

Article

EMS-Data-Based Load Modeling to Evaluate the Effect of Conservation Voltage Reduction at a National Level

Soon-Ryul Nam ^{1,*}, Sang-Hee Kang ¹, Joo-Ho Lee ², Eun-Jae Choi ², Seon-Ju Ahn ³ and Joon-Ho Choi ³

¹ Department of Electrical Engineering, Myongji University, Yongin 449-728, Korea; E-Mail: shkang@mju.ac.kr

² Department of System Operation and Control, Korea Power Exchange, Seoul 135-791, Korea; E-Mails: leejooho@kpx.or.kr (J.-H.L.); toto@kpx.or.kr (E.-J.C.)

³ Department of Electrical Engineering, Chonnam National University, Gwangju 500-757, Korea; E-Mails: sjahn@chonnam.ac.kr (S.-J.A.); joono@chonnam.ac.kr (J.-H.C.)

* Author to whom correspondence should be addressed; E-Mail: ptsouth@mju.ac.kr; Tel.: +82-31-330-6361; Fax: +82-31-330-6816.

Received: 28 May 2013; in revised form: 12 July 2013 / Accepted: 15 July 2013 /

Published: 25 July 2013

Abstract: This paper proposes a linearized load model to evaluate the effect of conservation voltage reduction at a national level. In this model, the respective active and reactive linearizing parameters for active and reactive loads in a power system are estimated using energy management system (EMS) data resulting from conservation voltage reductions. To verify the validity of the linearized load model, PSS/E simulations were conducted for a test power system. Given that conservation voltage reductions are usually executed in the range of 2.0%–5.0%, the proposed model was found to be sufficient to accurately evaluate the effect of conservation voltage reduction. Additionally, Korean EMS data were used to estimate the linearizing parameters for aggregated loads in an actual power system.

Keywords: conservation voltage reduction; energy management system; linearized load modeling; linearizing parameter; PSS/E simulations

1. Introduction

Energy is an important aspect of daily life and ongoing human development [1]. Owing to the associated complexities and uncertainties [2–4], decision makers and planners are facing increased pressure to respond more effectively to a number of energy-related issues and conflicts, including conservation voltage reduction (CVR), which is a reduction in energy consumption resulting from a reduction in feeder voltage [5]. Although CVR leads to out-of-range voltages for some customers [6], it is widely used on account of its two key benefits: peak load reduction and lower annual energy consumption. In Korea, CVR is mainly used for peak load reduction (for example, five times in the summer of 2012 and twelve times in the winter of 2012). To analyze the effects of CVR at a national level, load modeling should first be carried out. Load modeling is the process of defining load characteristics via mathematical formulas that describe the characteristics of load changes in response to voltage and frequency variations. Load modeling techniques can be classified as either component based [7–11] or measurement based [12–24], depending on the modeling procedure. In component-based load modeling, measuring devices need not be installed in the field. However, this type of procedure is not efficient for describing the characteristics of rapidly changing loads, as each individual load must be analyzed in the laboratory before aggregating the loads. Component-based load modeling might be appropriate for use as a complement to measurement-based load modeling. On the other hand, measurement-based load modeling can accurately reflect load characteristics by direct measurement of the loads. Therefore, most current research on load modeling is focused on measurement-based methods, even though these methods require installation of an additional measuring device for every load in the power system. Measurement-based load modeling can be sub-classified into static load modeling [12–14] and dynamic load modeling [15–24]. Although dynamic load modeling can reflect the transient characteristics of loads, it requires high-density data samples on the time axis. In contrast, static load modeling requires relatively low-density data samples. In other words, when the measuring devices have low sampling rates, dynamic load modeling cannot be used, and only static load modeling is feasible. In this study, static load modeling was selected based on the realistic constraint that high-performance measuring devices, such as digital fault recorders and power quality meters, may not be installed on every bus in a modern power system.

The purpose of this paper is to propose a static load model for evaluating the effect of conservation voltage reduction at a national level. The model is defined as a linearized load model based on energy management system (EMS) data. The paper is divided into five sections, including this Introduction. Section 2 describes the formulation of the linearized load model, and Section 3 presents PSS/E simulation results for the model. In Section 4, the linearizing parameters for aggregated loads in an actual Korean power system are estimated. Our conclusions are presented in Section 5.

2. Linearized Load Modeling Based on EMS Data

Load modeling describes the characteristics of numerous intricately connected loads in a relatively brief way. In particular, static load modeling only includes the steady-state characteristics of the loads. ZIP modeling and exponential modeling are representative static load modeling methods. In contrast, dynamic load modeling includes both transient characteristics and steady-state characteristics.

State-variable equation modeling and induction-machine modeling are representative dynamic load modeling methods. Because EMS data are usually sampled every few seconds, they do not include the transient characteristics of loads. For example, in Korea, EMS data are sampled every 4 s. Therefore, it is not appropriate to use EMS data to estimate the parameters of dynamic load modeling. On the other hand, the parameters of static load modeling can be estimated using EMS data because only steady-state characteristics are required for static load modeling. In particular, ZIP modeling has a simple structure, and its parameters can be estimated with only a few data samples. Moreover, since ZIP modeling can represent the physical meaning of loads and it is used by many electrical companies to operate their power systems, it is one of the most appropriate modeling techniques for estimating parameters based on the EMS data. In ZIP modeling, a load is composed of constant impedance (Z), constant current (I), and constant power (P) elements. Assuming that k denotes the k^{th} conservation voltage reduction, the active power consumption of a load is given by:

$$P_{af}(k) = P_{bf}(k) \cdot p_Z \cdot \left(\frac{V_{af}(k)}{V_{bf}(k)} \right)^2 + P_{bf}(k) \cdot p_I \cdot \left(\frac{V_{af}(k)}{V_{bf}(k)} \right) + P_{bf}(k) \cdot p_P \quad (1)$$

where:

$$p_Z + p_I + p_P = 1,$$

$P_{bf}(k)$: Active power consumption of the load before the k^{th} conservation voltage reduction;

$P_{af}(k)$: Active power consumption of the load after the k^{th} conservation voltage reduction;

$V_{bf}(k)$: Terminal voltage before the k^{th} conservation voltage reduction;

$V_{af}(k)$: Terminal voltage after the k^{th} conservation voltage reduction;

p_Z : Constant impedance fraction of the active power consumption;

p_I : Constant current fraction of the active power consumption;

p_P : Constant power fraction of the active power consumption.

