718	0.530+j6.503	0.515+j6.610
7	0.5+j 9.674	0.575+j9.970	0.547+j9.372	0.519+j9.728
9	0.5+j12.438	0.468+j12.901	0.4772+j12.107	0.487+j12.173
11	0.5+j15.202	0.521+j15.937	0.542+j16.152	0.531+j15.795

Table 2. Estimated harmonic emission levels of the supply system

Harmonic order	Set value of U_{sh} (V)	PLSM (%)	IFM (%)	Our method (%)
Fundamental	400	0.87	1.42	1.35
3	12	1.49	1.81	1.51
5	8	1.27	1.51	0.91
7	7	2.36	2.56	1.75
9	5	2.01	4.33	1.36
11	5	3.29	3.61	1.29

From Tables 1 and 2, it can be seen that our method estimated the harmonic impedance and harmonic emission level more accurately than the two contrastive methods. For the estimation of harmonic impedance of the supply system, the IMF had the highest error among the three methods; the PLSM had an overall small error, but performed poorly in some cases, such as the real part of the 7th harmonic impedance. The estimates by our method were close to the set values, except for the 5th harmonic impedance. For the estimation of harmonic emission level of the supply system, our method controlled the relative error within 1.75%, far lower than that of the other methods. Hence, our method can estimate the harmonic emission level of the supply system in an accurate manner.

5. FIELD TEST

The field test was carried out in a chemical plant of Yangzhou, China. The plant is powered by 10kV buses of a 35kV substation. Under the minimal operation mode, short circuit capacity of the 10kV outlet is 175.3MVA; under the maximal operation mode, that capacity is 241.6MVA. Two 20MVA power supplies are installed at the PCC. The power distribution network of the plant is shown in Figure 4.

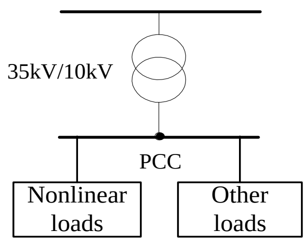


Figure 4. The power distribution network of the plant

The field test was arranged as follows: First, the 10kV bus voltage of the supply system and the 10kV outgoing current of the plant were sampled for 5s with a measuring device at the interval of 5min. The harmonics greater than the 20th were filtered out. The sampling frequency was set to 5,000Hz. Next, the fast Fourier transform (FFT) algorithm with Hanning window [24] was adopted to analyze the measured results by every 500 data points. Then, the harmonic voltage and current at the PCC were analyzed by our method. During the analysis, the harmonic emission level was estimated once for every 500 data points of measured voltage and current.

Due to the limit of space, this paper only lists the measured voltage and current values and the estimated impedance of the supply system corresponding to phase A in the 5th harmonic. The mean voltage, mean current and mean impedance of the supply system for the 5th harmonic wave at the PCC were 105.928V, 36.583A, and Z_{s5} is 0.167 + j2.471 Ω, respectively. The real and imaginary parts of the impedance are shown in Figure 5, where the abscissa n is the number of calculations. The 5th harmonic voltage of the system estimated by our method was 10.341V.

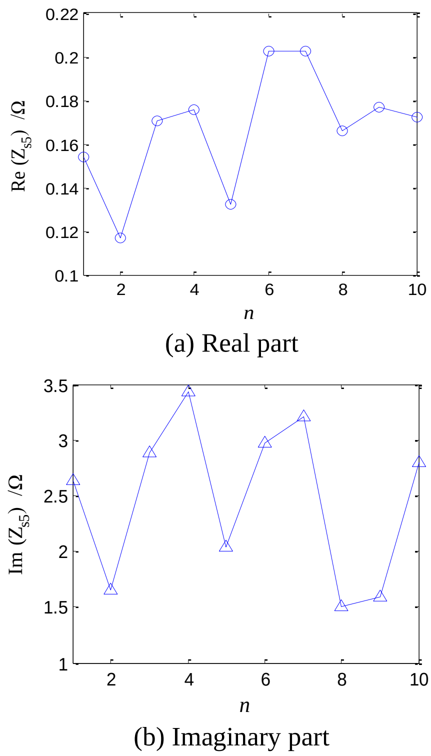


Figure 5. Estimated 5th harmonic impedance of the supply system

According to the maximal and minimal operation mode capacities of 10kV bus, the fundamental reference reactance of the supply system falls between 0.418Ω and 0.576Ω. For low harmonics of the supply system, the reactance on the same line satisfies $L_1=L_h/h$, where L_h is the hth harmonic reactance and L_1 is the fundamental reactance. The 5th harmonic reactance L_{s5} obtained by our method was 2.471Ω. Since $L_1=L_h/h$, L_1 equals 0.494Ω. The estimated is close to the mean value in the range of [0.418Ω, 0.576Ω].

According to Equation (16), the harmonic emission level of the consumer can be described as:

$$U_{c5} = U_{pcc5} - U_{s5} = 105.928 - 10.341 = 95.587\text{V}$$

Thus, the 5th harmonic emission level of the plant accounts for 90.24 % of the 5th harmonic emission level at the PCC. This means the plant is the main responsible party for harmonic pollution.

In real-world scenarios, the harmonic impedance of the consumer is usually much larger than that of the supply system. Therefore, the harmonic emission level of the consumer can also be calculated by $|U_{ch}| \approx |I_{pcch}||Z_{sh}|$. Substituting the values of Z_{s5} (2.477Ω) and I_{pcc5} (36.583A) into the equation, U_{c5} can be obtained as 90.616V, which is close to the estimated value of 95.587V. Hence, our method was proved to satisfy the engineering practice.

6. CONCLUSIONS

This paper puts forward a PCR-based method to estimate the harmonic emission levels of the supply system and the consumer. First, a regression equation was set up based on the complex relationship between harmonic voltage, harmonic current and harmonic impedance of the supply system at the PCC. Then, the PCR was introduced to estimate the harmonic emission levels of both the supply system and the consumer. The proposed method overcomes the multicollinearity between independent variables by removing the principal components with small variance in regression modeling, and retains much of the important information of the original independent variables, which has strong explanatory ability to dependent variables. The accuracy and feasibility of our method were proved through simulation and a field test.

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