New Power Quality Index in a Distribution Power System by Using RMP Model

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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 has adverse effect on the entire system, is determined. It is proven that the relative ranking based on the PQI matches that based on the distortion power directly computed from each harmonic load.**

***Index Terms*—Distortion power, distribution power system, harmonic pollution ranking (HPR), power quality index (PQI), 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 equipment on a consumer side, serious power quality problems can be caused by distorted currents from those nonlinear loads. In addition, the increase in nonlinear loads might even distort the grid voltage. As a 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 IEEE Standard 519 [1] and IEC-61000-3 Standard [2].

However, these limits are based on conventional power quality indexes (PQIs), 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. However, it is insufficient for analyzing the effects of polluted loads on an overall power system with the only THD factor. Therefore, a new PQI is necessary to deal with this issue. In addition, several PQIs 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 PQI to monitor the effect of each nonlinear load on a point of common coupling (PCC) of a 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 PQI (DPQI) to provide a solution for determining the relative harmonic pollution ranking (HPR) 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) and electric load harmonics [8], [9] required for computation of the proposed DPQI. Then, Section IV describes the overall procedure to implement the DPQI with consideration of PCC voltage distortion in practice. The simulation results are given in Section V. Finally, conclusions are addressed in Section VI.

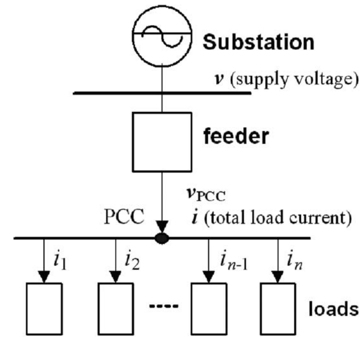

Fig. 1. One-line diagram of a typical distribution power network.

II. DPQI

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

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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 two factors.

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

The preceding two questions can be solved by computation of the electric LCR for each nonlinear load and THD of the load currents $(i_1, \ldots, i_n)$, respectively.

Then, the new PQI, i.e., the 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

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

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

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 important information of how much effect each load has 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.

In this study, the RMP model [5], [6], which is summarized in the next section, is applied to estimate the LCR and the nonlinear load harmonics required to obtain the proper THD of each load current. 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 (NNs). The main advantage of the RMP model over the NNs is that it has the *one-shot* training property [5]. In other words, it does NOT require iteration procedures during the process of obtaining a solution weight vector.

III. RMP Model

A. Multivariate Polynomial (MP) Model

The general MP model can be expressed as

$$g(\boldsymbol{\alpha}, \mathbf{x}) = \sum_{i}^{K} \alpha_i x_1^{n_1} x_2^{n_2}, \ldots, x_l^{n_l} \tag{3}$$

where the summation is taken over all nonnegative integers $n_1, n_2, \ldots, n_l$ 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 as $[x_1, \ldots, x_l]^T$ containing inputs. K is the total number of terms in $g(\boldsymbol{\alpha}, \mathbf{x})$.

The general MP model in (3) can be replaced with

$$g(\boldsymbol{\alpha}, \mathbf{x}) = \boldsymbol{\alpha}^T p(\mathbf{x}) \tag{4}$$

by using the parameter vector $\boldsymbol{\alpha}$ and the function $p(\mathbf{x})$, which is composed of variables of the regressor vector.

