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***Abstract* — In this paper, a new power quality index (PQI), which is directly related to the generation of distortion power from nonlinear harmonic loads, is introduced to determine their harmonic pollution ranking in a distribution power system. The electric load composition rate (LCR) and the total harmonic distortion (THD) for the estimated currents on each harmonic load are used to define the proposed PQI. The reduced multivariate polynomial (RMP) model with one-shot training property is applied to realize the PQI. Then, the ranking of distortion power for each nonlinear load, which have adverse effect on the entire system, is determined. It is proved that the relative ranking based on the PQI matches that on the distortion power computed directly from each harmonic load.**

Keywords-component; ***Distortion power, distribution power system, harmonic pollution ranking, power quality index, reduced multivariate polynomial (RMP) model***

I. Introduction

Generation of harmonics and the existence of waveform pollution in power system networks are important problems facing the power utilities. Due to the widespread proliferation of many nonlinear harmonic loads by various power-electronic-based equipments on a consumer side, serious power quality problems can be caused by distorted currents from those nonlinear loads. Also, the increase of nonlinear loads might even distort the grid voltage. As the result, a distributed power system can be placed in an undesired situation by these power quality problems. For example, it is known that a power outage may occur as a result of serious voltage distortion. To tackle these problems, the limits on the amount of harmonic currents and voltages generated by customers and/or utilities have been established in the IEEE standard 519 [1] and in the IEC-61000-3 standard [2]. However, these limits are based on the conventional power quality indices such as total harmonic distortion (THD), which determines how much the waveform is distorted with high-frequency harmonic components. The THD regulates the harmonic pollution of *each* load. But, it is insufficient for analyzing the effects of polluted loads on an overall power system with the only THD factor. Therefore, a new power quality index is necessary to deal with this issue. Also, several power quality indices and measurement methods [3]-[4] have been reported with the analysis of distorted current and voltage waveforms. However, in the authors' opinion, no research has investigated the use of the PQI, which focuses on the direct relationship between distortion power and harmonic problem. This paper introduces the new power quality index to monitor the effect of each nonlinear load on a point of common coupling (PCC) of distribution power system by using the concept of distortion power generated from each load.

This paper is organized as follows: Section II proposes the new distortion power quality index (DPQI) to provide a solution for determining the relative harmonic pollution ranking caused from each nonlinear load with respect to the generated distortion power. Section III describes the reduced multivariate polynomial (RMP) model [5]-[7], which is used to estimate the electric load composition rate (LCR) [7] required for computation of the proposed DPQI. Then, Section IV describes the overall procedure to implement the DPQI with consideration of a PCC voltage distortion in practice. The simulation results are given in Section V. Finally, conclusions are addressed in VI.

II. Distortion Power Quality Index

Fig. 1 shows a typical distribution power network. When the nonlinear loads are supplied from a sinusoidal voltage source, its injected harmonic current is referred to as contributions from the load. Harmonic currents cause harmonic voltage drops in the supply network and therefore distort the voltage at the PCC. Any loads, even linear loads, connected to the PCC, will have harmonic currents injected into them by the distorted PCC voltage. Such currents are referred to as contributions from the power system, or supply harmonics [8]. In this circumstance, a distortion power generation from each load depends mainly on the following two factors:

- How much current is injected from the PCC in Fig. 1 to each nonlinear load?
- To what extent current waveforms are distorted with high-frequency harmonic components?

The above two questions can be solved by computation of the electric load composition rate (LCR) for each nonlinear load and total harmonic distortion (THD) of the load currents (i_1, …, i_n), respectively.

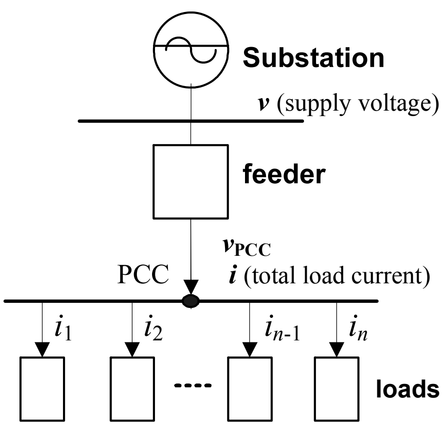

Fig. 1. One-line diagram of a typical distribution power network.

Then, the new PQI, namely, the distortion power quality index (DPQI), is now proposed. It is relevant to the distortion power of a certain electric load n, and can be obtained by inner product of the LCR and the THD as given in (1). The waveform of each load current in (1), can be represented by (2).

$$DPQI\,(n) = LCR\,(i_n) \cdot THD\,(i_n) \tag{1}$$

$$i_n(t)\big|_T = i_{n,1}(t)\big|_T + \sum_{h=2}^{\infty} i_{n,h}(t)\big|_T \tag{2}$$

where T is the period of the measured current i, and h is the number of high-frequency harmonic components. For all electric loads connected to the PCC in Fig. 1, the DPQI provides the important information of how much each load has the effect on the PCC with the relative ranking for harmonic pollution of distortion power generation. Without measuring real, apparent, and fundamental reactive powers from instrument readings, the DPQI uses the only load current waveforms. The LCR required to compute the DPQI is estimated by the reduced multivariate polynomial (RMP) model, which is summarized in the next Section.