Similarly, the reactive power consumption of a load is given by:

$$Q_{af}(k) = Q_{bf}(k) \cdot q_Z \cdot \left(\frac{V_{af}(k)}{V_{bf}(k)} \right)^2 + Q_{bf}(k) \cdot q_I \cdot \left(\frac{V_{af}(k)}{V_{bf}(k)} \right) + Q_{bf}(k) \cdot q_P \quad (2)$$

where:

$$q_Z + q_I + q_P = 1,$$

$Q_{bf}(k)$: Reactive power consumption of the load before the k^{th} conservation voltage reduction;

$Q_{af}(k)$: Reactive power consumption of the load after the k^{th} conservation voltage reduction;

q_Z : Constant impedance fraction of the reactive power consumption;

q_I : Constant current fraction of the reactive power consumption;

q_P : Constant power fraction of the reactive power consumption.

For the sake of consistency, Equations (1) and (2) can be normalized as:

$$P_n(k) = p_Z \cdot V_n^2(k) + p_I \cdot V_n(k) + p_P \quad (3)$$

$$Q_n(k) = q_Z \cdot V_n^2(k) + q_I \cdot V_n(k) + q_P \quad (4)$$

where:

$$P_n(k) = \frac{P_{af}(k)}{P_{bf}(k)} : \text{Normalized active power consumption;}$$

$$Q_n(k) = \frac{Q_{af}(k)}{Q_{bf}(k)} : \text{Normalized reactive power consumption;}$$

$$V_n(k) = \frac{V_{af}(k)}{V_{bf}(k)} : \text{Normalized terminal voltage.}$$

Given that the values of $P_n(k)$, $Q_n(k)$, and $V_n(k)$ can be obtained from EMS data, the active ZIP parameters (p_Z , p_I , p_P) and the reactive ZIP parameters (q_Z , q_I , q_P) are to be estimated.

To estimate the active ZIP parameters, the active objective function is defined as:

$$\min \sum_k \{p_Z \cdot V_n^2(k) + p_I \cdot V_n(k) + p_P - P_n(k)\}^2 \quad (5)$$

subject to: $p_Z + p_I + p_P = 1$; $p_Z \geq 0$, $p_I \geq 0$, $p_P \geq 0$.

If $\Delta V_n(k)$ denotes the voltage variation due to the k^{th} conservation voltage reduction, Equation (3) can be modified to:

$$P_n(k) = p_Z \cdot (1 + \Delta V_n(k))^2 + p_I \cdot (1 + \Delta V_n(k)) + p_P \quad (6)$$

This can be rearranged as follows:

$$\begin{aligned} P_n(k) &= p_Z \cdot (1 + 2\Delta V_n(k) + \Delta V_n^2(k)) + p_I \cdot (1 + \Delta V_n(k)) + p_P \\ &= (p_Z + p_I + p_P) + (2p_Z + p_I) \cdot \Delta V_n(k) + p_Z \cdot \Delta V_n^2(k) \\ &= 1 + (2p_Z + p_I) \cdot \Delta V_n(k) + p_Z \cdot \Delta V_n^2(k) \end{aligned} \quad (7)$$

Assuming that the voltage variation is small compared to the nominal voltage, Equation (7) can be simplified to:

$$P_n(k) \cong 1 + (2p_Z + p_I) \cdot \Delta V_n(k) = 1 + p_C \cdot \Delta V_n(k) \quad (8)$$

Note that Equation (8) is the basic form of linearized load modeling corresponding to the active power consumption of an aggregated load. In Equation (8), $p_C = 2p_Z + p_I$, and p_C is defined as an active linearizing parameter in this paper. Actually, this linearizing parameter can be used as an index to indicate the effect of conservation voltage reduction. When the voltage reduction in Equation (8) is constant, the reduction in normalized active power consumption increases linearly with respect to the active linearizing parameter.

It is reported that conservation voltage reduction is usually executed in the range of 2.0%–5.0% [25–27]. Accordingly, in this paper, the upper limit of voltage reduction is assumed to be 5.0%. By comparing Equations (7) and (8), the simplification error is readily seen to be $p_Z \cdot \Delta V_n^2(k)$, and this error is maximized when the load consists entirely of constant impedance, *i.e.*, $p_Z = 1.0$. Therefore, the maximum simplification error is 0.25% for a conservation voltage reduction. Since this error is quite small compared with the normalized active power consumption, it can be neglected, and hence

Equation (6) can be simplified to the linearized load model represented by Equation (8). Consequently, the active objective function of Equation (5) can be simplified to:

$$\min \sum_k \{1 + p_C \cdot \Delta V_n(k) - P_n(k)\}^2 \quad (9)$$

The equivalence of Equations (5) and (9) means that it is difficult to accurately determine the active ZIP parameters using EMS data resulting from conservation voltage reductions. Instead, only the relationship between the active ZIP parameters (*i.e.*, the active linearizing parameter) can be found. Therefore, when using EMS data resulting from conservation voltage reductions, the active linearizing parameter should be estimated instead of the active ZIP parameters. In a similar manner, the reactive objective function (corresponding to reactive power consumption) can be also simplified to:

$$\min \sum_k \{1 + q_C \cdot \Delta V_n(k) - Q_n(k)\}^2 \quad (10)$$

where $q_C = 2q_Z + q_I$, and q_C is defined as a reactive linearizing parameter. Equation (10) is the basic form of linearized load modeling corresponding to the reactive power consumption of an aggregated load. The reactive linearizing parameter should also be estimated using EMS data resulting from conservation voltage reductions.