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

$$s(\boldsymbol{\alpha}, \mathbf{x}) = \sum_{i=1}^{m} [y_i - g(\boldsymbol{\alpha}, \mathbf{x}_i)]^2 = [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}]^T[\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}] \tag{5}$$

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

$$\boldsymbol{\alpha} = (\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T\mathbf{y} \tag{6}$$

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

Note that (6) 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:

$$\begin{aligned} s(\boldsymbol{\alpha}, \mathbf{x}) &= \sum_{i=1}^{m} [y_i - g(\boldsymbol{\alpha}, \mathbf{x}_i)]^2 + b\|\boldsymbol{\alpha}\|_2^2 \\ &= [\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}]^T[\mathbf{y} - \mathbf{P}\boldsymbol{\alpha}] + b\boldsymbol{\alpha}^T\boldsymbol{\alpha} \end{aligned} \tag{7}$$

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

Minimizing the new objective function (7) results in

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

where $\mathbf{P} \in R^{m \times K}$, $\mathbf{y} \in R^{m \times 1}$, and $\mathbf{I}$ is the $K \times K$ identity matrix. The approximation capability of polynomials is well known from the Weierstrass approximation theorem [10], which states that every continuous function defined on an interval can be approximated as closely as desired by a polynomial function [5].

B. RMP Model

Based on the Weierstrass approximation theorem, the preceding 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 with 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 (9) is considered:

$$\hat{f}_{\text{MN}}(\boldsymbol{\alpha}, \mathbf{x}) = \alpha_0 + \sum_{j=1}^{r} (\alpha_{j1}x_1 + \alpha_{j2}x_2 + \cdots + \alpha_{jl}x_l)^j. \tag{9}$$

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 $f(\boldsymbol{\alpha}) = (\alpha_{j1}\ x_{j1} + \alpha_{j2}\ x_{j2} + \cdots + \alpha_{jl}\ x_{jl})^j$ about the point α_1 can be written as

$$f(\boldsymbol{\alpha}) = f(\alpha_1) + (\boldsymbol{\alpha} - \alpha_1)^T \nabla f(\overline{\boldsymbol{\alpha}}) \tag{10}$$

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

$$\hat{f}_{\mathrm{RMP}'}(\boldsymbol{\alpha}, \mathbf{x}) = \alpha_0 + \sum_{j=1}^{l} \alpha_j x_j + \sum_{j=1}^{r} \alpha_{l+j}(x_1 + x_2 + \cdots + x_l)^j + \sum_{j=2}^{r} \left(\boldsymbol{\alpha}_j^T \cdot \mathbf{x}\right)(x_1 + x_2 + \cdots + x_l)^{j-1}, \quad l \ge 2 \tag{11}$$

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

To include more individual high-order terms for (11), the RMP model can be rewritten as

$$\hat{f}_{\mathrm{RMP}}(\boldsymbol{\alpha}, \mathbf{x}) = \alpha_0 + \sum_{k=1}^{r}\sum_{j=1}^{l} \alpha_{kj} x_j^k + \sum_{j=1}^{r} \alpha_{rl+j}(x_1 + x_2 + \cdots + x_l)^j + \sum_{j=2}^{r} \left(\boldsymbol{\alpha}_j^T \cdot \mathbf{x}\right)(x_1 + x_2 + \cdots + x_l)^{j-1}, \quad l \ge 2. \tag{12}$$

The number of terms in this model can be expressed as $K = 1 + r + l(2r-1)$. It is noted that (12) has $(rl - l)$ more terms than (11) [6]. It is shown that the RMP model, in which the number of weight parameters linearly increases, is a much more efficient algorithm in a complicated polynomial system with higher order, compared with the MP model, in which the number of parameters exponentially increases with respect to the order of polynomials.

C. Evaluation of Performance

To evaluate the performance of the RMP model applied to the estimation problems, the RMSE and mean-absolute-percentage error (MAPE) in

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{m=0}^{n-1}(y_m - \hat{y}_m)^2}, \quad \mathrm{MAPE} = \frac{1}{n}\sum_{m=0}^{n-1}\left|\frac{y_m - \hat{y}_m}{y_m}\right| \tag{13}$$

where y_m and $\hat{y}_m$ are the actual and estimated values, respectively, and n represents the number of data samples, are computed with the measurement of the 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 can thus be used to compare the accuracy of the model on different series [11], [12].