III. Reduced Multivariate Polynomials Model to Estimate Electric Load Composition Rate

A. *Electric Load Composition*

For formulation of the load composition, the total electric current $i(t)$ in Fig. 1 is modeled by (3) with several electric load classes connected to the distribution power system.

$$i(t) = k_1 i_2(t) + k_2 i_2(t) + \cdots + k_{n-1} i_{n-1}(t) + k_n i_n(t) \tag{3}$$

where k_1, k_2, $k_{n\text{-}1}$, and k_n are the unknown coefficients, which provide the actual rate of the composition of each load current with respect to the total current. This rate is called as the LCR [7]. This LCR can provide a standard for harmonic current injection limits from each load with the benefit as an effective evaluation tool on the effects of individual load types. Also, the electric utility company may use the LCR to quantify the contribution of individual customers on a power distribution network for power quality degradation.

In this paper, the RMP model [5]-[6] is applied to estimate the LCR. This optimization technique is a kind of training algorithm to search the weight parameters for the nonlinear input-output mapping such as the neural networks. The main advantage of the RMP model over the neural networks is that it has the *one-shot* training property [6]. In other words, it does NOT require the iteration procedure during the process of obtaining a solution weight vector.

After estimating the LCR for the given loads with the RMP model, the real power (P), apparent power (S_a), fundamental reactive power (Q_B), and distortion power (D) for the each load can be computed by (4).

$$\begin{aligned}
P_n &= \frac{1}{N}\sum_{m=0}^{N-1} v(m)\cdot i_n(m) \\
S_{a,n} &= \sqrt{\frac{1}{N}\sum_{m=0}^{N-1} v(m)\cdot v(m)}\cdot\sqrt{\frac{1}{N}\sum_{m=0}^{N-1} i_n(m)\cdot i_n(m)} \\
Q_{B,n} &= S_{a,n}\cdot\sin\big((\theta-\varphi)_{\text{fundamenta l}}\big) \\
D_n &= \sqrt{S_n^2 - P_n^2 - Q_{B,n}^2}
\end{aligned} \tag{4}$$

where N is the number of samples obtained during the one period T. The subscript n denotes the each load class, which corresponds to the LCR for the total electric current $i(t)$ at the PCC. The detailed descriptions for the RMP optimization technique are summarized in below.

B. *Multivariate Polynomial Model*

The general multivariate polynomial (MP) model can be expressed as:

$$g(\boldsymbol{\alpha}, \mathbf{x}) = \sum_{i}^{K} \alpha_i x_1^{n_1} x_2^{n_2} \cdots x_l^{n_l}. \tag{5}$$

where the summation is taken over all nonnegative integers n_1, n_2, …, n_l for which $n_1 + n_2 + \cdots + n_l \leq r$ with r being the order of approximation. The vector $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_K]$ is the parameter vector to be estimated, and $\mathbf{x}$ denotes the regressor vector $[x_1, \ldots, x_l]^T$ containing inputs. K is the total number of terms in $g(\boldsymbol{\alpha}, \mathbf{x})$.

The general MP model in (5) can be replaced with (6) by using the parameter vector $\boldsymbol{\alpha}$ and the function $p(\mathbf{x})$, which is composed of variables of the regressor vector.

$$g(\boldsymbol{\alpha}, \mathbf{x}) = \boldsymbol{\alpha}^T p(\mathbf{x}) \tag{6}$$

Given m data points with $m > K$ and using the least-squares error minimization objective given by

$$s(\boldsymbol{\alpha}, \mathbf{x}) = \sum_{i=1}^{m} [y_i - g(\boldsymbol{\alpha}, \mathbf{x}_i)]^2 = [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}]^T [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}], \tag{7}$$

the parameter vector $\boldsymbol{\alpha}$ can be estimated as

$$\boldsymbol{\alpha} = (\mathbf{P}^T \mathbf{P})^{-1} \mathbf{P}^T \mathbf{y}, \tag{8}$$

where $\mathbf{P} \in R^{m\mathrm{x}K}$ denotes the Jacobian matrix of $p(\mathbf{x})$ and $\mathbf{y} = [y_1, \cdots, y_m]^T$.