3. Verification of the Linearized Load Model Using PSS/E Simulations

To verify the validity of the linearized load model, PSS/E simulations were performed for a test power system called SAVNW [28]. The test power system is provided by PSS/E and is depicted in Figure 1. The base frequency and base capacity were set at 60 Hz and 100 MVA respectively. To evaluate the effect of conservation voltage reduction, the test power system was modified to include a load connected through a distribution transformer. For this purpose, a new distribution bus 1531 was created, and was connected to transmission bus 153 via a distribution transformer with a leakage reactance of 0.1 pu. To preserve the load balance, the original load at transmission bus 153 was moved to the distribution bus 1531.

In the simulations, conservation voltage reductions were executed in two steps. In the first step, a voltage reduction of 2.5% was executed, and an additional voltage reduction of 2.5% was then executed in the second step. At the distribution bus 1531, the initial active power consumption of the load was 200 MW, and its active ZIP parameters were assigned the values $p_Z = 0.35$, $p_I = 0.13$, and $p_P = 0.52$, which are typical values used by Korea Electric Power Corporation (KEPCO). To evaluate the effect of the active linearizing parameter on conservation voltage reduction, it was assumed that the active ZIP parameters of the load were unknown, while the active linearizing parameter p_C was known to be 0.83. This is because the active linearizing parameter can be estimated using EMS data from conservation voltage reductions, and its value will be 0.83, as $p_C = 2p_Z + p_I$.

For comparison, two worst cases were considered: the p_Z^{\max} case (where p_Z has the maximum value) and the p_I^{\max} case (where p_I has the maximum value). Table 1 summarizes the active power variations due to conservation voltage reduction with different active ZIP parameters.

Figure 1. Test power system.

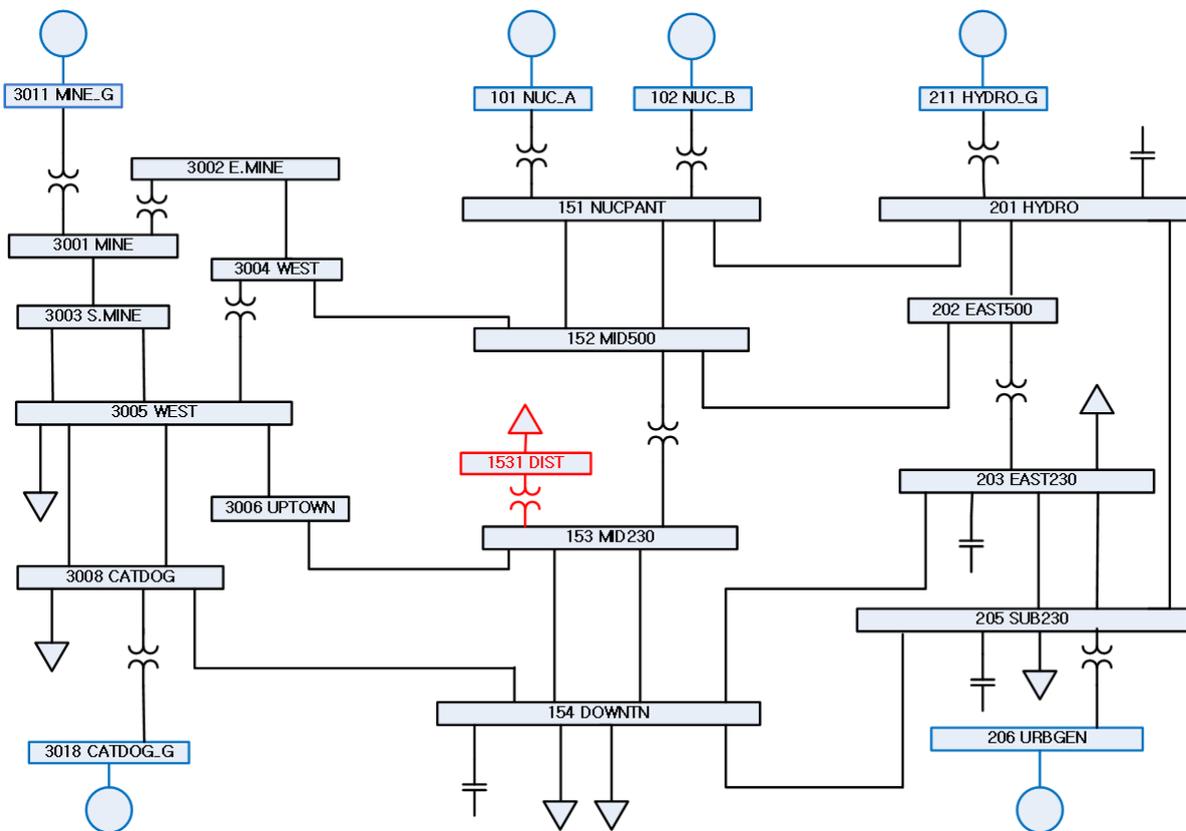


Table 1. Active power variations due to voltage reductions with different active ZIP parameters.