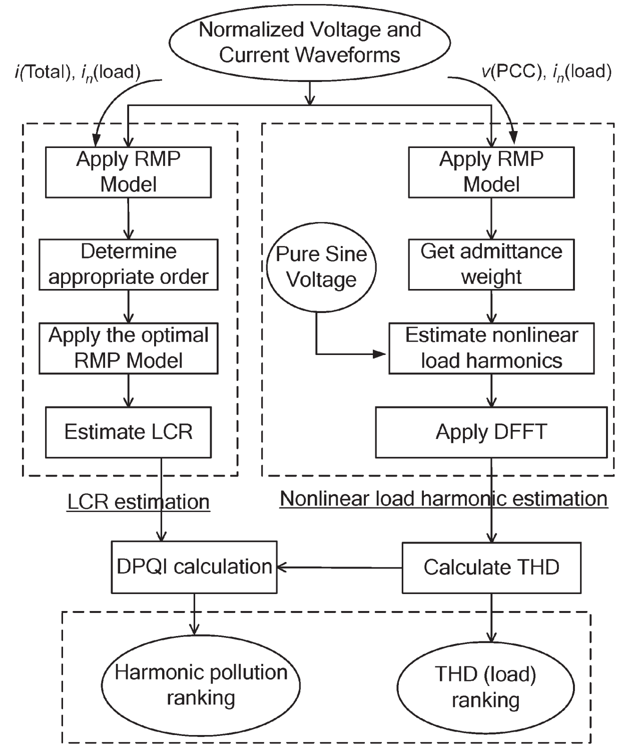

Fig. 2. Overall procedure to implement the DPQI.

IV. Implementation of DPQI

As mentioned before, it is necessary to compute the values of the LCR and THD for the harmonic load currents to implement the DPQI in (1). The RMP model is now applied to estimate the two aforementioned factors.

A. Overall Procedure to Calculate the DPQI by Using the RMP Model

The overall procedure to calculate the DPQI is shown in Fig. 2. The left flow of Fig. 2 shows how to estimate the LCR by applying the RMP model. 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.

B. Estimation of Electric Load Composition (LCR) by Using the RMP Model

For the formulation of load composition, the total electric current $i(t)$ in Fig. 1 is modeled by

$$i(t) = k_1 i_2(t) + k_2 i_2(t) + \cdots + k_{n-1} i_{n-1}(t) + k_n i_n(t) \tag{14}$$

with several electric load classes connected to the distribution power system, where $k_1, k_2, \ldots, k_{n-1}$, 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 the LCR.

The explanation about how to apply the RMP model is described as follows: Because (14) has the form of the first-order polynomial function, the RMP model with the first-order $(r = 1)$ in (12) may simply be applied. Its associated equation is given in (15). By comparing the relation between the coefficient vector $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5]^t$ and the LCR vector $\mathbf{k} = [k_1, k_2, k_3, k_4]^t$, the unknowns in

$$\begin{aligned}\hat{f}_{\mathrm{RMP}-1}(\boldsymbol{\alpha}, \mathbf{x}) &= \alpha_0 + \sum_{k=1}^{1}\sum_{j=1}^{4} \alpha_{kj} x_j^k \\ &\quad + \sum_{j=1}^{1} \alpha_{4+j}(x_1 + x_2 + \cdots + x_l)^j \\ &= \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 \\ &\quad + \alpha_5(x_1 + x_2 + x_3 + x_4) \\ &= \alpha_0 + (\alpha_1 + \alpha_5)x_1 + (\alpha_2 + \alpha_5)x_2 \\ &\quad + (\alpha_3 + \alpha_5)x_3 + (\alpha_4 + \alpha_5)x_4 \\ &= k_1 i_i + k_2 i_f + k_3 i_c + k_4 i_m \end{aligned} \tag{15}$$

which are k_1, k_2, k_3, and k_4, can be obtained.