Note that equation (8) involves computing the inverse of a matrix. Therefore, the problem of multicollinearity may arise if some linear dependences among the elements of $\mathbf{x}$ are present. A simple approach to improve numerical stability is to perform a weight decay regularization using the following error objective.

$$\begin{aligned} s(\boldsymbol{\alpha}, \mathbf{x}) &= \sum_{i=1}^{m} [y_i - g(\boldsymbol{\alpha}, \mathbf{x}_i)]^2 + b\|\boldsymbol{\alpha}\|_2^2 \\ &= [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}]^T [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}] + b\boldsymbol{\alpha}^T\boldsymbol{\alpha} \end{aligned} \tag{9}$$

where $\|\cdot\|_2$ denotes the l_2-norm, and b is a regularization constant.

Minimizing the new objective function (9) results in

$$\boldsymbol{\alpha} = (\mathbf{P}^T \mathbf{P} + b\mathbf{I})^{-1} \mathbf{P}^T \mathbf{y} \tag{10}$$

where $\mathbf{P} \in R^{m\mathrm{x}K}$, $\mathbf{y} \in R^{m\mathrm{x}1}$, and $\mathbf{I}$ is the K x K identity matrix.

The approximation capability of polynomials is well known from the Weierstrass approximation theorem [9], which states that every continuous function defined on an interval can be approximated as closely as desired by a polynomial function [5].

C. Reduced Multivariate Polynomial Model

Based on the Weierstrass approximation theorem, the above MP regression provides an effective way to describe complex nonlinear input-output relationships. However, for the rth-order model with input dimension l, the number of independent adjustable parameters would grow as l^r. Thus, the MP model would need a huge quantity of training data to ensure that the parameters are well determined. To significantly reduce the huge number of terms in the MP model, the following model in (11) is considered.

$$\hat{f}_{\mathrm{MN}}(\boldsymbol{\alpha}, \mathbf{x}) = \alpha_0 + \sum_{j=1}^{r} (\alpha_{j1}x_1 + \alpha_{j2}x_2 + \cdots + \alpha_{jl}x_l)^j \tag{11}$$

It is noted that this gives rise to a nonlinear estimation model where the weight parameters (α_{jl}) may not be estimated in a straightforward manner. Although an iterative search can be formulated to obtain some solutions, there is no guarantee that these solutions are global. To circumvent this problem, a linearized model is considered [6].

Assume that two points α and α_1 on the multinomial function are differentiable. By the mean value theorem, the multinomial function $f(\boldsymbol{\alpha}) = (\alpha_{j1} x_{j1} + \alpha_{j2} x_{j2} + \ldots, + \alpha_{jl} x_{jl})^j$ about the point α_1 can be written as

$$f(\boldsymbol{\alpha}) = f(\alpha_1) + (\boldsymbol{\alpha} - \alpha_1)^T \nabla f(\overline{\boldsymbol{\alpha}}) \tag{12}$$

where $\overline{\boldsymbol{\alpha}} = (1-\beta)\alpha_1 + \beta \cdot \boldsymbol{\alpha}$ for $0 \leq \beta \leq 1$. Let $\mathbf{x} = [x_1, \ldots, x_l]^T$. By omitting the reference point α_1 and those coefficients within $f(\alpha_1)$ and $\nabla f(\overline{\boldsymbol{\alpha}})$ and including the summation of weighted input terms, the following RMP model can be written as

$$\begin{aligned} \hat{f}_{\mathrm{RMP'}}(\boldsymbol{\alpha}, \mathbf{x}) &= \alpha_0 + \sum_{j=1}^{l} \alpha_j x_j + \sum_{j=1}^{r} \alpha_{l+j} (x_1 + x_2 + \cdots + x_l)^j \\ &+ \sum_{j=2}^{r} (\boldsymbol{\alpha}_j^T \cdot \mathbf{x})(x_1 + x_2 + \cdots + x_l)^{j-1}, l, r \geq 2, \end{aligned} \tag{13}$$

where the number of terms is given by $K = 1 + r(l+1)$.

To include more individual high-order terms for (13), the RMP model can be re-written as

$$\begin{aligned} \hat{f}_{\mathrm{RMP}}(\boldsymbol{\alpha}, \mathbf{x}) &= \alpha_0 + \sum_{k=1}^{r} \sum_{j=1}^{l} \alpha_{kj} x_j^k + \sum_{j=1}^{r} \alpha_{rl+j} (x_1 + x_2 + \cdots + x_l)^j \\ &+ \sum_{j=2}^{r} (\boldsymbol{\alpha}_j^T \cdot \mathbf{x})(x_1 + x_2 + \cdots + x_l)^{j-1}, l, r \geq 2. \end{aligned} \tag{14}$$

The number of terms in this model can be expressed as $K = 1 + r + l(2r - 1)$. It is noted that equation (14) has $(rl - l)$ more terms than equation (13) [6]. It is shown that the RMP model, in which the number of weight parameters increases linearly, is a much more efficient algorithm in a complicated polynomial system with the higher-order when compared to the MP model, in which the number of parameters increases exponentially with respect to the order of polynomials.