Model type	Case	ZIP parameter			Linearizing parameter	Voltage reduction (%)		
		p_Z	p_I	p_P		0.0	2.5	5.0
						Active power (MW)		
ZIP Model	KEPCO	0.350	0.130	0.520	0.830	200.0	195.9	192.0
Linearized	p_I^{\max}	0.000	0.830	0.170	0.830	200.0	195.9	191.8
Load Model	p_Z^{\max}	0.415	0.000	0.585	0.830	200.0	195.9	192.0

In the p_I^{\max} case, p_I was set equal to 0.83, as p_C must retain the value 0.83. Consequently, p_Z and p_P were set equal to 0.00 and 0.17, respectively. As Table 1 indicates, the active power savings in this case were almost identical to those of the actual ZIP model. With a 5.0% voltage reduction, the active power error was only -0.104% . In the p_Z^{\max} case, the active ZIP parameters were assigned the values $p_Z = 0.415$, $p_I = 0.000$ and $p_P = 0.585$. As in the p_I^{\max} case, the active power savings were almost identical to those of the actual ZIP model.

At the distribution bus 1531, the initial reactive power consumption of the load was 100 MVAR, and its reactive ZIP parameters were assigned the values $q_Z = 0.56$, $q_I = 0.08$ and $q_P = 0.36$, which are also typical values used by KEPCO. As in the active power cases, it was assumed that the reactive ZIP parameters were unknown, but the reactive linearizing parameter q_C was known to be 1.20. This is because the reactive linearizing parameter can be estimated using EMS data from conservation voltage reductions, and its value will be 1.20 because $q_C = 2q_Z + q_I$. Table 2 summarizes the reactive power

variations due to conservation voltage reductions with different reactive ZIP parameters. In the q_I^{\max} case, q_I was set equal to 0.80, as $(2q_Z + q_I)$ must retain the value 1.20, and $(q_Z + q_I)$ should not exceed 1.00. Consequently, q_Z and q_P were set equal to 0.20 and 0.00, respectively. As Table 2 indicates, the reactive power savings in the q_I^{\max} case were almost identical to those of the actual ZIP model. With a 5.0% voltage reduction, the reactive power error was only -0.106% . In the q_Z^{\max} case, the reactive ZIP parameters were assigned the values $q_Z = 0.60$, $q_I = 0.00$, and $q_P = 0.40$. As in the q_I^{\max} case, the reactive power savings in the q_Z^{\max} case are almost identical to those of the actual ZIP model.

Thus, it was demonstrated that the linearized load model is sufficient to accurately evaluate the effect of conservation voltage reduction.

Table 2. Reactive power variations due to voltage reductions with different reactive ZIP parameters.

Model type	Case	ZIP parameter			Linearizing parameter q_C	Voltage reduction (%)		
		q_Z	q_I	q_P		0.0	2.5	5.0
ZIP Model	KEPCO	0.560	0.080	0.360	1.200	100.0	97.10	94.20
Linearized Load Model	q_I^{\max}	0.200	0.800	0.000	1.200	100.0	97.00	94.10
	q_Z^{\max}	0.600	0.000	0.400	1.200	100.0	97.10	94.20

4. Modeling Aggregated Loads Based on EMS Data

Korean EMS data were used to estimate the linearizing parameters for the loads in an actual power system. These data are sampled every 4 s from 1746 transformer banks at the various substations. Since raw Korean EMS data are saved for each individual transformer bank, aggregated loads were modeled for each of them. To find the linearizing parameters for the aggregated loads, more than two sets of conservation voltage reduction data are required for each transformer bank, and thus it was assumed that the transformer bank loads have the same linearizing parameters for the same season and time of day. The raw EMS data were divided into four groups according to the season: spring (March–May), summer (June–August), fall (September–November), and winter (December–February). Each group was subdivided into three subgroups according to the time of day: daytime (08:00–16:00), evening (16:00–24:00), and night (24:00–08:00).

Details of the data acquisition process are described in [14]. The voltage, active power, and reactive power are continuously monitored by a data acquisition program connected to the Korean EMS. The data are saved when the voltage variation is greater than 1% (six samples before voltage variation, and 20 samples afterwards). The saved data are periodically checked and are utilized to find the linearizing parameters for the transformer bank loads.

4.1. Case I: 344th Transformer Bank

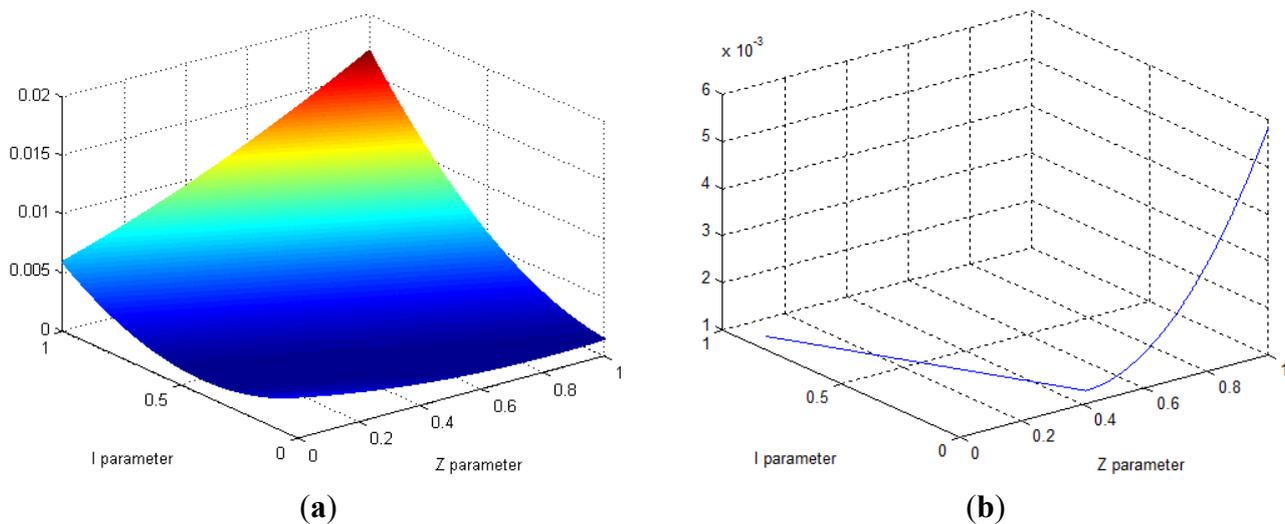
Table 3 lists a portion of the Korean EMS data for the 344th transformer bank, for voltage variations occurring on winter evenings. Using the data in this table, the active objective function of Equation (9) was calculated, and the results are shown in Figure 2a. Figure 2b shows the minimum

active objective function errors according to the variation in p_Z . As Figure 2b indicates, the minimum errors are almost the same at points where the active linearizing parameter p_C is equal to 0.818. This means that it is difficult to find ZIP parameters using EMS data from conservation voltage reductions, as was mentioned in Section 2. Therefore, the linearizing parameter is more appropriate for modeling aggregated loads when using EMS data from conservation voltage reductions.