In a physical application in the existence of noise and/or complex correlations among the nonlinear harmonic loads, the relatively high-order RMP model might preferably be used to enhance the estimation accuracy. However, the very high order RMP model requires extensive computation and memory in real-time operation. Therefore, it is important to determine the optimal number of order r in (12) of the RMP model, depending on its application. After carrying out several tests, the sixth-order $(r = 1)$ RMP model is used to estimate the LCR. 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. 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

$$\begin{aligned} P_n &= \frac{1}{N}\sum_{m=0}^{N-1} v(m)\cdot i_n(m) \\ S_{a,n} &= \sqrt{\frac{1}{N}\sum_{m=0}^{N-1} v(m)\cdot v(m)}\cdot\sqrt{\frac{1}{N}\sum_{m=0}^{N-1} i_n(m)\cdot i_n(m)} \\ Q_{B,n} &= S_{a,n}\cdot\sin\left((\theta-\varphi)_{\mathrm{fundamental}}\right) \\ D_n &= \sqrt{S_n^2 - P_n^2 - Q_{B,n}^2} \end{aligned} \tag{16}$$

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. 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. In addition, the electric utility company may use the LCR to quantify the contribution of individual customers on a power distribution network for power quality degradation.

C. Estimation of Nonlinear Load Harmonics and THD by Using the RMP Model

As mentioned before, harmonic currents at nonlinear loads might have the distorted 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, for example, 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 a nonsinusoidal 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 [13], [14] and critical impedance measurement method [15] yield results to a certain degree of accuracy. However, they are based on some fundamental assumptions, such as prior knowledge of the source impedance. To overcome this drawback, the NN algorithm has been used in [8] and [9].

To predict the nonlinear load harmonics by the NN, the weighting vectors of the NN for load harmonics (this is called 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 sixth-order $(r = 6)$ RMP model replaces the conventional recurrent NN in [8]. Due to the one-shot training property of the RMP model, the nonlinear load harmonics can be estimated in a 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 the 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.

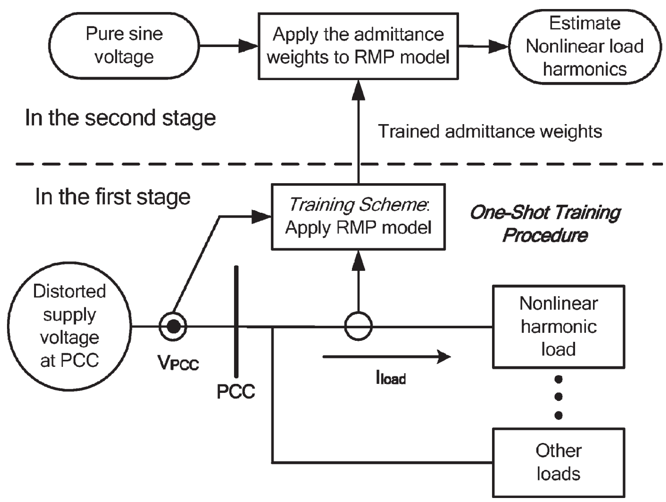

Fig. 3. Estimation procedure for nonlinear load harmonics.

After estimating nonlinear electric load harmonics using the RMP model, the discrete fast Fourier transform is applied to the predicted load harmonics currents in each load. Then, the THD is computed by

$$\mathrm{THD}(i_n) = \left(\sqrt{\sum_{h=2}^{\infty} i_h^2 / i_1}\right) \times 100\ [\%] \tag{17}$$

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

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

$$i(t) = 880.0\cos(\omega t) + 185.5\cos(3\omega t - 2^\circ) + 75.0\cos(5\omega t - 4^\circ) + 65.0\cos(7\omega t - 6^\circ) \tag{18}$$

for *one phase*. Its waveform is shown in Fig. 4. Its fundamental frequency is 60 Hz, and the line-to-line voltage at the service entrance is 480 V (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 and the fundamental.