D. Evaluation of Performance

To evaluate the performance of the RMP model applied to the estimation problems, the root-mean-square error (RMSE) and mean-absolute-percentage error (MAPE) in (15) are computed with the measurement of actual current waveforms. The RMSE uses the absolute deviation between the estimated and actual quantities. Due to squaring, the RMSE gives more weight to larger errors than smaller ones. The MAPE is, on the other hand, dimensionless, and thus can be used to compare the accuracy of the model on different series [10].

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{m=0}^{n-1}(y_m-\hat{y}_m)^2},\quad \text{MAPE}=\frac{1}{n}\sum_{m=0}^{n-1}\left|\frac{y_m-\hat{y}_m}{y_m}\right|, \quad (15)$$

where y_m and $\hat{y}_m$ are the actual and estimated values, respectively, and n represents the number of data samples.

IV. Implementation of DPQI

A. Overall Procedure

As mentioned before, it is necessary to compute the LCR and THD for the load currents to implement the DPQI in (1). The overall procedure is shown in Fig. 2.

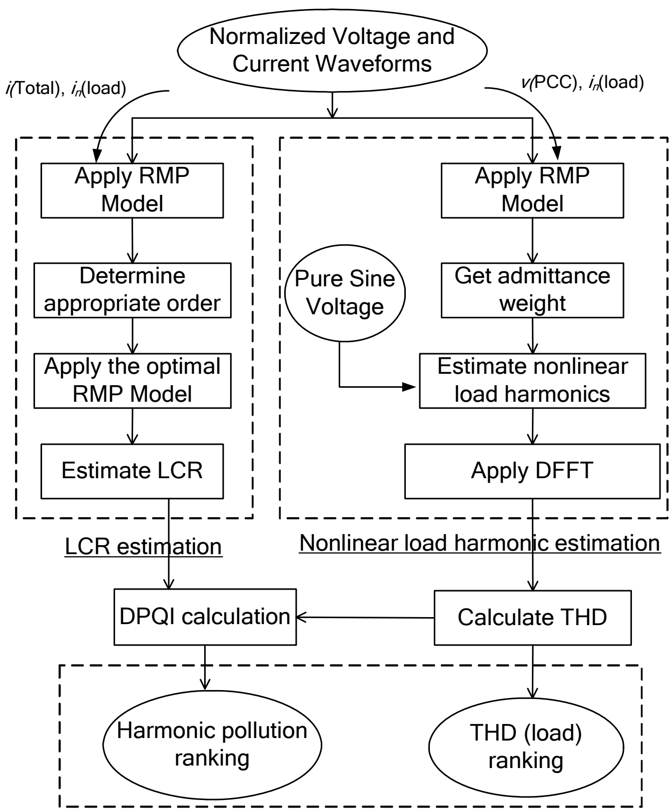

Fig. 2. Overall procedure to implement the DPQI.

The left flow of Fig. 2 shows how to estimate the LCR by applying the RMP model. It is important to determine the optimal number of order, r in (14) of the RMP model. Though the selection of optimal order depends on its application, the relatively high-order RMP model (at the cost of acceptable computation efforts) can be preferably used in the case with the nonlinear complex correlations between the distorted harmonic load currents and the PCC voltage. More detailed explanation is given in [7] with the full description of how to select the proper order of the RMP model applied to estimate the LCR.

In the meanwhile, the right flow of Fig. 2 shows how to calculate the THD for the nonlinear load harmonics predicted by the RMP model when the voltage at the PCC in Fig. 1 is not a purely sinusoidal waveform. Generally, it has slight harmonics in practice. Note that the proposed DPQI in (1) exploits distortion in the only current waveform without considering that in voltage for both the LCR and THD. To take into account the case in existence of a distorted voltage, the nonlinear load harmonics are predicted by the same RMP model to calculate the proper THD. More details are given in the next sub-section. Thereafter, the discrete-fast-Fourier transform (DFFT) is applied to the predicted load harmonics currents in each load. Then, the THD is computed by (16).

$$THD\ (i_n) = \left(\sqrt{\sum_{h=2}^{\infty} i_h^2}\ /\ i_1\right)\times 100 \qquad [\%] \qquad (16)$$

where i_1 and i_h are the values of fundamental and harmonic components in the estimated load currents, respectively.

B. Estimation of Nonlinear Load Harmonics

As mentioned before, harmonic currents at nonlinear loads might have the distorted the PCC voltage, v_{PCC} in Fig. 1. Then, the nonlinear correlation between the distorted v_{PCC} and load current harmonics occurs. This relationship is complex and therefore difficult to analyze.