Table 3. Korean EMS data for the 344th transformer bank on winter evenings

Variation number	Voltage (kV)		Active power (MW)		Reactive power (MVAR)	
	Before	After	Before	After	Before	After
1	23.925	23.525	23.856	23.300	6.6667	6.4755
2	23.869	23.449	22.551	22.340	5.4362	5.3044
3	23.948	23.578	22.345	22.123	4.2452	4.0826
4	24.052	23.633	21.611	21.380	3.6168	3.5685
5	23.885	23.288	24.498	24.267	2.4412	2.3731

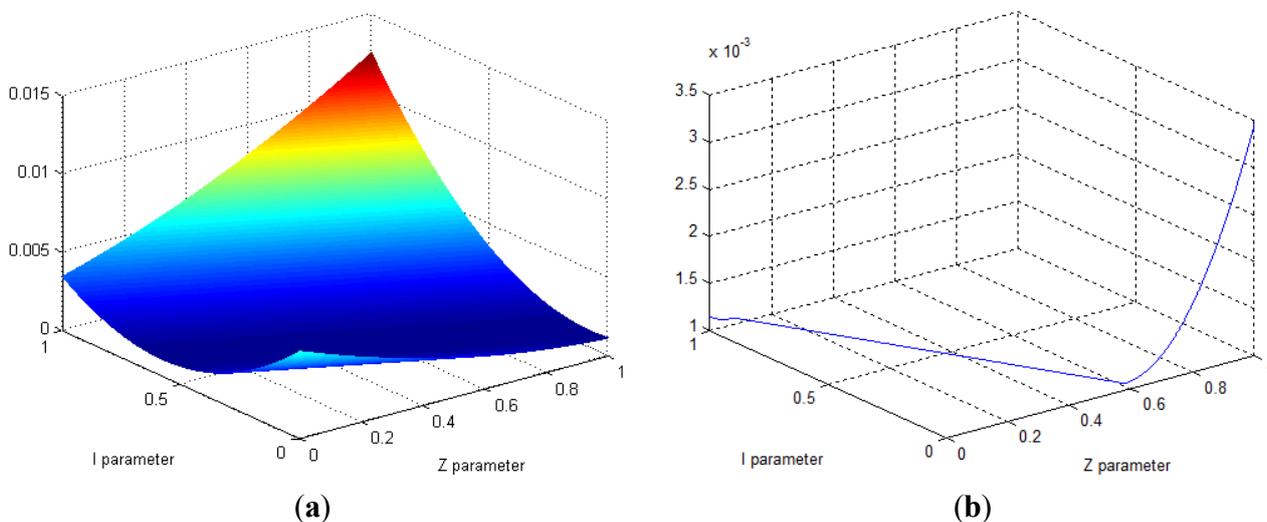
Figure 2. Active power results for the 344th transformer bank on winter evenings: (a) errors obtained from the active objective function; (b) minimum active objective function errors according to the variation in p_Z .



To estimate the reactive linearizing parameter for the reactive load of the 344th transformer bank on winter evenings, the reactive objective function of Equation (10) was also calculated, and the results are shown in Figure 3a. Figure 3b shows the minimum reactive objective function errors according to the variation in q_Z . The results are similar to those obtained for the active objective function, and the minimum errors are almost the same at points where the reactive linearizing parameter q_C is equal to 1.155.

Therefore, for the 344th transformer bank on winter evenings, the estimated values of the active and reactive linearizing parameters are 0.818 and 1.155, respectively, which are close to the typical values used by KEPCO (Seoul, Korea).

Figure 3. Reactive power results for the 344th transformer bank on winter evenings: (a) errors obtained from the reactive objective function; (b) minimum reactive objective function errors according to the variation in q_z .



4.2. Case II: 1509th Transformer Bank

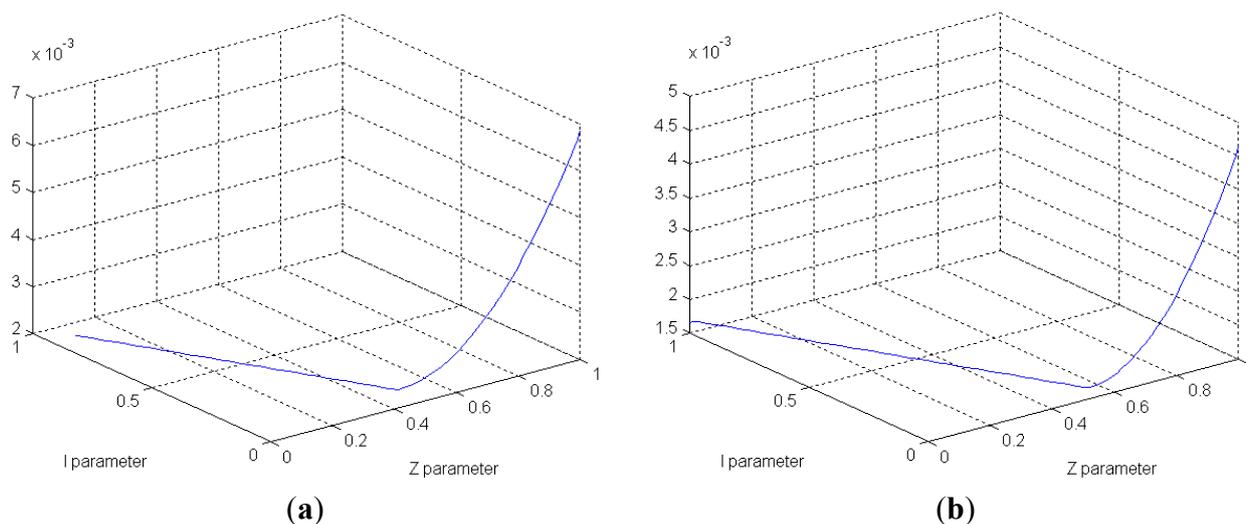
Table 4 lists a portion of the EMS data for the 1509th transformer bank, for voltage variations occurring on summer days.