When the electric loads are supplied from the distorted voltage, it is assumed that four typical loads are connected to the PCC, as shown in Fig. 1. 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, as their (normalized) currents are described in Table I. In addition, the corresponding waveforms are given in Fig. 5.

In Table I, the incandescent lighting consists of a filament of tungsten, which is composed of iron inside glass bulb filled with argon [16]. It can be modeled as a linear load with pure resistance, and therefore, its current has the same amount of harmonic distortion with the THD of 3.1633% as the distorted supplied voltage. The fluorescent lighting is driven by high-frequency switched ballast, which is generally employed by half-bridge inverter and *LC* filters [17], [18]. For the computer,

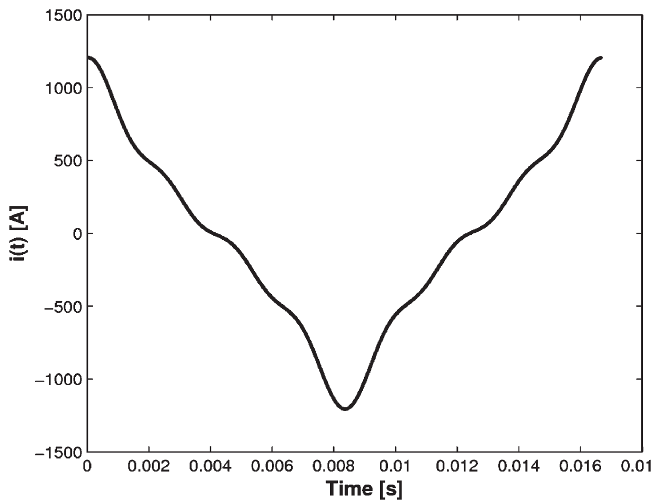

Fig. 4. Total electric load current $i(t)$ at the PCC during one period T of the fundamental.

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 (ωt) + 0.03 cos (3ωt-4°) + 0.01 cos (5ωt-5°)
Fluorescent lighting	$i_f(t)$ = 1.0 cos (ωt-3°) + 0.48 cos (3ωt-5°) + 0.35 cos (5ωt-3°) + 0.28 cos (7ωt-2°)
Computers	$i_c(t)$ = 1.0 cos (ωt) + 0.28 cos (3ωt-1°) + 0.05 cos (5ωt-8°) + 0.03 cos (7ωt-10°)
Motor drives	$i_m(t)$ = 1.0 cos (ωt) + 0.15 cos (5ωt-8°) + 0.11 cos (7ωt-10°)

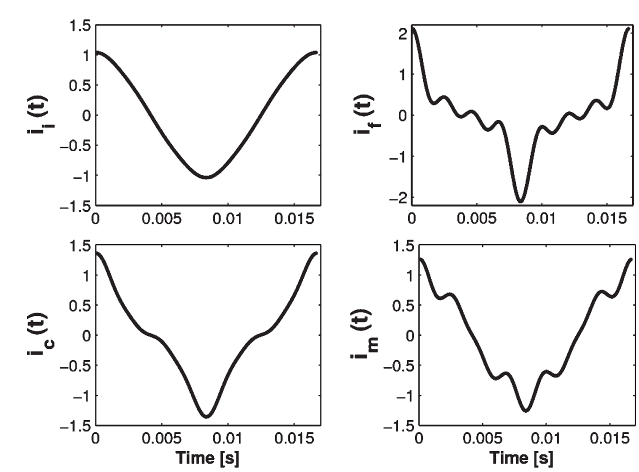

Fig. 5. Current waveforms in typical-load classes during one period T of the fundamental (normalized).