The estimation of LCR in (1) can be carried out without considering whether a pure sinusoidal or a distorted voltage is supplied to several loads. The reason is that it deals with the only portion of each load current over the total current at the PCC. However, when the THD is calculated, the additional consideration for nonlinear load harmonics is necessary in the existence of distorted v_{PCC} in Fig.1. This problem even exists when a single load is connected to the PCC. If the true harmonic current injections from the load were known, then a utility could penalize the offending consumer in some appropriate way, including say a special tariff or insist on corrective action by the consumer. Simply measuring the harmonic currents at each individual load is not sufficiently accurate since these harmonic currents may be caused by not only the nonlinear load, but also by a non-sinusoidal PCC voltage. This is not a new issue and researchers have proposed tools based on traditional power system analysis methods to solve this problem. The harmonic active power method [11] and critical impedance measurement method [12] yield results to a certain degree of accuracy. However, they are based on some fundamental assumptions like prior knowledge of the source impedance. To overcome this drawback, the neural network algorithm is used in [8].

To predict the nonlinear load harmonics by the neural network (NN), the weighting vectors of the NN for load harmonics (this is called as the *admittance weights*) are trained in the first stage, as shown in Fig. 3, with a distorted v_{PCC} and current waveforms, which should be measured in the practical situation. In this paper, the RMP model replaces the conventional recurrent neural network (RNN) in [8]. Due to the one-shot training property of the RMP model, the nonlinear load harmonics can be estimated in more exact and effective manner than the other conventional NNs.

At any moment in time after the one-shot training by the RMP model has converged, its trained admittance weights are transferred to the second stage, where the RMP model is supplied with a mathematically generated sine-wave voltage to estimate its output. Therefore, the output of RMP model in the second stage represents the currents that the nonlinear loads would have injected when a sinusoidal voltage source is supplied at the PCC. In other words, this gives the same information that could have been obtained by quickly removing the distorted PCC voltage (if this were possible) and connecting a pure sinusoidal voltage to supply the nonlinear load, except that it is not necessary to actually do this interruption.

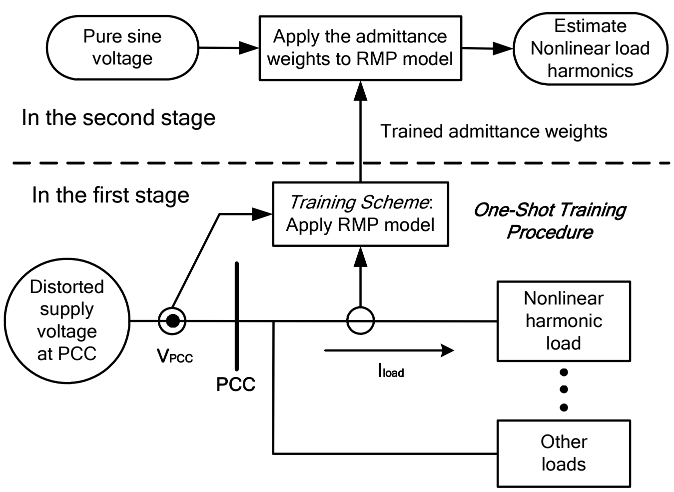

Fig. 3. Estimation procedure for nonlinear load harmonics.

V. Simulation Results

A. System Data for Simulation

Assume that the total current $i(t)$ at the PCC in Fig. 1 is measured during one period T of the fundamental, and its Fourier analysis indicates the composition in (17) for *one phase*. Its waveform is shown in Fig. 4. The fundamental frequency in Fig. 4 is 60 Hz, and the line-to-line voltage at the service entrance is 480V (used as a peak value) nominal and distorted with the THD of 3.1633 % (by the third and fifth harmonic components). The number of data samples for the computer simulation is 16,667, which is high enough to satisfy the *Nyquist* theorem with respect to the other high-frequency components as well as the fundamental.

$$i(t) = 880.0\cos(\omega t) + 185.5\cos(3\omega t - 2^\circ) + 75.0\cos(5\omega t - 4^\circ) + 65.0\cos(7\omega t - 6^\circ). \quad (17)$$

When the electric loads are supplied from the distorted voltage, the typical load classes for the total current $i(t)$ are given in Table I and Fig. 5. These typical load classes consist of incandescent lighting, fluorescent lighting, computer, and motor drive, which are denoted by the subscripts i, f, c, and m, respectively. It is known that the incandescent lighting is the linear load with a pure resistance, and therefore it has the same amount of harmonics as the supplied voltage. Also, the other three loads generate nonlinear harmonic currents.

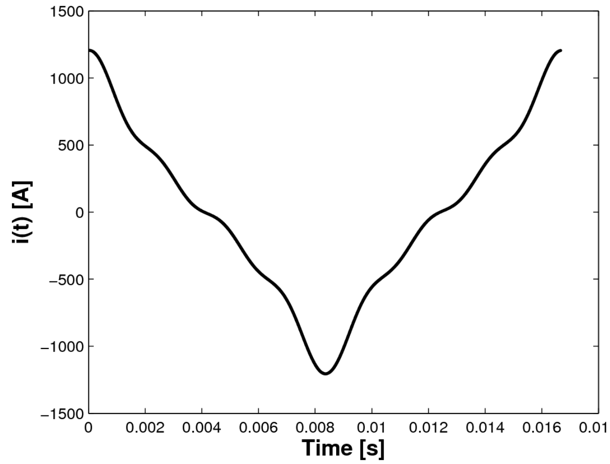

Fig. 4. The total electric load current $i(t)$ at the PCC during one period T of the fundamental.