As in the previous case, the active and reactive objective functions of Equations (9) and (10) were calculated using the EMS data from the table. Figure 4a,b show the minimum errors of the active and reactive objective functions according to the variation in p_z and q_z , respectively. As the figures indicate, the estimated values of the active and reactive linearizing parameters are 0.823 and 1.029, respectively. In this case, the active linearizing parameter is close to the typical value used by KEPCO, but the reactive linearizing parameter differs somewhat from the typical value.

Table 4. Korean EMS data for the 1509th transformer bank on summer days.

Variation number	Voltage (kV)		Active power (MW)		Reactive power (MVAR)	
	Before	After	Before	After	Before	After
1	24.085	23.669	28.503	28.389	6.7556	6.6122
2	23.662	23.215	19.472	19.384	4.8135	4.7296
3	24.085	23.639	37.74	37.662	6.3672	6.2591
4	23.662	23.180	19.269	19.203	2.0635	2.0415
5	24.088	23.675	33.897	32.390	7.9982	7.9739

Figure 4. Results for the 1509th transformer bank on summer days: **(a)** minimum active objective function errors according to the variation in p_Z , **(b)** minimum reactive objective function errors according to the variation in q_Z .



4.3. Case III: 346th Transformer Bank

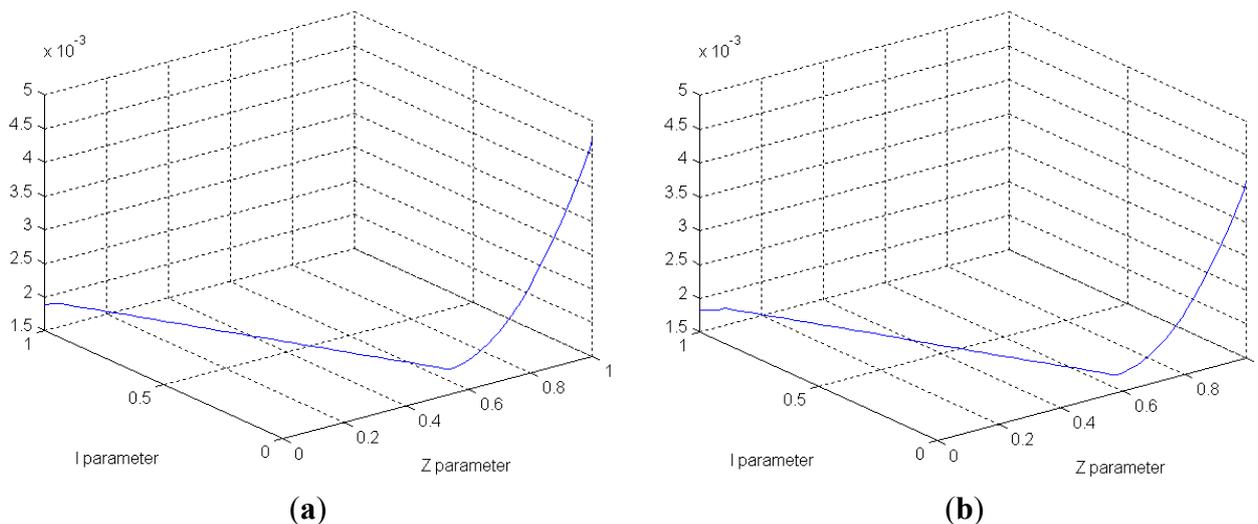
Table 5 lists a portion of the EMS data for the 346th transformer bank, for voltage variations occurring on summer days.

The active and reactive objective functions of Equations (9) and (10) were calculated using the EMS data from the table. Figure 5a,b show the minimum errors of the active and reactive objective functions according to the variation in p_Z and q_Z , respectively. As the figure indicates, the estimated values of the active and reactive linearizing parameters are 1.067 and 1.152, respectively. In contrast to the results of Case II, the reactive linearizing parameter is close to the typical value used by KEPCO, but the active linearizing parameter differs somewhat from the typical value.

Table 5. Korean EMS data for the 346th transformer bank on summer days.

Variation number	Voltage (kV)		Active power (MW)		Reactive power (MVAR)	
	Before	After	Before	After	Before	After
1	23.761	23.347	15.146	15.030	3.5245	3.5201
2	23.533	23.175	16.669	16.643	5.4516	5.3461
3	23.462	23.037	17.495	17.458	5.5834	5.4823
4	23.575	23.099	17.500	17.344	5.5351	5.3153
5	23.887	23.519	17.330	17.280	4.9352	4.9110

Figure 5. Results for the 346th transformer bank on summer days: (a) minimum active objective function errors according to the variation in p_Z ; (b) minimum reactive objective function errors according to the variation in q_Z .



4.4. Case IV: 673th Transformer Bank

Table 6 lists a portion of the EMS data for the 673th transformer bank, for voltage variations occurring on winter evenings.