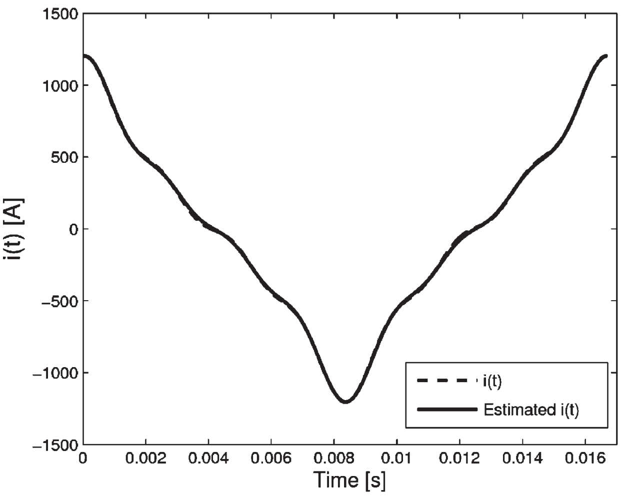

Fig. 6. Estimation for the total current by the RMP model.

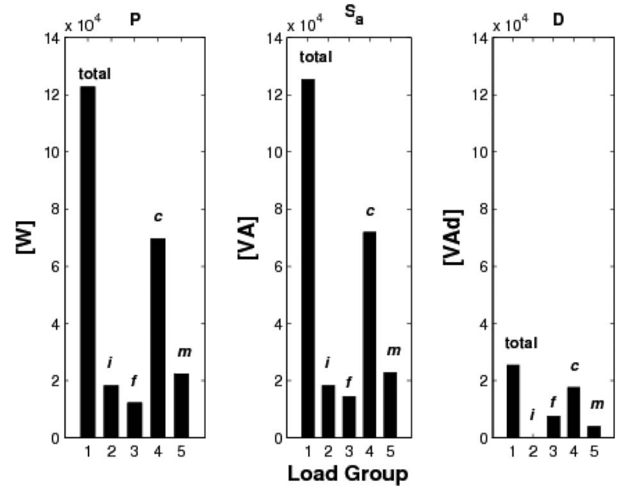

Fig. 7. Real power, apparent power, and distortion power of each load.

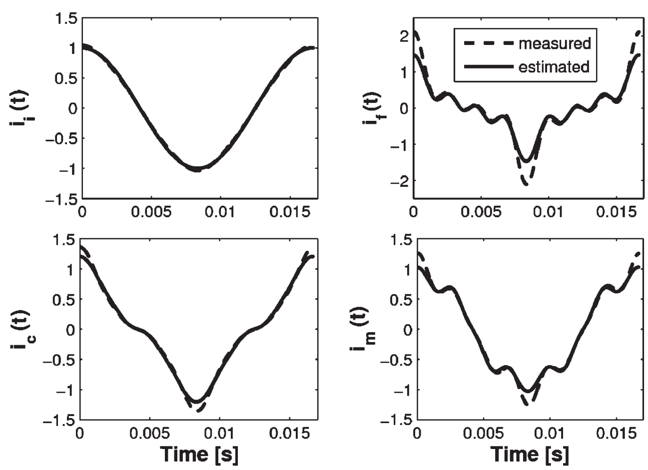

Fig. 8. Estimation for each load current by the RMP model.

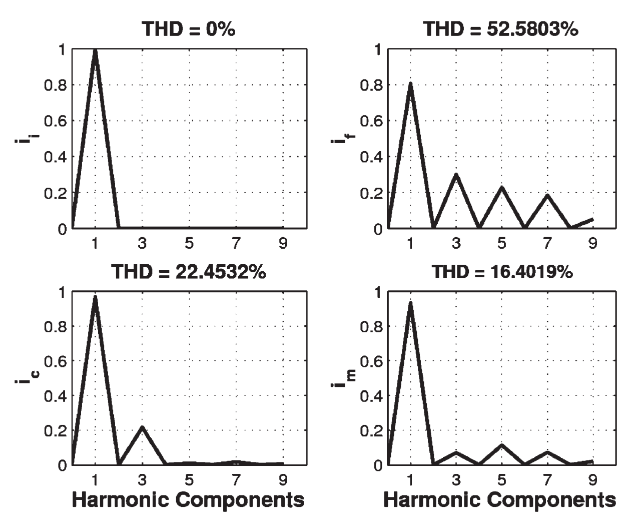

Fig. 9. Estimated harmonic components of each electric load current.