TABLE I

Currents Waveforms in Typical Load Classes -Normalized

Electric load type	Electric current waveform (Reference: voltage waveform)
Incandescent lighting	$i_i(t) = 1.0\cos(\omega t) + 0.03\cos(3\omega t\text{-}4^\circ) + 0.01\cos(5\omega t\text{-}5^\circ)$
Fluorescent lighting	$i_f(t) = 1.0\cos(\omega t\text{-}3^\circ) + 0.48\cos(3\omega t\text{-}5^\circ) + 0.35\cos(5\omega t\text{-}3^\circ) + 0.28\cos(7\omega t\text{-}2^\circ)$
Computers	$i_c(t) = 1.0\cos(\omega t) + 0.28\cos(3\omega t\text{-}1^\circ) + 0.05\cos(5\omega t\text{-}8^\circ) + 0.03\cos(7\omega t\text{-}10^\circ)$
Motor drives	$i_m(t) = 1.0\cos(\omega t) + 0.15\cos(5\omega t\text{-}8^\circ) + 0.11\cos(7\omega t\text{-}10^\circ)$

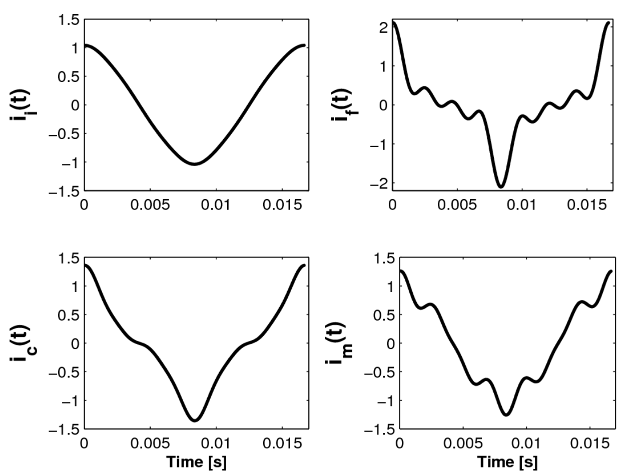

Fig. 5. Currents waveforms in typical load classes during one period T of the fundamental – normalized.

The loads given in Table 1 are only illustrated as one example. According to the some specific circumstances, the other load types can be represented, for example, commercial buildings, warehouses, and water treatment facilities, etc.

B. Estimation Performance of LCR

The solution vector obtained by applying the RMP model to (3) is $\mathbf{L} = [k_1, k_2, k_3, k_4]^t = [\mathrm{LCR}(i_i), \mathrm{LCR}(i_f), \mathrm{LCR}(i_c), \mathrm{LCR}(i_m)]^t = [0.1500, 0.0992, 0.5669, 0.1840]^t$ (normalized). The order of six (r=6) is used in the applied RMP model (see the reference [7] for more details). Then, the estimation result for the total current $i(t)$ at the PCC by the RMP model is shown in Fig. 6. The values of RMSE and MAPE for evaluation of the performance of the RMP model are 0.0091 and 0.0274 %, respectively, which are reasonably acceptable. Thereafter, the distortion power vector for each load computed by (4) with the estimated LCR is $\mathbf{D} = [D_i, D_f, D_c, D_m]^t = [0, 7605, 17627, 4053]^t$ and shown in Fig. 7. It is clearly shown from Fig. 7 that the 'computer' has the worst effect on the system by increasing the power quality problem with the highest value of D among the four different types of loads.

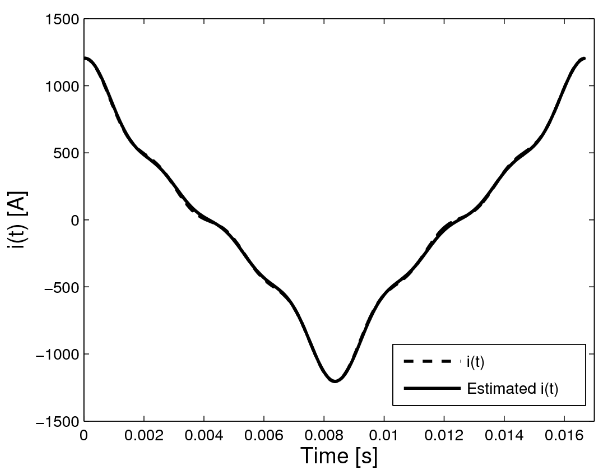

Fig. 6. Estimation for the total current by the RMP model.