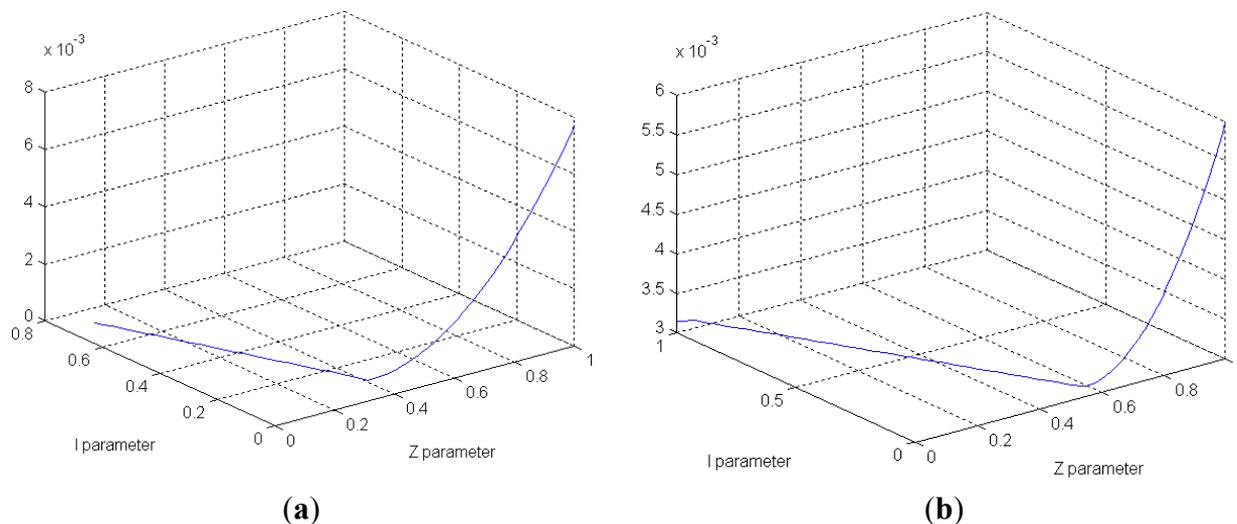
The active and reactive objective functions of Equations (9) and (10) were calculated using the EMS data in the table. Figure 6a,b show the minimum errors of the active and reactive objective function according to the variation in p_Z and q_Z , respectively. As the figure indicates, the estimated values of the active and reactive linearizing parameters are 0.628 and 1.092, respectively. In this case, the active and reactive linearizing parameters both differ somewhat from the typical values used by KEPCO.

Comparison of the estimation results from Case I to Case IV shows that typical values cannot be used as linearizing parameters for all aggregated loads, especially during different seasons and at different times of day. Therefore, to accurately evaluate the effect of conservation voltage reduction, linearizing parameters should be separately estimated according to the transformer bank, season, and time of day.

Table 6. Korean EMS data for the 673th transformer bank on winter evenings

Variation number	Voltage (kV)		Active power (MW)		Reactive power (MVAR)	
	Before	After	Before	After	Before	After
1	23.444	23.091	5.8985	5.7845	181.83	180.37
2	23.398	23.751	1.0472	1.0551	200.83	201.88
3	24.105	23.740	0.9336	0.9183	179.30	175.19
4	23.205	22.856	3.1273	3.1125	205.57	196.50
5	23.419	23.046	3.2868	3.2719	182.35	174.01

Figure 6. Results for the 673th transformer bank on winter evenings: (a) minimum active objective function errors according to the variation in p_z ; (b) minimum reactive objective function errors according to the variation in q_z .



5. Conclusions

This paper proposed an EMS-data-based static load model for evaluating the effect of conservation voltage reduction at a national level. Because EMS data are saved for each transformer bank, an aggregated load model is required to use these data for static load modeling. Although a ZIP model is one of the most appropriate load models due to its simple structure and practicality, it cannot be used for aggregated load modeling based on EMS data resulting from conservation voltage reductions. Given that conservation voltage reductions are usually executed in the range of 2.0%–5.0%, it is difficult to accurately determine ZIP parameters using EMS data obtained from conservation voltage reductions. Therefore, this paper introduced a linearized model for aggregated static loads. In this linearized model, the active and reactive linearizing parameters are estimated for the active and reactive loads, respectively, using EMS data from conservation voltage reductions. Since EMS is widely used in modern power systems, and its data are readily available, the linearized load model can be used to evaluate the effect of conservation voltage reduction without installing additional measuring devices.

To verify the validity of the linearized load model, PSS/E simulations were conducted for a test power system, and the linearized load model was found to be sufficient to accurately evaluate the effect of conservation voltage reduction. Korean EMS data were used to estimate the linearizing parameters for transformer bank loads in an actual power system. Assuming that the transformer bank loads have the same linearizing parameters for the same season and time of day, raw EMS data were divided into four groups according to the season, and each group was subdivided into three subgroups according to the time of day. The linearizing parameters were estimated using EMS data for each subgroup. As expected, the estimation results for the linearizing parameters varied according to transformer bank, season, and time of day. Thus, to evaluate the effect of conservation voltage reduction, linearizing parameters must first be accurately estimated for each transformer bank, season, and time of day. For this purpose, EMS data are continuously being accumulated. Once a sufficient

quantity of EMS data has been secured, it will be possible to evaluate and forecast the effect of conservation voltage reduction via linearized load modeling.

Acknowledgments

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. 2011-0011432).

Conflict of Interest

The authors declare no conflict of interest.