there are various power electronic devices such as switch-mode power supply and inductive/capacitive loads in its inside. Due to the effects of those components inside the fluorescent lighting and computer, their currents can generate all kinds of odd harmonic currents. Therefore, it is reasonably acceptable that they are modeled with the third-, fifth-, and seventh-order harmonic components. The motor drive has the special characteristic that its generated harmonic currents include all odd harmonics, except for the triplen harmonics by the actions of 6 or 12 pulse rectifiers [19]. Therefore, its current has the fifth- and seventh-order harmonics, and not the third, as shown in Table I.

According to some specific circumstances, other load types can be applied, e.g., commercial buildings, warehouses, and water treatment facilities.

B. Estimation Performance of LCR

The solution vector obtained by applying the RMP model to (14) is $\mathbf{L} = [k_1, k_2, k_3, k_4]^t = [\text{LCR}(i_i), \text{LCR}(i_f), \text{LCR}(i_c), \text{LCR}(i_m)]^t = [0.1500, 0.0992, 0.5669, 0.1840]^t$ (normalized). As mentioned before, the order of six $(r = 6)$ is used in the applied RMP model (see [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.

C. Estimation Performance of Nonlinear Load Harmonics

As described in Section IV-C, the RMP model of six orders (same as in the LCR estimation) 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. In addition, the THD [%] of the

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

TABLE III
DPQI AND 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

measured (in Table I) and estimated currents are compared in Table II. It is clearly shown that there is a small difference in THD values between the measured and estimated currents. This is not surprising, because the estimated currents are obtained to detect the effects by the only nonlinear load harmonics, with the assumption that a pure sinusoidal voltage is applied in the PCC.

Note that the distorted PCC voltage can also deteriorate the 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 different types of loads in physical quantity.

D. Determination of HPR

With the estimated LCR and THD previously obtained, 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 HPR can finally be 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 the power quality problem with the highest HPR, even though its THD value is not highest among the four different 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 $\mathbf{D}$ (given in Section V-B) by the total sum of distortion powers. It is shown that each value of D_R closely matches 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.

As shown in (16), distortion power is directly related with the power factor, which is a very important index to evaluate the efficiency of power transmission. One of the practical benefits of the proposed DPQI is that it can determine the hidden inefficient nonlinear loads, which produce much distortion powers, and therefore degrade the system power quality but meet the harmonic regulation standards, in a distribution power system without directly measuring them. Moreover, when many customers participate in an electric market as active main body under the future smart-grid environment, the proposed DPQI is expected to play an important role in managing the efficient power usage with good power quality between consumers and utilities.

VI. CONCLUSION

This paper has proposed a new DPQI to determine the HPR of several nonlinear loads using only current waveforms. The computation of the DPQI has required the computation of the LCR and the THD of the load currents. The LCR has successfully been estimated by the RMP model with the one-shot training property. This RMP model has also been applied to predict the nonlinear harmonics of measured currents when the voltage at the 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 with the other traditional NNs. It has been proven by simulation results that the proposed DPQI can be used as the appropriate power quality.

The proposed DPQI is expected to provide the important information to a supervisory control and data acquisition system or an advanced metering infrastructure for monitoring and regulating the power quality in a more effective manner.

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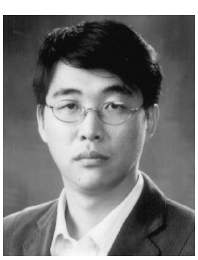

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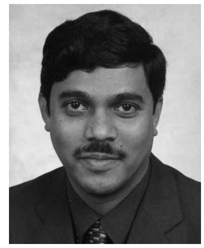

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