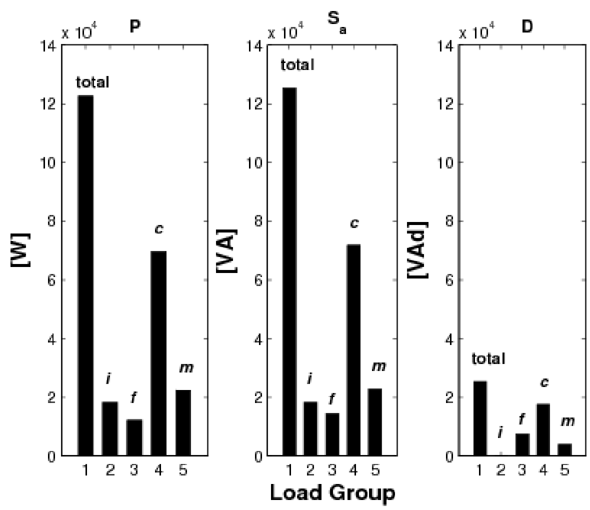

Fig. 7. The real power, apparent power, and distortion power of each load.

C. Estimation Performance of Nonlinear Load Harmonics

As described in Section IV-*B*, the RMP model of six-order is trained to determine the admittance weights in the first stage of Fig. 3 when the distorted voltage with the THD of 3.1633 % is supplied. Thereafter, the load harmonics are now estimated with the same RMP model in the second stage by applying the pure sinusoidal voltage.

The estimation results by the RMP model are shown in Fig. 8, and the corresponding harmonic components of estimated currents are shown in Fig. 9. Also, the THD [%] in measured (in Table I) and estimated currents are compared in Table II. It is not surprising to observe small difference in THD values of measured and estimated currents. Note that the distorted PCC voltage can also deteriorate power quality of all load currents (even the linear load with pure resistance such as incandescent lighting) by increasing the THD. In other words, the difference between the measured and estimated currents means the effect of the distorted PCC voltage on the different types of loads in physical quantity.

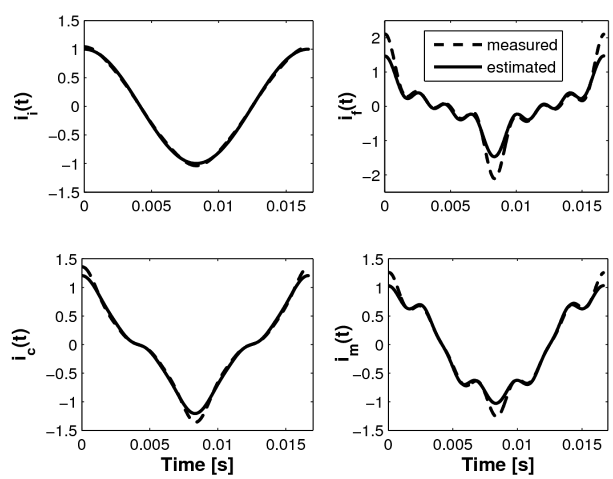

Fig. 8. Estimation for each load current by the RMP model.

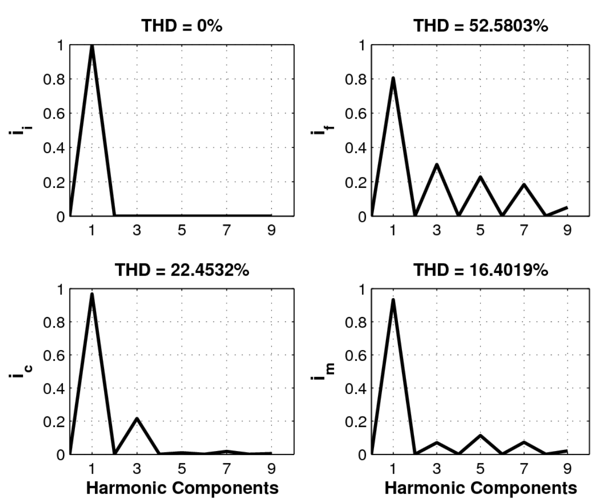

Fig. 9. Estimated harmonic components of each electric load current.

TABLE II
COMPARISON OF THD [%] IN MEASURED AND ESTIMATED CURRENTS

Load type	Incandescent lighting	Fluorescent lighting	Computers	Motor drives
THD [%] of measured currents	3.1633	65.6758	28.6020	18.6012
THD [%] of estimated currents	0	52.5803	22.4532	16.4019

D. Determination of Harmonic Pollution Ranking

With the LCR and THD obtained in above, the DPQI for each load *n* is determined by (1). Then, its normalized relative ratio ($DPQI_R$) of $[0, 0.2488, 0.6072, 0.1440]^t$ is obtained. The associated harmonic pollution ranking (HPR) can be finally determined by the order of magnitude of the $DPQI_R$ given in Table III. Each factor of $DPQI_R$ indicates how much each load takes the portion of distortion power generated from each load with respect to a PCC in an overall system. It is clearly shown from the result in Table III that the 'computer' has the worst effect on the system by aggravating power quality problem with the highest HPR even though its THD value is not highest among the different four types of loads.