References

1. Amin, S.M.; Gellings, C.W. The North American power delivery system: Balancing market restructuring and environmental economics with infrastructure security. *Energy* **2006**, *31*, 967–999.
2. Dong, C.; Huang, G.H.; Cai, Y.P.; Xu, Y. An interval-parameter minimax regret programming approach for power management systems planning under uncertainty. *Appl. Energy* **2011**, *88*, 2835–2845.
3. Cai, Y.P.; Huang, G.H.; Tan, Q.; Yang, Z.F. An integrated approach for climate-change impact analysis and adaptation planning under multi-level uncertainties—Part I: Methodology. *Renew. Sustain. Energy Rev.* **2011**, *15*, 2779–2790.
4. Zeng, Y.; Cai, Y.P.; Huang, G.H.; Dai, J. A review on optimization modeling of energy systems planning and GHG emission mitigation under uncertainty. *Energies* **2011**, *4*, 1624–1656.
5. De Steese, J.G.; Merrick, S.B.; Kennedy, B.W. Estimating methodology for a large regional application of conservation voltage reduction. *IEEE Trans. Power Syst.* **1990**, *5*, 862–870.
6. Belvin, R.C.; Short, T.A. Voltage Reduction Results on a 24-kV Circuit. In Proceedings of IEEE PES Transmission and Distribution Conference and Exposition (T&D), Orlando, FL, USA, 7–10 May 2012; pp. 1–4.
7. Chen, C.S.; Wu, T.H.; Lee, C.C.; TzengJoseph, Y.M. The application of load models of electric appliances to distribution system analysis. *IEEE Trans. Power Syst.* **1995**, *10*, 1376–1382.
8. Price, W.W.; Wirgau, K.A.; Murdoch, A.; Mitsche, J.V.; Vaahedi, E.; El-Kady, M. Load modeling for power flow and transient stability computer studies. *IEEE Trans. Power Syst.* **1988**, *3*, 180–187.
9. Kim, J.; Shim, K.B.; Kim, J.H. Load modeling of electric locomotive using parameter identification. *J. Electr. Eng. Technol.* **2007**, *2*, 145–151.
10. Chang, H.H. Non-intrusive demand monitoring and load identification for energy management systems based on transient feature analyses. *Energies* **2012**, *5*, 4569–4589.
11. Ahmed, Z.; Alexander, G.; Muhammad, A.I.; Sutharshan, R. Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey. *Sensors* **2012**, *12*, 16838–16866.
12. Dias, L.G.; El-Hawary, M.E. Nonlinear parameter estimation experiments for static load modelling in electric power systems. *IEEE Proc. C Gener. Trans. Distrib.* **1989**, *136*, 68–77.

13. Li, Y.; Chiang, H.D.; Choi, B.K.; Chen, Y.T.; Huang, D.H.; Lauby, M.G. Representative static load models for transient stability analysis: Development and examination. *IEEE Proc. C Gener. Trans. Distrib.* **2007**, *1*, 422–431.
14. Lee, S.H.; Son, S.E.; Lee, S.M.; Cho, J.M.; Song, K.B.; Park, J.W. Kalman-filter based static load modeling of real power system using K-EMS data. *J. Electr. Eng. Technol.* **2012**, *7*, 304–311.
15. Hiskens, I.A. Nonlinear dynamic model evaluation from disturbance measurements. *IEEE Trans. Power Syst.* **2001**, *16*, 702–710.
16. Pereira, L.; Kosterev, D.; Mackin, P.; Davies, D.; Undrill, J.; Zhu, W. An interim dynamic induction motor model for stability studies in the WSCC. *IEEE Trans. Power Syst.* **2002**, *17*, 1108–1115.
17. Knyazkin, V.; Canizares, C.A.; Soder, L.H. On the parameter estimation and modeling of aggregate power system loads. *IEEE Trans. Power Syst.* **2004**, *19*, 1023–1031.
18. Renmu, H.; Jin, M.; Hill, D.J. Composite load modeling via measurement approach. *IEEE Trans. Power Syst.* **2006**, *21*, 663–672.
19. Choi, B.K.; Chiang, H.D.; Li, Y.; Li, H.; Chen, Y.T.; Huang, D.H.; Lauby, M.G. Measurement-based dynamic load models: Derivation, comparison, and validation. *IEEE Trans. Power Syst.* **2006**, *21*, 1276–1283.
20. Jin, M.; Dong, H.; He, R.M.; Dong, Z.Y.; Hill, D.J. Reducing identified parameters of measurement-based composite load model. *IEEE Trans. Power Syst.* **2008**, *23*, 76–83.
21. Choi, B.K.; Chiang, H.D. Multiple solutions and plateau phenomenon in measurement-based load model development: Issues and suggestions. *IEEE Trans. Power Syst.* **2009**, *24*, 824–831.
22. Bai, H.; Zhang, P.; Ajarapu, V. A novel parameter identification approach via hybrid learning for aggregate load modeling. *IEEE Trans. Power Syst.* **2009**, *24*, 1145–1154.
23. Chen, Q.; Jua P.; Shi, K.Q.; Tang, Y.; Shao, Z.Y.; Yang, W.Y. Parameter estimation and comparison of the load models with considering distribution network directly or indirectly. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 965–968.
24. Liang, X.; Xu, W.; Chung, C.Y.; Freitas, W.; Xiong, K. Dynamic load models for industrial facilities. *IEEE Trans. Power Syst.* **2012**, *27*, 69–80.
25. Independent Electricity System Operator (IESO). *Voltage Reduction Test Report*; IESO: Ontario, Canada, 2010; pp. 5–6.
26. System Operations Division. *Emergency Operations Manual*; PJM: Valley Forge, PA, USA, 2011; pp. 32–33.
27. Electricity Regulatory Commission. *Korean Electricity Market Rule*; Korea Power Exchange: Seoul, Korea, 2013; pp. 46–48.
28. Siemens Power Technologies International. *PSS/E Program Operation Manual*; Siemens Industry: Schenectady, NY, USA, 2010; pp. 1339–1345.