The relationship between the DPQI and distortion powers is now evaluated through one-to-one comparison with the $DPQI_R$ and the relative distortion power ratio (D_R). The D_R of $[0, 0.3057, 0.5939, 0.1004]^t$ is obtained after dividing the distortion power vector **D** (given in Section V-*B*) by the total sum of distortion powers. It is shown that each value of D_R matches closely to its corresponding $DPQI_R$ value. Therefore, it is validated that the proposed DPQI can be used as a decision-making index for the power quality ranking with only current waveforms of nonlinear loads without requiring direct measurement of the distortion powers.

TABLE III
DPQI AND HARMONIC POLLUTION RANKING (HPR)

Load type	Incandescent lighting	Fluorescent lighting	Computers	Motor drives
THD [%]	3.1633	65.6758	28.6020	18.6012
THD Ranking	**4**	**1**	**2**	**3**
DPQI	0	5.2160	12.7287	3.0180
$DPQI_R$	0	0.2488	0.6072	0.1439
HPR	**4**	**2**	**1**	**3**
D_R	0	0.2597	0.6019	0.1384

VI. CONCLUSIONS

This paper proposed a new distortion power quality index (DPQI) to determine the harmonic pollution ranking (HPR) of several nonlinear loads using the only current waveforms. The computation of the DPQI requires computation of the load composition rate (LCR) and the total harmonic distortion (THD) of the load currents. The LCR was successfully estimated by the reduced multivariate polynomial (RMP) model with the one-shot training property. This RMP model was also applied to predict the nonlinear harmonics of measured currents when the voltage at the point of common coupling (PCC) was distorted. It can be preferably used in a practical situation without disconnecting each load from the PCC with the higher convergence speed and accuracy when compared to the other traditional neural networks. It was finally proved that the proposed DPQI can be used as the appropriate power quality index without requiring the direct measurement of powers.

The proposed DPQI can be embedded in a supervisory control and data acquisition (SCADA) system to monitor and regulate the power quality in a distribution power system more easily.

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REFERENCES

[1] *IEEE Standard for IEEE Recommended Practices and Requirements for Harmonic Control in Electrical Power Systems,* IEEE Std. 519, 1992.

[2] *Electromagnetic Compatibility (EMC) - Part 3*: *Limits-Section VI*: *Assessment of Emission Limits for Distorting Loads in MV and HV Power Systems*, IEC 61000-3-6, 1996, 1996.

[3] Tao Lin and A. Domijan, "On Power Quality Indices and Real Time Measurement," *IEEE Trans. on Power Delivery*, Vol.20, No.4, pp. 2552-2562, October 2005.

[4] Y.-J. Shin, E.J. Powers, M. Grady, and A. Arapostathis, "Power Quality Indices for Transient Disturbances," *IEEE Trans. on Power Delivery*, Vol.21, No.1, pp. 253-261, January 2006.

[5] K-A. Toh, Q-L. Tran, and D. Srinivasan, "Benchmarking a Reduced Multivariate Polynomial Pattern Classifier," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 26, No. 6, pp. 740-755, June 2004.

[6] K-A. Toh, W-Y. Yau, and X. Jiang, "A Reduced Multivariate Polynomial Model for Multimodal Biometrics and Classifiers Fusion," *IEEE Trans. on Circuit and Systems for Video Trchnology*, Vol.14, No.2, pp. 224-233, Feb. 2004.

[7] Soon Lee and Jung-Wook Park, "A Reduced Multivariate Polynomial Model for Estimation of Electric Load Composition," *in Proc. of IEEE 42nd IAS Annual Meeting*, pp. 1505-1511, September 2007.

[8] J. Mazumdar, R.G. Harley, F.C. Lambert and G.K. Venayagamoorthy "Neural Network Based Method for Predicting Nonlinear Load Harmonics," *IEEE Trans. on Power Electronics*, Vol.22, No.3, pp. 1036-1045, May 2007.

[9] W. R. Wade, "An Introduction to Analysis," Prentice Hall, Upper Saddle River, New Jersey, 2000.

[10] Mesut E. Baran, Lavelle A. A, Frank Hanson, and Jeffery M. Johnson, "Load Estimation for Load Monitoring at Distribution Substation," *IEEE Trans. on Power Systems*, Vol.20, No.1, pp. 164-170, Feb. 2005.

[11] W. Lu, X. Liu, and Y. Liu, "An Investigation on the Validity of Power-Direction Method for Harmonic Source Determination," *IEEE Trans. on Power Delivery*, Vol.18, No.1, pp. 214-219, Jan. 2003.

[12] Li Chun, W. Xu, and T. Tayjasanant, "A Critical Impedance Based Method for Identifying Harmonic Sources", *IEEE Trans. on Power Delivery*, Vol.19, No.2, pp. 671-678, April. 2004.